Near-Real-Time Snow Cover Fraction Estimation

using Linear Spectral Unmixing of Sentinel-2 MSI Top-of-Atmosphere Reflectance Data

Lars Keuris, Markus Hetzenecker, Gabriele Schwaizer, Thomas Nagler and Nico Mölg

enveo

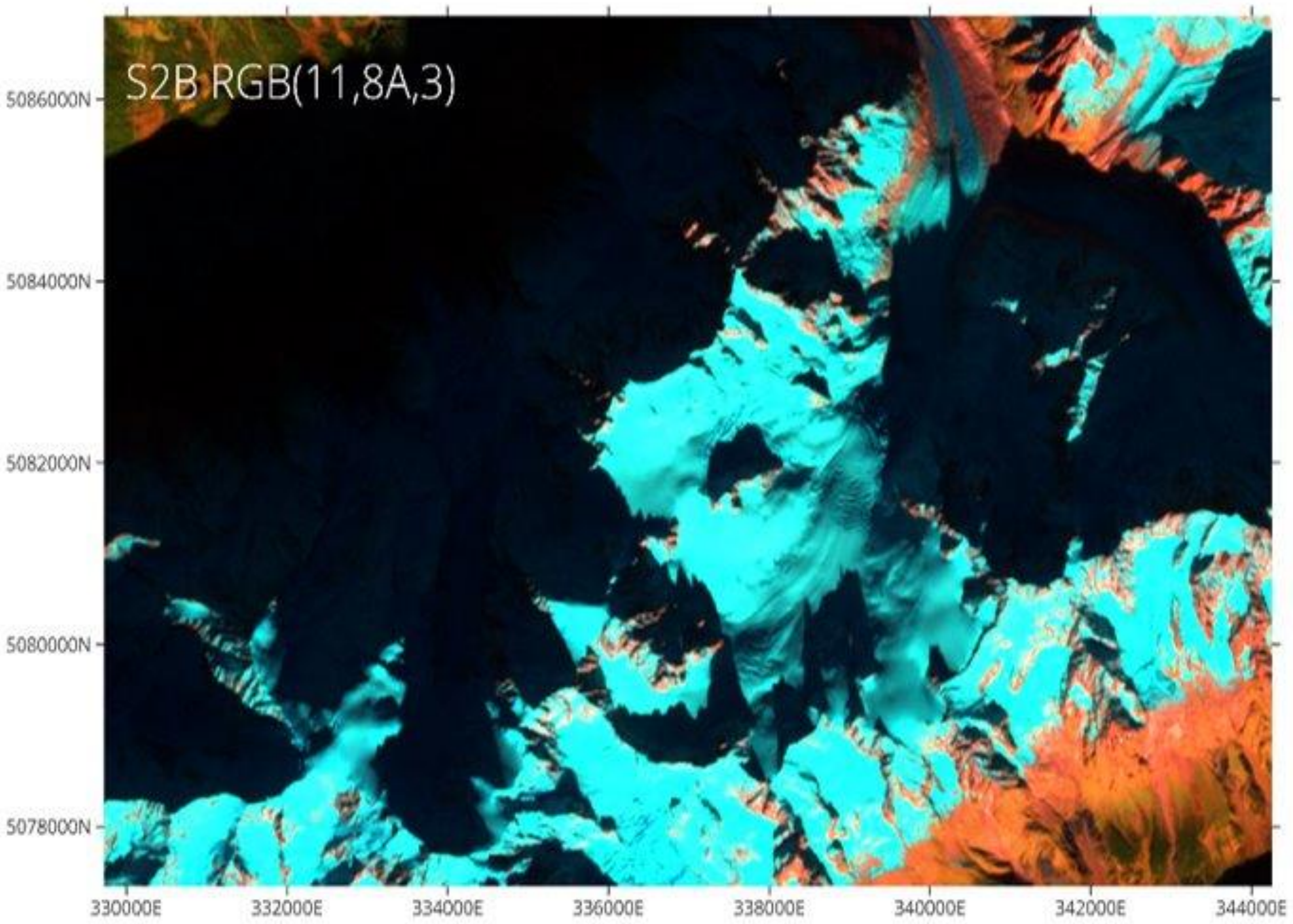
AlpSnow

snow cci

Estimating SCF in Mountainous Terrain [1/2]

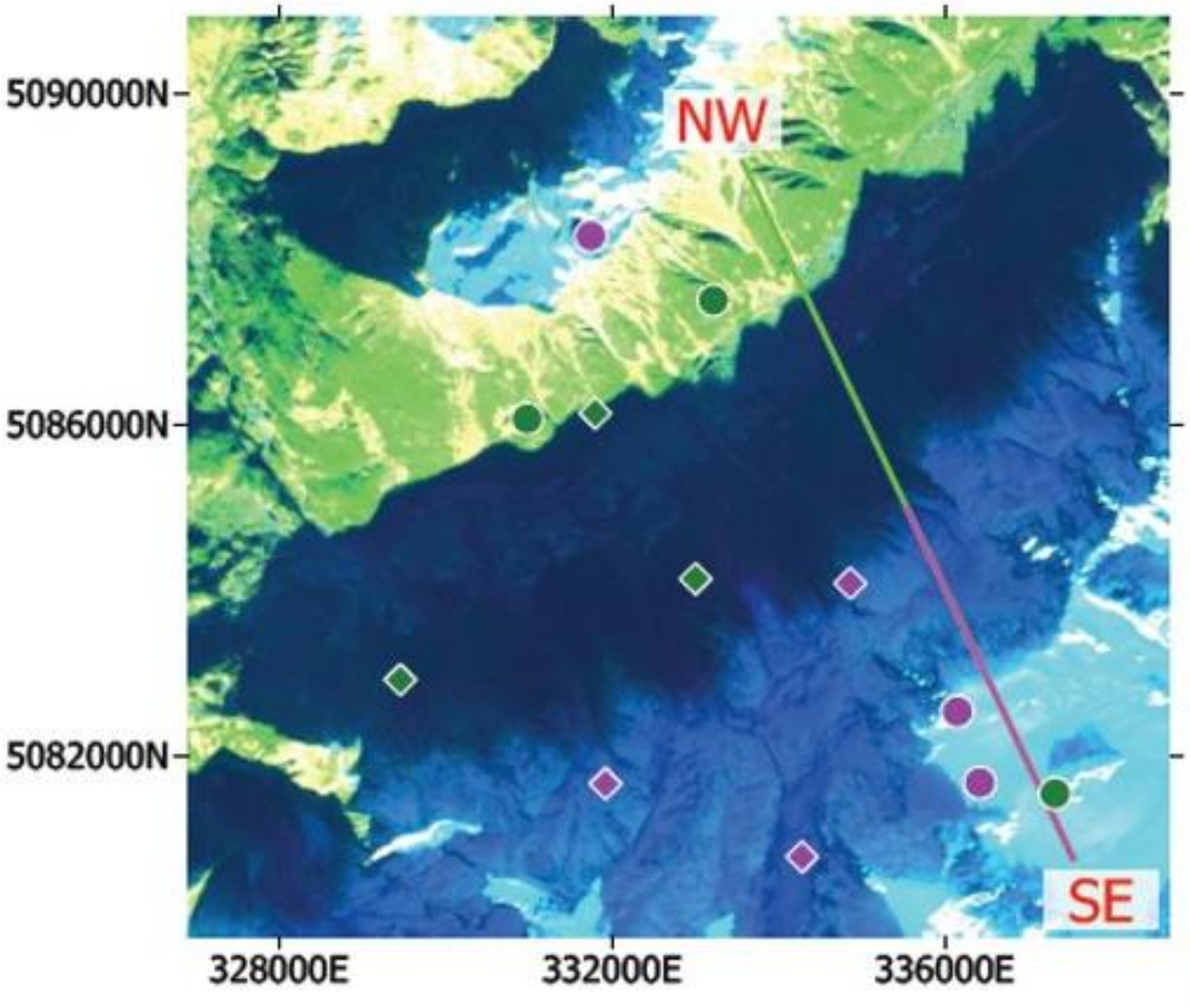
- Challenges using spectral information:
  - Variability within surface classes
    - Vegetation
    - Rock
    - Snow
  - Spectral signature depends on illumination conditions

- Adaptive method required that incorporates multiple spectral bands

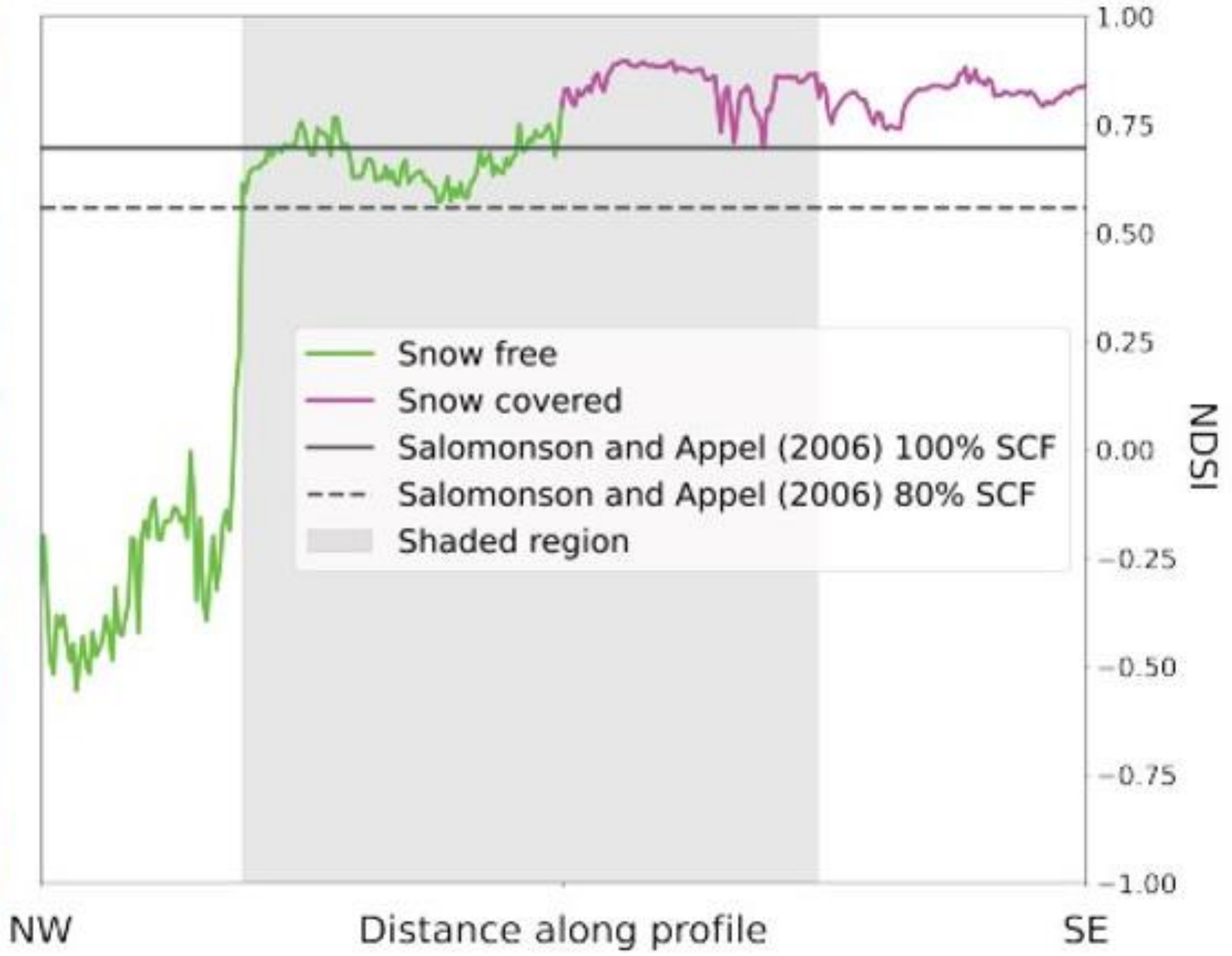


25 November 2020, Alps (32TLR)

Estimating SCF in Mountainous Terrain [2/2]



25 November 2020 in the Alps (32TLR) with the RGB colors scaled from 0 to 0.25, 0 to 0.15 and 0 to 0.15



Methodology [1/3]
MultiSpectral Unmixing for mixed pixels

- Multispectral Unmixing
  - Constrained linear least-squares problem

$$y = Ax$$

Observation vector, design matrix, parameter vector

$$y = \begin{bmatrix} r^{obs}_{\lambda_1} \\ \vdots \\ r^{obs}_{\lambda_M} \end{bmatrix} \quad A = \begin{bmatrix} r^{snowfree}_{\lambda_1} & r^{snow}_{\lambda_1} \\ \vdots & \vdots \\ r^{snowfree}_{\lambda_M} & r^{snow}_{\lambda_M} \end{bmatrix} \quad x = \begin{bmatrix} f_{snowfree} \\ f_{snow} \end{bmatrix}$$

Subject to sum-to-one and non-negativity constraint

$$\hat{x} = (A^T A)^{-1} A^T y$$

- Error propagation

$$Q_{\hat{x}\hat{x}} = (A^T Q_{yy}^{-1} A)^{-1}$$

- Uncorrelated noise in observations

$$Q_{\hat{x}\hat{x}} = \sigma_y^2 (A^T A)^{-1}$$

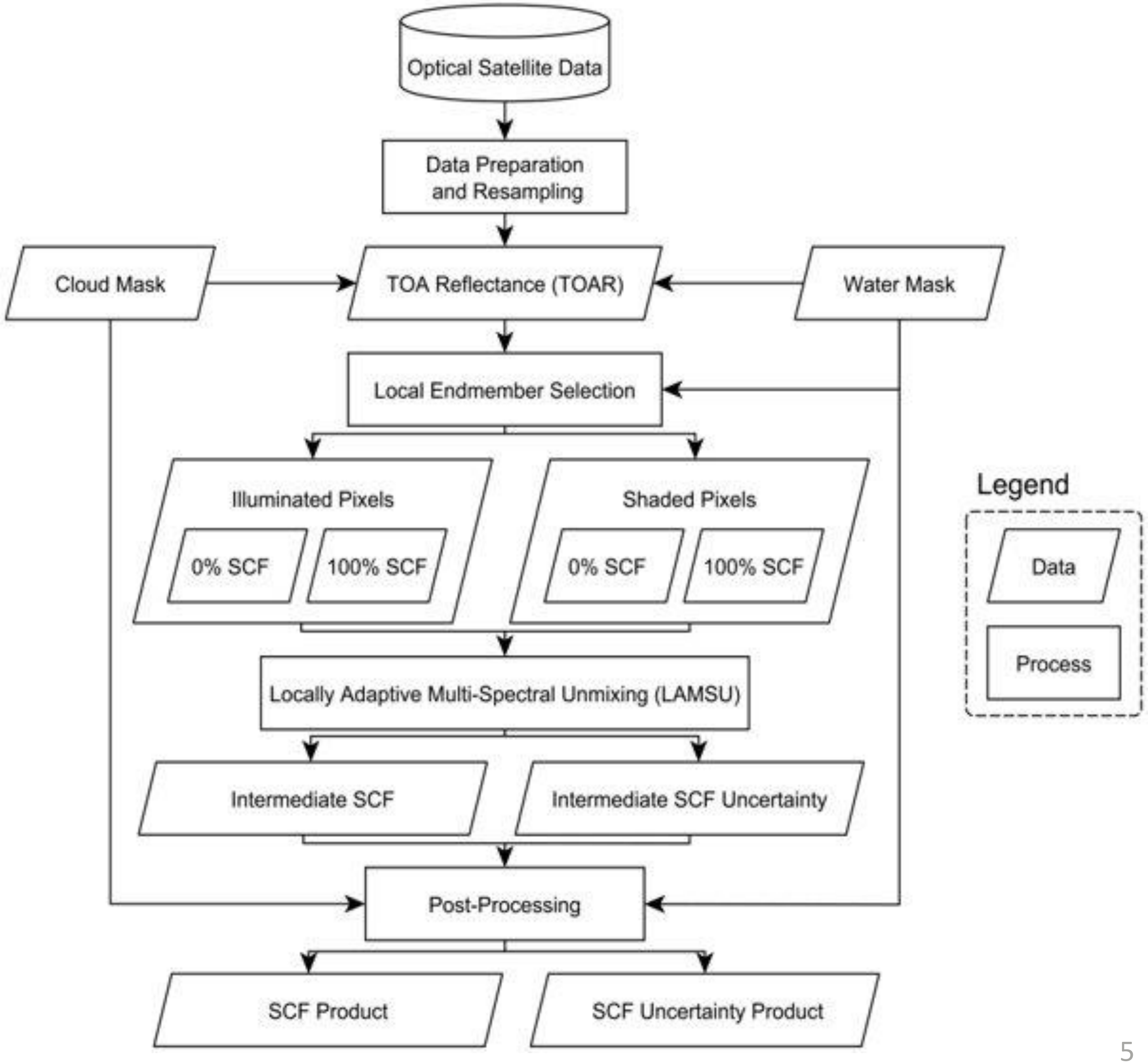
$$\sigma_y^2 = \frac{(y - A\hat{x})^T (y - A\hat{x})}{M - N}$$

- Degrees of freedom

$$M - N$$

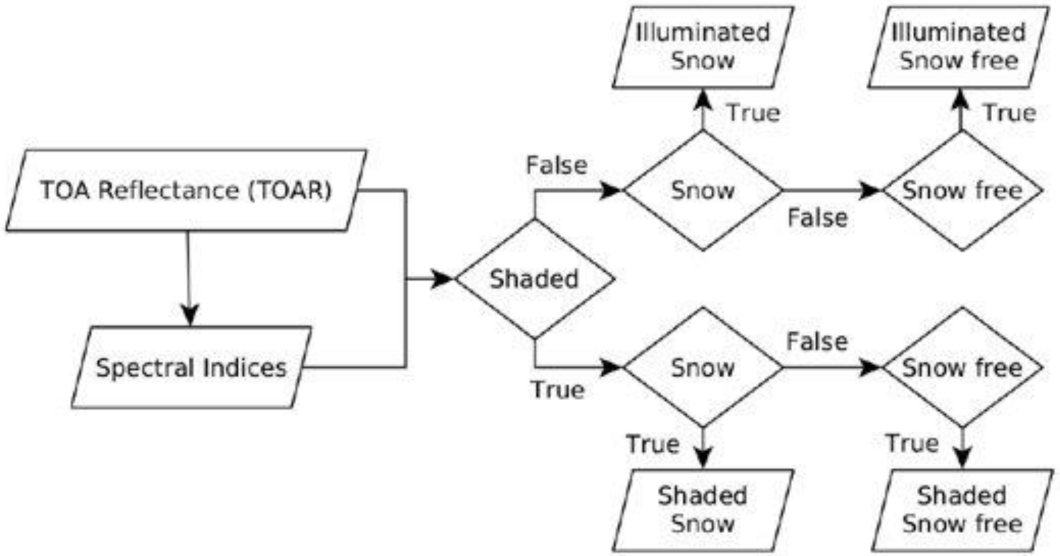
Methodology [2/3]
LAMSU: Locally Adaptive MultiSpectral Unmixing

- Multispectral Unmixing
  - Endmembers extracted from the image (separately for illuminated and shaded areas)
  - Use of nearby endmembers
  - Use of multiple combinations
  - Ensemble SCF
- Characteristics
  - Locally adaptive to:
    - Intra-class variability
    - Illumination conditions
  - Robustness
- Uncertainty estimate
  - Error propagation



Methodology [3/3]

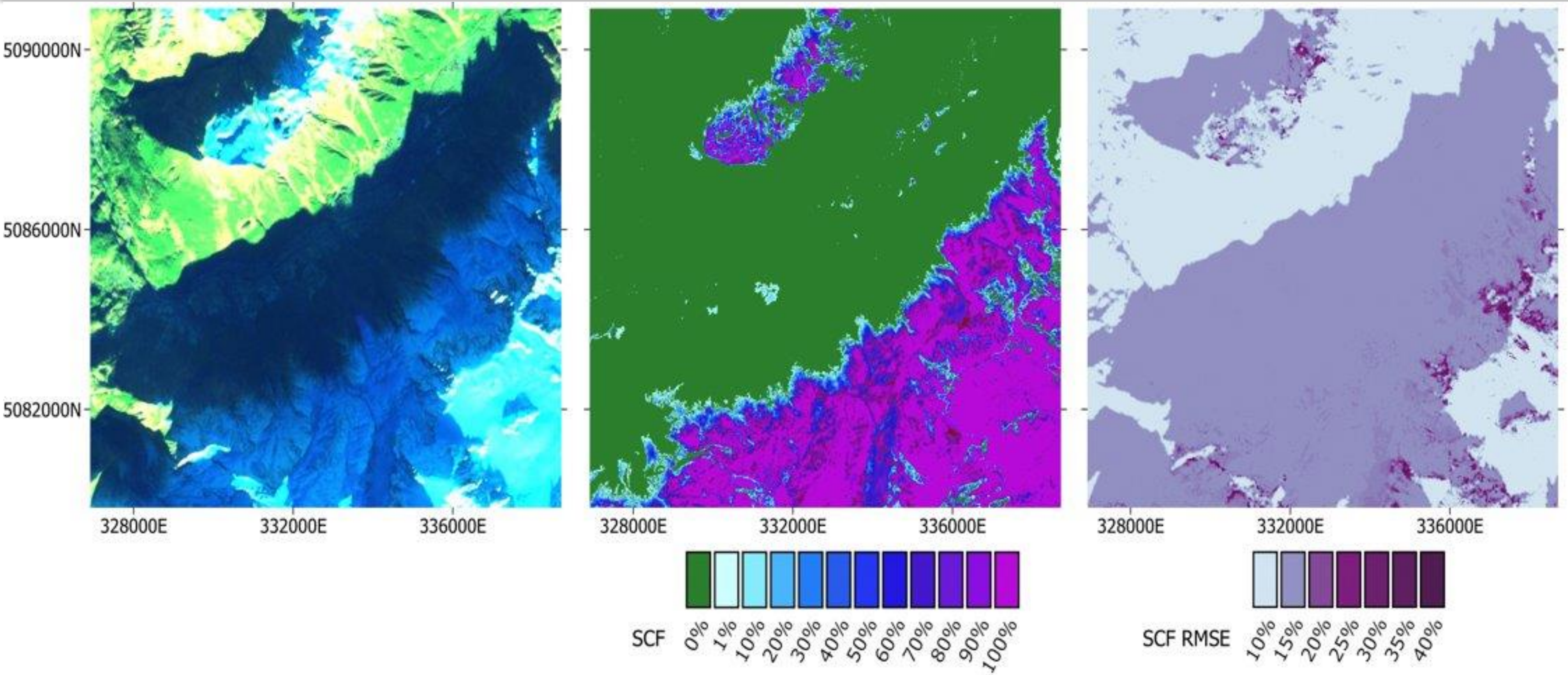
LAMSU: Locally Adaptive MultiSpectral Unmixing



№	Spectral Index	Characteristic
1	$\frac{r_{560}-r_{1610}}{r_{560}+r_{1610}}$	Increases with snow presence and shade. Also known as the NDSI [23].
2	$\frac{r_{860}-r_{650}}{r_{860}+r_{650}}$	Increases with vegetation presence and decreases within shade. Also known as the NDVI [41].
3	$\frac{2.5\cdot(r_{860}-r_{650})}{r_{860}+2.4\cdot r_{650}+1}$	Increases with vegetation presence and decreases within shade. Also known as the two-band EVI [42].
4	$2^{\frac{r_{560}+r_{660}-r_{860}-r_{1610}}{r_{560}+r_{660}+r_{860}+r_{1610}}}$	Increases with snow presence, but is more robust and sensitive to snow in the shade than the NDSI.
5	$2^{\frac{2\cdot r_{560}-r_{660}-r_{1610}}{2\cdot r_{560}+r_{660}+r_{1610}}}$	Same as (4), but is less sensitive to vegetation.
6	$2^{\frac{2\cdot r_{560}-r_{650}-r_{850}}{2\cdot r_{560}+r_{650}+r_{850}}}$	Same as (4), but is more sensitive to shade than snow.
7	$2^{\frac{2\cdot r_{650}-r_{860}-r_{1610}}{2\cdot r_{650}+r_{860}+r_{1610}}}$	Same as (4), but is less sensitive to snow.
8	$\frac{r_{560}-r_{650}}{r_{560}+r_{650}}$	Increases with shade and is close to zero for snow.
9	$\frac{r_{650}-r_{1610}}{r_{650}+r_{1610}}$	Increases with snow presence and shade. Slightly lower sensitivity to snow presence and shade than (1).
10	$\frac{r_{860}-r_{1610}}{r_{860}+r_{1610}}$	Increases with snow presence and shade. Lower sensitivity to snow presence and shade (in particular in illuminated areas) than (1).
11	$\frac{r_{860}-r_{2200}}{r_{860}+r_{2200}}$	Increases with snow presence and shade. Lower sensitivity to snow presence and shade (in particular in illuminated areas) than (1).

SCF Example: S2B T32TLR - 25 Nov 20

LAMSU: Locally Adaptive MultiSpectral Unmixing



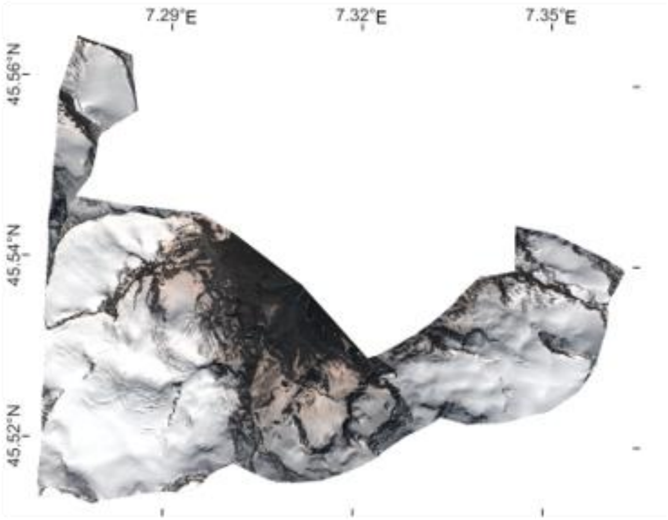
Validation [1/3]: Strategy

LAMSU: Locally Adaptive MultiSpectral Unmixing

- Preparation of reference snow maps
  - Very-High-Resolution WV-2/3 data (<2 m) over Alpine regions
  - Binary snow classification using a supervised machine learning method
  - Aggregation of snow maps to S2 resolution

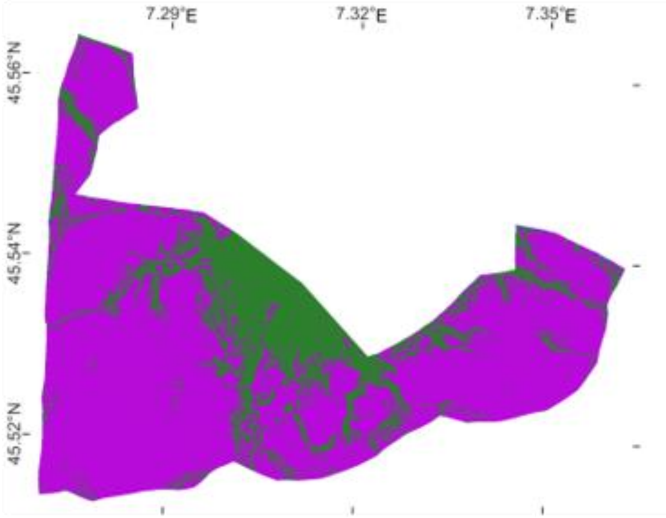
- S2 SCF evaluation
  - Pixel-wise comparison (Monte Carlo: 50% / 50% sampling)
  - Calculation of statistical metrics (Bias, RMSE)
  - Validation is independent of snow-free/snow distribution

Validation [2/3]: Reference Data Preparation
LAMSU: Locally Adaptive MultiSpectral Unmixing

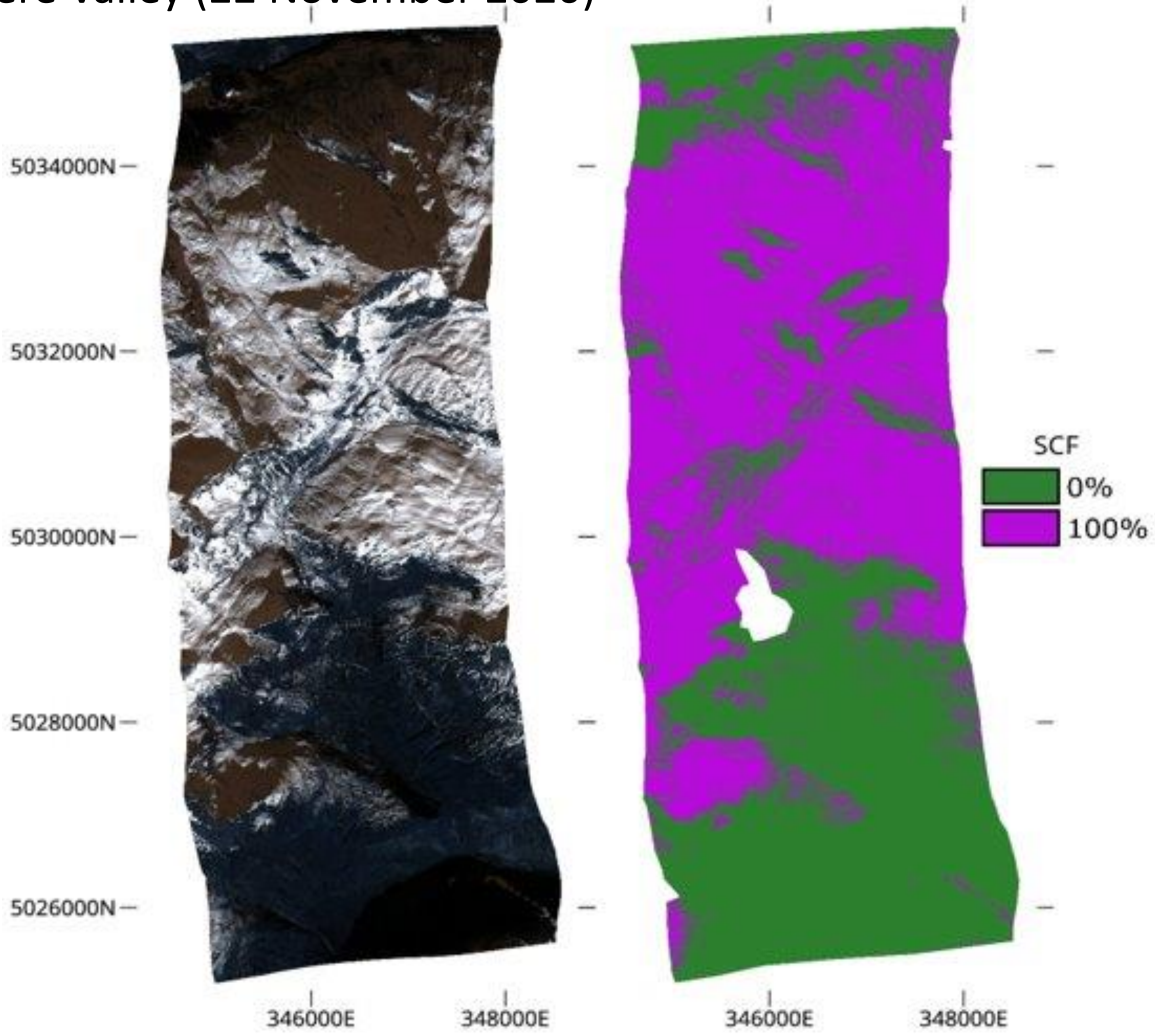


Aosta Valley (23 June 2020)

Binary snow map (0.30 m)



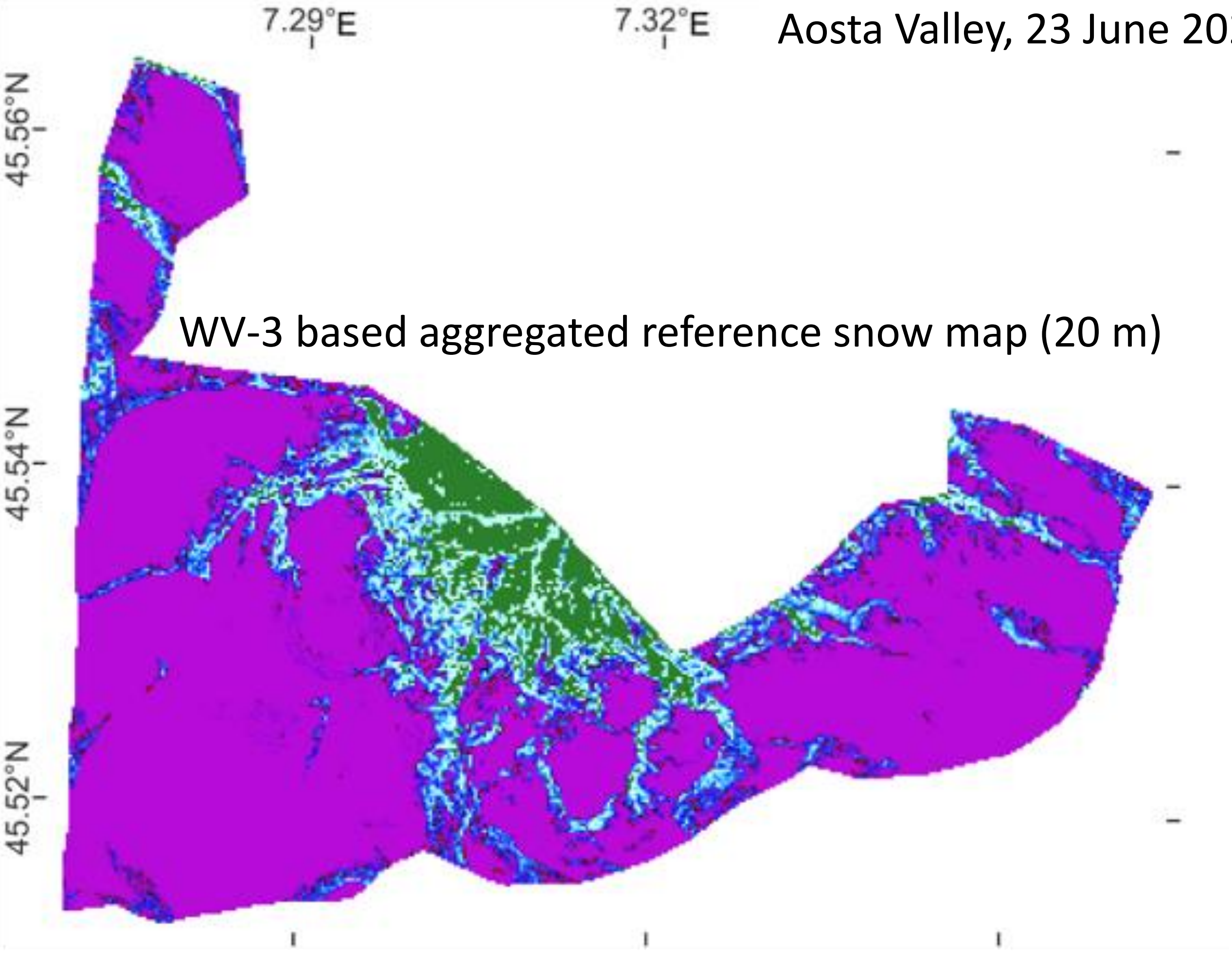
Isere Valley (22 November 2020)



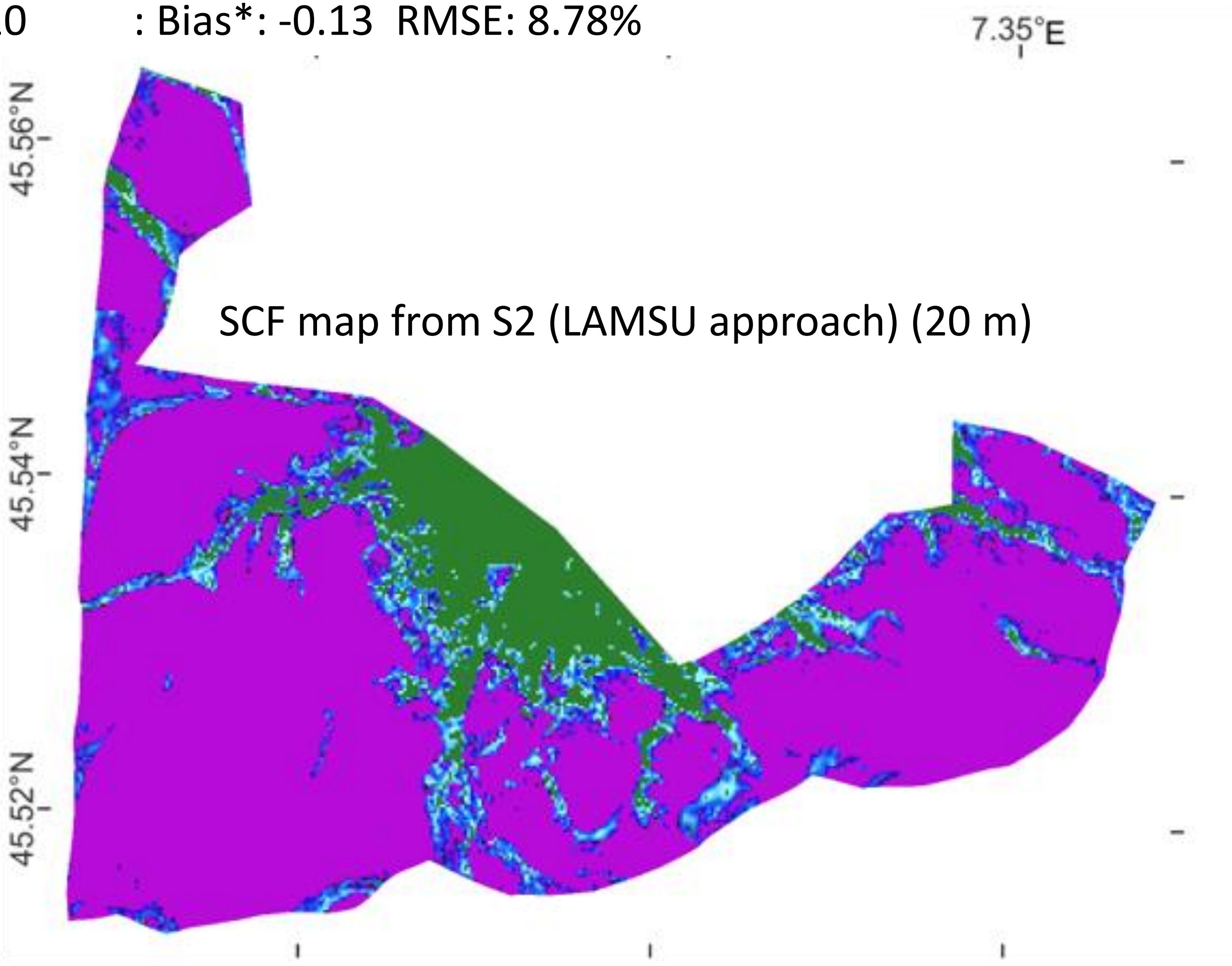
Binary snow map (1.20 m)

Validation [3/3]: Results
LAMSU: Locally Adaptive MultiSpectral Unmixing

Isere Valley, 22 November 2020 : Bias*: +2.88 RMSE: 15.08%
Aosta Valley, 23 June 2020 : Bias*: -0.13 RMSE: 8.78%



WV-3 based aggregated reference snow map (20 m)



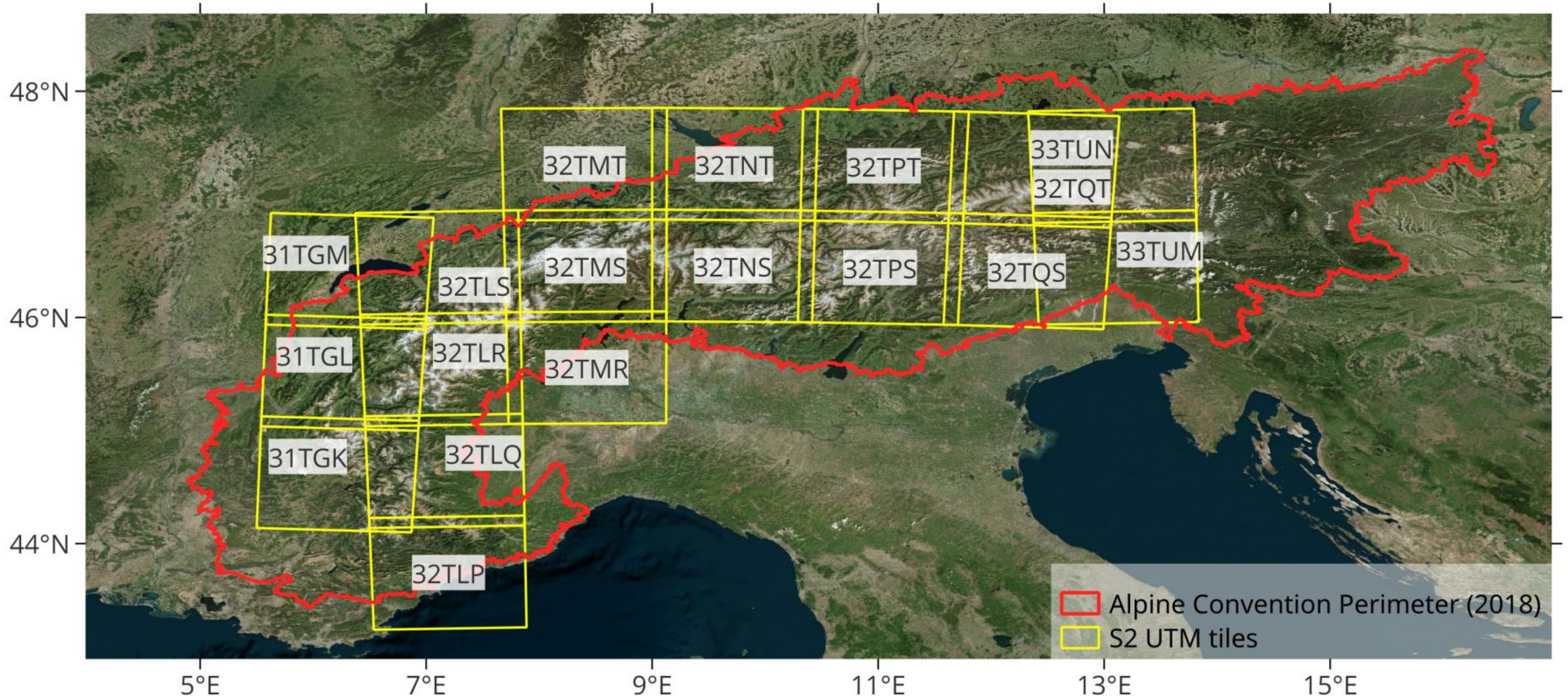
SCF map from S2 (LAMSU approach) (20 m)

*Bias is WV-3 SCF minus S2 SCF

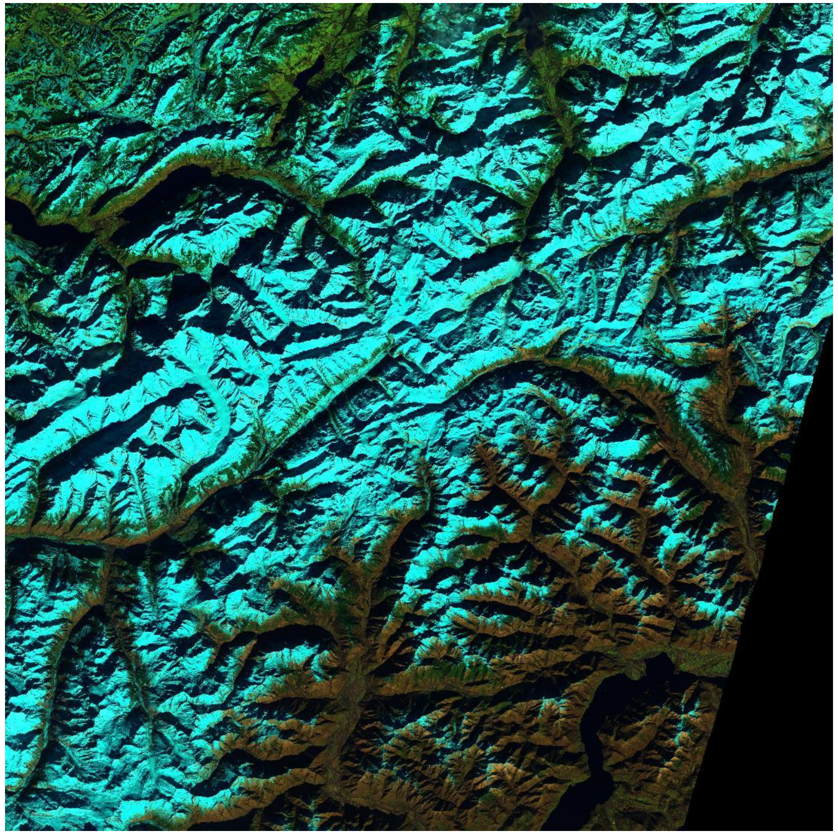
LAMSU: NRT Demonstration [1/3]

- Demonstrator
  - Mountainous terrain
  - Updates 4 times a day
  - 18 UTM tiles
  - Proof of concept
  - Best-effort basis
- Currently 800+ tiles
  - Quicklook
  - S2 LAMSU SCF
  - S2 LAMSU SCF RMSE

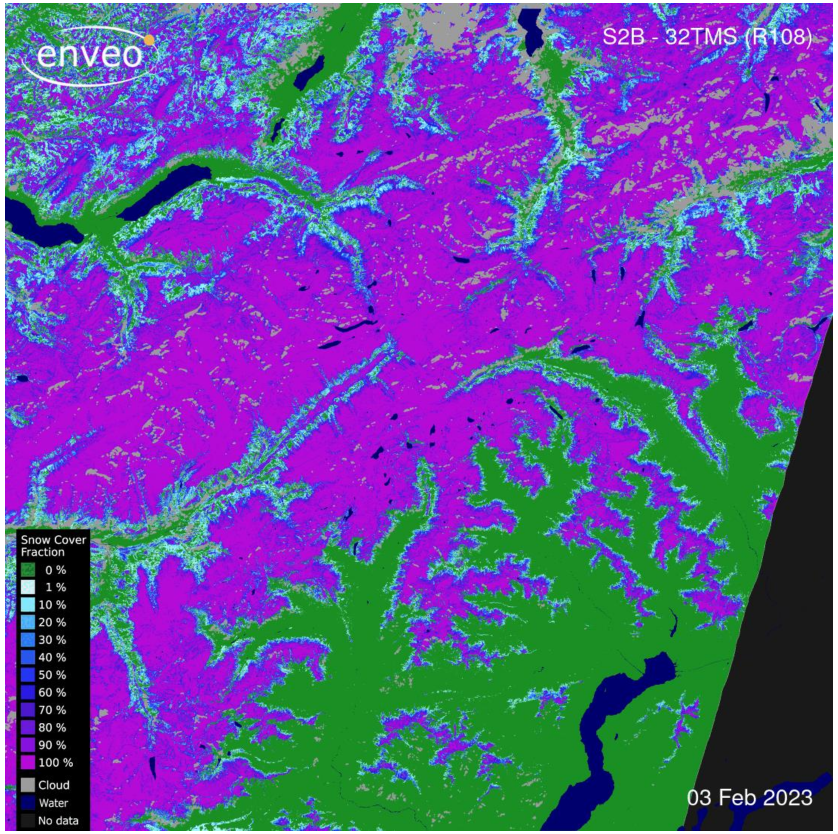
- SCF method : LAMSU
- Cloud detection: S2Cloudless
- Water mask: Global Surface Water Dataset



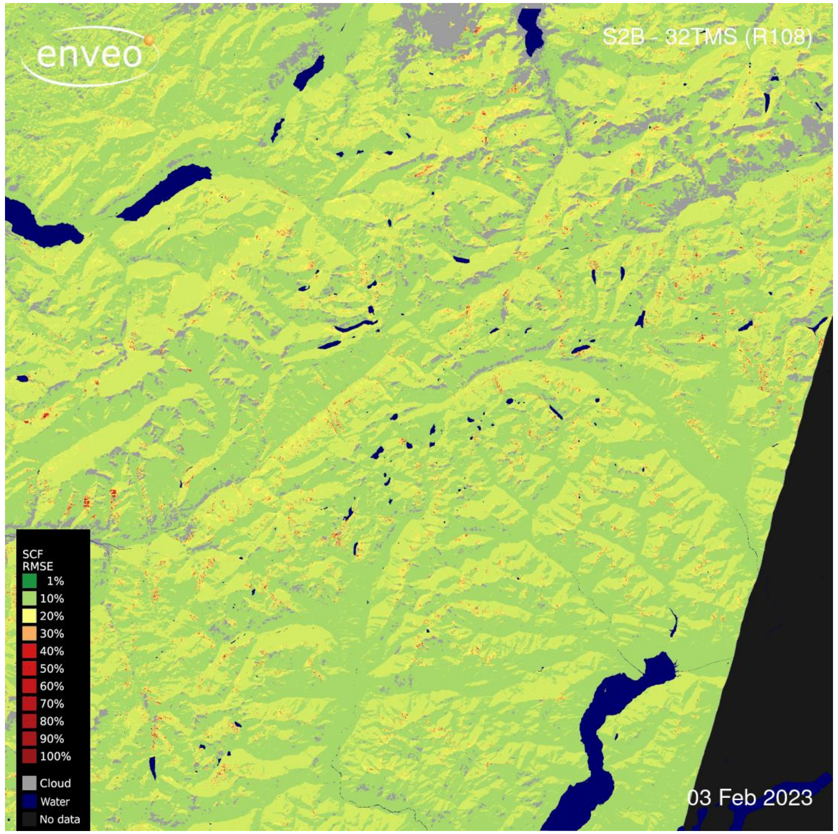
NRT Processor Demonstration [2/3]



S2B – 03 February 2023 (32TMS)



SCF



SCF RMSE

LAMSU: NRT Processor Demonstration [3/3]

- https://projects.enveo.at/service/hiressnow

Prototype High-Resolution Snow Service for the Alps

The Near-Real-Time (NRT) processor started on 20-10-2022. This website is a prototype demonstrator for the generation of snow cover fraction (SCF) maps in a near-real-time fashion. Although this is nothing new on its own, the SCF maps displayed are generated using a locally adaptive multi-spectral unmixing (LAMSU) approach. The LAMSU approach is advancing the snow monitoring effort in several ways.

Current-day multi-spectral unmixing approaches are difficult to scale as they are commonly set-up with a spectral library for its endmembers. The spectral library limits the applicability and scalability of the approach as a whole. Instead, LAMSU adapts to each scene and cleverly selects and weighs endmembers. Furthermore, shaded regions are treated separately, because the spectral signatures (of the endmembers) are altered drastically. This makes the LAMSU approach globally applicable and well scalable.

Furthermore, uncertainty metrics are crucial; for understanding, for transparency, for model input, for intercomparison and more. The LAMSU approach incorporates a rudimentary, quantitative uncertainty approximation and encourages other snow monitoring services to do so too. In addition, the full variance-covariance matrix of the Sentinel-2 L1C top-of-atmosphere (TOA) reflectances are included in the estimation of each SCF pixel. In the latter case, the SCF estimate can be considered statistically optimal (SO). The quantification of the full variance-covariance matrix for the Sentinel-2 L1C TOA reflectances has been made possible thanks to the help of Javier Gorroño and the work done in [1].

In the table below you will find five columns. The first column shows a Sentinel-2 MSI true color composite. The second and third column show the SCF and SCF RMSE. The fourth and fifth column show the SCF and SCF RMSE when considering the full variance-covariance matrix of the Sentinel-2 MSI (L1C) TOA reflectances.

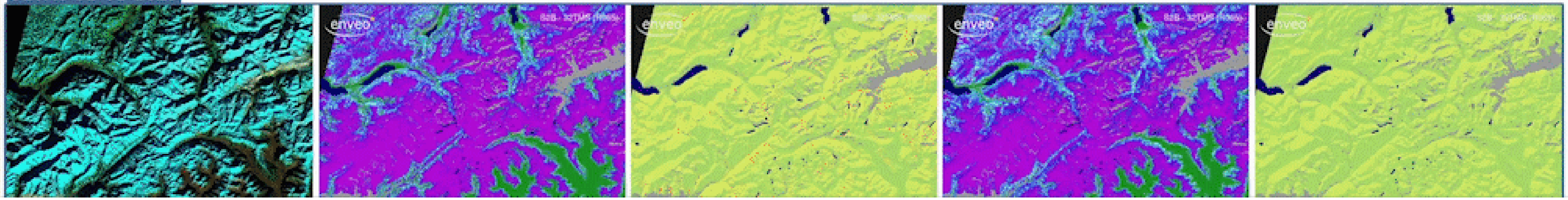
The cloud mask has been derived using the *Sentinel Hub's cloud detector for Sentinel-2 imagery*, which is also known as s2cloudless (Python source). The water mask is taken from the Global Surface Water Explorer (Copernicus programme) dataset for the year 2021 and is freely available here [2].

Select date ☐: 02 - 02 - 2023
Select UTM tile: 32TMS
Filter

39 results found for 32TMS for all dates.

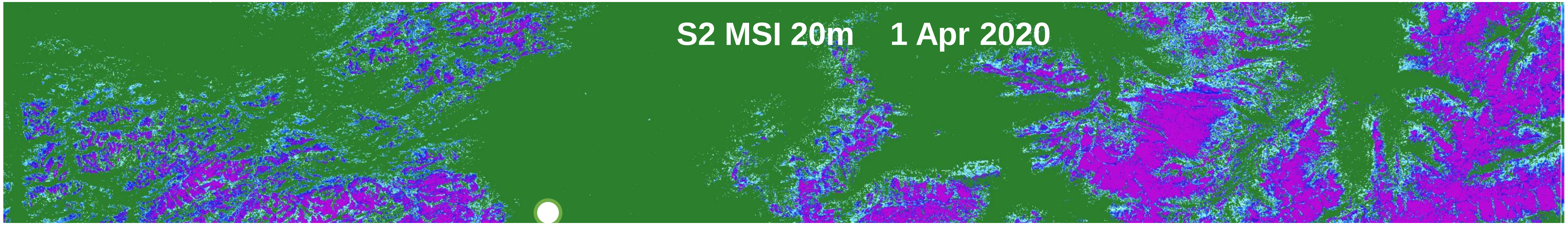
False Color Composite	SCF	SCF RMSE	SCF (SO)	SCF RMSE (SO)

32TMS 31-01-2023

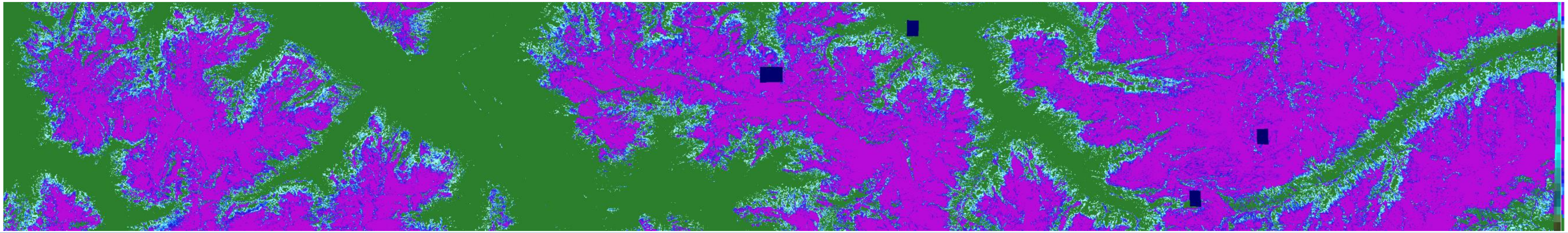


SCAN ME

Multi-sensor and Multi-resolution Snow Map



RMSE / Bias	Sentinel-2 MSI	Landsat 8 OLI	Sentinel-3 SLSTR/OLCI	Suomi NPP VIIRS	Terra MODIS
Sentinel-2 MSI	-	-	9.68	7.35	6.99
Landsat 8 OLI	-	-	4.92	4.33	5.32
Sentinel-3 SLSTR/OLCI	-1.46	0.76	-	8.19	8.93
Suomi NPP VIIRS	-0.34	1.28	0.65	-	8.86
Terra MODIS	0.47	1.71	2.16	2.15	-



Conclusions

- The developed algorithm (LAMSU) exploits the spectral capabilities of a multispectral sensor and accounts for varying illumination conditions (shaded, illuminated areas) and surface classes.
- The performance of the algorithm has been estimated by intercomparison with a limited data set of snow extent products from very high resolution WorldView-3 data revealing RMSE < 16% and Bias < 3%.
- The method has the potential for global snow monitoring using medium range satellite data such as Sentinel-3. First products show promising results but further development, testing and validation in different environments needed.
- Further R&D on consistency between current sensors and expansion towards hyperspectral sensors (ENMAP, PRISMA, Copernicus CHIME) is ongoing.