

Leveraging Satellite Data for High-Resolution Snow Monitoring: Scaling with openEO

Valentina Premier, Nicola Ciapponi, Michele Claus, Riccardo Barella, Carlo Marin

Institute for Earth Observation, Eurac Research, Bolzano, Italy

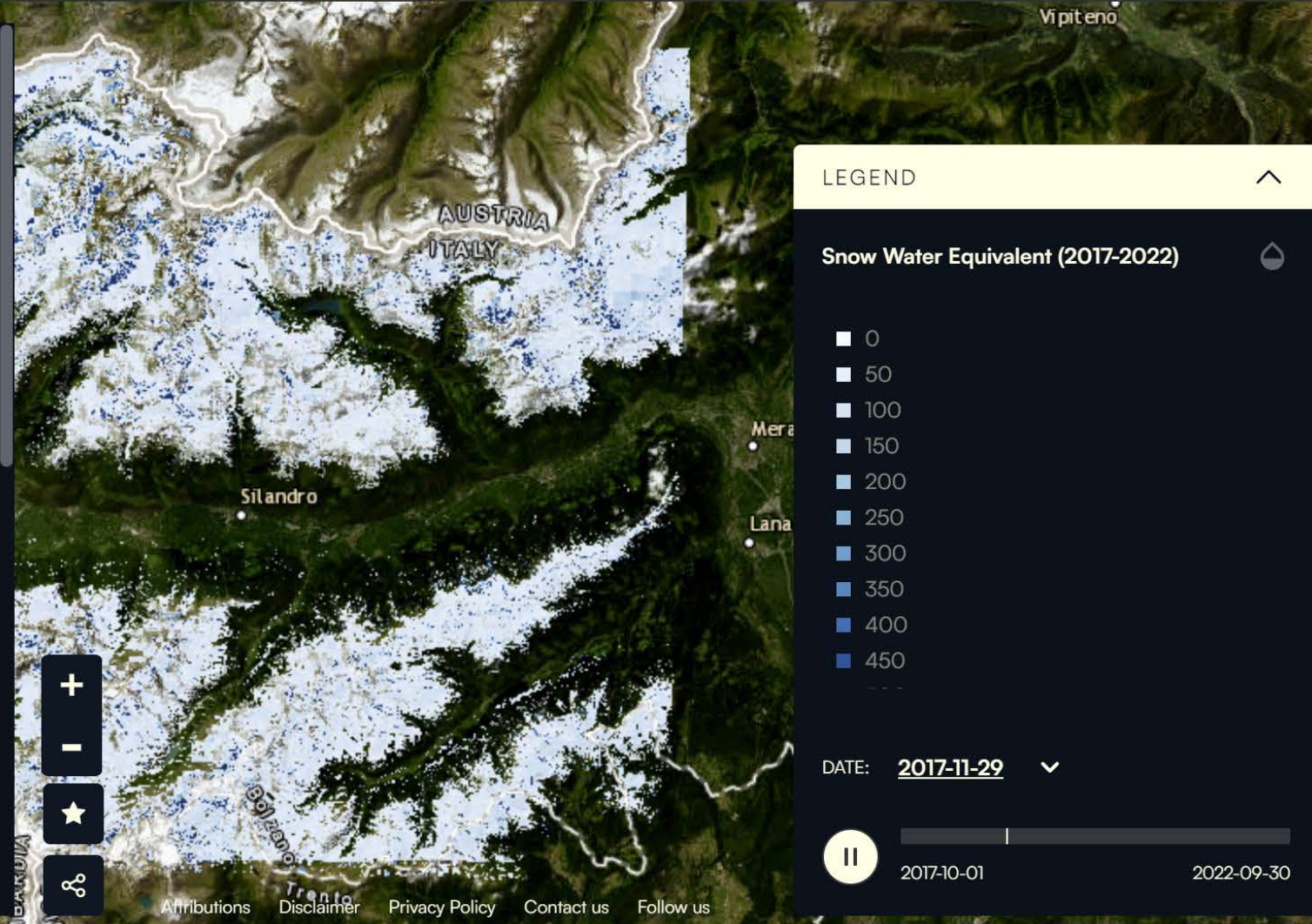


← Back to EU-snow monitor.

GEOSTORY

High resolution Snow Water Equivalent in selected alpine mountain regions

Decision makers need detailed information on the amount of water stored in the snowpack to improve how they manage water resources in a timely and efficient manner. The 50 m resolution Snow Water Equivalent maps and



The Alpine Snowpack: the Water of the Future

- Ecos
- Supp
- Can

ance
interactions
iations
get

- Stre
- Gro
- Wa

ction
ing



What do we want to implement?

1. Accurate Snow Cover Fraction (SCF)
2. Accurate Snow Cover Area (SCA)
3. Estimation of the Snow Water Equivalent (SWE)



What do we want to achieve?

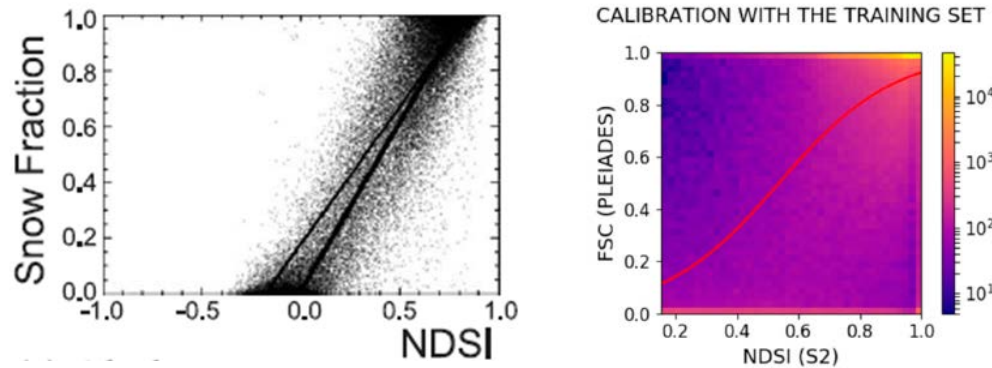
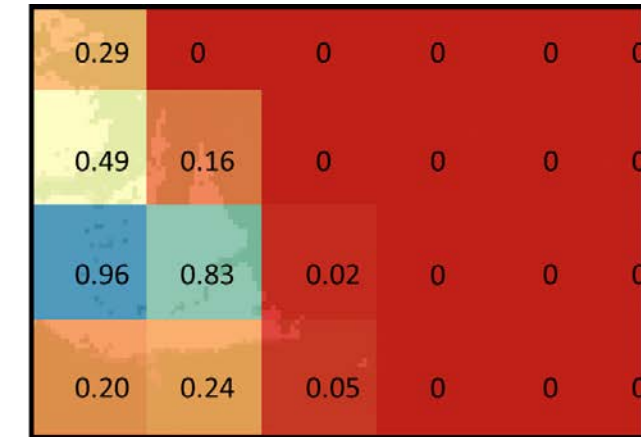
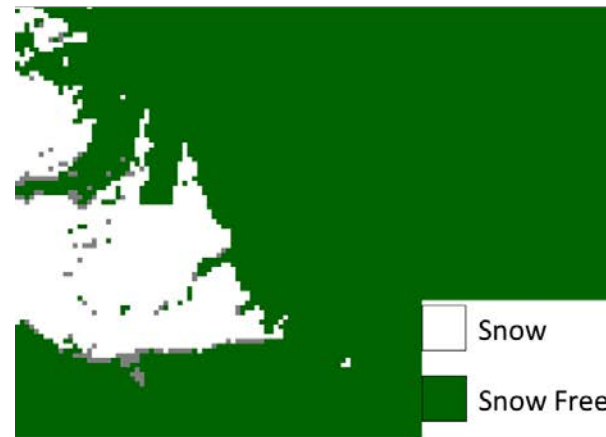
- High temporal (daily) and spatial (20 m) resolution information to monitor quick changes

How can we achieve it?

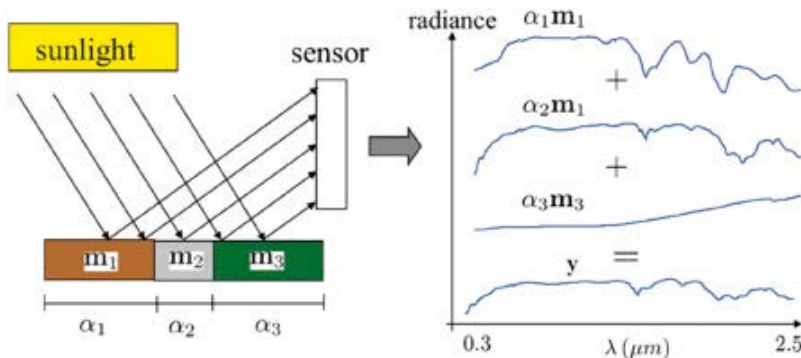
- Need of multi-temporal and multi-source data (e.g., MODIS, Landsat, Sentinel-2, Sentinel-1, auxiliary data..)
- Large-scale processing requires scalable solutions like provided by openEO

Snow Cover Fraction (SCF)

- The Snow Cover Fraction (SCF) represents the percentage of pixel (with a given size!) covered by snow.
- State of the art methods are based on:
 - Regression on the NDSI e.g., [1] [2]



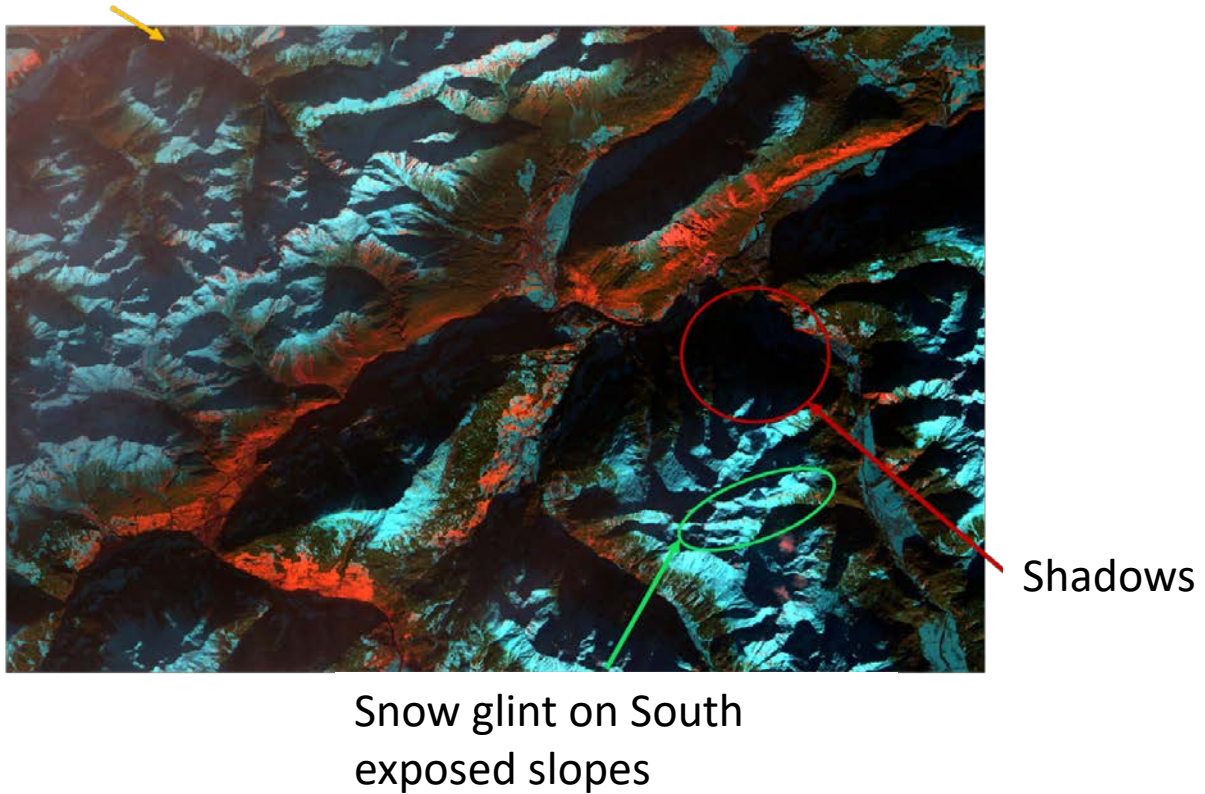
- Multispectral linear unmixing e.g., [3]



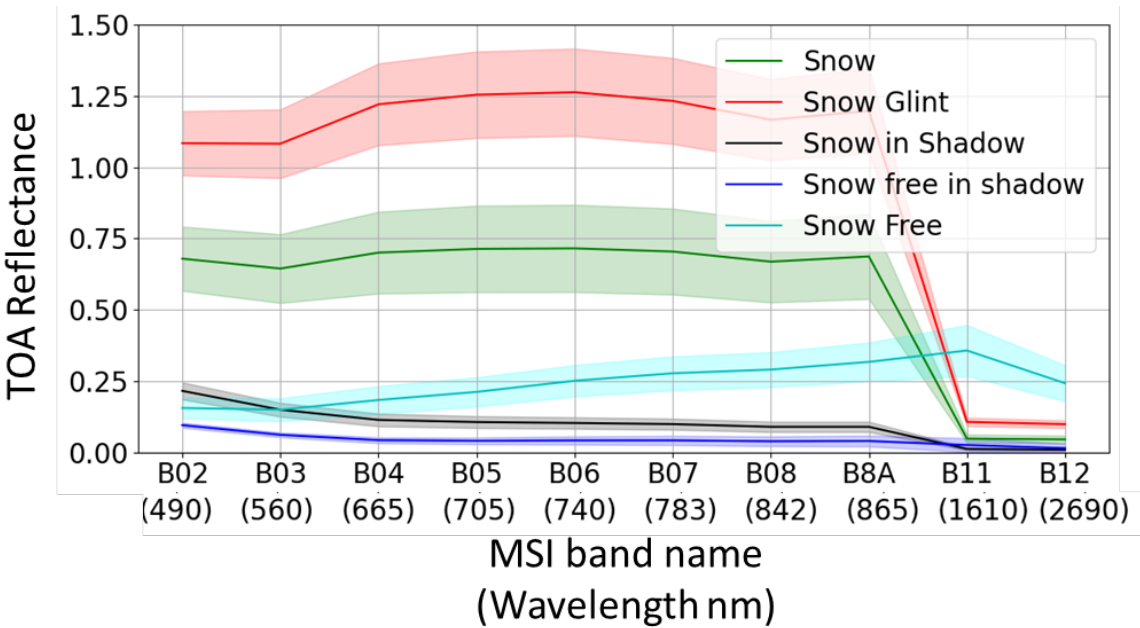
$$R_{\lambda} = \sum_{i=1}^N \alpha_i m_{\lambda,i} + \varepsilon_{\lambda}$$

- [1] Salomonson, Vincent V., and I. Appel. "Estimating fractional snow cover from MODIS using the normalized difference snow index." *Remote sensing of environment* 89.3 (2004): 351-360.
- [2] Gascoin, S.; Barrou Dumont, Z.; Deschamps-Berger, C.; Marti, F.; Salgues, G.; López-Moreno, J.I.; Revuelto, J.; Michon, T.; Schattan, P.; Hagolle, O. Estimating Fractional Snow Cover in Open Terrain from Sentinel-2 Using the Normalized Difference Snow Index. *Remote Sens.* **2020**, *12*, 2904. <https://doi.org/10.3390/rs12182904>
- [3] Bair, Edward H., Timbo Stillinger, and Jeff Dozier. "Snow Property Inversion from Remote Sensing (SPIReS): A generalized multispectral unmixing approach with examples from MODIS and Landsat 8 OLI." *IEEE Transactions on Geoscience and Remote Sensing* 59.9 (2020): 7270-7284.

Atmospheric disturbance Sentinel-2 L1C 01/01/2021



Ambiguities on spectral signature and NDSI



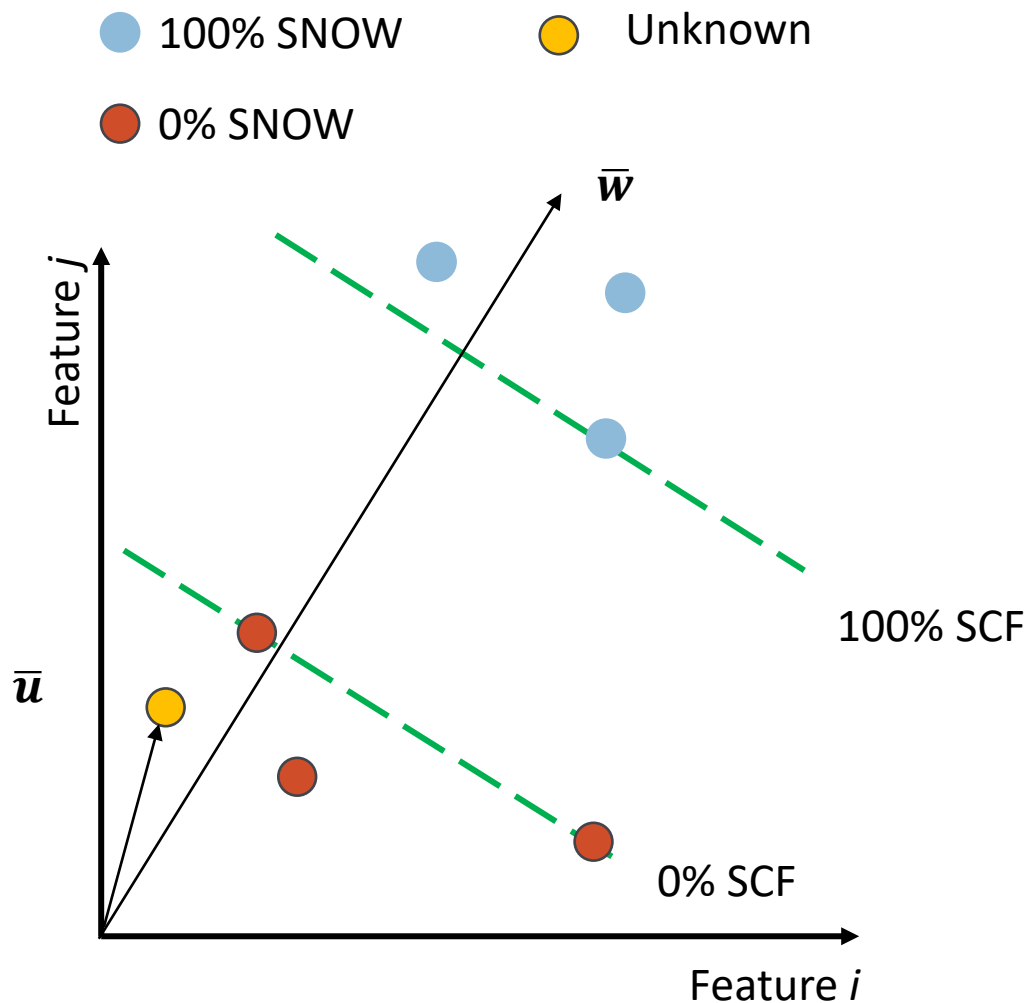
SoA method for **SCF** retrieval **fail** in challenging winter conditions of **illumination** and **atmospheric disturbance**

Aim of the work

- Develop an **unsupervised method able to** take into account the **different illumination and atmosphere conditions to classify the fractional snow cover**.
- This method has been developed with a **particular attention on**:
 - **Able to identify the fraction snow cover**;
 - **Reliability** under **challenging situation**;
 - **Temporal stability**;
 - High level of **automatization and speed of the processing**.

Barella, R., Marin, C., Gianinetto, M., & Notarnicola, C. (2022, July). A novel approach to high resolution snow cover fraction retrieval in mountainous regions. In *IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium* (pp. 3856-3859). IEEE.

Unmixing – Maximization of class distance



- We use a **Support Vector Machine (SVM)** to infer the SCF.
- The definition of the **decision function** is **completely based on the trainings**, in particular on some trainings called **Support Vectors**
- We have to select **training samples of pure classes "Snow" and "Snow Free"**
- If this condition is satisfied **we can relate the distance to the hyperplane with the SCF** (linear function, sigmoid...)

Unsupervised endmember collection

- In this phase we extract **PURE snow** and **snow free** pixels
- The selection is based on **spectral indexes**
- Two different criteria must be used for bright and shadowed areas

Bright areas

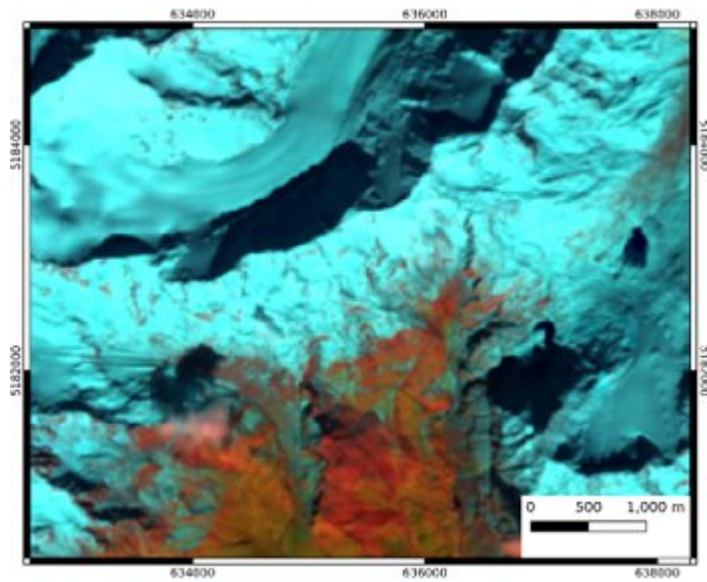
- **Spectral indexes** commonly used can be applied

Shadowed areas

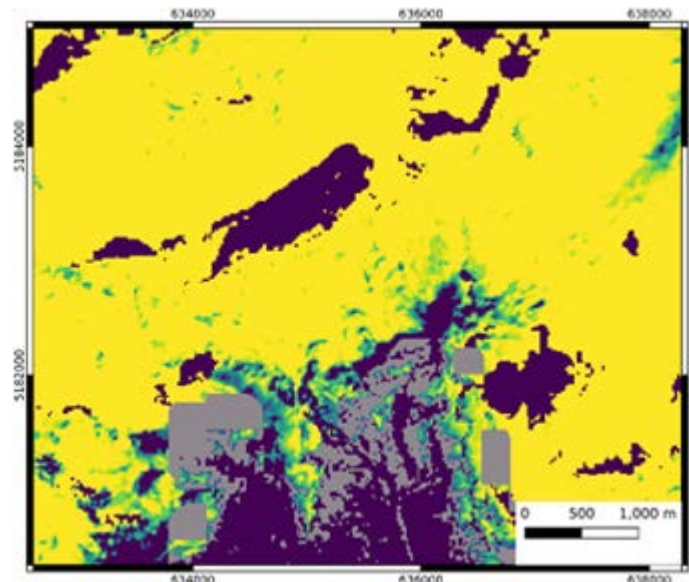
- **Dark areas identification** using **DEM** and **spectral information**
- A **dedicated** and **enhanced** version of **NDSI** helps in endmembers identification

Results: Senales

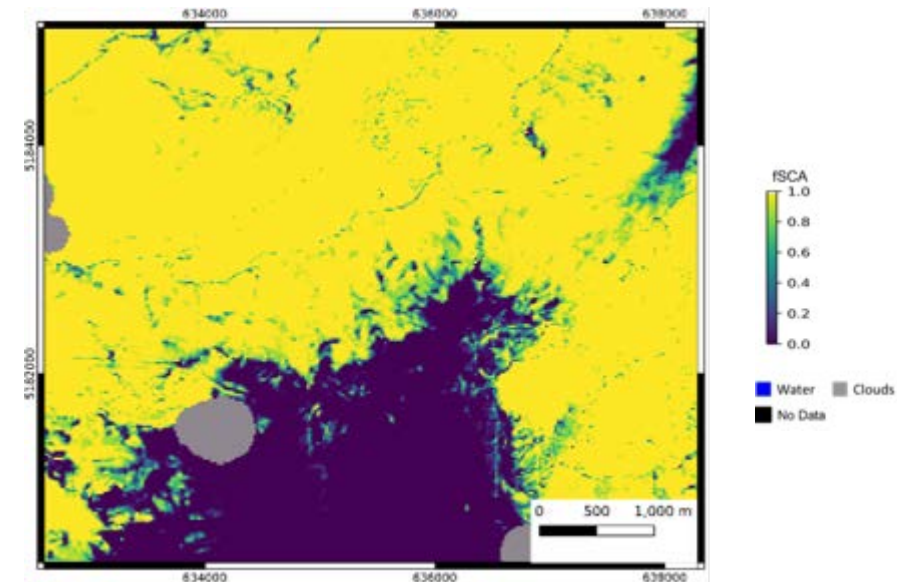
RGB FC



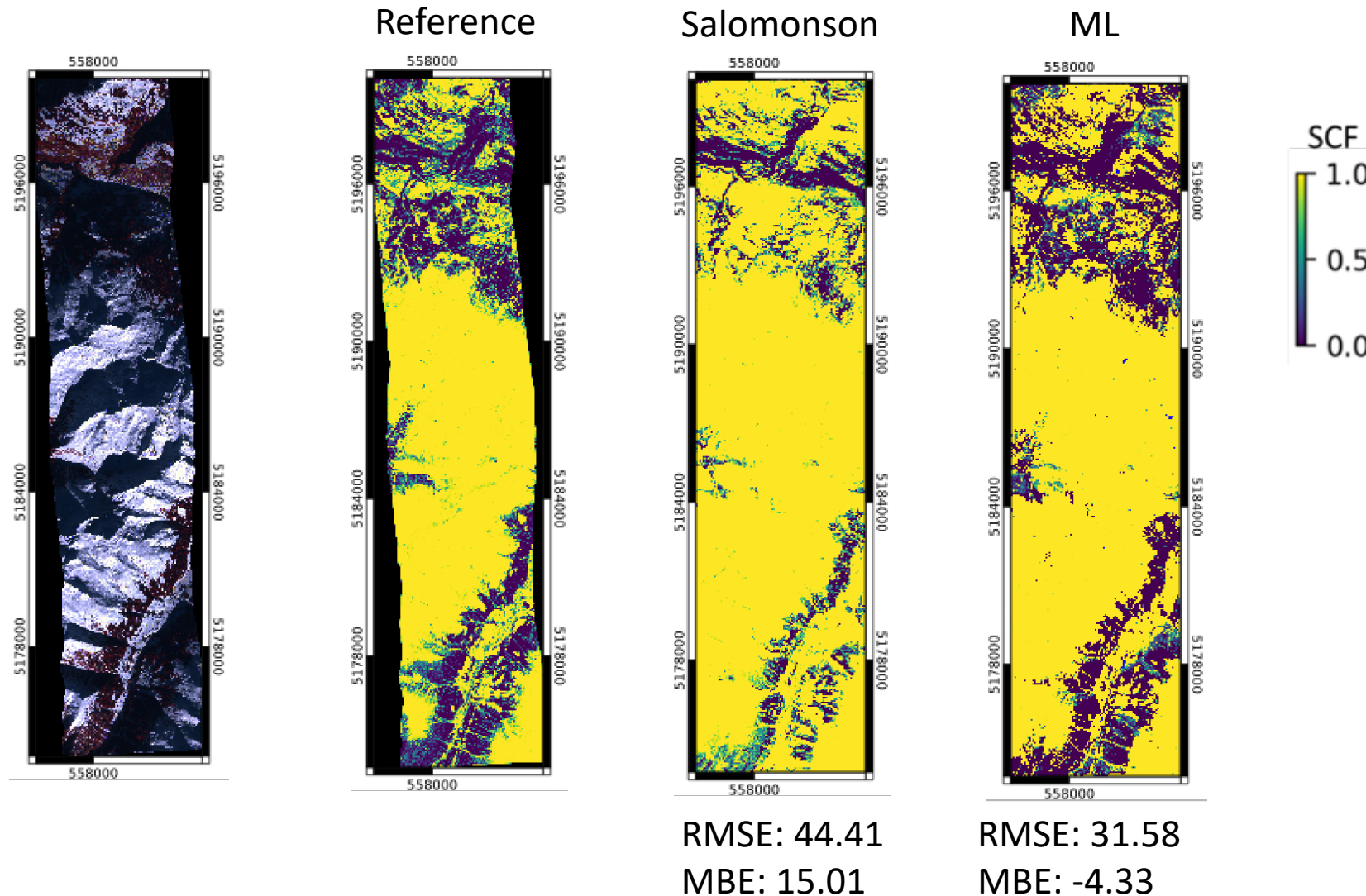
Copernicus snow product



Machine learning method



Validation results: single model



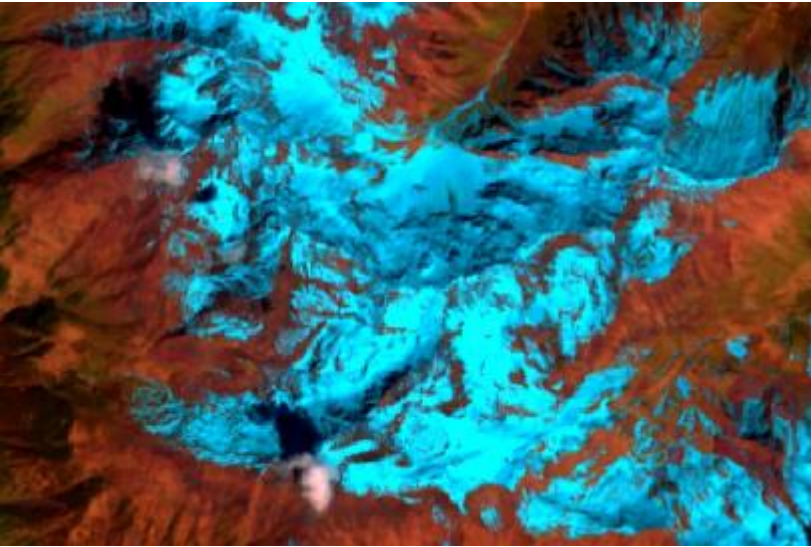
- Metrics are computed considering only the fractional pixels

Snow Cover Area (SCA)

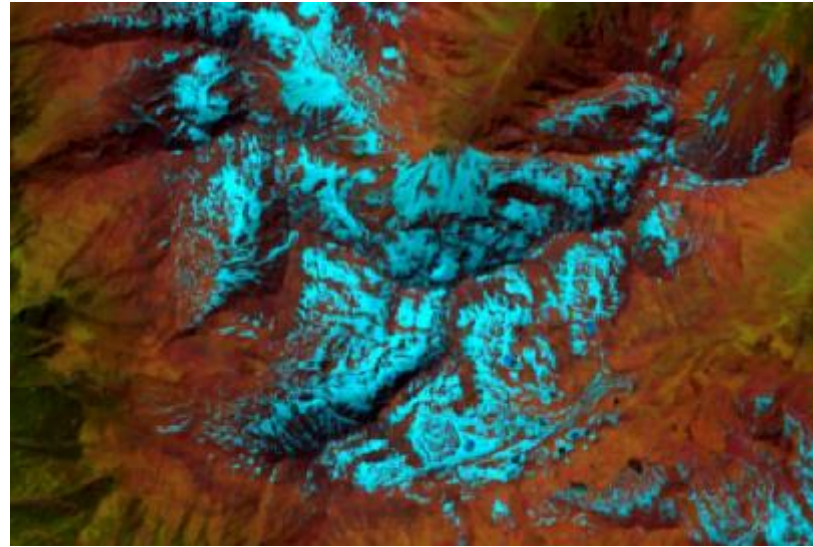
Inter-annual snow patterns

Inter-annual spatial **patterns** are both affected by the local **topography** and **meteorology**. Similar characteristics in terms of **elevation**, **slope**, and **aspect** lead to **similar response** during and after a meteorological event (snow accumulation, distribution, and melting).

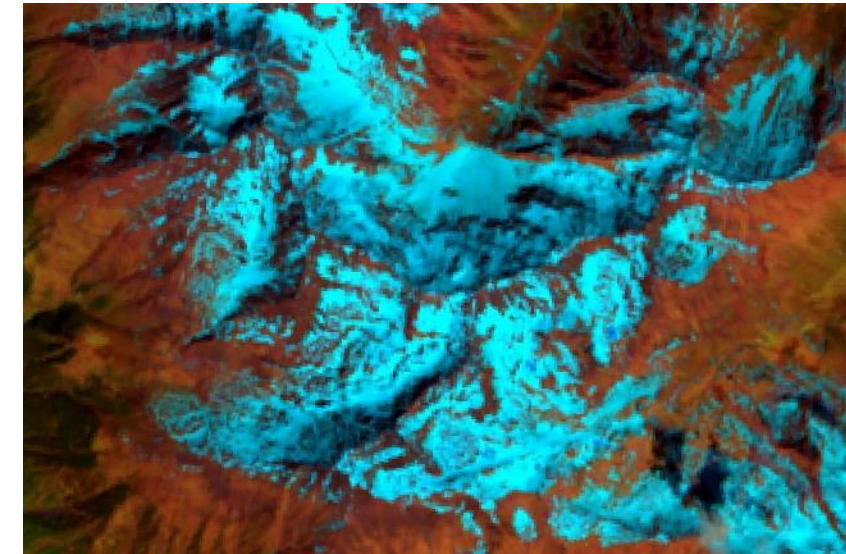
17/05/2017



26/06/2019



21/05/2020



Sentinel-2 RGB (SWIR, NIR, RED) false color composition

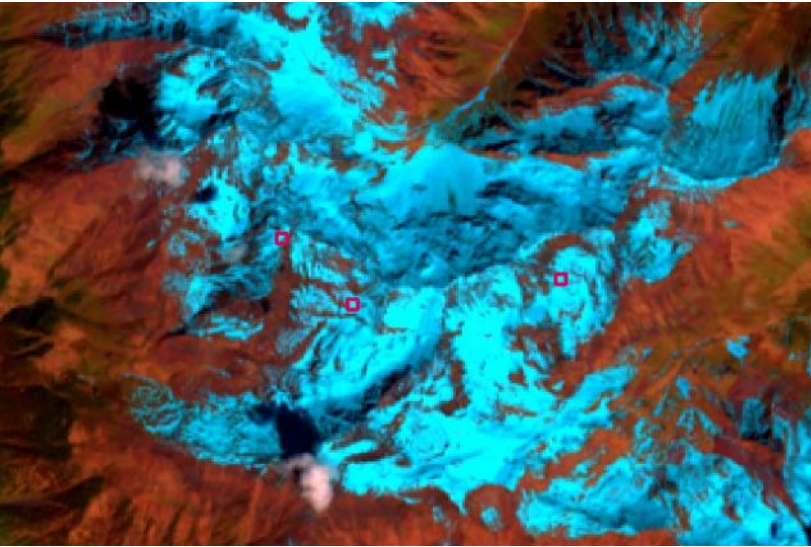
Mendoza, P. A., Musselman, K. N., Revuelto, J., Deems, J. S., López-Moreno, J. I., & McPhee, J. (2020). Interannual and seasonal variability of snow depth scaling behavior in a subalpine catchment. *Water Resources Research*, 56(7), e2020WR027343.

Yang, K., Musselman, K. N., Rittger, K., Margulis, S. A., Painter, T. H., & Molotch, N. P. (2022). Combining ground-based and remotely sensed snow data in a linear regression model for real-time estimation of snow water equivalent. *Advances in Water Resources*, 160, 104075.

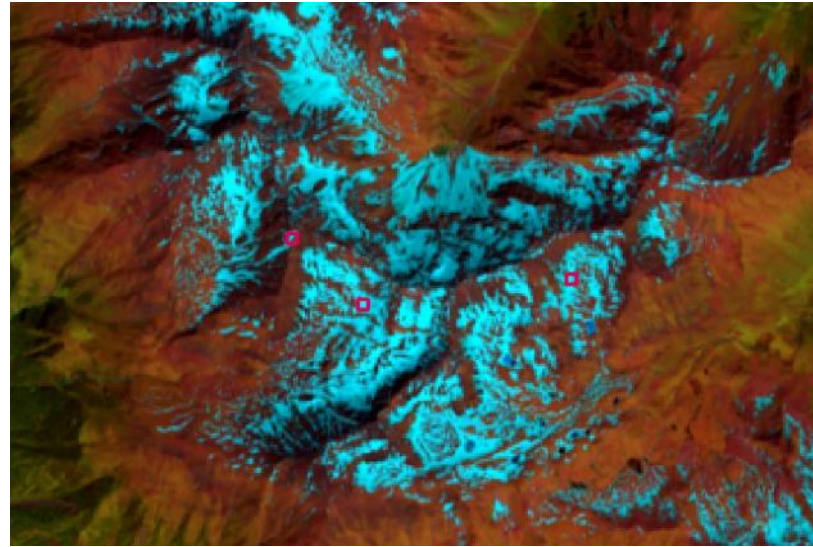
Inter-annual snow patterns

Inter-annual spatial **patterns** are both affected by the local **topography** and **meteorology**. Similar characteristics in terms of **elevation**, **slope**, and **aspect** lead to **similar response** during and after a meteorological event (snow accumulation, distribution, and melting).

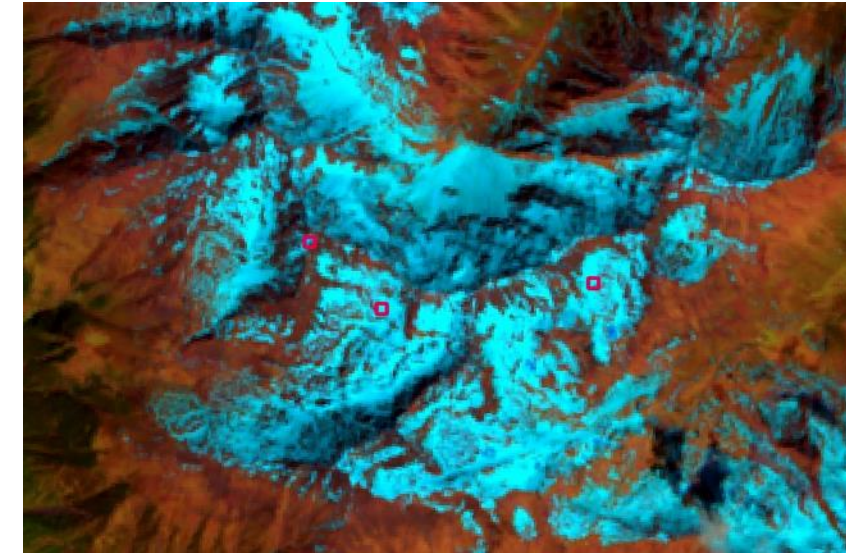
17/05/2017



26/06/2019



21/05/2020

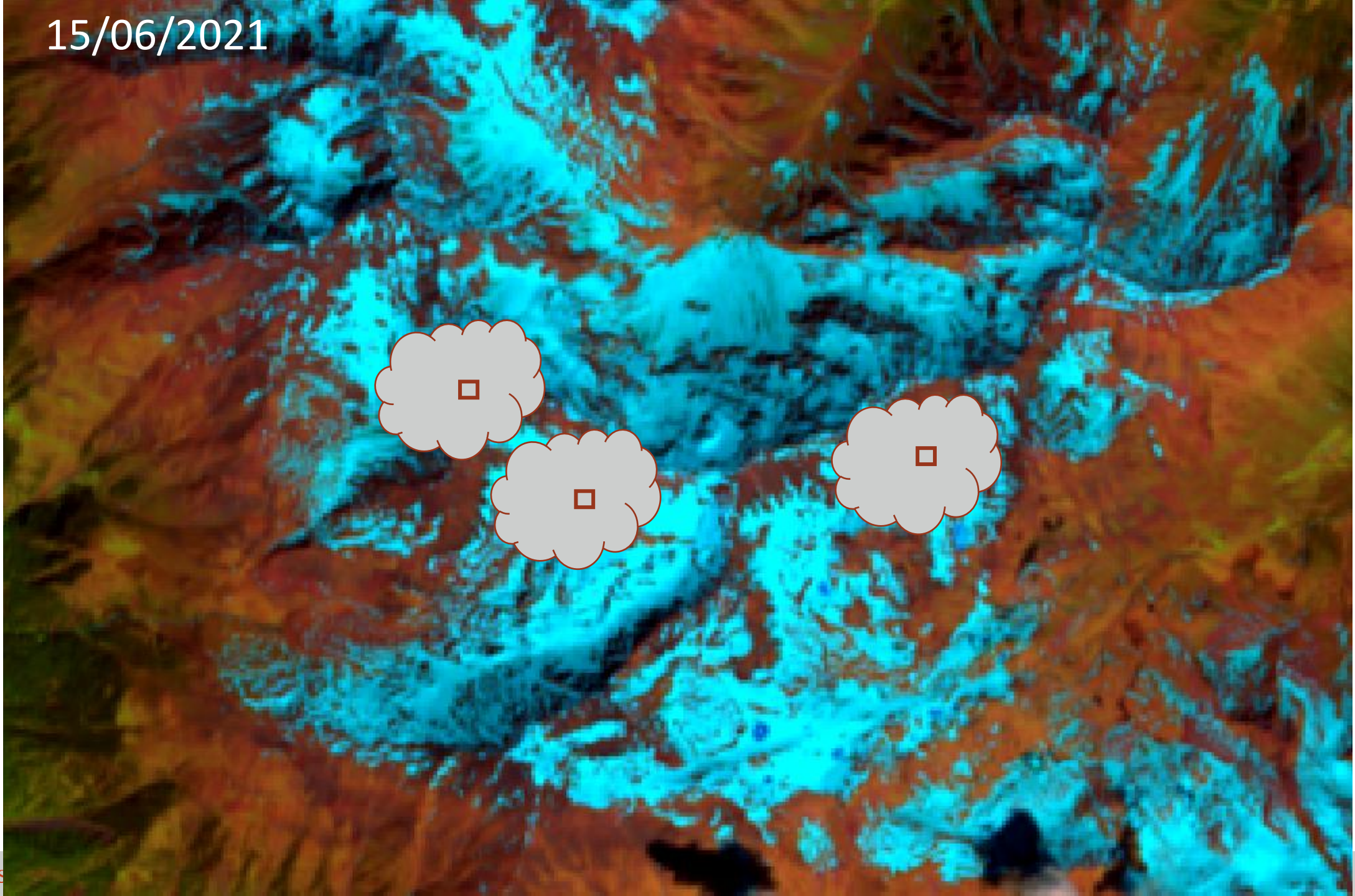


Sentinel-2 RGB (SWIR, NIR, RED) false color composition

Mendoza, P. A., Musselman, K. N., Revuelto, J., Deems, J. S., López-Moreno, J. I., & McPhee, J. (2020). Interannual and seasonal variability of snow depth scaling behavior in a subalpine catchment. *Water Resources Research*, 56(7), e2020WR027343.

Yang, K., Musselman, K. N., Rittger, K., Margulis, S. A., Painter, T. H., & Molotch, N. P. (2022). Combining ground-based and remotely sensed snow data in a linear regression model for real-time estimation of snow water equivalent. *Advances in Water Resources*, 160, 104075.

15/06/2021



15/06/2021

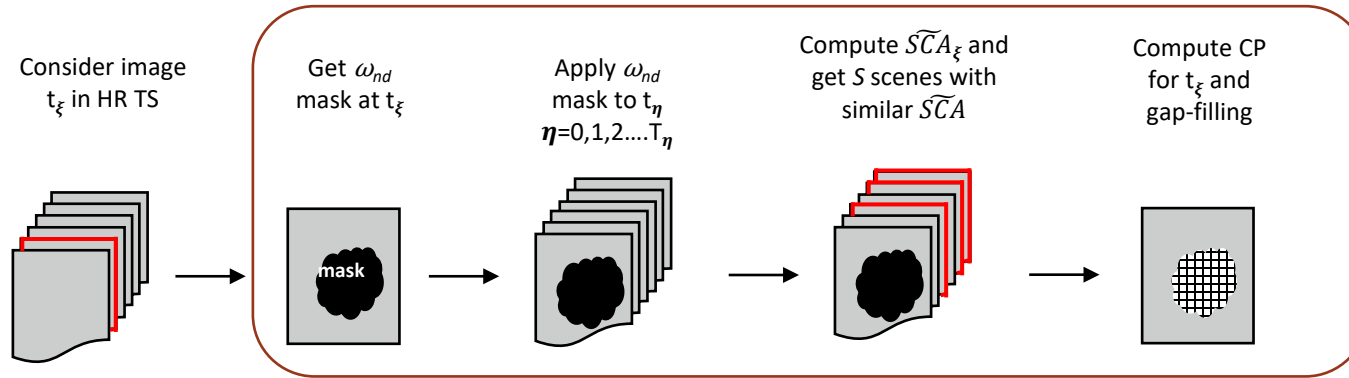
We can learn from the
history and from the **context**

Aim of the work

- Given the fact that current satellite missions do not present **daily high-resolution acquisitions** and images are often affected by **cloud obstruction**, we want to develop a method that fuses high and low-resolution images (Sentinel-2/Landsat and MODIS/VIIRS/Sentinel-3)
- Exploit the **spatial pattern repetition** to perform gap-filling and downscaling steps that are based on **multi-temporal** analyses

Premier, V., Marin, C., Steger, S., Notarnicola, C., & Bruzzone, L. (2021). A novel approach based on a hierarchical multiresolution analysis of optical time series to reconstruct the daily high-resolution snow cover area. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 9223-9240.

GAP-FILLING: remove the clouds



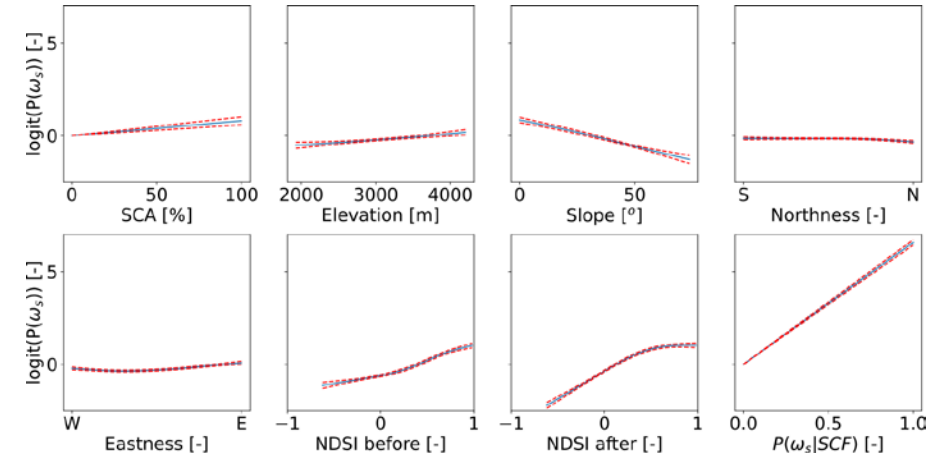
- Applied to any HR maps with gaps;
- Based on the partial observed/reconstructed SCA, denoted as \widetilde{SCA} ;
- Conditional probability to observe a pixel as snow given the historical HR snow pattern persistence:

$$P_i(\omega_s | \widetilde{SCA}) = \frac{\sum_{s=0}^S x_i^s}{S}, i \in \text{mask}$$

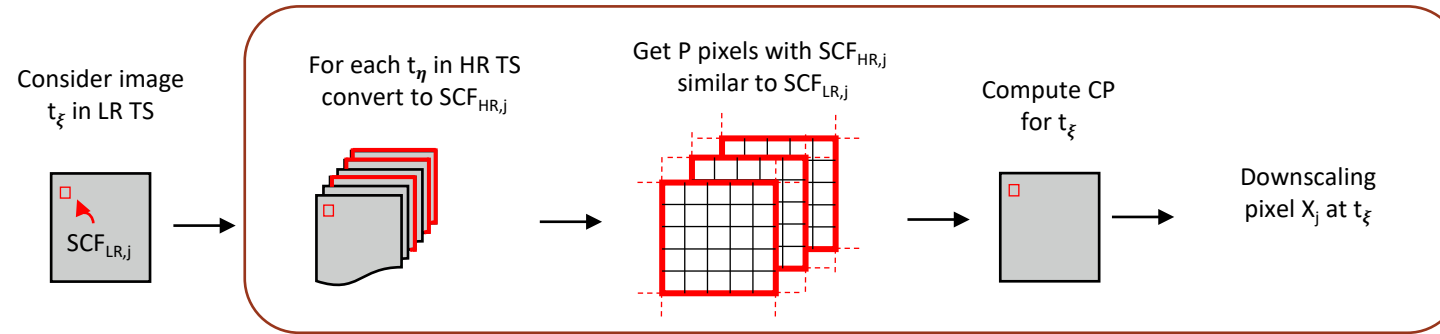
- Hence, it follows:

$$\begin{aligned} x_i &= \omega_s \text{ if } P_i(\omega_s | \widetilde{SCA}) = 1 \\ x_i &= \omega_{sf} \text{ if } P_i(\omega_s | \widetilde{SCA}) = 0 \end{aligned}$$

Generalized Additive Model (GAM)



DOWNSCALING: from MODIS to Sentinel-2 resolution



- Applied when a LR map is available for the date to be reconstructed;
- Based on the observed/interpolated SCF;
- Conditional probability to observe a pixel as snow given the historical LR snow pattern persistence:

$$P_i(\omega_s | SCF_{HR,j}) = \frac{\sum_{p=0}^P x_i^p}{P}, x_i \subset X_j$$

- Hence, it follows:

$$x_i = \omega_s \quad \text{if} \quad \begin{cases} P_i(\omega_s | SCF_{LR,j}) = 1 \\ SCF_{LR,j} = 1 \end{cases}$$

$$x_i = \omega_{sf} \quad \text{if} \quad \begin{cases} P_i(\omega_s | SCF_{LR,j}) = 0 \\ SCF_{LR,j} = 0 \end{cases}$$

Snow Water Equivalent (SWE)

Daily HR SWE reconstruction

1. Snow Cover Fraction Identification from Multispectral Images



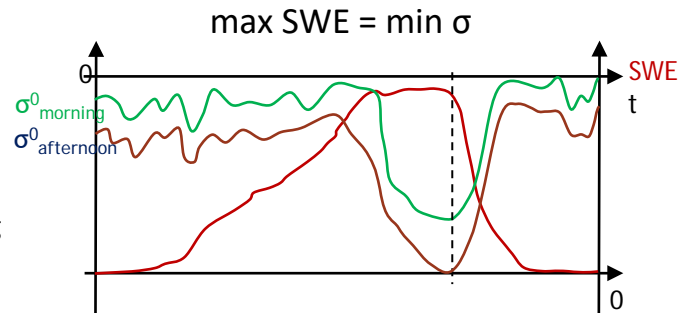
2. Downscaling and Temporal Gap-filling of Snow Cover Area Maps



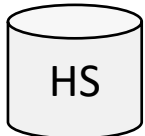
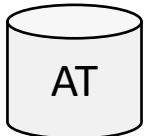
3. Melting Phases Identification from Multitemporal SAR Data



Backscattering
time series

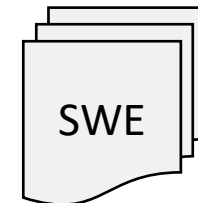
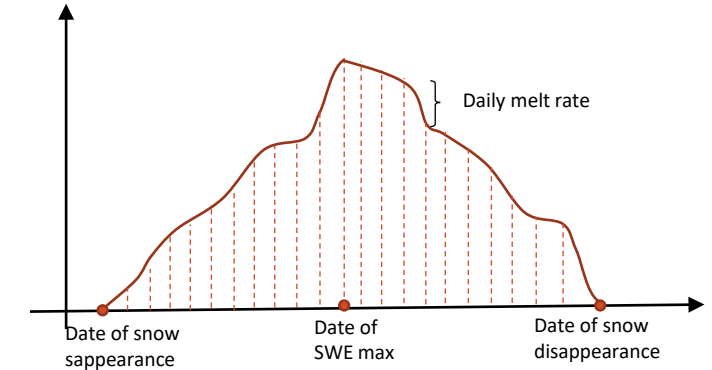


4. Use of in-situ data (e.g., air temperature, snow depth)



5. High-Resolution Snow Water Equivalent (SWE) Reconstruction

Date of snow
appearance and
disappearance
(pixel-wise)



Aim of the work

- Exploit **multi-source high-resolution satellite data** for **snow water equivalent (SWE) reconstruction**
- Use a simple degree day model that is forced by accurate satellite information on snow duration and snowmelt timing

Premier, V., Marin, C., Bertoldi, G., Barella, R., Notarnicola, C., & Bruzzone, L. (2023). Exploring the use of multi-source high-resolution satellite data for snow water equivalent reconstruction over mountainous catchments. *The Cryosphere*, 17(6), 2387-2407.

Proposed SWE reconstruction

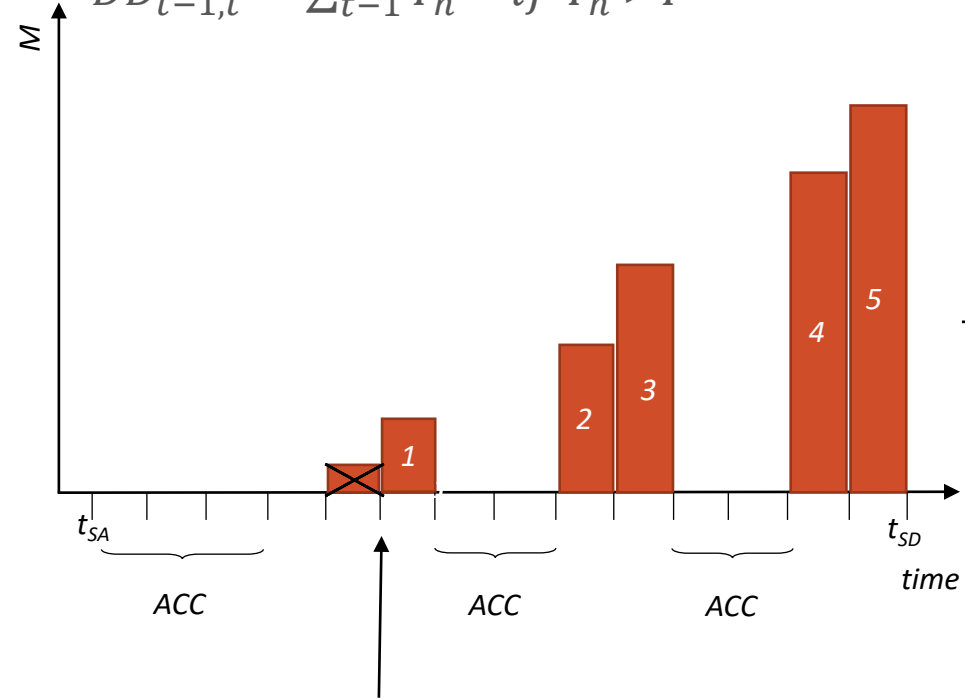
Computation of the total mass

$$A_{tot} = M_{tot}$$

Potential melting estimation

$$M_{t-1,t}[mm] = a[mm^{\circ}C^{-1}d^{-1}]DD_{t-1,t}[^{\circ}Cd]$$

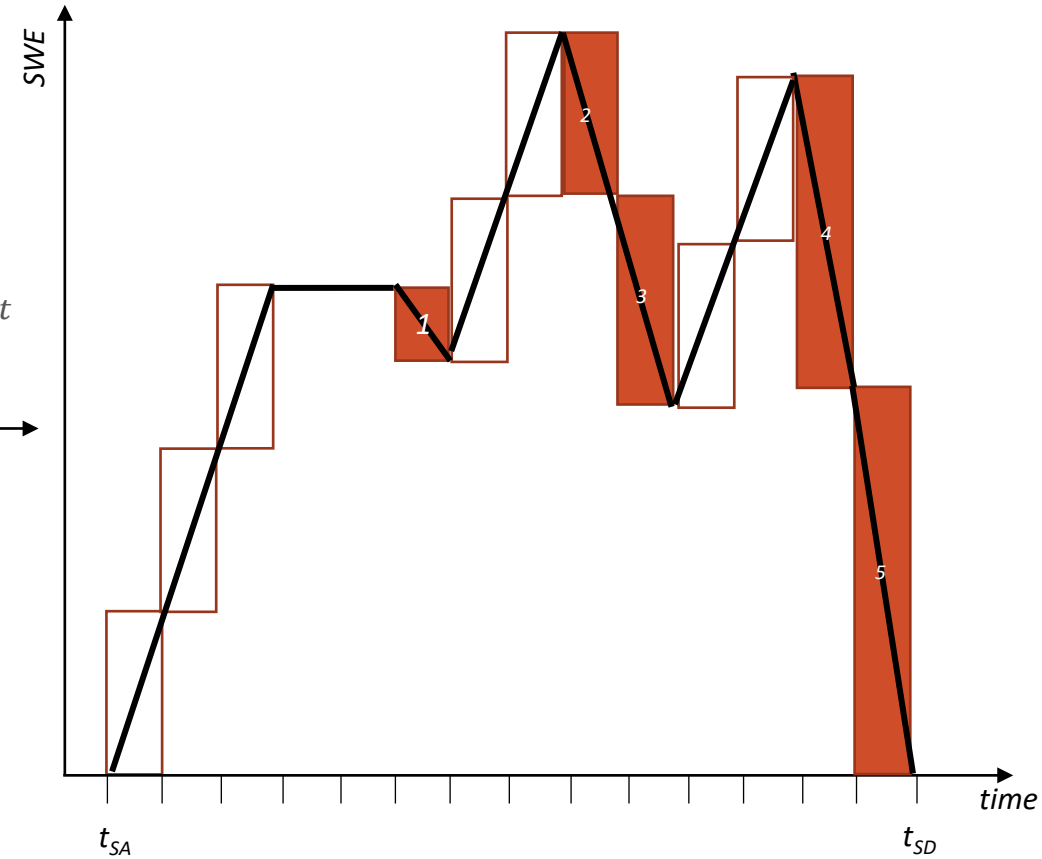
$$DD_{t-1,t} = \sum_{t-1}^t T_h \quad \text{if } T_h > \hat{T}$$



Accumulation estimation

$$A_{t-1,t} = k_{t-1,t} A_{tot}$$

SWE temporal reallocation



Results

South Fork catchment, Sierra Nevada, California (4th July 2019)

Proposed



Evaluation metrics for 14 dates:

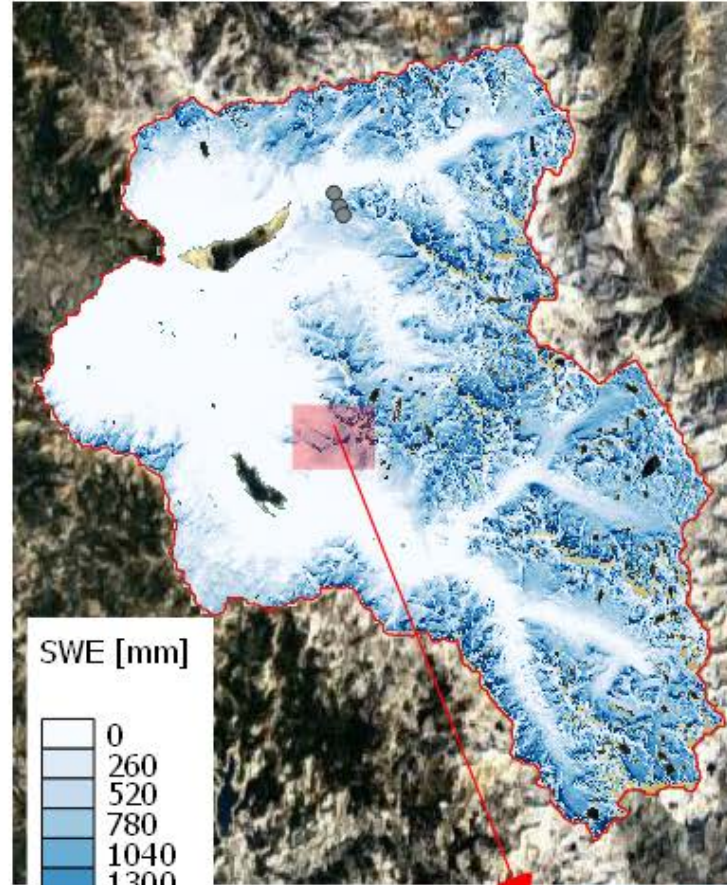
BIAS -40 mm

RMSE 216 mm

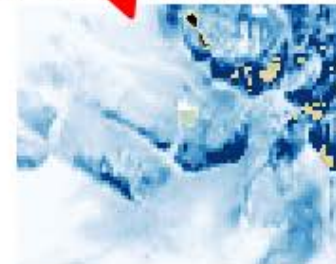
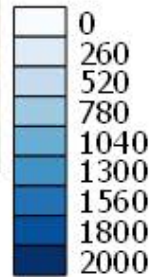
Correlation 0.729



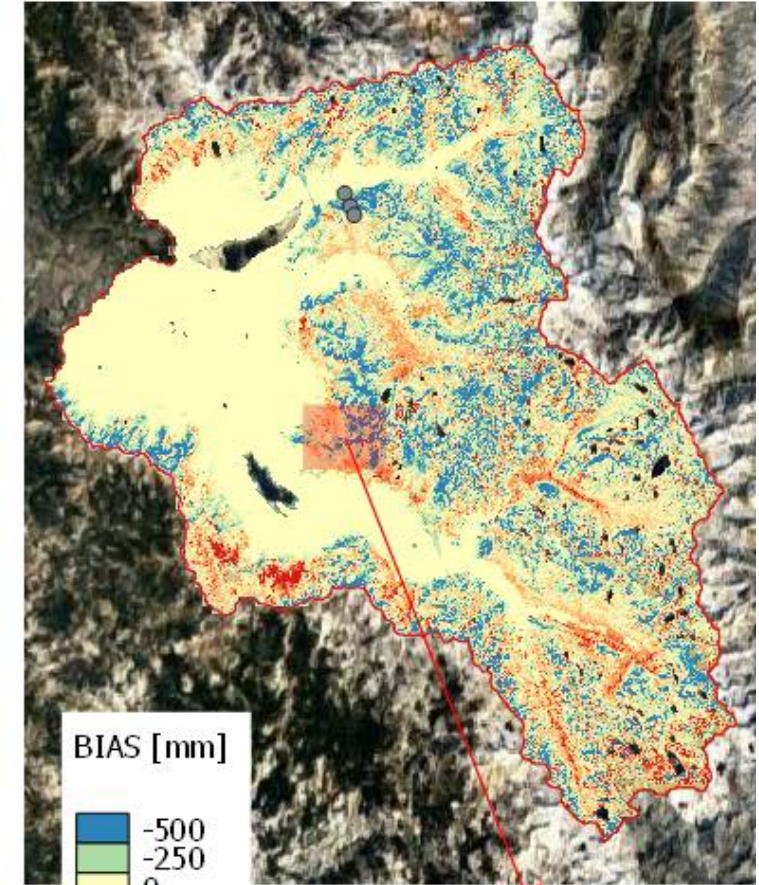
ASO



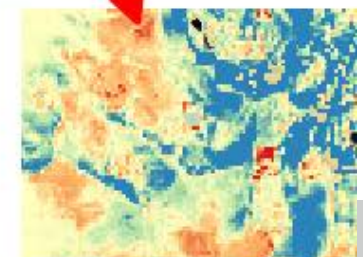
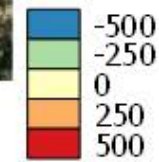
SWE [mm]



BIAS

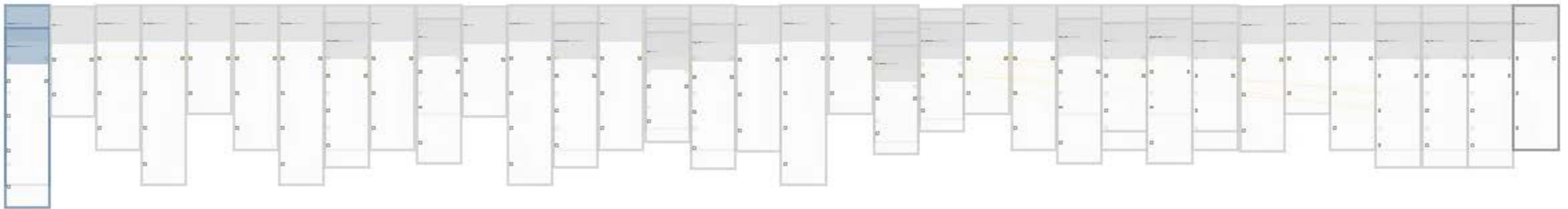


BIAS [mm]



Current advantages/challenges

- Easy access to several earth observation datasets and auxiliary data, as required by our multi-source methods;
- Possibility to work with several back-ends (e.g., CDSE);
- Standardized processes but also possibility to define user defined functions (UDFs);
- Open-source code.
- Standardized processes might not be sufficient for complex algorithms;
- Challenges when working with long time-series;
- Sometimes difficult to debug.



Thanks for your attention