Improving the estimation of the snow fraction from Sentinel-2 L2A data for the Copernicus Land pan European HR-WSI production

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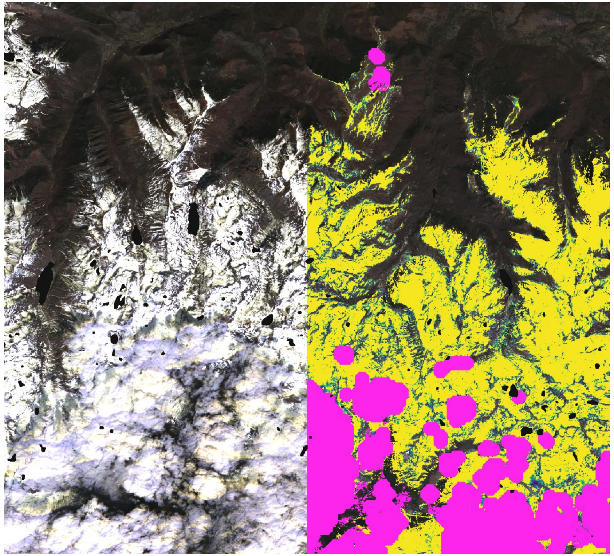
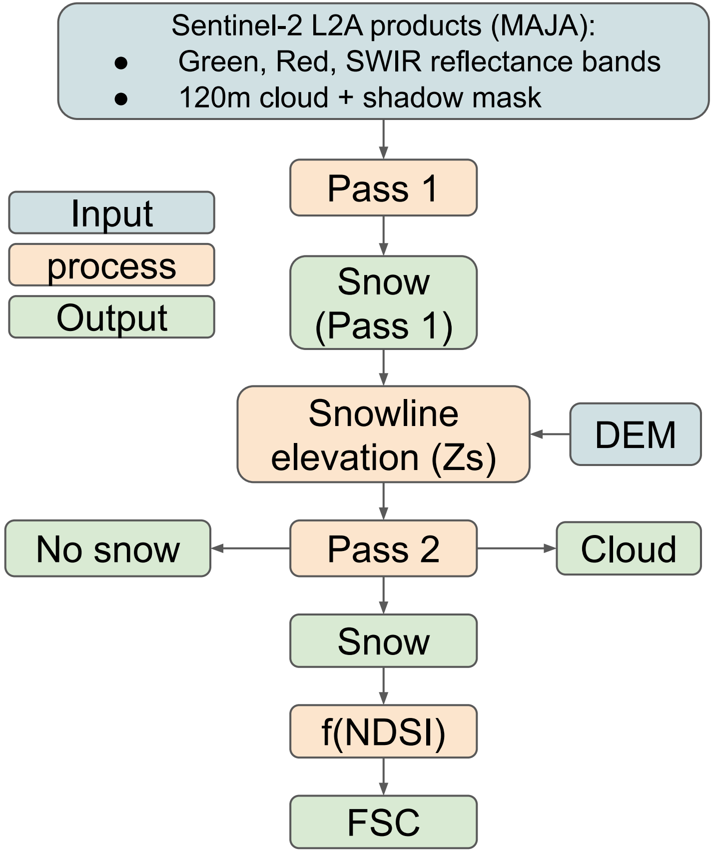
Context: Let-It-Snow algorithm

Sentinel-2 - 20m Fractional Snow cover

- Surface Reflectance & Elevation model (DEM)
- Snow cover presence (snow/no-snow)
- Refines MAJA cloud mask to recover snow pixels
- Fractional Snow Cover (FSC) (0-100%)

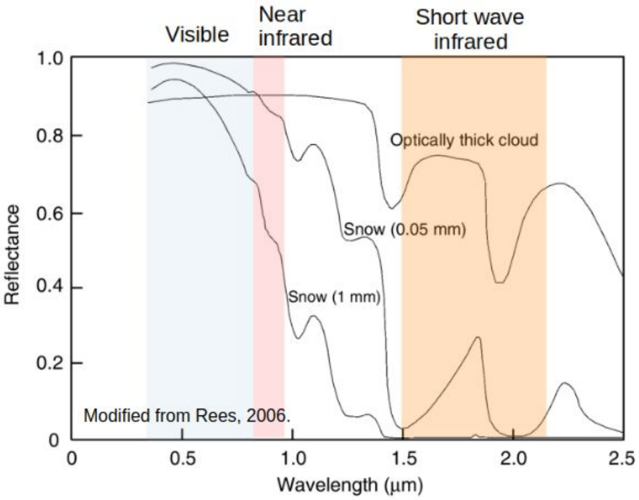




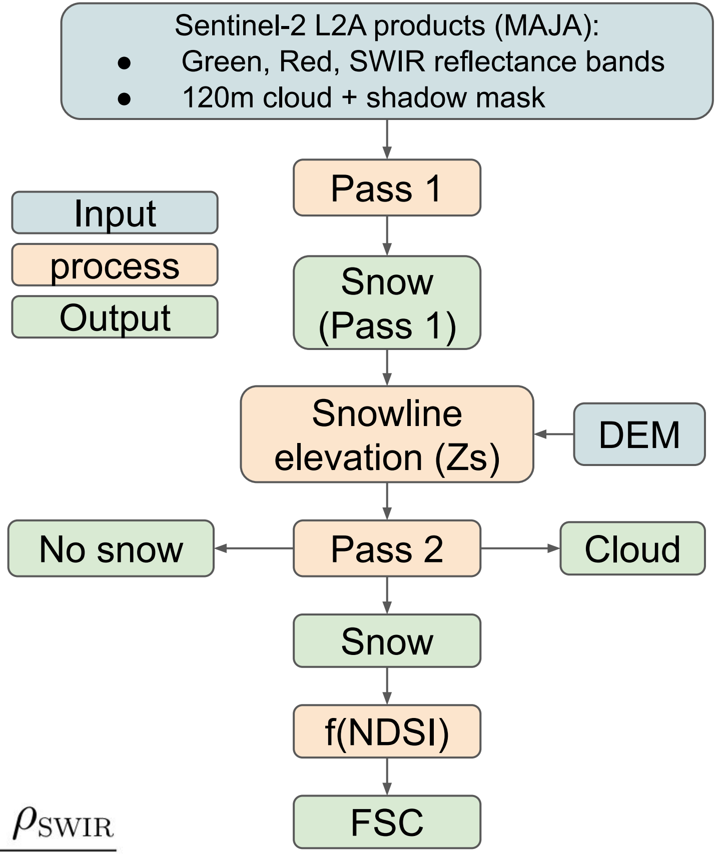
Context: Let-It-Snow algorithm

Fractional Snow Cover (0-100%)

- FSC > 0 if Snow
- FSC = 1.45*NDSI-0.01 (Salomonson & Appel, 2004)



$$\mathrm{NDSI} = \frac{\rho_{\mathrm{green}} - \rho_{\mathrm{SWIR}}}{\rho_{\mathrm{green}} + \rho_{\mathrm{SWIR}}}$$

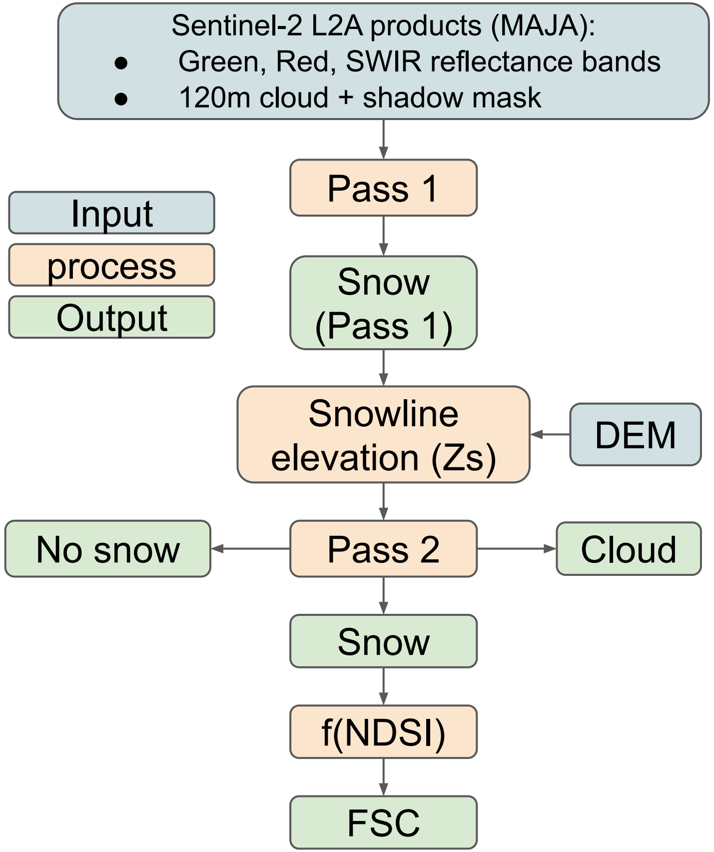


Context: FSC current limitations

Method developed for MODIS data (500m resolution) over North America

1) Need to validate LIS FSC over the climatological variability of European mountains.

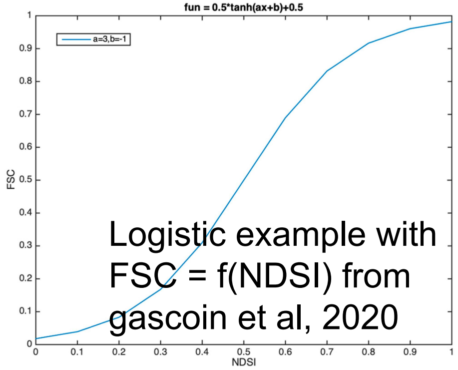
2) Need to explore new FSC methods adapted for Sentinel-2.



Proposed solution

- LIS FSC validation:
  - Snow maps from Very High Resolution (VHR) satellites used as reference.
  - Validation over three categories: normal (clean) pixels, shaded pixels, snow pixels previously identified as clouds.

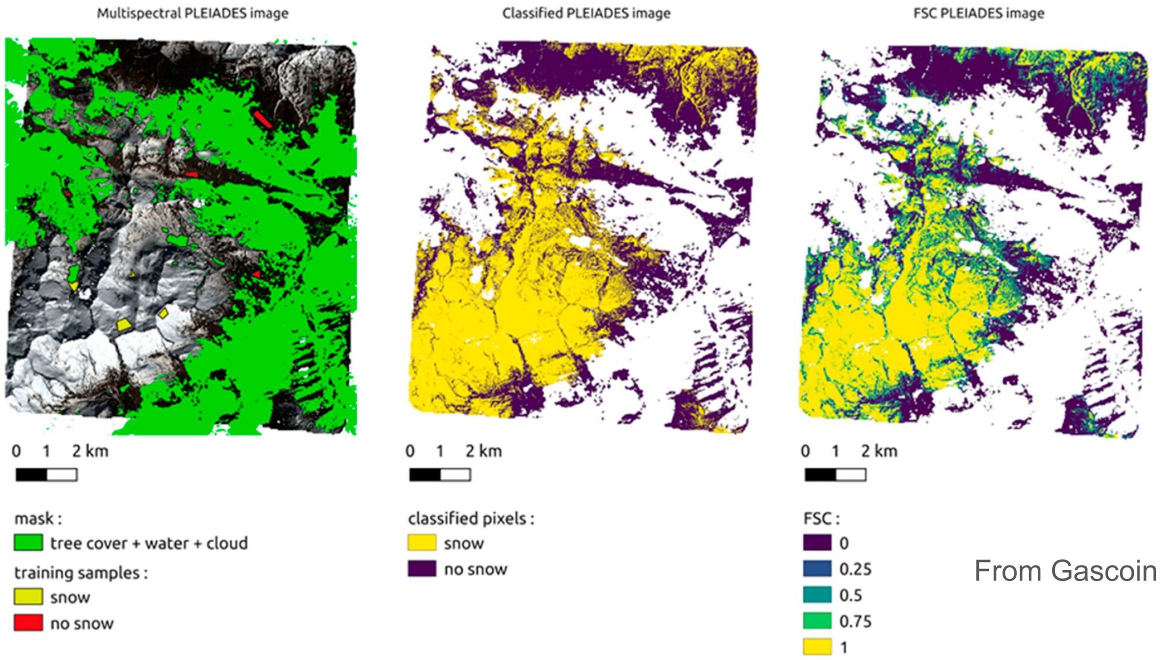
- New methods to explore:
  - Additional features (DEM, other reflectance bands…)
  - Linear and Logistic regressions
  - Random Forest model (machine learning)



Logistic example with FSC = f(NDSI) from gascoin et al, 2020

Very High Resolution (VHR) reference dataset

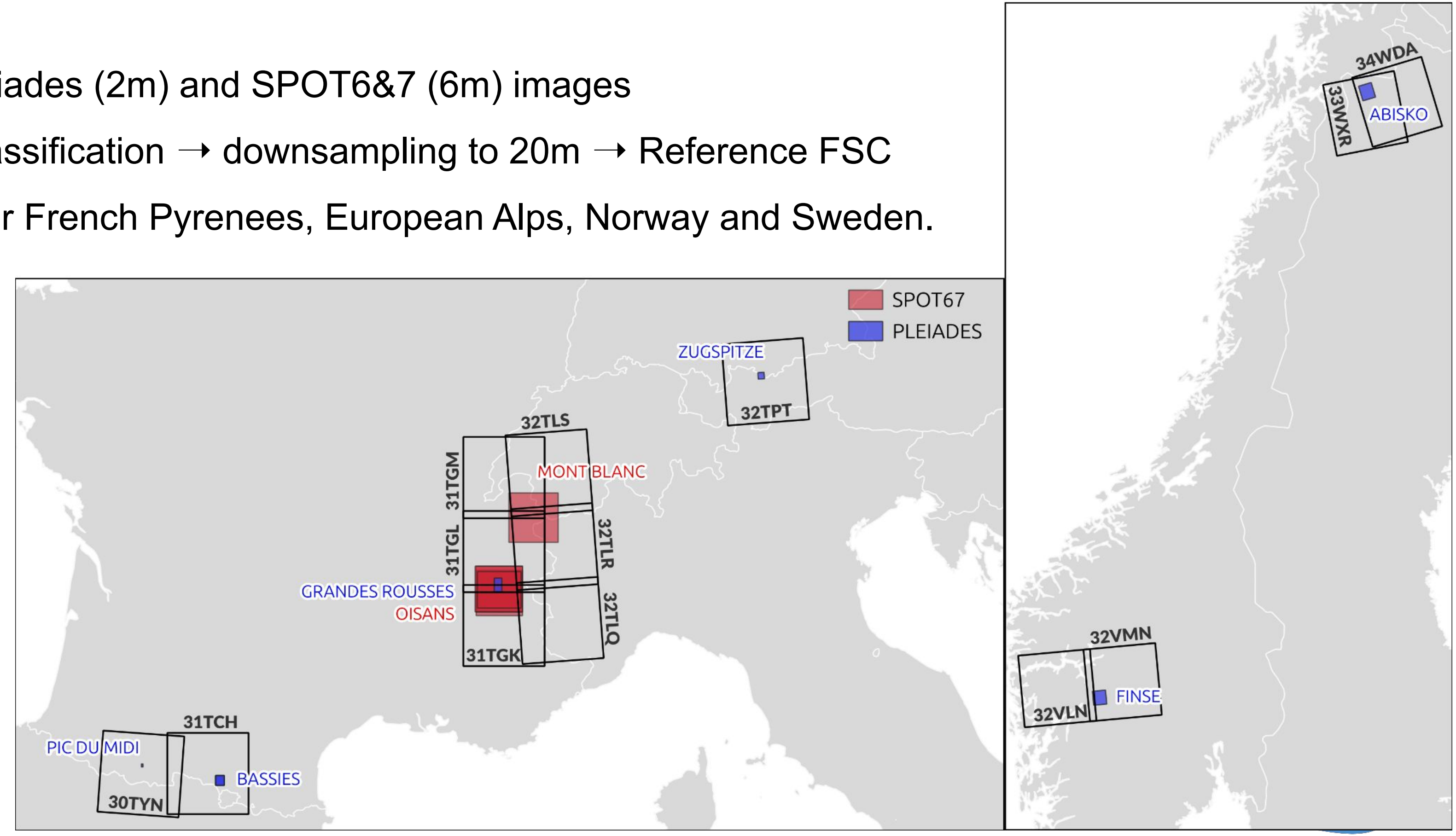
- VHR Pleiades (2m) and SPOT6&7 (6m) images
- Snow classification → downsampling to 20m → Reference FSC



From Gascoin et al, 2020

Very High Resolution (VHR) reference dataset

- VHR Pléiades (2m) and SPOT6&7 (6m) images
- Snow classification → downsampling to 20m → Reference FSC
- Data over French Pyrenees, European Alps, Norway and Sweden.



Sentinel-2 dataset

Selecting L2A:

- Maximum time gap of 3 days between L2A and VHR (Gascoin et al, 2020).
- Best Available Pixel composite of multiple L2A products for one VHR (cloud and nodata removal).

Masking pixels:

- Tree Cover Density; Water mask; Clouds.
- No-snow pixels.

We remove no-snow pixels from the study because the ability for LIS to detect the presence of snow was already evaluated (Barrou Dumont et al. 2021).

	AREA	IMAGES		TILES
		VHR	L2A	
PLEIADES	ABISKO	1	6	34WDA
	BASSIES	5	11	31TCH
	FINSE	1	5	32VMN 32VLN
	GRANDE ROUSSES	1	2	31TGL 31TGK
	PIC DU MIDI	1	2	30TYN
	ZUGSPITZE	1	1	32TPT
SPOT6&7	MONT BLANC	1	4	32TLS 31TGM 32TLR 31TGL
	OISANS	4	22	31TGL 31TGK 32TLR 32TLQ

LIS FSC Validation

- Root Mean Squared Error (RMSE)
- Good overall performances because FSC=100 is more prevalent and LIS tends to overestimate
- Higher uncertainties in pixels initially labelled as cloud by MAJA and in shaded areas.

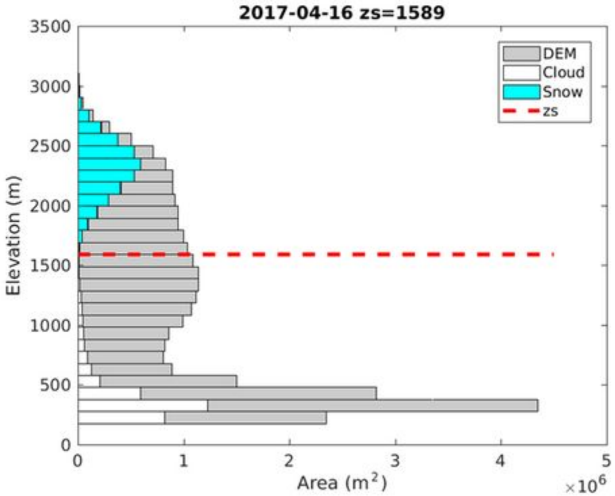
RMSE	CLEAN PIXELS		SHADED PIXELS		PREVIOUS CLOUDS	
AREAS	$FSC_{VHR} \leq 100$	$FSC_{VHR} \leq 50$	$FSC_{VHR} \leq 100$	$FSC_{VHR} \leq 50$	$FSC_{VHR} \leq 100$	$FSC_{VHR} \leq 50$
ALL	16	55	23	72	35	40
BASSIES	23	54	23	74	39	44
MONT BLANC	30	55	33	66	45	49
OISANS	13	56	22	73	NaN	NaN
GRANDES ROUSSES	7	32	5	51	NaN	NaN
PIC DU MIDI	13	31	17	61	NaN	NaN
ZUGSPITZE	37	60	36	68	NaN	NaN
FINSE	25	56	25	61	42	55
ABISKO	13	46	8	58	NaN	NaN

New methods: Additional features

Additional features available in the processing chain:

- Sentinel-2 L2A Reflectance: Blue, Green, Red, NIR (B08), SWIR (B11).
- DEM → snowline elevation ZS calculated by LIS for each product.

Why ZS?
To better differentiate between areas with elevation differences and to avoid overfitting to static DEM.



example from gascoin et al 2019

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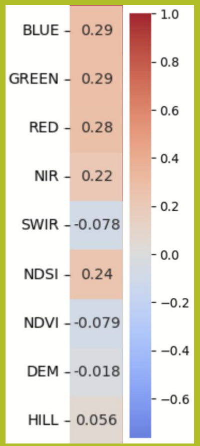
New methods: models

- Regression model (RL):
  - Useful features: NDSI, BLUE, GREEN, RED, SWIR, DEM, ZS
  - Linear model consistently better than logistic model.
  - Works better if it knows if pixel is shaded or a previous cloud

- Machine Learning (RF):
  - Random Forest Regressor from scikit-learn
  - Useful features: NDSI, BLUE, GREEN, RED, NIR, SWIR, ZS
  - ZS replaces DEM with better performances
  - RF does not need to know if pixel is shaded or a previous cloud

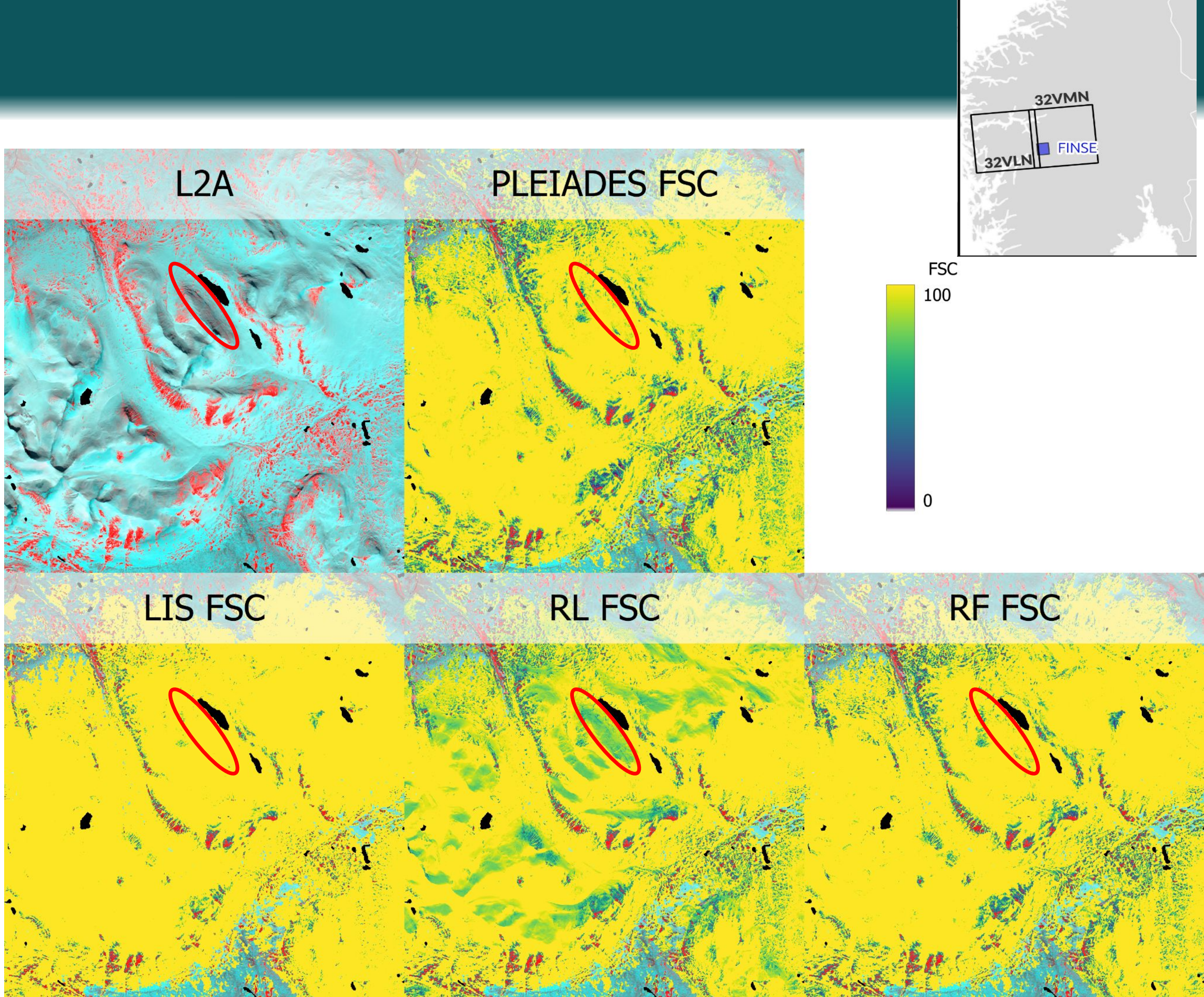
Why Machine Learning? Weak correlations between FSC_{VHR} and individual features
→ interest in statistical approaches.



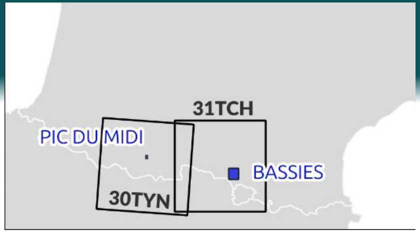
Results: Finse

- 75% pixels used in training the models

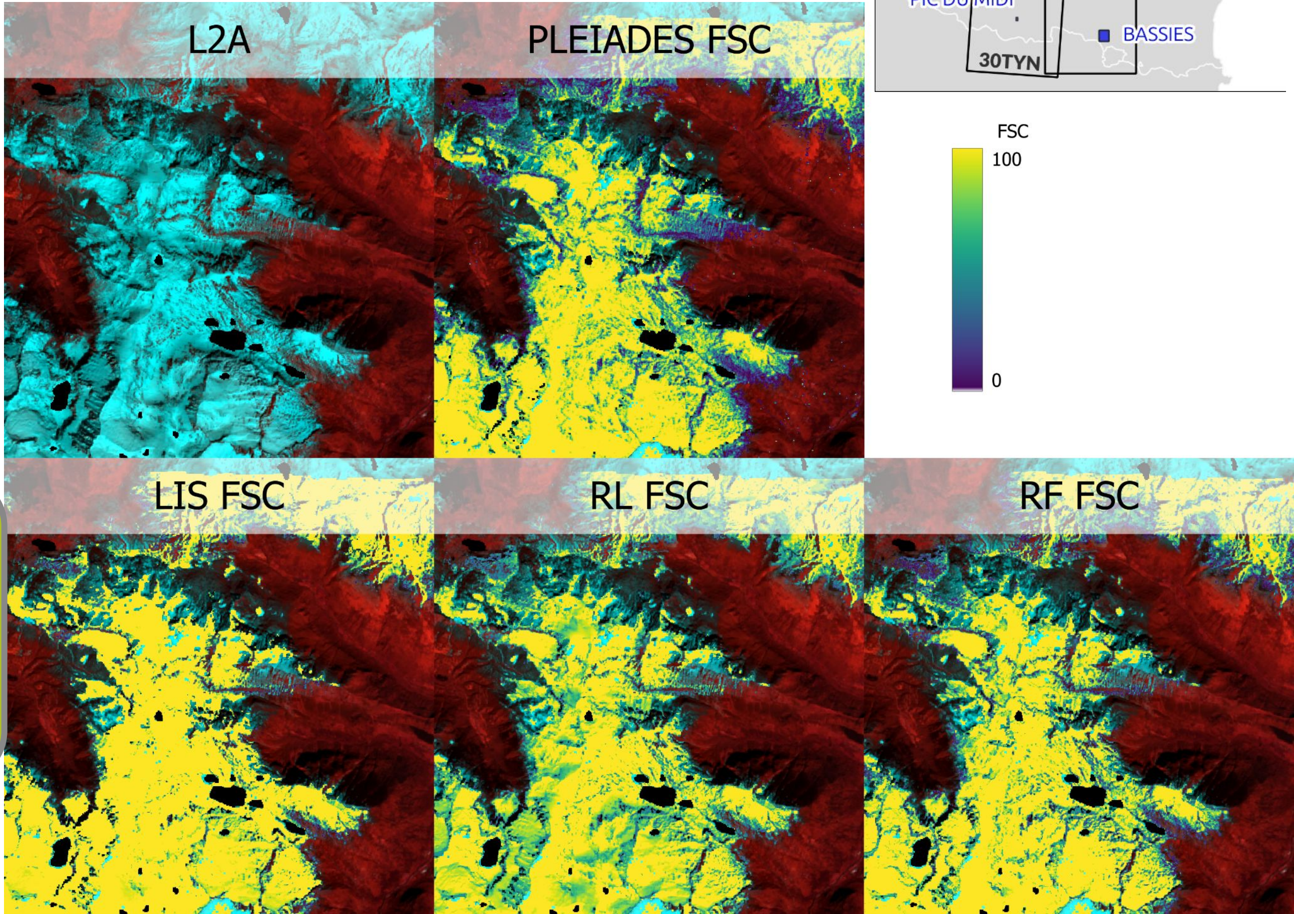
- RF better than RL at correctly estimating the FSC in less illuminated areas.



Results: Bassies



- Not included in training
- RF gives result closer to VHR



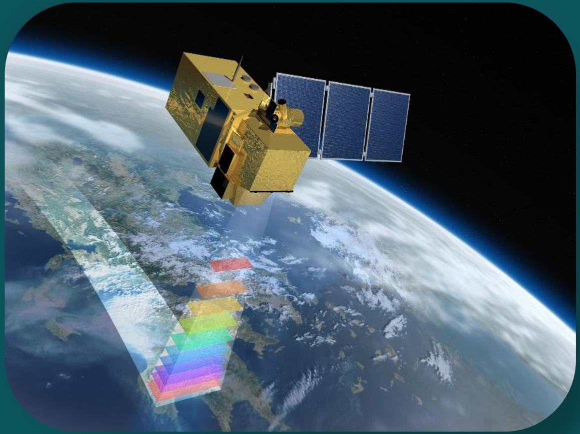
Overall performances over all areas:

Clean pixels	RF | RL | LIS
RMSE (total)	11 | 13 | 16
RMSE ($FSC_{VHR} \leq 50$)	39 | 43 | 55

Conclusion

- Evaluation of LIS current FSC method
  - Good performances for high FSC but high uncertainties for low FSC.
- FSC alternative methods
  - Train/test dataset covering the French Pyrenees, European Alps and Scandinavian mountains
  - RF & RL improve over all regions and over pixels with lower FSC
  - RF & RL make smaller errors
  - RL didn’t adapt to changes in illumination
  - RF has overall the best performances

Thank you for your attention.



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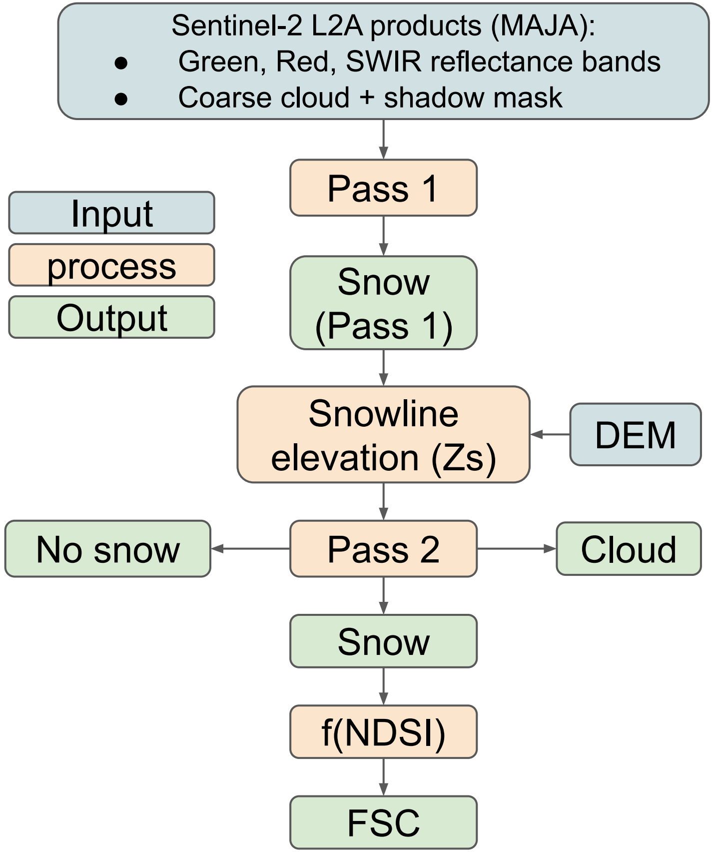
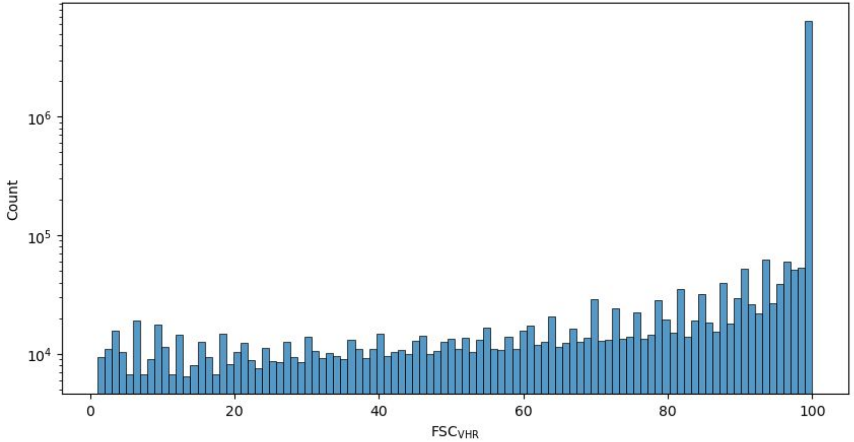
Context: FSC current limitations

- Method developed for MODIS data (500m resolution) over North America
- Positive bias toward FSC = 100%
- Low predictivity for FSC < 100% (Imperatore et al., under redaction)
- Higher uncertainties in pixels initially labelled as cloud by MAJA and under shaded areas.



Train/test dataset

- 8×10^6 pixels
- 75/25% split into train/test dataset
- 75/25% ratio respected for each category:
  - AREA, DEM (±300m), FSC_{VHR}(1-100%).
- Full snow covers are orders of magnitude more prevalent.



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Method LR: Linear Regression

Step 1: fit over the reflectance bands, DEM, ZS and Hillshade

- Clean pixels: SHW == CLD == 0
- ex: $FSC = a_{ndsi}NDSI + a_{blue}BLUE + \ldots + b$

The model is fit for each possible combination of NDSI + a subset of features

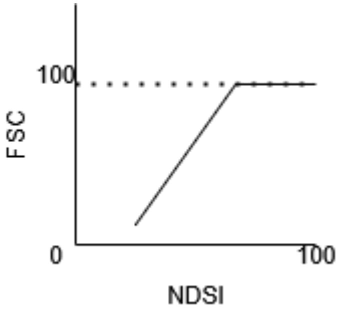
Step 2: fit a coefficient ‘s’ at shaded snow pixels

- Applied only to reflectance bands
- SHW ==1
- ex: $FSC = s\times(a_{blue}BLUE + \ldots) + a_{ndsi}NDSI + a_{zs}ZS + \ldots + b$

Step 3: fit a coefficient ‘c’ at snow pixels initially labeled as clouds

- Applied only to reflectance bands
- CLD==1
- ex: $FSC = c\times s\times(a_{blue}BLUE + \ldots) + a_{ndsi}NDSI + a_{zs}ZS + \ldots + b$

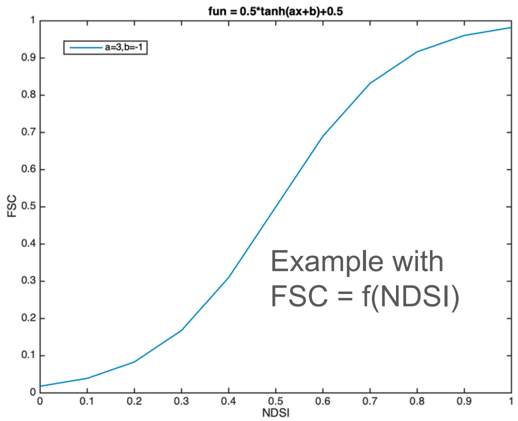
The FSC is clamped between 1 and 100 during the fit



Method SR: Logistic (Sigmoid) Regression

Same method as linear regression but with a sigmoid:

- ex: $FSC = b_1 \times \tanh(c \times s \times (a_{blue} BLUE + \ldots) + a_{ndsi} NDSI + a_{zs} ZS + \ldots + b_2) + b_3$
- built on the method of gascoin et al, 2020
- Results not shown because consistently lower performance than LR



Results: Models

- LR model:

a_{NDSI}	a_{BLUE}	a_{GREEN}	a_{RED}	a_{SWIR}	a_{DEM}	a_{HILL}	a_{ZS}	s	c	b
0.3	0.01	-0.007	-0.01	-0.007	0.01	-0.001	0.001	1.55	1.16	-0.02

negligible because HILL $\in[-1,1]$

negligible

- RF model:
  - Useful features: NDSI, BLUE, GREEN, RED, NIR, SWIR, ZS
  - ZS replaces DEM with better performances
  - RF does not need to know if pixel is shaded or a previous cloud

Method RF: Random Forest

RandomForestRegressor from scikit-learn

Step 1: pre-processing

- extend FSC_{VHR}=100 by randomly adding between 0 and 20
- discourage the RF from underestimating areas with FSC_{VHR}=100

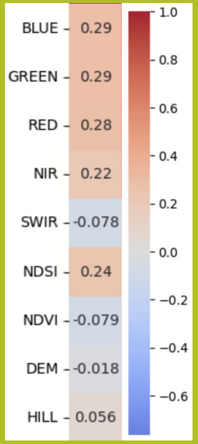
Step 2: hyper-parameters tuning

- reduces over-fitting, reduces model size

Step 3: model fitting

- over all features at the same time
- identifies less useful features

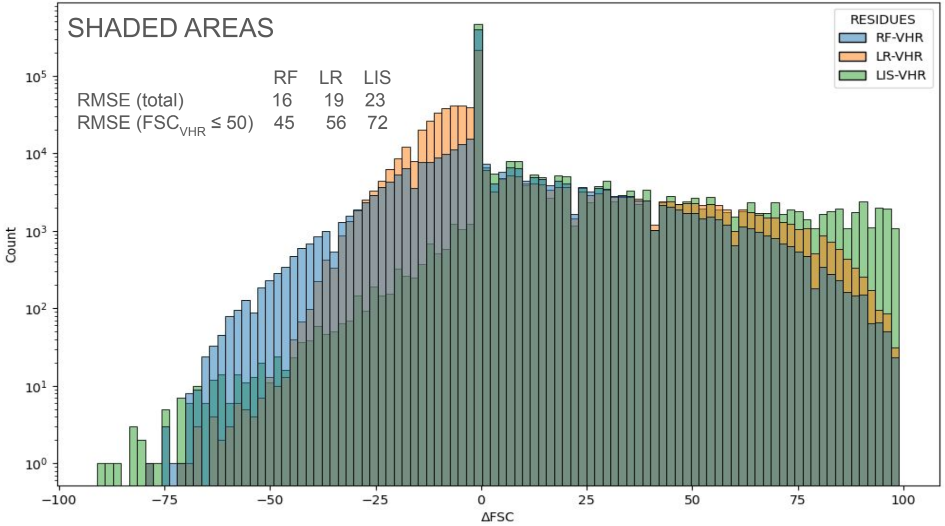
Why machine learning? Weak correlations between FSC_{VHR} and individual features
→ interest in statistical approaches.

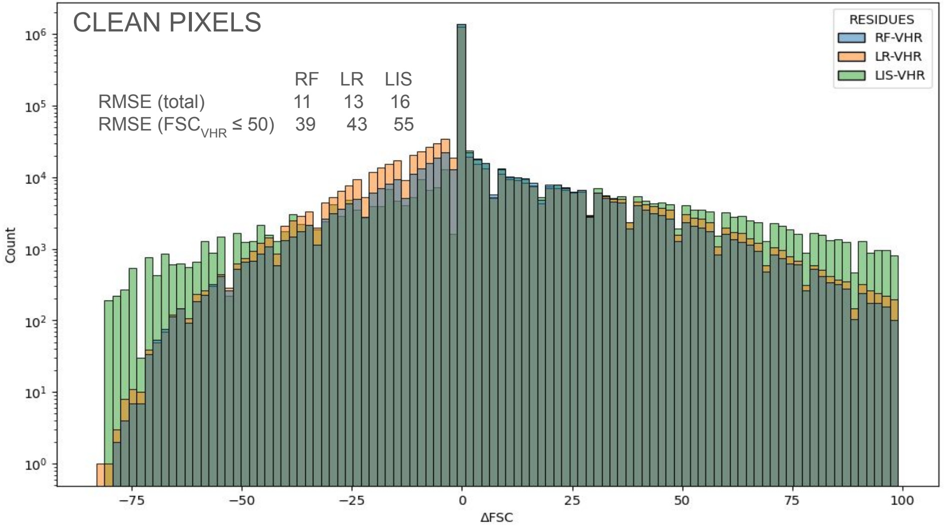


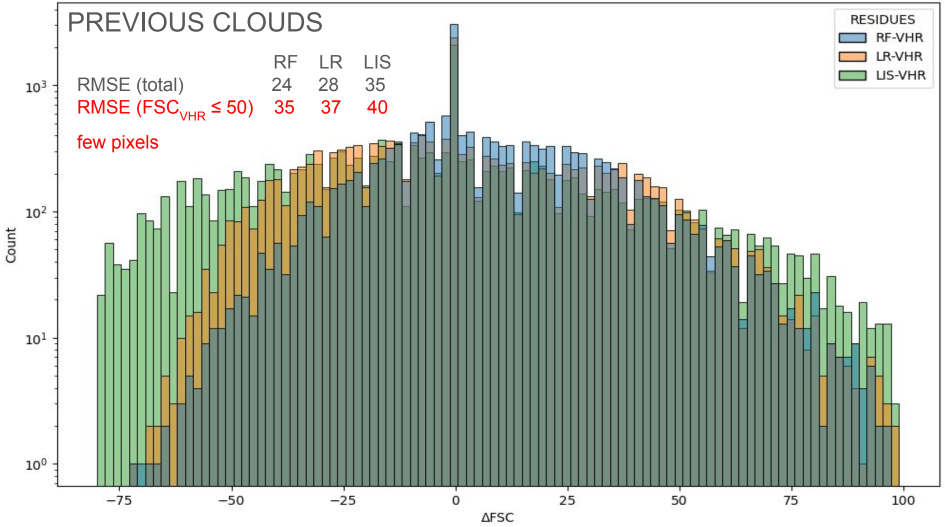
Results: Performances

Comparison of RL & RF vs. LIS

- Best RMSE from RF
- RL & RF make smaller residues and underestimate FSC more







Perspectives

- Cover other areas with more Pleiades images.
- Test the european model outside of Europe.
- Use hillshade estimations to adapt RL to changes of reflectance values in less illuminated areas.
- LIS estimates one ZS value for an entire L2A product:
  - risk of overfitting over the ZS values of the training dataset
  - explore generating ZS values for subsections of one L2A product
- Explore other machine learning methods:
  - clusterisation
  - SVR

References

- V. V. Salomonson and I. Appel, "Development of the Aqua MODIS NDSI fractional snow cover algorithm and validation results," in IEEE Transactions on Geoscience and Remote Sensing, vol. 44, no. 7, pp. 1747-1756, July 2006
- N. Imperatore, S. Gascoin, M. Lafaysse, M. Dumont, J-B, Hernandez, A. Mauss, and S. Guével,, "Evaluation of VIIRS snow cover products over France mountains using Sentinel-2" under redaction and aimed at IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing.
- Gascoin, S., Barrou Dumont, Z., Deschamps-Berger, C., Marti, F., Salgues, G., López-Moreno, J.I., Revuelto, J., Michon, T., Schattan, P., Hagolle, O., 2020. Estimating Fractional Snow Cover in Open Terrain from Sentinel-2 Using the Normalized Difference Snow Index. Remote Sensing 12, 2904.
- Barrou Dumont, Z., Gascoin, S., Hagolle, O., Ablain, M., Jugier, R., Salgues, G., Marti, F., Dupuis, A., Dumont, M., Morin, S., 2021. Brief communication: Evaluation of the snow cover detection in the Copernicus High Resolution Snow & Ice Monitoring Service. The Cryosphere 15, 4975–4980.