Laboratoire Hubert Curien
UMR ▪ CNRS ▪ 5516 ▪ Saint-Étienne

TELECOM Paris

IP PARIS

Inria

Atelier Télédec@USMB, 23 juin 2026

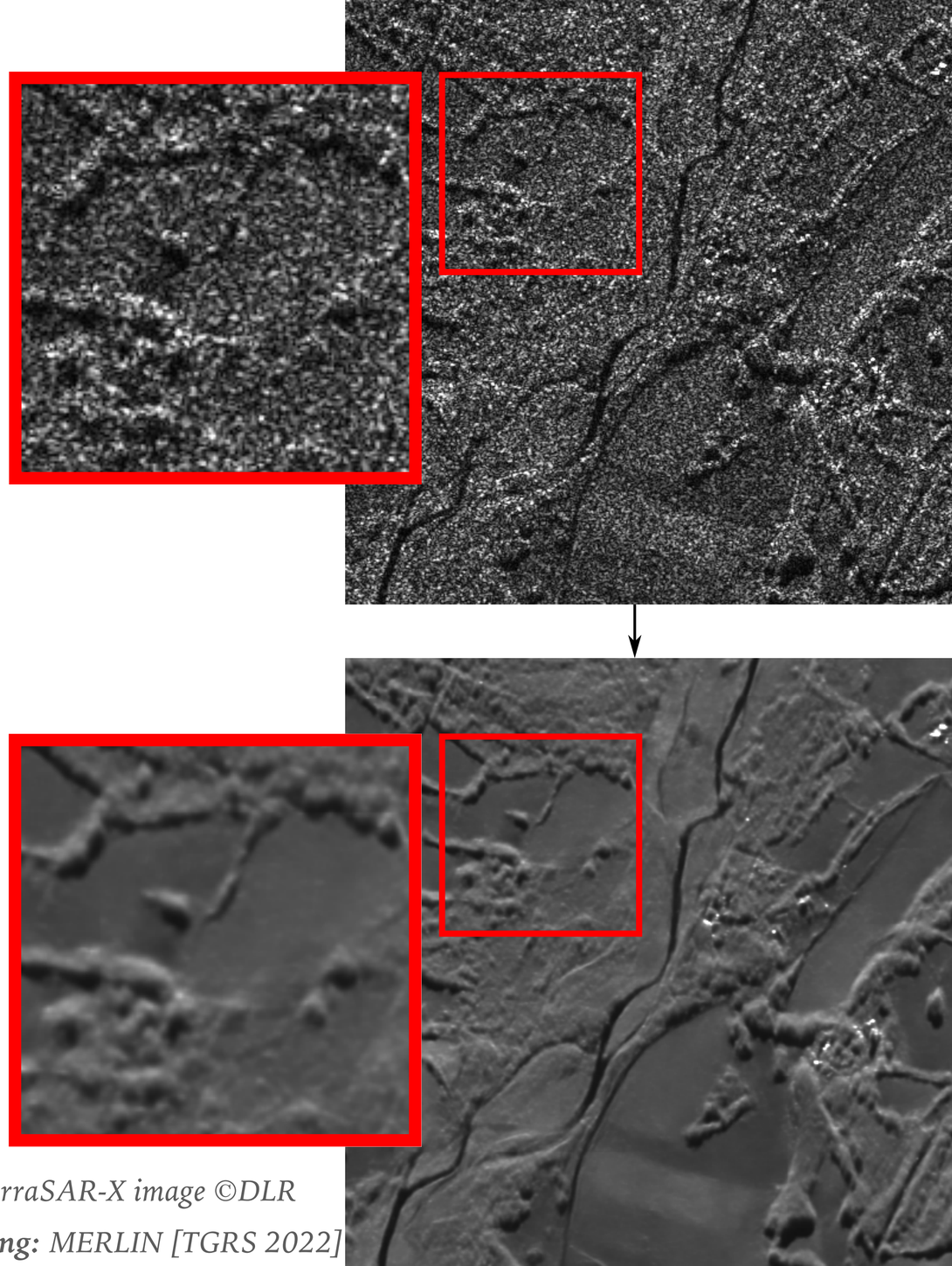
Self-supervised learning strategies for SAR imaging

Loïc DENIS[1,2], Florence TUPIN[2], Emanuele DALSASSO[3]

[1]*Laboratoire Hubert Curien, UMR CNRS-Université Jean Monnet-IOGS, Saint-Etienne*

[2]*LTCI, Télécom Paris, Institut Polytechnique de Paris, Palaiseau*

[3]*THOTH, Inria Grenoble Alpes*



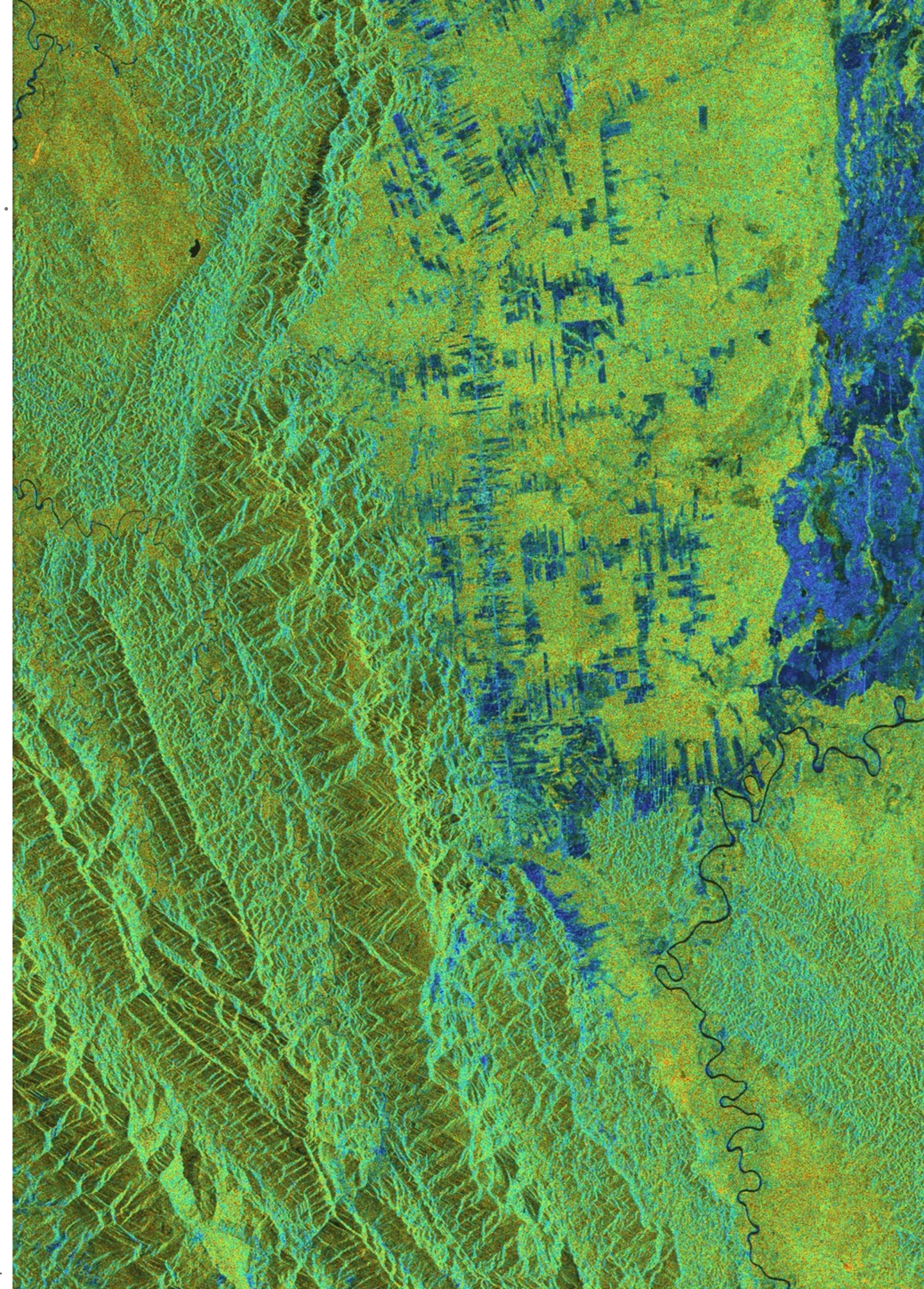
Data: *TerraSAR-X image ©DLR*

Processing: *MERLIN [TGRS 2022]*

MOTIVATION FOR SELF-SUPERVISED LEARNING

- Synthetic Aperture Radar images are very **different** from optical images
- They suffer from strong **fluctuations** due to speckle, decoherence, or thermal noise
- Noiseless ground truth are **not** readily **available**

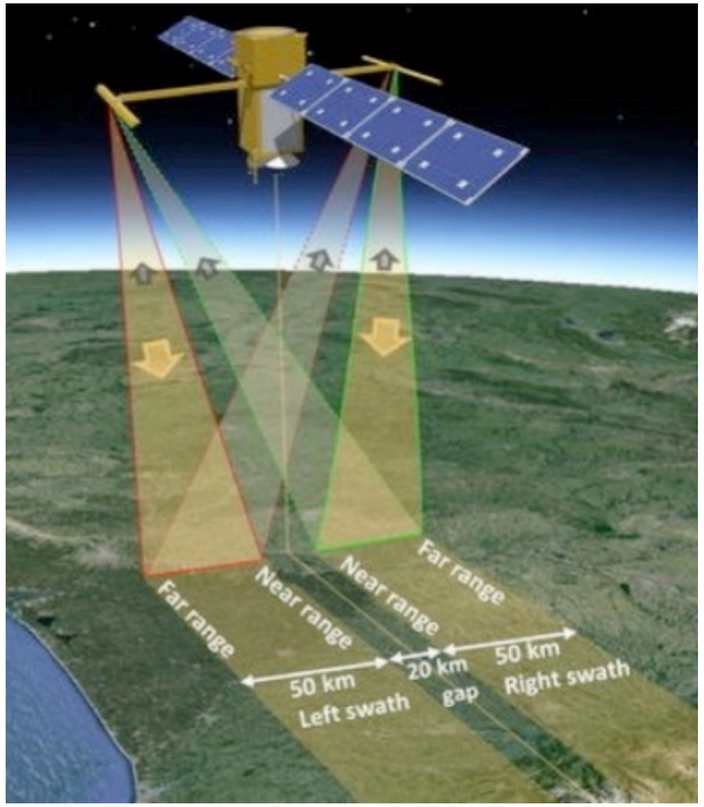
Can we train (deep) models
directly on SAR data,
without clean references?



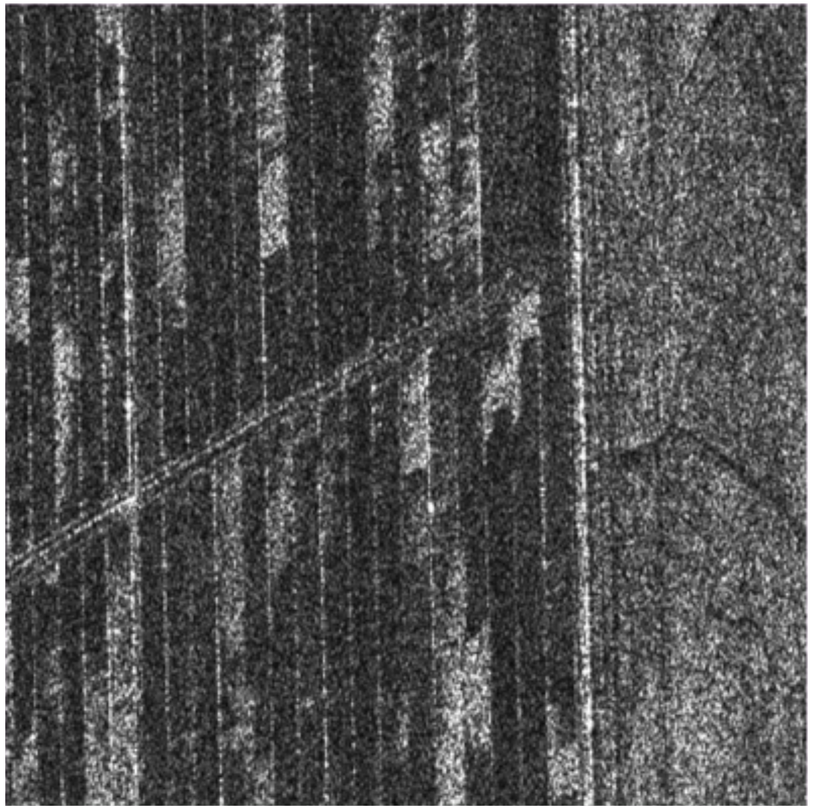
Andean foothills, polarimetric SAR image by BIOMASS©ESA

MOTIVATION FOR SELF-SUPERVISED LEARNING

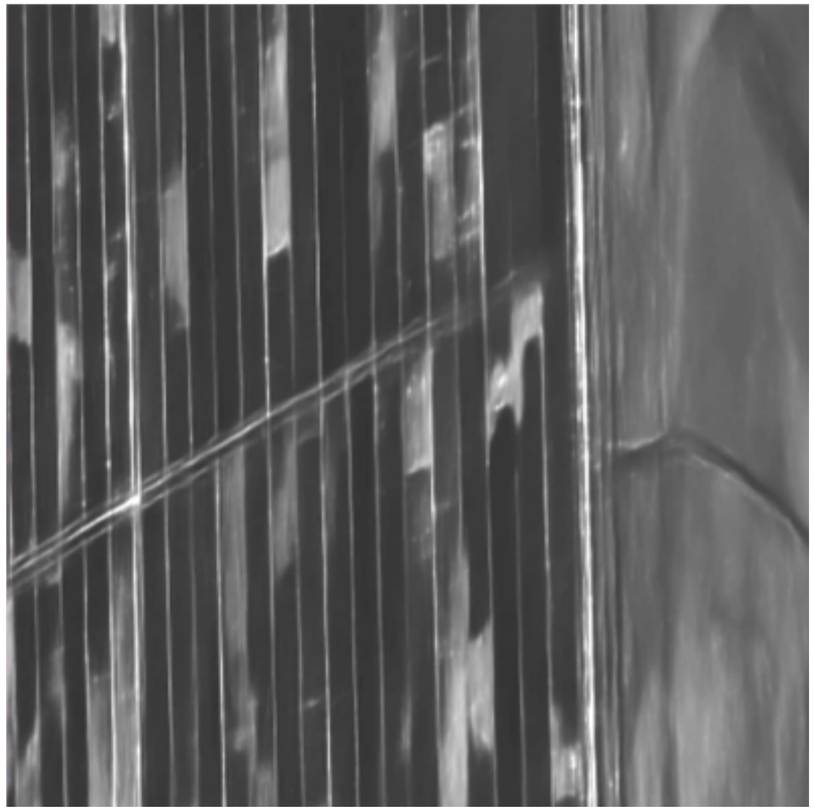
- Self-supervised learning is crucial for new imaging systems:



SWOT satellite ©CNES



a SWOT image ©CNES/NASA



restored image

PhD Stella Basso-Lacroix

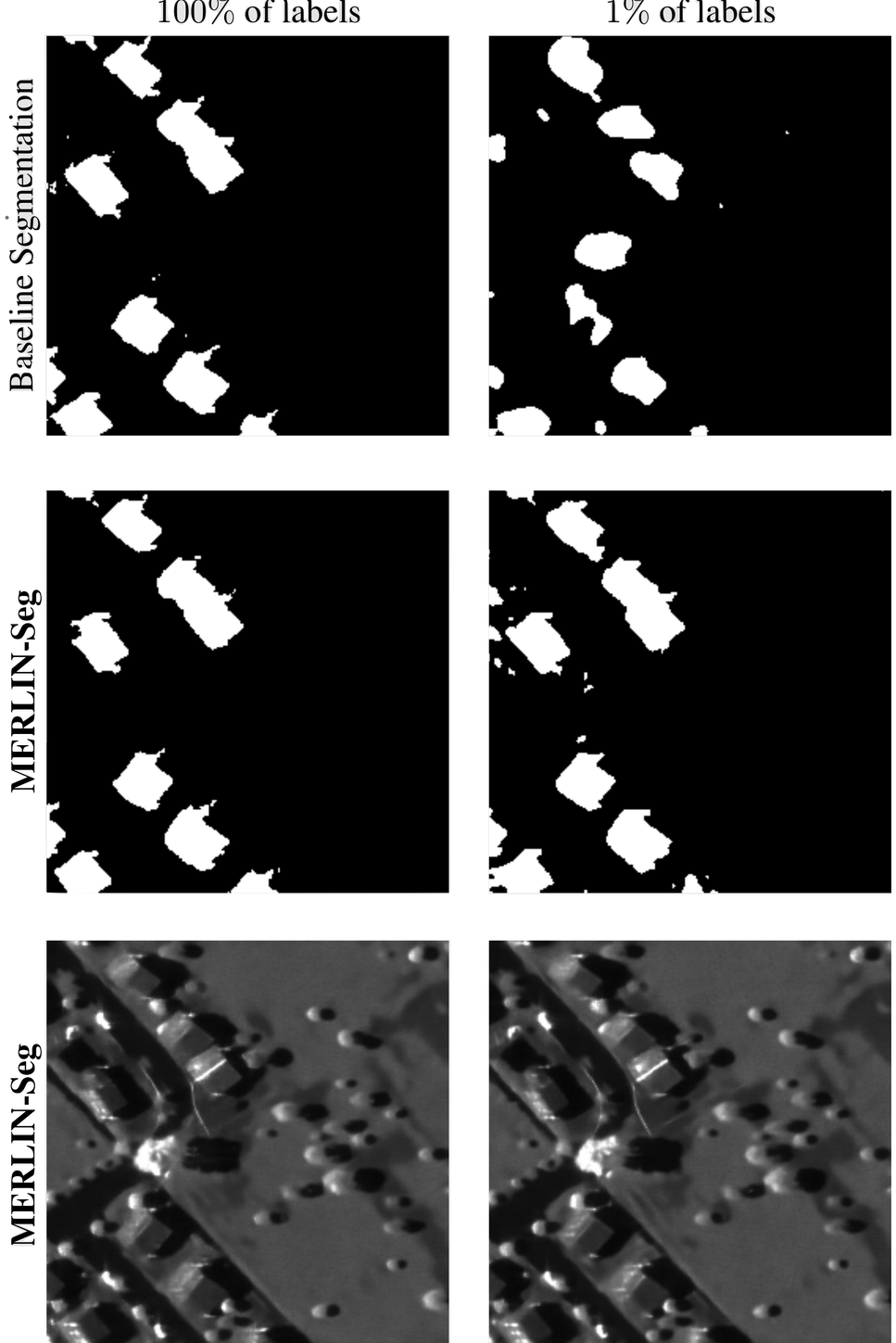
MOTIVATION FOR SELF-SUPERVISED LEARNING

In this talk: focus on despeckling & polarimetric or interferometric estimation

Solving these tasks requires learning a **representation** that can be useful for other tasks:

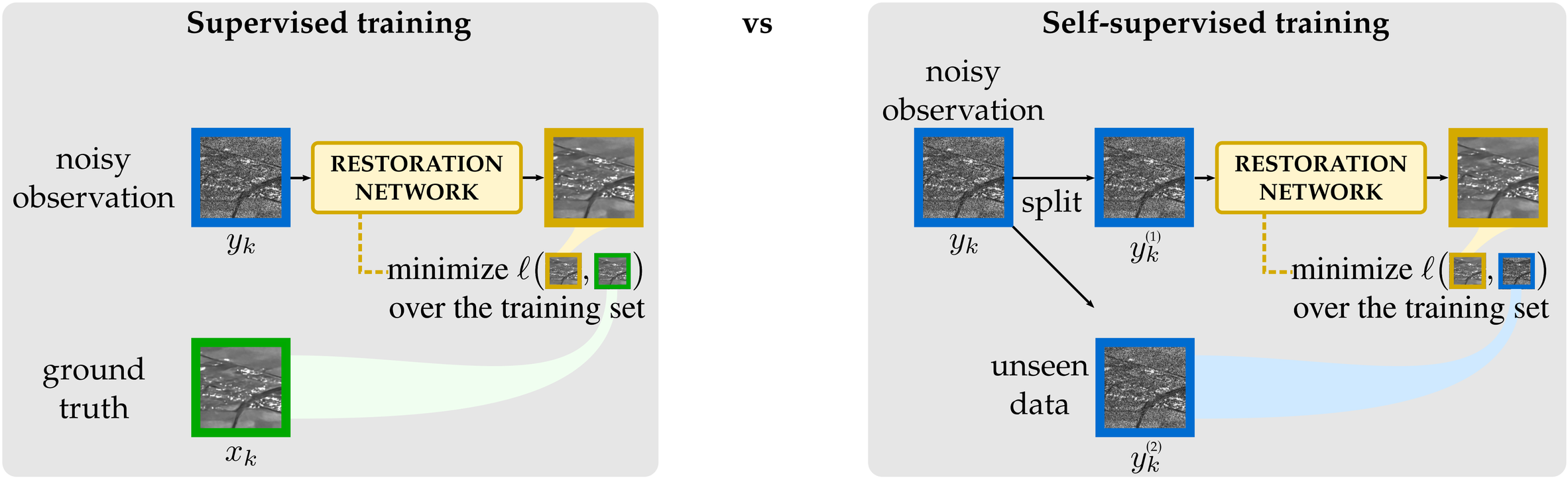
- segmentation

- regression (e.g., height estimation from a single image)

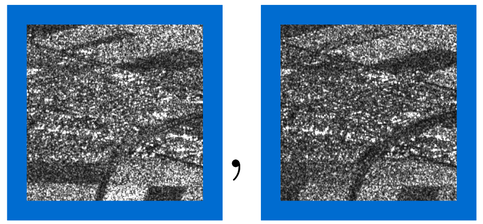


Dalsasso, E., Rambour, C., Trouvé, N., & Thome, N. (2024). MERLIN-Seg: self-supervised despeckling for label-efficient semantic segmentation. *Computer Vision and Image Understanding*, *241*, 103940.

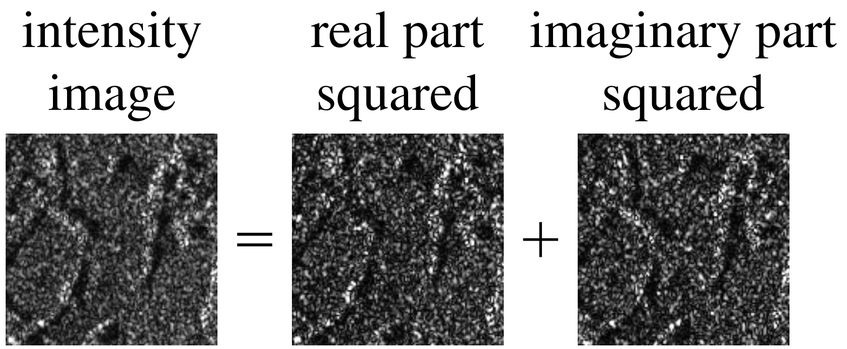
SUPERVISED VS SELF-SUPERVISED LEARNING FOR IMAGE RESTORATION



STRUCTURE OF THE PRESENTATION:



1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS



2. SELF-SUPERVISED LEARNING BASED ON THE REAL / IMAGINARY PART DECOMPOSITION

1. Generate many projections
2. single-channel despeckling
3. Recombine the projections

3. EXTENDING SELF-SUPERVISED LEARNING TO MULTI-CHANNEL SAR IMAGES: POLARIMETRY & INTERFEROMETRY

1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

Learning to denoise images **without** clean images is **possible**!

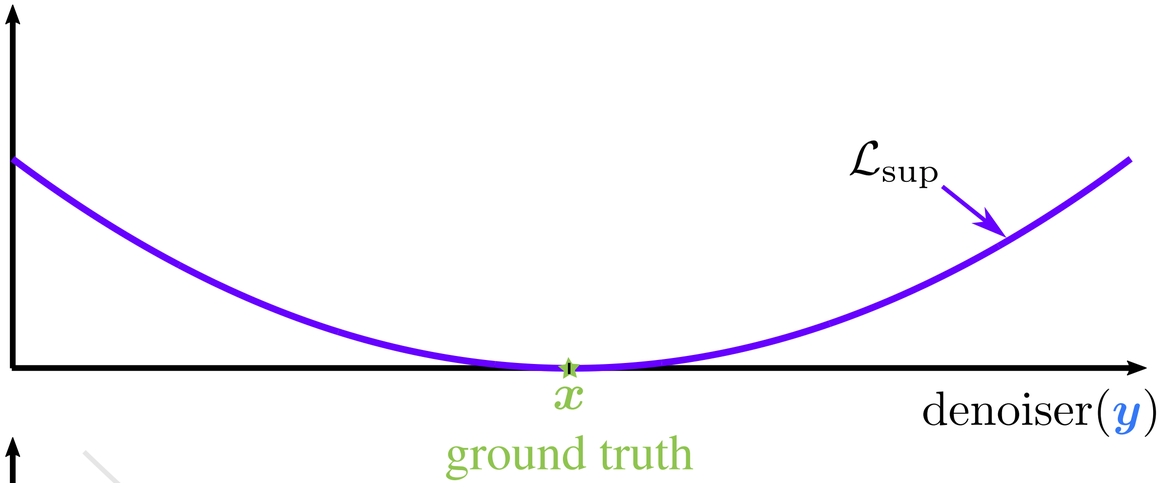
Noise2Noise [Lehtinen, ICML 2018]: use pairs of noisy observations

Supervised loss

$$\mathcal{L}_{\text{sup}} = \mathbb{E}_{\boldsymbol{x}} \left\{ \mathbb{E}_{\boldsymbol{y}|\boldsymbol{x}} \left[\|\text{denoiser}(\boldsymbol{y}) - \boldsymbol{x}\|^2 \right] \right\}$$

noisy image

ground truth

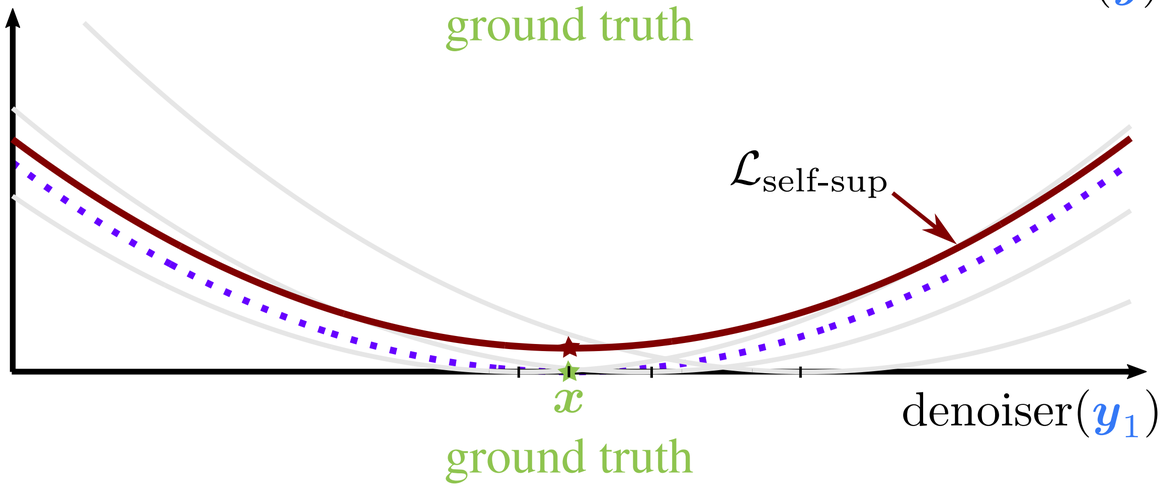


Unsupervised loss

$$\mathcal{L}_{\text{self-sup}} = \mathbb{E}_{\boldsymbol{x}} \left\{ \mathbb{E}_{\boldsymbol{y}_1,\boldsymbol{y}_2|\boldsymbol{x}} \left[\|\text{denoiser}(\boldsymbol{y}_1) - \boldsymbol{y}_2\|^2 \right] \right\}$$

noisy image

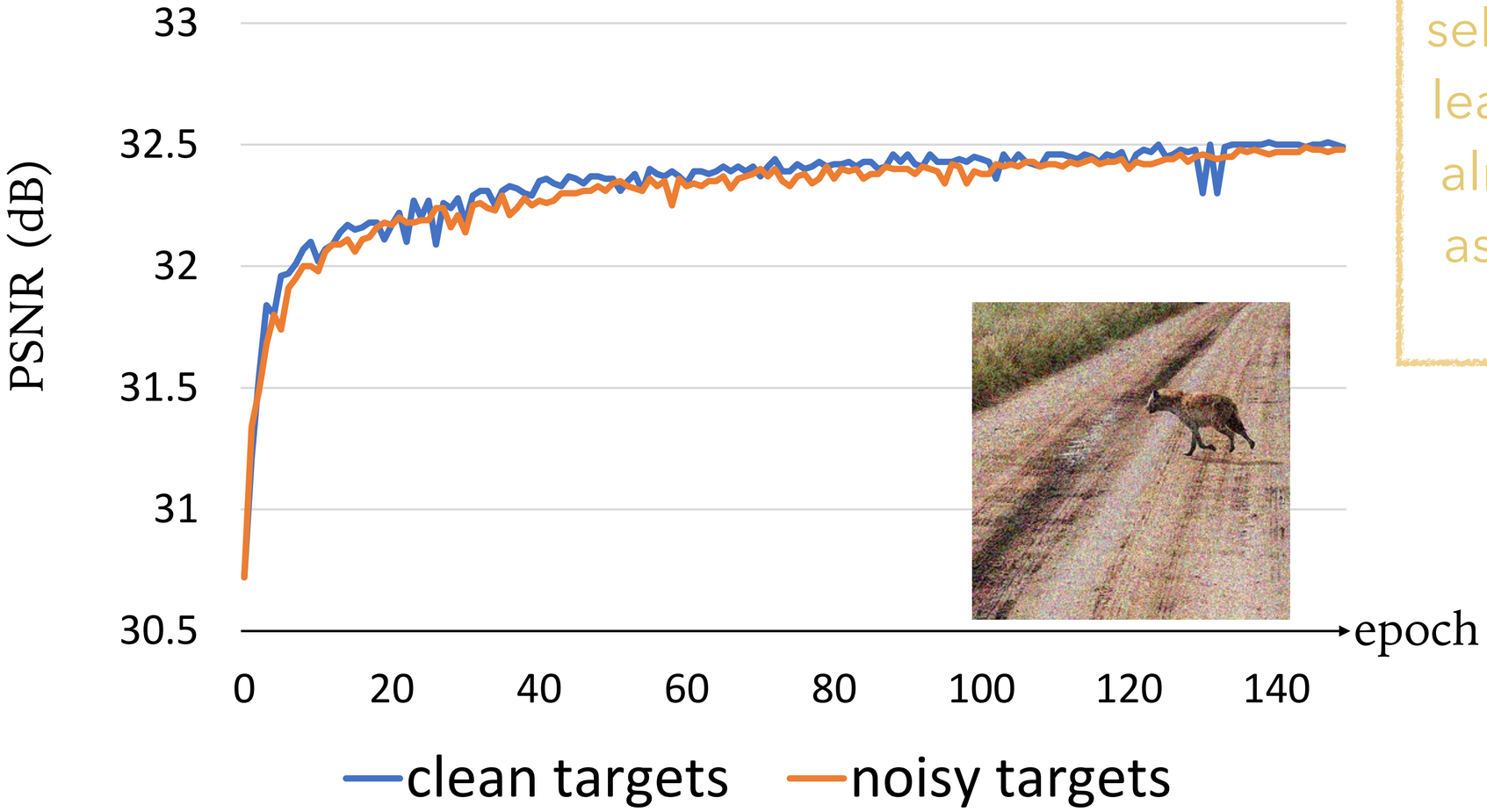
another noisy observation of the same image $\boldsymbol{x}$



1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

Learning to denoise images **without** clean images is **possible**!

Noise2Noise [Lehtinen *et al.*, ICML 2018]: use pairs of noisy observations

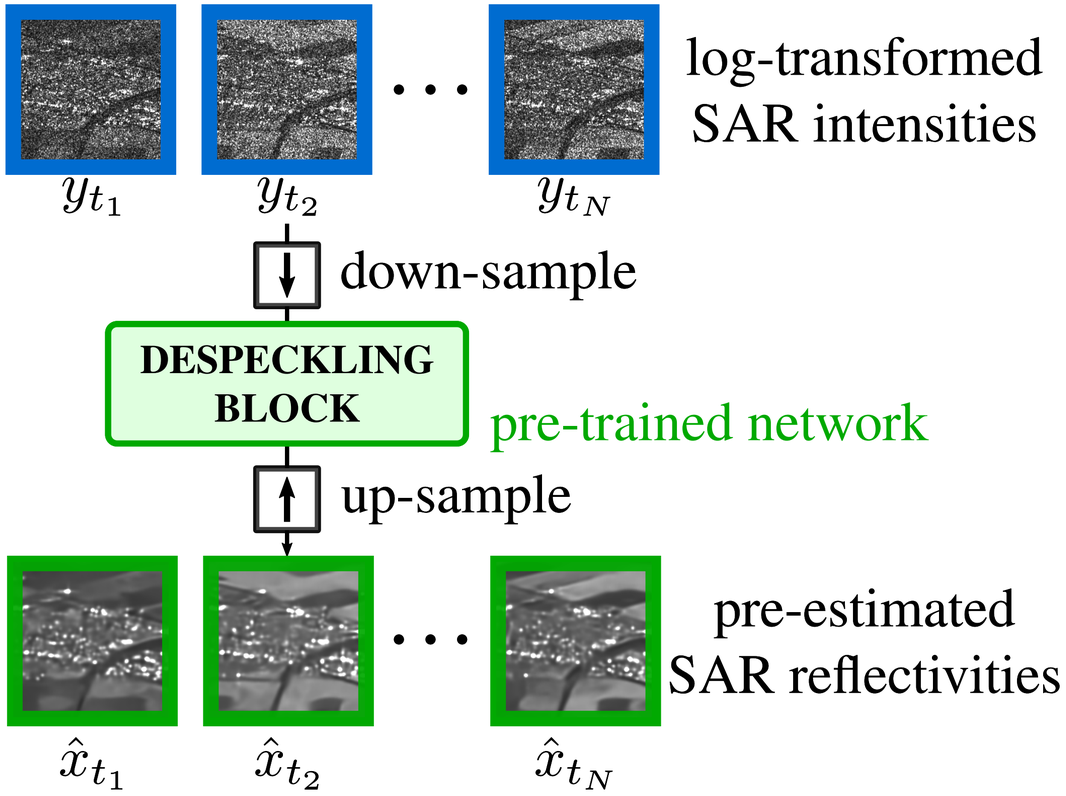


self-supervised learning works almost as well as supervised learning!

1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

Application to SAR despeckling, using pairs of images captured at different dates: SAR2SAR [Dalsasso *et* al., TGRS 2021]

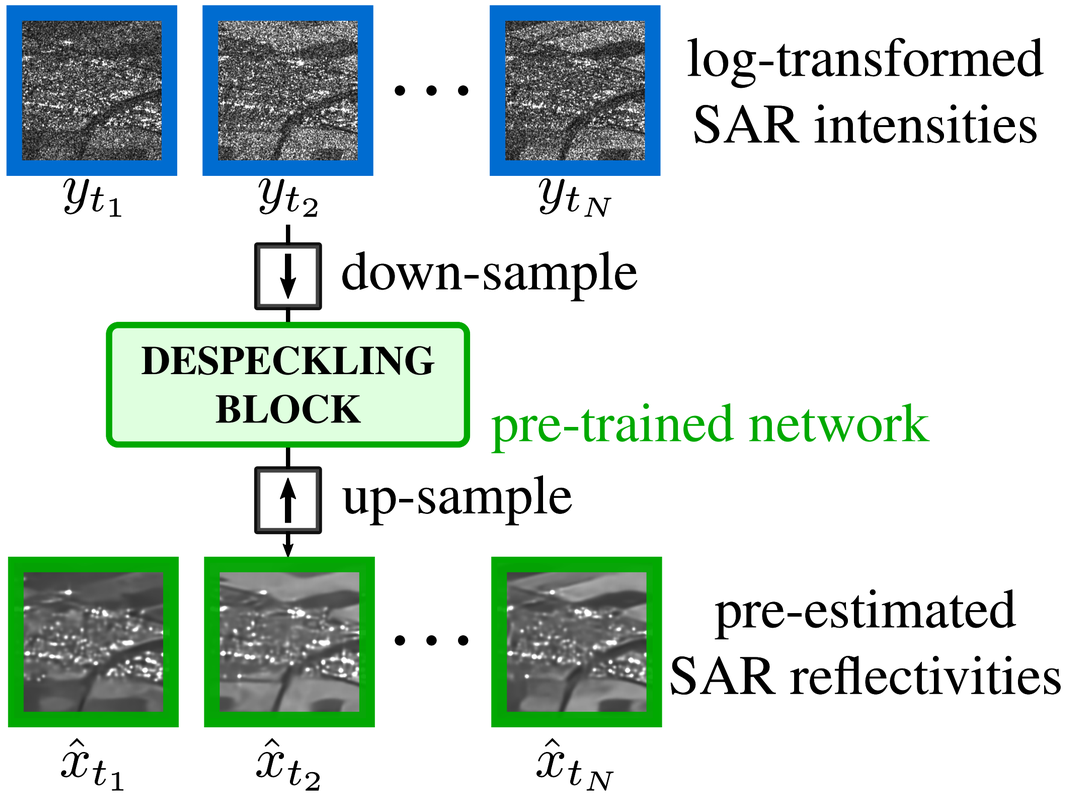
1. Pre-estimate reflectivities



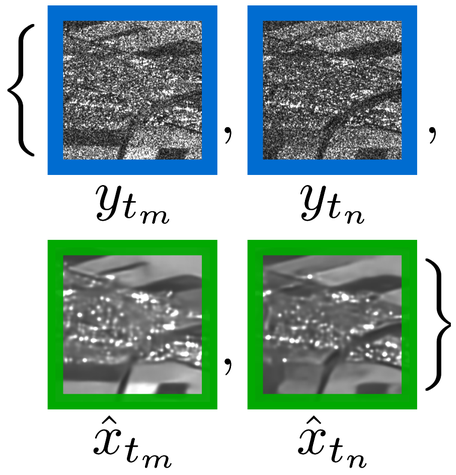
1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

Application to SAR despeckling, using pairs of images captured at different dates: SAR2SAR [Dalsasso *et* al., TGRS 2021]

❶ Pre-estimate reflectivities

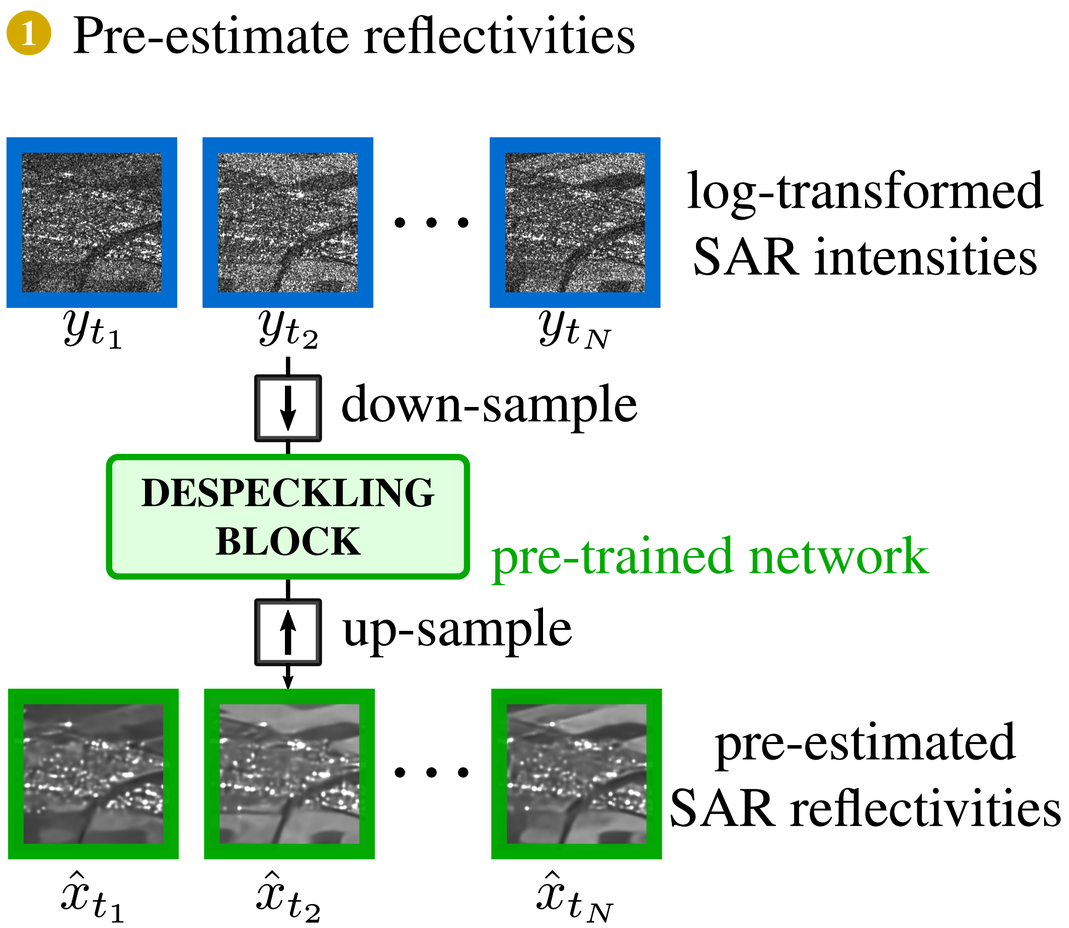


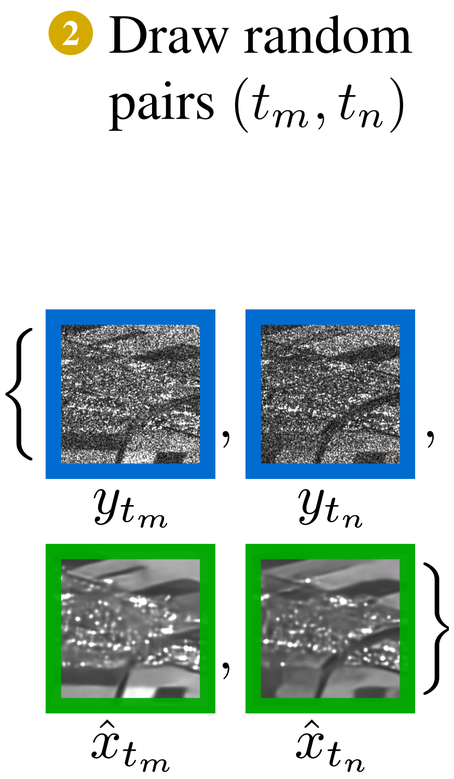
❷ Draw random pairs (t_m, t_n)

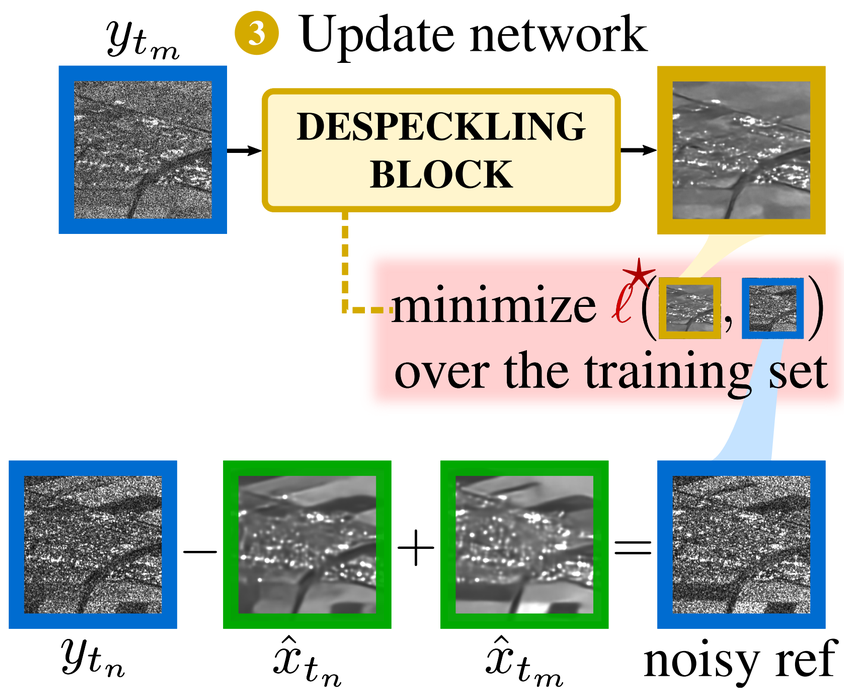


1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

Application to SAR despeckling, using pairs of images captured at different dates:
SAR2SAR [Dalsasso *et* al., TGRS 2021]





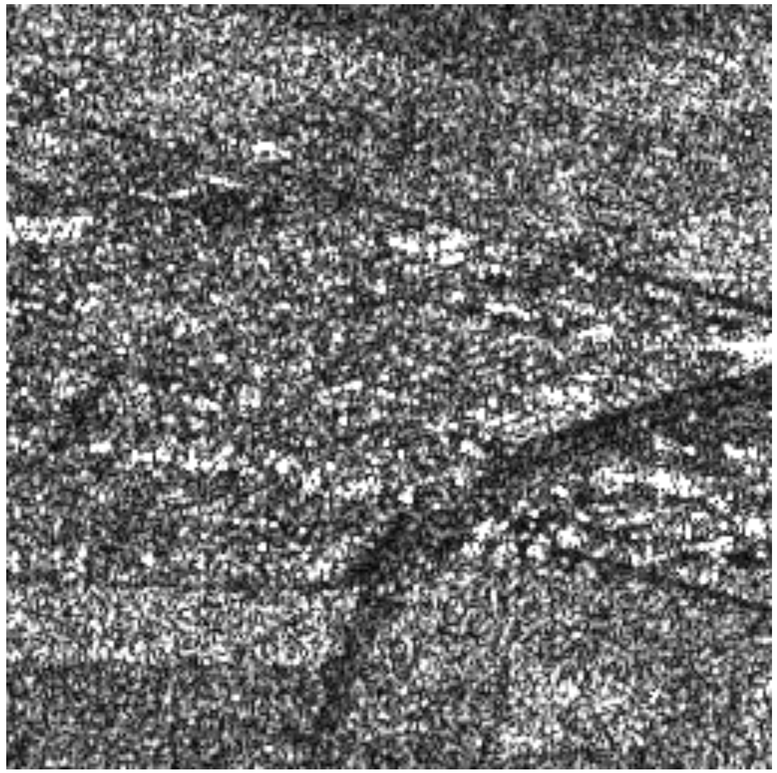


PhD Emanuele Dalsasso

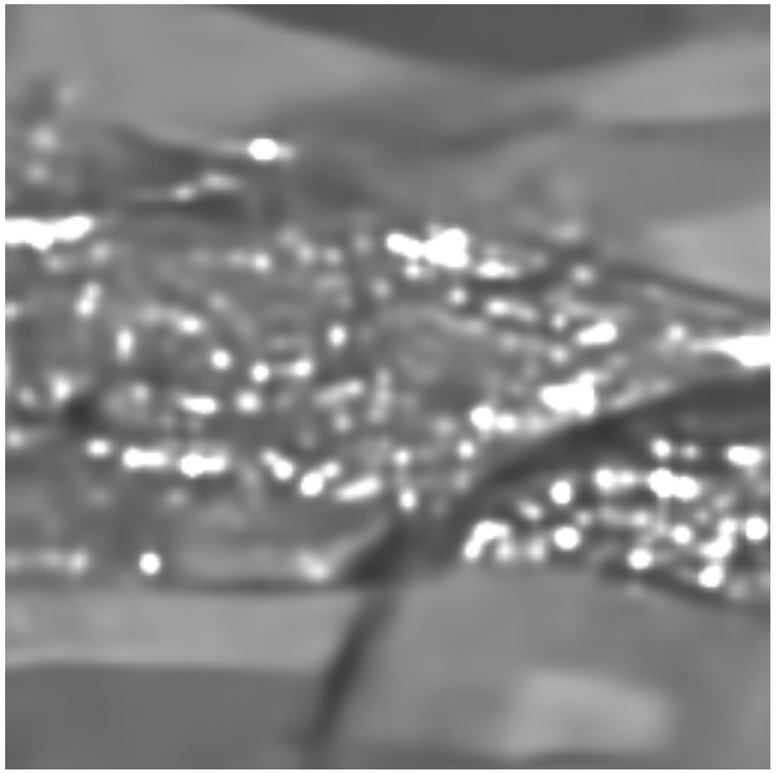
1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

Application to SAR despeckling, using pairs of images captured at different dates: SAR2SAR [Dalsasso *et* al., TGRS 2021]

Restoration results with SAR2SAR: Sentinel-1 SLC IW image (©ESA, image not pre-processed)



Single-look Sentinel-1 image



Restored image (SARCNN)

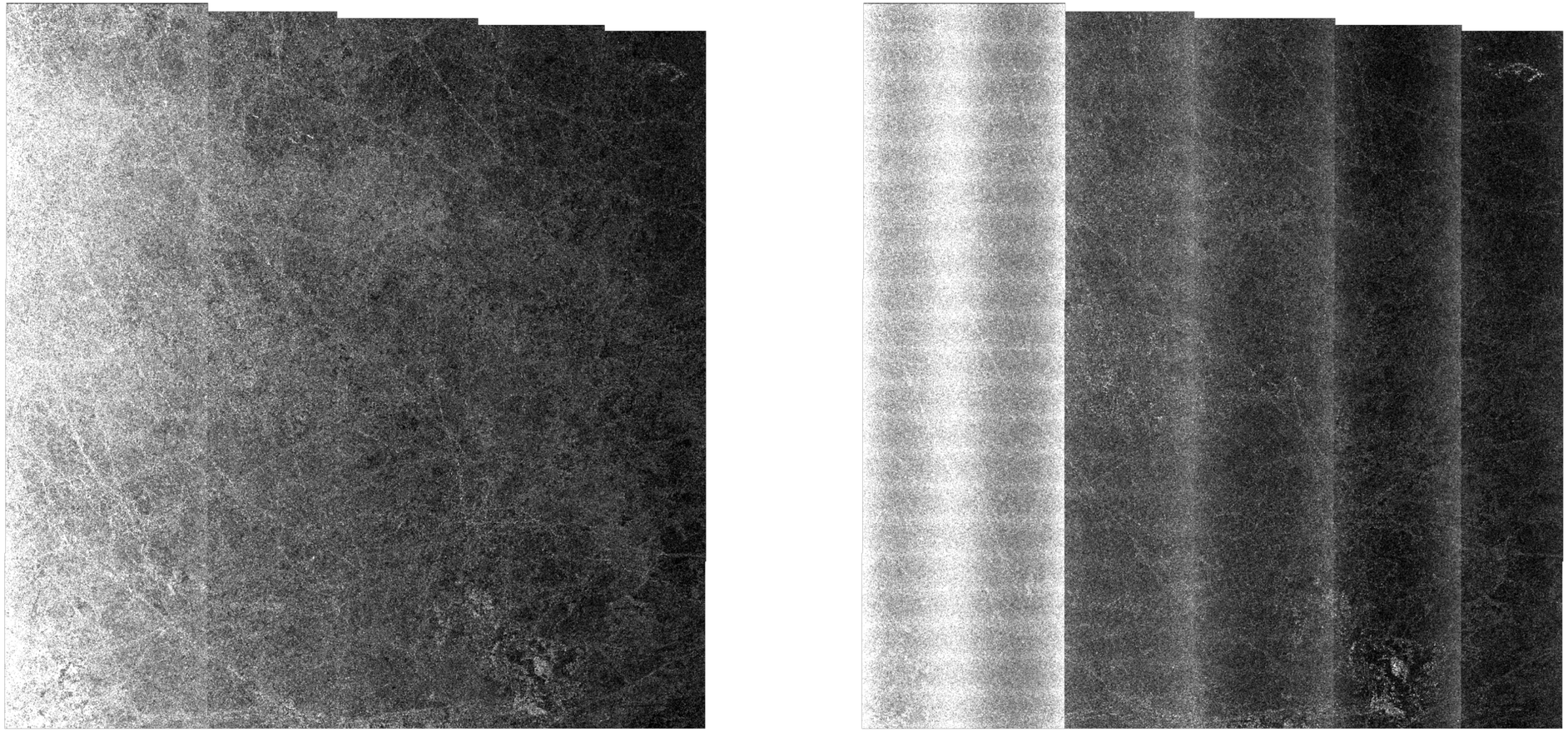


Restored image (SAR2SAR)

1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

Application to SAR despeckling **and thermal noise debiasing**, using pairs of images captured at different dates [Meraoumia *et* al., TGRS 2025]

Classification of **sea ice** from Sentinel-1 images is challenging because of **speckle** fluctuations and **thermal noise**:

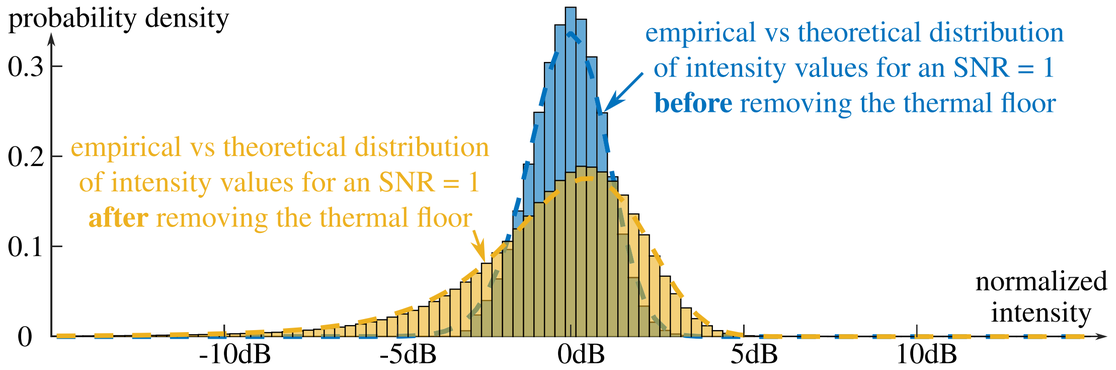


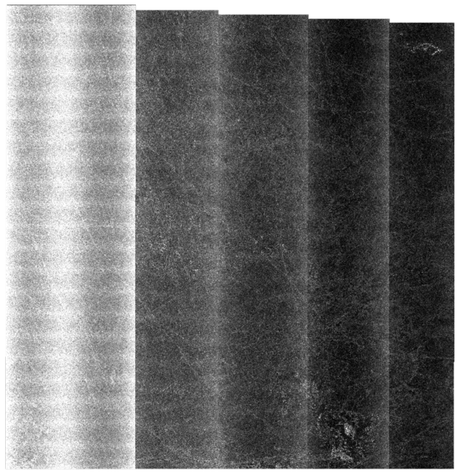
Sentinel-1 EW image of sea ice: (HH polarization) (HV polarization)

1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

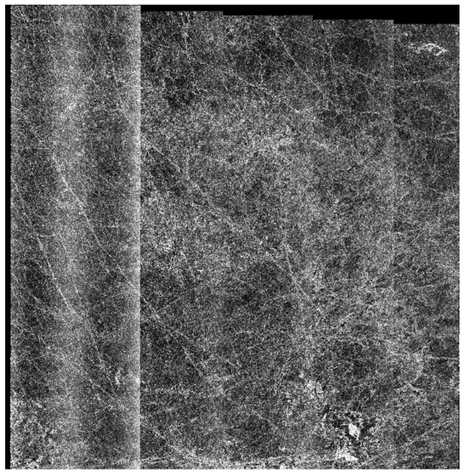
Application to SAR despeckling **and thermal noise debiasing**, using pairs of images captured at different dates [Meraoumia *et* al., TGRS 2025]

The thermal noise bias can be subtracted, but this changes the statistics of speckle!





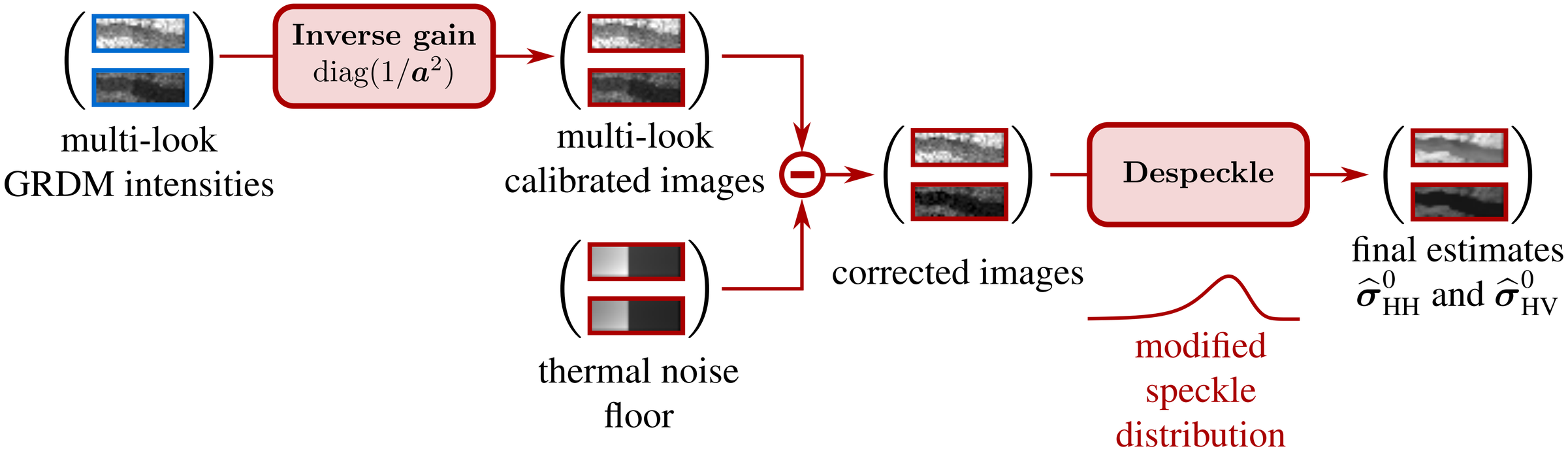
HV image before correction



HV image after correction

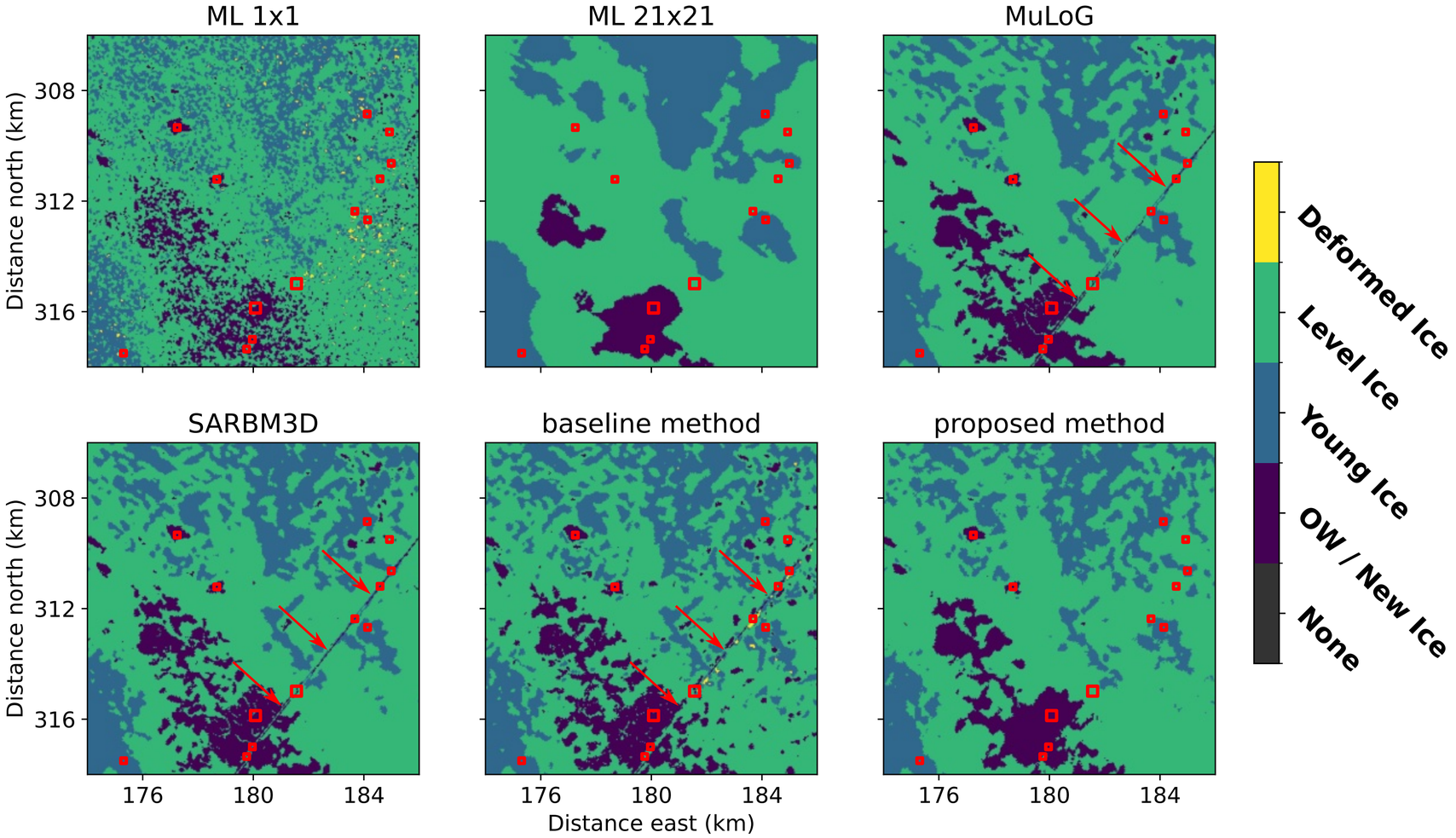
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Application to SAR despeckling **and thermal noise debiasing**, using pairs of images captured at different dates [Meraoumia *et* al., TGRS 2025]



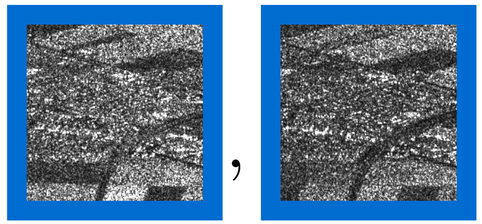
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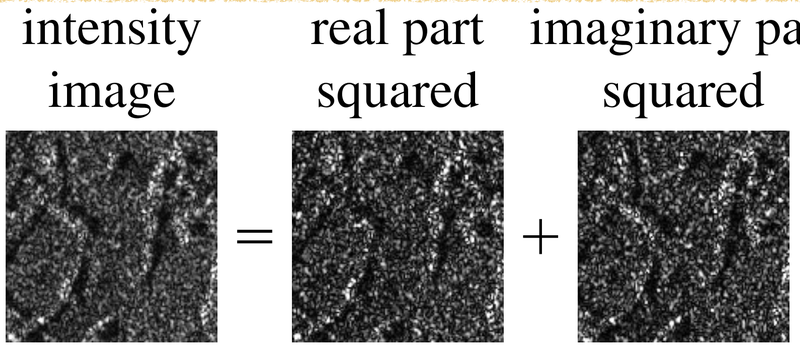


Compared to the multi-looking or despeckling baselines, our approach better preserves details and avoids artifacts between swaths

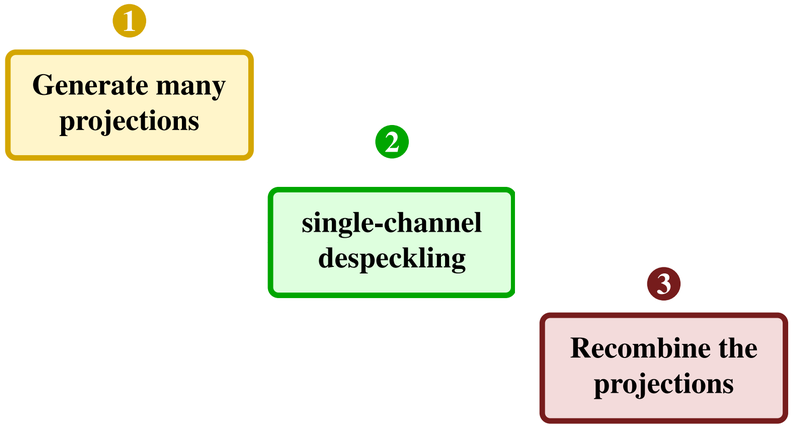
STRUCTURE OF THE PRESENTATION:



1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS

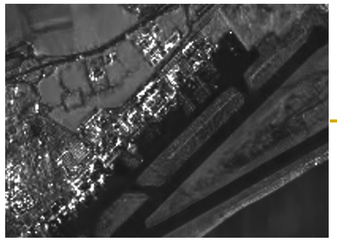


2. SELF-SUPERVISED LEARNING BASED ON THE REAL / IMAGINARY PART DECOMPOSITION



3. EXTENDING SELF-SUPERVISED LEARNING TO MULTI-CHANNEL SAR IMAGES: POLARIMETRY & INTERFEROMETRY

SELF-SUPERVISED LEARNING BY DECOMPOSING INTO REAL & IMAGINARY PARTS

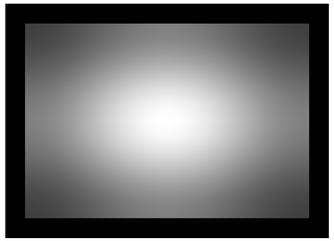


reflectivity
$\boldsymbol{r}$

$\mathbf{x} \mapsto \sqrt{\mathbf{x}}$

$\sqrt{\boldsymbol{r}}$

$\boldsymbol{s}$



0-padding and
spectral apodization
(in Fourier domain)

$\boldsymbol{z}$

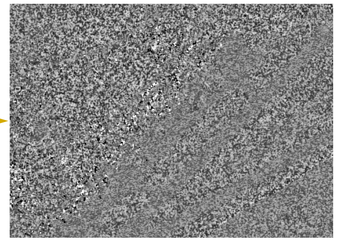
SAR imaging system H

$\tilde{\boldsymbol{z}}$

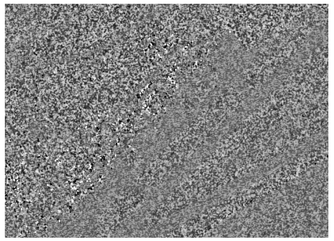
linear +
real-valued if and only if
the transfer function
has Hermitian symmetry

independent

single-look complex image



real part

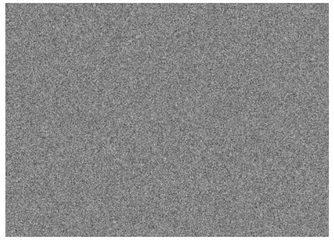


imaginary part

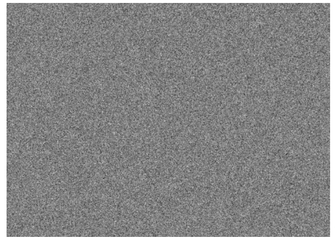
$\mathcal{N}(\mathbf{0}, \frac{1}{2}\mathbf{H}\mathrm{diag}(\boldsymbol{r})\mathbf{H}^\top)$

(spatially
correlated)

complex speckle



real part



imaginary part

$\mathcal{N}(\mathbf{0}, \frac{1}{2}\mathbf{I})$

(spatially
uncorrelated)

independent

$\tilde{\boldsymbol{a}}$

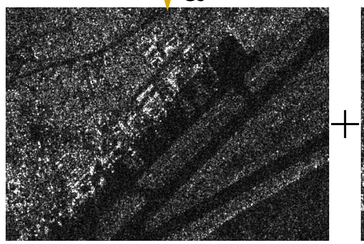
$\mathbf{x} \mapsto \mathbf{x}^2$

$\tilde{\boldsymbol{a}}^2$

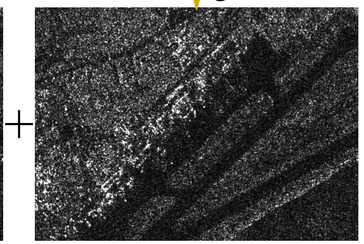
$\tilde{\boldsymbol{b}}$

$\mathbf{x} \mapsto \mathbf{x}^2$

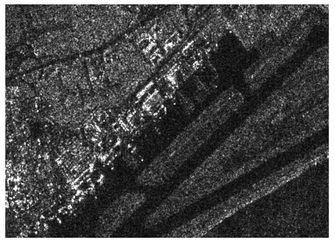
$\tilde{\boldsymbol{b}}^2$



+



=



intensity image

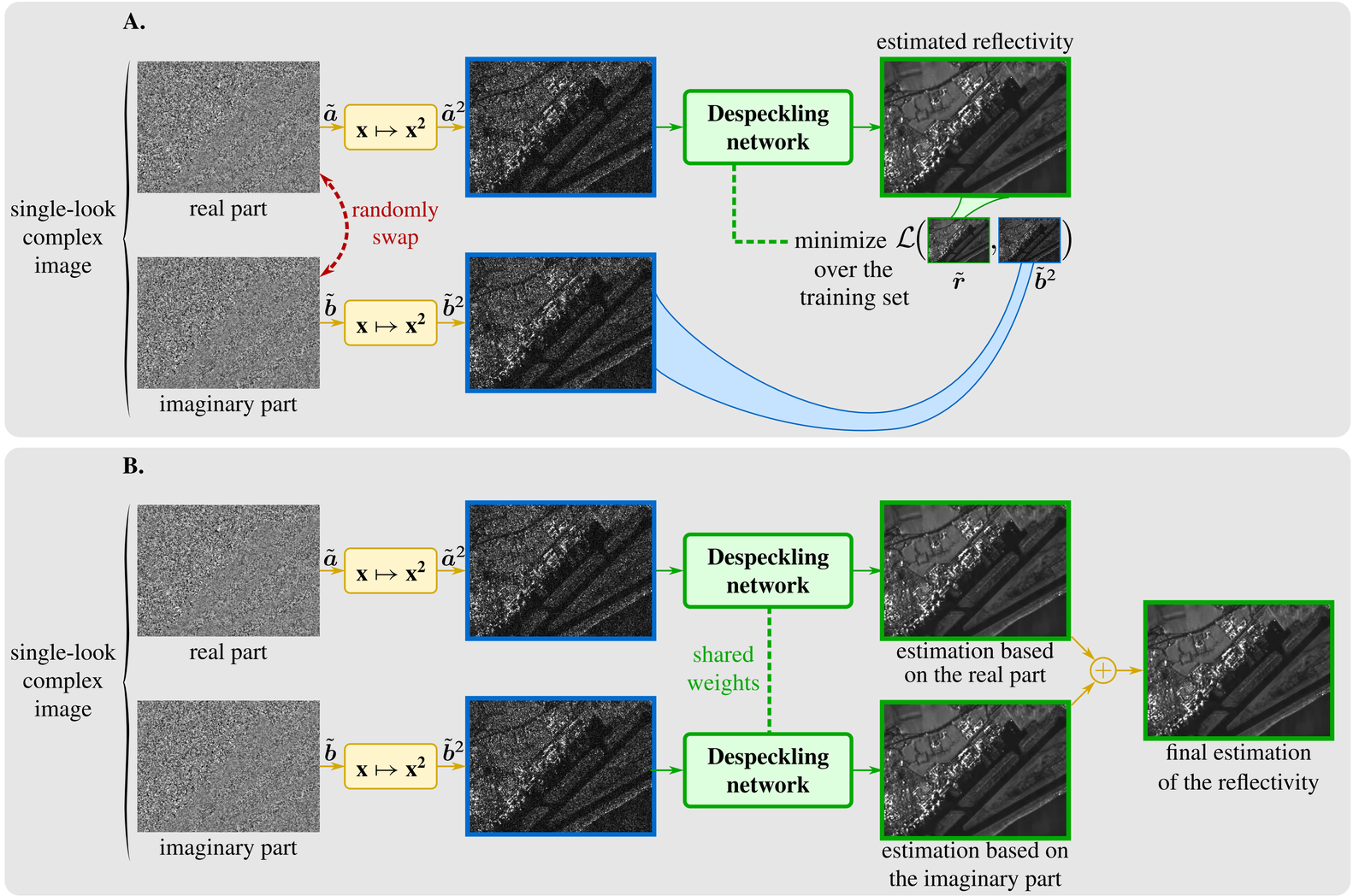
independent

SELF-SUPERVISED LEARNING BY DECOMPOSING INTO REAL & IMAGINARY PARTS

If H is real-valued, i.e., if the transfer function has Hermitian symmetry, then the speckle is **independent** in the real/imag. parts

SELF-SUPERVISED LEARNING BY DECOMPOSING INTO REAL & IMAGINARY PARTS

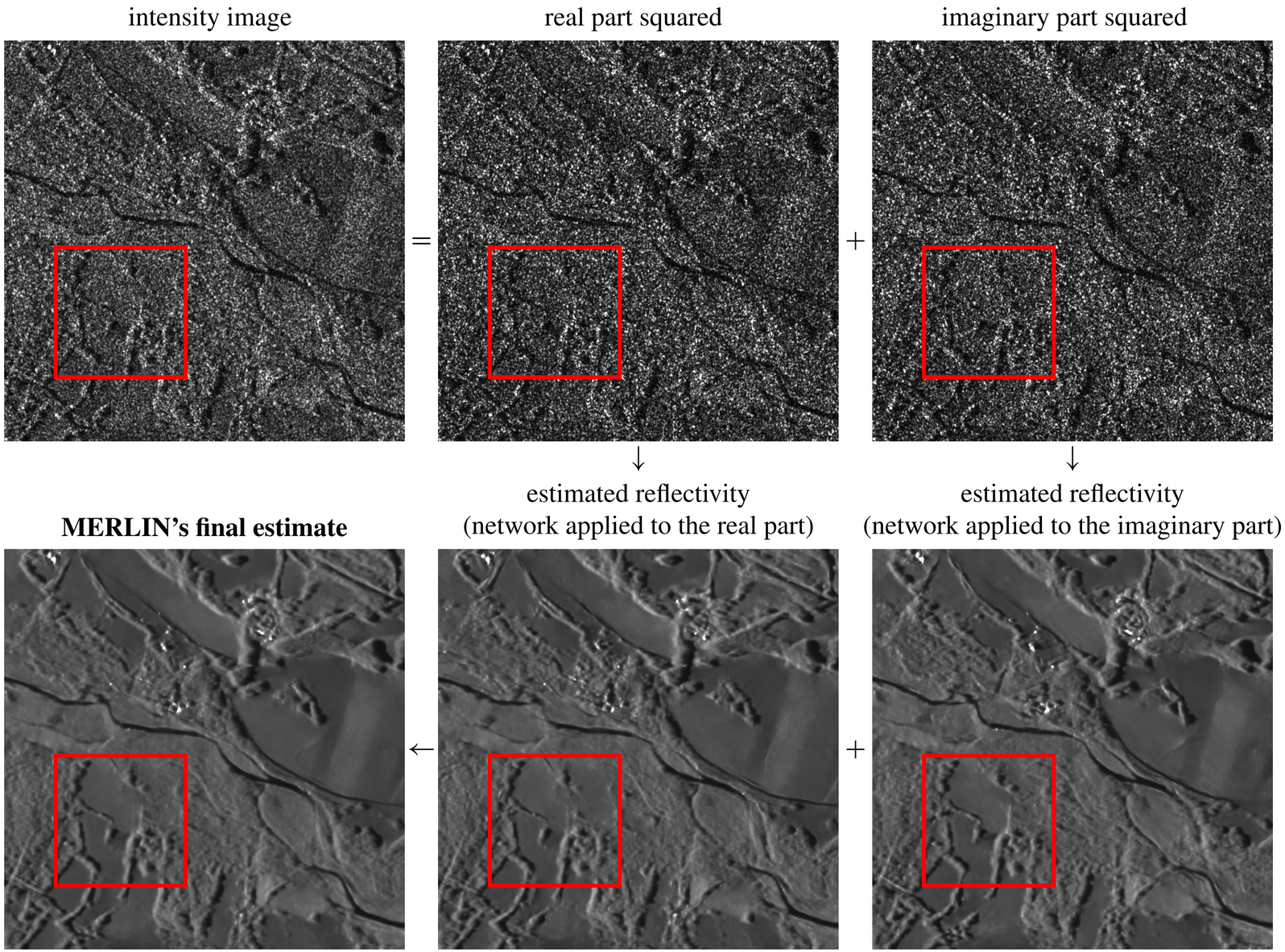
→ self-supervised learning strategy:



Dalsasso, E., Denis, L., & Tupin, F. (2022). As if by magic: Self-supervised training of deep despeckling networks with MERLIN. *IEEE trans. on Geoscience and Remote Sensing*.

PhD Emanuele Dalsasso

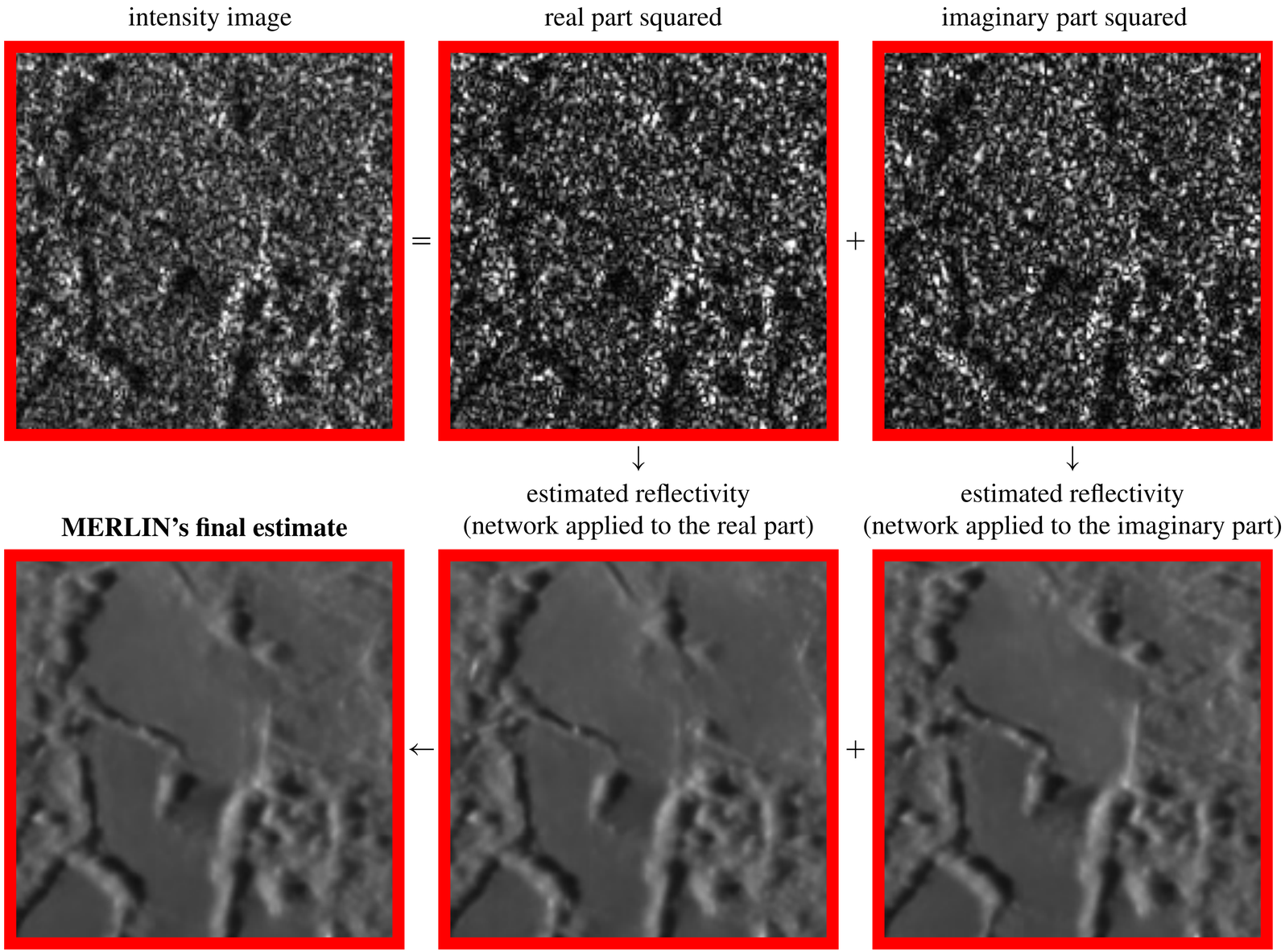
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PhD Emanuele Dalsasso

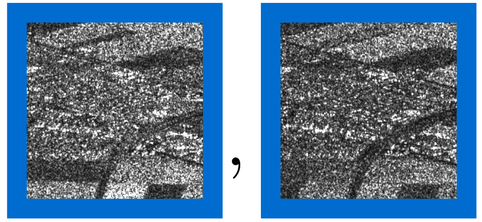
SELF-SUPERVISED LEARNING BY DECOMPOSING INTO REAL & IMAGINARY PARTS



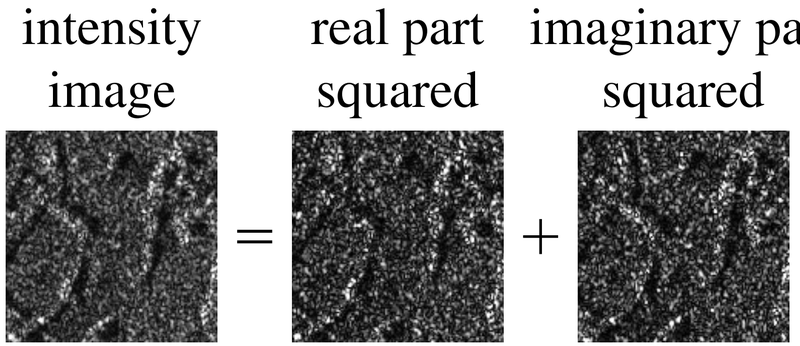
Dalsasso, E., Denis, L., & Tupin, F. (2022). As if by magic: Self-supervised training of deep despeckling networks with MERLIN. *IEEE trans. on Geoscience and Remote Sensing*.

PhD Emanuele Dalsasso

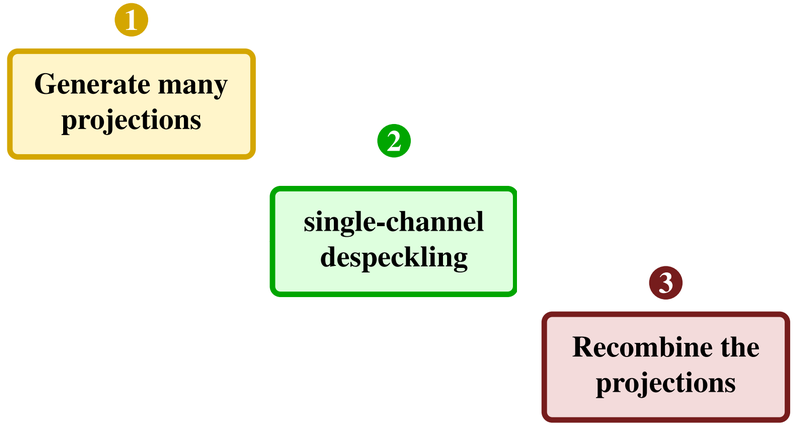
STRUCTURE OF THE PRESENTATION:



1. SELF-SUPERVISED LEARNING BASED ON IMAGE PAIRS



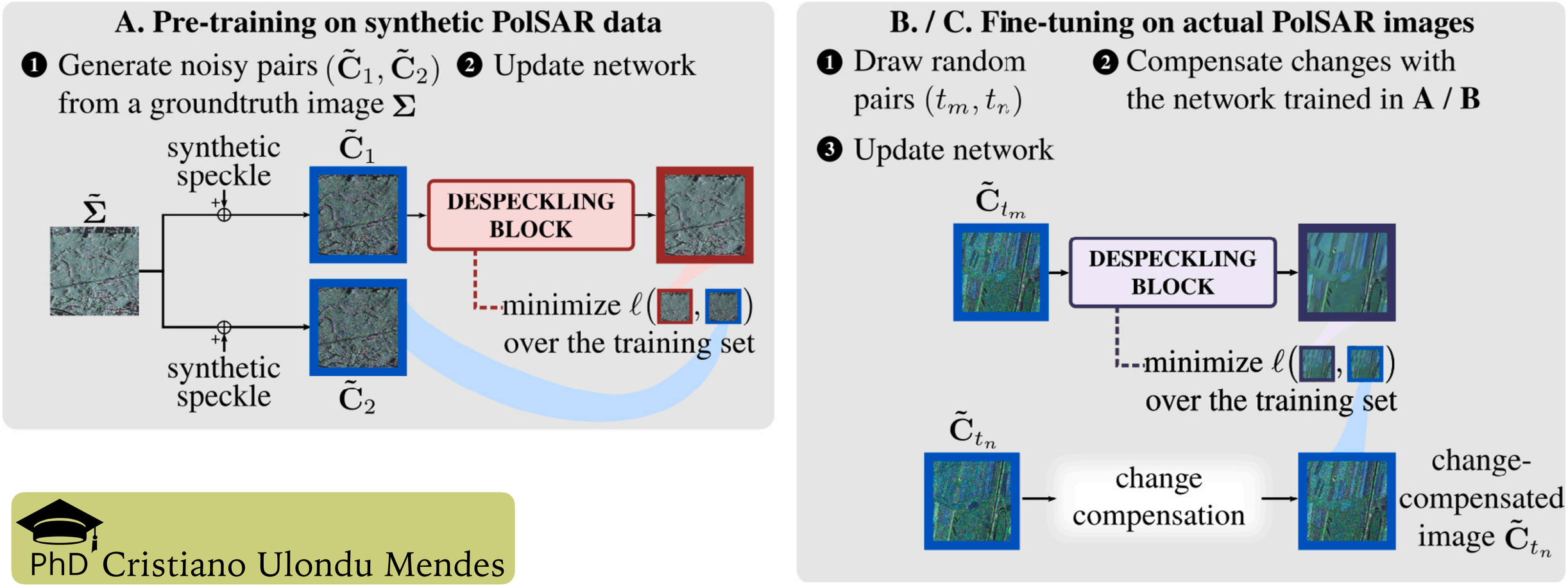
2. SELF-SUPERVISED LEARNING BASED ON THE REAL / IMAGINARY PART DECOMPOSITION



3. EXTENDING SELF-SUPERVISED LEARNING TO MULTI-CHANNEL SAR IMAGES: POLARIMETRY & INTERFEROMETRY

EXTENSIONS TO POLSAR AND INSAR → POLSAR2POLSAR

Using pairs of polarimetric images at 2 dates

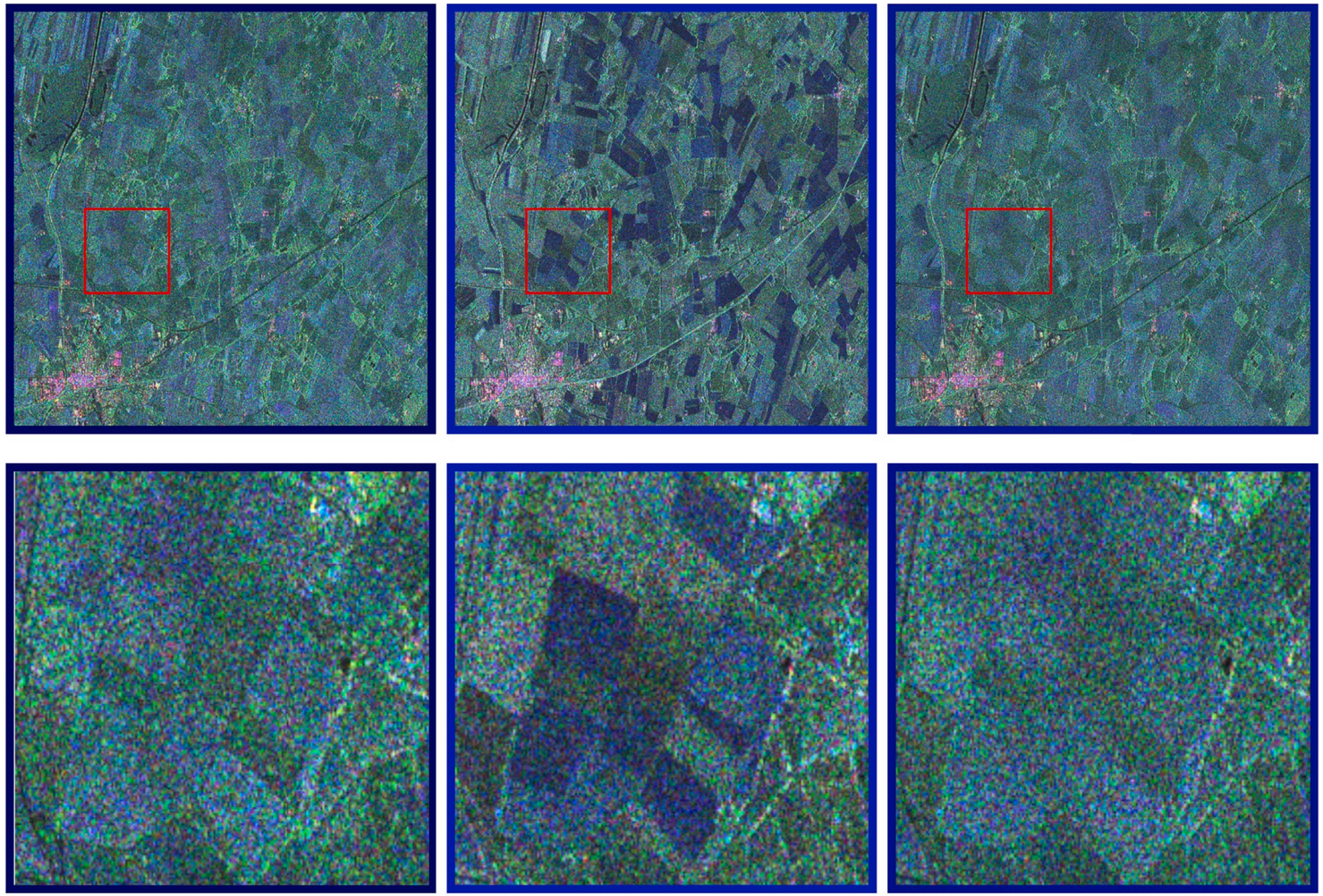


PhD Cristiano Ulondu Mendes

Mendes, C. U., Dalsasso, E., Zhang, Y., Denis, L., & Tupin, F. (2025). PolSAR2PolSAR: A semi-supervised despeckling algorithm for polarimetric SAR images. ISPRS J. Photo. Remote Sensing.

EXTENSIONS TO POLSAR AND INSAR → POLSAR2POLSAR

Change compensation:



(a) $\mathbf{C}_{t_m}$ (b) $\mathbf{C}_{t_n}$ (c) Change-compensated image $\bar{\mathbf{C}}_{t_n}$

- Pre-estimate $\boldsymbol{\Sigma}_1$ and $\boldsymbol{\Sigma}_2$
- Compute factorizations:

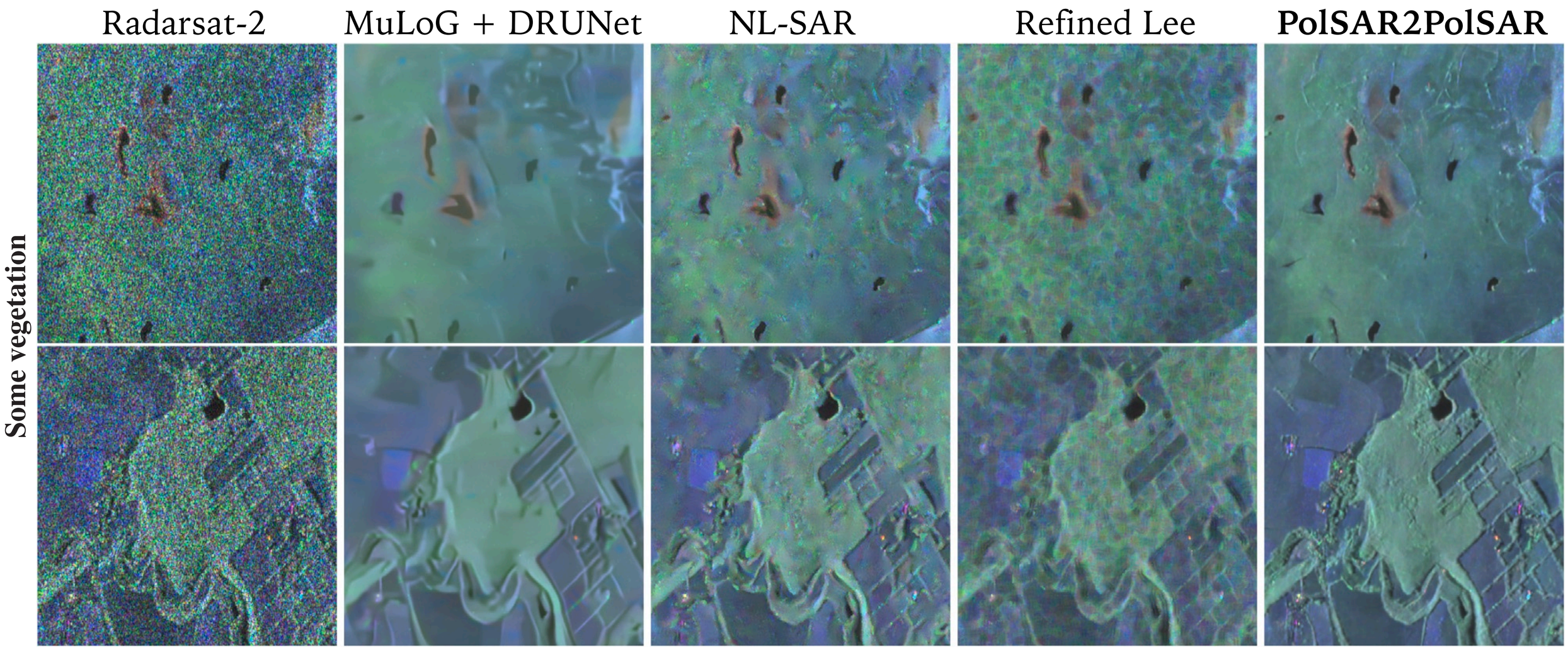
$$\boldsymbol{\Sigma}_1 = \mathbf{A}_1\mathbf{A}_1^\dagger \text{ and } \boldsymbol{\Sigma}_2 = \mathbf{A}_2\mathbf{A}_2^\dagger$$

- Replace $\mathbf{C}_2$ by:

$$\tilde{\mathbf{C}}_2 = \mathbf{A}_1(\mathbf{A}_2)^{-1}\mathbf{C}_2(\mathbf{A}_2^\dagger)^{-1}\mathbf{A}_1^\dagger.$$

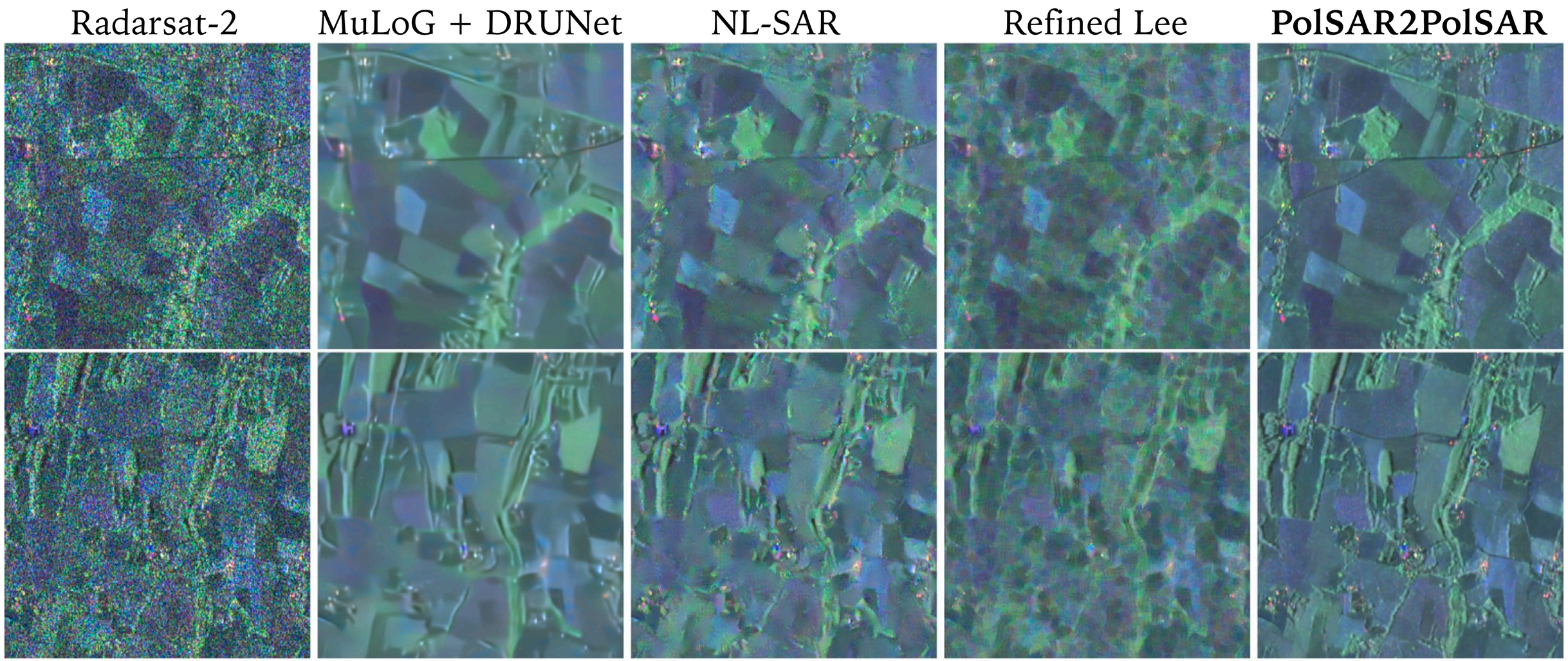
EXTENSIONS TO POLSAR AND INSAR → POLSAR2POLSAR

Results:



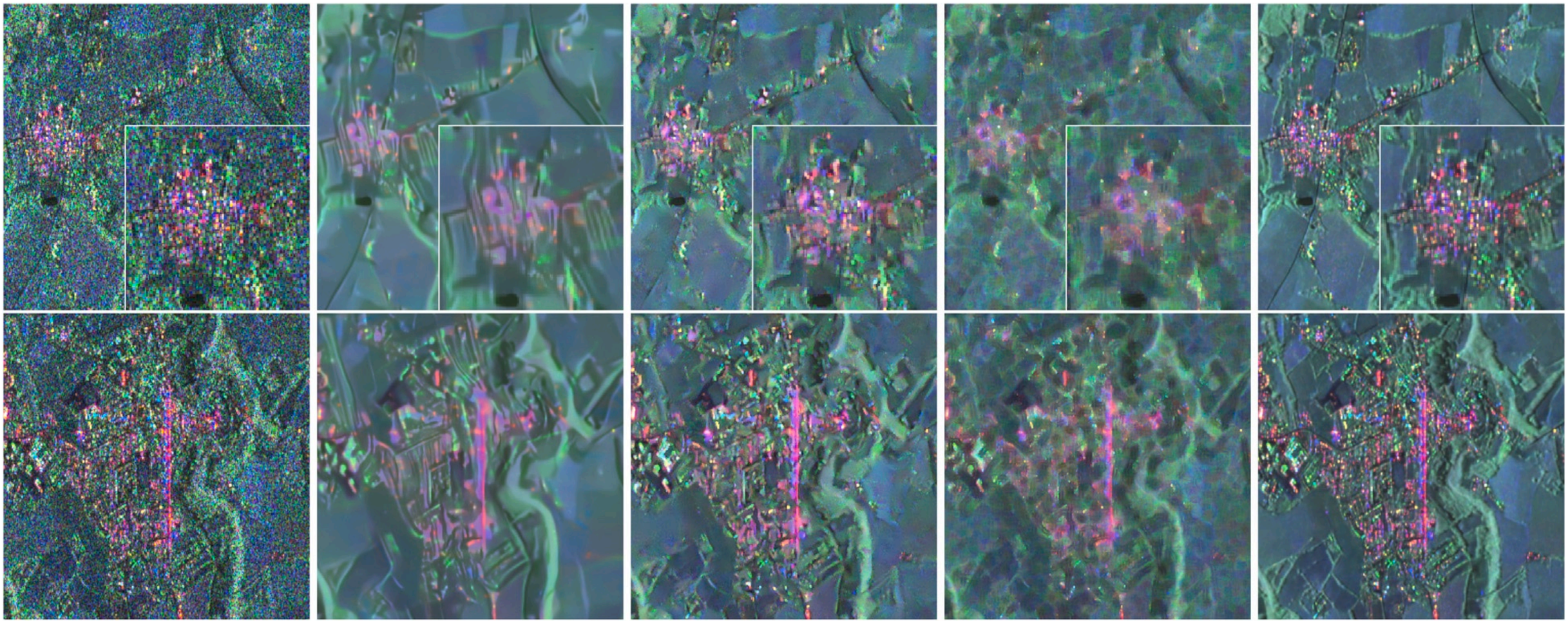
EXTENSIONS TO POLSAR AND INSAR → POLSAR2POLSAR

Results:



EXTENSIONS TO POLSAR AND INSAR → POLSAR2POLSAR

Results:



EXTENSIONS TO POLSAR AND INSAR → REAL / IMAGINARY DECOMPOSITION?

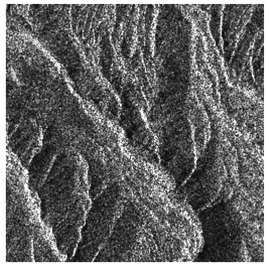
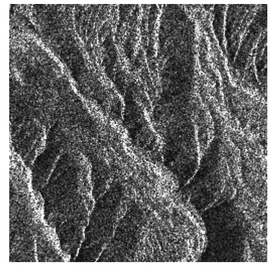
The extension of MERLIN, i.e., the decomposition into real and imaginary parts does

not work [Denis, « Comments on PolMERLIN », IEEE GRSL 2024]:

Real / imaginary parts of the speckle are not independent because of polarimetric/ interferometric covariances!

EXTENSIONS TO POLSAR AND INSAR → REAL / IMAGINARY DECOMPOSITION?

- *Projecting* a vector $\boldsymbol{z}$ of complex amplitudes on a direction $\boldsymbol{p}_k$ gives a single-channel SLC image:

$$z_k = \boldsymbol{p}_k^\dagger \boldsymbol{z} \qquad \text{e.g.,} \quad z_k = (0.2 + 0.5j) \times$$  $$+ (0.1 - 0.3j) \times$$ 

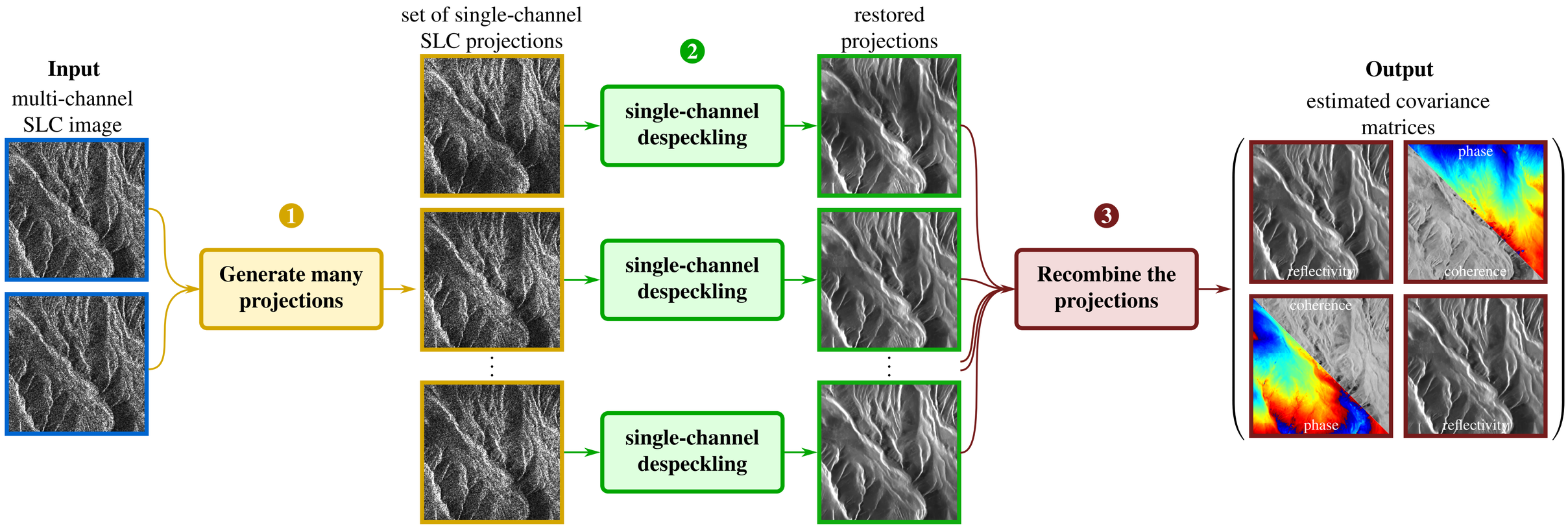
→ simulation of images acquired with a different polarization mode (e.g., circular polarization from linear polarization)

- The real and imaginary parts of the projection z_k are independent!
- The reflectivity corresponding to this projection is a *projection of the covariance matrix*:

$$\mathbb{E}[\,|\boldsymbol{p}_k^\dagger \boldsymbol{z}|^2] = \mathbb{E}[\boldsymbol{p}_k^\dagger \boldsymbol{z}\boldsymbol{z}^\dagger \boldsymbol{p}_k] = \boldsymbol{p}_k^\dagger \mathbb{E}[\boldsymbol{z}\boldsymbol{z}^\dagger] \boldsymbol{p}_k = \boldsymbol{p}_k^\dagger \mathbf{C} \boldsymbol{p}_k = \mathrm{vec}(\boldsymbol{p}_k \boldsymbol{p}_k^\dagger)^\dagger \mathrm{vec}(\mathbf{C})$$

A GENERIC APPROACH TO MULTI-CHANNEL DESPECKLING: MUCHAPRO

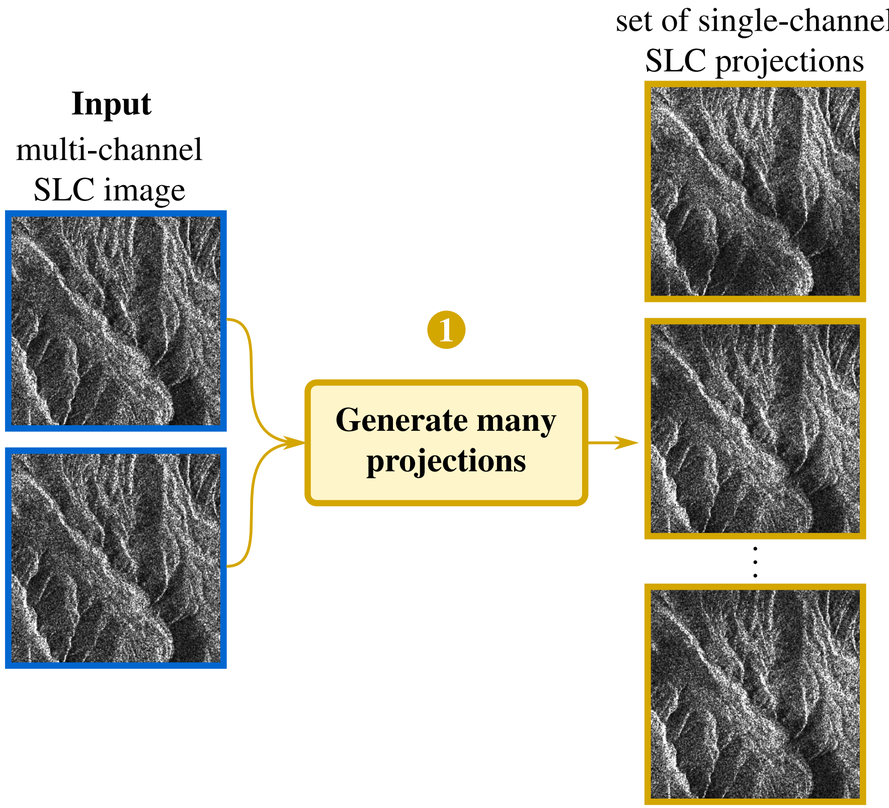
Proposed approach: MuChaPro (Multi-Channel Projection)



Denis, L., Dalsasso, E., & Tupin, F. (2025). Just project! Multichannel despeckling, the easy way. IEEE Transactions on Geoscience and Remote Sensing.

A GENERIC APPROACH TO MULTI-CHANNEL DESPECKLING: MUCHAPRO

➤ Proposed approach: **MuChaPro** (**Mu**lti-**Cha**nnel **Pro**jection)



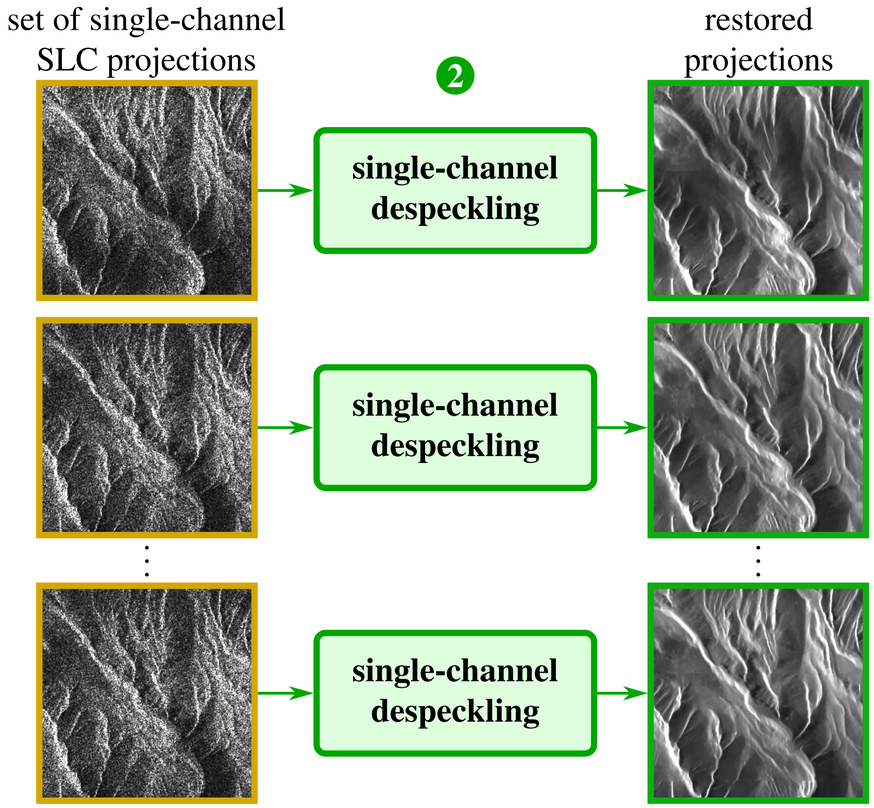
1) Generate projections from the multi-channel SLC image z:

Let $\{\boldsymbol{p}_k\}_{k=1..K}$ be a set of K directions (those directions can be normalized: $\forall k, \|\boldsymbol{p}_k\| = 1$)

We generate K single-channel SLC images by projection: $z_k = \boldsymbol{p}_k^\dagger z$

A GENERIC APPROACH TO MULTI-CHANNEL DESPECKLING: MUCHAPRO

➤ Proposed approach: **MuChaPro** (**Mu**lti-**Cha**nnel **Pro**jection)



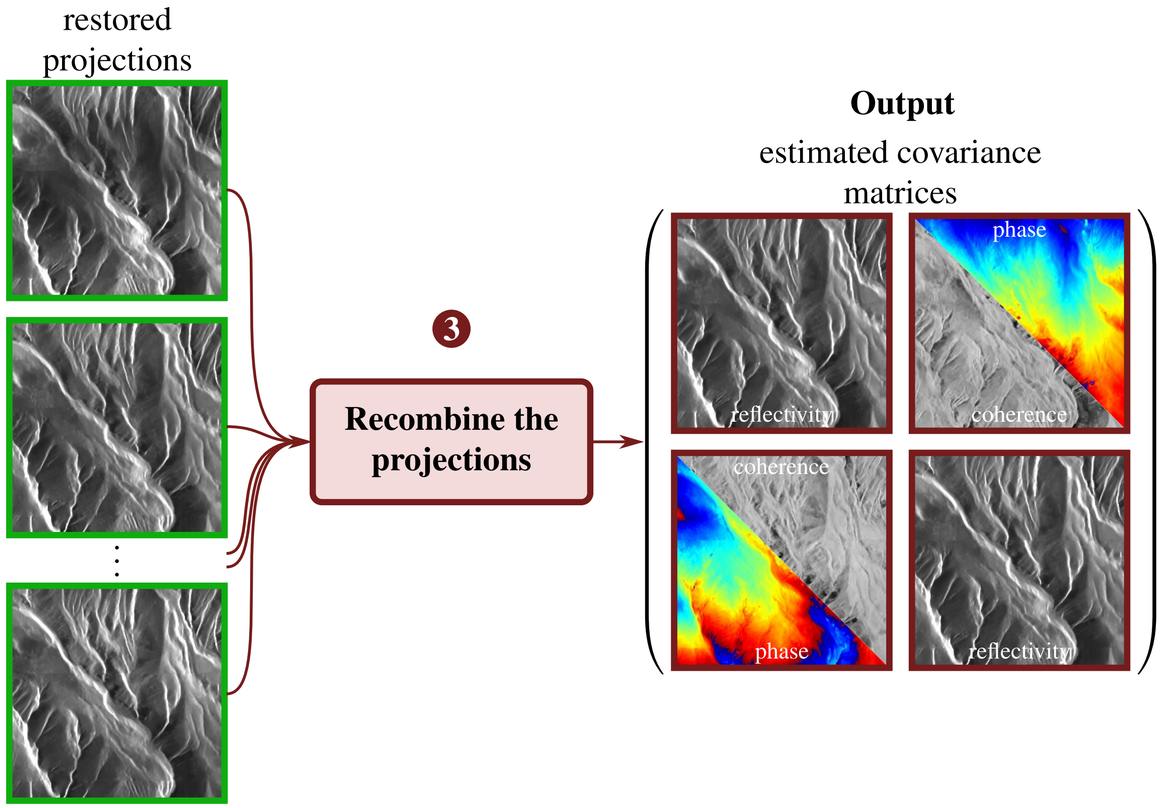
2) Despeckle the single-channel projections z_k:

this gives estimates $\hat{v}_k$ of the projection of the covariance

$$\mathbb{E}[\,|\boldsymbol{p}_k^\dagger z|^2] = \mathbb{E}[\boldsymbol{p}_k^\dagger z z^\dagger \boldsymbol{p}_k] = \boldsymbol{p}_k^\dagger \mathbb{E}[z z^\dagger]\boldsymbol{p}_k = \boldsymbol{p}_k^\dagger \mathbf{C}\boldsymbol{p}_k \equiv \boldsymbol{v}_k$$

A GENERIC APPROACH TO MULTI-CHANNEL DESPECKLING: MUCHAPRO

➤ Proposed approach: **MuChaPro** (**Mu**lti-**Cha**nnel **Pro**jection)

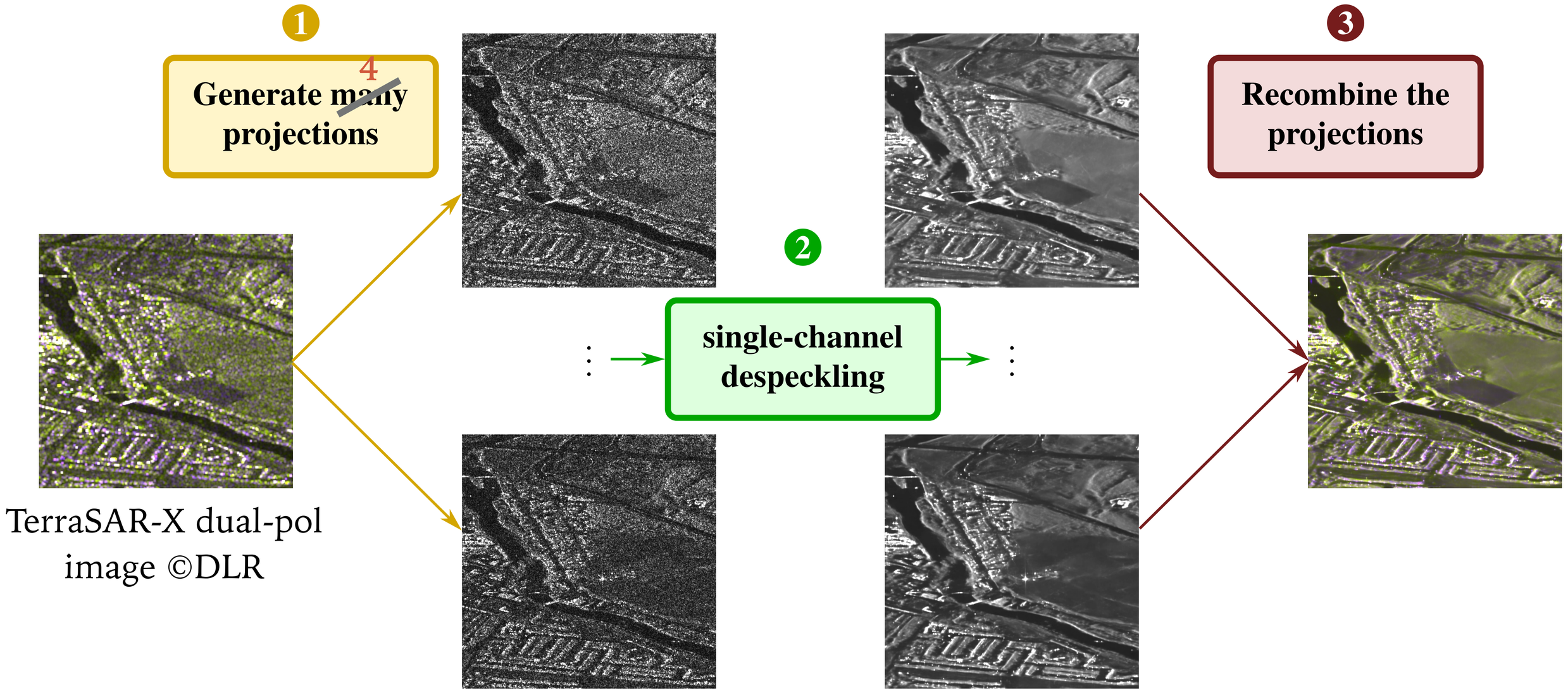


3) Reconstruct the covariance $\widehat{\mathbf{C}}$ by inverting the projections $\widehat{\boldsymbol{v}}_k$:

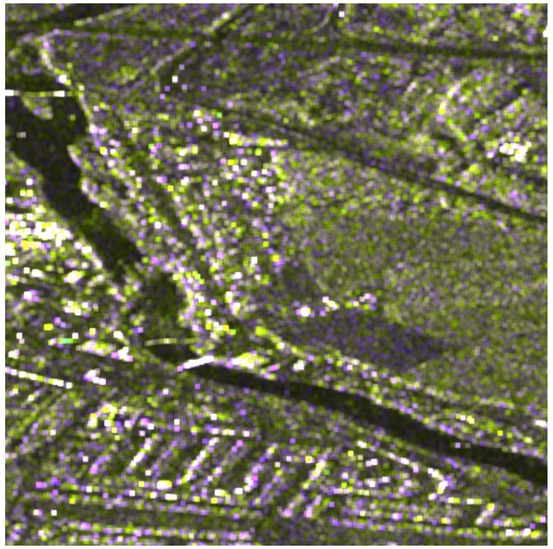
$$\widehat{\mathbf{C}}\,(\text{MuChaPro}) = \arg\min_{\mathbf{C}} \sum_k \left(\boldsymbol{p}_k^\dagger \mathbf{C} \boldsymbol{p}_k - \widehat{\boldsymbol{v}}_k \right)^2$$

(a linear least-squares problem: easy!)

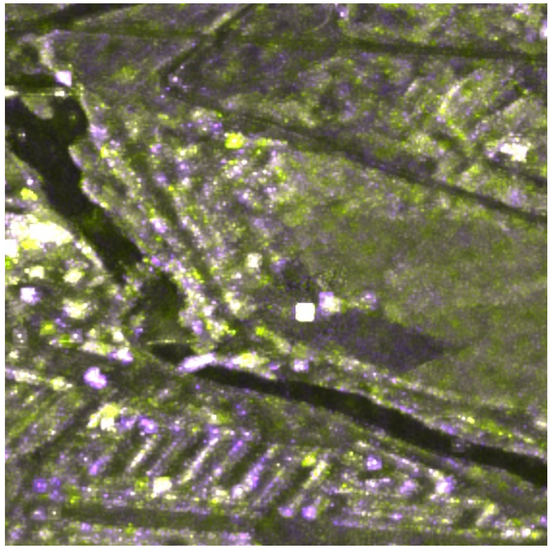
MUCHAPRO: DUAL-POL ILLUSTRATION



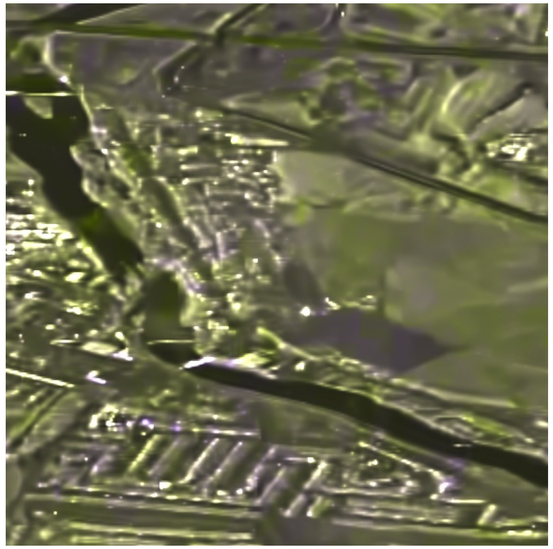
MUCHAPRO: DUAL-POL ILLUSTRATION



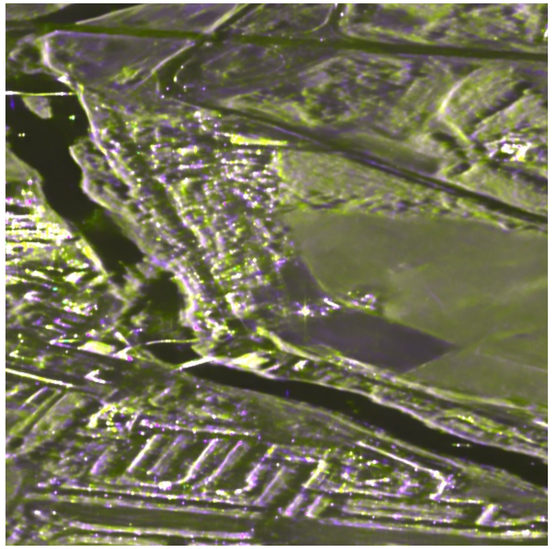
5x5 multilooking



non-local model-free restoration [Aghababaei *et al.* 2021]

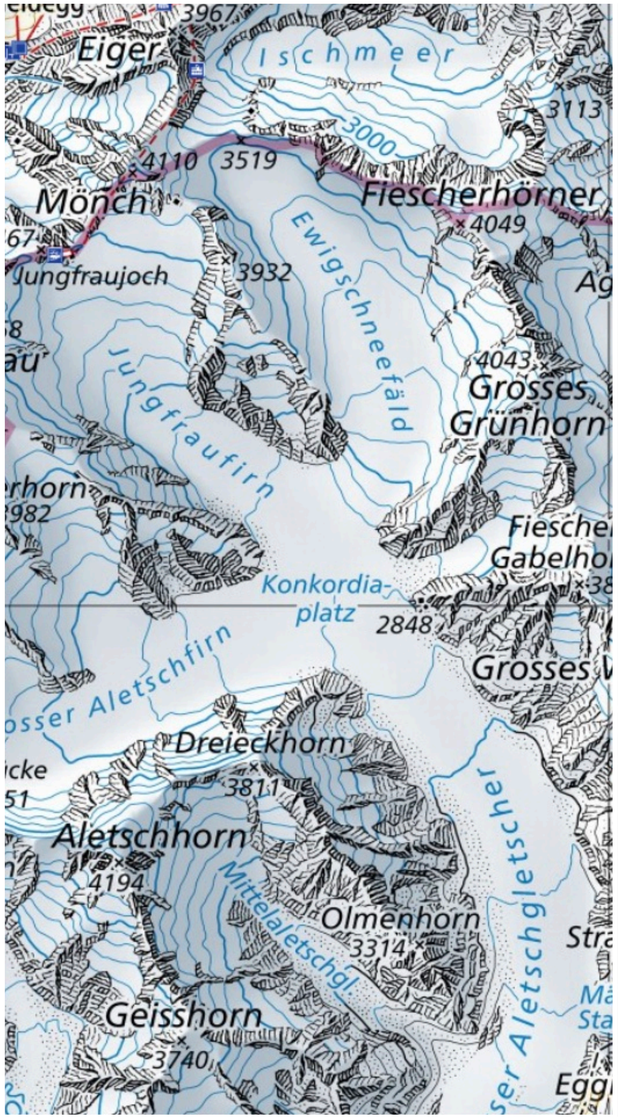


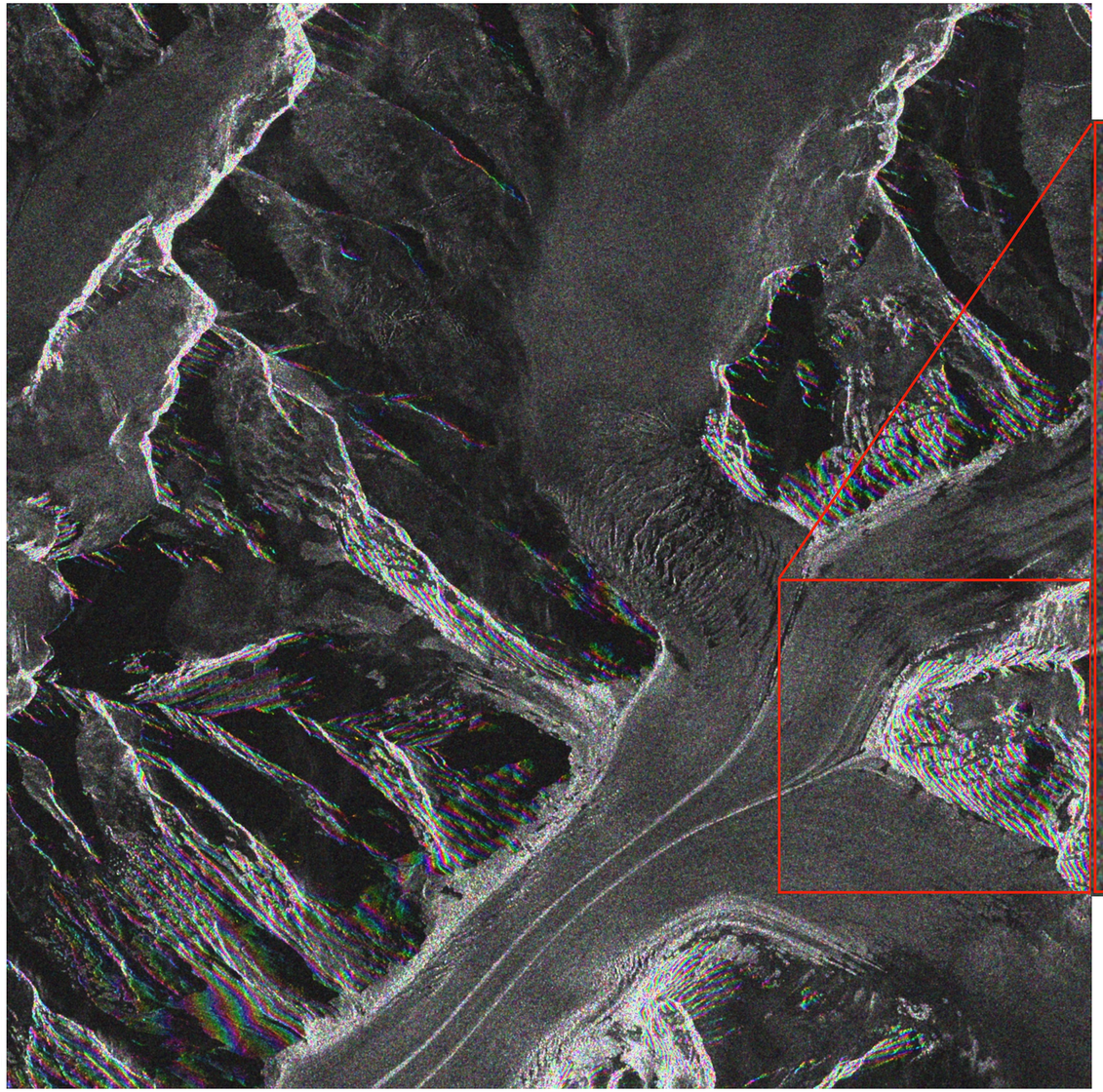
plug-and-play ADMM restoration [Deledalle *et al.* 2017]



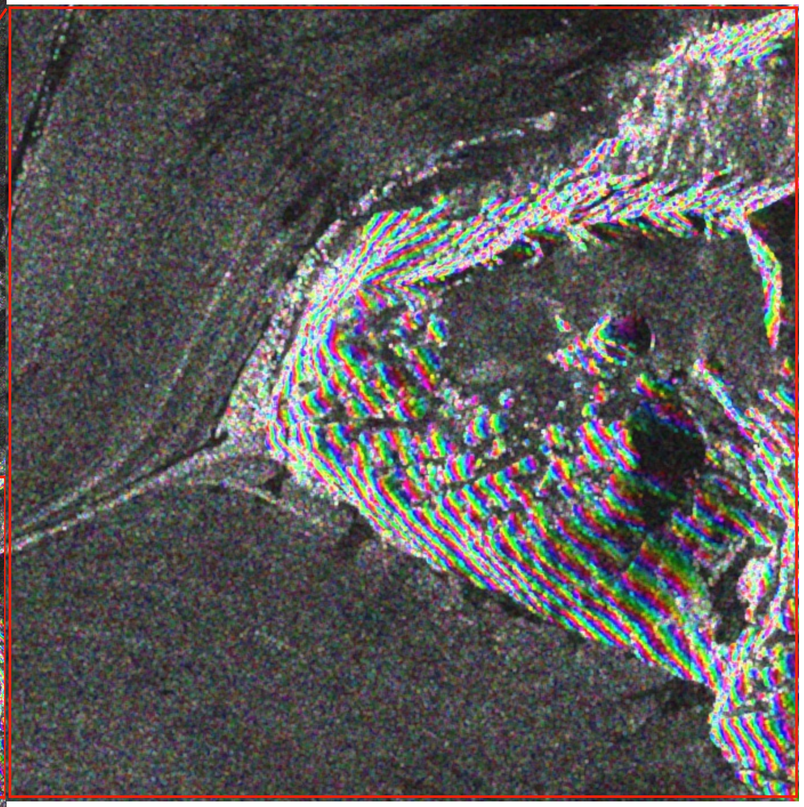
proposed: MuChaPro + MERLIN

MUCHAPRO: INSAR ILLUSTRATION



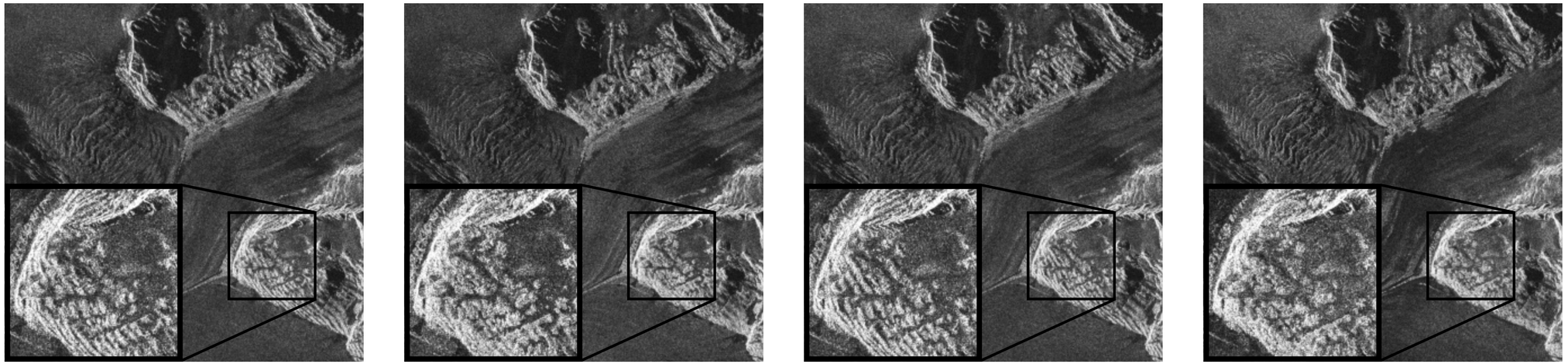


TerraSAR-X interferogram © DLR
July 4, 2020 and July 15, 2020

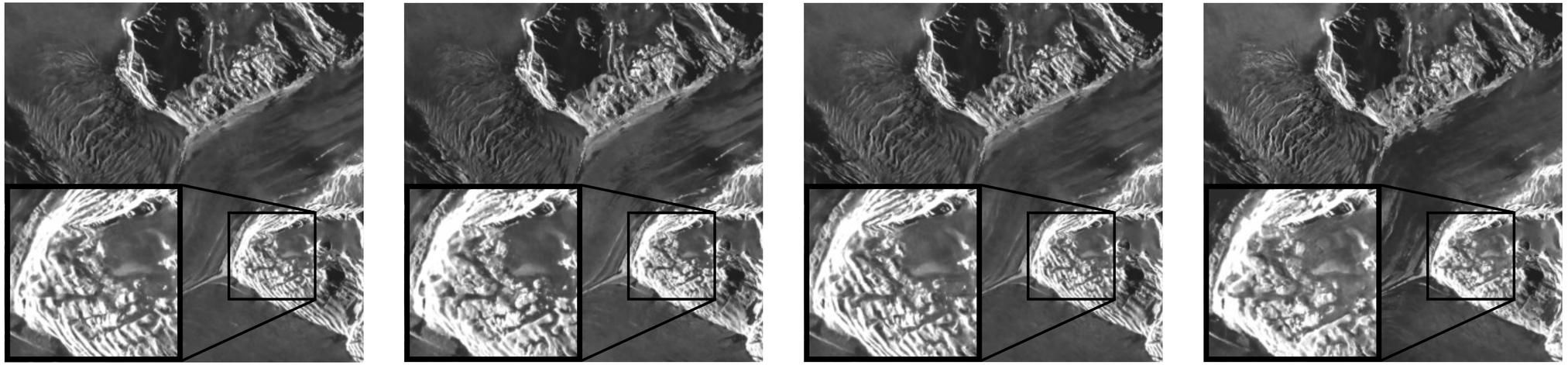


hue: interferometric phase
saturation: coherence
value: reflectivity

MUCHAPRO: INSAR ILLUSTRATION

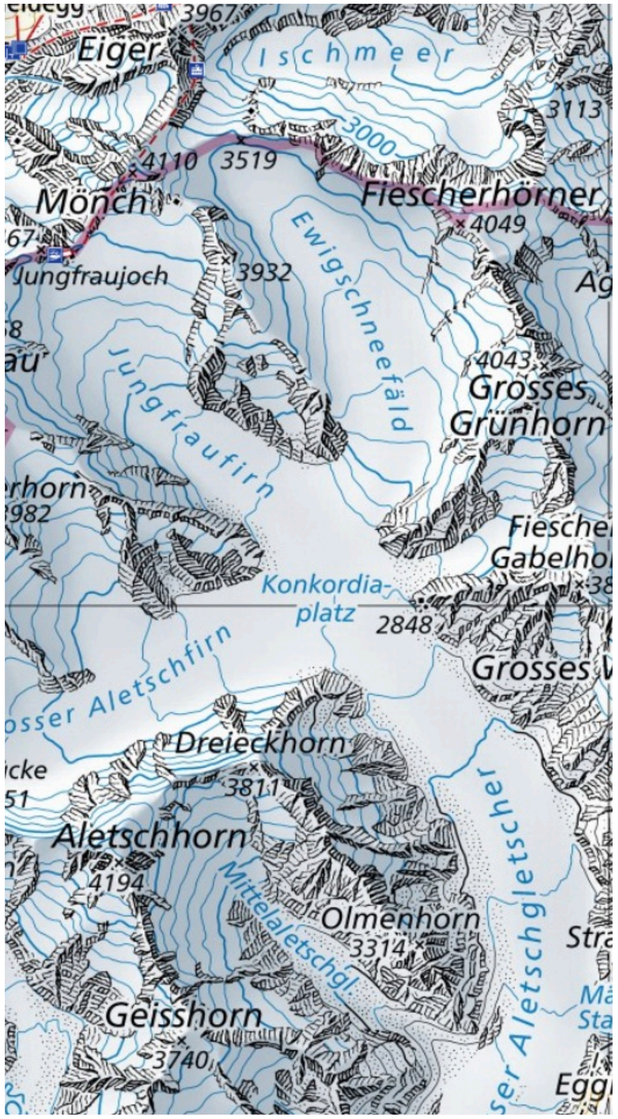


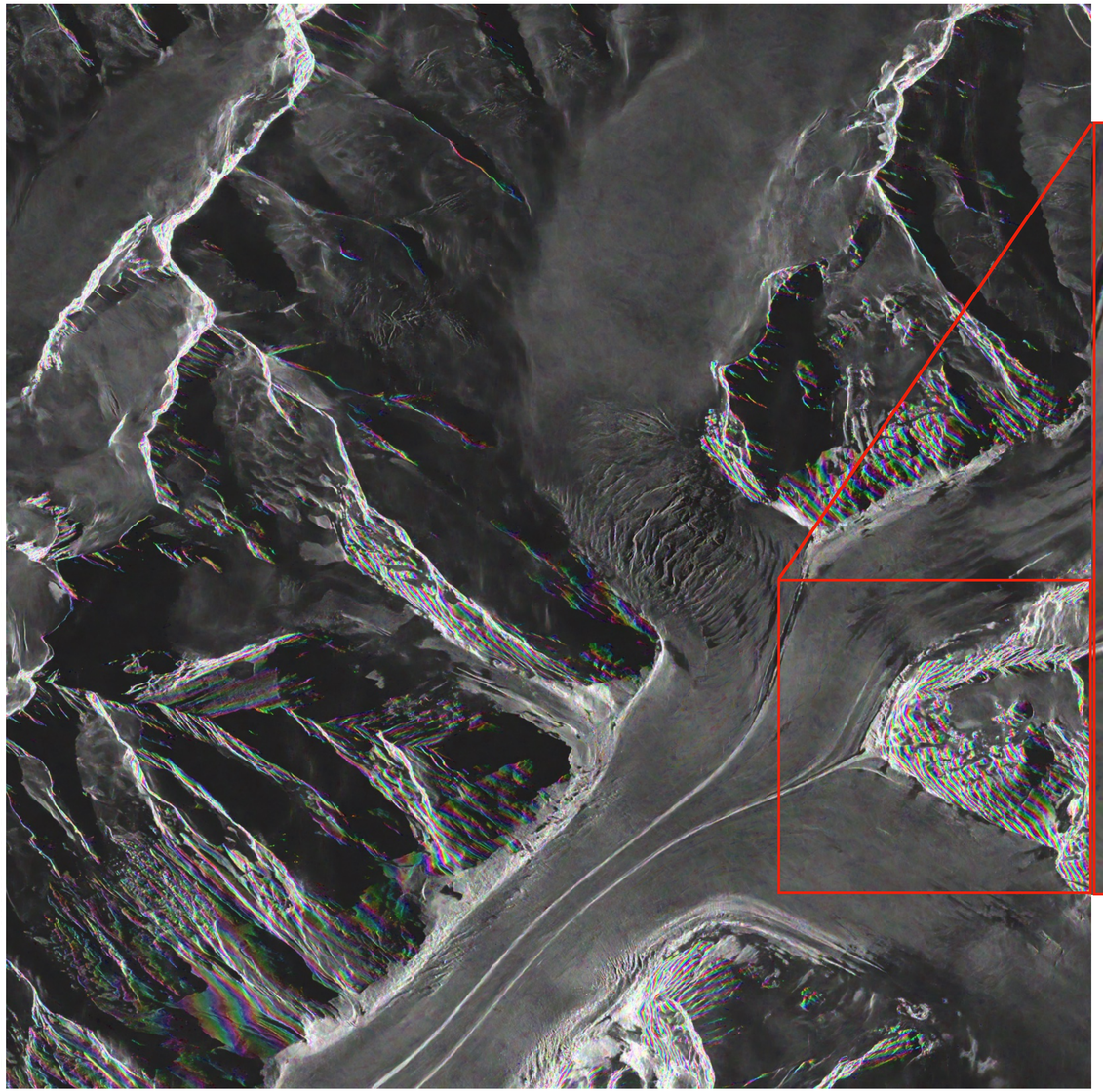
(a) amplitude of the 4 SLC projections produced by MuChaPro



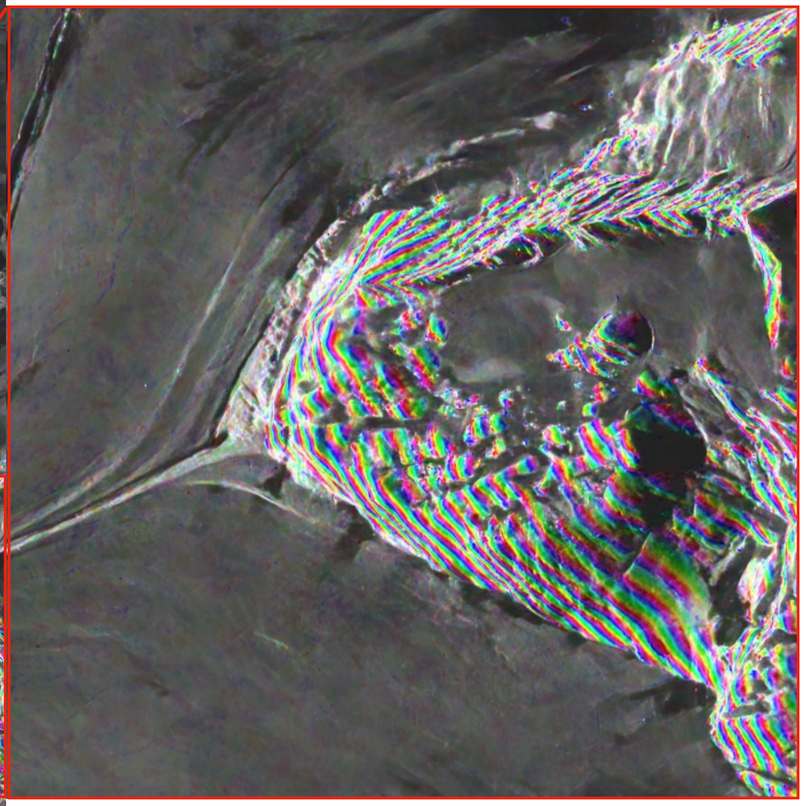
(b) corresponding despeckled projections (obtained with MERLIN)

MUCHAPRO: INSAR ILLUSTRATION



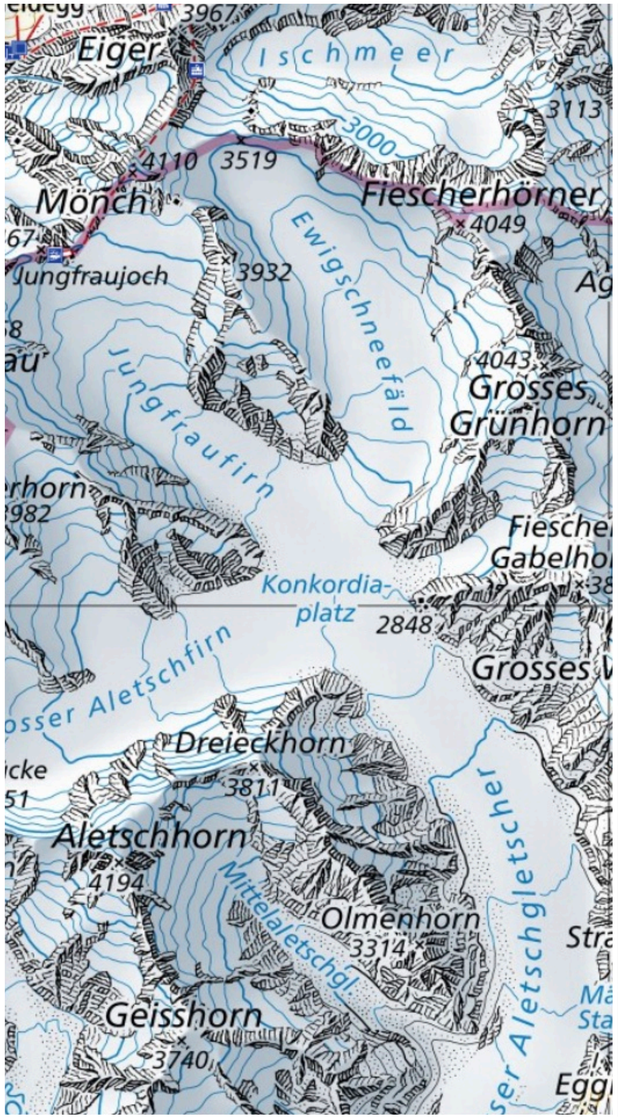


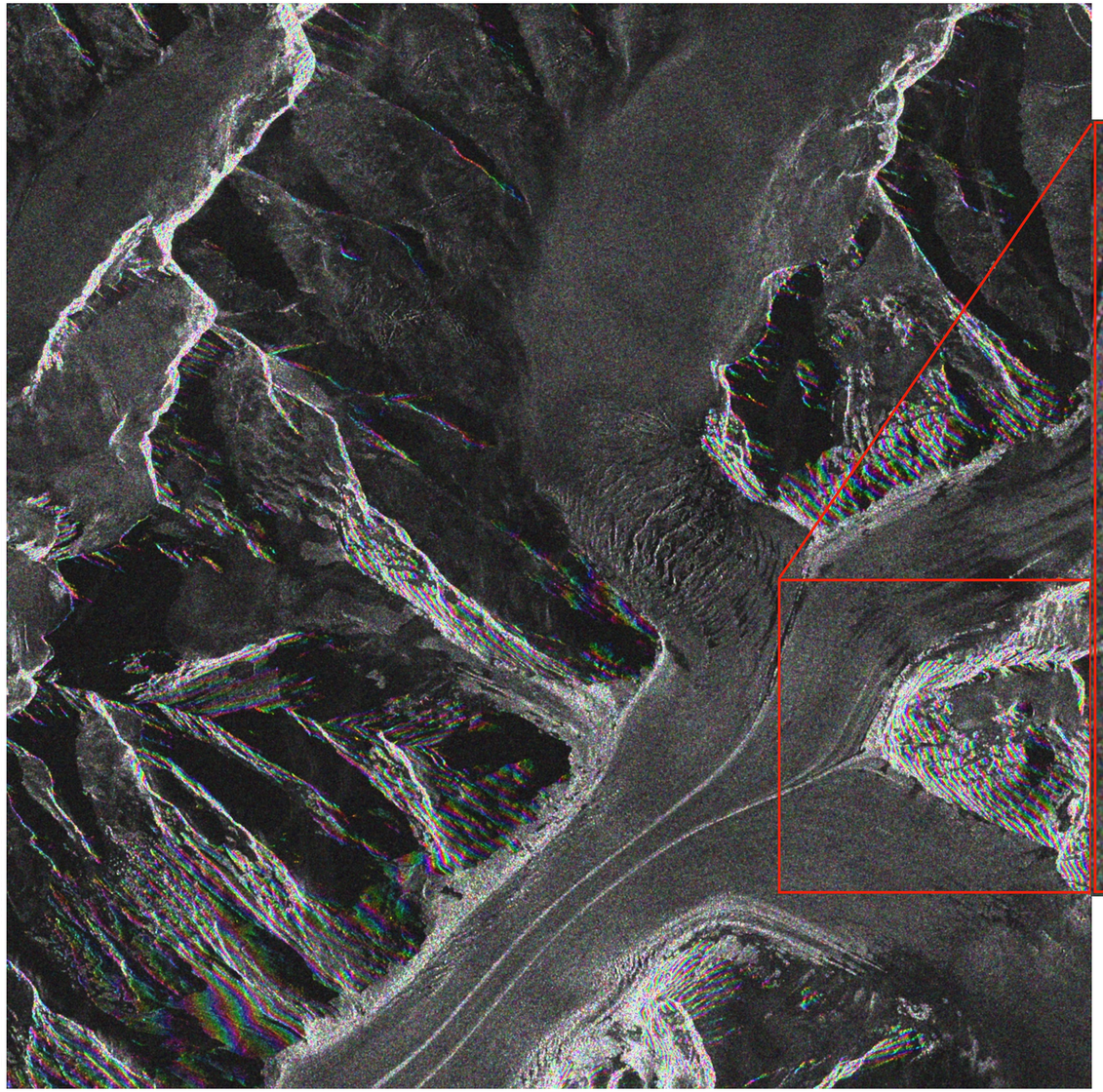
TerraSAR-X interferogram © DLR
July 4, 2020 and July 15, 2020



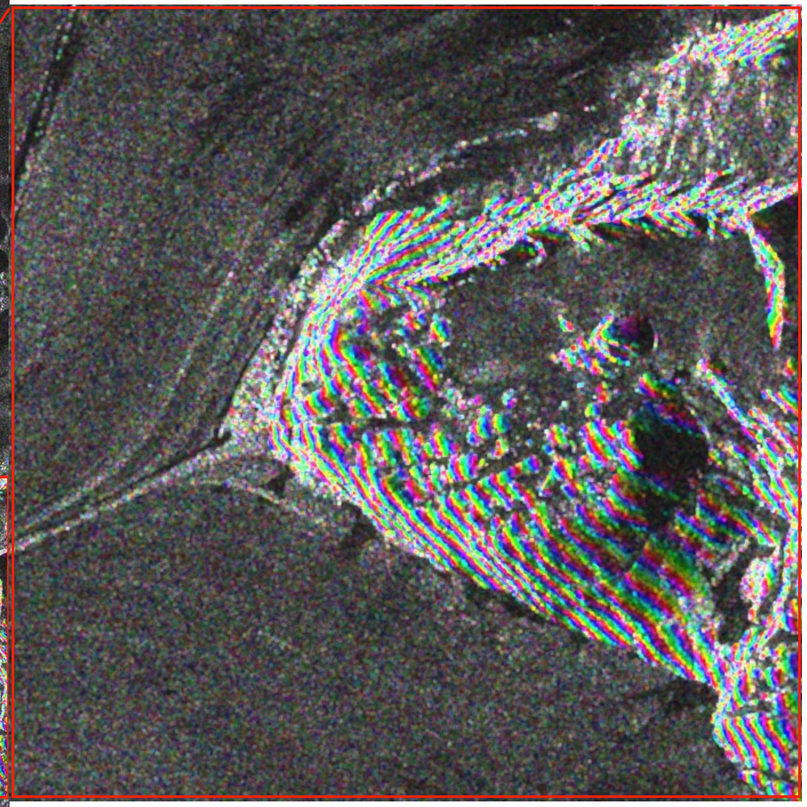
hue: interferometric phase
saturation: coherence
value: reflectivity

MUCHAPRO: INSAR ILLUSTRATION



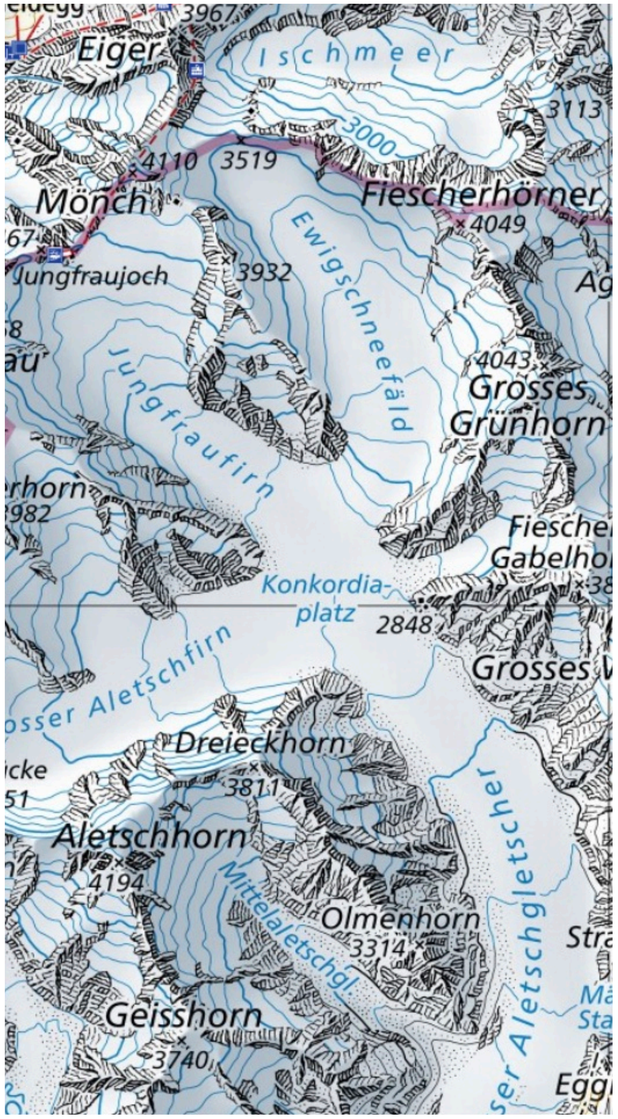


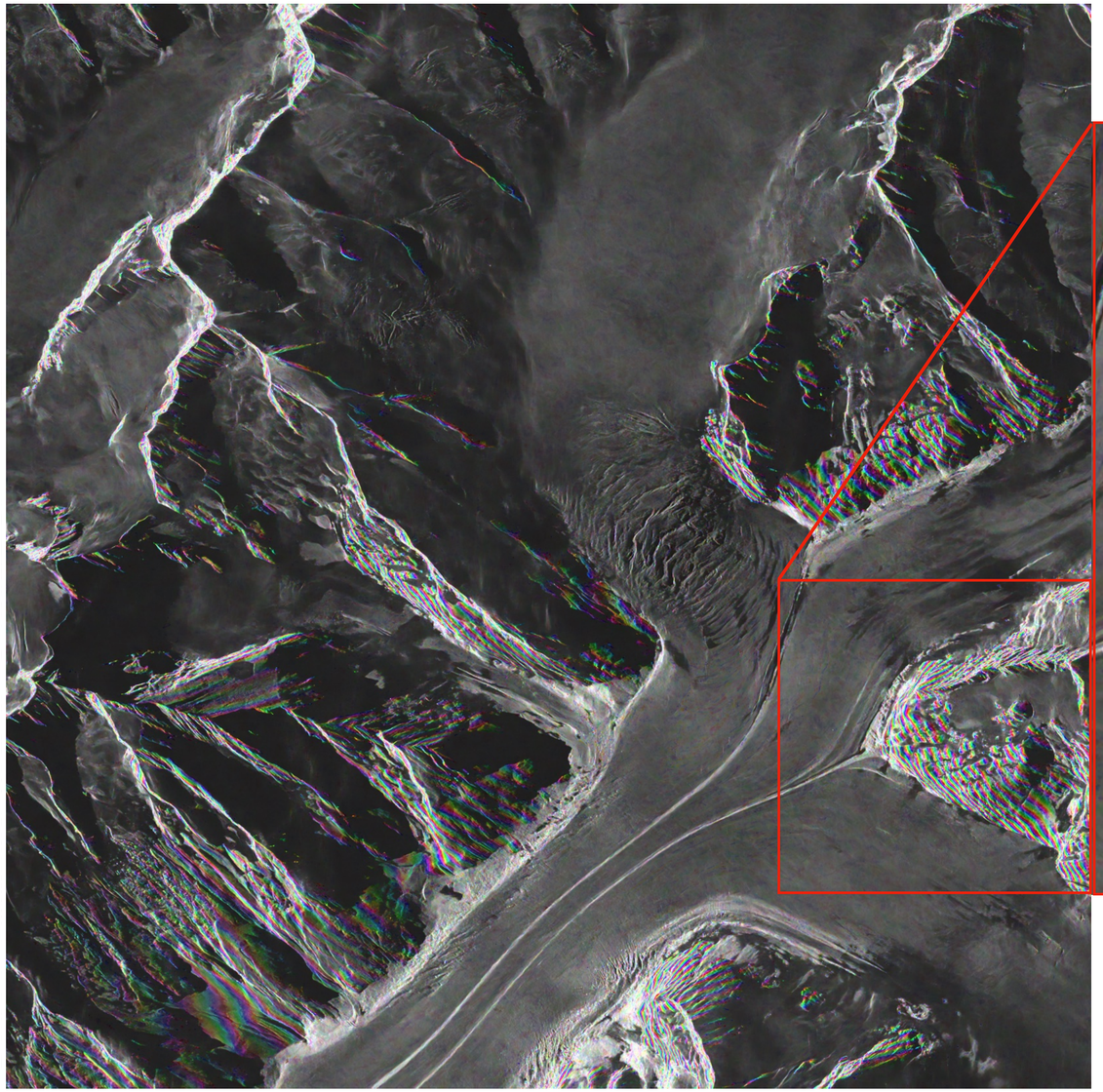
TerraSAR-X interferogram © DLR
July 4, 2020 and July 15, 2020

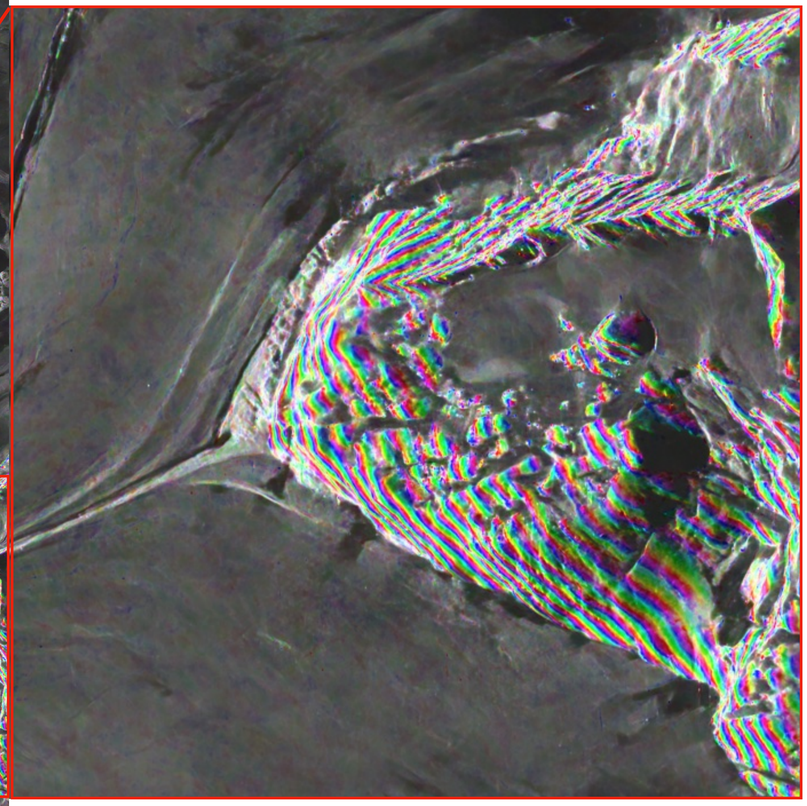


hue: interferometric phase
saturation: coherence
value: reflectivity

MUCHAPRO: INSAR ILLUSTRATION



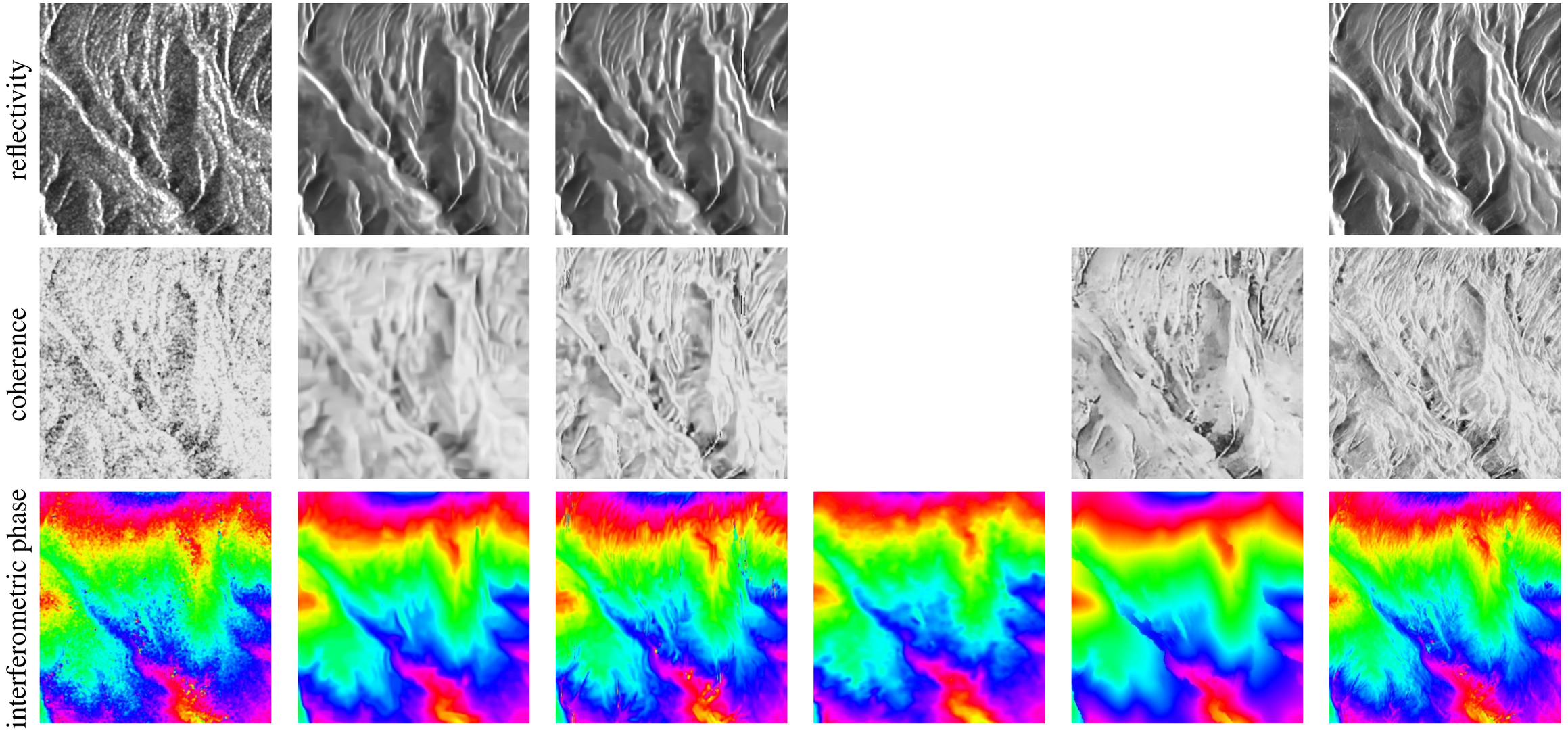




TerraSAR-X interferogram © DLR
July 4, 2020 and July 15, 2020

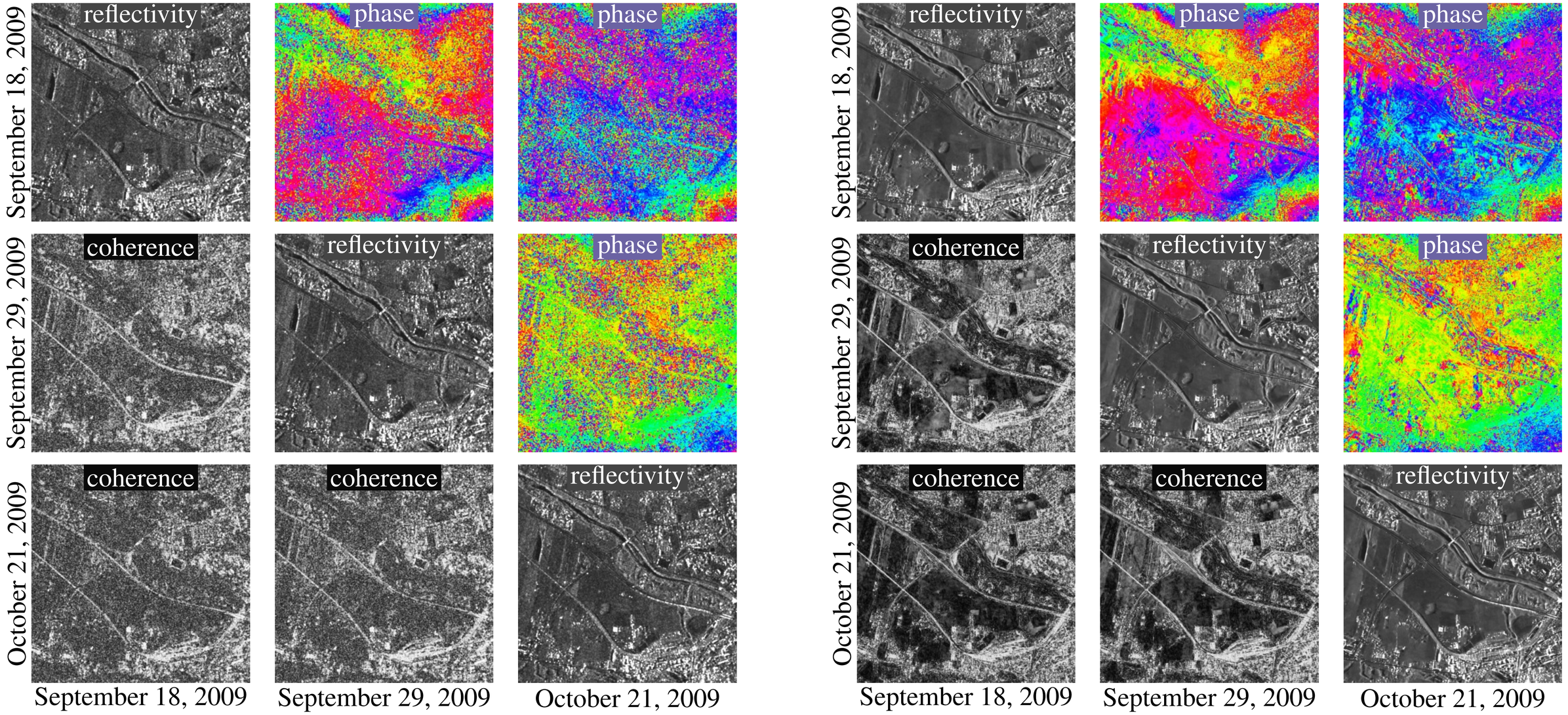
hue: interferometric phase
saturation: coherence
value: reflectivity

MUCHAPRO: ANOTHER INSAR ILLUSTRATION (TERRASAR-X, COLORADO)



(a) 5×5 multilook (b) MuLoG BM3D (joint processing) (c) MuChaPro with MuLoG BM3D (d) InSAR-MONET (e) Φ-NET (f) **MuChaPro with MERLIN**

MUCHAPRO: INSAR ILLUSTRATION WITH 3 DATES



(a) 5×5 multilook

(b) **MuChaPro with MERLIN**

CONCLUDING WORDS

Pairs of images… or… real/imaginary decompositions… can be used to **learn**!

