Assimilation of screen-level variables for soil moisture analysis into the multilayer soil model INM RAS - MSU

Svetlana Travova [1], Mikhail Tolstykh [1, 2]

[1] : Hydrometcenter of Russia, Moscow, Russia; makhnorylova@gmail.com

[2] : G.I.Marchuk Institute of Numerical Mathematics of the Russian Academy of Sciences (INM RAS), Moscow, Russia

Outline

- SL-AV global atmosphere model
- Multilayer soil model INM RAS-MSU
- Assimilation of scree-level variables for soil moisture analysis of INM RAS-MSU model
- Observation operator of SEKF
- Results of numerical experiments

SL-AV global atmosphere model

(Semi-Lagrangian, based on Absolute Vorticity equation)

Russian global atmosphere model, that is used for operational forecasts in Hydrometcenter of Russia

- It has *original* dynamical core (finite-difference semi-implicit semi-Lagrangian) in vorticity-divergence formulation (unstaggered grid (Z grid), 4th order finite differences, option for variable resolution in latitude)
- Many parameterization algorithms from ALADIN/ALARO consortium
- RRTMG-LW, CLIRAD SW radiation
- Own developments: multilayer soil model, sea ice treatment, marine stratocumulus

10-days operational medium-range forecasts
0.225° in lon, 0.16°-0.24° in lat, 51 levs.
0.1° in lon 0.08-0.12° in lat 104 lev under trials

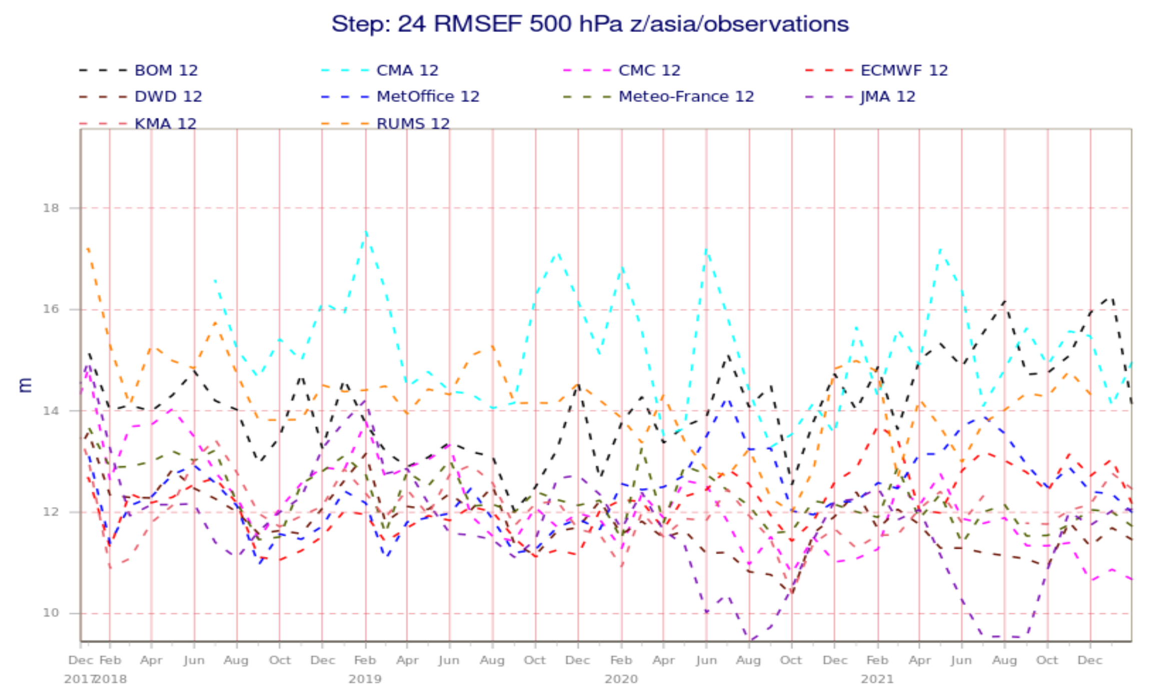
LETKF-based ensemble prediction system
0.9° in lon, 0.72° in lat, 96 levs

***Tolstykh M., Shashkin V., et.al** .Vorticity-divergence semi-Lagrangian global atmospheric model SL-AV20: dynamical core. - Geosci. Model Dev., 10, 1961–1983, 2017*

SL-AV global atmosphere model

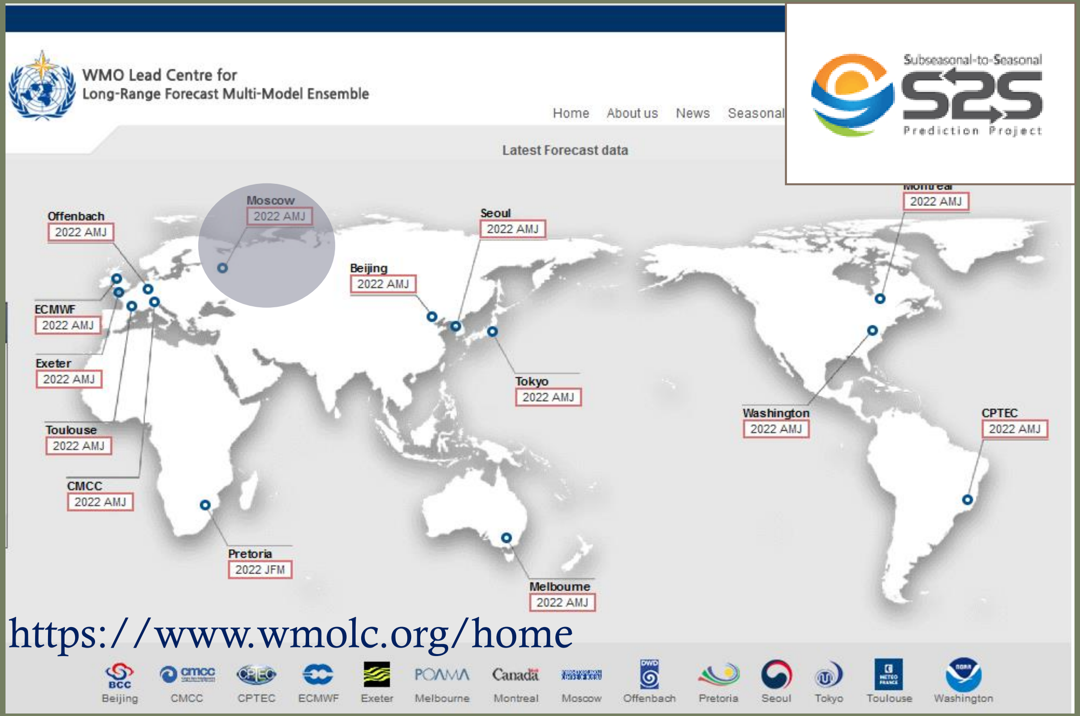
Forecasts & verification

10-days operational medium range forecasts



Lead Centre for Deterministic Numerical Weather Prediction (NWP)
Verification: http://apps.ecmwf.int/wmolcdnv/

Subseasonal and seasonal probabilistic forecasts



https://www.wmolc.org/home

WMO S2S Prediction project

1.4°x1.1°L28 currently,
0.9°x0.72°L96, by the end of this year.

The multilayer soil model INM RAS-MSU

is used in the weather forecast system SL-AV and
INM RAS climate model (INMCM, CMIP program)

$$\rho C \frac{\partial T}{\partial t} = \frac{\partial}{\partial z}\lambda \frac{\partial T}{\partial z} + L_i \rho F_i - L_v \rho F_v \ ,$$

$$\frac{\partial W_l}{\partial t} = \frac{\partial}{\partial z}\lambda_l \left(\frac{\partial W_l}{\partial z} + \delta \frac{\partial T}{\partial z} \right) + \frac{\partial \gamma}{\partial z} - F_i - F_v - R - E_r \ ,$$

$$\frac{\partial W_v}{\partial t} = \frac{\partial}{\partial z}\lambda_v \frac{\partial W_v}{\partial z} + F_v \ ,$$

$$\frac{\partial W_i}{\partial t} = F_i$$

t - time, *sec*; z – depth, *cm*;

T — soil temperature, °*C*;

W_l, W_v, W_i — mass soil water content (as fractions of dry soil mass) in liquid, gaseous (water vapor) and solid (ice) state respectively, *gr*/*gr*;

C — specific (per unit mass of dry soil) soil heat capacity, *cal*/(*gr* · *K*);

ρ – density of dry soil, gr/cm^3;

λ — soil heat conductivity coefficient, *cal*/(*cm*·*sec*·*K*);

λ_l, λ_v — liquid water and water vapor diffusion coefficients in soil, cm^2/sec;

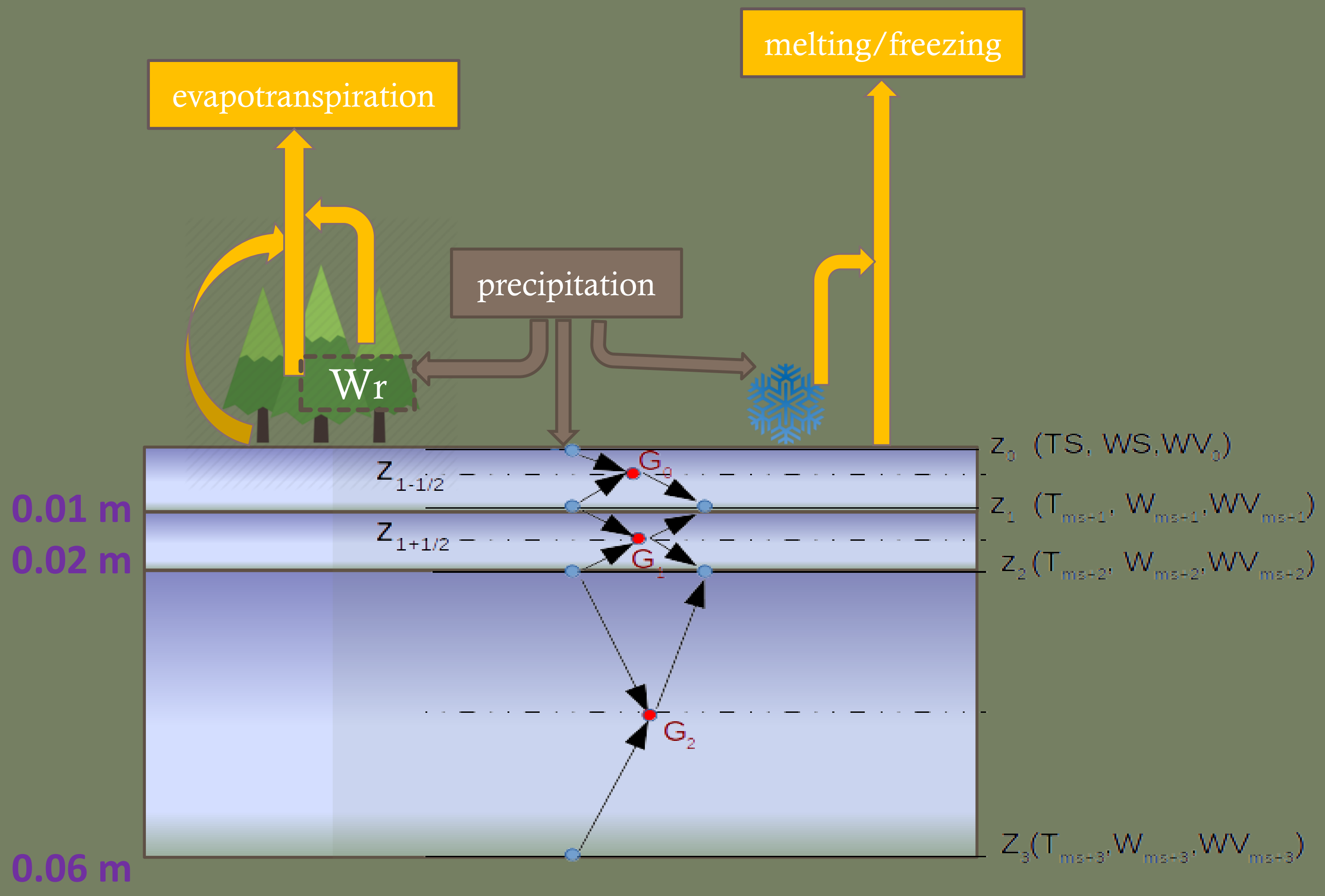
γ — hydraulic conductivity coefficient, *cm*/*sec*;

L — specific heat of melting/freezing, *cal*/gr;

F_i, R, E_r — the speed of freezing (melting) water, subsurface runoff and water uptake by roots respectively, sec^{-1}.

Volodin E.M. and Lykosov V.N. *Parametrization of heat and moisture transfer in the soil-vegetation system for use in atmospheric general circulation models: 1. Formulation and simulations based on local observational data. – Izvestiya. Atmospheric and Oceanic Physics, 1998, vol. 34, № 4, pp. 405-416.*

The multilayer soil model INM RAS-MSU + surface processes from ISBA



Atmospheric forcing for the soil model :

- precipitation
- radiation
- low level model temperature and specific humidity
- low level model horizontal components of the wind speed

Prognostic variables of the soil model:

- soil moisture (8 layers)
- ice soil (8 layers)
- water vapor (8 layers)
- soil temperature (8 layers)
- snow water equivalent

Root fractions:

[0.0412, 0.0437, 0.14, 0.28, 0.31, 0.16, 0.0196]

Depths of soil levels:

0, 1, 2, 6, 18, 54, 162, 486, 1458 cm

Travova S.V., Stepanenko V.M., et al. *Quality of soil simulation by the INM RAS-MSU soil scheme as a part of the SL-AV weather prediction model. – Russian Meteorology and Hydrology, 2022.*

The simplified extended Kalman filter

(“dynamical” optimal interpolation; Balsamo J.-P. 2004, Mahfouf J.-F. 2009, 2010)

Forecast step

$$\mathbf{w}^b_{t_2} = M_{t_1}\left(\mathbf{w}^a_{t_1}\right)$$

$\mathbf{w}^b_{t_2}$ - forecast vector of deep soil moisture [w_n, w_{n+1}]

$\mathbf{w}^a_{t_1}$ - previous analysis vector [w_n, w_{n+1}]

M_{t_1} - forecast model operator

Analysis step

$$\boldsymbol{w}^a_{t_1} = \boldsymbol{w}^b_{t_1} + \mathbf{K}_{t_1}\left[\mathbf{y}_{t_1} - H_{0\rightarrow 1,t_1}\left(\boldsymbol{w}^b_{t_0}\right)\right]$$

$\mathbf{y}_{t_1}$ - observation vector at moment t_1 (screen-level temperature and relative humidity at grid point);

$H_{0\rightarrow 1,t_1}\left(\boldsymbol{w}^b_{t_0}\right)$ - fist guess of screen-level temperature and relative humidity (non-linear observation operator);

$\mathbf{K}_{t_1}$ - Kalman gain matrix at moment t_1.

Kalman gain matrix

$$\mathbf{K}_{t_1} = \mathbf{B}\mathbf{H}^T_{0\rightarrow 1,t_1}\left(\mathbf{H}_{0\rightarrow 1,t_1}\mathbf{B}\mathbf{H}^T_{0\rightarrow 1,t_1} + \mathbf{R}\right)^{-1},$$

$\mathbf{B}$ - background error covariance matrix;

$\mathbf{R}$ - observation error covariance matrix;

$\mathbf{H}_{0\rightarrow 1,t_1}$ - linear observation operator.

$$\mathbf{R} = \begin{pmatrix} \sigma^2_{T_{2M}} & 0 \\ 0 & \sigma^2_{RH_{2M}} \end{pmatrix} \qquad \mathbf{B} = \begin{pmatrix} \sigma^2_{b_n} & \sigma_{b_n}\sigma_{b_{n+1}} \\ \sigma_{b_{n+1}}\sigma_{b_n} & \sigma^2_{b_{n+1}} \end{pmatrix}$$

$$\sigma_{T_{2\mathrm{M}}} = 1K, \quad \sigma_{\mathrm{RH}_{2\mathrm{M}}} = 10\% \qquad \sigma_{w_{b_n}} = 0.2\left(w_{fc_n} - w_{wilt_n}\right)$$

Linear estimation of observation operator H

Using finite differences, we have:

$$H_{0\to 1,t_1}\left(\boldsymbol{w}^b_{t_0} + \delta w_{t_0}\right) \cong H_{0\to 1,t_1}\left(\boldsymbol{w}^b_{t_0}\right) + \mathbf{H}_{0\to 1,t_1}\left(\boldsymbol{w}^b_{t_0}\right)\delta w_{t_0}$$

$$\downarrow$$

$$\mathbf{H}_{0\to 1,t_1}(\boldsymbol{w}^b_{t_0}) = \frac{H_{0\to 1,t_1}\left(\boldsymbol{w}^b_{t_0} + \delta w_{t_0}\right) - H_{0\to 1,t_1}(w)}{\delta w_{t_0}}$$

$$\mathbf{H}_{0\to 1,t_1}\left(\boldsymbol{w}^b_{t_0}\right) = \begin{pmatrix} \dfrac{\partial T^{t_1}_{2\text{м}}}{\partial w_{n,t_0}} & \dfrac{\partial T^{t_1}_{2\text{м}}}{\partial w_{n+1,t_0}} \\ \dfrac{\partial RH^{t_1}_{2\text{м}}}{\partial w_{n,t_0}} & \dfrac{\partial RH^{t_1}_{2\text{м}}}{\partial w_{n+1,t_0}} \end{pmatrix}$$

$\delta w_{n,t_0}$ - perturbation of n-th soil layer;

$$\delta w_n = [weight_n \cdot SWI_n, weight_{n+1} \cdot SWI_{n+1}]$$

$$SWI_n = \frac{w_n - w_{wilt_n}}{w_{fc_n} - w_{wilt_n}}$$

To check that these perturbations are small enough to reproduce tangent linear behavior of the observation operator, the Jacobians computed with positive and negative perturbations:

$$\frac{\partial T^{+,t_1}_{2\text{м}}}{\partial w_{n,t_0}} = \frac{T^{t_1}_{2\text{м}}\left(w_{n,t_0} + \delta w_{n,t_0}\right) - T^{t_1}_{2\text{м}}\left(w_{n,t_0}\right)}{\delta w_{n,t_0}}$$

$$\frac{\partial T^{-,t_1}_{2\text{м}}}{\partial w_{n,t_0}} = \frac{T^{t_1}_{2\text{м}}\left(w_{n,t_0} - \delta w_{n,t_0}\right) - T^{t_1}_{2\text{м}}\left(w_{n,t_0}\right)}{-\delta w_{n,t_0}}$$

$$\frac{\partial T^{t_1}_{2\text{м}}}{\partial w_{n,t_0}} = 0.5 \cdot \left(\frac{\partial T^{+,t_1}_{2\text{м}}}{\partial w_{n,t_0}} + \frac{\partial T^{-,t_1}_{2\text{м}}}{\partial w_{n,t_0}}\right)$$

It requires 4 additional model runs, that is computationally expensively.

The solution: using off-line land surface model for extra-runs with atmosphere forcing, that was got from the coupled model

Off-line land surface model. Principal ideas

Diagnostic equations of screen-level temperature and relative humidity

$$T_{2M} = \frac{c_p(q_s)T_s + (\varphi_s - \varphi_{2m}) + \alpha_h(c_p(q_L)T_L - c_p(q_s)T_s + (\varphi_L - \varphi_s))}{c_p(q_{2M})}$$

q_s , q_L , q_{2M} - specific air humidity at the surface (s) , low model level (L) and screen-level observation (2M);

T_s, T_L , T_{2M} - air temperature at the surface (s), low model level (L) and screen-level observation (2M);

φ_s, φ_L , φ_{2M} - geopotential at the surface (s), low model level (L) and screen-level observation (2M);

c_p - specific air heat capacity at constant pressure;

α_h - turbulent coefficient

$$RH_{2M} = \frac{e}{e_{sat}} = \frac{p_{2M}\, q_{2M}\; R_a/R_v}{e_{sat}(1 + q_{2M}(R_v/R_a - 1))}$$

$$q_{2M} = q_s + \alpha_h(q_L - q_s)$$

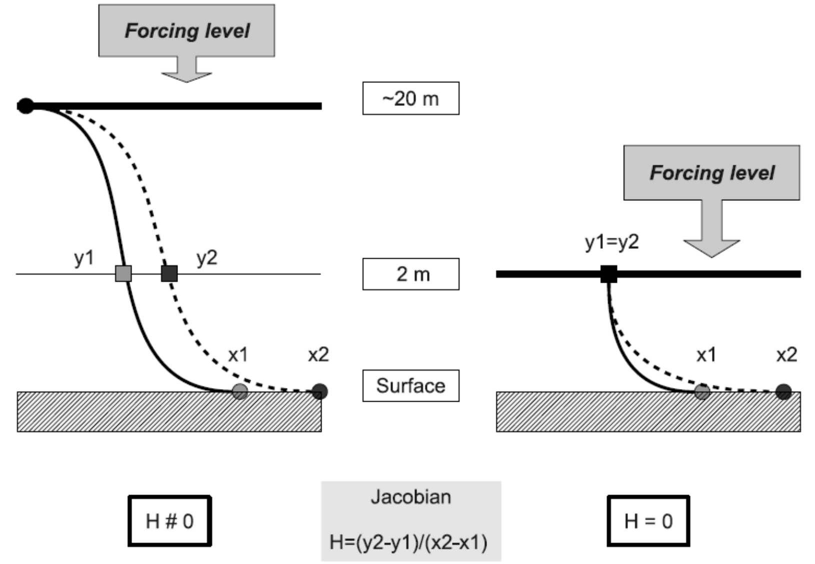
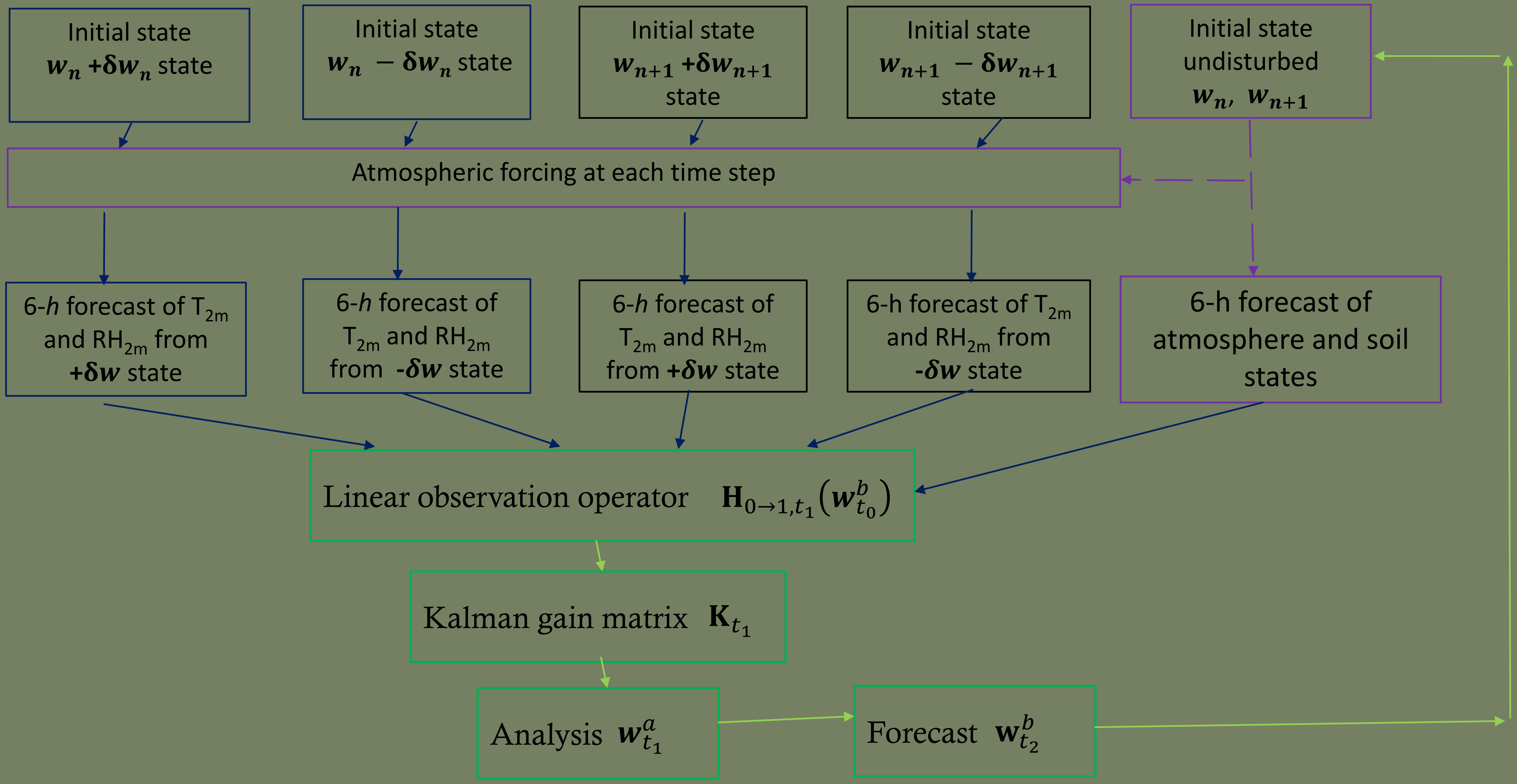


Figure 1. Estimation of the Jacobian of the observation operator for screen level parameters (defined as **y**) with respect to soil variables (defined as **x**) according to the height of the forcing level in an off-line soil analysis scheme. The solid curve is a schematic reference profile in the surface layer, and the dashed curve is a perturbed profile through changes at the surface. (left) The possibility of having nonzero Jacobian elements when the forcing level is above 2 m. (right) Screen level parameters are unchanged when the forcing level is at 2 m leading to zero Jacobian elements.

Mahfouf, J.-F., et al *(2009), A comparison of two off-line soil analysis schemes for assimilation of screen level observations, J. Geophys. Res., 114, D08105, doi:10.1029/2008JD011077*

We can guess from this equations: improvements of surface temperature should decrease screen-level temperature errors. So, using screen-level observations for soil temperature and moisture analysis is physically justified

Scheme of assimilation system



Initial state $\boldsymbol{w}_n + \boldsymbol{\delta w}_n$ state

Initial state $\boldsymbol{w}_n - \boldsymbol{\delta w}_n$ state

Initial state $\boldsymbol{w}_{n+1} + \boldsymbol{\delta w}_{n+1}$ state

Initial state $\boldsymbol{w}_{n+1} - \boldsymbol{\delta w}_{n+1}$ state

Initial state undisturbed $\boldsymbol{w}_n,\ \boldsymbol{w}_{n+1}$

Atmospheric forcing at each time step

6-*h* forecast of T_{2m} and RH_{2m} from $+\boldsymbol{\delta w}$ state

6-*h* forecast of T_{2m} and RH_{2m} from $-\boldsymbol{\delta w}$ state

6-*h* forecast of T_{2m} and RH_{2m} from $+\boldsymbol{\delta w}$ state

6-h forecast of T_{2m} and RH_{2m} from $-\boldsymbol{\delta w}$ state

6-h forecast of atmosphere and soil states

Linear observation operator $\mathbf{H}_{0\rightarrow 1,t_1}(\boldsymbol{w}^b_{t_0})$

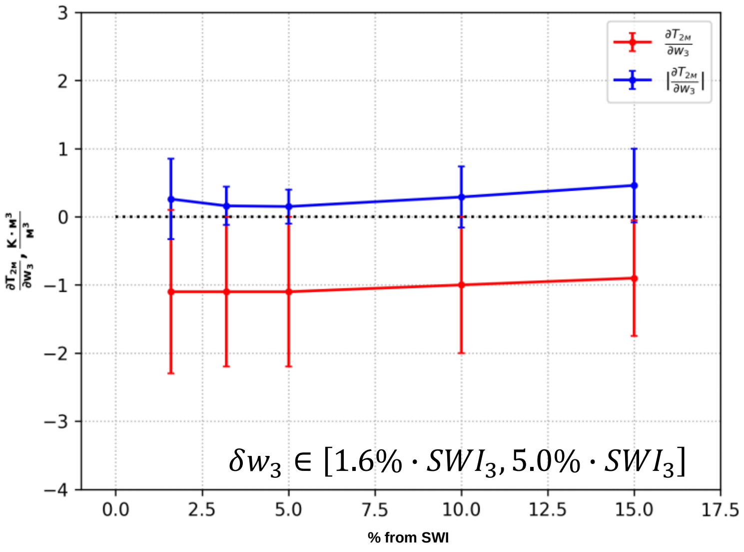
Kalman gain matrix $\mathbf{K}_{t_1}$

Analysis $\boldsymbol{w}^a_{t_1}$

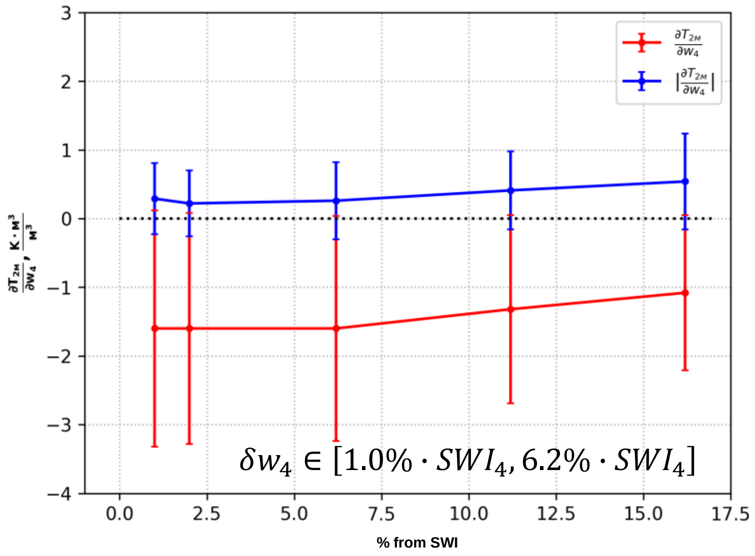
Forecast $\mathbf{w}^b_{t_2}$

Linear estimation of observation operator *H*

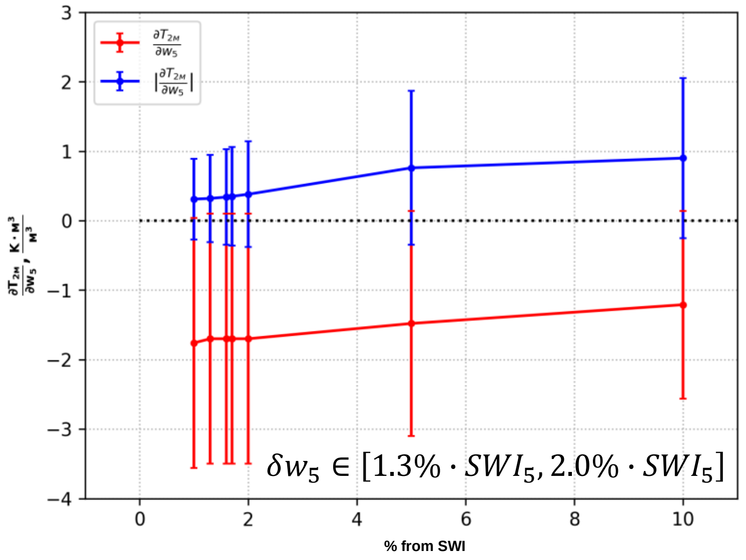
Offline LSM. 6 cm



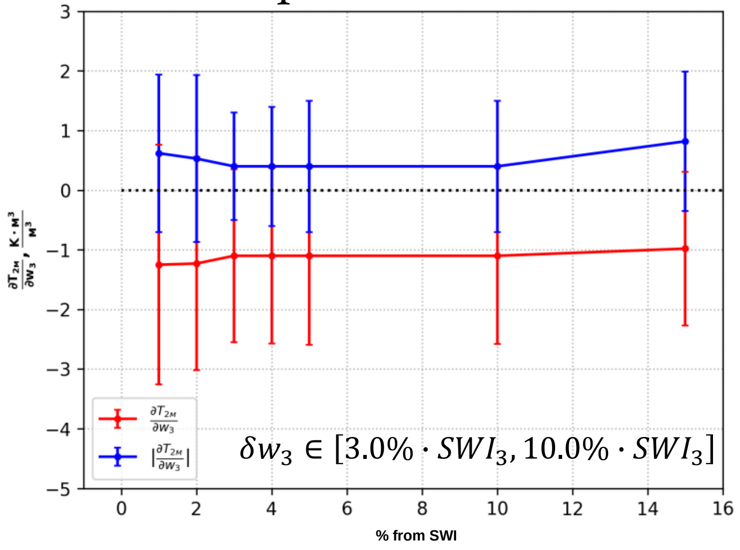
18 cm



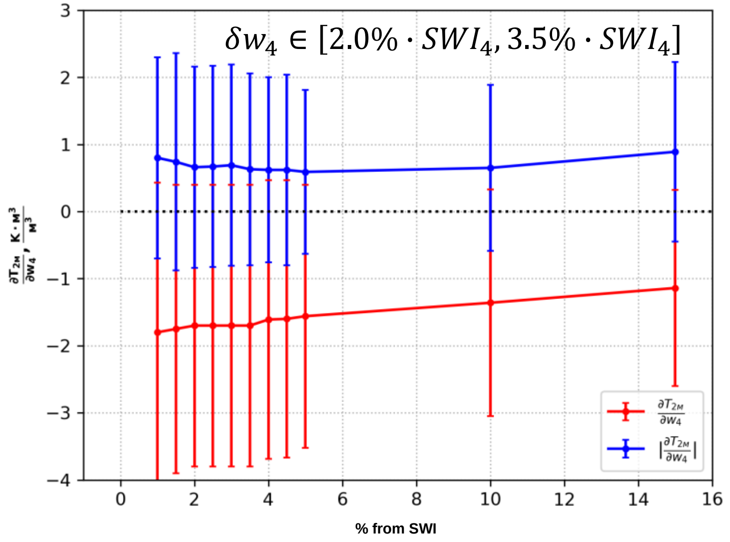
54 cm



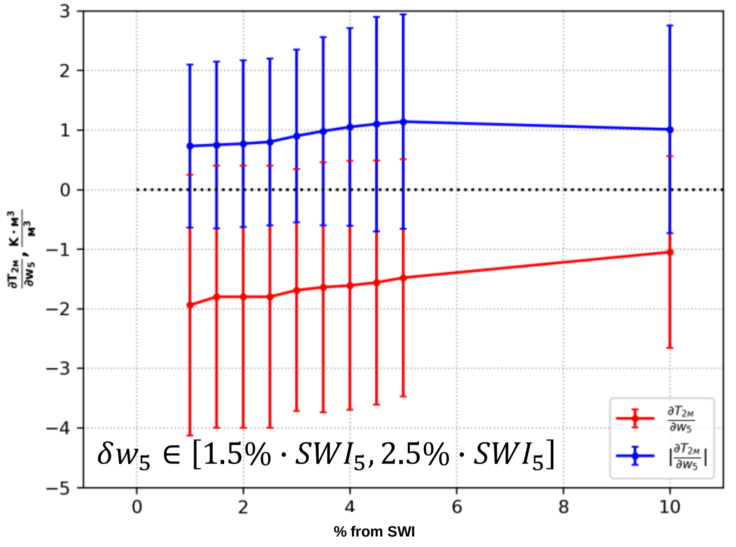
Coupled LSM. 6 cm



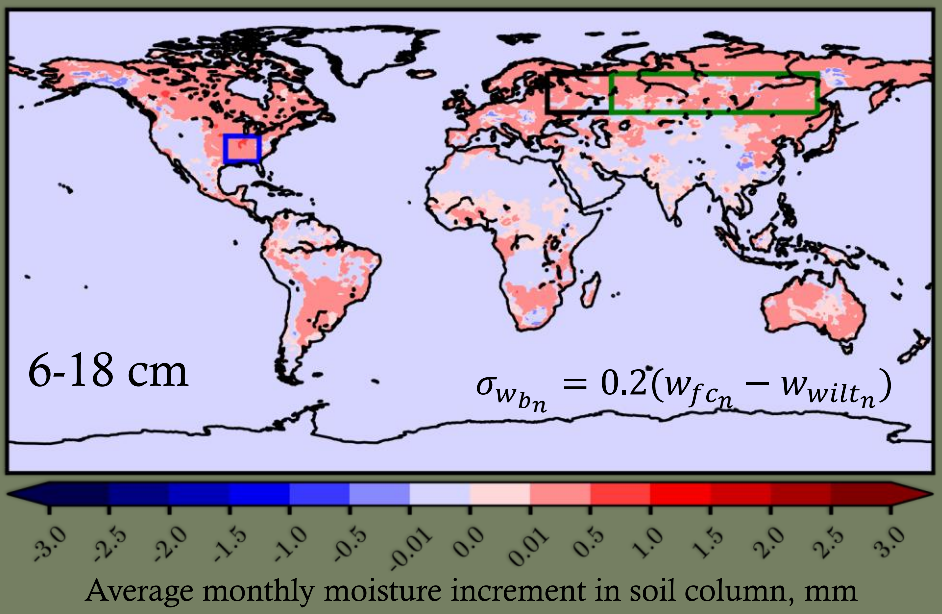
18 cm

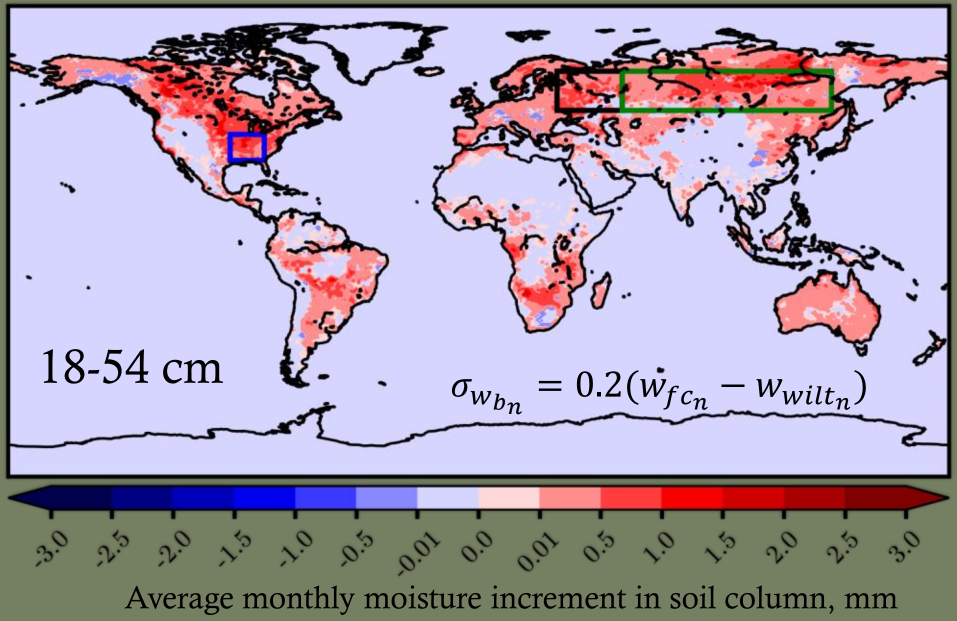


54 cm

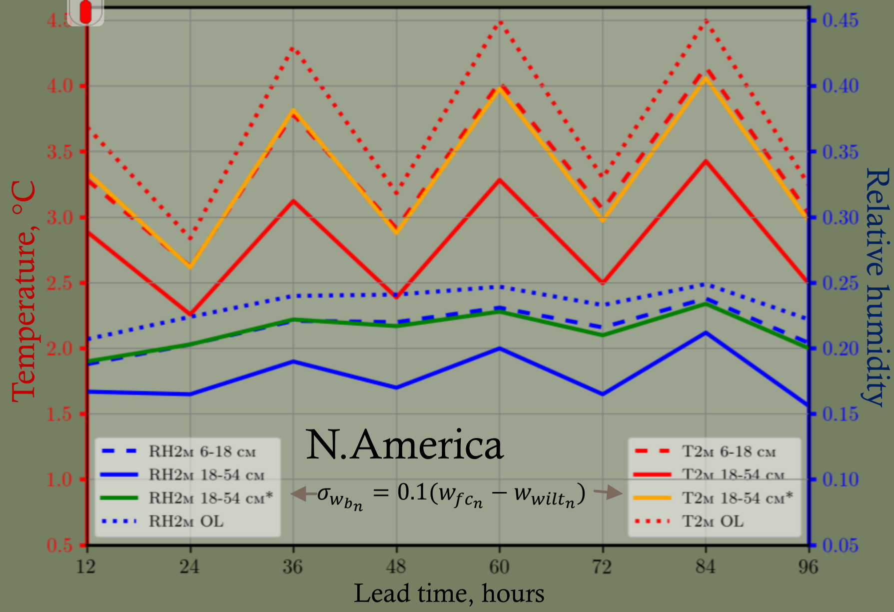


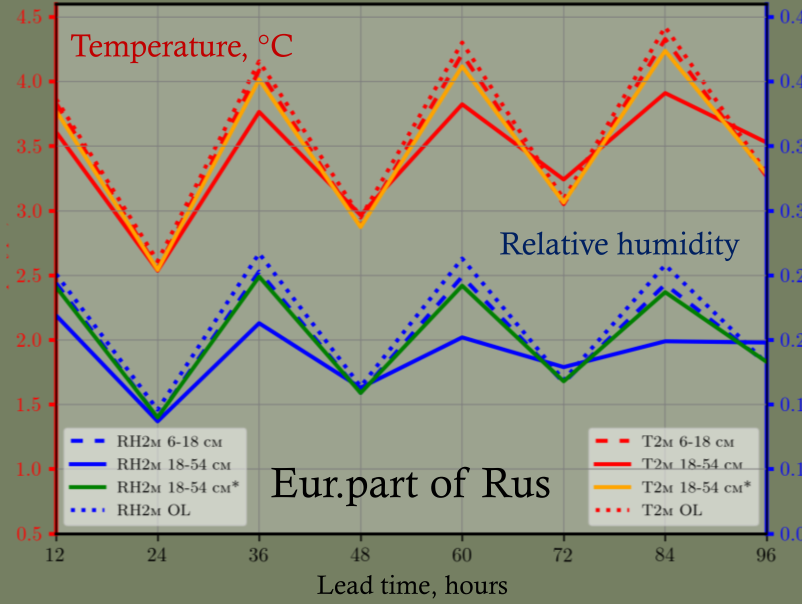
Soil analysis increments. “6-18 cm” vs “18-54 cm” vs “OL”

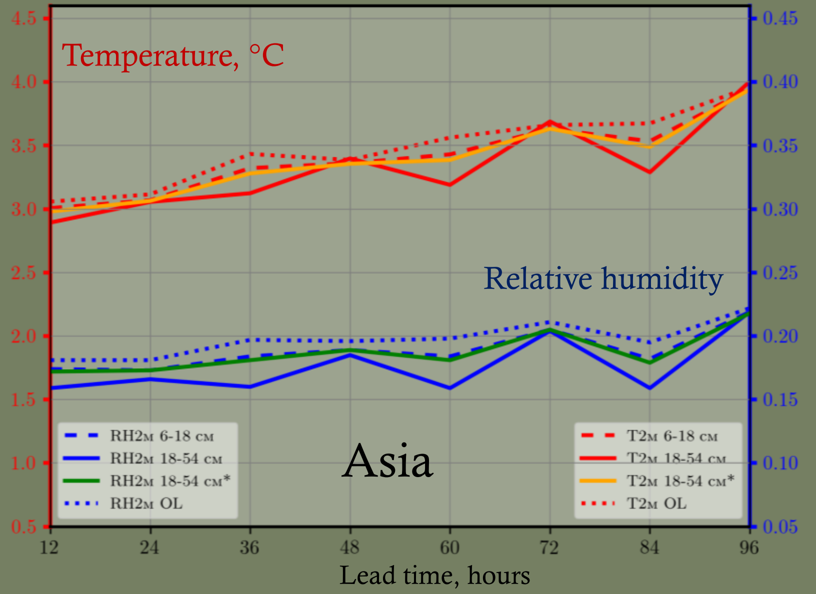




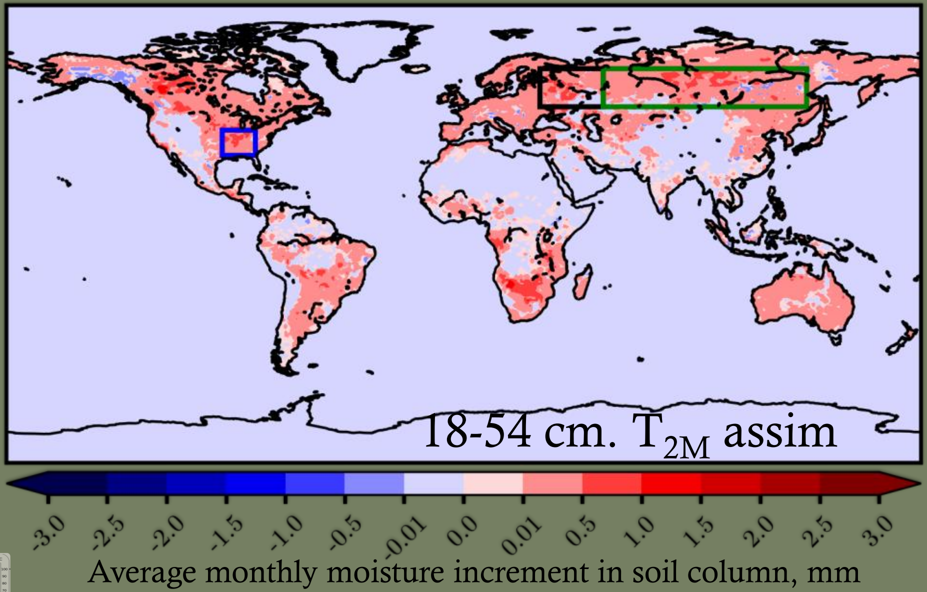
RMSE of screen-level forecasts SL-AV(L96 0,9˚x0,72˚) with soil initialization system. July 2014

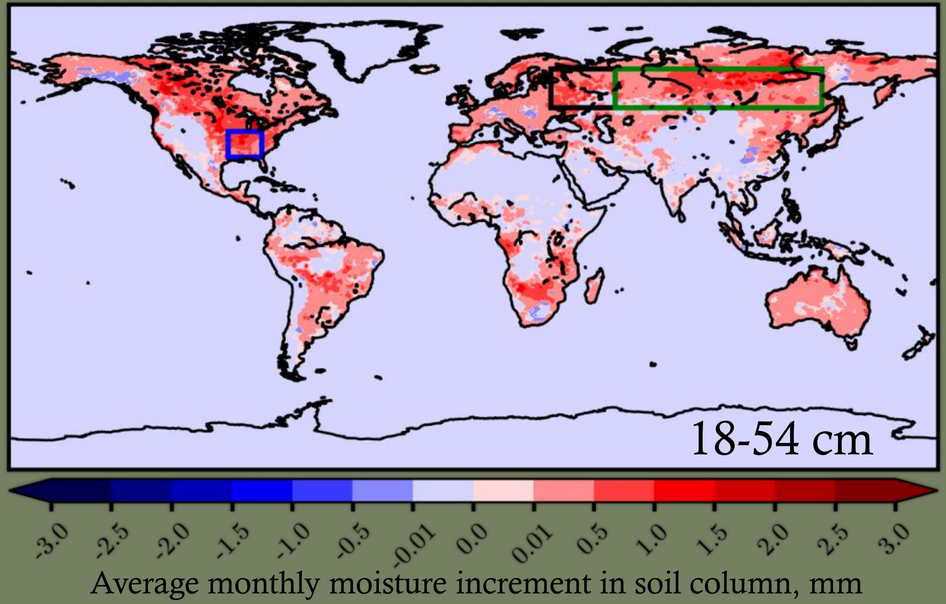




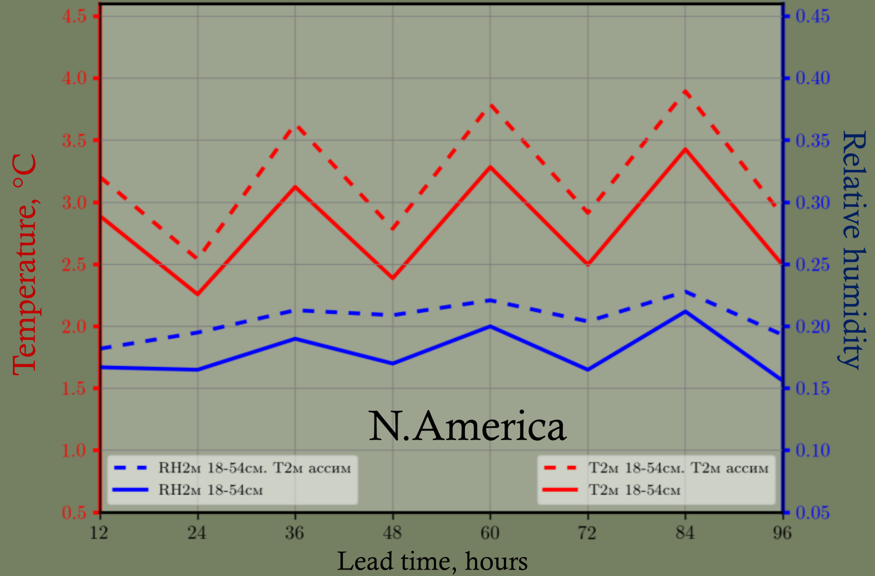


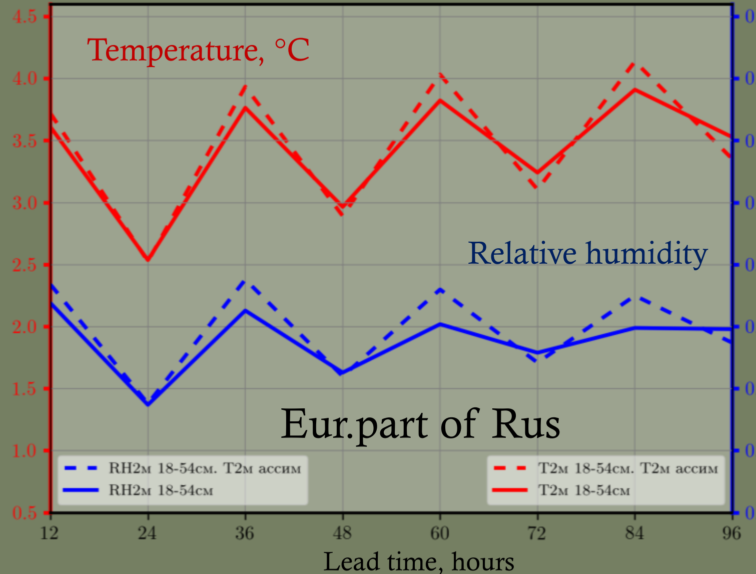
Soil analysis increments. “18-54 cm. T_{2M} assim” vs “18-54 cm”

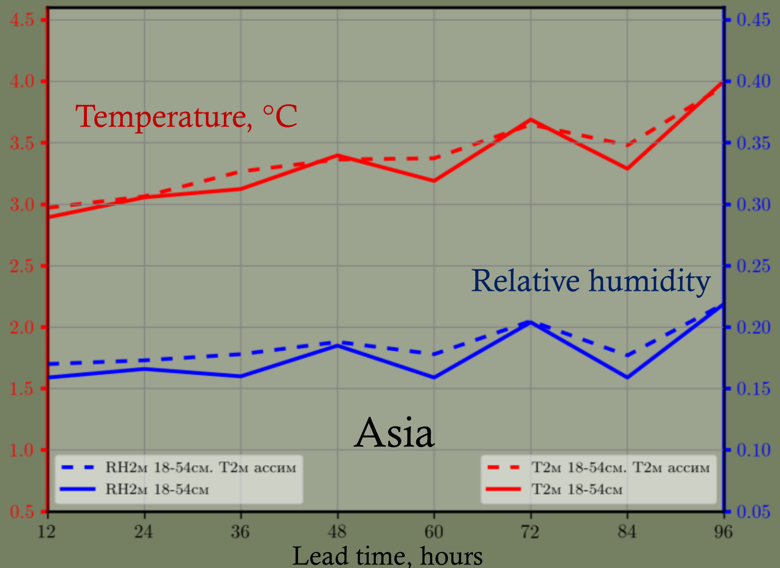




RMSE of screen-level forecasts SL-AV(L96 0,9˚x0,72˚) with soil initialization system. July 2014







Conclusions

This research presents the soil moisture analysis system for the multilayer soil model INM RAS-MSU as part of the global atmospheric model SL-AV. It's based on a point-wise Simplified Extended Kalman Filter (SEKF). The analysis scheme is developed within an offline version of the land surface model for the initialization of soil water content in numerical weather prediction model.

Validation of tangent linear hypothesis for observation and model operators shows, that from eight evaluated layers the best results are obtained for layers with depths 6 cm, 18 cm and 54 cm.

First experiments with this system show improvements of screen-level forecasts up to 96-hours lead time at in different regions of the world. Optimistic results of soil analysis usage for medium-range forecasts led to long-range forecast experiments.

Flexibility of the assimilation system allows to modify it for assimilation not only moisture, but also soil temperature. Such experiments are planned in the future.

Thank you for attention!

This work was partially supported by the Russian Science Foundation (grant 21-17-00254)