High-Resolution, Country-Scale Snow Depth Estimation From Satellite Images

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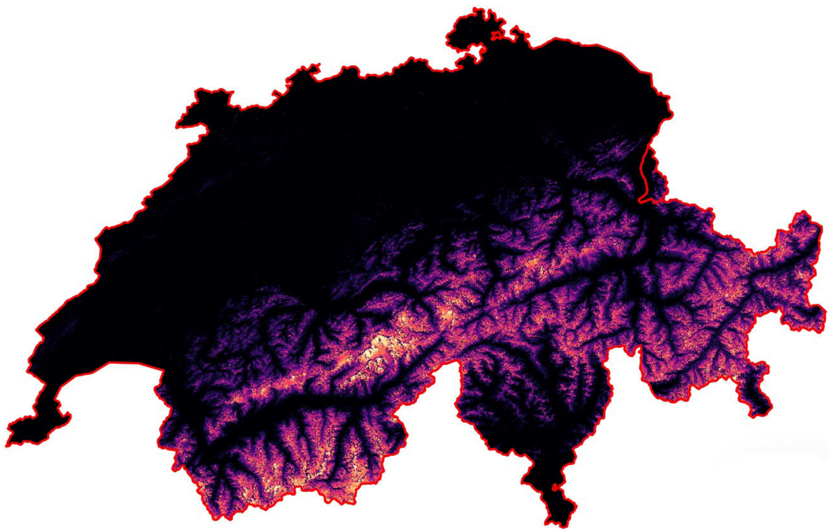
Motivation, Objectives, and Context

Objective



- Large scale, real-time snow depth mapping
  - Switzerland and Liechtenstein, but can be extended
- High spatial and temporal resolution
  - New snow depth map every **7 days**
  - Spatial resolution of **10 m GSD**
- Requiring only remote sensing data, no ground measurements
  - Sentinel-1 (SAR), Sentinel-2 (multispectral optical), DEM
- Why?
  - Safety evaluation for snow activities and alpine communities
  - Meltwater estimation ⇒ planning for hydroelectric energy and strong melt events
  - Long term monitoring of snow dynamics

Context

Previous snow depth products mostly belong to one of two groups:

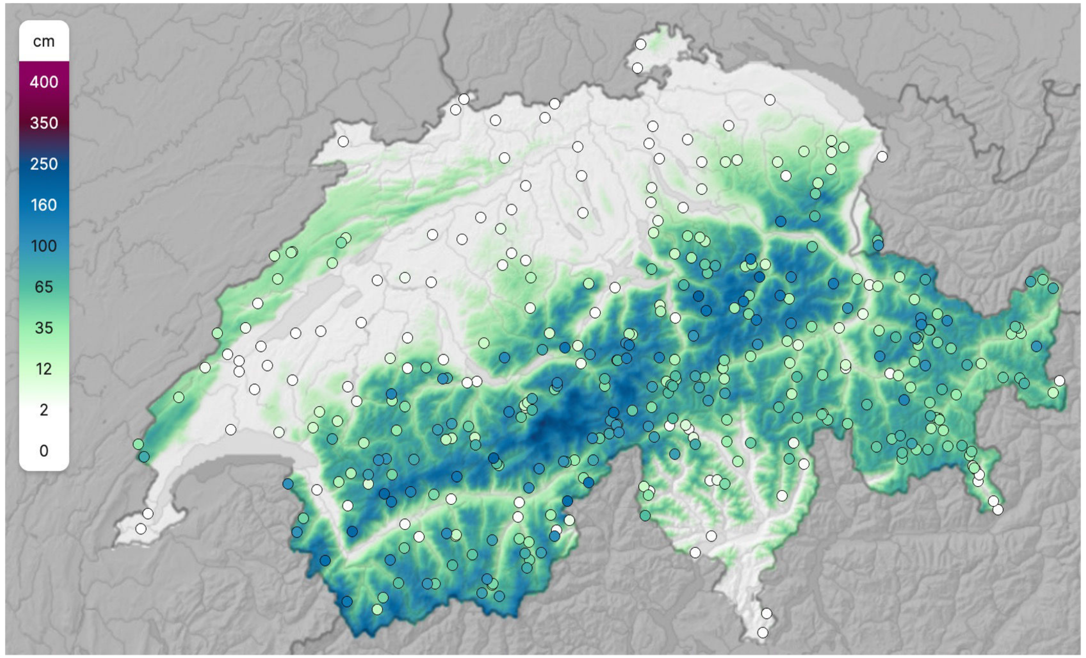
- Low resolution (e.g. 1 km GSD), large scale maps based on scalable variables (e.g. meteorology data, ground measurements[1])
- Localised, high resolution snow depth maps produced by comparing two DSMs

This work is a collaboration with ExoLabs, who produce daily high resolution snow depth maps using TCAM.[2]

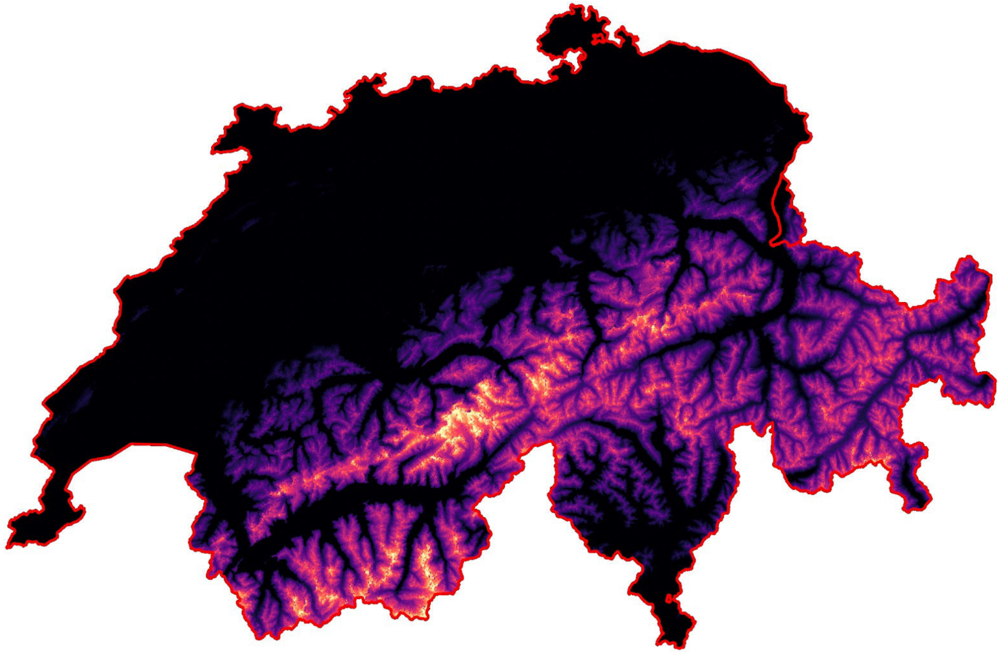
[1] https://www.slf.ch/en/avalanche-bulletin-and-snow-situation/snow-maps/information-about-snow-depth.html

[2] Wulf, Hendrik, et al. "High-resolution snow depth monitoring for entire mountain ranges." 2020 7th Swiss Conference on Data Science (SDS). IEEE, 2020.

Snow Depth Products



SLF Hydrology snow depth map, 1 km GSD


ExoLabs snow depth map, 10 m GSD

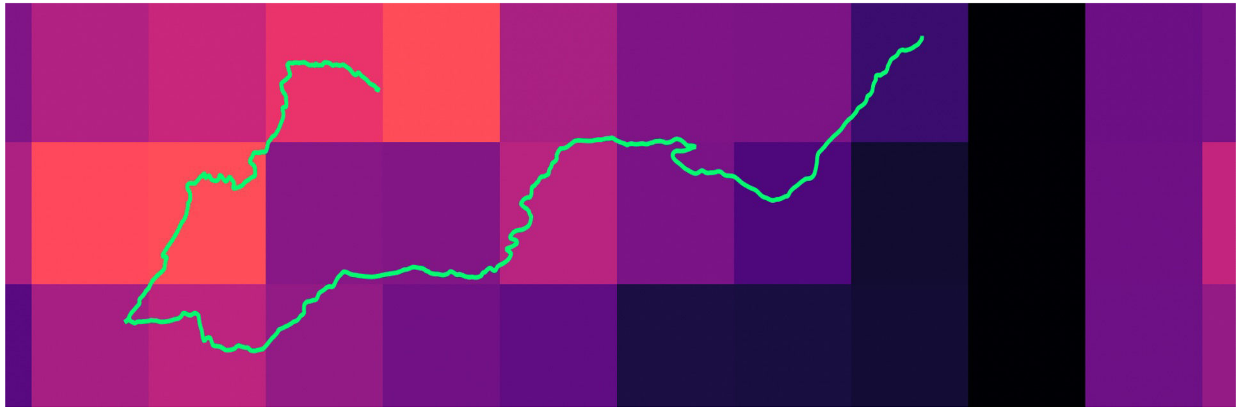
Resolution of Different Products

Ski touring path

Resolution of Different Products

Ski touring path

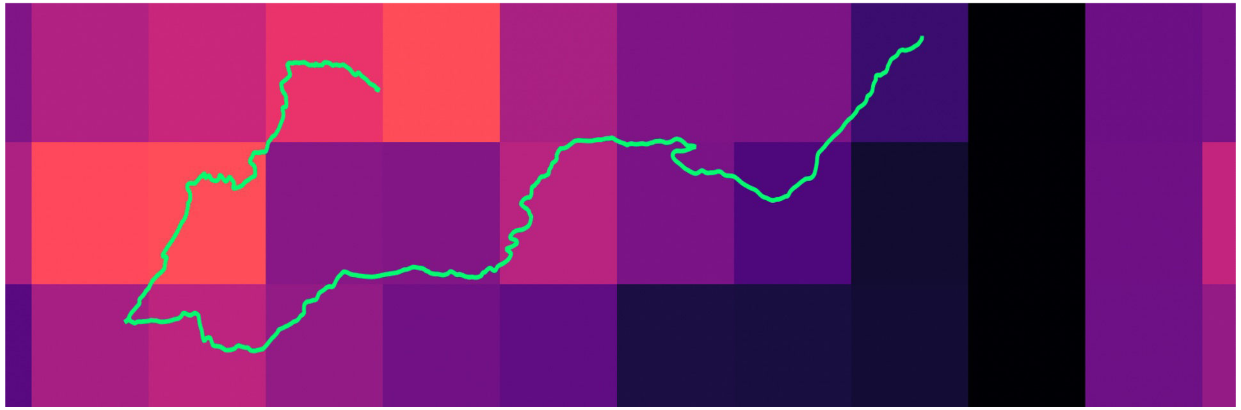
Snow depth map at 1 km GSD

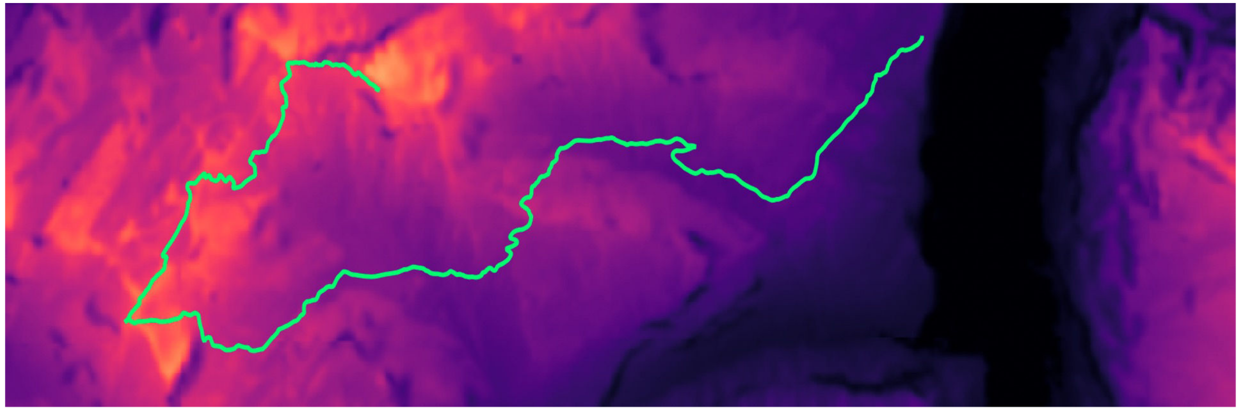


Resolution of Different Products

Ski touring path

Snow depth map at 1 km GSD



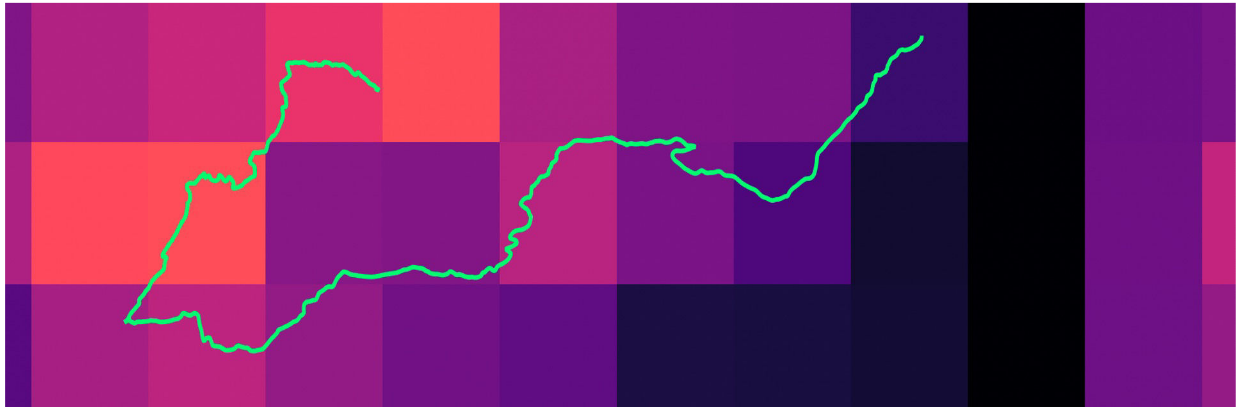


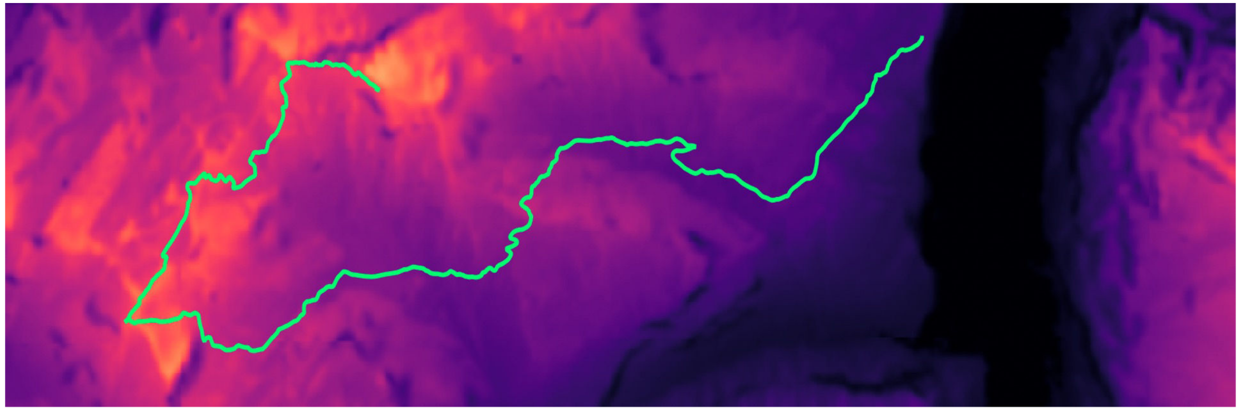
TCAM snow depth map at 10 m GSD

Resolution of Different Products

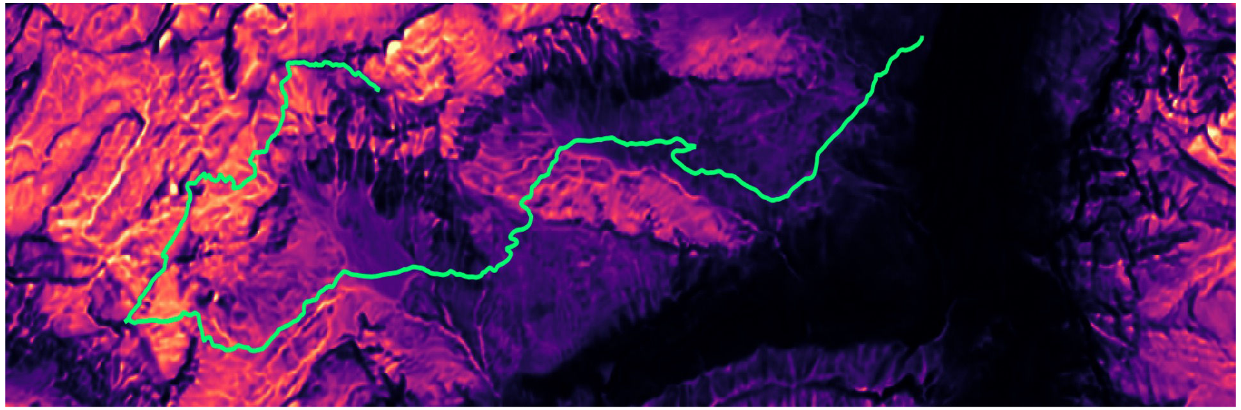
Ski touring path

Snow depth map at 1 km GSD





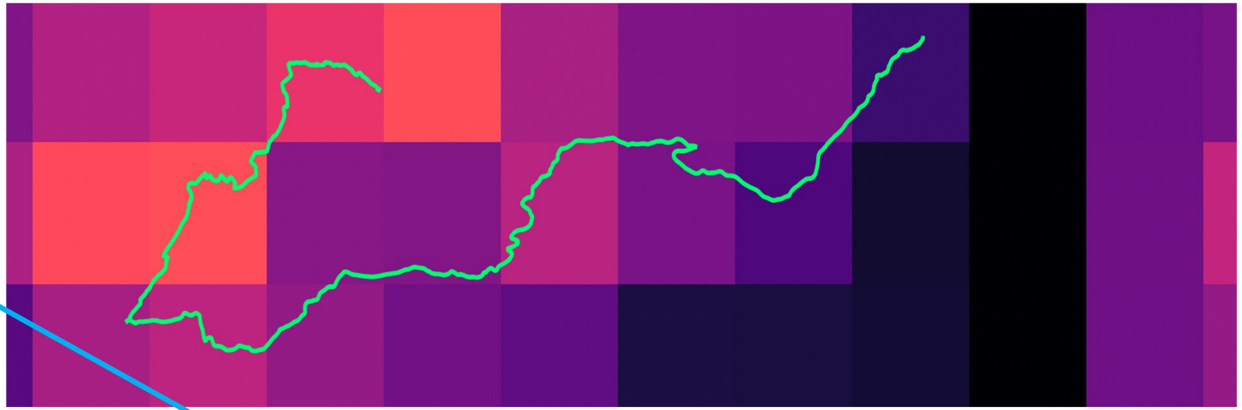
TCAM snow depth map at 10 m GSD

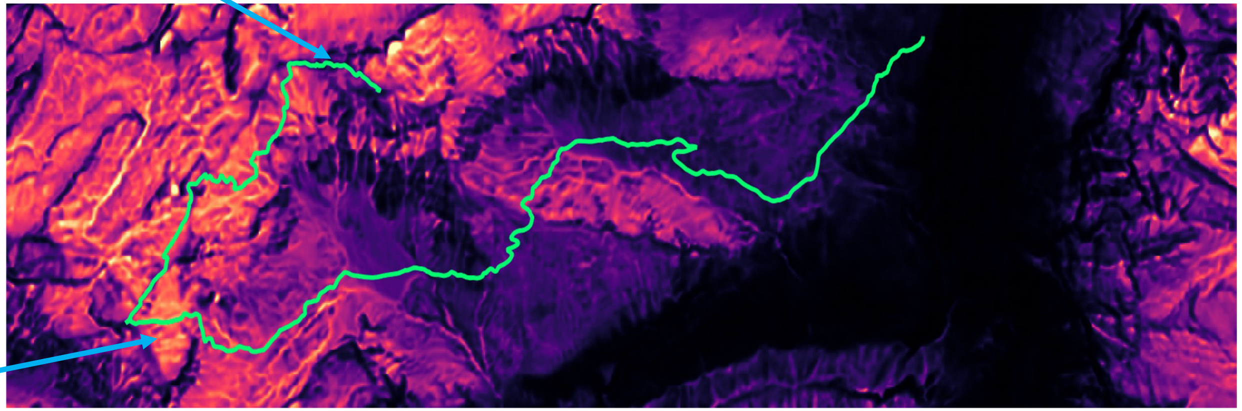


Current results at 10 m GSD

Resolution of Different Products

Snow depth map at 1 km GSD





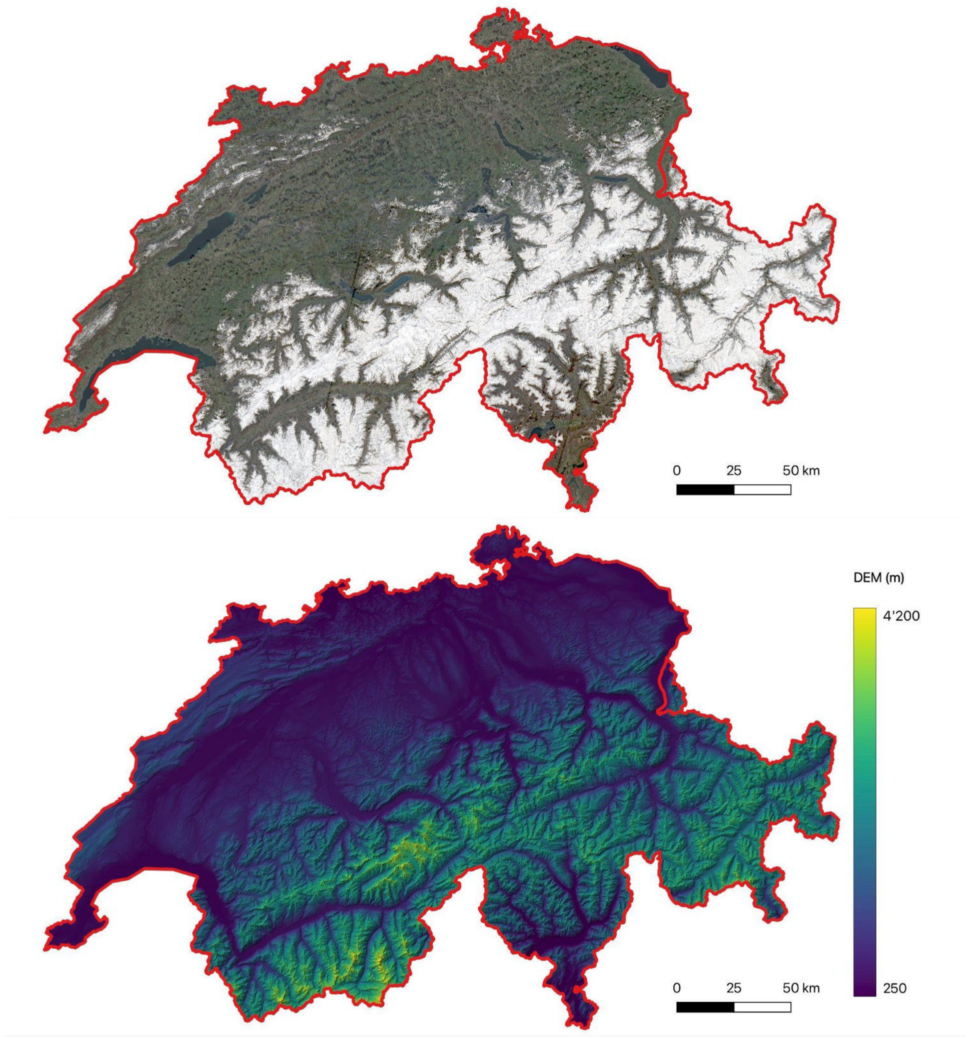
Current results at 10 m GSD

Technical Details

Method Overview

Main steps:

1. Satellite (optical and SAR) images are accumulated for 7 days
2. Images are combined with DEM and manually computed features
3. ConvGRU network extracts information from temporal and spatial patterns
4. Probabilistic regression is used for producing uncertainty estimates



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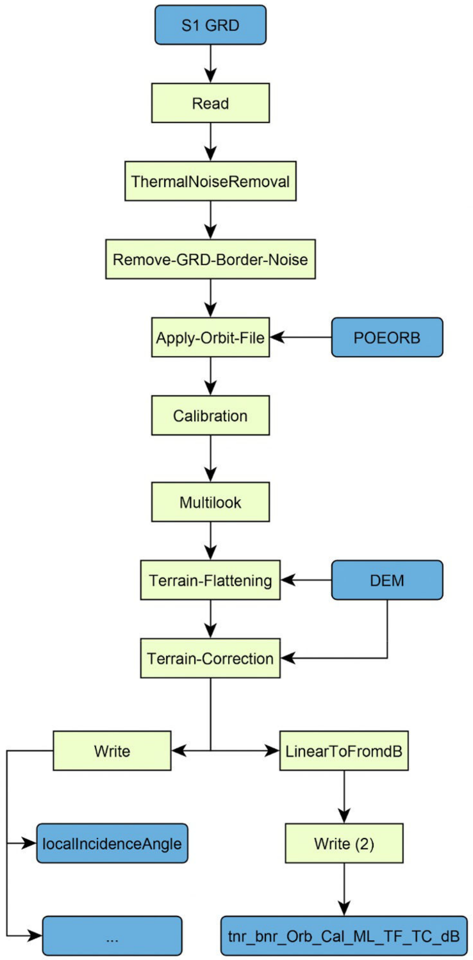
Data Preprocessing

- **DEM**: compute features from elevation map
  - Aspect
  - Slope
  - TRI
  - TPI
- **Sentinel-1 (SAR)**:
  - Preprocessing (thermal and border noise, terrain…)[1] Mosaicking
  - Temporal stack
- **Sentinel-2 (multispectral optical)**:
  - Cloud masking
  - Mosaicking
  - Temporal stack



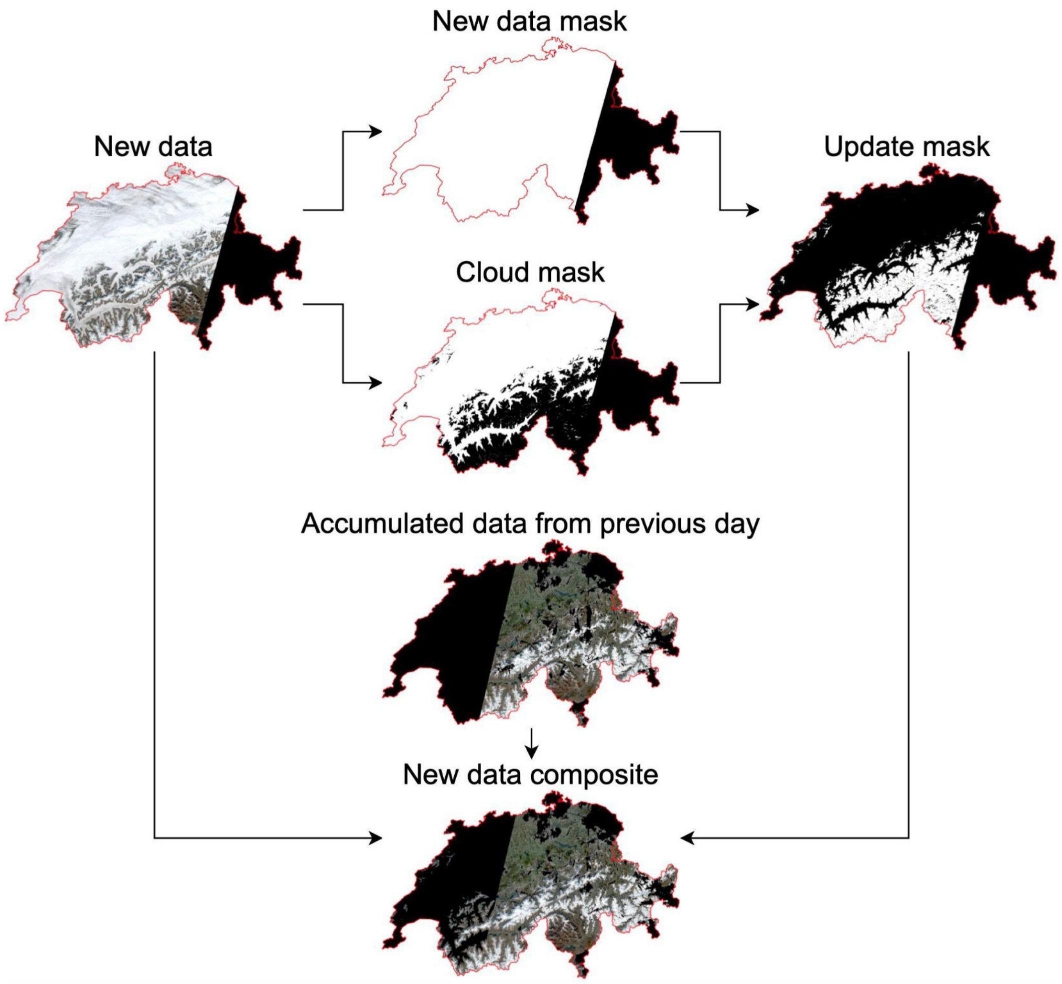
Sentinel-1 preprocessing with SNAP

[1] Truckenbrodt, John, et al. "Towards Sentinel-1 SAR analysis-ready data: A best practices assessment on preparing backscatter data for the cube." *Data* 4.3 (2019): 93.

Temporal Stacking

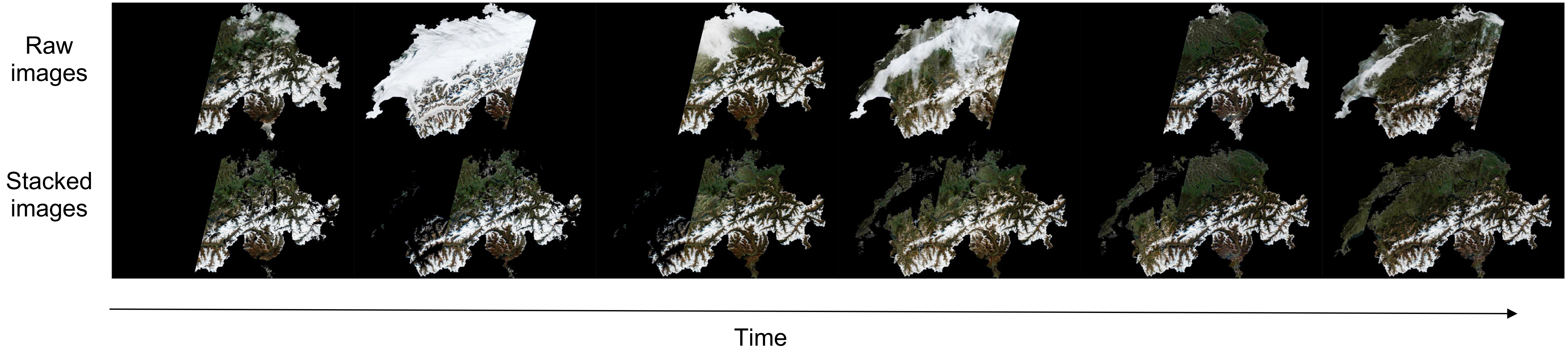
Target resolution in time: new map every 7 days – not in sync with the Sentinel satellites.

Sentinel-2 images also suffer from cloud occlusions and shadows – aim to minimise their impact.



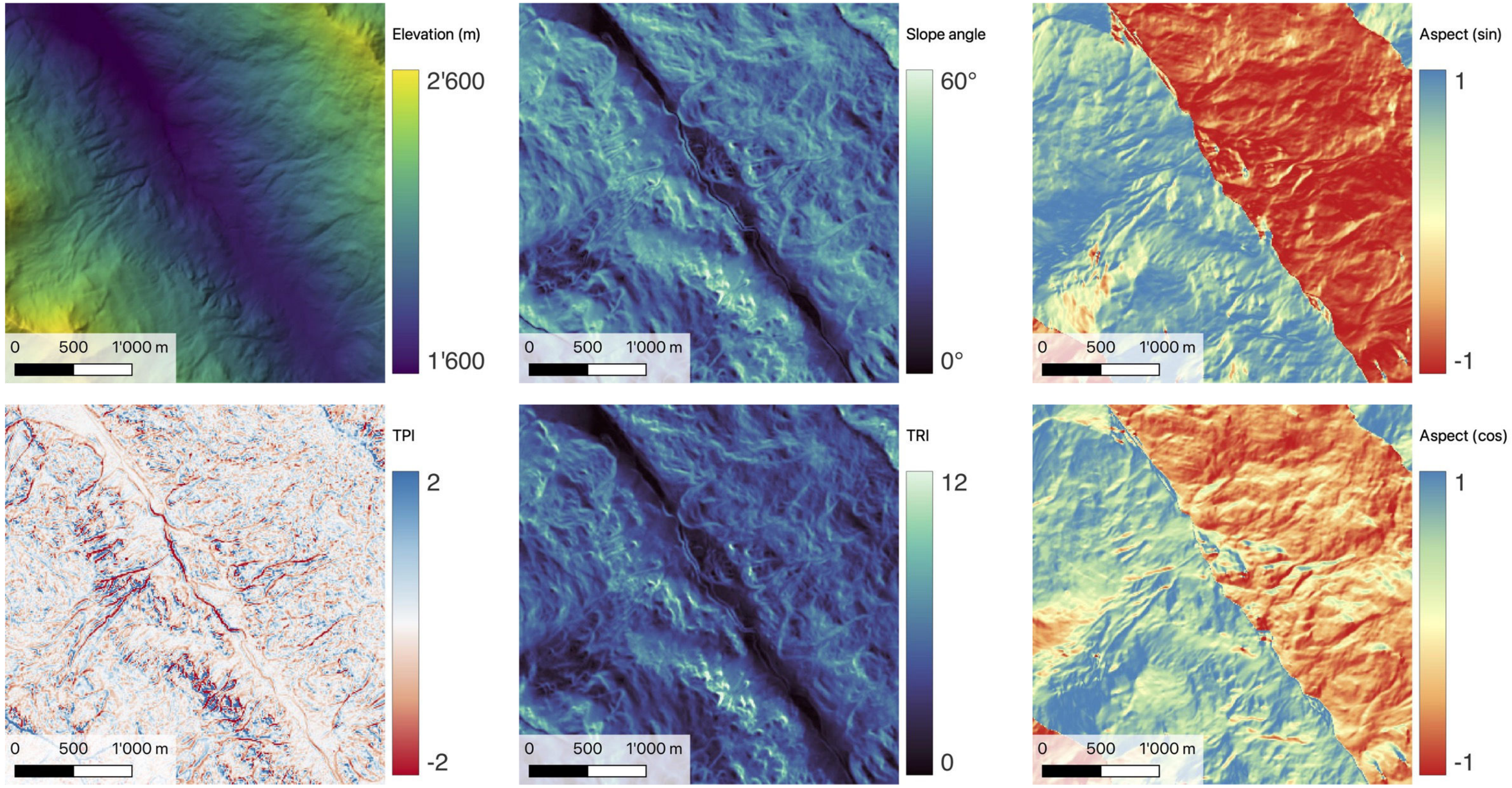
Temporal Stacking

Maintain a running, clean time-series with the latest information for each pixel.

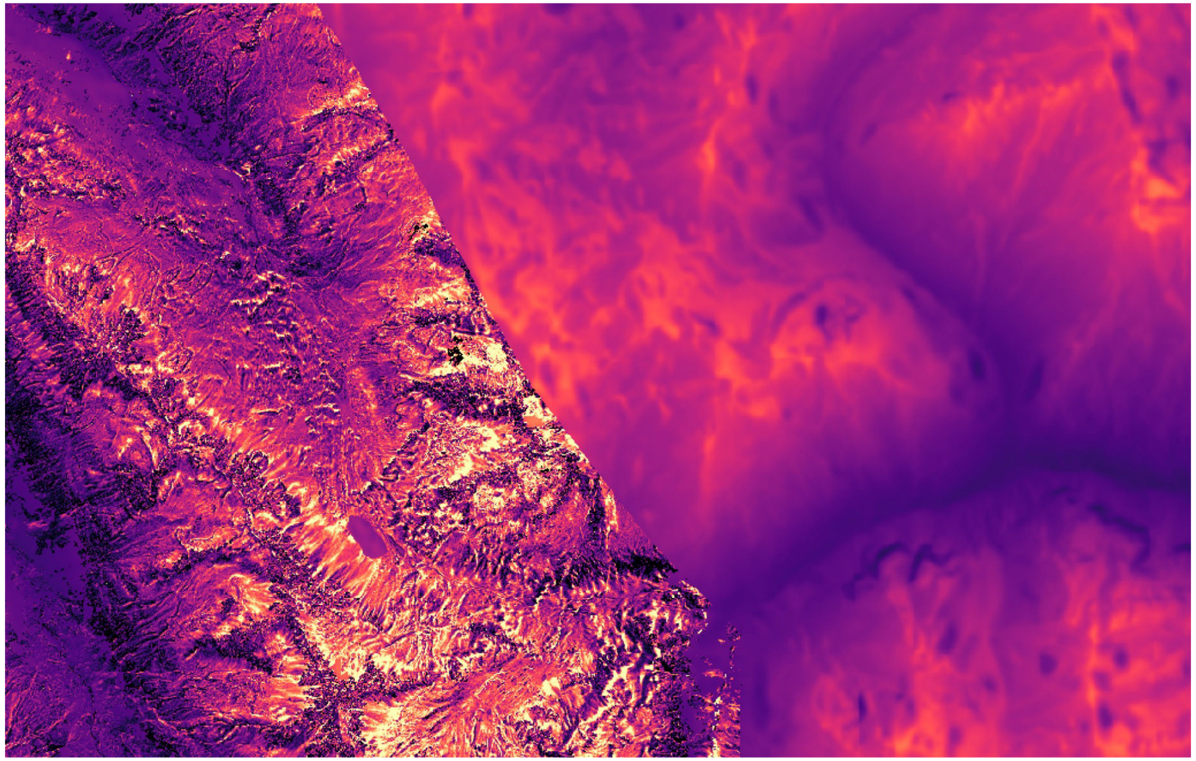


Elevation and Terrain Data

Pre-computation of terrain characteristics from high-resolution DEM.



Fine Details



Ultracam map from SLF/SwissTopo vs. TCAM map, both at 10 m GSD. The Ultracam data contains a lot more high frequency information.

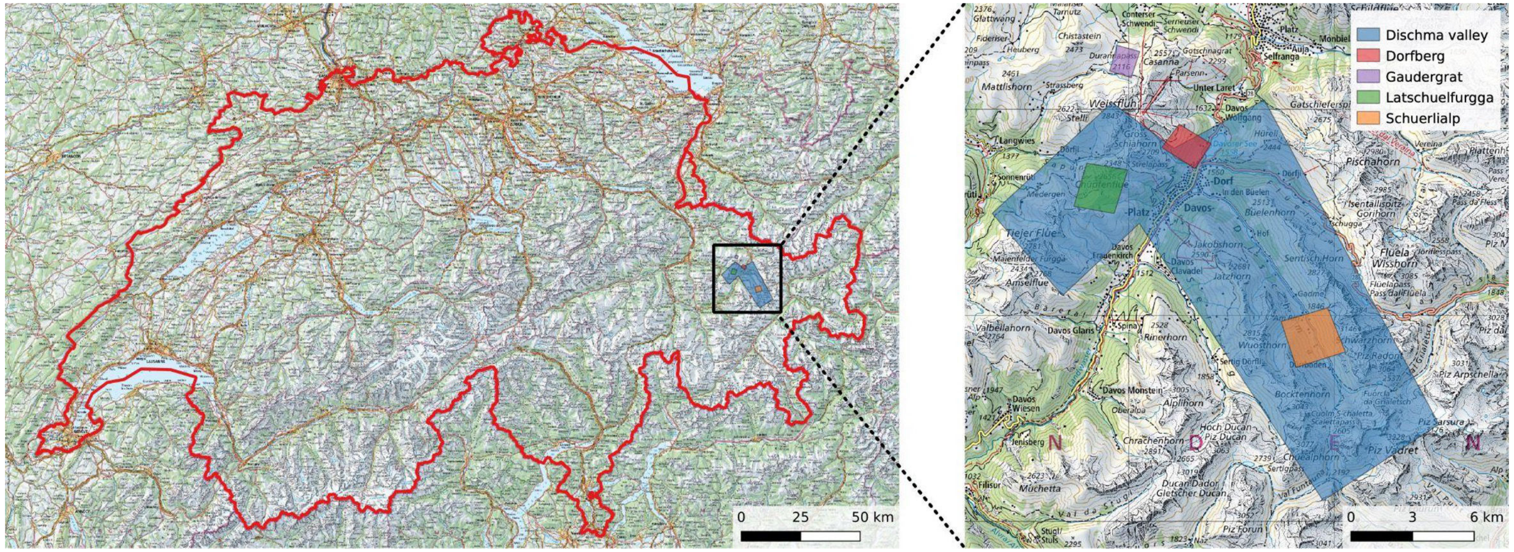
Much of the **high frequency details** present in high resolution snow depth maps are missing from TCAM maps

These details correlate with observables like the terrain and the snow line.

Goal: learn the details from the available high-resolution data.

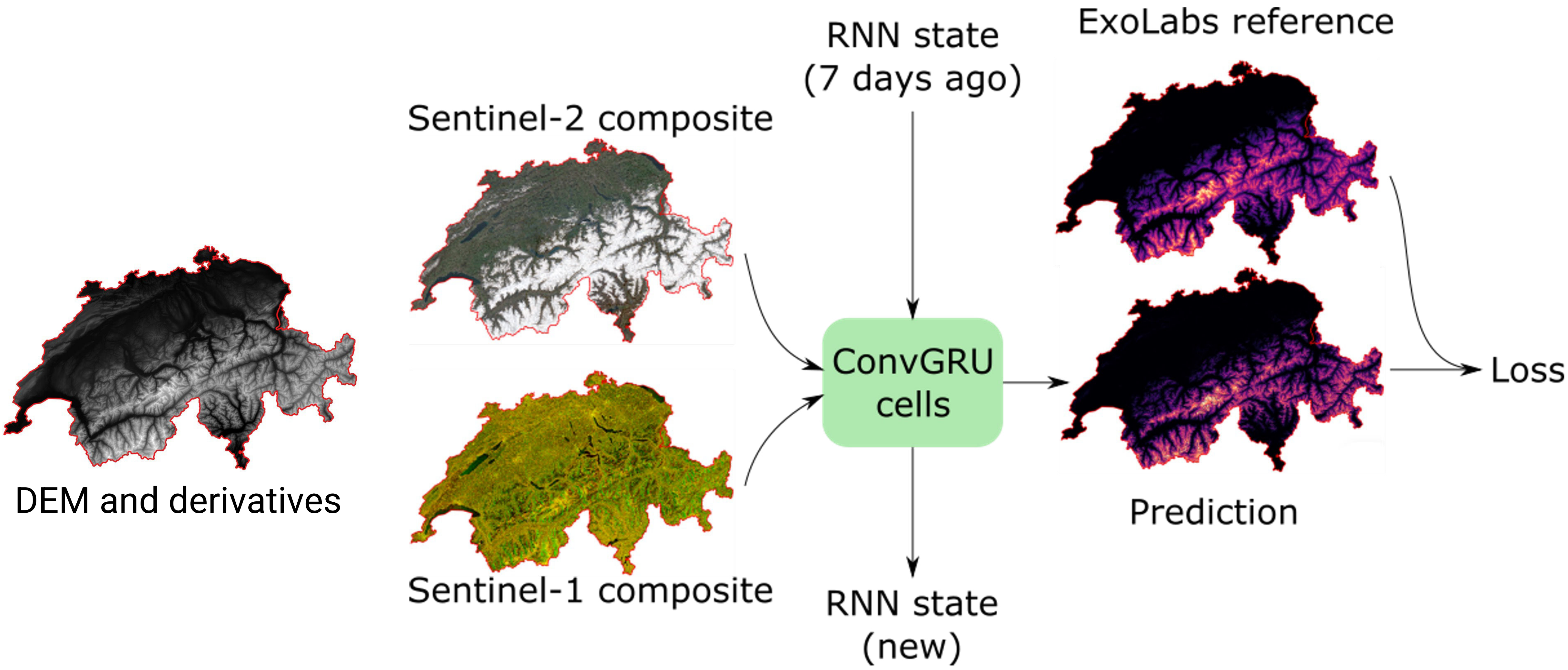
Available High-Fidelity Data

High quality snow depth maps are available for sparse dates and locations.

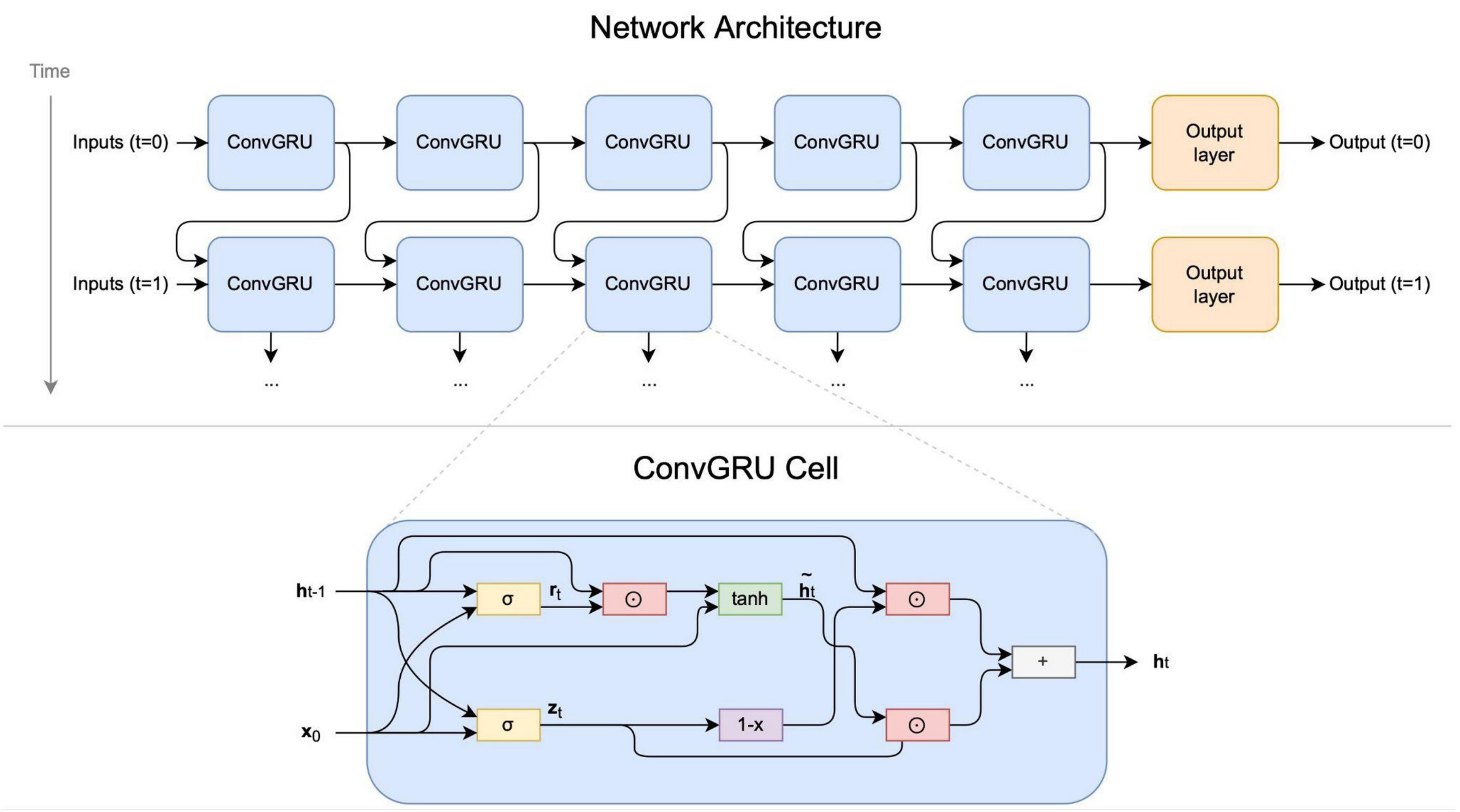


Location	Date
Dischma valley	16/03/2019 06/04/2020 16/04/2021
Dorfberg	11/12/2020 25/02/2021
Gaudergrat	12/12/2018 12/03/2019 07/02/2020 17/02/2020
Latschüelfurgga	18/12/2020 24/02/2021 26/03/2021
Schürlialp	18/02/2019 22/04/2020

Method Overview

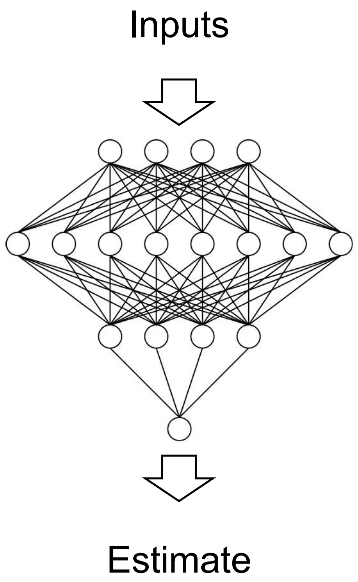


Architecture Details – ConvGRU Network



Probabilistic Deep Learning

Standard regression



Probabilistic Deep Learning

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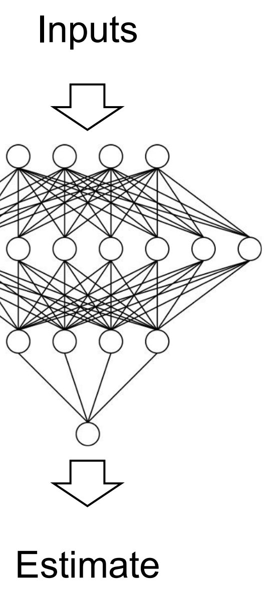
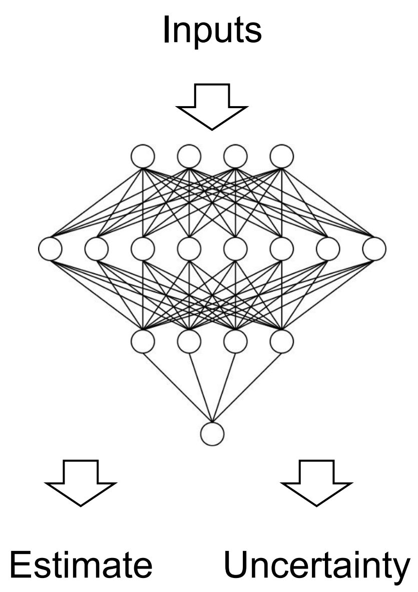


Probabilistic regression



Probabilistic Deep Learning

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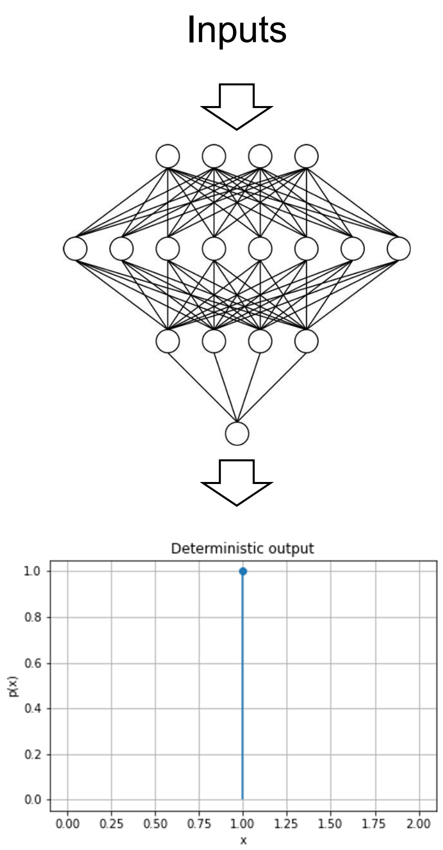
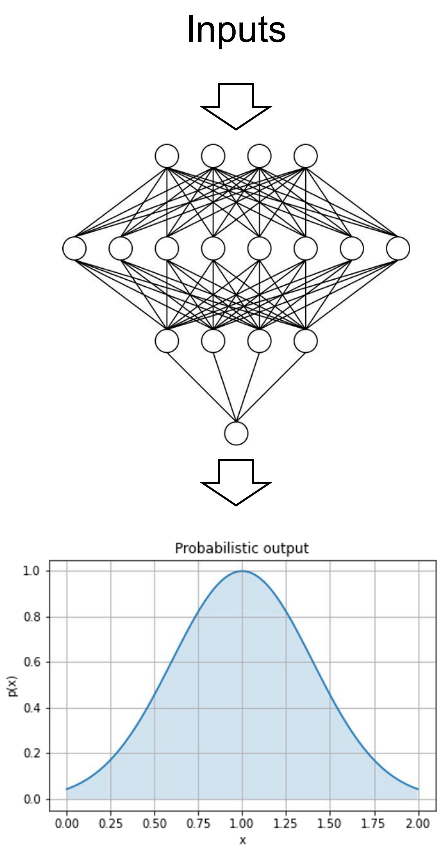
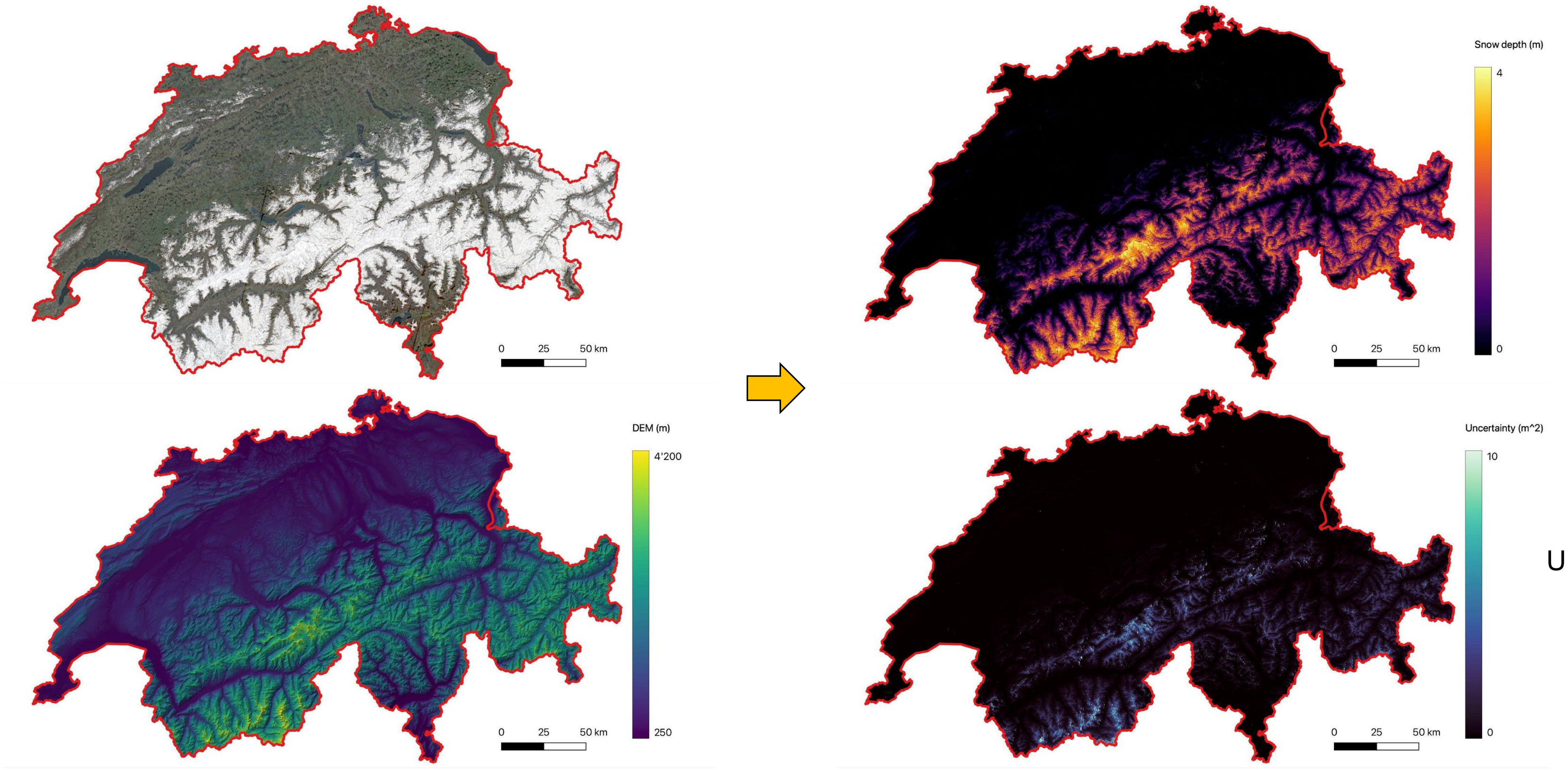


Probabilistic regression



Results

Qualitative Results

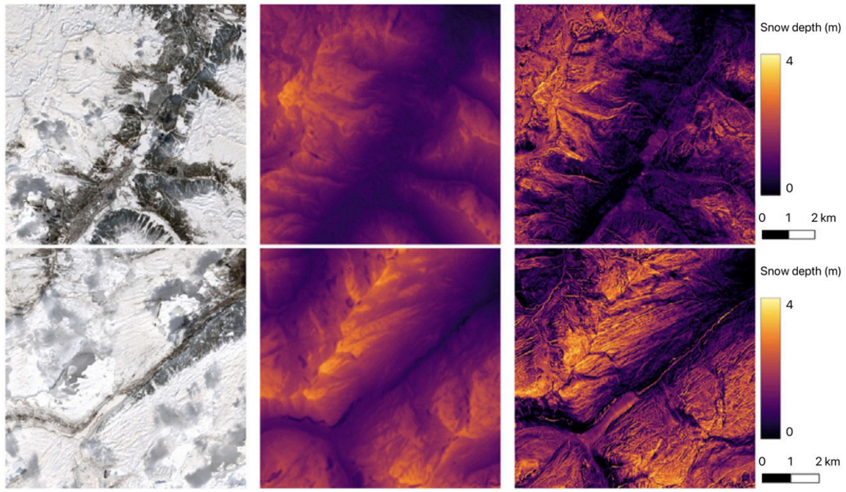


Snow depth

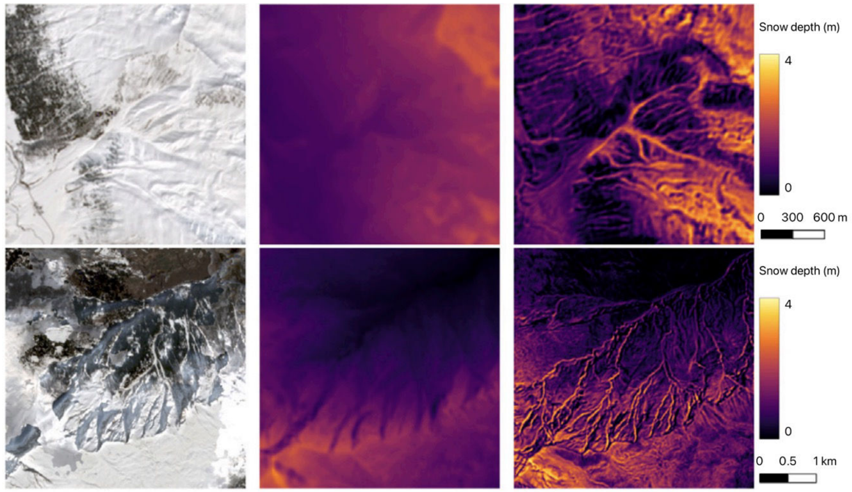
Uncertainty

Qualitative Results

The learned model produces results with fine details due to snow accumulation and melting patterns, which previous maps were not able to model.



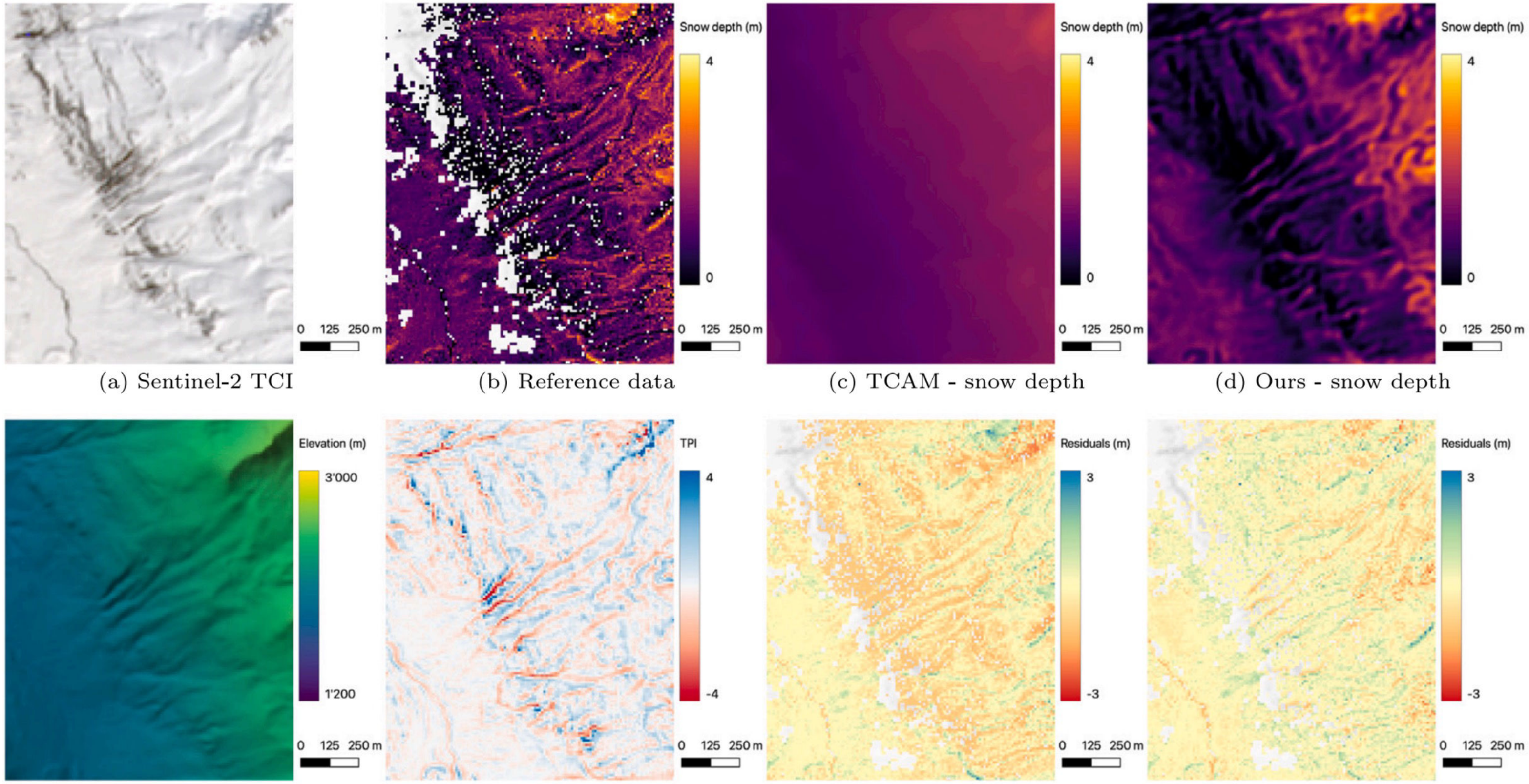
TCI ExoLabs Ours



TCI ExoLabs Ours

Qualitative Results

These details match the high resolution maps used for validation.



(a) Sentinel-2 TCI (b) Reference data (c) TCAM - snow depth (d) Ours - snow depth

(e) Elevation map (f) Topographic position index (g) TCAM - residuals (h) Ours - residuals

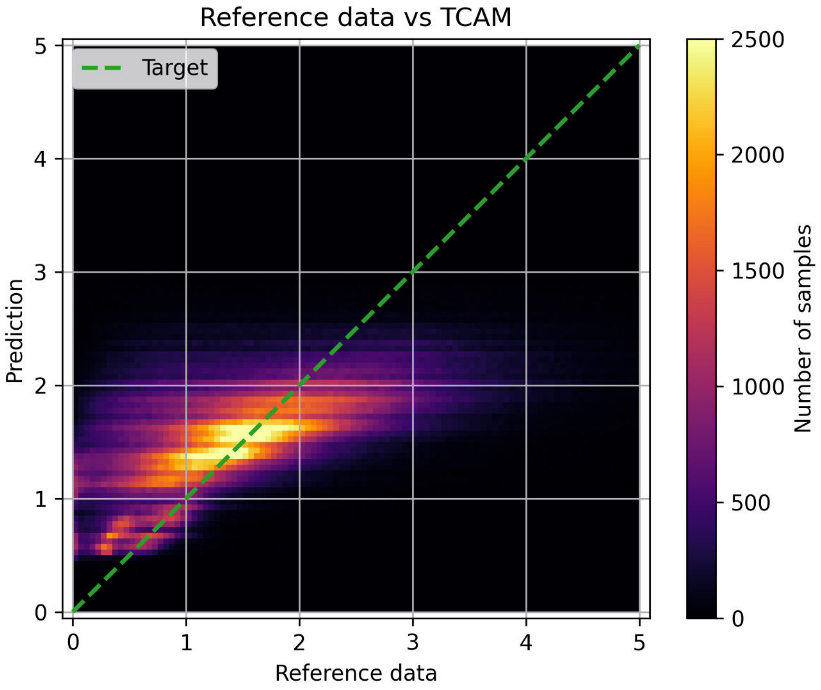
Quantitative Results

Quantitative evaluations against high-resolution airborne ground truth show a significant improvement over previous large-scale methods.

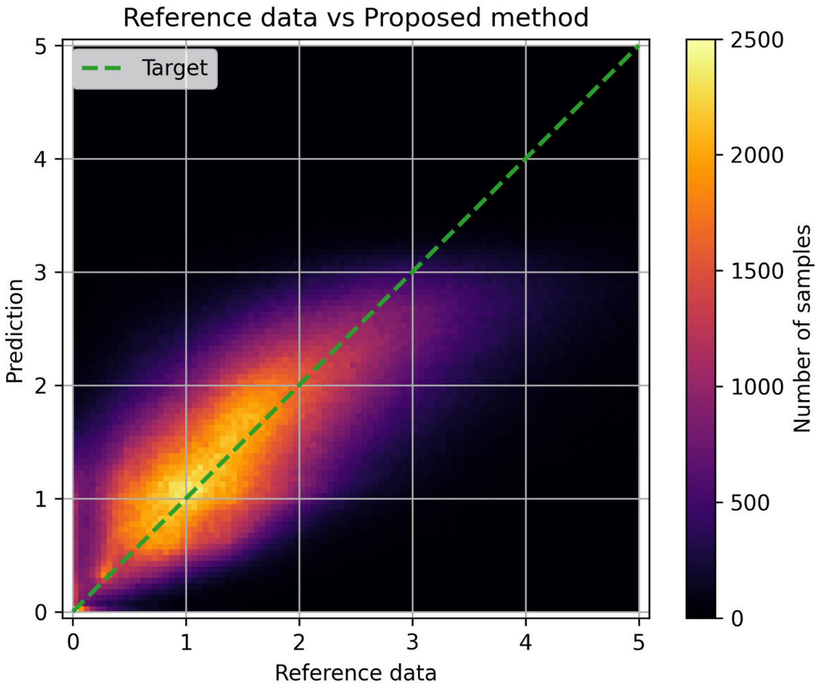
Method	All dates				Winter 2020/2021			
Ablation	MAE (↓)	RMSE (↓)	ρ (↑)	ME (0)	MAE (↓)	RMSE (↓)	ρ (↑)	ME (0)
TCAM	–	–	–	–	0.69 (+0.11)	0.94 (+0.14)	0.51 (−0.17)	0.07
Proposed method	0.68	0.91	0.59	0.08	0.58	0.80	0.68	0.06
No S2	0.69 (+0.01)	0.93 (+0.02)	0.59 (0.00)	0.22	0.64 (+0.06)	0.88 (+0.08)	0.63 (−0.05)	0.26
No S1	0.72 (+0.04)	0.95 (+0.04)	0.53 (−0.06)	0.06	0.61 (+0.03)	0.83 (+0.03)	0.65 (−0.03)	−0.03
No DEM	0.70 (+0.02)	0.94 (+0.03)	0.55 (−0.04)	0.01	0.64 (+0.06)	0.87 (+0.07)	0.61 (−0.07)	−0.08
PT only	0.74 (+0.06)	1.00 (+0.09)	0.50 (−0.09)	0.19	0.67 (+0.09)	0.92 (+0.12)	0.56 (−0.12)	0.15
FT only	0.67 (−0.01)	0.91 (0.00)	0.59 (0.00)	0.11	0.58 (0.00)	0.79 (−0.01)	0.69 (+0.01)	0.06
MSE	0.66 (−0.02)	0.89 (−0.02)	0.62 (+0.03)	0.11	0.57 (−0.01)	0.79 (−0.01)	0.69 (+0.01)	0.07
No recurrence	2.23 (+1.55)	2.50 (+1.59)	0.19 (−0.40)	−1.85	2.58 (+2.00)	2.78 (+1.98)	0.30 (−0.38)	−2.53

Quantitative Results

Scatter plots of estimated vs. reference values.



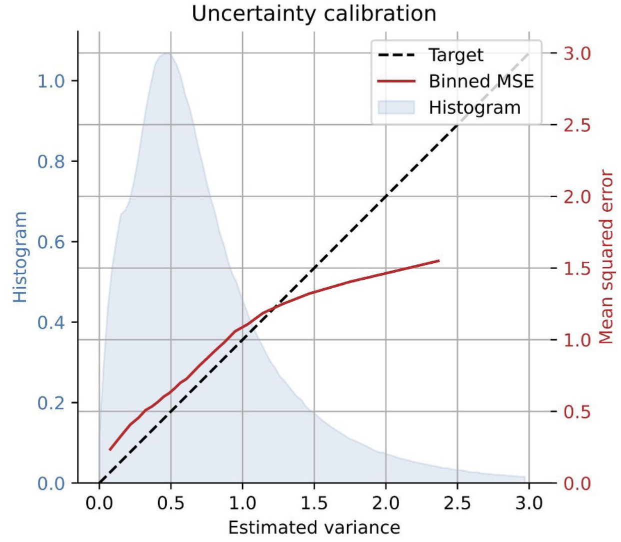
Old ExoLabs maps

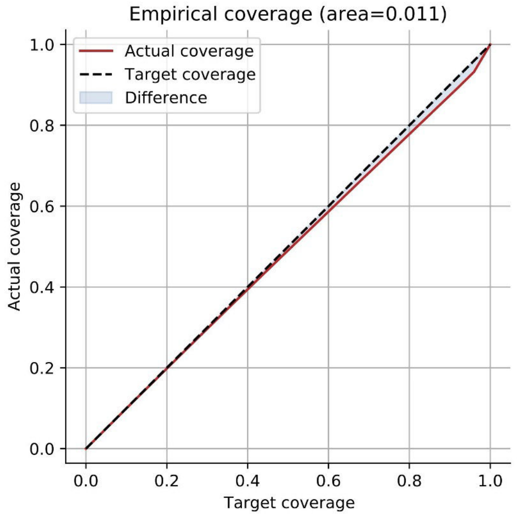


New maps

Results – Uncertainty Estimation

Regressed uncertainty estimates are well calibrated.



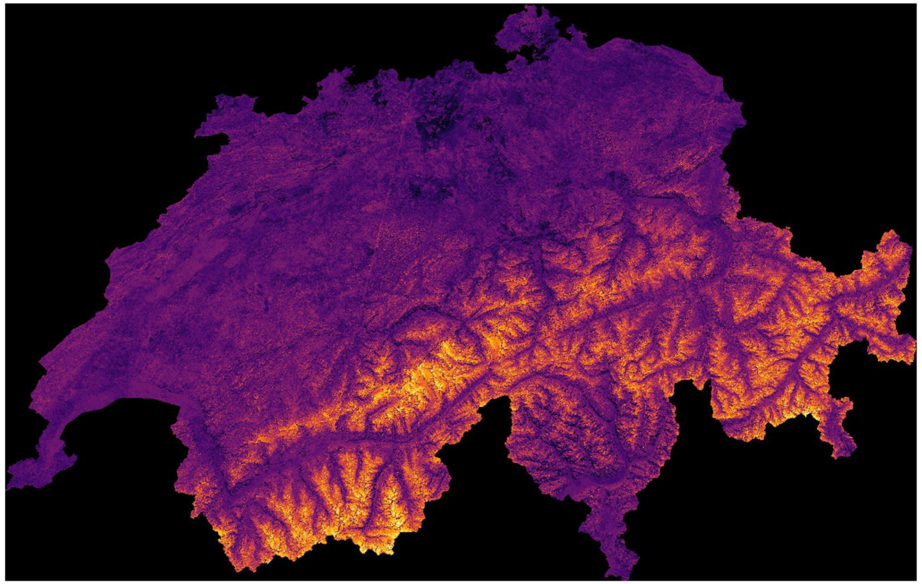


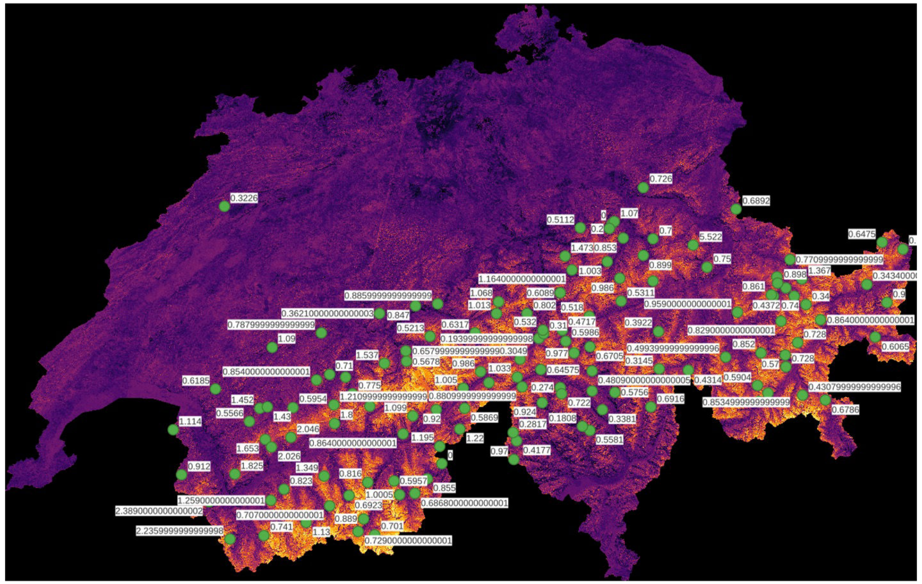
Model	ECE (↓)	ABC (↓)	$\overline{\sigma^2}$
Proposed method	0.190	0.011	0.80
No S2	0.241 (+0.051)	0.020 (+0.009)	0.78
No S1	0.389 (+0.199)	0.047 (+0.036)	0.79
No DEM	0.163 (−0.027)	0.002 (−0.009)	0.86
PT only	0.917 (+0.727)	0.279 (+0.268)	0.09
FT only	0.256 (+0.066)	0.024 (+0.013)	0.75
No recurrence	2291 (+2291)	0.273 (+0.262)	2296

Local Bayesian Adjustment with Point-wise Data

To go further, we can integrate ground measurements of snow depth, if available.

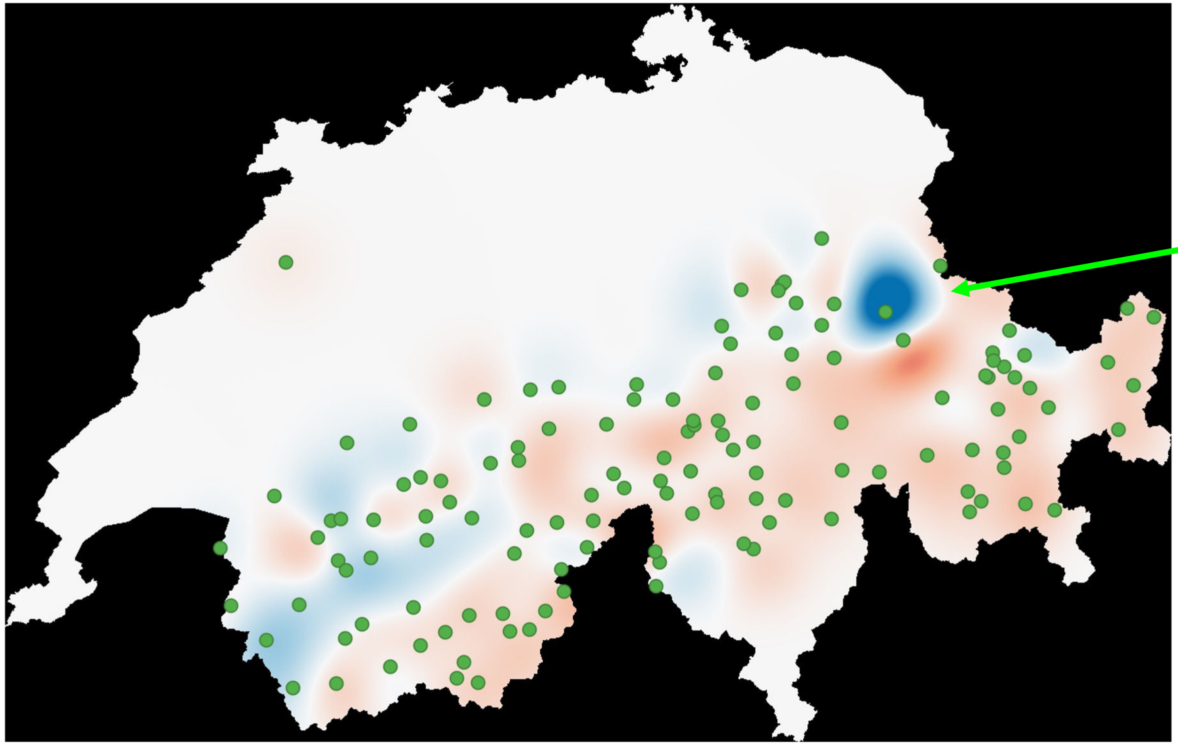
Fortunately, the network of automated measurement stations (IMIS) is fairly dense in Switzerland.





Local Bayesian Adjustment with Point-wise Data

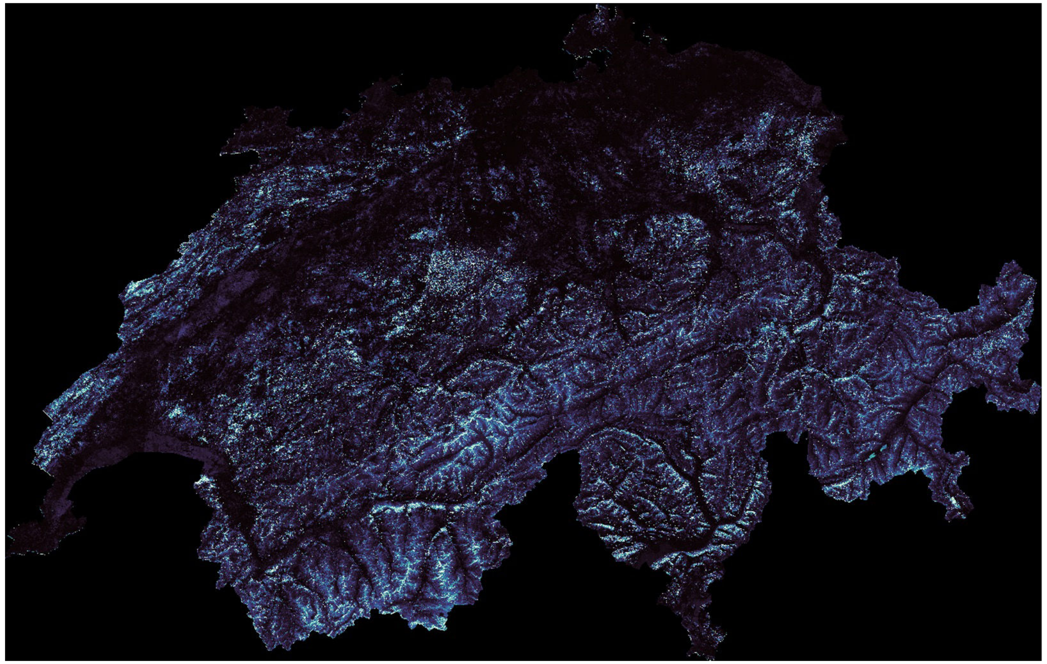
Main idea: compute the residuals (differences) at ground stations, fit a Gaussian Process that estimates the residuals for every point in the grid.

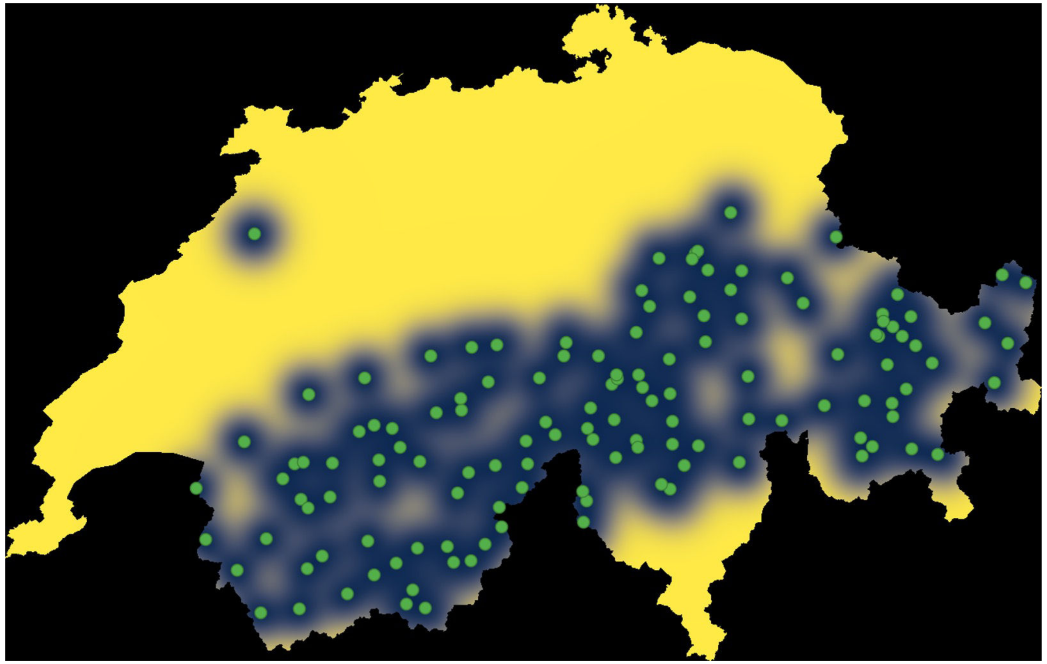


Large residual at Pizol
(artificially introduced)

Local Bayesian Adjustment with Point-wise Data

The Gaussian Process also delivers uncertainties for the estimated residuals.

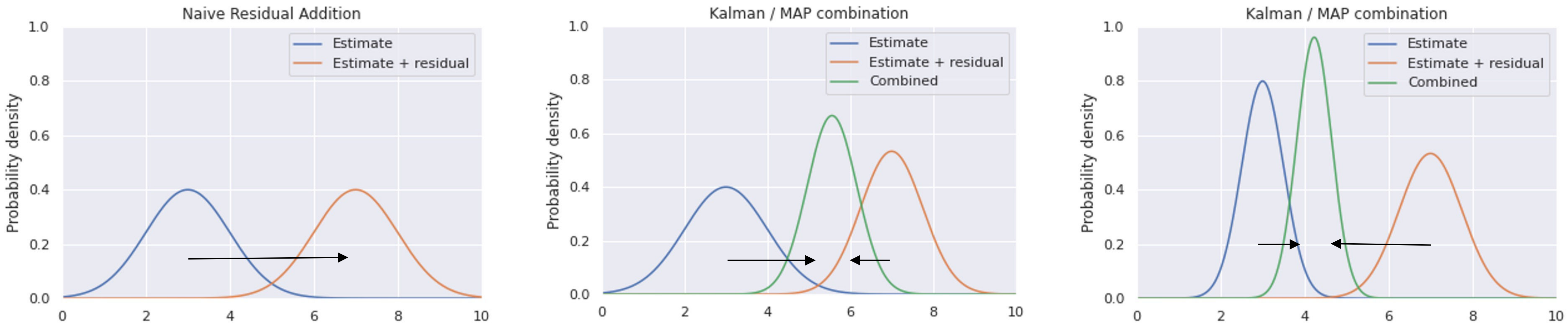




Local Bayesian Adjustment with Point-wise Data

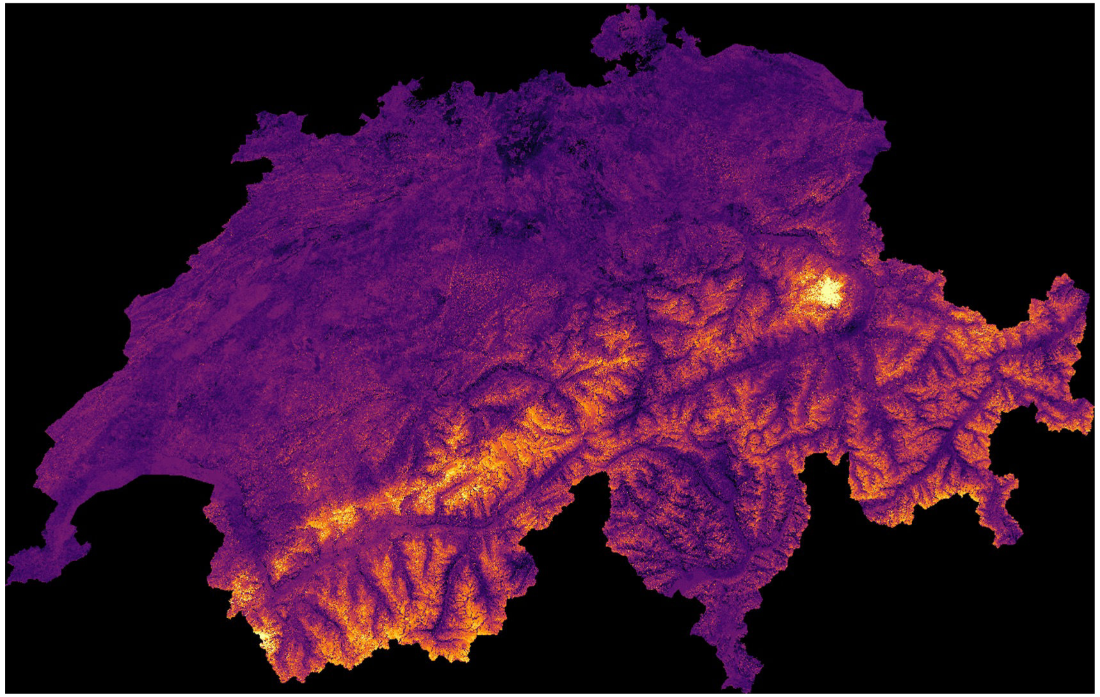
Can we do better than than simply adding the estimated residuals? Yes!

Solution: maximum a posteriori (MAP) / Kalman adjustment of predictions.

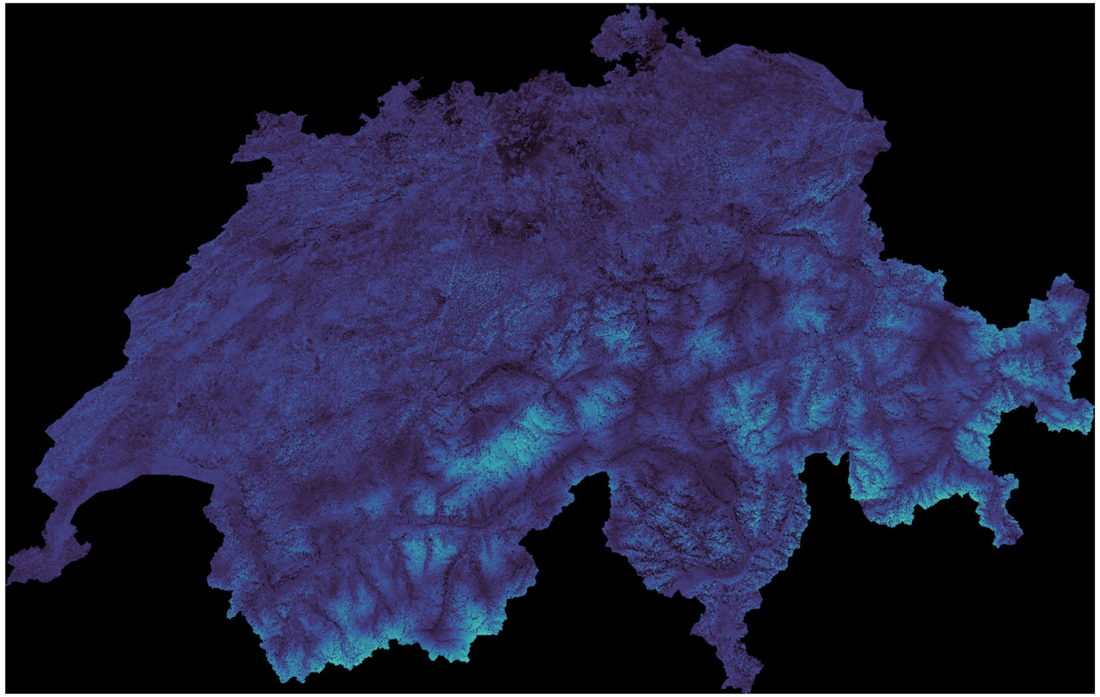


Local Bayesian Adjustment with Point-wise Data

MAP estimate means we also obtain a-posteriori uncertainties.



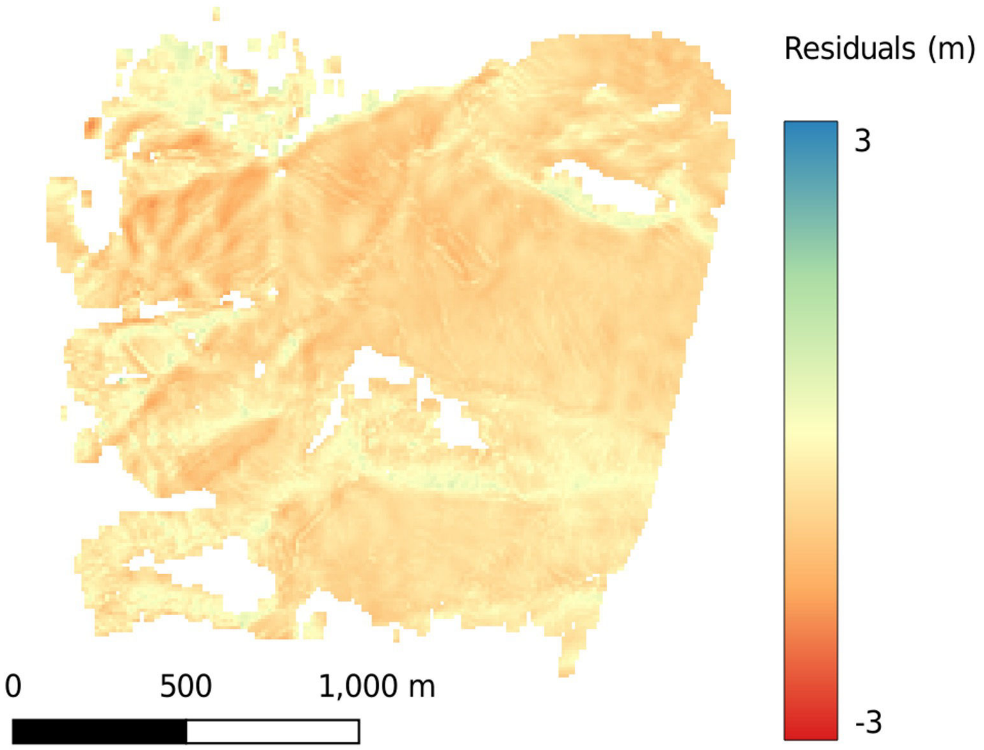
Final estimates



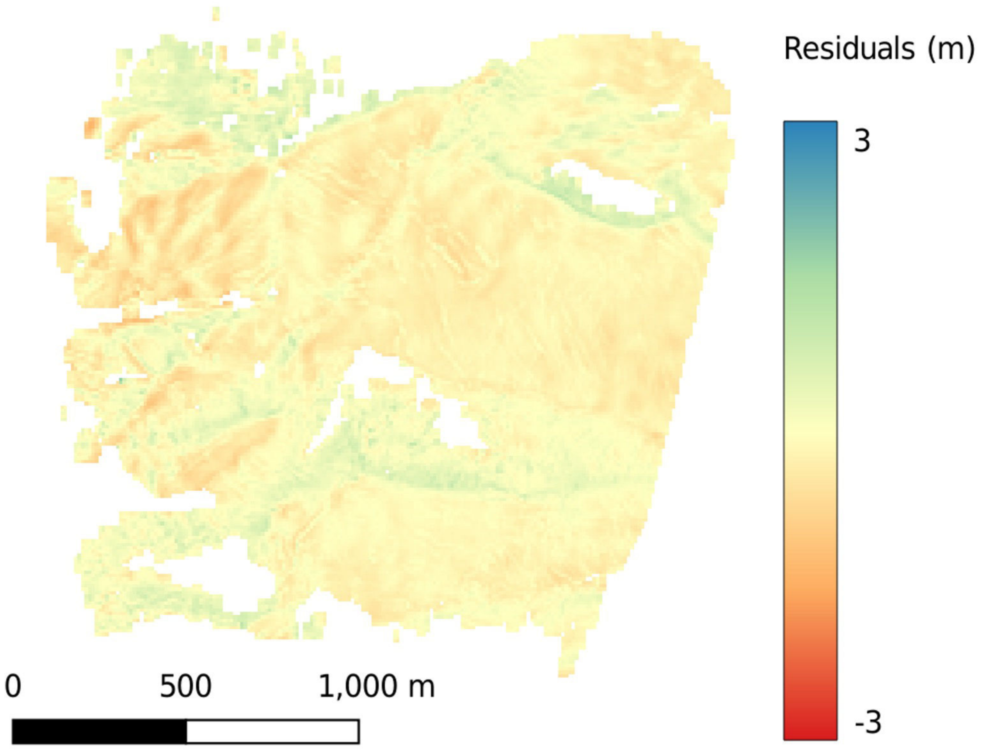
A posteriori uncertainty map

Local Bayesian Adjustment with Point-wise Data

Adjustment with sparse points works very well, since errors are spatially correlated.



Residuals of initial results



Residuals of adjusted results

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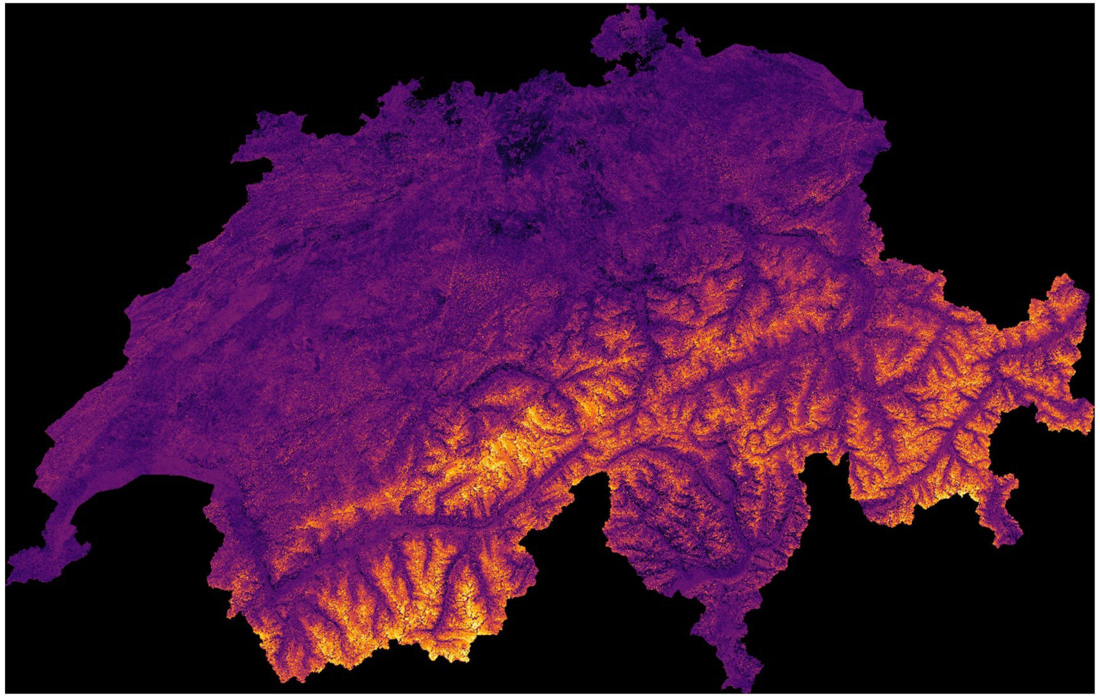
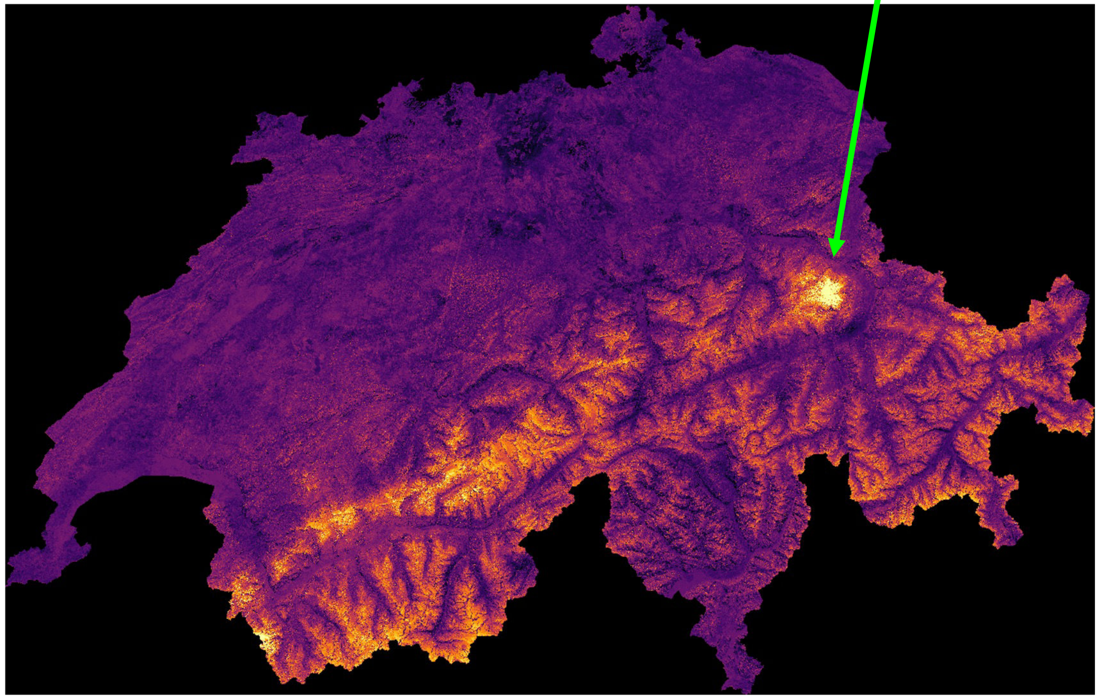
Local Bayesian Adjustment with Point-wise Data

Adjustment balances smoothness against locally adapted updates.

Strong correction in Pizol



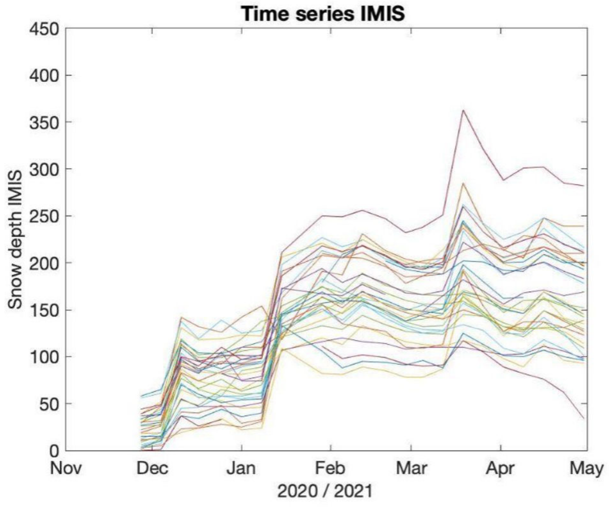
Initial estimate for 22.01.2023



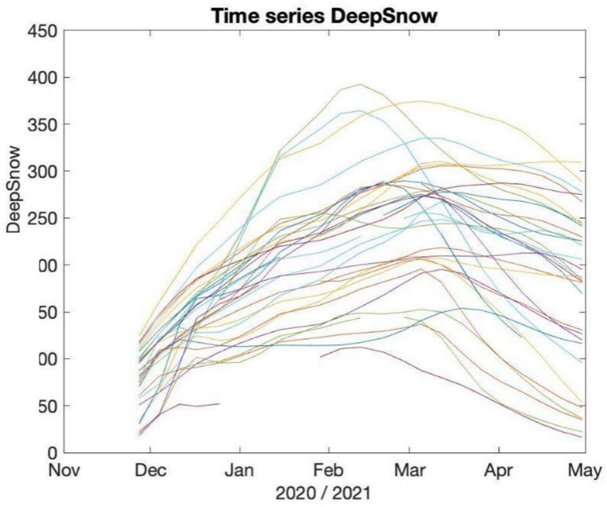
Final estimate for 22.01.2023

Temporal Profile

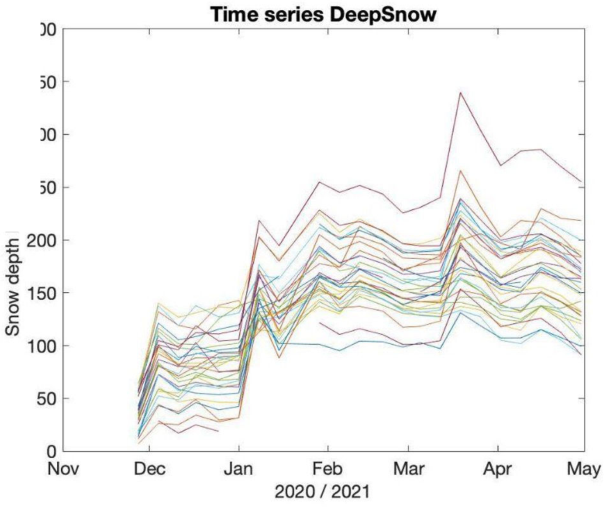
…which leads to more accurate snow depth time series.



Ground measurements



RNN

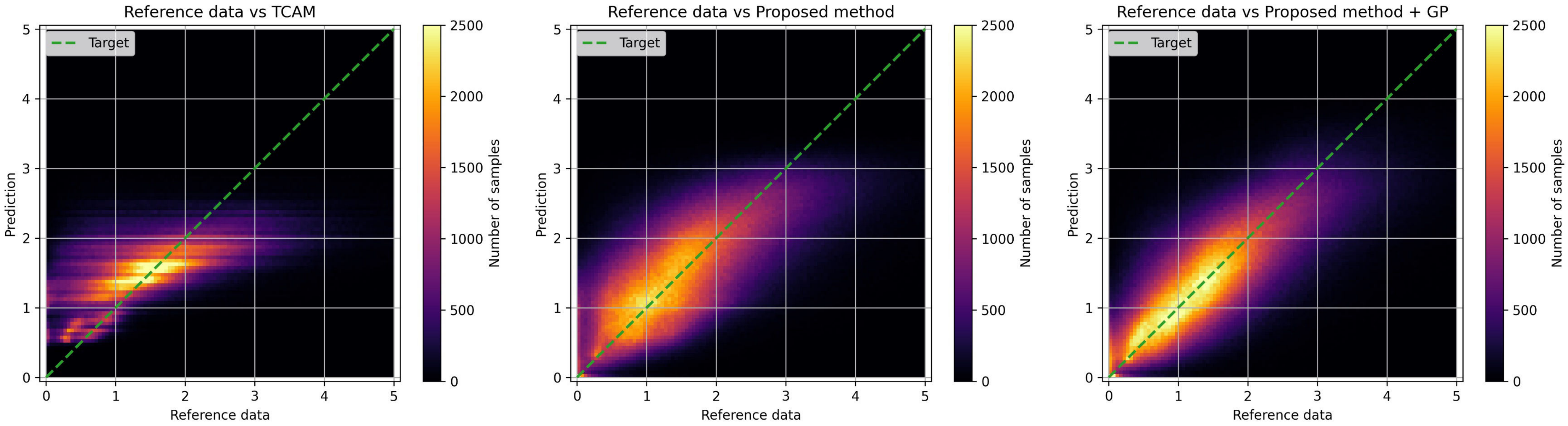


RNN + GP

Results

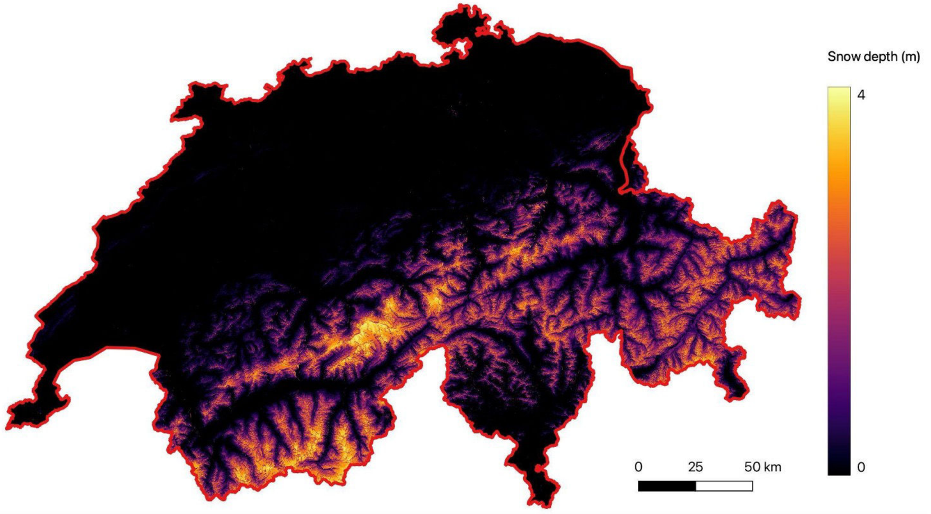
Local Bayesian Adjustment with Point-wise Data

Adjustment with in-situ data further increases the accuracy of the snow depth maps.



Conclusion

1. **Snow maps of much higher quality** than before, can be produced weekly, at 10 m GSD, from scalable / free data sources.
2. Spatially explicit, calibrated **uncertainty maps** to help users interpret the snow depth estimates for downstream tasks.
3. Optionally, **corrections based on ground measurements** further improve accuracy, approaching that of stereo VHR satellite methods.



Caye Daudt, Rodrigo et al., «Snow depth estimation at country-scale with high spatial and temporal resolution» ISPRS Journal of Photogrammetry and Remote Sensing 197, 105-121

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SLF ExoLabs EcoVision PRS Photogrammetry Remote Sensing ETH zürich


Rodrigo Caye Daudt


Jan Wegner


Hendrik Wulf


Reik Leiterer


Konrad Schindler


Elisabeth Hafner


Yves Bühler