Surface Analysis Using the LETKF

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Introduction

Moving towards the multi-layer explicit snow scheme (ISBA-ES) suggest using adjusted/new DA schemes. A more advanced surface data assimilation scheme would allow for i) flexible observation vector (including satellite observations with advanced footprints), an extended control vector (snow water equivalent, density, heat/temperature). The local ensemble transform Kalman filter (LETKF) (Hunt et al 2007), is simple to implement, scalable and effective. However, ensemble based methods rely on realistic ensembles which is one of the main challenges with the LETKF.

The Local Ensemble Transform Kalman Filter

The LETFK is performed independently on every model grid point. For each point the relevant observations are selected and used. The LETKF update equations are:

$$\mathbf{x}^a = \bar{\mathbf{x}}^b + \mathbf{X}^b\mathbf{w}^a$$
$$\mathbf{w}^a = \mathbf{W}^a + \bar{\mathbf{w}}^a$$
$$\bar{\mathbf{w}}^a = \tilde{\mathbf{P}}^a(\mathbf{Y}^b)^T\mathbf{R}^{-1}(\mathbf{y}^o - \bar{\mathbf{y}}^b)$$
$$\mathbf{W}^a = [(k-1)\tilde{\mathbf{P}}^a]^{1/2}$$
$$\tilde{\mathbf{P}}^a = [(k-1)\mathbf{I}/\rho + (\alpha \circ (\mathbf{Y}^b)^T\mathbf{R}^{-1})\mathbf{Y}^b]^{-1}$$

where $\mathbf{x}$ represent the ensemble control vector, $\mathbf{X}$ the ensemble anomalies, a and b indicate analysis and background respectively, $\mathbf{w}$ is the transformation weights between the background and the analysis, $\mathbf{Y^b}$ represent the ensemble observation equivalent. $\tilde{\mathbf{P}}$ and $\mathbf{R}$ are the error covariance matrices. ρ and α are tunable parameters for inflating the background error covariance matrix and to apply localization (inflation of $\mathbf{R}$), respectively.

Multi-layer Physics

Moving from a single to a multi-layer soil and snow schemes drastically increase the number of prognostic variables relative to the current force-restore option. With the explicit snow and diffusion soil schemes, analysis updates should be consistent and preferably computed using the same assimilation scheme.

Variable	ISBA Force - Restore	ISBA Diffusion
soil temperature	2	14
soil water content	2	14
snow water equivalent	1	12
snow density	-	12
snow heat (temperature)	-	12
total	5	64

Table 1. Illustration of the potential increase in analyzed variables from ISBA Force-Restore to ISBA Diffusion Models

Ensemble Generation

The LETKF relies on a realistic ensemble to distribute observation information to the state variables and care has to be taken when generating the ensemble members. In this work, ensemble members are constructed by perturbing the atmospheric forcing input. In this way the model physics ensures "realistic" relationships between the control variables, and thus reliable ensemble covariance and following increments. We use cross correlated noise between the forcing parameters in a temporal AR(1) process. The filter also use the ensemble correlations to spread the observed information spatially, so spatial patterns are required in the noise fields. We have used a 2D convolution and a random remapping of precipitation to obtain these spatial patterns, more advanced methods should be considered in future work.

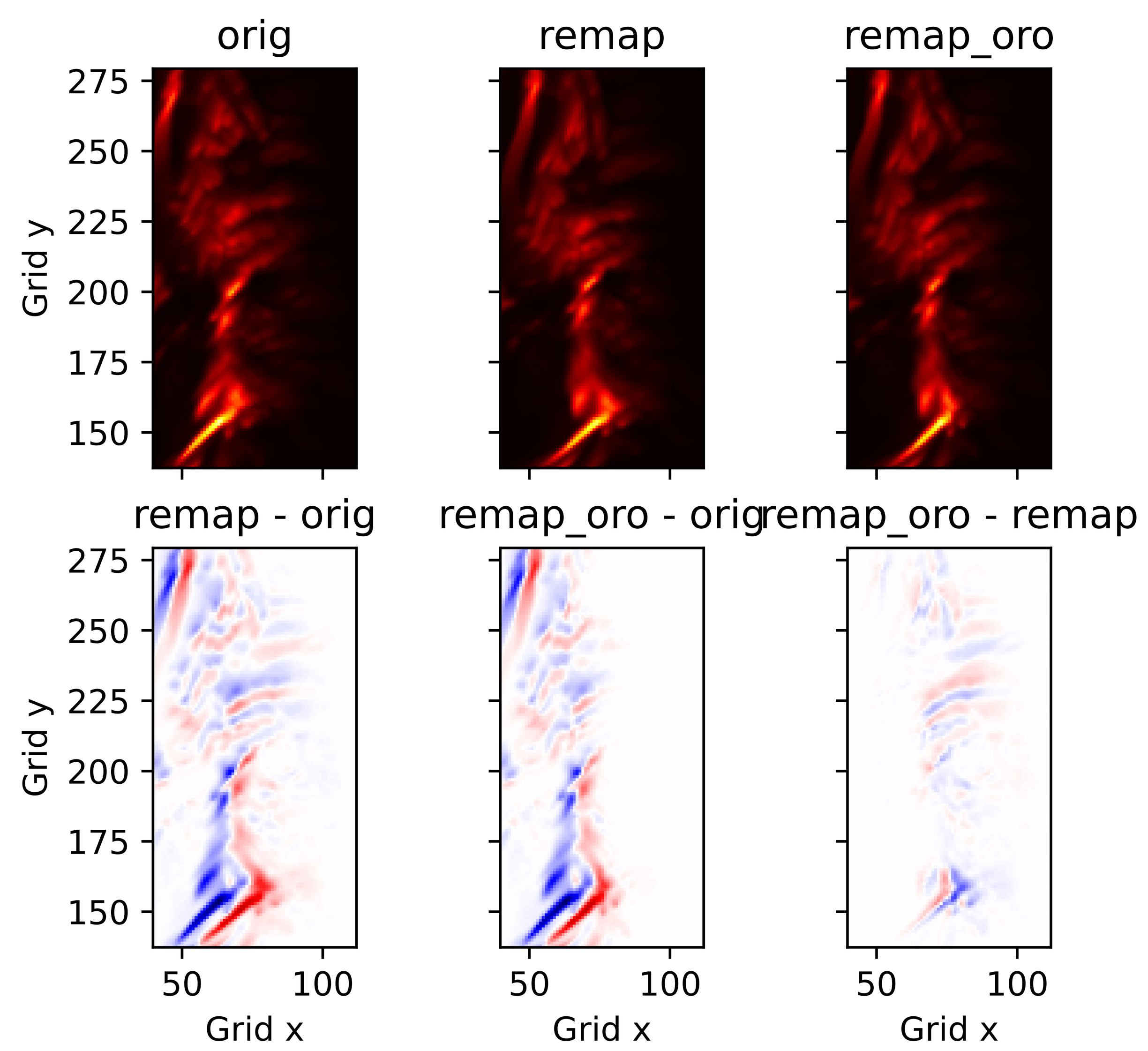

Figure 1. Remapping of precipitation forcing using random index advection. Orig denote the deterministic precipitation field, remap the basic remapping, and remap_oro an adjusted version where remapping is dampened in areas with steep and high topography. Upper panels show precipitation fields, and lower show the differences.

Experimental Setup

	Forcing	DA	Members
Ref	Nordic analysis	-	1
ctrl	MEPS	-	1
open loop	MEPS + pert	-	15
daexp	as openloop	sd obs from Ref	15

Table 2. Experiments

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Results

Initial tests using snow depth observations indicate positive impact at observation locations (Fig. 2) and in terms of error-spread relation (Fig. 3). The filter is able to adjust the state in most situations, which suggest physical consistency of the ensemble. Perturbations to air temperature forcing were later added to help rapid melting events.

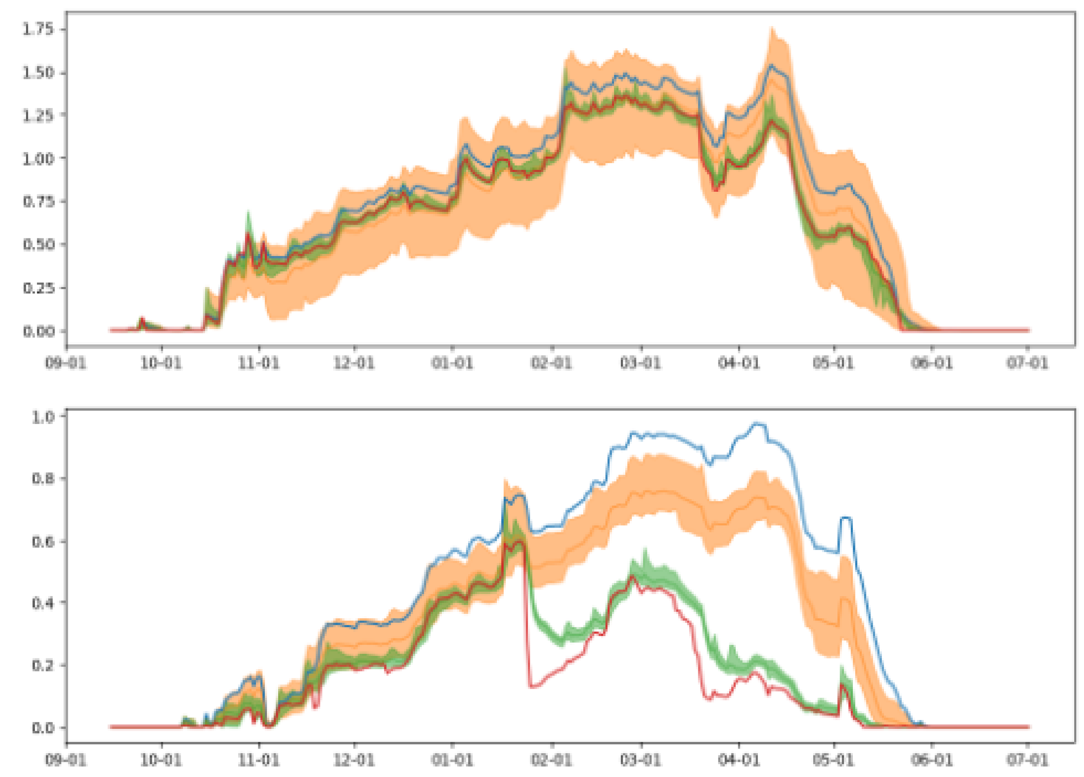

Figure 2. Time-series of snow depth at two observation locations

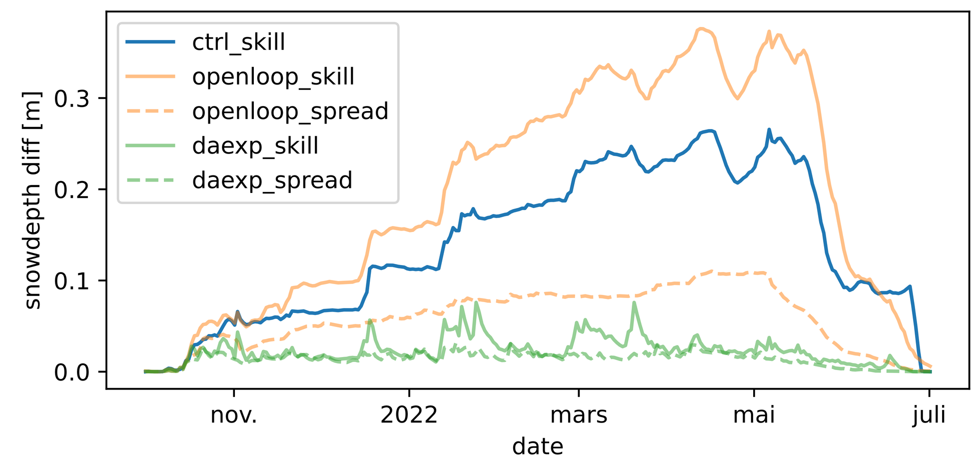

Figure 3. Spread-Skill time-series at observation locations

Spatial Impact

By using synthetic observations from a reference experiment, we can measure the impact of our analysis away from the observation locations. Figure 4 shows the average impact of the analysis update through the difference in root mean squared error between the analysis and first guess. Overall, the filter performs well over flat areas and poorly over mountainous areas. The latter suggest that the ensemble generation needs more development.

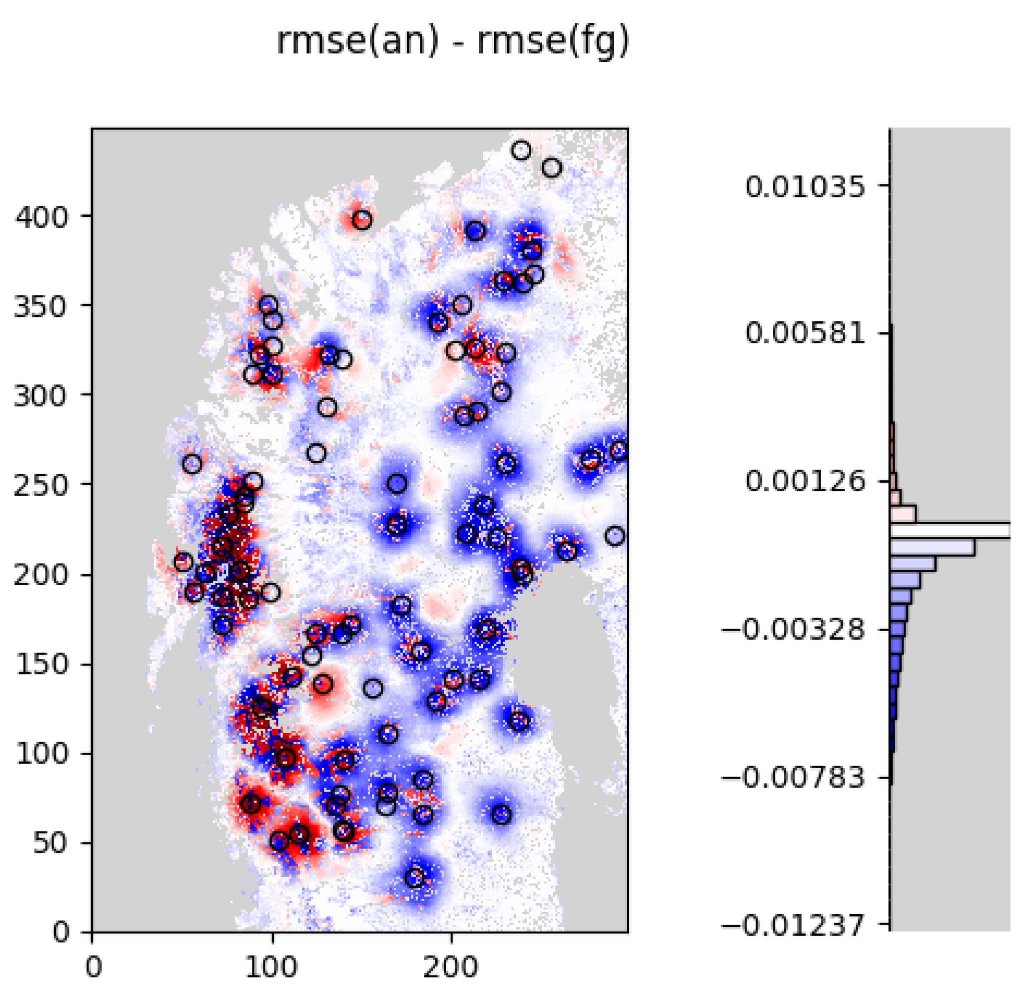

Figure 4. RMSE(analysis) - RMSE(first guess) snow depth 150 day average

Future Work

- Investigate variable transformation of bounded and undefined variables.
- Extend observation and control vectors to include assimilation of snow temperature.
- Assimilate satellite observations of e.g. snow cover.
- Improve ensemble generation by using machine learning methods: i) increase ensemble size using emulators, ii) sample from complex distributions using generative models.

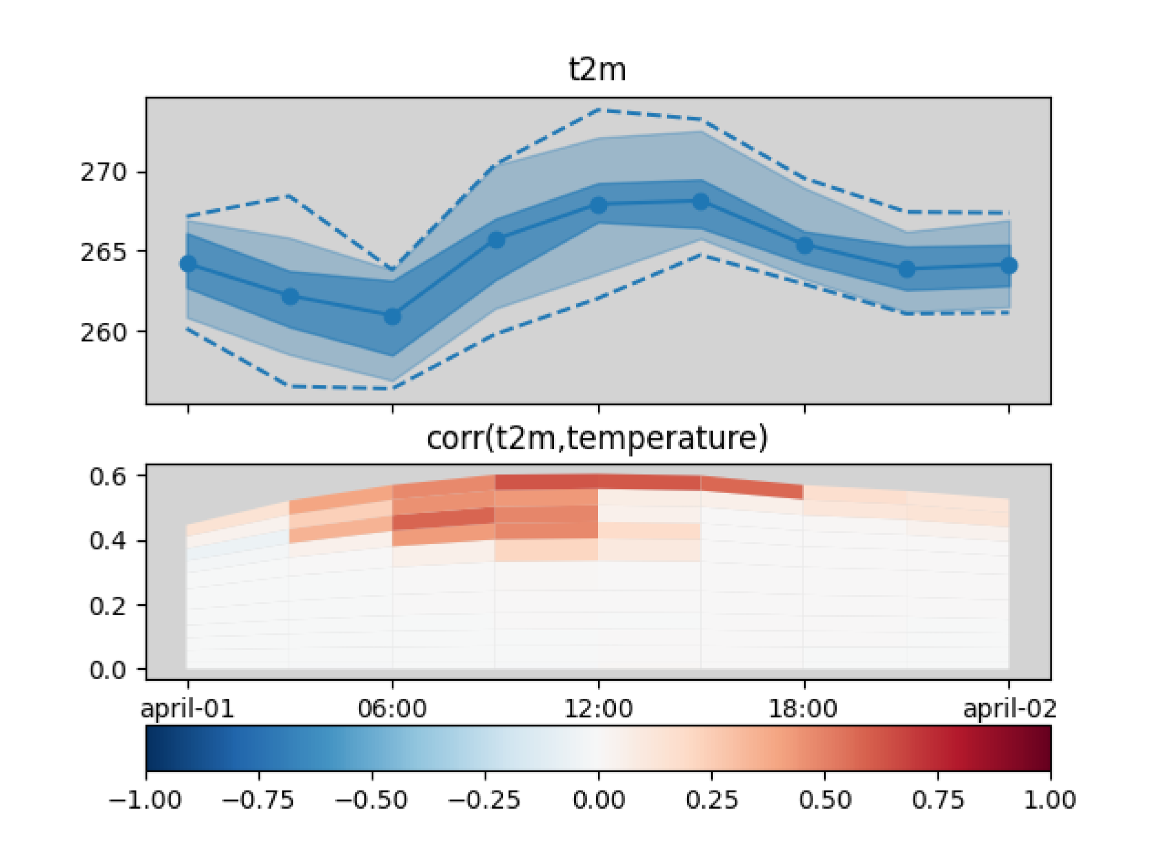

Figure 5. Time-series of T2m ensemble spread (top) and ensemble correlation between T2m and snow temperature per model level.