

11th Workshop of International Precipitation Working Group – Tokyo Institute of Technology

# Correcting Snowfall Elevation Gradients by using Sentinel-1 Based Snow Depth Observations

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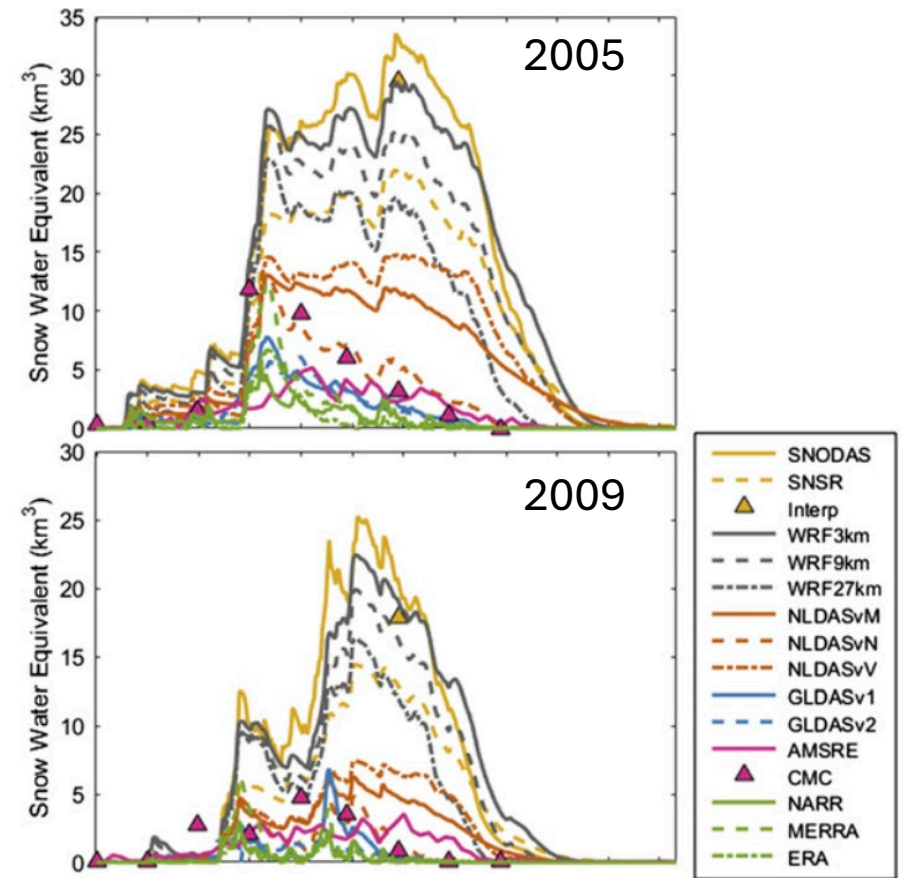
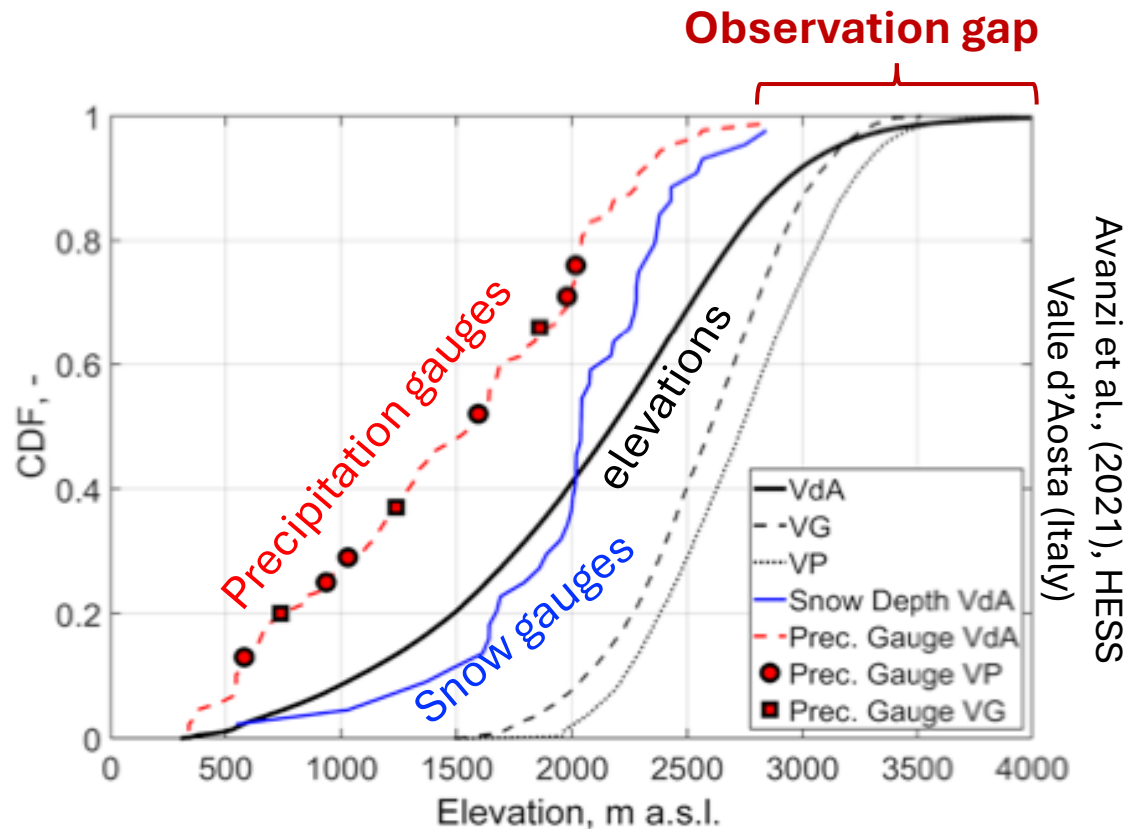
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# Snow estimates are uncertain



Wrzesien et al., (2017), JHM  
Sierra Nevada (California)

Errors in SWE modeling estimations are caused by uncertainties in:

- **Orographic Precipitation Amounts;**
- Rain/Snow Partitioning;
- Ablation (melt) Parameterization

$$\alpha * P \pm V - M = \frac{dSWE}{dt} \quad \alpha = \text{Snow Correction Factor}$$

# Sentinel-1 snow depth observations

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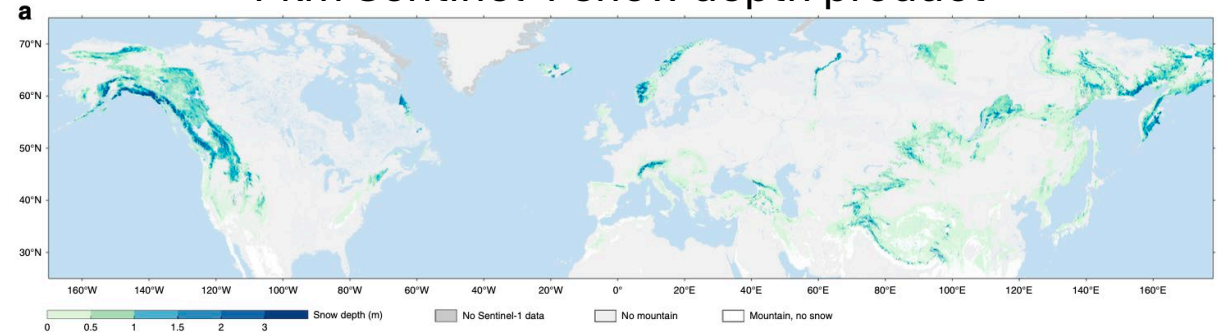
## Snow depth variability in the Northern Hemisphere mountains observed from space

Lievens et al. (2019)

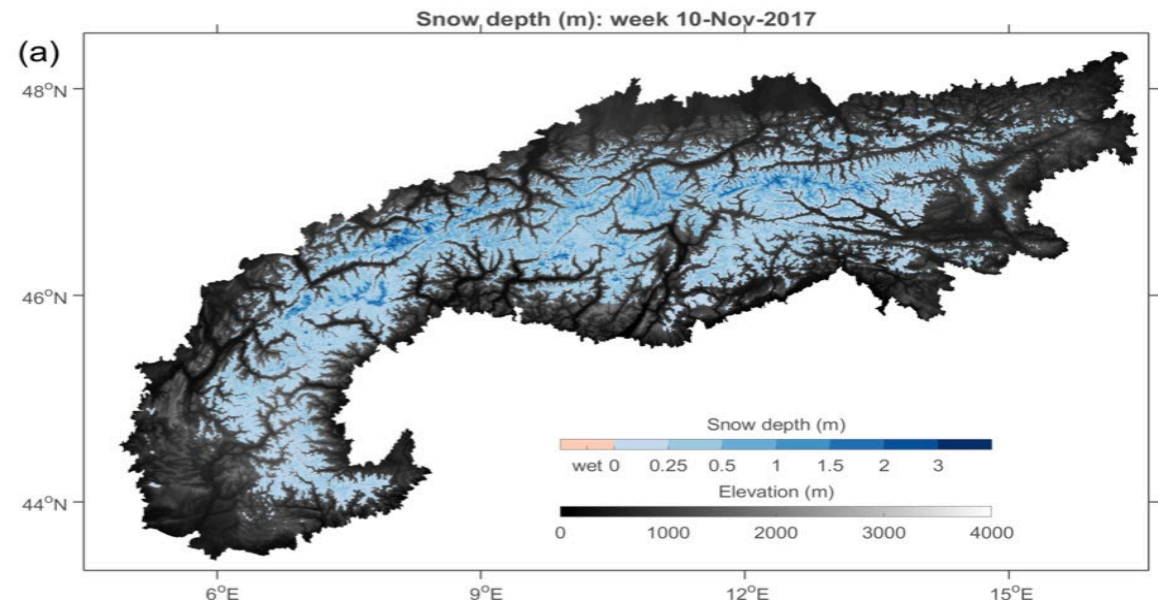
### Sentinel-1 Snow depth data:

- Derived from C-band radar backscatter
- Increase spatial sample vs. in-situ observations
- 100 m - 1 km; every ~6-12 days
- 2017-present
- Good only for dry snow
- Not good for shallow snow

1 km Sentinel-1 snow depth product



Lievens et al., (2019), *Nature Communications*



100 m Sentinel-1 snow depth product

Lievens et al., (2022), *The Cryosphere*

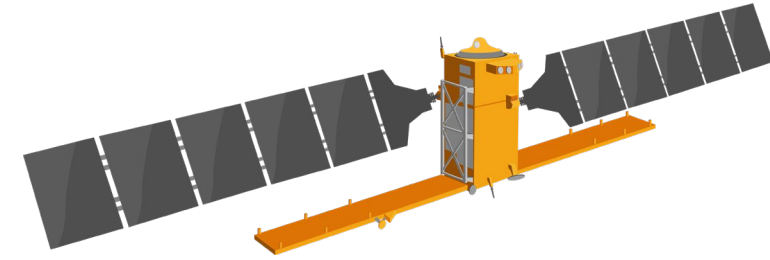
# Can we correct snowfall using Sentinel-1 SD?

$$SWE = SWE(\rho, SD)$$

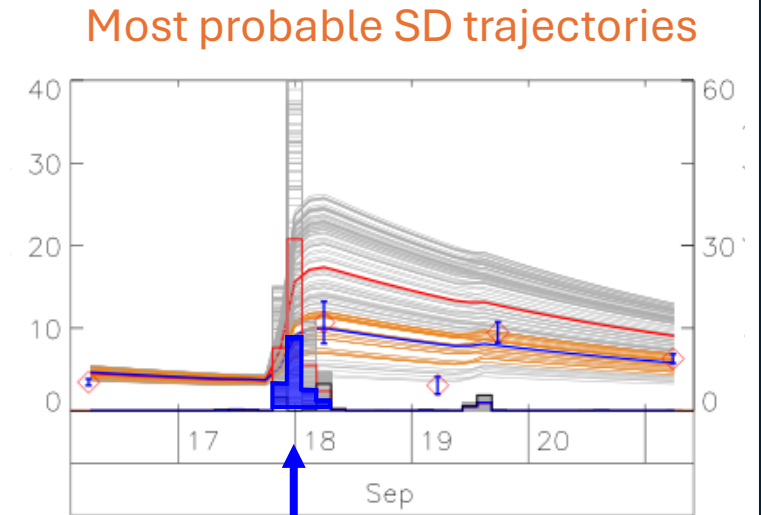
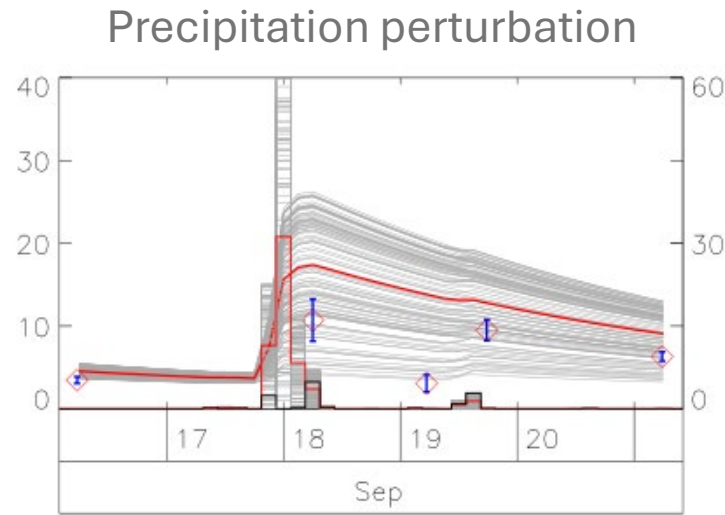
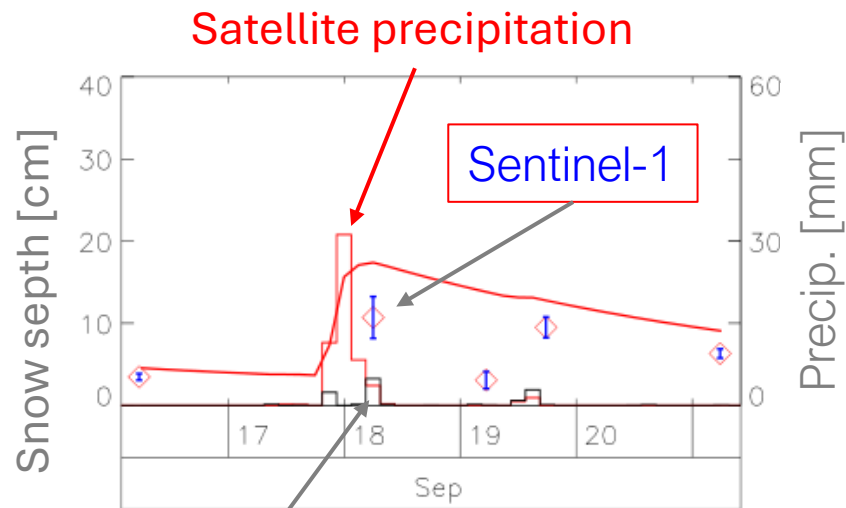
$$\alpha * P \pm V - M = \frac{dSWE(\rho, SD)}{dt}$$

$$SD = f(\rho, P, T, \vartheta[\alpha, \dots], \varepsilon)$$

Modelled SD      Observed SD from S-1



## Particle Batch Smoother (PBS) concept



True snowfall

$$P_i = P * \alpha$$

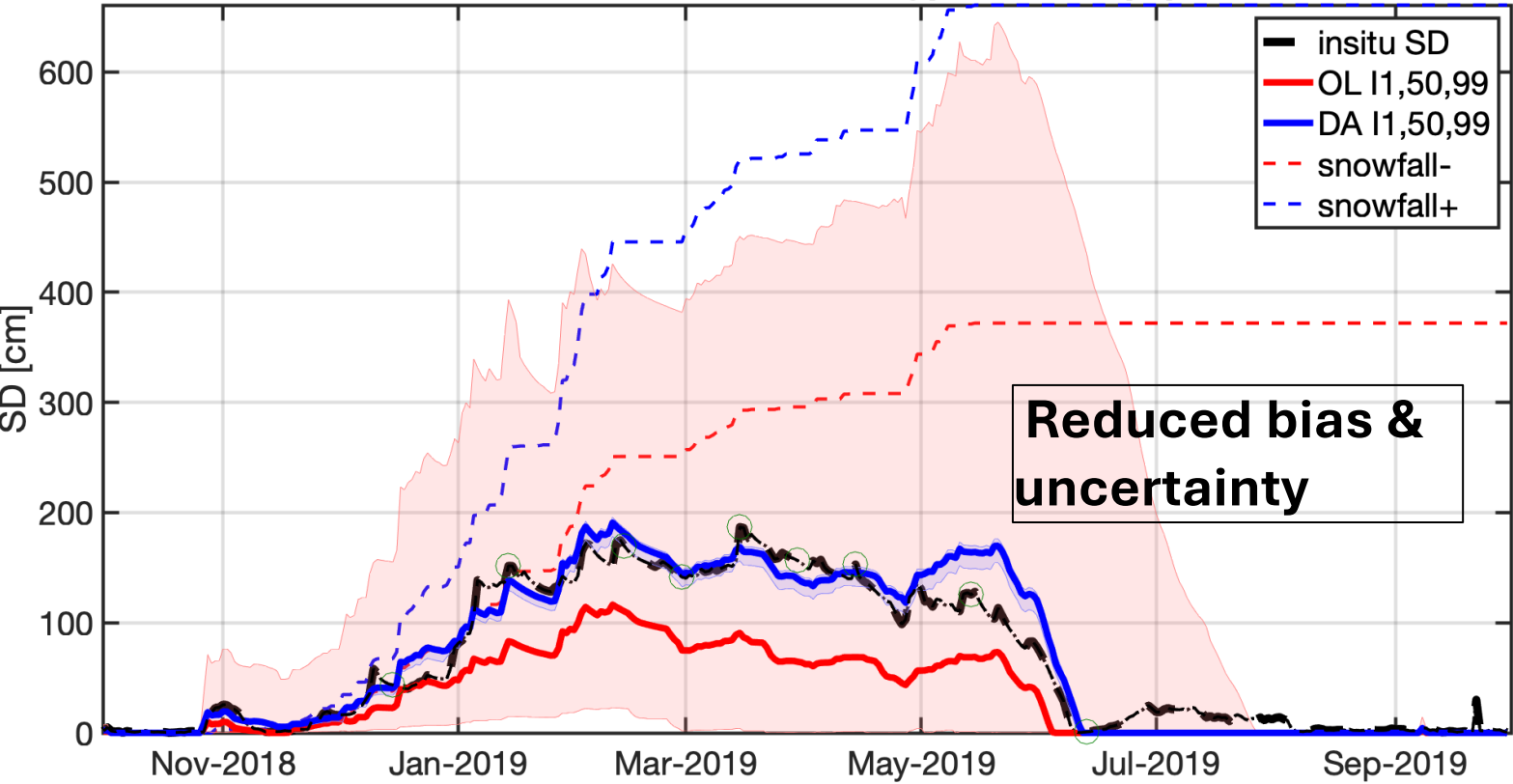
$$\alpha \sim \log(\mu, CV)$$

$$\mu = 1(\text{unbias}), CV = 100\%$$

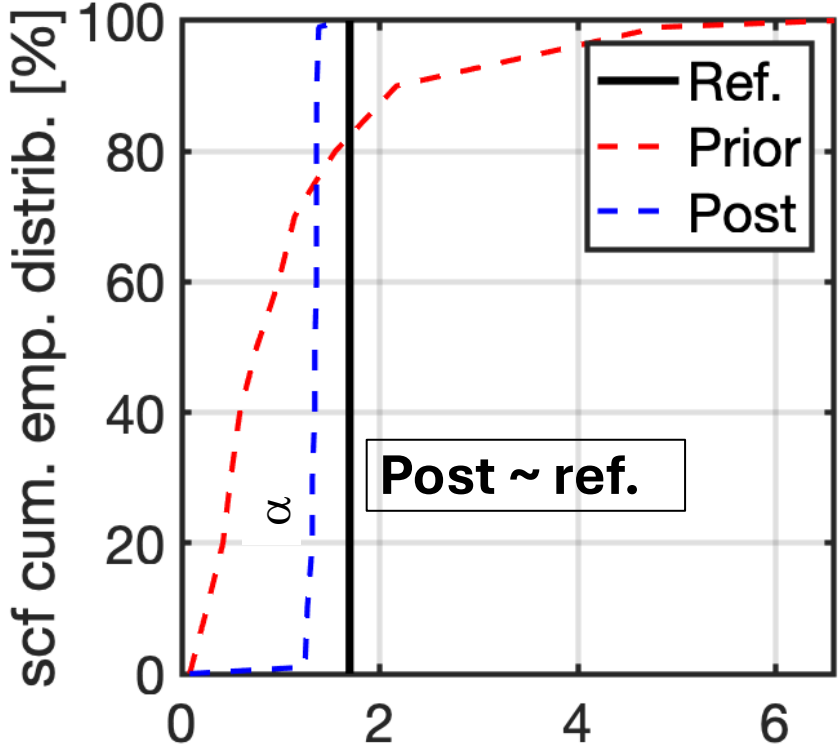
Corrected snowfall product

# Results – point scale observation

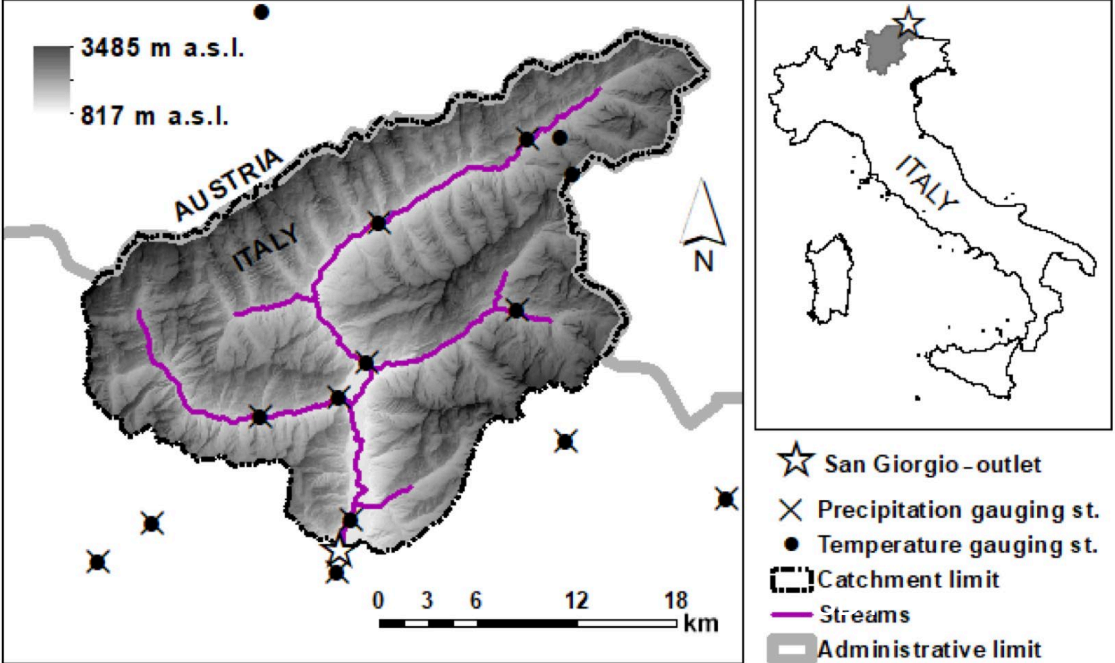
Snow depth and cumulative snowfall



Distributions of the snow correction factor ( $\alpha$ )

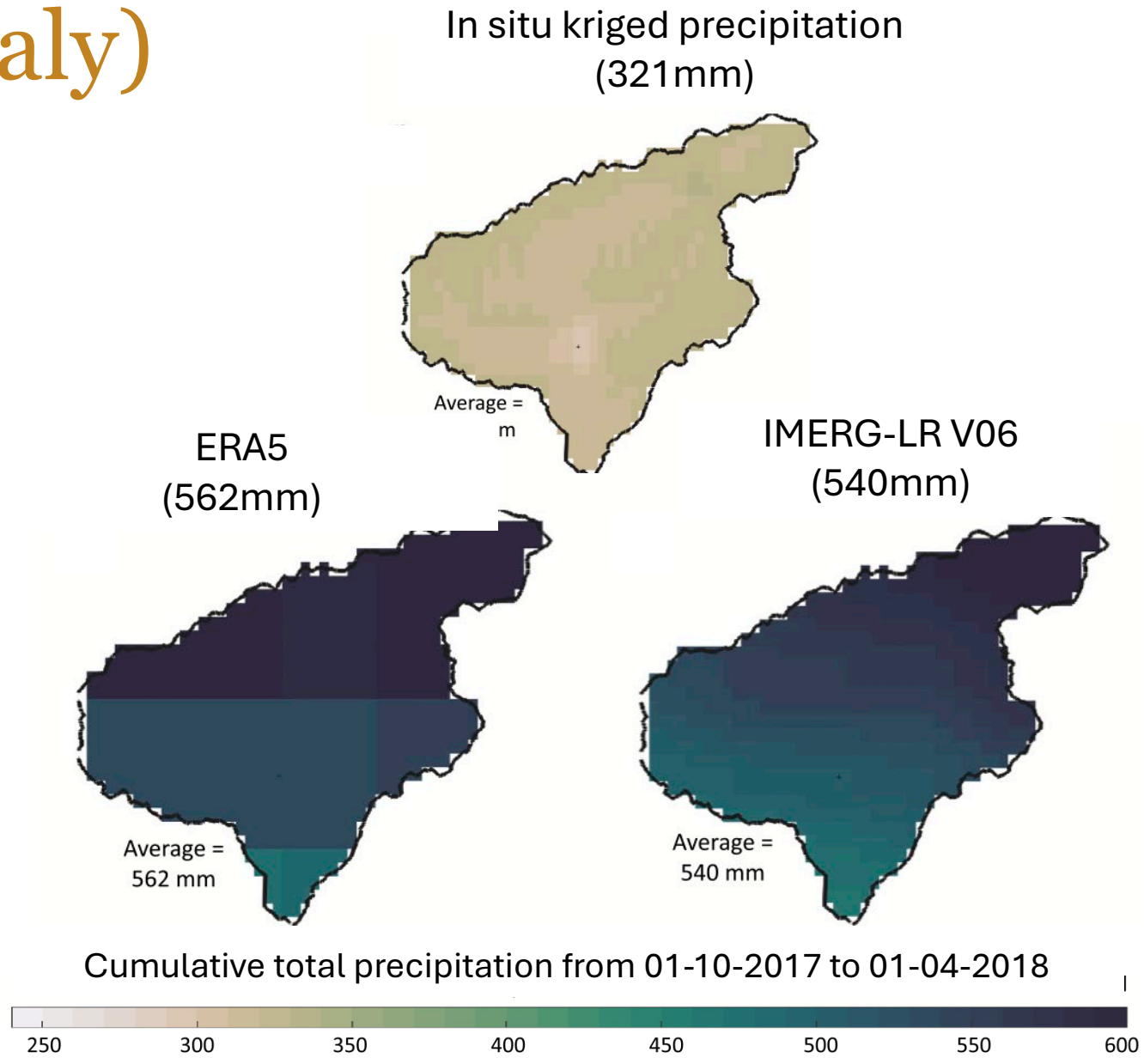


# Test-Case Alto Adige (Italy)



**Aurino Basin**, northern Italy (614 km<sup>2</sup>)

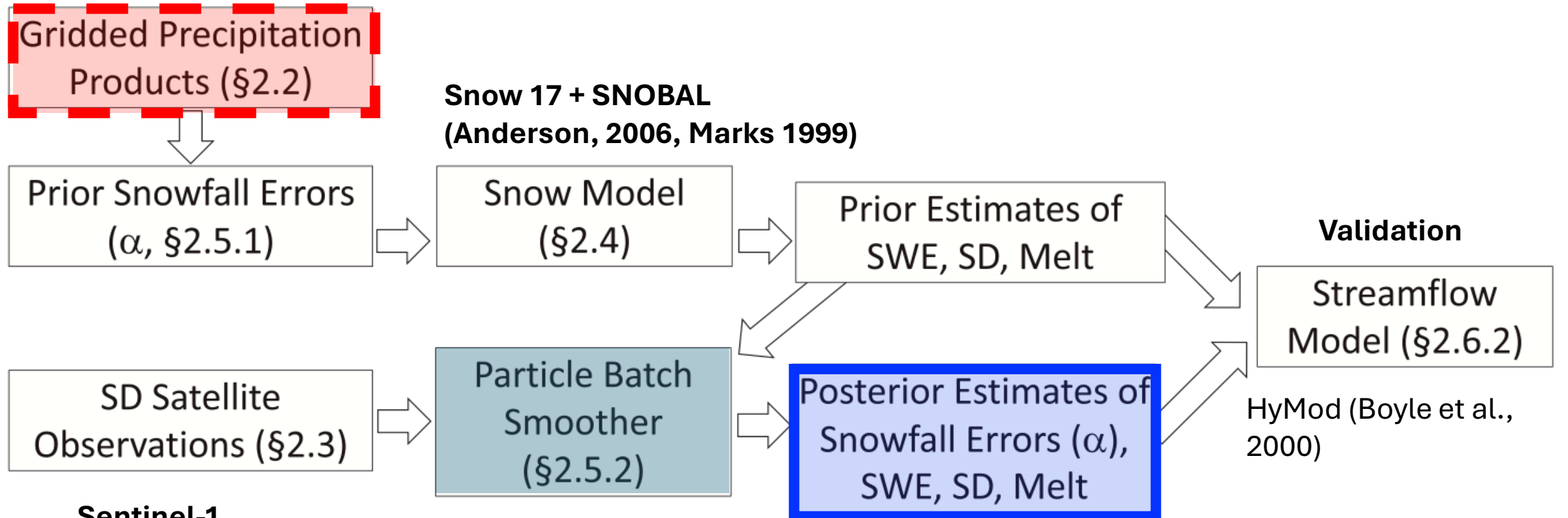
Additional Data:  
Streamflow gauge “San Giorgio” (2016-2019)  
2 ground-based snow depth sensors



Cumulative total precipitation from 01-10-2017 to 01-04-2018

# Experimental setup

IMERG-LR V06, ERA5, In situ P



**Snow 17 + SNOBAL**  
(Anderson, 2006, Marks 1999)

**Validation**

Streamflow  
Model (§2.6.2)

HyMod (Boyle et al.,  
2000)

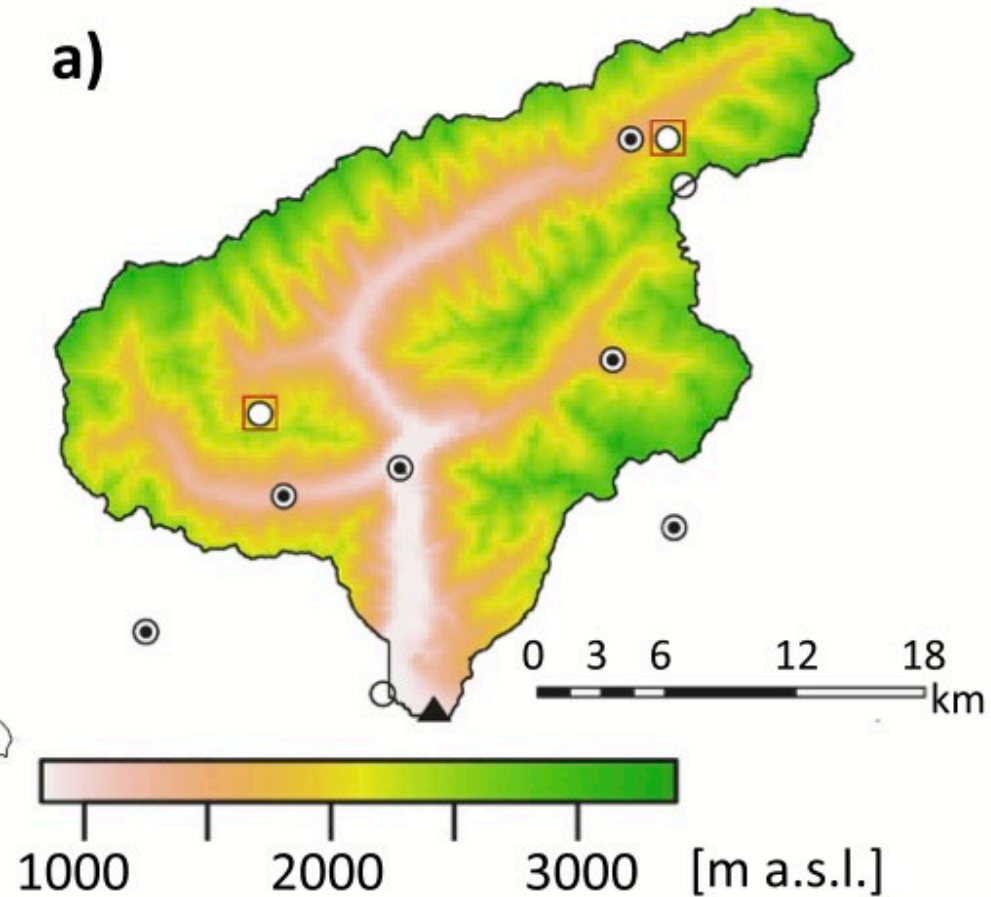
**Sentinel-1**

$N_{ENS} = 200$   
 $\alpha \sim \log(\mu, CV)$   $\mu = 1$  (unbias),  $CV = 100\%$   
DA of 1 snow depth obs per month

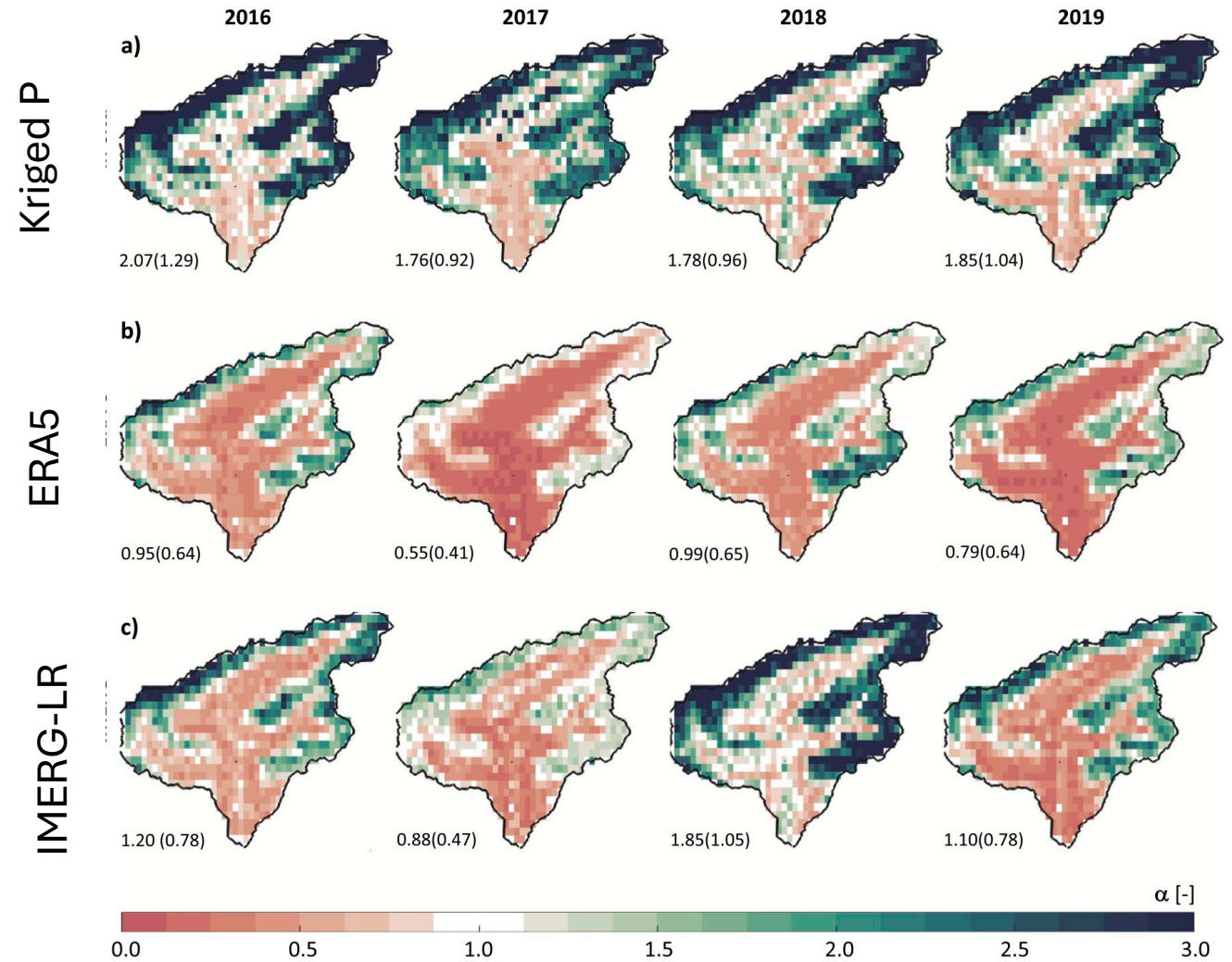
# Snowfall Orographic Patterns

Elevation and obs. locations

a)



Snowfall correction factor ( $\alpha$ )



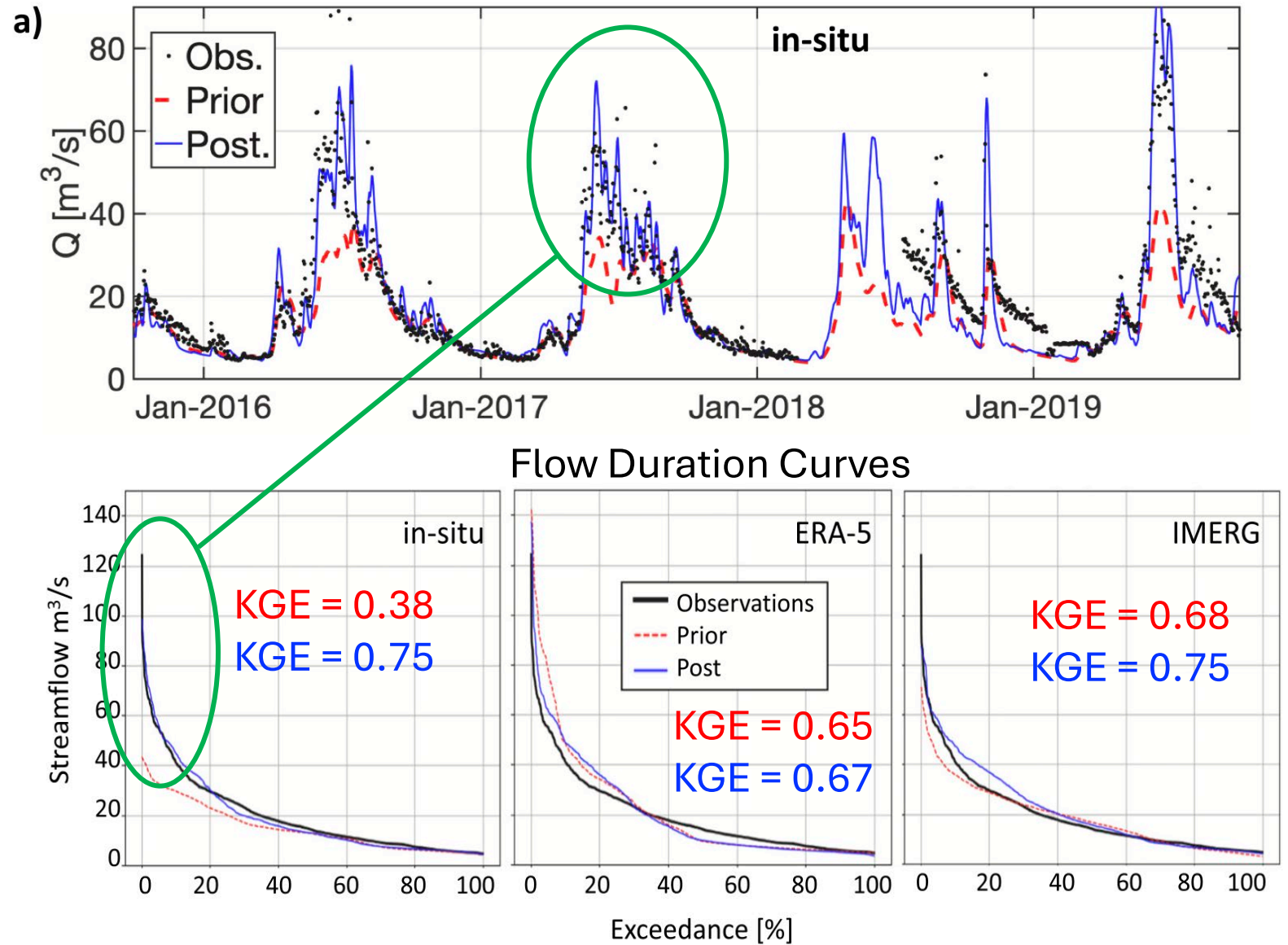
Giroto et al., (2024), STOTEN



# Streamflow

- Improvements in streamflow estimates especially during summer high flows

The higher elevation (increased snow) releases water via snowmelt more slowly than the prior case (colder temperature, and longer travel times)



# Second Test Case: Aosta Valley

## Models

- Snow Model: GEOframe - Hock model (Formetta et al., 2014) + SNOBAL
- Streamflow Model: GEOframe (Bancheri et al., 2019)

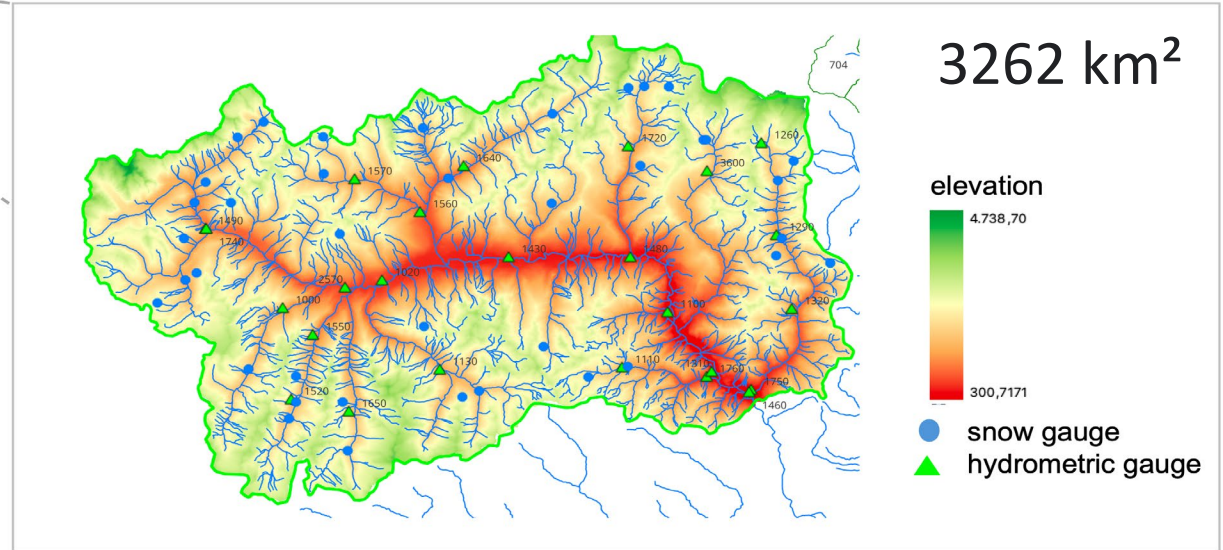
## Validation data:

- Streamflow gauge: 13 gauges (2015-2018)
- More than 30 ground-based snow depth sensors

## Particle Batch Smoother:

$$N_{\text{ENS}} = 100$$

- DA over the storms during Jan 2017 to Apr 2017 and Jan 2018 to Apr 2018



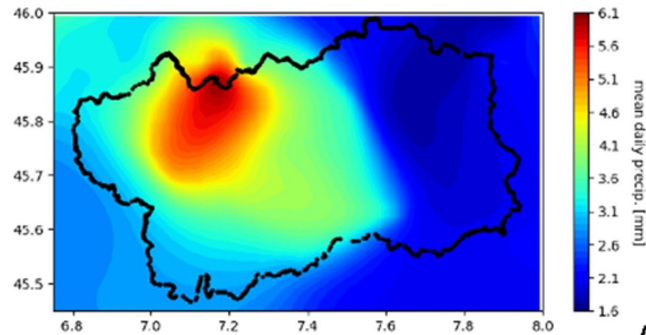
310-4810 m - mean elevation=2000 m

## Precipitation data:

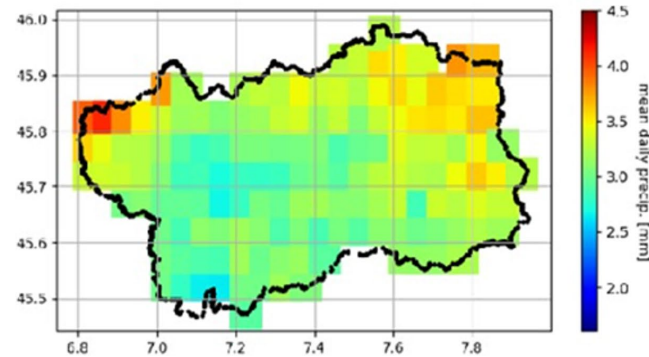
- 1) interpolated over 83 rain gauges
- 2) EMO-1arc minute (Gongalo et al. 2020)
- 3) CHIRPS (5 km) (Harrison et al. 2022)

# Second Test Case: Aosta Valley

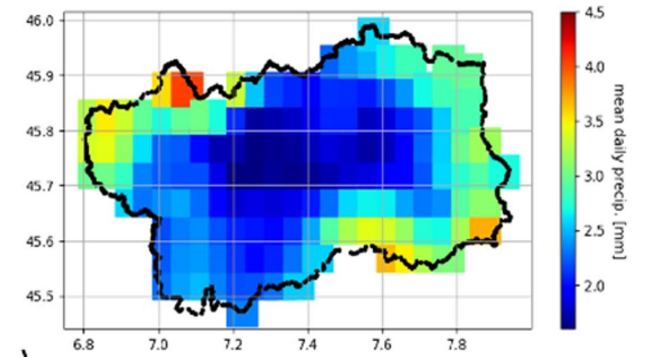
mean daily precipitation: EMO, 1-arcmin, daily



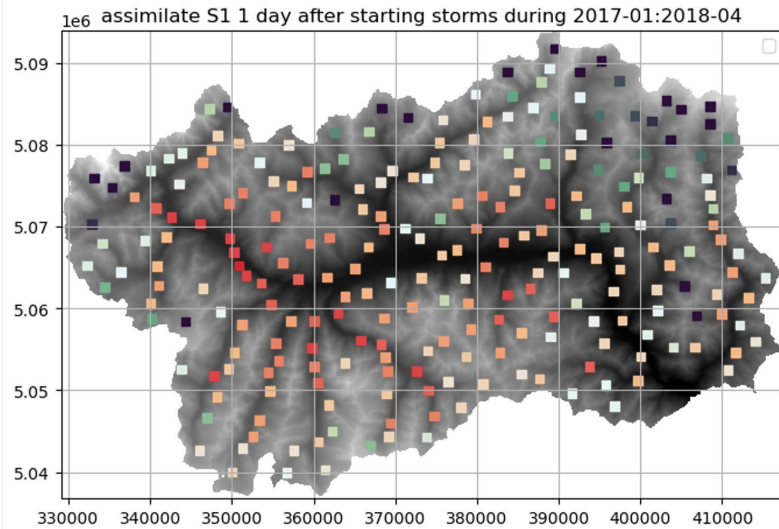
mean daily precipitation: chirps, 5 km, daily



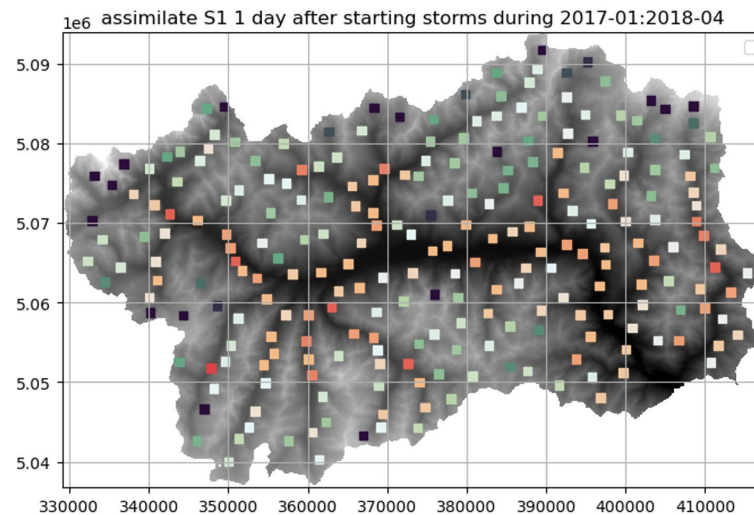
mean daily precipitation: kriging, 5 km, daily



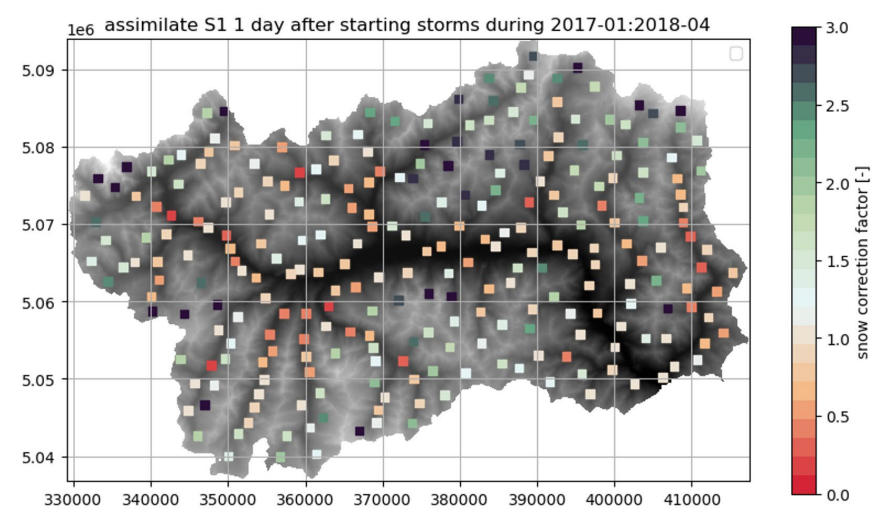
correction coef of snowfall-EMO-1



correction coef of snowfall-CHIRPS



correction coef of snowfall-kriging



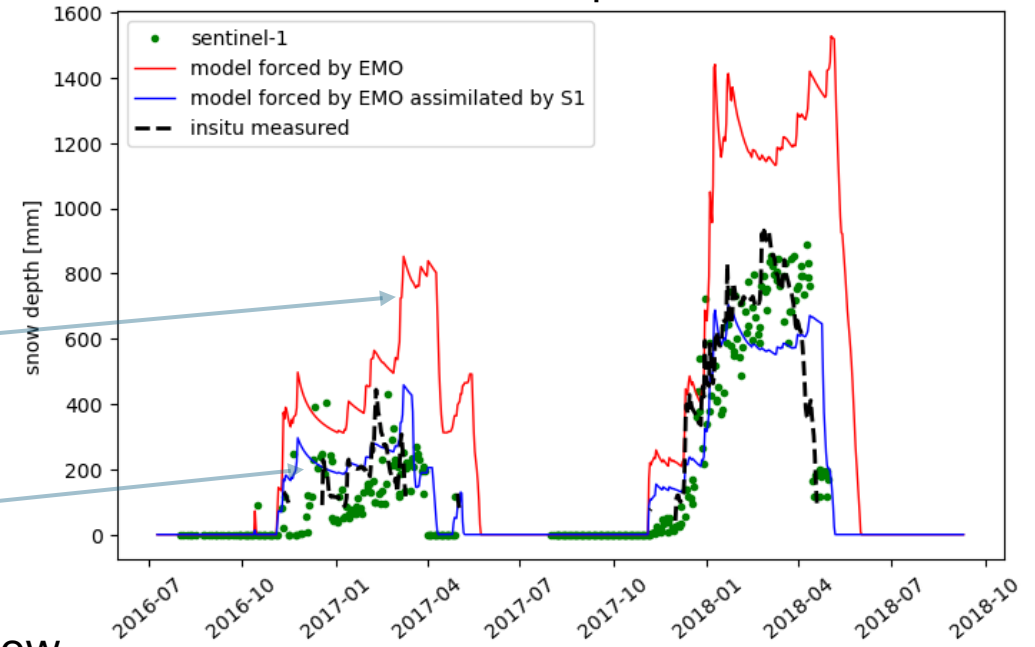
# Effect on river discharge

- Snow model: GEOframe - Hock model (Formetta et al., 2014) + SNOBAL (Anderson, 2006, Marks 1999)
- Streamflow Model: GEOframe (Bancheri et al., 2019)
- Model forced with EMO-1 precipitation

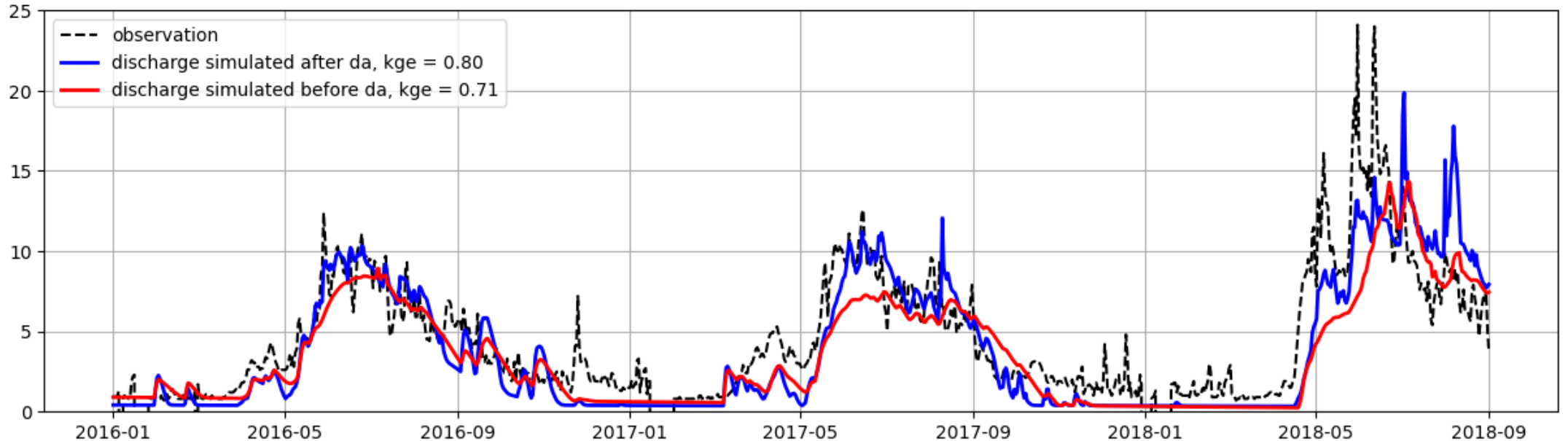
With original EMO

With corrected EMO

### Snow depth



### Streamflow



# Conclusions

- **Accurate SWE and streamflow predictions** depend on **accurate snowfall** estimates
- We developed a **Particle Batch Smoother** Data Assimilation technique to correct solid precipitation with **Sentinel-1 snow depth** data
- Our results suggest that:
  - SWE (SD) **orographic patterns** are more visible after DA
  - Evidence of **improve streamflow** estimates, especially in summer flow

## Future developments:

- Developing **correction factors** for satellite precipitation (e.g., IMERG products over the Alps and European Mountains ranges)
- Implementing **near real time correction of snowfall** using classical Particle filter.

# References

1. Giroto, M., Formetta, G., Azimi, S., Bachand, C., Cowherd, M., De Lannoy, G., Lievens, H., Modanesi, S., Raleigh, M.S., Rigon, R. and Massari, C., 2024. Identifying snowfall elevation patterns by assimilating satellite-based snow depth retrievals. *Science of The Total Environment*, 906, p.167312.
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3. Harrison, L., Landsfeld, M., Husak, G. et al. Advancing early warning capabilities with CHIRPS-compatible NCEP GEFS precipitation forecasts. *Sci Data* 9, 375 (2022). <https://doi.org/10.1038/s41597-022-01468-2>
4. Anderson, E. A. (2006). Snow accumulation and ablation model–SNOW-17. US National Weather Service, Silver Spring, MD, 61.
5. Gomes, Goncalo; Thiemig, Vera; Skøien, Jon Olav; Ziese, Markus; Rauthe-Schöch, Armin; Rustemeier, Elke; Rehfeldt, Kira; Walawender, Jakub; Kolbe, Christine; Pichon, Damien; Schweim, Christoph; Salamon, Peter (2020): EMO: A high-resolution multi-variable gridded meteorological data set for Europe. European Commission, Joint Research Centre (JRC) [Dataset] doi: 10.2905/0BD84BE4-CEC8-4180-97A6-8B3ADAAC4D26 PID: <http://data.europa.eu/89h/0bd84be4-cec8-4180-97a6-8b3adaac4d26>  
Harrison, L., Landsfeld, M., Husak, G. et al. Advancing early warning capabilities with CHIRPS-compatible NCEP GEFS precipitation forecasts. *Sci Data* 9, 375 (2022). <https://doi.org/10.1038/s41597-022-01468-2>.
6. Lievens, H., Brangers, I., Marshall, H. P., Jonas, T., Olefs, M., & De Lannoy, G. (2022). Sentinel-1 snow depth retrieval at sub-kilometer resolution over the European Alps. *The Cryosphere*, 16(1), 159-177.