

Preliminary Results from Ensemble Kalman Filter based Land Data Assimilation for the Soil Diffusion ISBA model

by

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ACC  RD

A Consortium for CONvection-scale modelling
Research and Development

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Outline of the talk

1. Introduction
2. Basics of Land Data Assimilation system
3. Ensemble Kalman Filter based Land Data Assimilation system
4. Simulation of test cases
5. Results
6. Future Plans



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2024 plans

Coupled land-atmosphere data assimilation



- **ECMWF:** (1) Outer loop land-atmosphere coupled data assimilation developments in the ECMWF IFS and evaluation for global reanalysis, (2) Coupled skin temperature assimilation developments in the IFS

MOTIVATION

- **SMHI:** Outer loop coupled DA developments in HARMONIE-AROME.

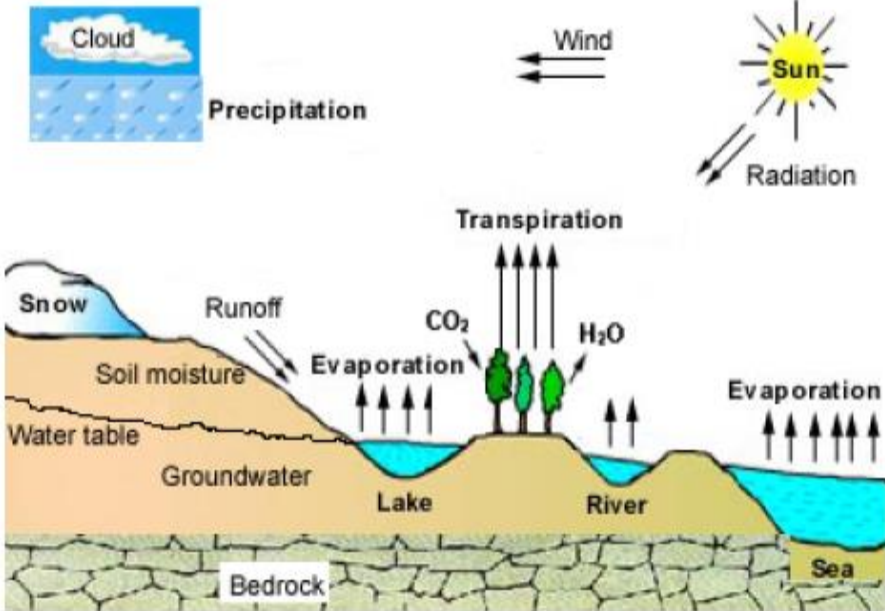
- **Met Norway:** (1) Bring the LDAS developments from WP1 into the HARMONIE-AROME coupled system, (2) coupled DA developments in HARMONIE-AROME

Land surface-atmosphere interaction

Land covers about 30% of the Earth's surface.

The land surface consists of soil, vegetation, snow, glaciers, inland water, mountains, animals, human beings, their shelters, and much more.

Land surface processes, in principal, refer to the exchanges of heat, water, CO₂, and other trace constituents among these components.

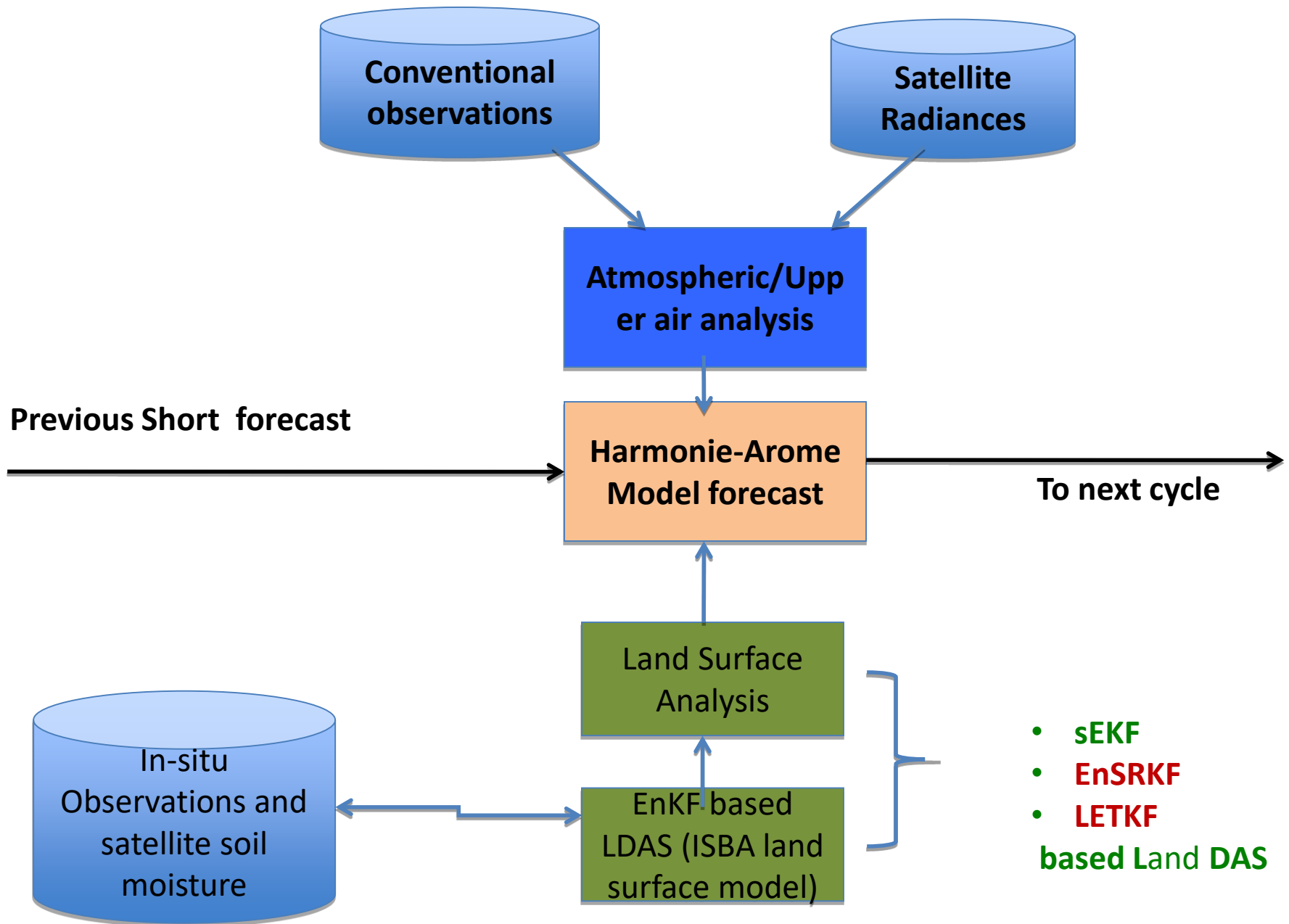


Time scales	Driving mechanism of Land-atmospheric interaction
Seconds to Hour	exchange momentum, energy, water, carbon dioxide and other chemical constituents between the land surface and the atmosphere
Day to seasons	changes in the store of soil moisture, changes in snowpack, changes in carbon allocation, and vegetation phenology
years to centuries	vegetation structure and function (e.g., disturbance, land use, stand growth) is strongly determined by climate influences

The surface variability not only determines the microclimate but also affects the mesoscale atmospheric circulation

Purpose of Land Data Assimilation

- Soil Moisture strongly influences the partitioning of available energy into sensible and latent heat flux and hence the evolution of the lower atmospheric conditions.
- Imperfect parameterisations of land surface and soil processes and failures in simulating precipitation and cloud cover can lead to considerable drifts of soil moisture; assimilation is needed to control forecast drifts.
- The use of in-situ land surface observations is unfeasible, because no extensive observation network exists.
- Conventional data, e.g. screen-level parameters (T2m and RH2m), and satellite data (eg. ASCAT), can be used to adjust soil moisture in an assimilation framework.
- **Soil Moisture Observations – In-situ** (limited) & **Satellite** (latest addition-SMAP)
- In NWP – Soil moisture is required for initialize the model forecast (soil moisture controls the partitioning of the energy at soil-atmosphere interface)– Requirement of **soil moisture analysis**



Basic Schematic of Land data Assimilation (WCDA; de Rosnay et al 2022)

Kalman Filter and its different flavors: Overview

- ▶ **Kalman filter (Kalman, 1960)** : propagation and update of state error covariance and mean for a linear stochastic system
- ▶ **Extended Kalman Filter (Smith et al., 1962)** : Propagation of state error covariance with linearised version of the model
- ▶ **Ensemble Kalman filter (Evensen, 1994; Burgers et al., 1998)** : Monte-Carlo approximation of state error covariance and its update; propagation of state error covariance and mean by ensemble integration
- ▶ **Ensemble square root filter (Anderson 2001; Bishop et al. 2001; Whitaker and Hamill 2002; also Pham 2001)** : deterministic representation and update of state error covariance in ensemble form
- ▶ The Kalman Filter provides a **recursive** solution of the least squares minimization problem in the **linear** case.
- ▶ The Kalman Filter provides optimal solution for the **current** state of the system given past observations.
- ▶ The **state of the DA system** at any stage is given by (i) state estimate \mathbf{x} and (ii) state error covariance estimate \mathbf{P} .
- ▶ The assimilation cycle breaks into two stages: **propagation** and **analysis**.

$$\mathbf{x}^f(t_i) = \mathbf{M}_{i-1} [\mathbf{x}^a(t_{i-1})]$$

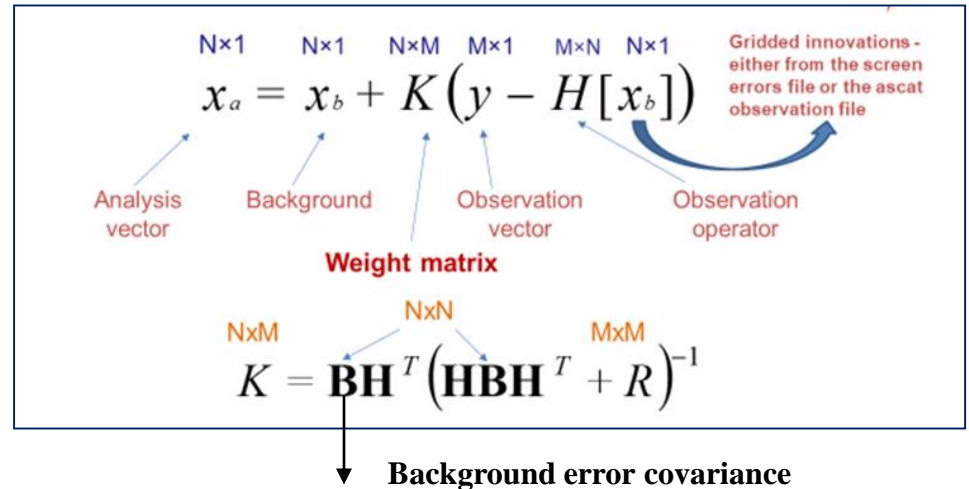
- ▶ The sensitivity of analysis to innovation = **Kalman gain**,
$$\mathbf{x}^a - \mathbf{x}^f = \mathbf{K} [\mathbf{y} - H(\mathbf{x}^f)].$$

Extended Kalman filter (EKF)

- ▶ $H(\mathbf{x})$, $M(\mathbf{x})$ are nonlinear
- ▶ EKF: uses the estimate

$$\mathbf{M}_i = \nabla_x M_i(\mathbf{x}^a)_{,i}$$

$$\mathbf{H}_i = \nabla_x H_i(\mathbf{x}^f)_i$$



Requires

$$|\nabla_x \mathbf{M}_i(\mathbf{x} + \delta\mathbf{x}) - \nabla_x \mathbf{M}_i(\mathbf{x})| < |\nabla_x \mathbf{M}_i(\mathbf{x})|, \text{ (M is tangent linear of model)}$$

$$|\nabla_x \mathbf{H}_i(\mathbf{x} + \delta\mathbf{x}) - \nabla_x \mathbf{H}_i(\mathbf{x})| < |\nabla_x \mathbf{H}_i(\mathbf{x})|, \text{ (H is linearized observation operator)}$$

- ▶ Therefore, for EKF to work the state must be “linearly” constrained - that is, constrained to a degree when linearised operators can be applied within the limits or the characteristic uncertainty range.

Introduction. Why Ensemble Kalman filter (EnKF) ?

Problems with EKF:

- Non-scalable: \mathbf{P} (evolving forecast error covariance) is an $n \times n$ matrix (where order of the number of degrees of freedom of the model)
- Can be numerically inconsistent: positive definiteness of \mathbf{P}
- Requires linearization \rightarrow prone to instability

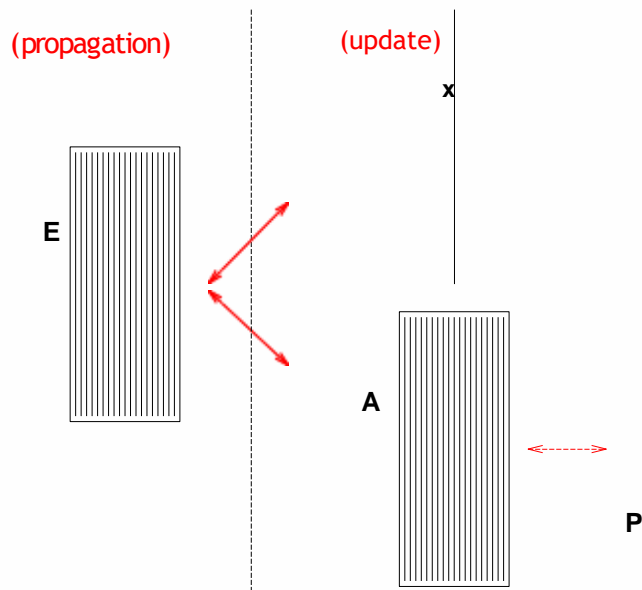
Advantages of EnKF

- Ensemble Kalman filter does not require the development of a linear and adjoint model.
- EnKF does not require the linearization of the evolution of the forecast error covariance.
- EnKF solves the limitations of saturated soil moisture in EKF, thus less requirements of non-linearity issues.
- EnKF can handle non-Gaussian uncertainty more effectively due to its ensemble-based approach. Suitable for large-scale problems
- Involves *approximation* of sensitivities \rightarrow robust
- Makes it possible to treat rank problems by localization
- Makes it possible to assimilate asynchronous observations

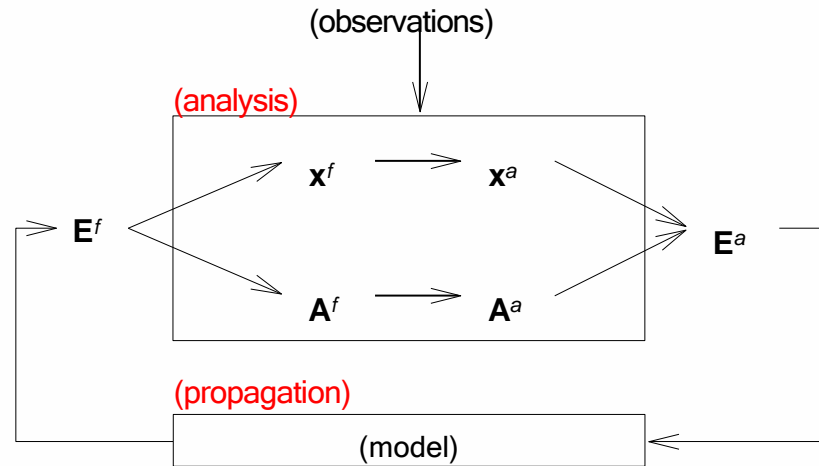
Ensemble Kalman filter (EnKF)

EnKF: EnKF represents the state as an ensemble of state vectors. Ensemble \mathbf{E} of model state carries both the state mean \mathbf{x} and the state error covariance \mathbf{P} . Each ensemble member represents a possible state estimate, and the ensemble evolves through the system dynamics and assimilation of observations.

EnKF: role of the ensemble



EnKF: workflow



EnSRF: EnSRF is designed to be more robust than EnKF, especially in situations where EnKF may encounter stability issues. The use of the square root update mechanism helps maintain stability and positive semidefinite covariance matrices.

$$\mathbf{x}_k^f(t_i) = M_{i-1}^k [\mathbf{x}_k^a(t_{i-1})],$$

$$\mathbf{P}^f \approx \frac{1}{K-1} \sum_{k=1}^K (\mathbf{x}_k^f - \bar{\mathbf{x}}^f)(\mathbf{x}_k^f - \bar{\mathbf{x}}^f)^T$$

Harmonie-Arome Model Configuration Used in the Study

code: https://github.com/josteinblyverket/Harmonie/tree/EnKF_CY46h1

multi-layer physics: ISBA-DIF , 3-L for Snow scheme , Soil heat capacity = 2.0E-5

Surface analysis: **ENSRKF for Land DA**

Experiment: start at 2024-01-01, 3h cycling for 3 weeks.

Multi-Layer surface physics

Force-restore

- **ISBA-3L** 3 layer soil (top, root, deep)
- **D95** bulk snow scheme
- **OI** surface analysis

Multi-layer physics

- **ISBA-DIF** 14 layer soil (0.01m, ..., 12m)
- **MEB** Multi Energy Balance for vegetation
- **SEKF** Simplified Extended Kalman Filter for surface analysis (constant **B**)
- Ensemble Square Root Kalman Filter for surface analysis (for Soil Moisture)
- LETKF Filter for surface analysis (For Soil Moisture)



MOTIVATION

Task 1.2 (Lead - SMHI): Develop ensemble-based filter LDAS approaches for soil moisture (M3-18)

ISBA: Diffusion soil

- The heat and soil moisture transfers within the soil are computed using **14 layers up to a 12 m depth**.
- The depth of the 14 layers (see figure) have been **chosen to minimize numerical errors in solving the finite-differenced diffusive equations**, especially in the uppermost meter of the soil. The same default grid thicknesses are used everywhere.
- Hydrological grids, enclosed by the solid black lines in the figure, are defined by root depth for vegetated surfaces. Thus **the soil water prognostic equations do not extend as deeply as the thermal computations**.
- The root depth is essential for the transpiration estimates.

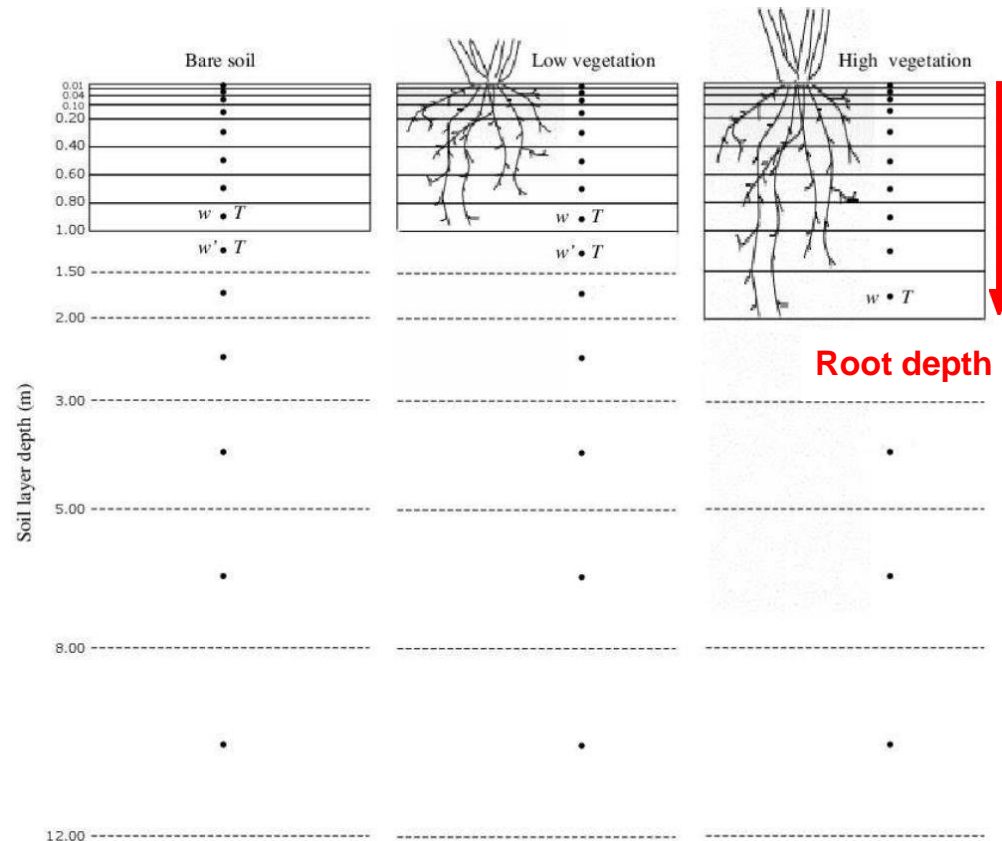


Figure 4.7 in SURFEX Scientific documentation for v8.1, P. Le Moigne, February 23, 2018.

http://www.umr-cnrm.fr/surfex/IMG/pdf/surfex_scidoc_v8.1.pdf

Decharme et al. 2011, doi:10.1029/2011JD016002

Source: Patrick Samuelsson

Results

1) Perturbations are applied following Charrois et al 2016; Fields are perturbed using the spatial-temporal perturbation methodology are precipitation, shortwave downward radiation and longwave downward radiation (additive). For surface, soil moisture perturbations are multiplicative while the soil temperature perturbations are additive.

2) **AIM of analysis:** Spread in perturbations of screen level variables and soil moisture (surface to root zone).

3) Ensemble Kalman filter based land data assimilation system for Harmonie-Arome system tested for two domains : `SOR_TEST` (smaller) and `METCOOP25D` (bigger). *As of now only the SYNOP observations are assimilated.* Experiments are run for to test the impact of domains and initial conditions on the growth of perturbation of the land surface variable like `TG1`, `TG7`, `TG14`, `WG1`, `WG7` and `WG14`.

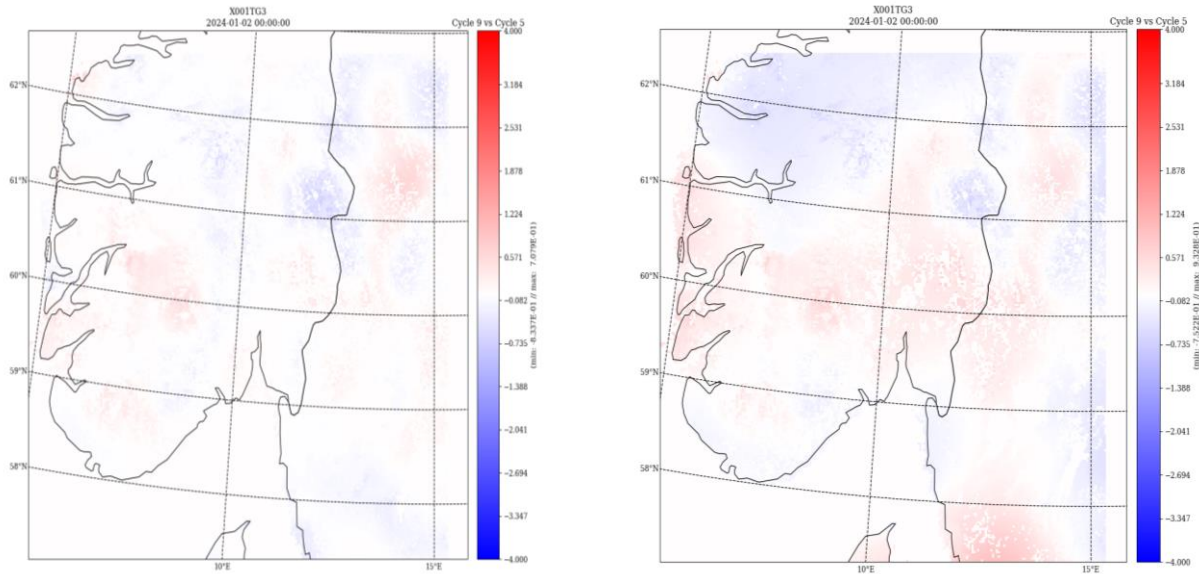


Figure : Illustration of soil temperature differences (K) in layer 3 without (left) and with (right) state perturbations of soil temperature over `SOR_TEST` domain.

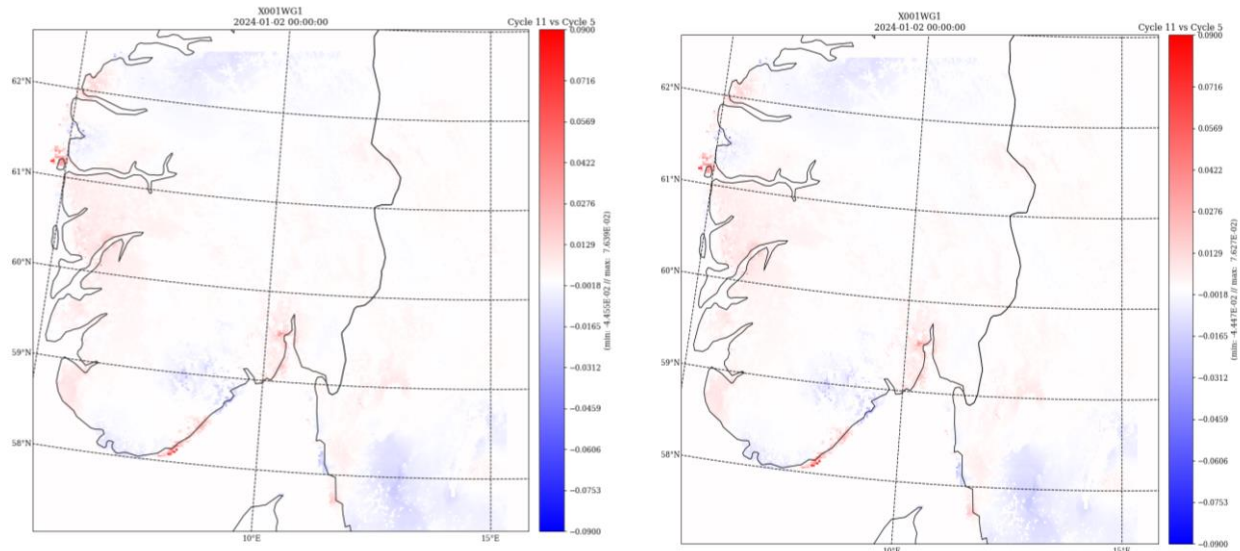


Figure : Illustration of soil moisture differences (m^3/m^3) in layer 1 without (left) and with (right) state perturbations of soil moisture over *SOR_TEST* domain.

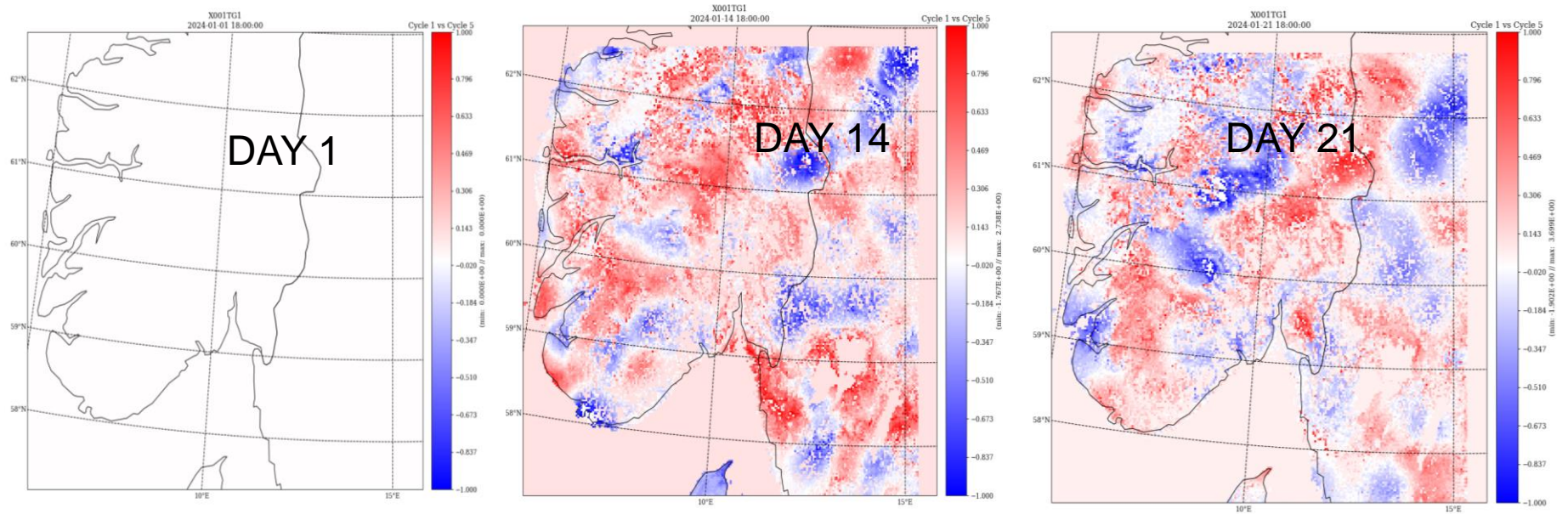


Figure: Illustration of soil temperature differences (K) in layer 1 with state perturbations over *SOR_TEST* domain valid day-1, day-14 and day-21

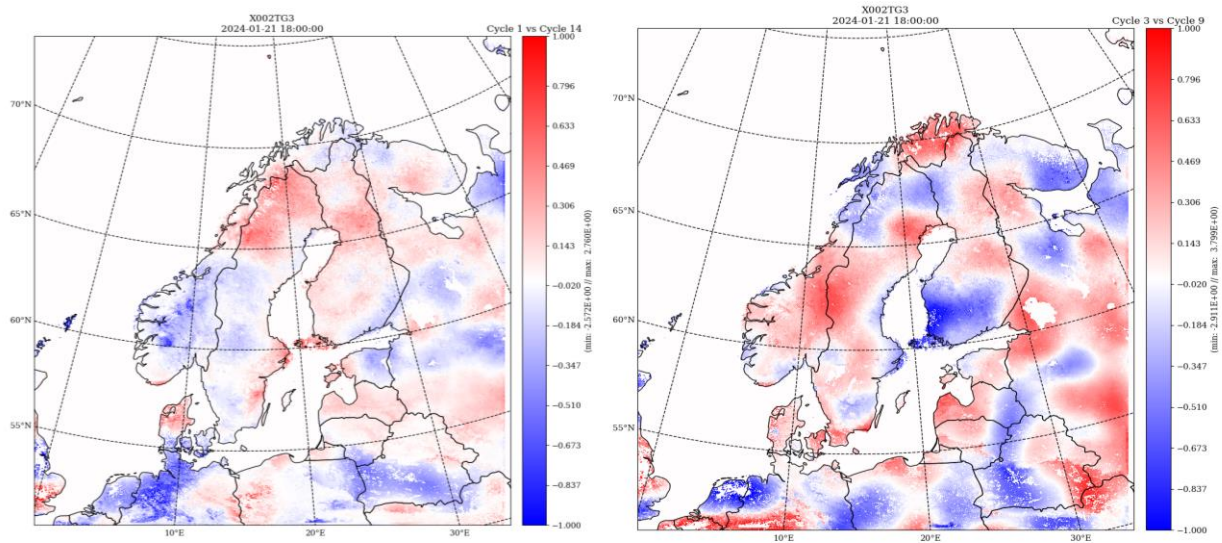


Figure : Illustration of soil temperature differences (K) in layer 3 without (left) and with (right) state perturbations of soil temperature over METCOOP25D domain.

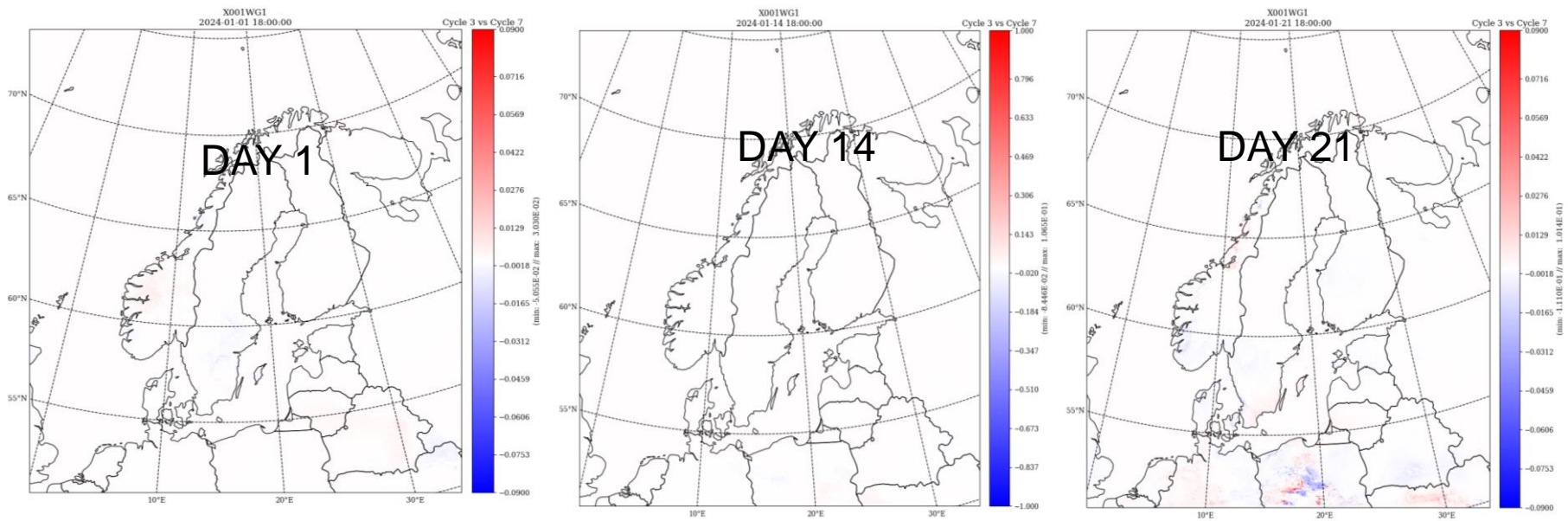


Figure: Illustration of soil moisture differences (m^3/m^3) in layer 1 with state perturbations over METCOOP25D domain valid at day-1, day-14 and day-21

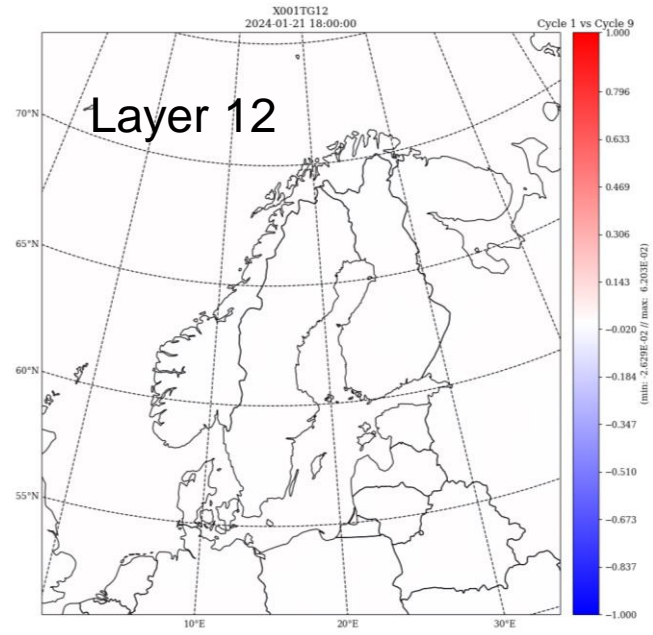
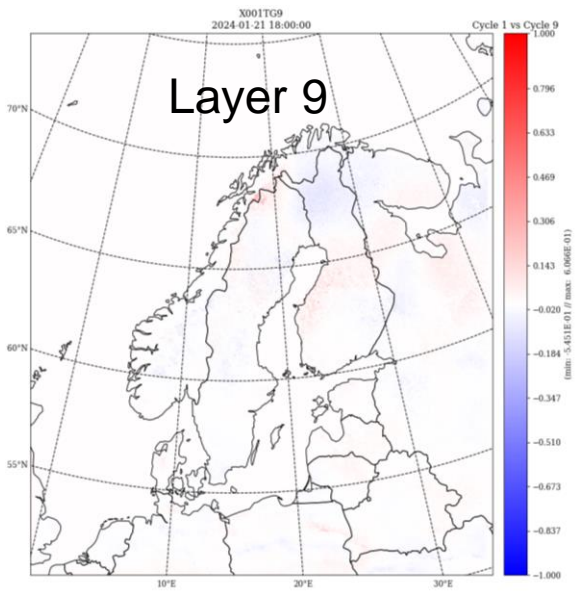
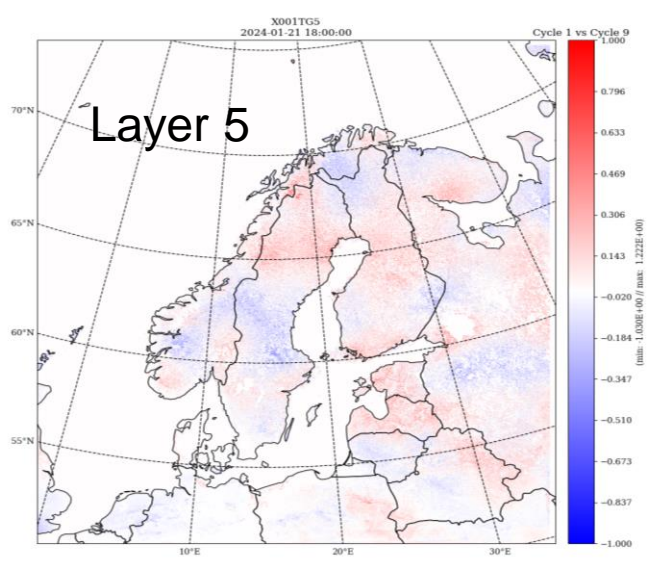
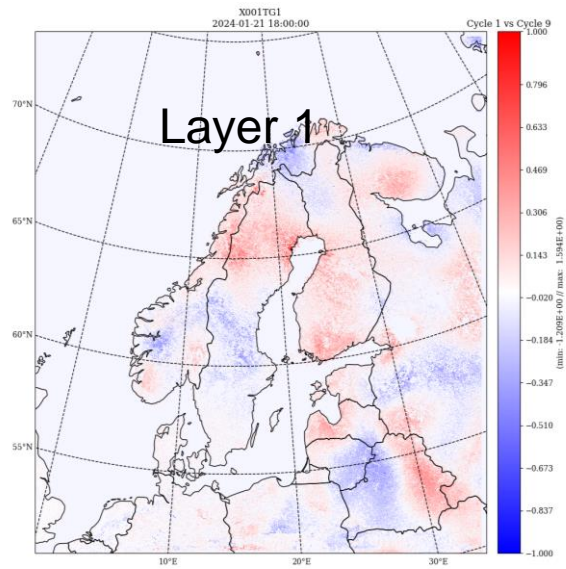


Figure: Illustration of spread of soil temperature differences (K) in layer 1 to layer 12 with state perturbations over METCOOP25D domain valid at day-21

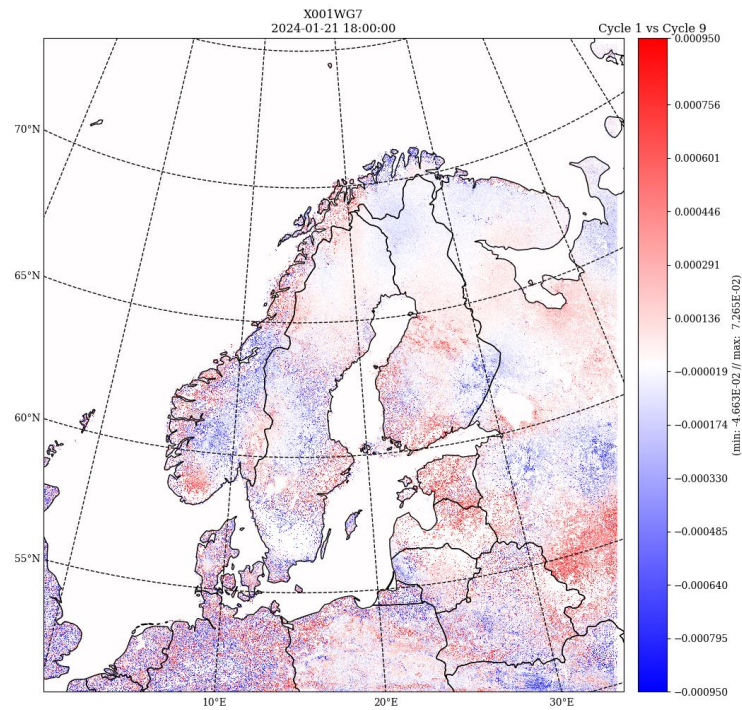


Figure: Illustration of soil moisture differences (m^3/m^3) in layer 7 with state perturbations of soil moisture over METCOOP domain

Future Plans

- To develop the Ensemble Kalman filter based Soil moisture assimilation system (regional) over European domain.
- Development of an OFFLINE LDAS system for Soil moisture using LETKF algorithm.

Thanks