AI4SAR

Artificial Intelligence for Advanced SAR Processing

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EODC: Dragana Milinkovic, Senmao Cao, Christian Briese
JR: Karlheinz Gutjahr, Sead Mustafic, Katharina Hofer-Schmitz, Ana Gregorac
TUW: Anice Jahanjoo, Maximilian Thiessen, Thomas Gärtner
Airbus: Wolfgang Koppe, Tatjana Bürgmann, Anna-Lena Erdmann

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Project objectives

1 Develop an advanced pre-processing of SAR data based on AI to reduce the speckle effect.

2 Concept utilisation to filter the complex-value SAR data for advanced interferometry.

3 Develop sub-pixel SAR-to-optical matching techniques based on AI resp. ML methods.

To **demonstrate** the usability and to **validate** the products via UCs:

UC validators

1. **Data Cube ingestion** to facilitate distribution of the data.
2. **Forest monitoring** to demonstrate the novel SAR pre-processing.
3. **Deformation monitoring** based on advanced phase and coherence estimation.
4. **GCP transfer** from SAR to optical images.

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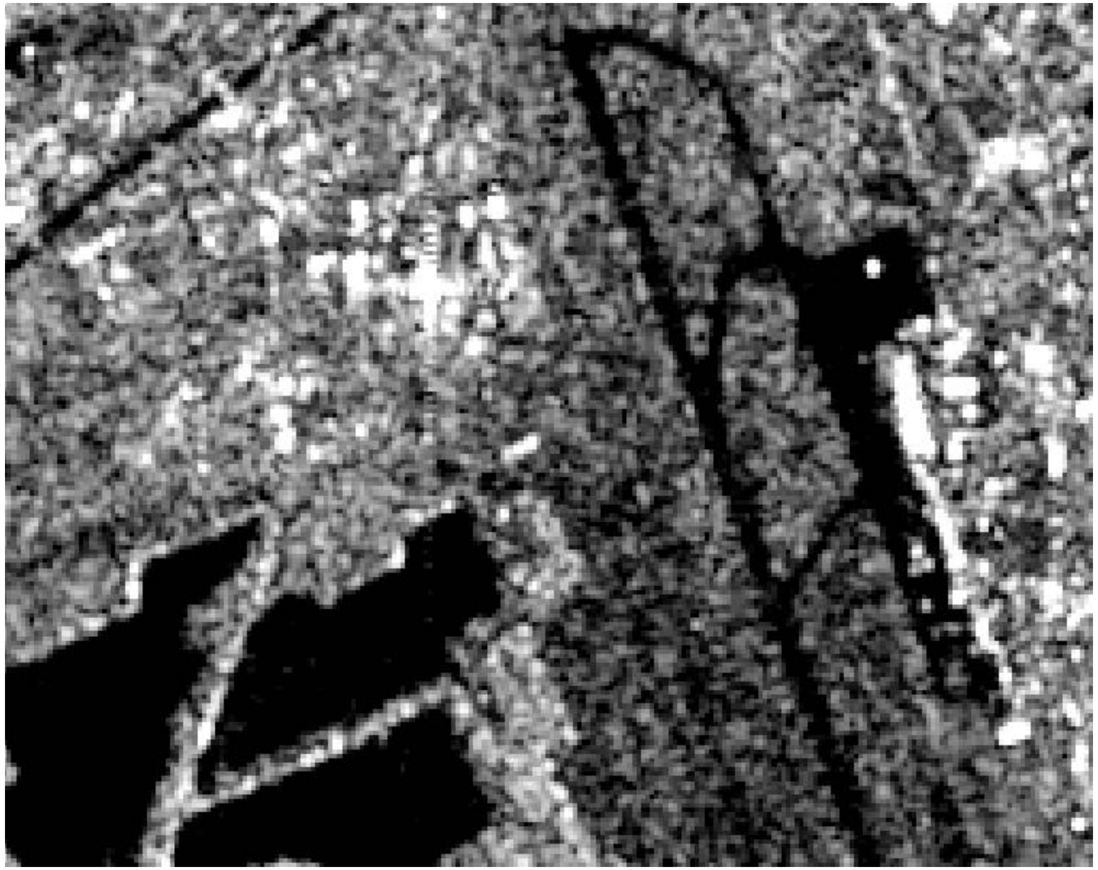
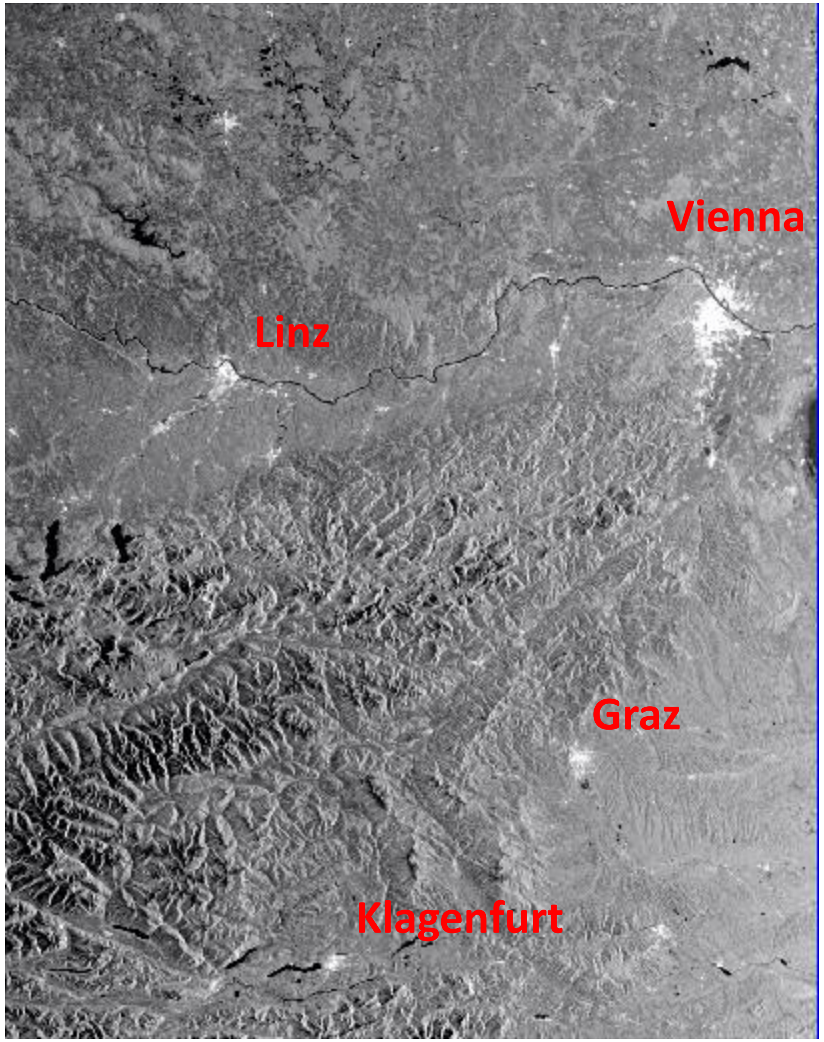
Speckle

- Arises from local constructive or destructive interference
- Inherent property of any SAR image
- Homogeneous areas appear „noisy“



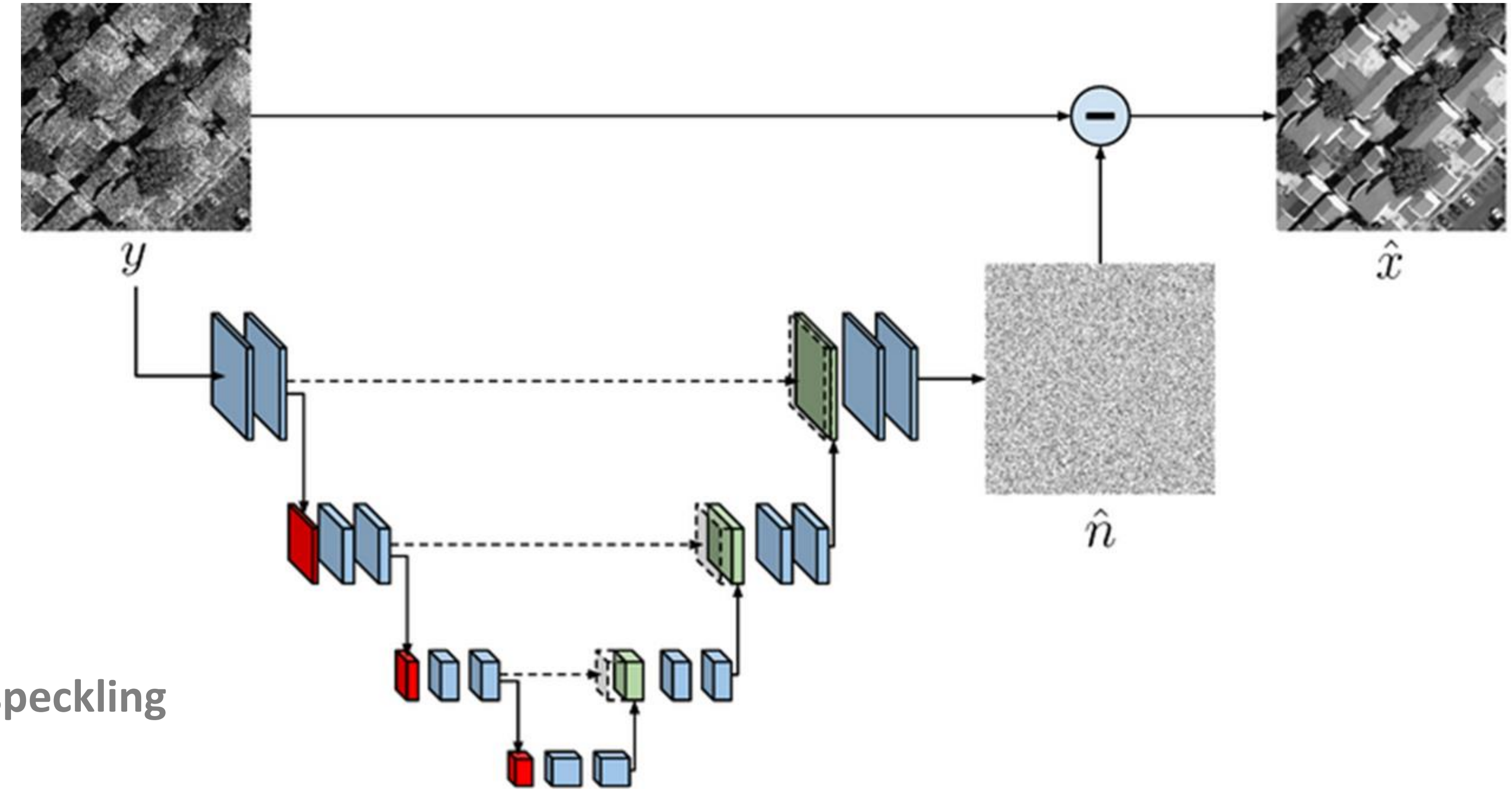
Despeckling of S1-GRD Products

- Noisy dataset used:
  - 75 acquisitions [03.01.2021 - 15.06.2022]
  - Descending orbit 022 and VV polarization
- Pre-processing:
  - Co-registration
  - Radiometric correction to beta naugt [dB]
- Reference dataset:
  - Multi-temporal mean
  - Image size: ~ 249 x 318 km^2



Despeckling Using Neural Network

- **U-Net** NN adaptions for SAR despeckling
  - Learn noise

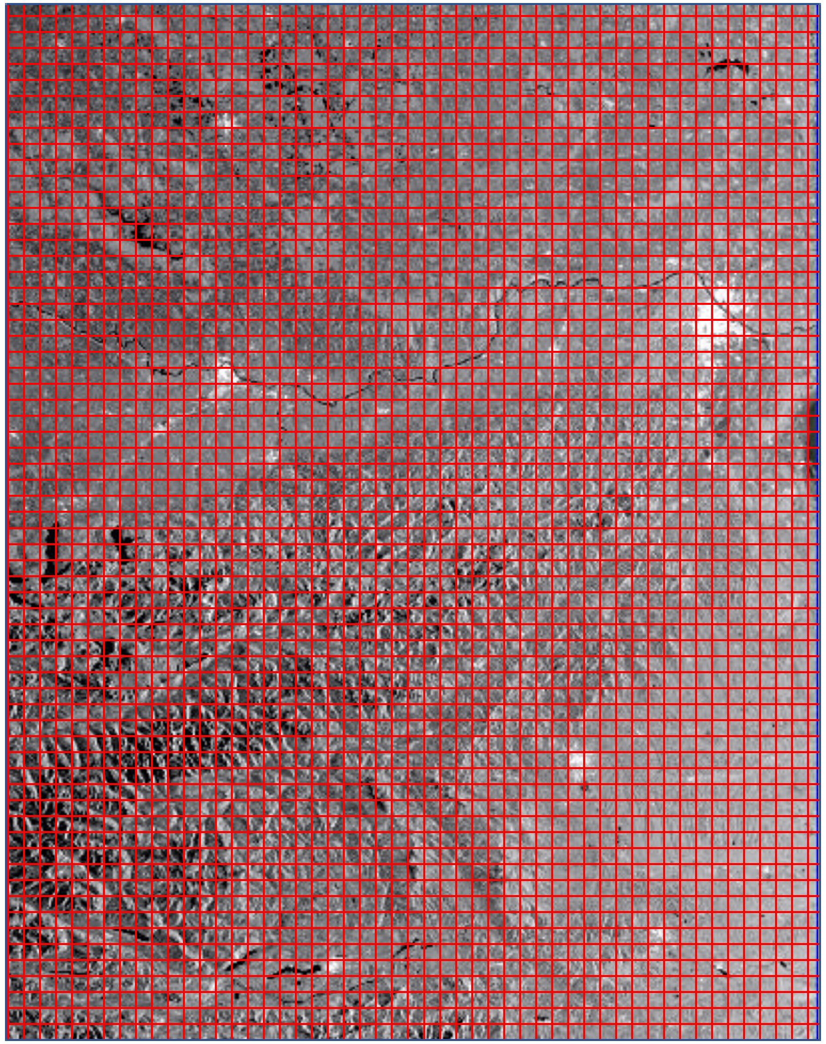


Lattari et al., 2019
Deep Learning for SAR Image Despeckling
Remote Sensing , Vol. 11, No. 13

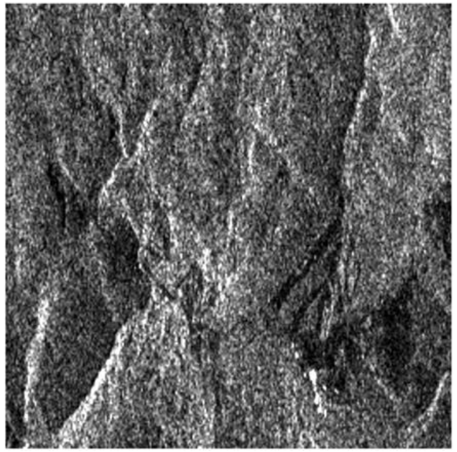
Preparation and Training

- Tiling of
  large input images to
  small tiles (348 x 348)
  ~11.000 tiles in total

- Reduction of dB range to
  [0,1] interval



Tiles: 348 x 348 Pixel



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Experiments

- Training of UNET
  - 1 epoch (first and max.)
  - 3 epochs close in time (summer season)
  - 6 epochs regularly distributed over the year

- For comparison
  - „Classical“ Lee Filter [1]
  - SAR-CNN [2] (work in progress)
  - SAR2SAR [3]

[1] Lee, 1980
Digital Image Enhancement and Noise Filtering by Use of Local Statistics
IEEE Transactions on Pattern Analysis and Machine Intelligence , Vol. 2, No. 2

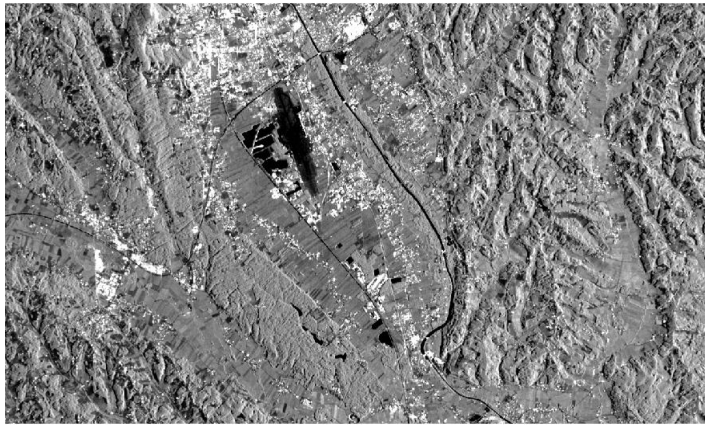
[2] Chierchia et al., 2017
SAR image despeckling through convolutional neural networks
IEEE international geoscience and remote sensing symposium (IGARSS)

[3] Dalsasso et al., 2021
SAR2SAR: A Semi-Supervised Despeckling Algorithm for SAR Images
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing , Vol. 14

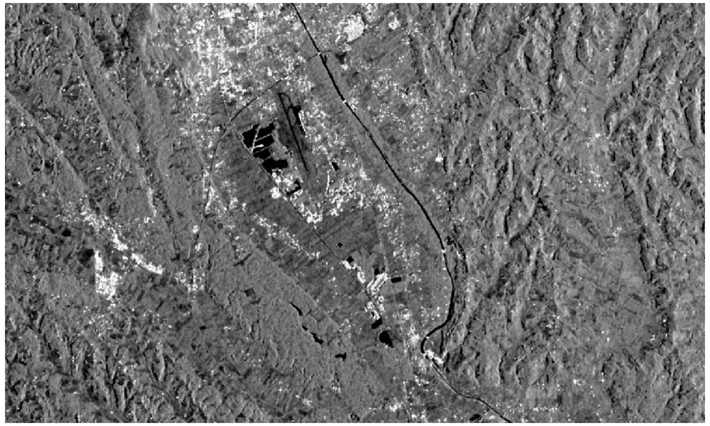
First Results

2021-01-03

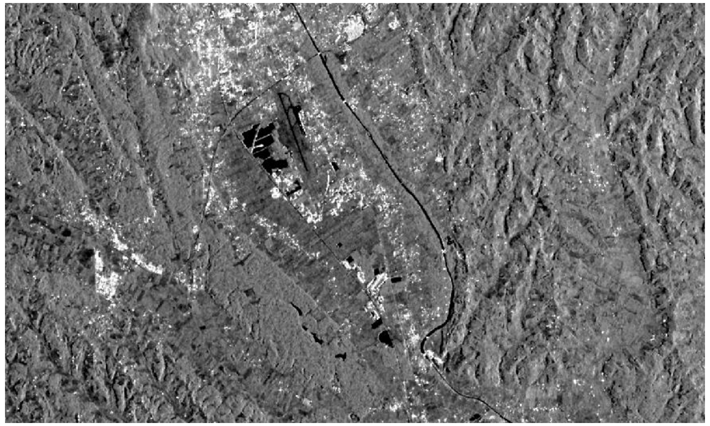
Lee



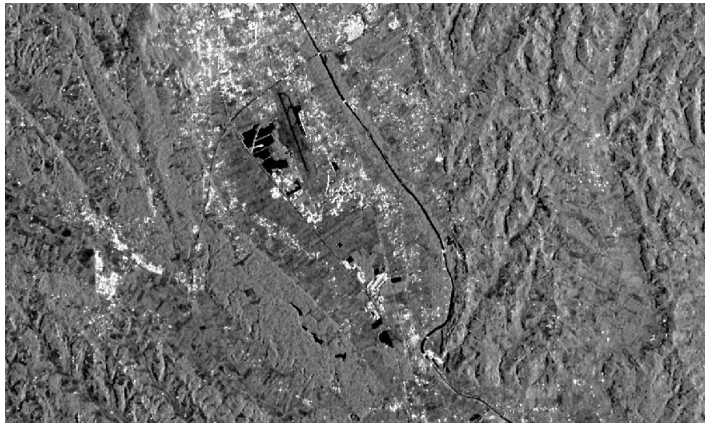
Multi-temporal Mean



Training with 1 epoch

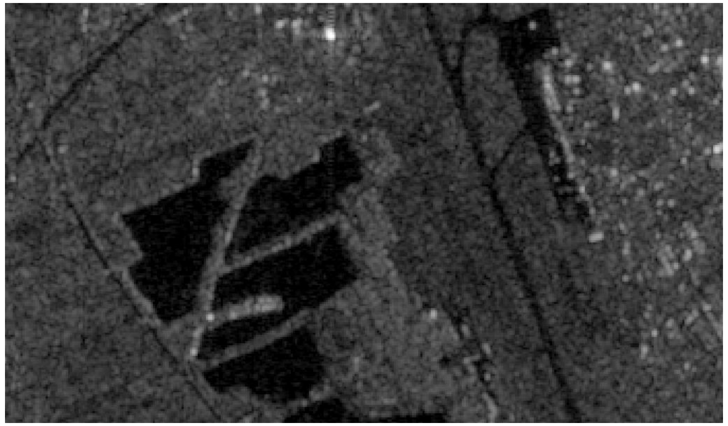


Training with 3 epochs

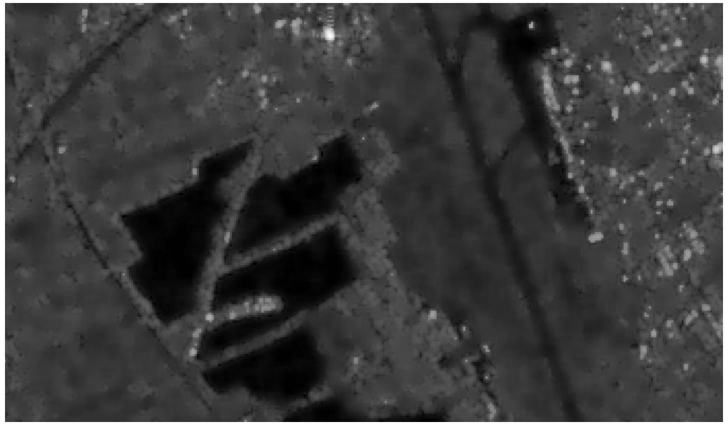


Training with 6 epochs

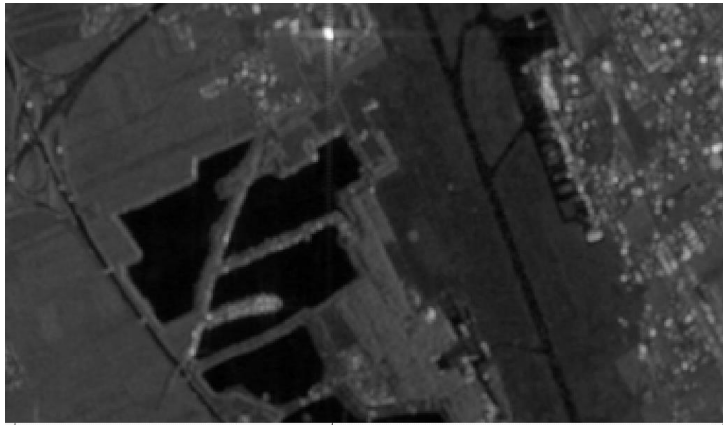
First Results (Zoom-In)



2021-01-03



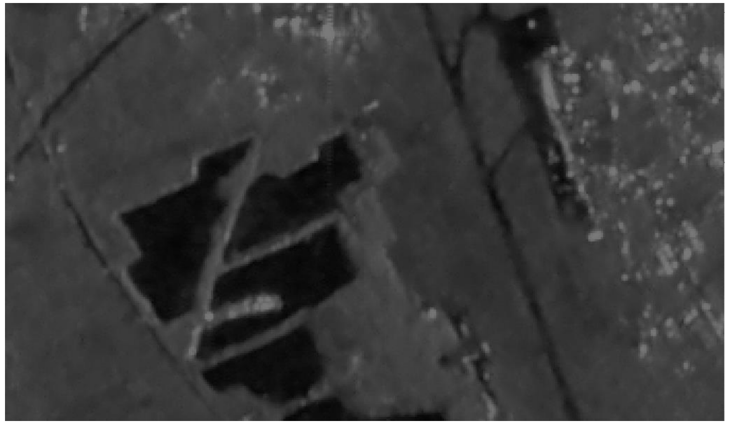
Lee



Multi-temporal Mean

Training with 1 epoch

Training with 3 epochs



Training with 6 epochs

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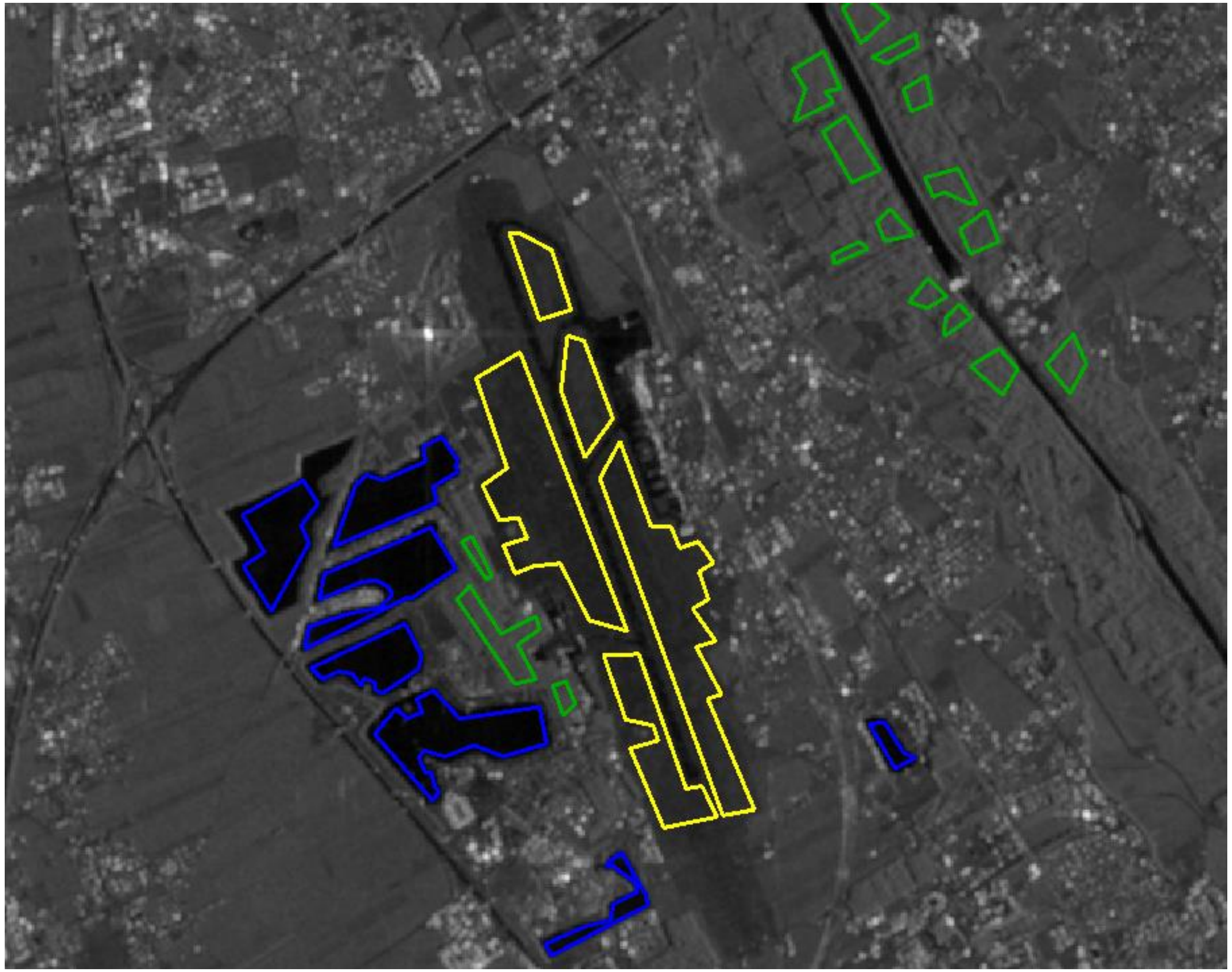
Validation

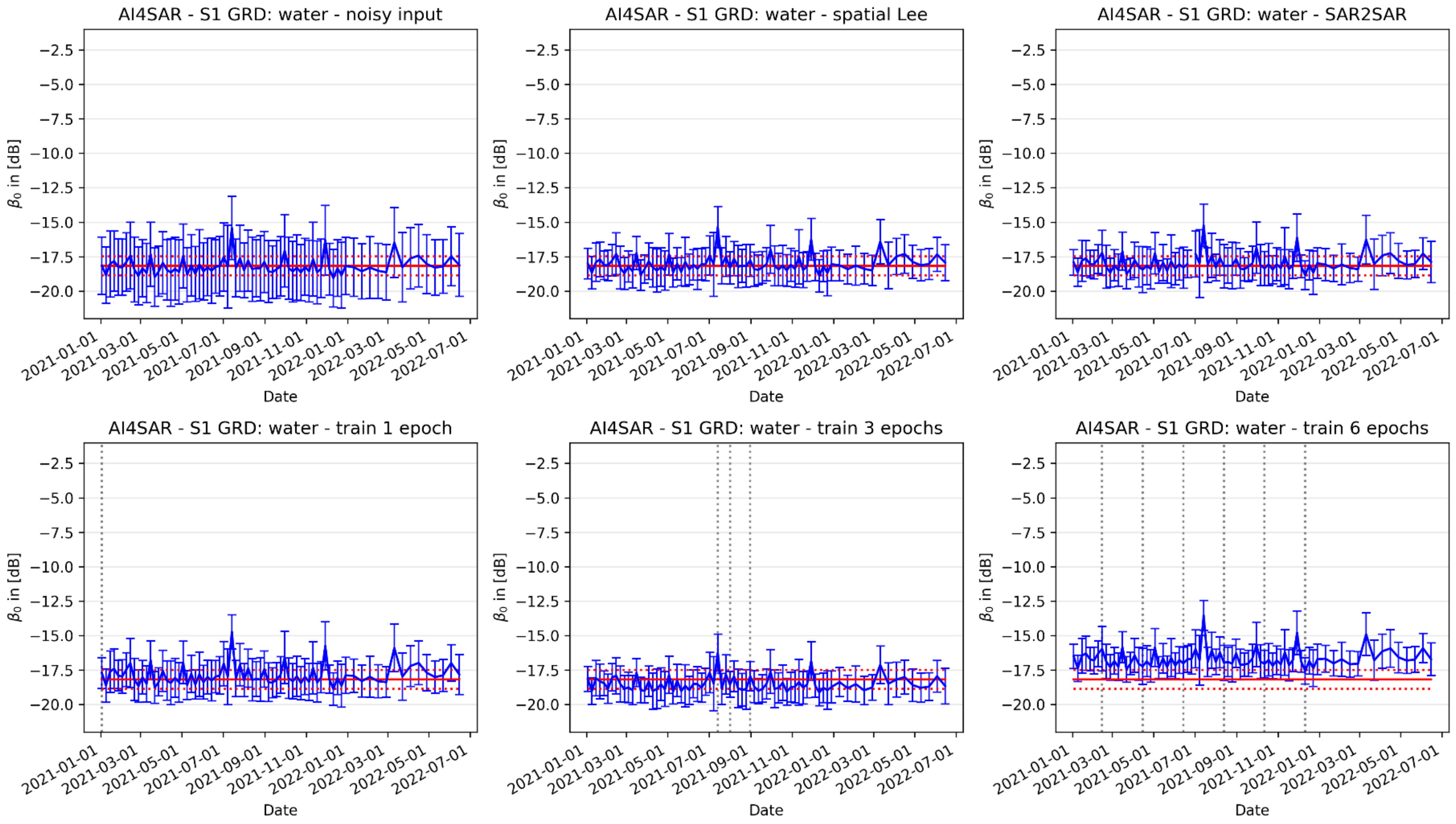
Manually selected classes:

1. Permanent water (blue)
2. Forest (green)
3. Meadow (yellow)

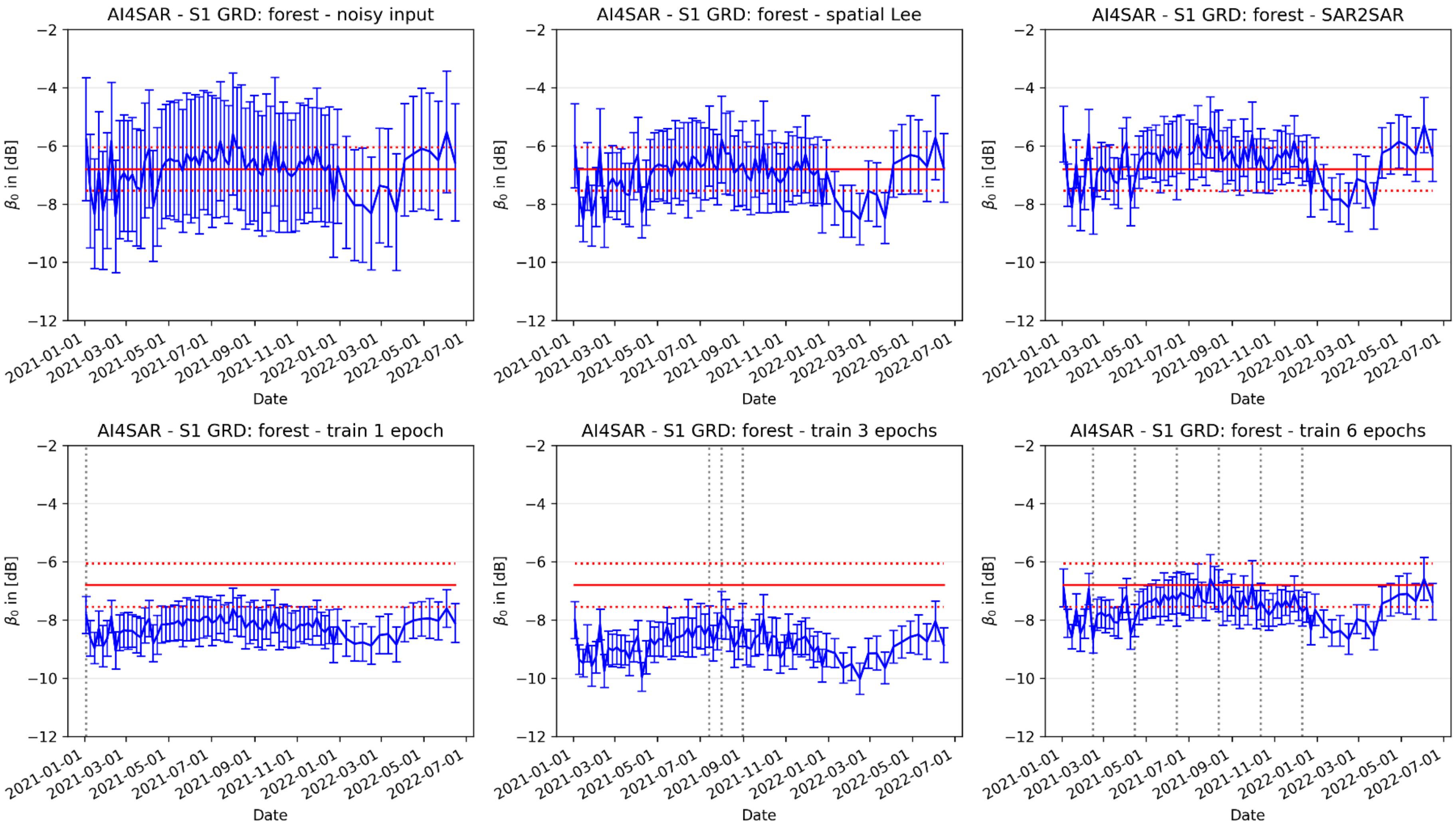
Evaluate mean and std dev per class and epoch



Validation: Water



Validation: Forest



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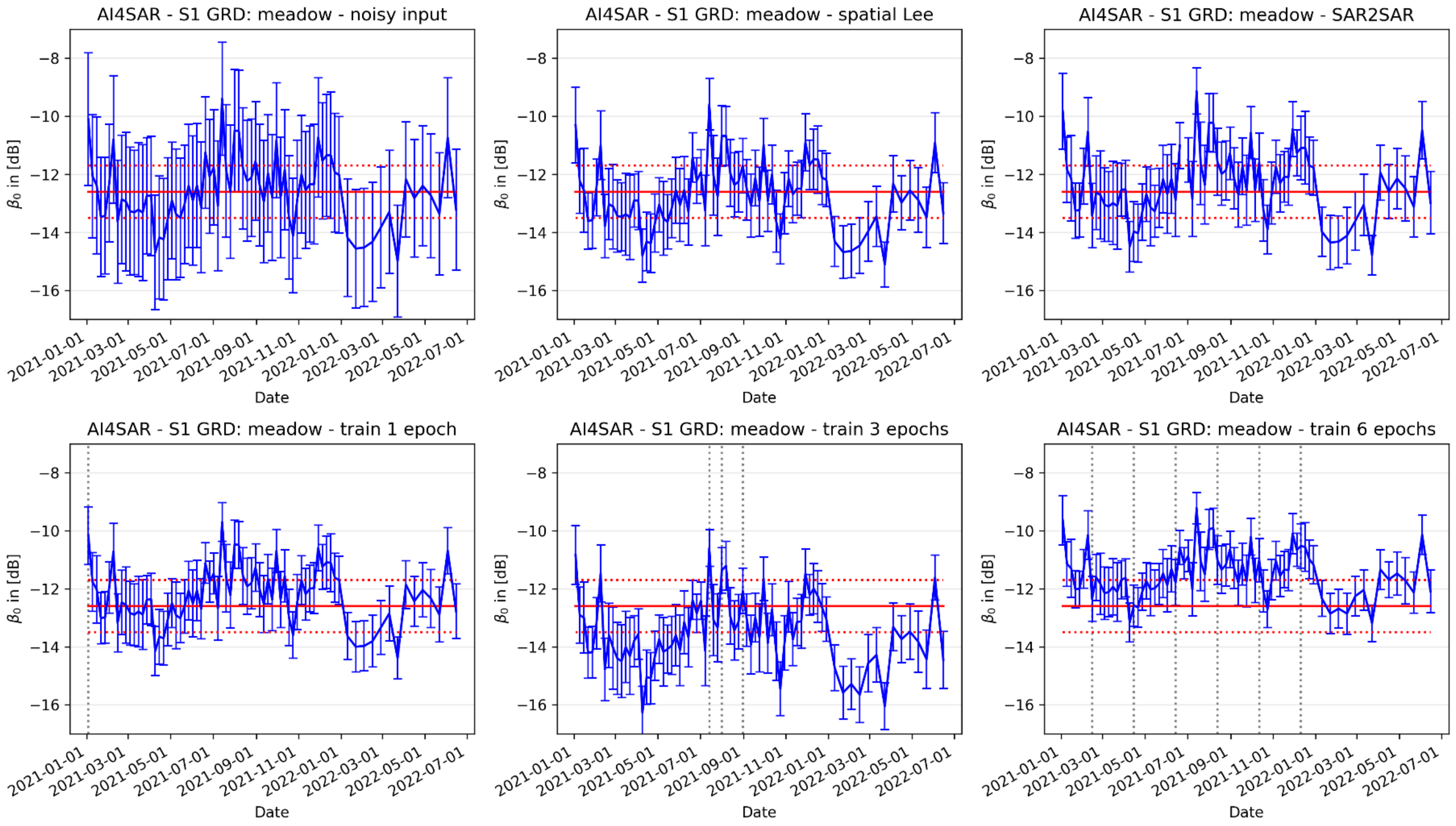
Validation: Meadows



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Validation: Summary

	Permanent Water		Forest		Meadow	
	Avg. Mean	Avg. Std Dev	Avg. Mean	Avg. Std Dev	Avg. Mean	Avg. Std Dev
Noisy Input	-18.17 dB	2.21 dB	-6.80 dB	2.03 dB	-12.60 dB	2.10 dB
MT Mean	-18.17 dB	0.69 dB	-6.80 dB	0.74 dB	-12.60 dB	0.90 dB
Lee	**-18.03 dB**	1.30 dB	**-6.99 dB**	1.19 dB	**-12.75 dB**	1.05 dB
SAR2SAR	-17.96 dB	1.31 dB	-6.58 dB	0.90 dB	-12.37 dB	1.06 dB
Training 1	-17.86 dB	1.36 dB	-8.24 dB	0.65 dB	-12.24 dB	0.93 dB
Training 1 m	-18.89 dB	1.24 dB	-8.34 dB	0.80 dB	-13.66 dB	1.11 dB
Training 3	-18.50 dB	1.17 dB	-8.81 dB	0.61 dB	-13.52 dB	0.95 dB
Training 6	-16.67 dB	**1.12 dB**	-7.56 dB	**0.60 dB**	-11.51 dB	**0.74 dB**

Bauer-Marschallinger et al., 2021
The normalised Sentinel-1 Global Backscatter Model, mapping Earth's land surface with C-band microwaves
Sci Data, Vol. 8, No. 277

Perm. water bodies: −18.85 +/- 2.53 dB
Closed forest, mixed: −9.84 +/- 1.18 dB
Herbaceous vegetation: −13.71 +/- 3.06 dB

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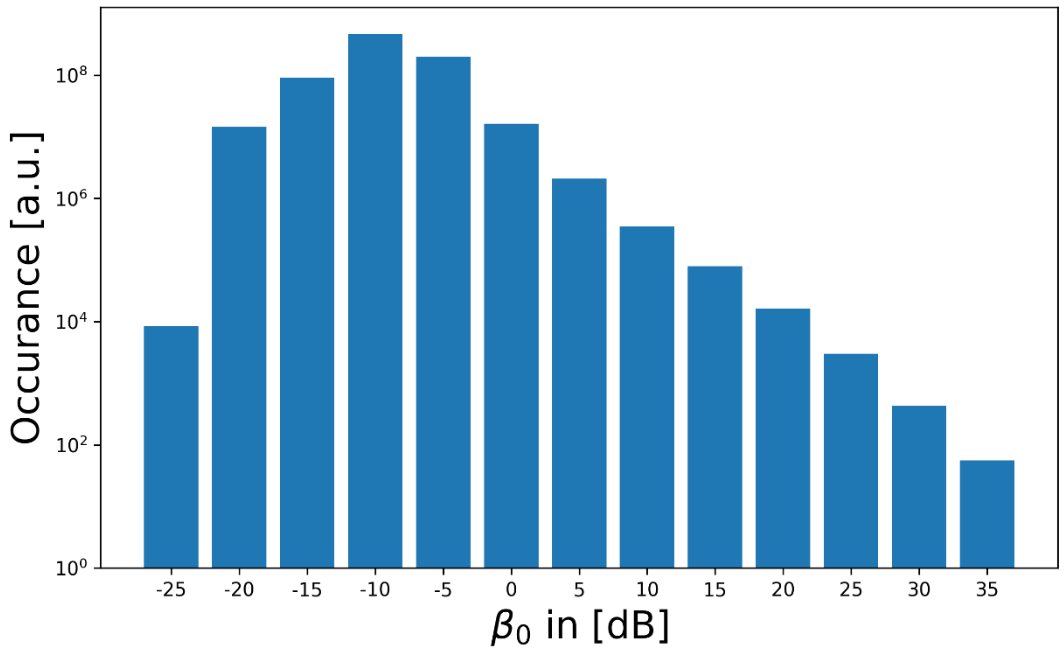
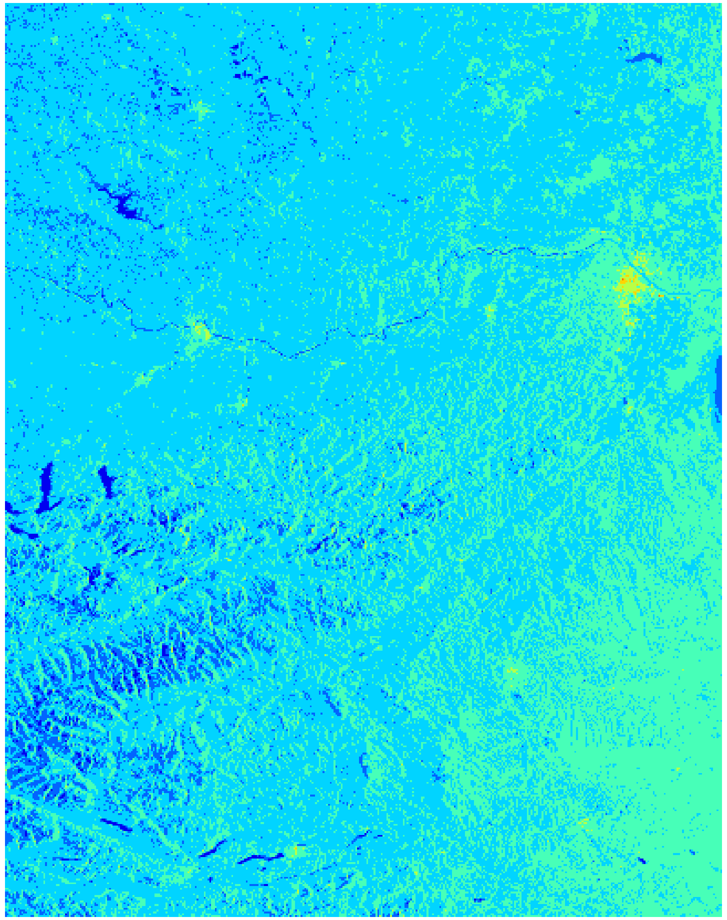
Backscatter Distribution

Logarithmic scale !



-25 dB	-20 dB	-15 dB	-10 dB	-5 dB	0 dB	5 dB	10 dB	15 dB	20 dB	25 dB
8.5e3	14e6	0.9e9	0.5e9	0.2e9	16e6	2.1e6	0.4e6	79e3	20e3	3e3



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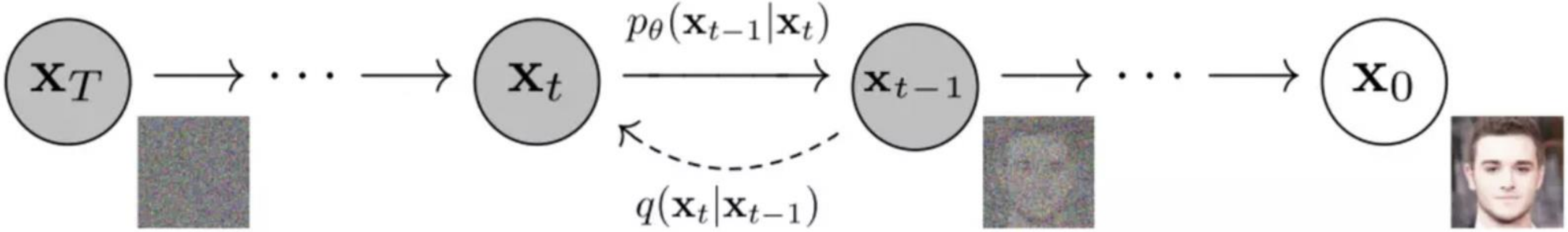
Despeckling Using Diffusion Probabilistic Models

- Forward Diffusion process

  Adding Gaussian noise in T diffusion time step.

- Reverse diffusion process

  Denoising until it reaches the desired image x0



Ho et al., 2020
Denoising diffusion probabilistic models
Advances in Neural Information Processing Systems, Vol. 33, No. 13

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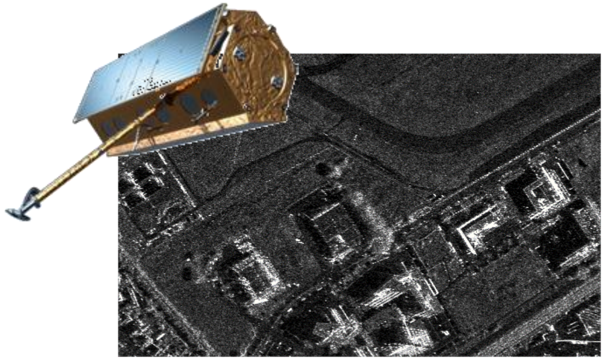
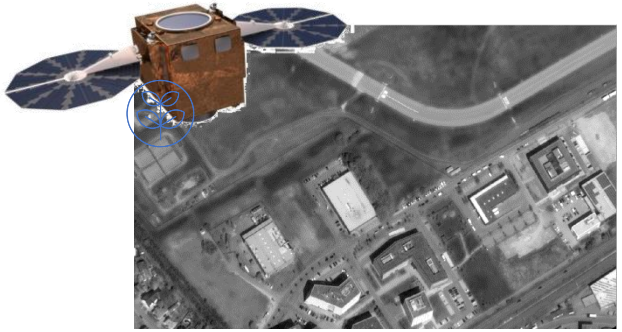
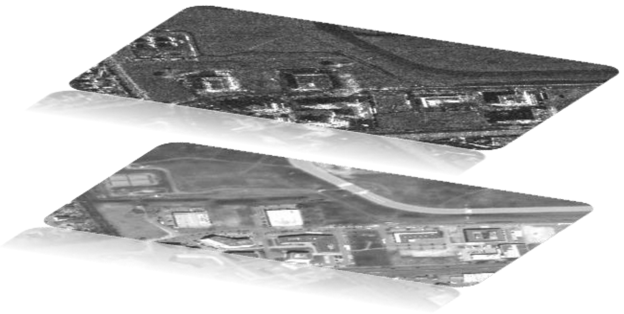
Complementary information of SAR and optical satellite imagery bring great potentials for data fusion

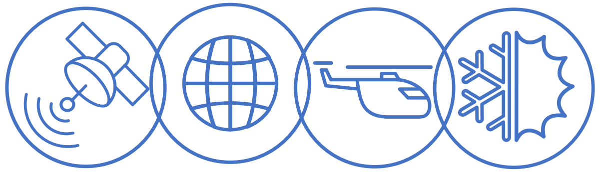


- Independent of clouds
- Physical surface properties
- Geolocation accuracy

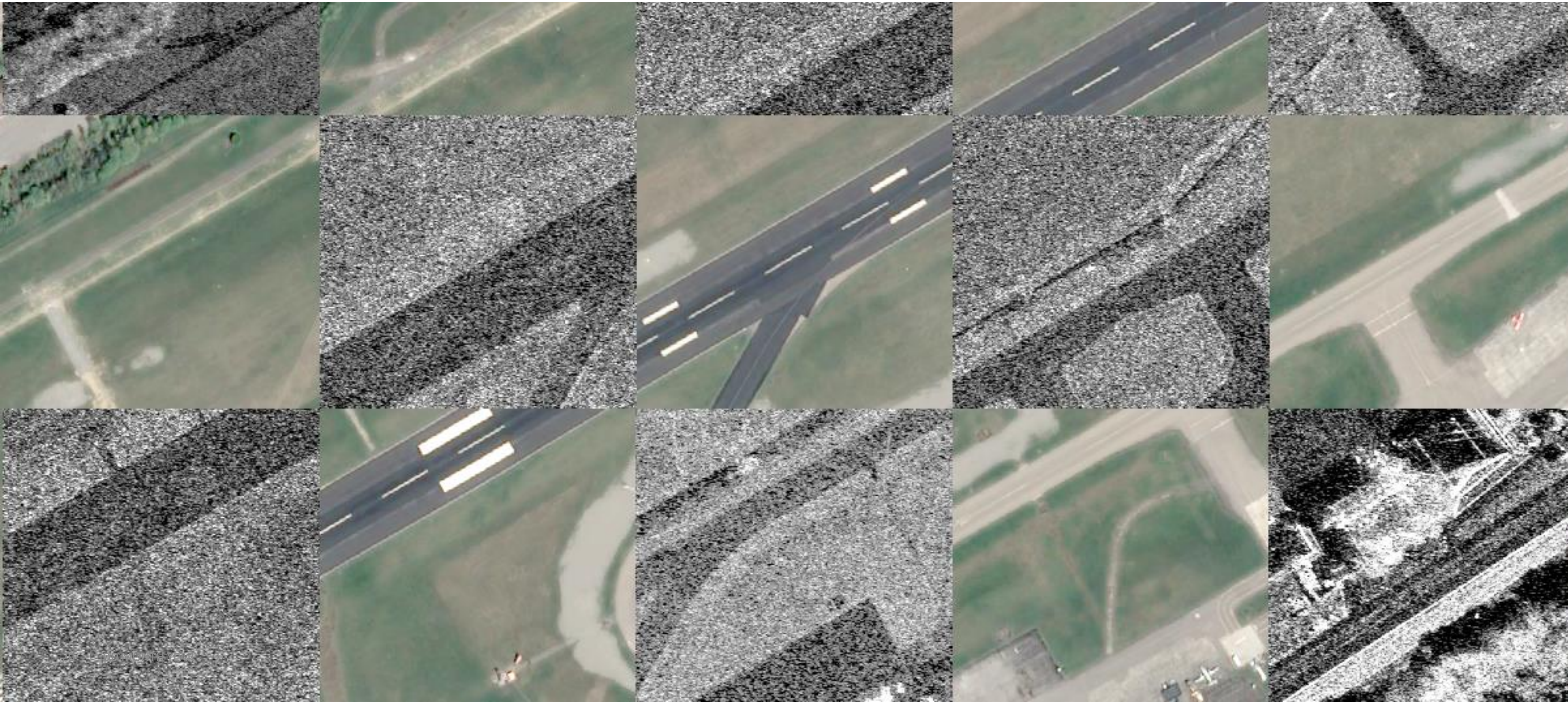


- Intuitive interpretation
- Chemical surface properties
- Multispectral





Problem: Before data fusion a precise matching and registration of images is necessary.



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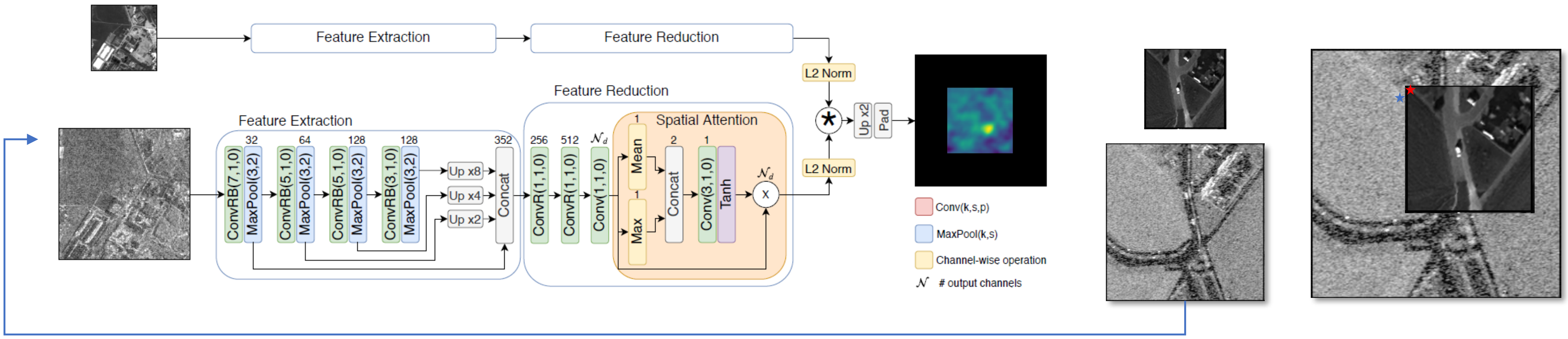
Deep Learning Approach

Training Dataset → Train the Neural Networks "from scratch" → Inference on Test Dataset → Matched Images



Hughes et al., 2019

Deep Learning for SAR-Optical Image Matching

IEEE International Geoscience and Remote Sensing Symposium (IGARSS)

Results Test Site Friedrichshafen, Germany

Location of matched paches. Accuracy in pixel

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Thanks for your attention!

karlheinz.gutjahr@joanneum.at