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A Wavelet Temporal Analysis of Polarimetric Decomposition Parameters over Alpine Glaciers

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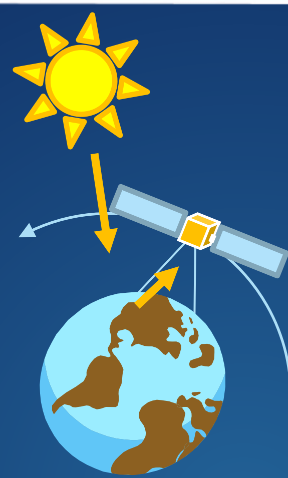
Outline

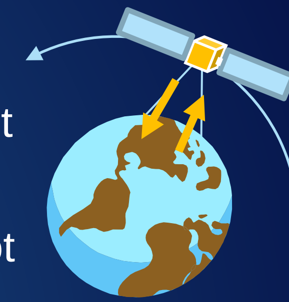
Imaging with Synthetic Aperture Radar

Passive optical sensors:

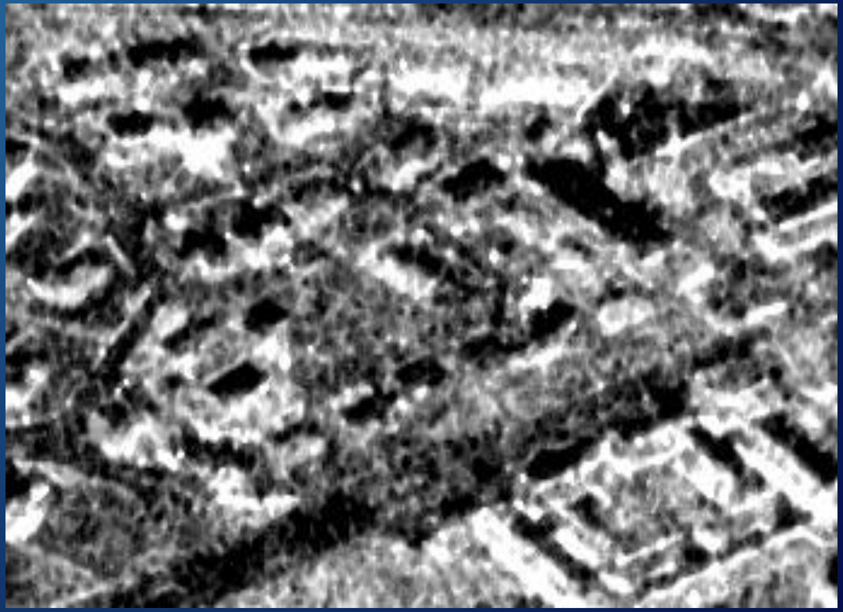


- ✓ For useful data, the two scenes should have:
  - Sunlight condition;
  - Clouds absence.
- ✓ "Human-friendly" images.

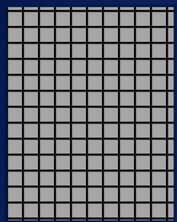
Microwave active sensors:



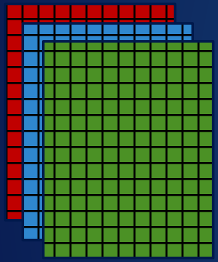
- ✓ Acquisitions are independent from sunlight and weather conditions.
- ✓ Image interpretation is not straightforward.

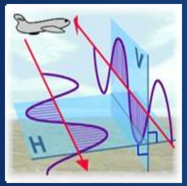


Information Enhancement in SAR imagery



- ✓ A large part of SAR imagery presents spatial resolution of decades of meters and a single polarimetric channel.
- ✓ This information has been largely exploited in the literature.
- ✓ The recent technological trend has moved to the acquisition of data with more polarimetric channels.





Polarimetric SAR (PolSAR) imagery

- Two (i.e., dual-pol) or four (i.e., full-pol) polarimetric channels;
- Polarimetric scattering discriminate larger number of targets.

Single-pol SAR image of Los Angeles (HH)

Full-pol SAR Pauli RGB image of Los Angeles (R: HH-VV; G: HV; B:HH+VV)

Motivation

- ✓ The continuous acquisition of dual- and full-polarimetric SAR images open novel opportunities for exploiting image time series for monitoring applications.
- ✓ The literature proposed some methodologies for exploiting single-pol SAR image time series for multi-temporal CD analysis.
- ✓ The polarimetric multi-temporal information has been mainly exploited for the analysis of temporal trend of features in specific applications (e.g., snow monitoring or crop monitoring).

Open issue: the use of full-polarimetric information in image time series has been poorly exploited for detecting changes with different evolution.

Aim of the contribution

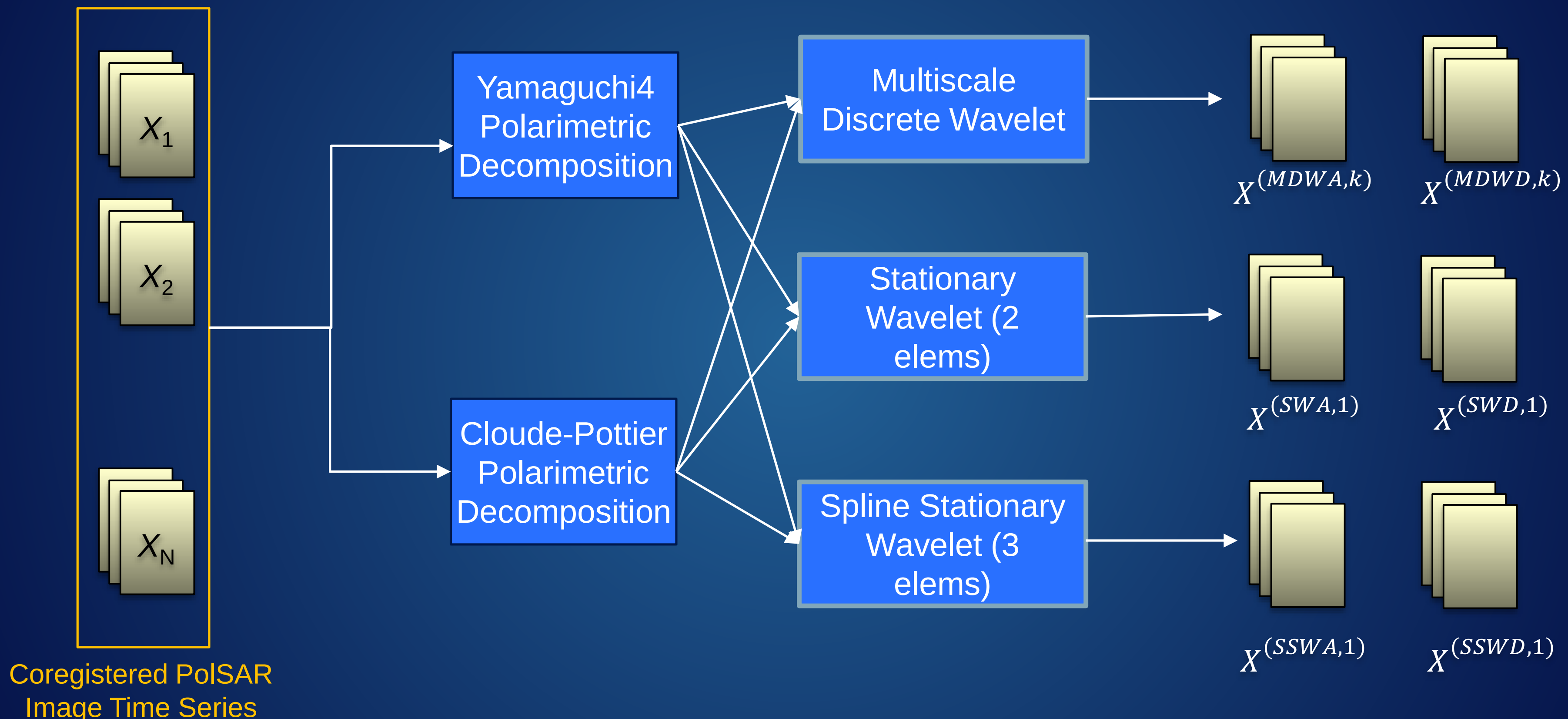
✓ The proposed contribution aims at defining a joint arithmetic-geometric wavelet framework for the analysis of full-polarimetric image time series.

✓ The framework includes:
- The selection of polarimetric decomposition features carrying the relevant scattering information of the targets.
- The selection of wavelet transforms relevant for the sparse representation of the multi-temporal decompostion features.

✓ The information in the framework both:
- Separates natural classes based on their multi-temporal content.
- Detectes multi-temporal changes and characterize their evolution.

✓ The contribution will test the proposed framework on real multitemporal PolSAR dataset acquired from Radarsat-2 mission over the Argentière glacier.

Proposed approach



Polarimetric Scattering Information

- ✓ Scattering information can be represented with the Pauli scattering vector k_p.

$$k_p = {}^{1}/_{\sqrt{2}}\,[S_{hh} + S_{vv},\ S_{hh} - S_{vv},\ 2S_{hv}]$$

- ✓ Three main mechanisms associated:
  - Double bounce (HH-VV)
  - Volume scattering (HH+VV)
  - Surface scattering (HV)

- ✓ Distributed targets are represented with average scattering information of Coherency matrix T or its polarimetric decompositions.

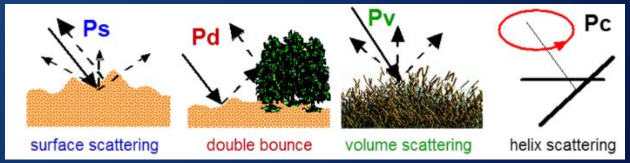
$$T = \langle k_p, k_p \rangle = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ T_{21} & T_{22} & T_{23} \\ T_{31} & T_{32} & T_{33} \end{bmatrix}$$

- ✓ Yamaguchi4 decomposition (Y4D) considers the scattering combination of different mechanisms [1].

Coefficients for scattering power

$$T = f_s T_s + f_d T_d + f_v T_v + f_c T_c$$

Coherency associated to elementary targets



[1] Yamaguchi, Y., et al. "Four-component Scattering Power Decomposition with Rotation of Coherency Matrix." *IEEE Transactions on Geoscience and Remote Sensing* 49.6 (2011): 2251-2258.

Eigen-based Decomposition

- ✓ Cloude-Pottier decomposition (CPD) is applied on T, obtaining eigenvectors v_i and eigenvalues λ_i.

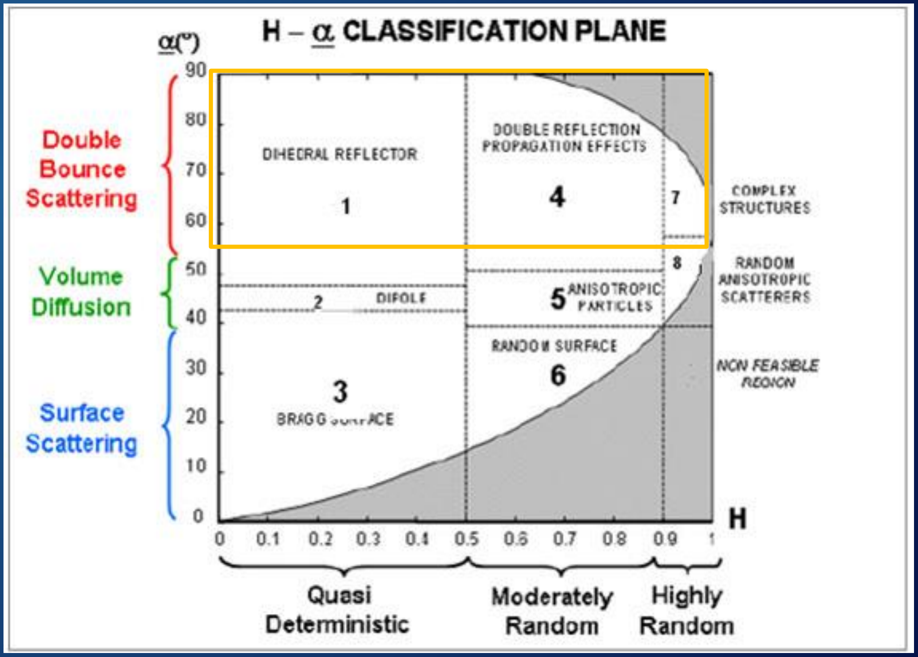
- ✓ Three parameters are derived [2]:

$$v_i = [\cos\alpha_i\,, \sin\alpha_i \cos\beta_i\, e^{i\delta_i}, \sin\alpha_i \sin\beta_i\, e^{i\gamma_i}]^T$$

  - Entropy H: measuring scattering degree of randomness.
  - Anisotropy A: measuring the importance of second dominant mechanism.
  - Mean alpha α: measuring the average scattering mechanism.

$$H = \sum_{i=1}^{3} \frac{\lambda_i}{\sum_{j=1}^{3}\lambda_j} \log\left(\frac{\lambda_i}{\sum_{j=1}^{3}\lambda_j}\right)$$

$$A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} \qquad \alpha = \sum_{i=1}^{3} \frac{\alpha_i \lambda_i}{\sum_{j=1}^{3}\lambda_j}$$



[2] Cloude, S. R., and Pottier, E. "An Entropy Based Classification Scheme for Land Applications of Polarimetric SAR." *IEEE transactions on geoscience and remote sensing* 35.1 (1997): 68-78.

Temporal Wavelet Framework

- ✓ Let us consider a signal temporal sequence X_t for a fixed position (x,y).
- ✓ L-taps wavelet filter with response W_b is applied on it.
- ✓ Two filters for approximation ($b = A$) and detail ($b = D$) wavelet component are considered.

Arithmetical Wavelet

- ✓ It is applied under the assumption of additive Gaussian noise.

$$X_{t-l}^{(Wab,k+1)}(x,y) = \sum_{l=0}^{L-1} W_b(l) X_{t-l}^{(WaA,k)}(x,y)$$

Geometrical Wavelet

- ✓ It is applied in presence of variables characterized by multiplicative noise [3].

$$X_{t-l}^{(Wgb,k+1)}(x,y) = \exp\left(\sum_{l=0}^{L-1} W_b(l) \log\left(X_{t-l}^{(WgA,k)}(x,y)\right)\right)$$

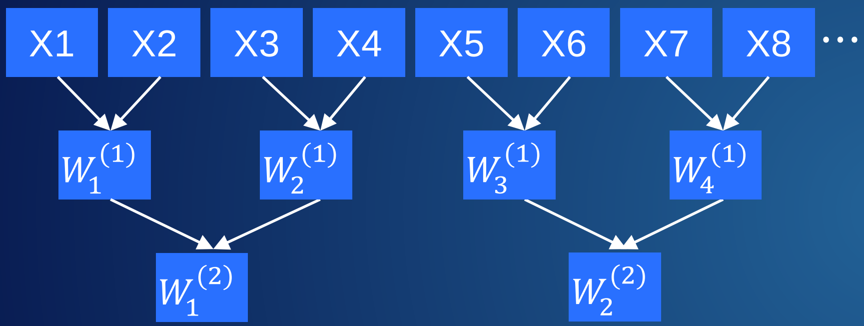
[3] Atto, A.M., et al. "Wavelet Operators and Multiplicative Observation Models—Application to SAR Image Time-series Analysis." *IEEE Transactions on Geoscience and Remote Sensing* 54.11 (2016): 6606-6624..

Wavelet Strategies

Without loss of generality, let us consider arithmetical wavelet on the time series.

Selection of Haar wavelet family, with coefficients $\frac{1}{\sqrt{2}}[1,1]$ and $\frac{1}{\sqrt{2}}[1,-1]$.

Multi-scale DWT on two scale levels (MDW)

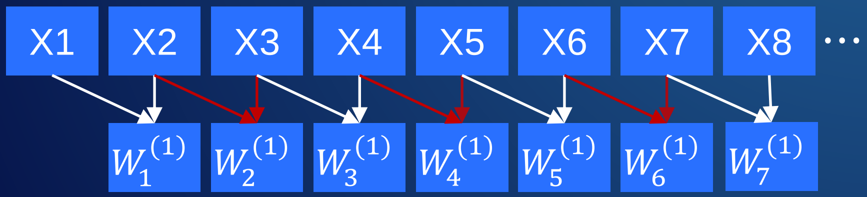


$$X_t^{(MDWa,k)} = \left\{X_t^{(MDWaA,k)}, X_t^{(MDWaD,k)}\right\}$$

$$X_t^{(MDWaA,k+1)} = \frac{1}{\sqrt{2}}\left(X_{t-1}^{(MDWaA,k)} + X_t^{(MDWaA,k)}\right);$$

$$X_t^{(MDWaD,k+1)} = \frac{1}{\sqrt{2}}\left(X_{t-1}^{(MDWaA,k)} - X_t^{(MDWaA,k)}\right);$$

Stationary wavelet on sequential pairs (SW)



$$X_t^{(SWa,1)} = \left\{X_t^{(SWaA,1)}, X_t^{(SWaD,1)}\right\}$$

$$X_t^{(SWaA,1)} = \frac{1}{\sqrt{2}}\left(X_{t-1} + X_t\right);$$

$$X_t^{(SWaD,1)} = \frac{1}{\sqrt{2}}\left(X_{t-1} - X_t\right);$$

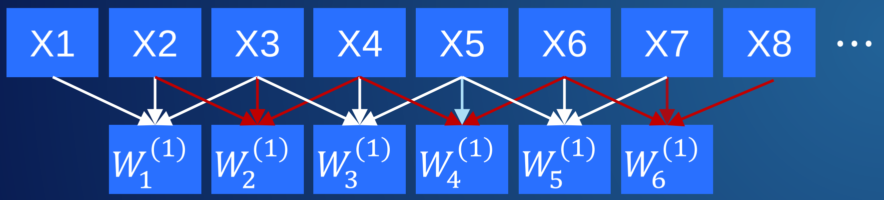
Difference (ratio) comparison operator equivalent to the Haar arithmetical (geometrical) temporal wavelet.

Wavelet Strategies

Let us assume the use of arithmetical wavelet on the time series.

Selection of Haar wavelet family, with coefficients $\frac{1}{\sqrt{2}}[1,1]$ and $\frac{1}{\sqrt{2}}[1,-1]$.

Spline wavelet on sequential triplets (SSW)



$$X_t^{(SSWa,1)} = \left\{X_t^{(SSWaA,1)}, X_t^{(SSWaD,1)}\right\}$$

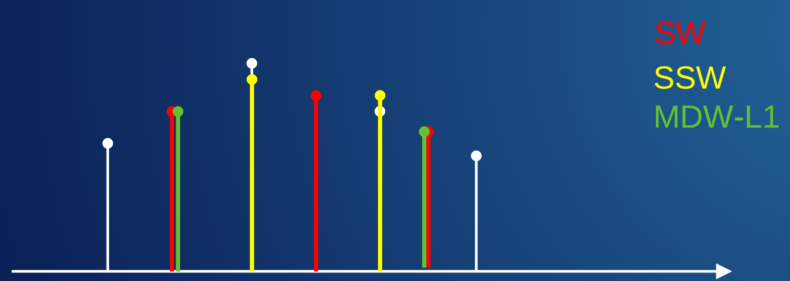
$$X_t^{(SSWaA,1)} = \frac{1}{\sqrt{6}}\left(X_{t-2} + 2X_{t-1} + X_t\right);$$

$$X_t^{(SSWaD,1)} = \frac{1}{\sqrt{6}}\left(X_{t-2} - 2X_{t-1} + X_t\right);$$

Approximation and Detail Components

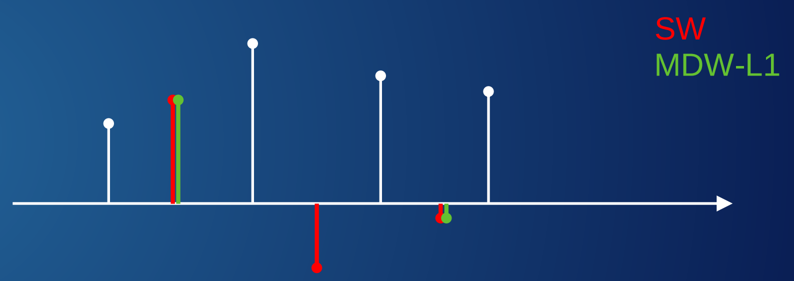
Approximation

- ✓ It can be used for a robust separation of the classes present in the image using the multi-temporal infomration.

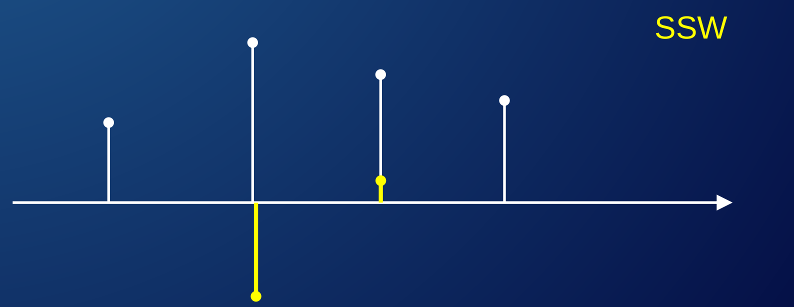


Detail

- ✓ It provides information about the change in the feature.
- ✓ For SW and MDW, the change is associated to a temporal variation.



- ✓ For SSW the change is associated to a variation of the variation rate.



Experimental setup

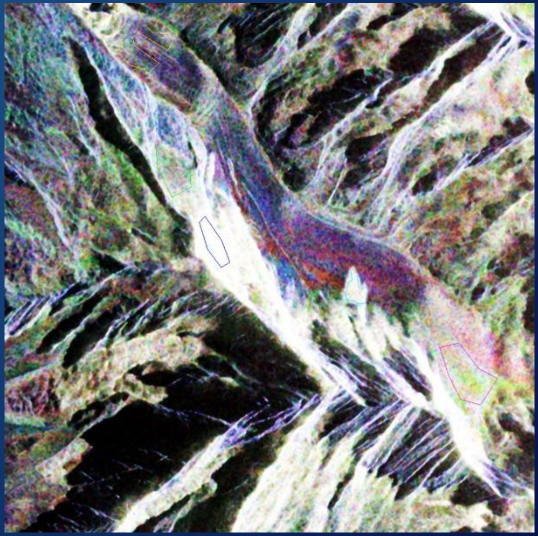
Scene: Argentière glacier area (France)

✓ 7 Multi-temporal Full-polarimetric SAR images from Radarsat-2 acquired in January-June, 2011

✓ Based on a preliminary similarity analysis with Gaussian and Gamma distribution, the wavelet selection led:

- Arithmetical wavelet for CPD features;
- Geometrical wavelet for Y4D features.

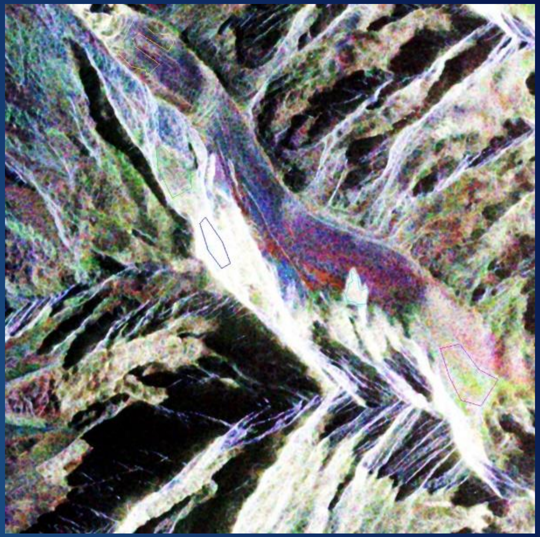
✓ Given the short temporal size of the time series, MDW strategy was not taken into account here.

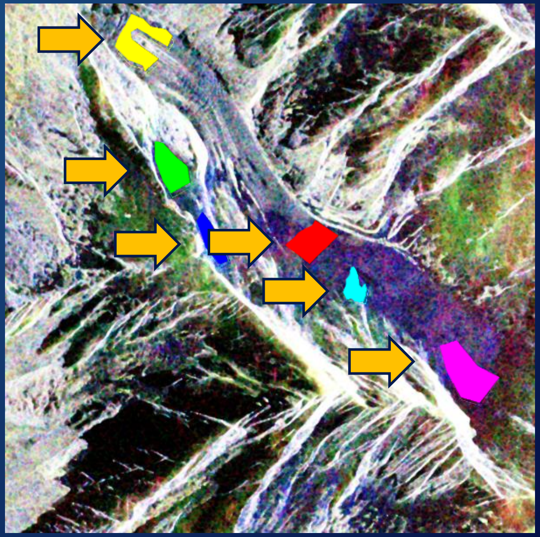


Experimental setup

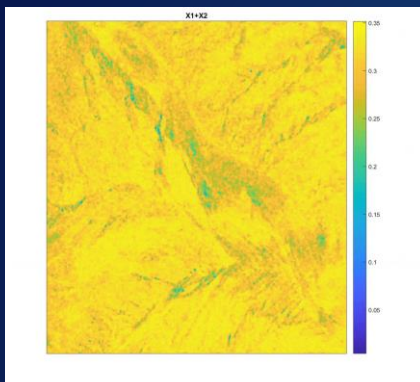
Scene: Argentière glacier area (France)

- ✓ 7 Multi-temporal Full-polarimetric SAR images from Radarsat-2 acquired in January-June, 2011
- ✓ Six regions of interest considered for local analysis.
  - Rognon glacier (north-south);
  - Ablation of Argentière (2400-2700m);
  - Avalanche area;
  - Accumulation area of the upper Argentière.

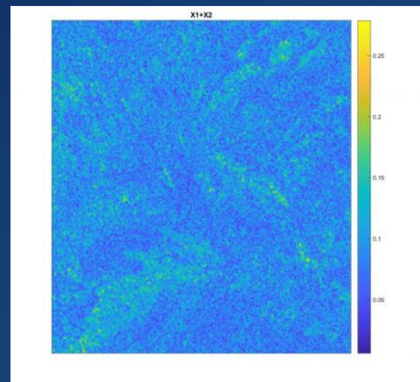




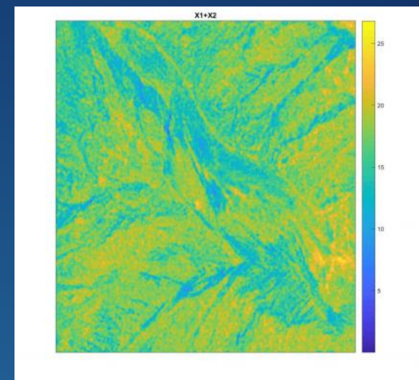
Experimental Results – SW Approximation



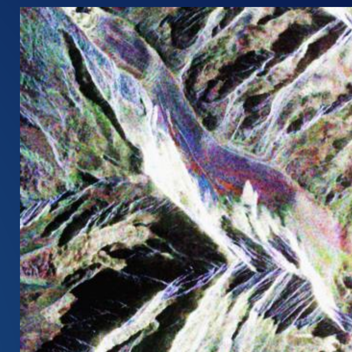
Entropy



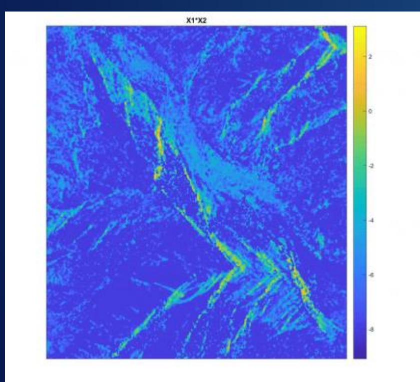
Anisotropy



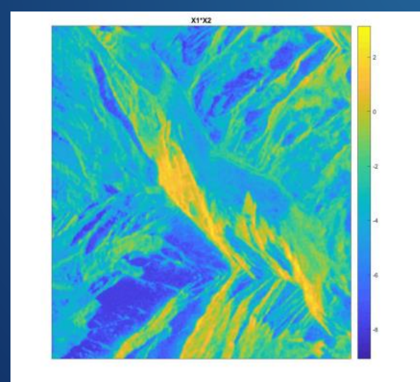
Alpha



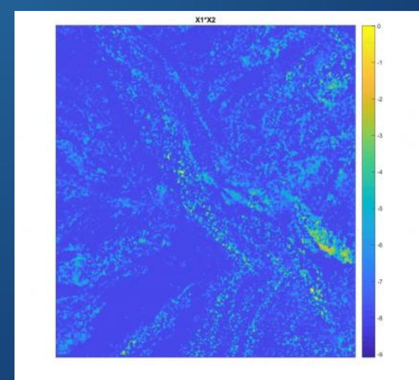
Pauli RGB



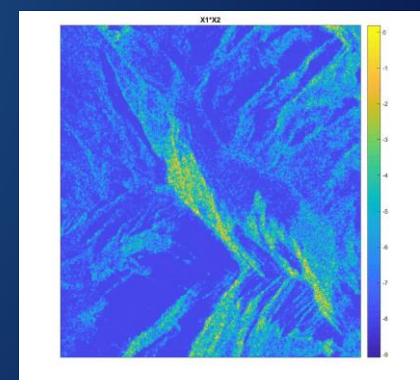
Surface



Volume

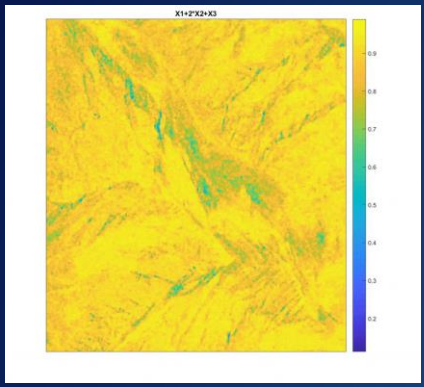


Double
Bounce

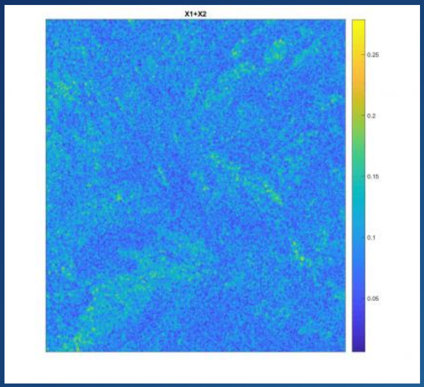


Helix

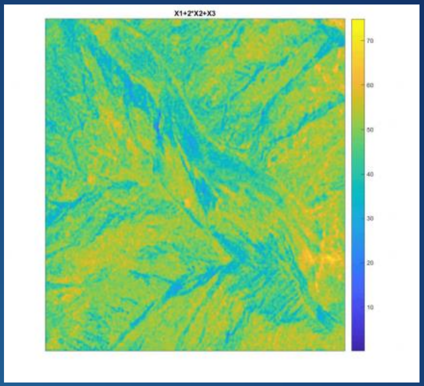
Experimental Results – SSW Approximation



Entropy

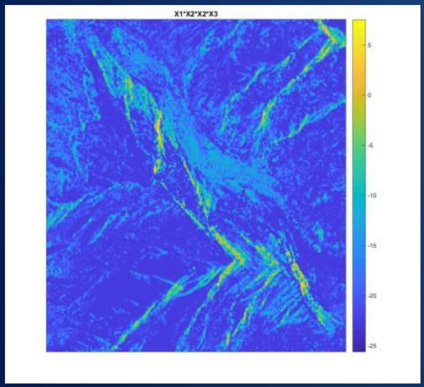


Anisotropy

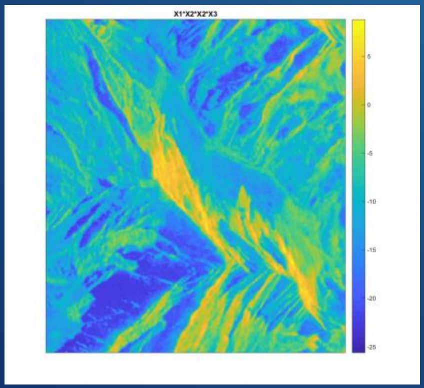


Alpha

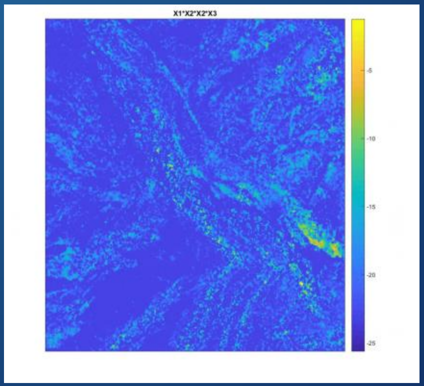
Pauli RGB



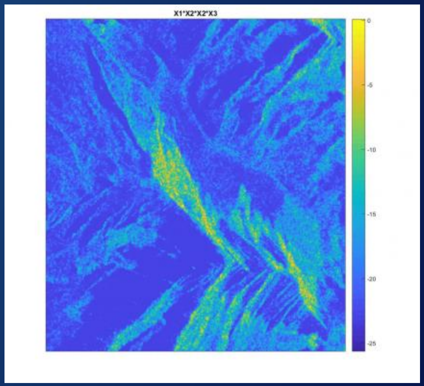
Surface



Volume

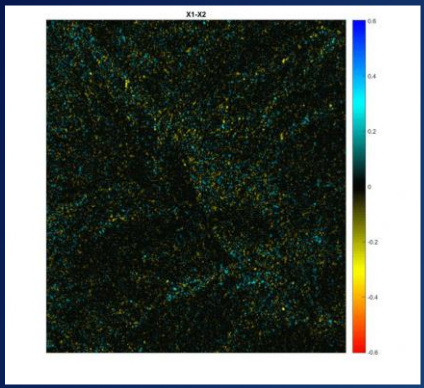


Double Bounce

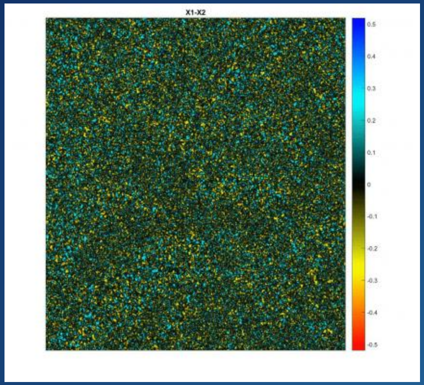


Helix

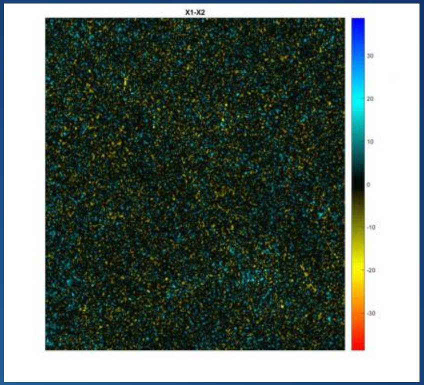
Experimental Results – SW Detail



Entropy

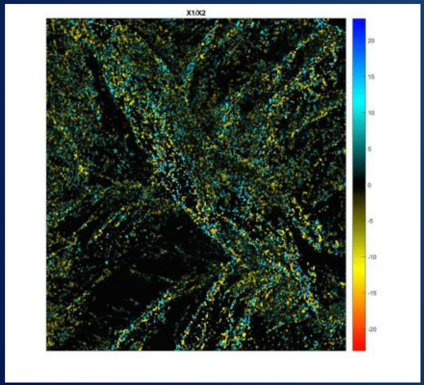


Anisotropy

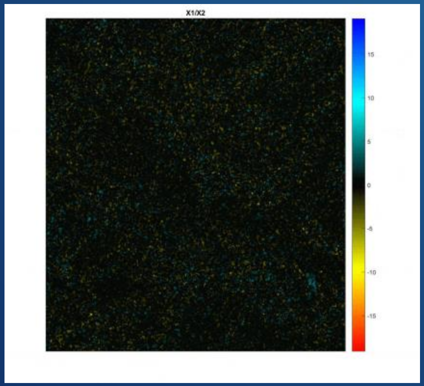


Alpha

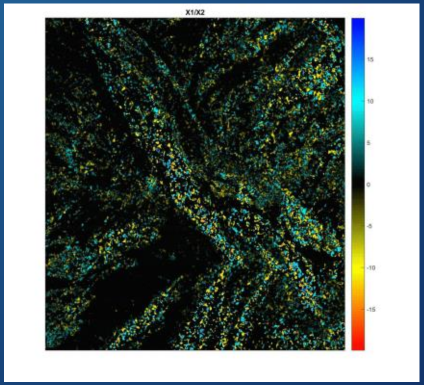
Pauli RGB



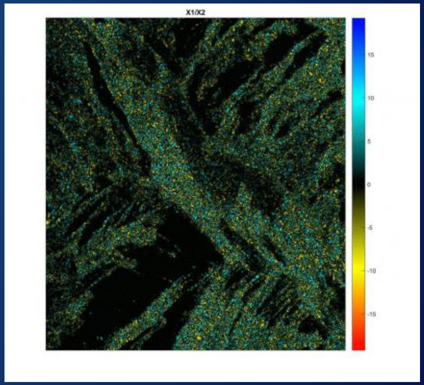
Surface



Volume

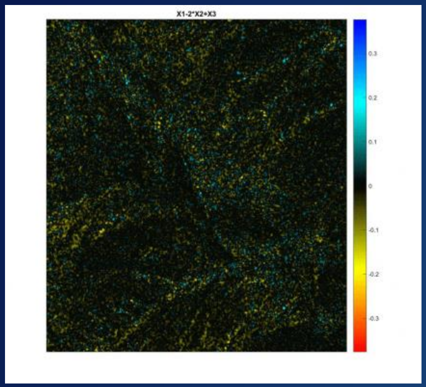


Double
Bounce

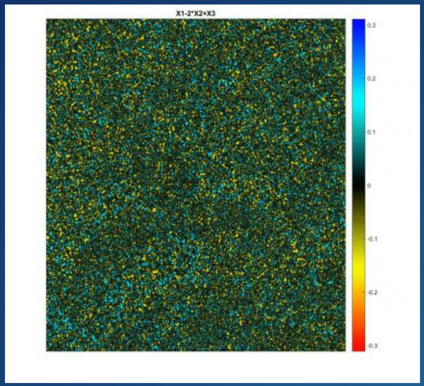


Helix

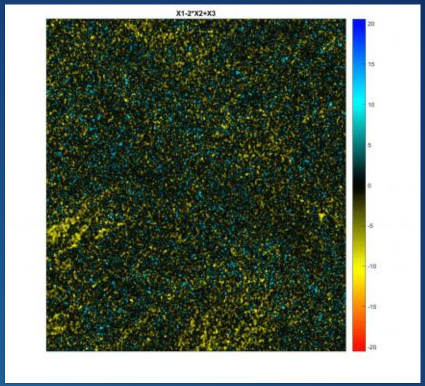
Experimental Results – SSW Detail



Entropy

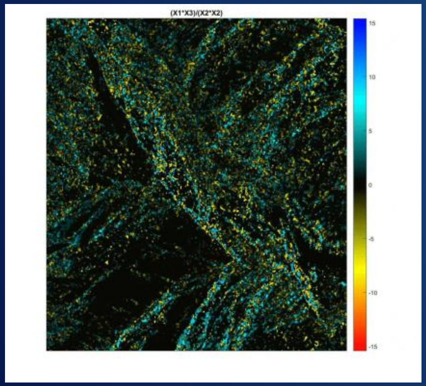


Anisotropy

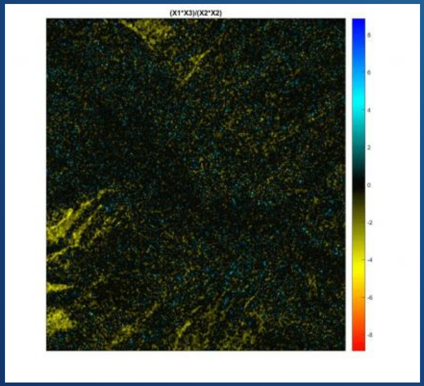


Alpha

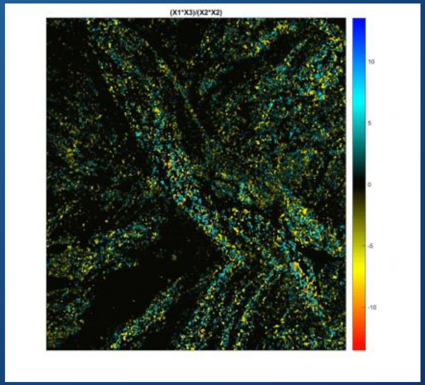
Pauli RGB



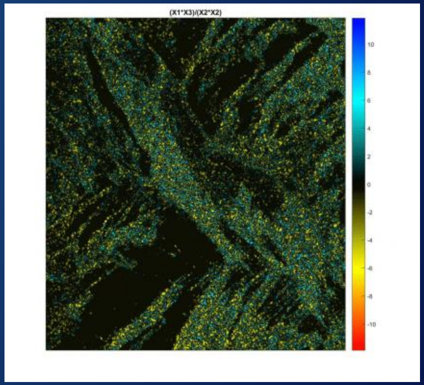
Surface



Volume

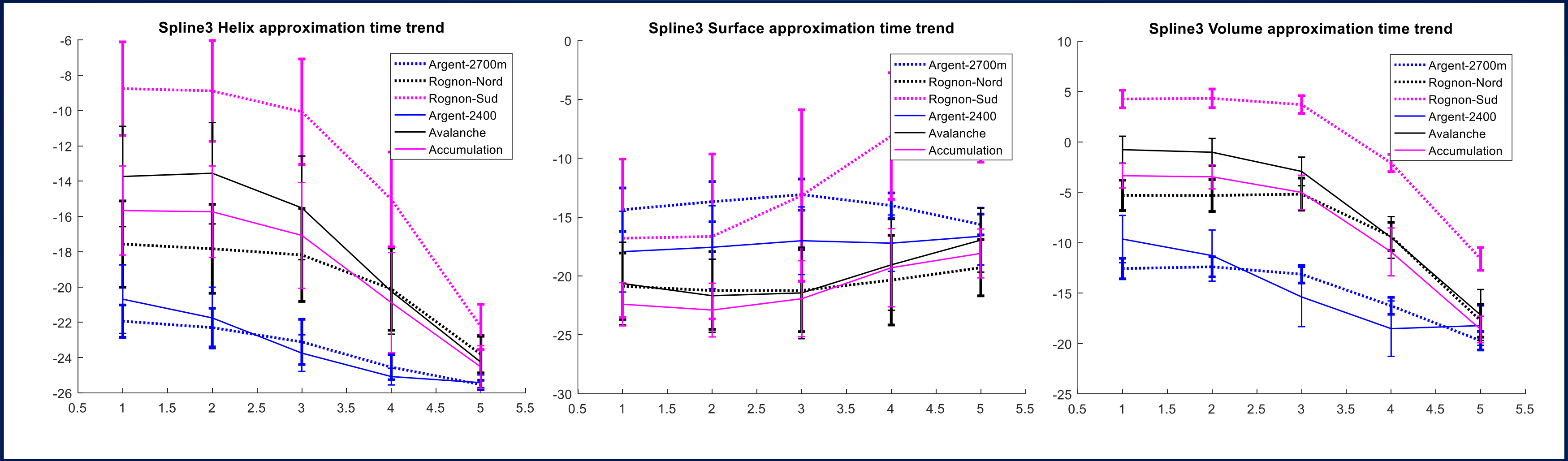


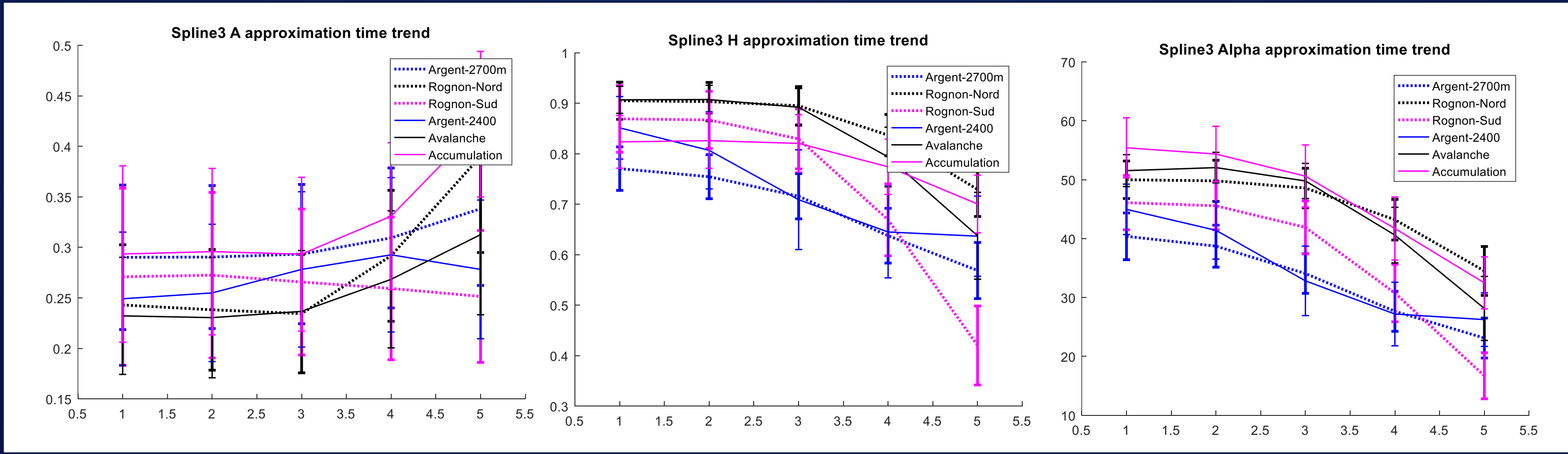
Double
Bounce



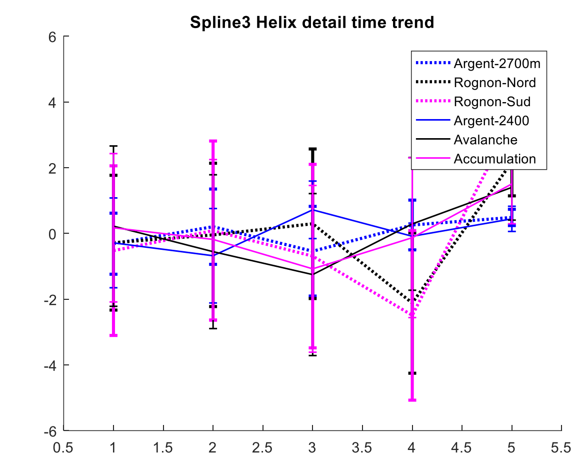
Helix

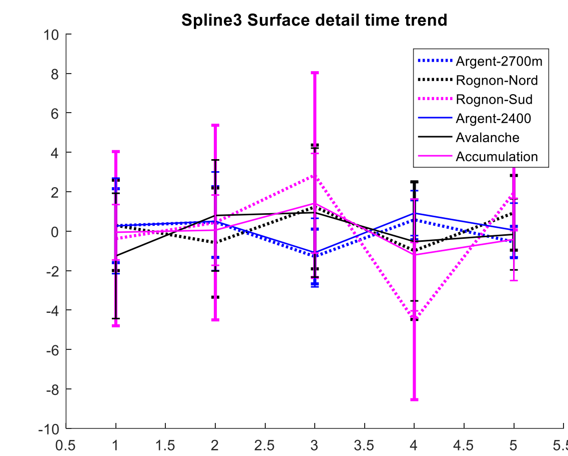
Experimental results – Local Analysis

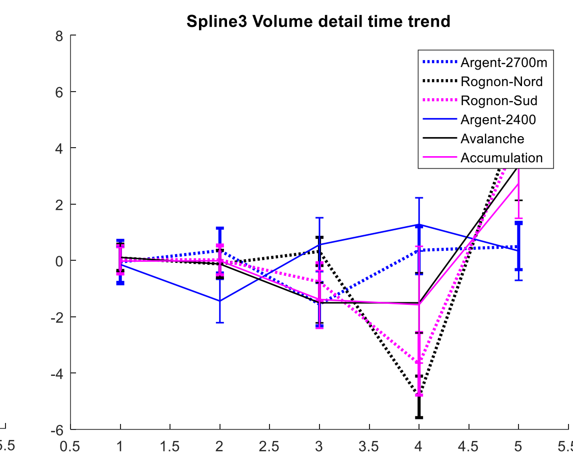


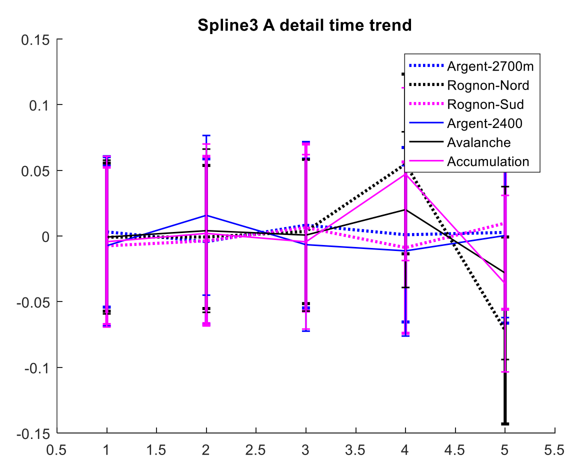


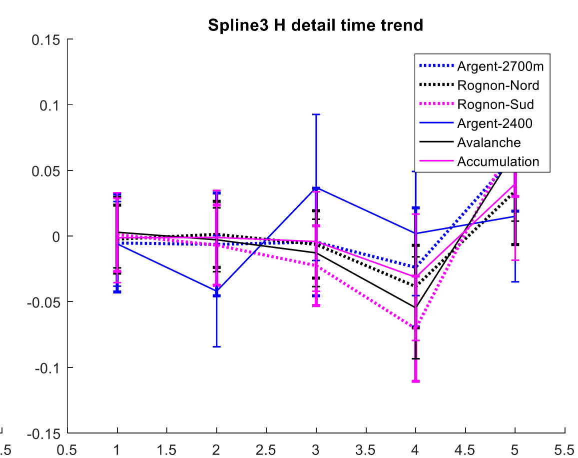
Experimental results – Local Analysis

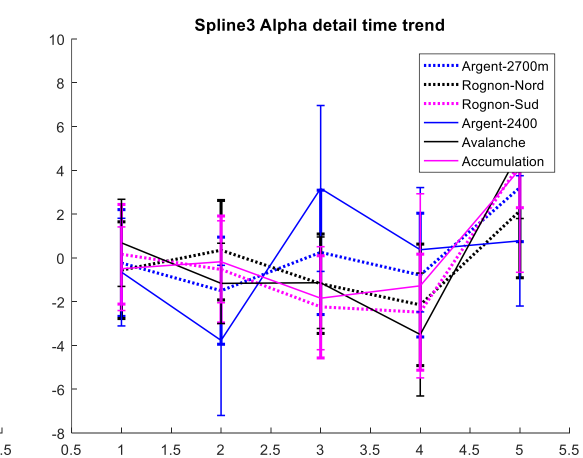












Time-series Spatio-temporal Descriptors

Approximation

- ✓ It can be used for a robust separation of the classes present in the image using the multi-temproal infomration.
- ✓ An Overall Class Separation Indicator ($OCSI$) is defined for measuring the global effectiveness of the class separation.

$$OCSI(w,X) = \sum_{c1}\sum_{c2\neq c1}\sum_{t}\frac{\left|\mu_{wXt}^{(c1)} - \mu_{wXt}^{(c2)}\right|}{\sqrt{\left(\sigma_{wXt}^{(c1)}\right)^2 + \left(\sigma_{wXt}^{(c2)}\right)}}$$

Detail

- ✓ It provides information about the change or the change velocity.
- ✓ Two indices are defined:
  - Change Rate R_C, describing the smoothness degree;
  - dynamicity index δ, describing the overall change in the time series.

$$\delta(w,X) = \sum_{c}\sum_{t}\frac{\left|\mu_{wXt}^{(c1)}\right|}{\left(\sigma_{wXt}^{(c1)}\right)}$$

$$R_C(w,X) = \sum_{c}\left[\max_{t}\left(\frac{\left|\mu_{wXt}^{(c1)}\right|}{\left(\sigma_{wXt}^{(c1)}\right)}\right)\Big/\sum_{t}\frac{\left|\mu_{wXt}^{(c1)}\right|}{\left(\sigma_{wXt}^{(c1)}\right)}\right]$$

Experimental results – Local Analysis

Overall Class Separation Indicator	SW	SSW	MDW
H	101.1425	87.7184	67.0577
A	37.3631	30.8456	25.4238
α	115.5167	102.6236	74.0808
Aggregate (Eigen-based)	84.6741	73.7292	55.5208
f_d	24.0888	20.5587	15.1726
f_h	114.4109	122.2092	68.6441
f_s	30.5785	78.1185	62.2078
f_v	284.6874	253.6868	171.4954
Aggregate (Power-based)	129.4414	118.6433	79.38

Experimental results – Local Analysis

Dynamicity	SW	SSW	MDW
H	3.4835	2.7232	2.2891
A	1.1174	0.9527	0.7635
α	$\boxed{4.4582}$	3.0593	2.7089
Aggregate (Eigen-based)	3.0197	2.2451	1.9205
f_d	2.2224	1.4850	1.2574
f_h	$\boxed{8.0742}$	5.1397	3.8863
f_s	2.4793	1.8746	0.7537
f_v	7.2983	6.9903	4.7206
Aggregate (Power-based)	5.0186	3.8724	2.6545

Change Rate	SW	SSW	MDW
H	0.5976	0.4709	$\boxed{0.8755}$
A	0.4974	0.4359	0.7167
α	0.4663	0.4210	0.7601
Aggregate (Eigen-based)	0.5204	0.4426	0.7841
f_d	0.3917	0.5709	$\boxed{0.6901}$
f_h	0.5546	0.6227	0.8994
f_s	0.3930	0.3824	0.5540
f_v	0.5784	0.4855	0.8752
Aggregate (Power-based)	0.4794	0.5154	0.7547

Conclusions and Future Developments

Conclusions

- ✓ We presented a novel framework based on temporal wavelet transform for analysis of polariemtric image time series.
- ✓ The framework considered different wavelet strategies and polariemtric features for discriminating both differnt temporal evolution on the changes and multi-temporal classes.
- ✓ A sensitivity analysis on the features was conducted for looking at those more sensitive to temporal changes.
- ✓ Experimental results in glacier evolution scenario showed the effectiveness of the proposed framework in separating classes and tracking change evolution.

Future Developments

- ✓ Integrating the framework with a unsupervised/supervised CD strategy.
- ✓ Combinating features from the application of different wavelet families.
- ✓ Exploiting wavelet decomposition in both spatial and temporal domain.