Innovation and digital transformation to the service of the Public Administration

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Super-resolution of sentinel-1 imagery using an enhanced attention network and real ground truth data

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Main motivation

Why have we super-resolved S1?

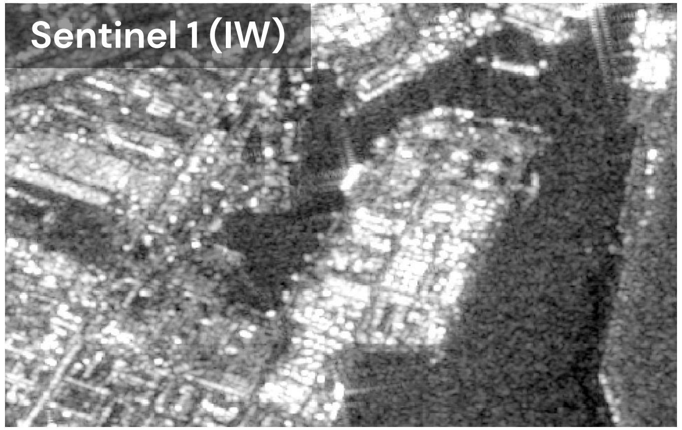
Sentinel-1 (S1) provides freely available SAR imagery

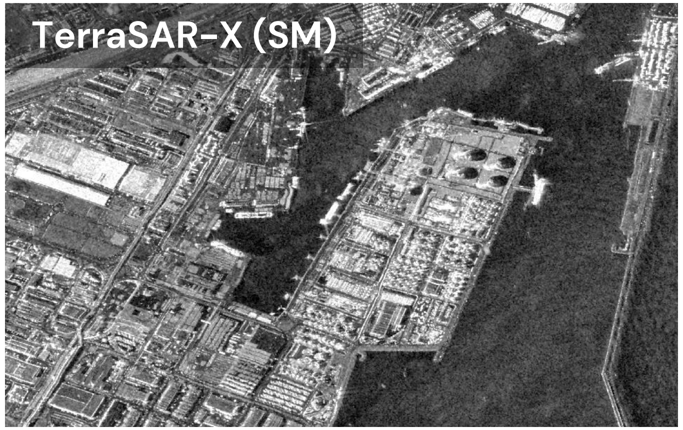
Main Challanges

- **Limited spatial resolution**
- **Speckle noise**

Previous Works in S1 SR

- Based on **generative** approaches implying **hallucination risks** [1].
- Using **VHR SAR imagery as Ground Truth** ($$$) [2].





1. Ce Zheng, Xue Jiang, Ye Zhang, Xingzhao Liu, Bin Yuan, and Zhixin Li. Self-normalizing generative adversarial network for super-resolution reconstruction of sar images. In IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium, pp. 1911–1914. IEEE, 2019.

2. Longgang Wang, Mana Zheng, Wenbo Du, Menglin Wei, and Lianlin Li. Super-resolution sar image reconstruction via generative adversarial network. In 2018 12th International Symposium on Antennas, Propagation and EM Theory (ISAPE), pp. 1–4. IEEE, 2018.

Our proposal

What does our proposal consists of?

To develop a Deep learning-based method to **super-resolve S1** Interferometric Wide Swath (IW) mode imagery and **reduce its speckle** noise.

Main features

1. Using **S1 sensor** in Stripmap (SM) mode **as ground-truth**
   - Free and consistent information (angles, polarization, wavelength, among others)

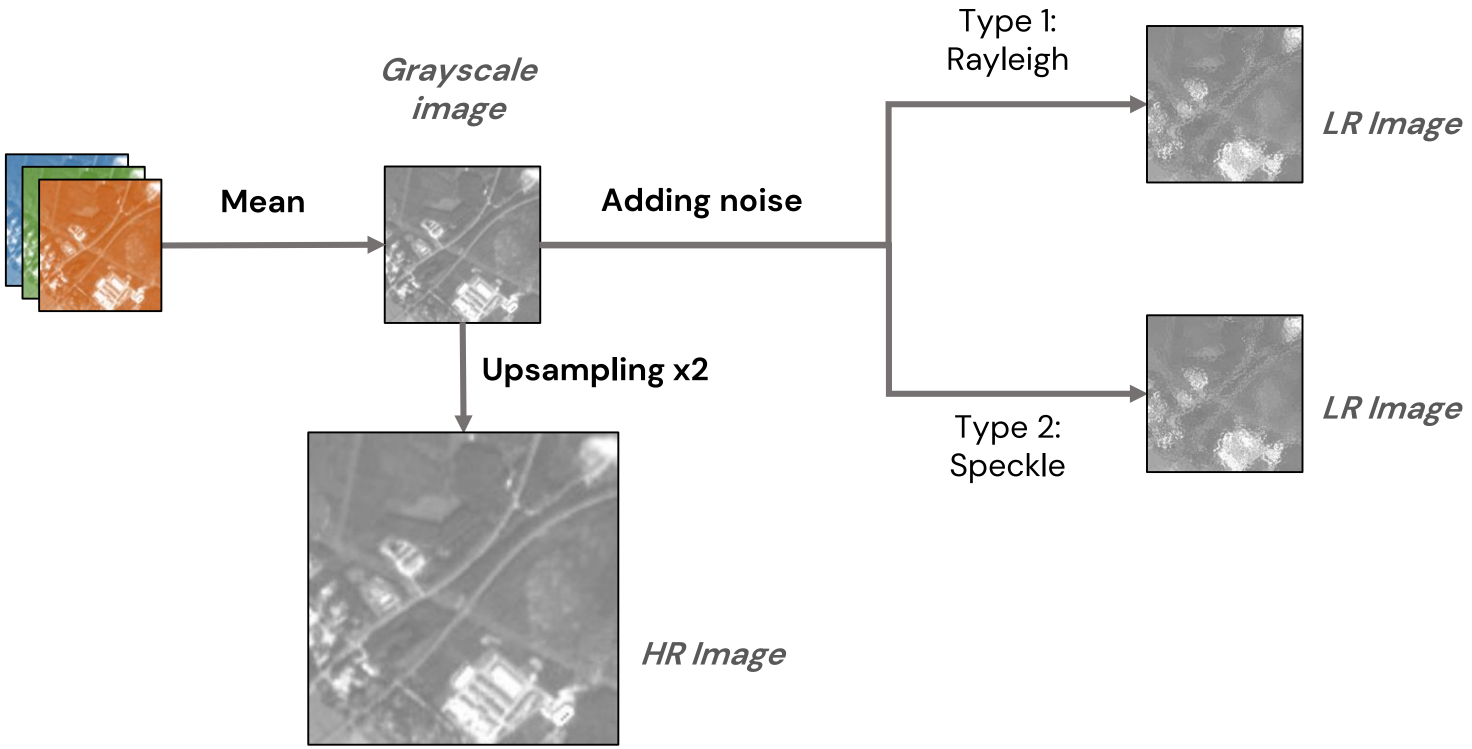
2. **Avoiding** the usage of **generative neural networks**

3. **Training in two phases** to infuse despeckling knowledge: 1) pre-training and 2) finetuning

Preparation of pre-training dataset

Based on a set of multi-temporal acquisitions of S1 and Sentinel-2 (S2) across 44 Spanish cities [3].

1st Strategy: Using S2 data
(introducing two types of synthetic noise)

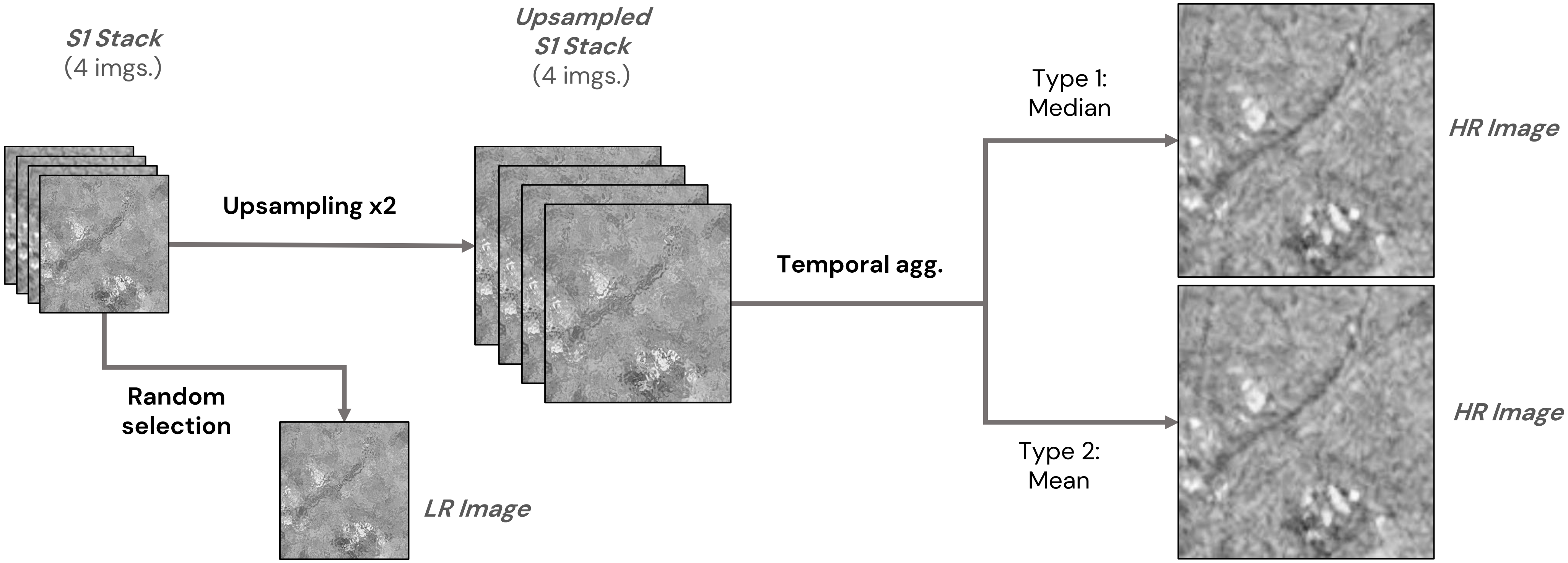


3. Christian Ayala, Rubén Sesma, Carlos Aranda, and Mikel Galar. A deep learning approach to an enhanced building footprint and road detection in high-resolution satellite imagery. Remote Sensing, 13(16), 2021.

Preparation of pre-training dataset

Based on a set of multi-temporal acquisitions of S1 and Sentinel-2 (S2) across 44 Spanish cities [3].

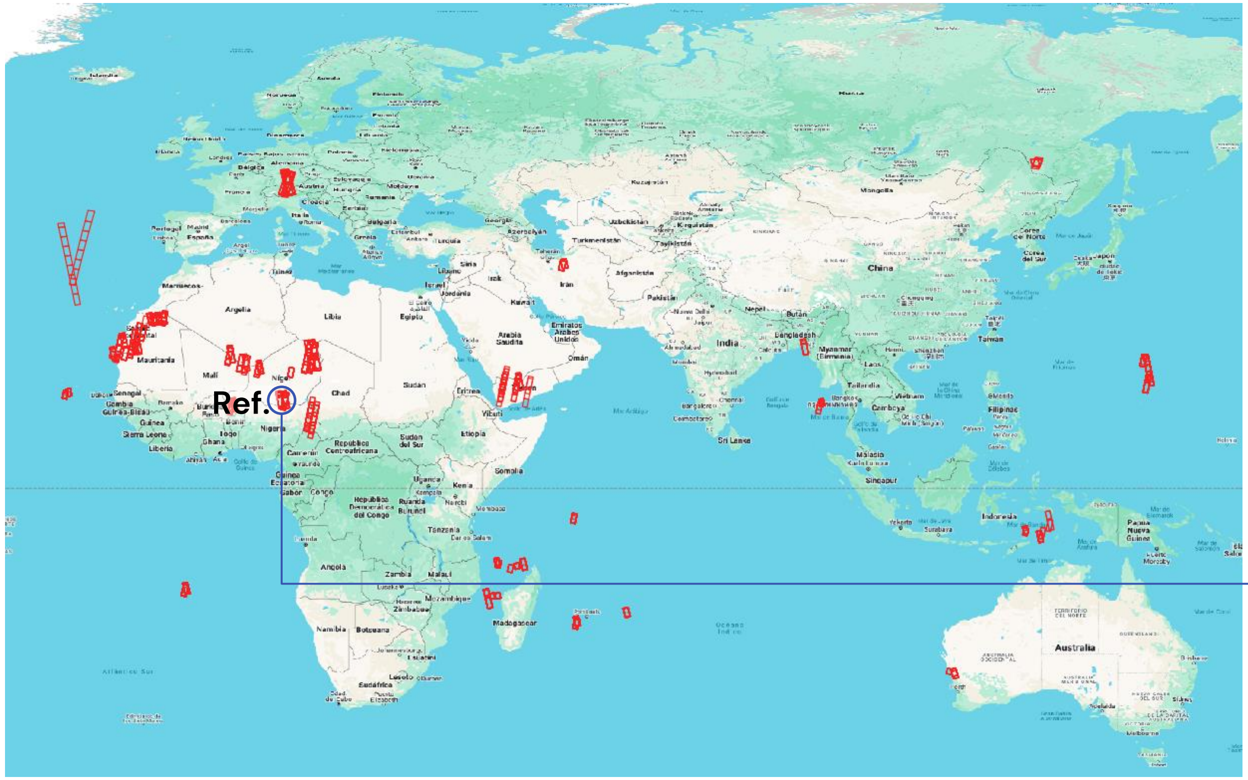
2nd Strategy: Using S1 data
(perform two types of temporal aggregations)



3. Christian Ayala, Rubén Sesma, Carlos Aranda, and Mikel Galar. A deep learning approach to an enhanced building footprint and road detection in high-resolution satellite imagery. Remote Sensing, 13(16), 2021.

Preparation of finetuning dataset

The dataset comprises pairs of S1 IW and SM images covering four areas of interest (25,871 km^2).

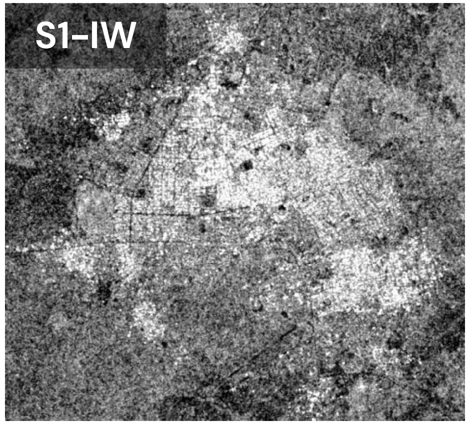


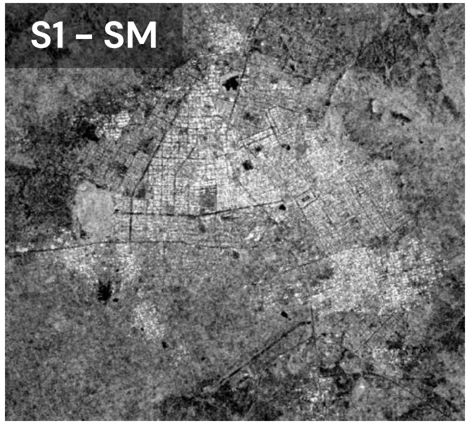
There are approximately 4.7K S1 SM acquisitions available worldwide

Main characteristics

- Located in continental zones
- Similar acquisition times (< 1 day)
- SM beams from S3 to S6 to match IW incidence angle range.
- Ascending flight direction.
- Dual vertical polarizations (VV+VH).
- S1 SM radiometrically aligned with IW ones by histogram matching.

Ref.





Training setup

Architecture

The Second Order Attention Network [4]. Two main elements:

- Second-order channel attention module.
- Non-locally enhanced residual group structure.

We use 20 residual groups, each comprising 10 residual blocks, based on preliminary experiments.

General settings

- 100 training epochs with OneCycleLR scheduler using a maximum learning rate of 0.001.
- Batches of 128 24 × 24 low-resolution samples.
- Loss function: combination of the L2 and Total Variation losses [5].
- In the finetuning phase the number of epochs was reduced to 30.

4. Tao Dai, Jianrui Cai, Yongbing Zhang, Shu-Tao Xia, and Lei Zhang. Second-order attention network for single image super-resolution. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 11065–11074, 2019

5. Puyang Wang, He Zhang, and Vishal M Patel. Sar image despeckling using a convolutional neural network. IEEE Signal Processing Letters, 24(12):1763–1767, 2017.

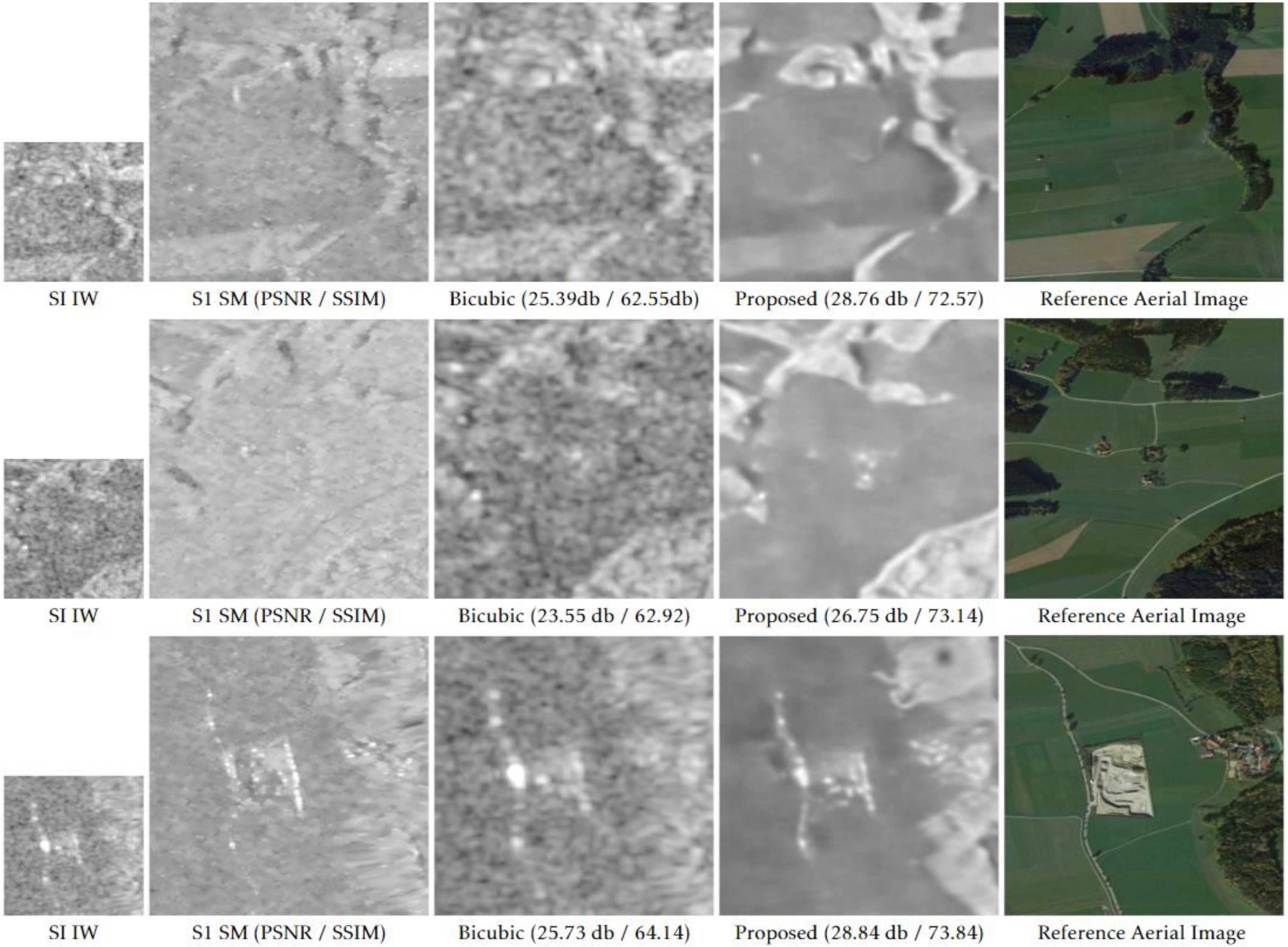
Quantitative assessment

Experiment	SSIM	RMSE	PSNR (dB)
Baseline (bicubic)	64.61	0.5711	28.45
End-to-end	75.33	0.3419	30.68
PT S2 + Speckle	75.31	0.3236	30.92
PT S2 + Rayleigh	75.33	**0.2608**	**31.86**
PT S1 + Mean	**75.36**	0.3165	31.02
PT S1 + Median	75.32	0.3254	30.90

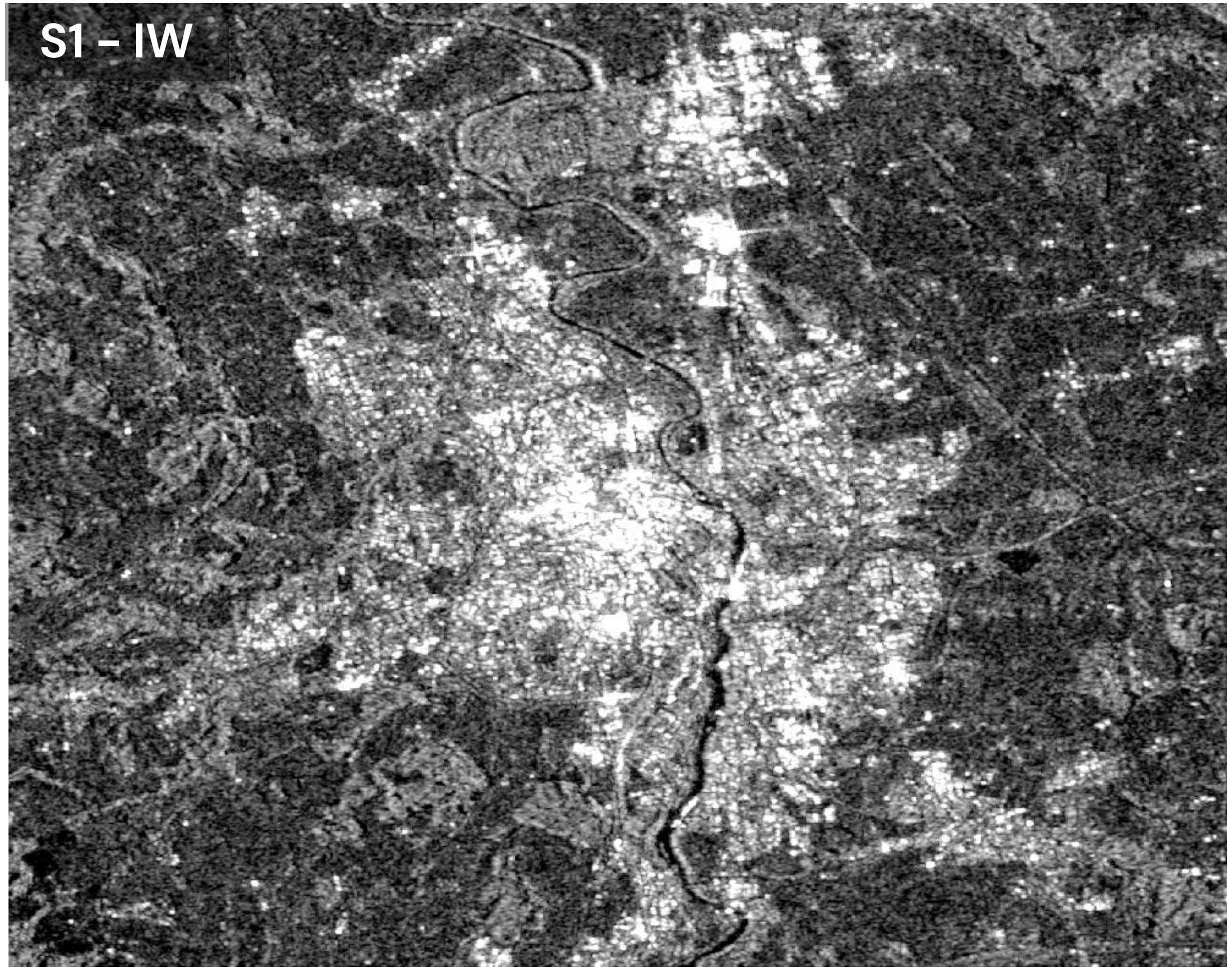
- All models outperform the baseline.
- Differences between the models are evident in terms of RMSE and PSNR, but they achieve similar SSIM results, suggesting **SSIM may not be adequate for evaluating SAR super-resolution**.
- Based on these metrics, our **preferred model is PT S2 + Rayleigh**.

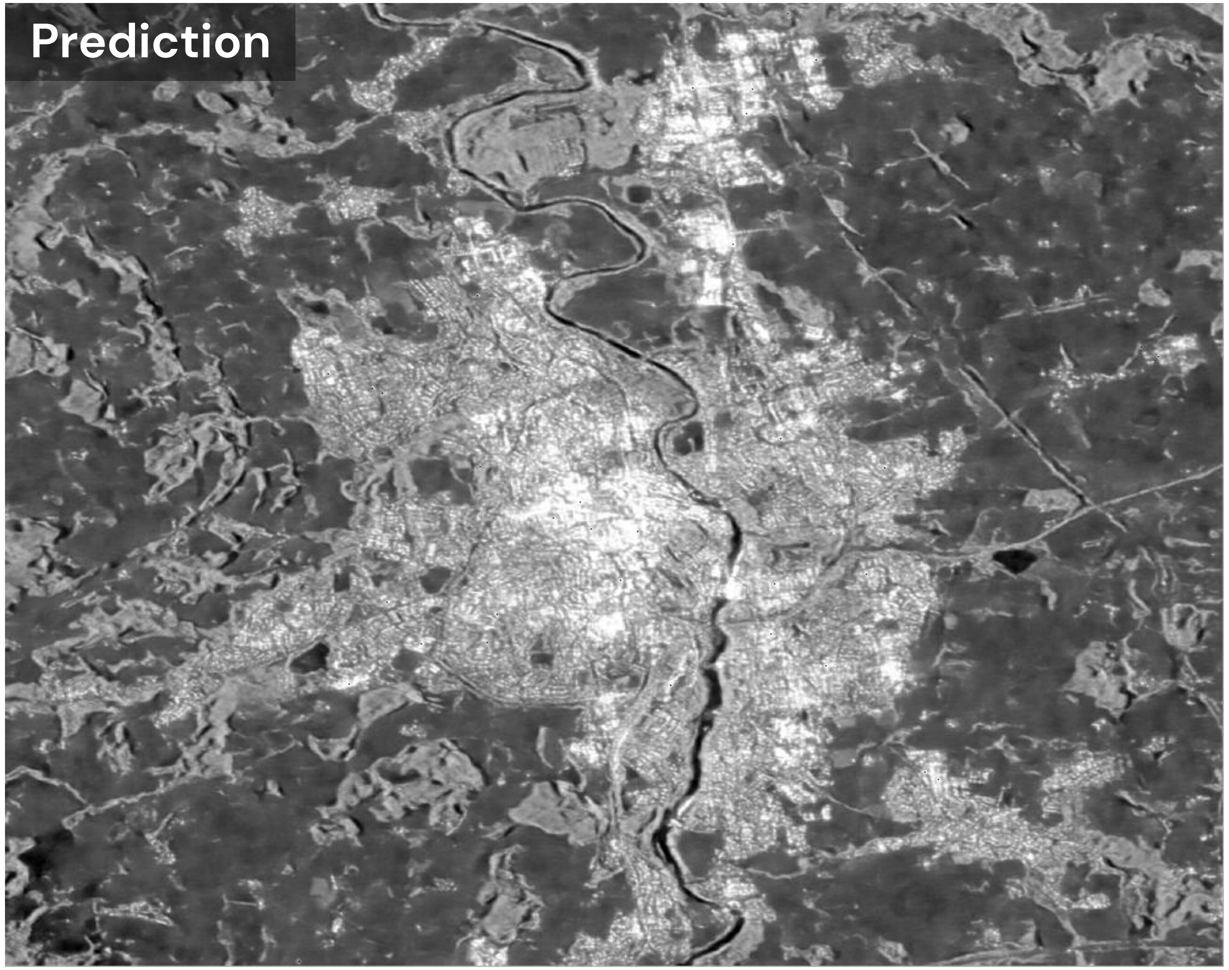
Inspecting some patches

Qualitative evaluation shows that PT2 + Rayleigh **enhances clarity and sharpness** while maintaining a natural appearance, without introducing synthetic artifacts.

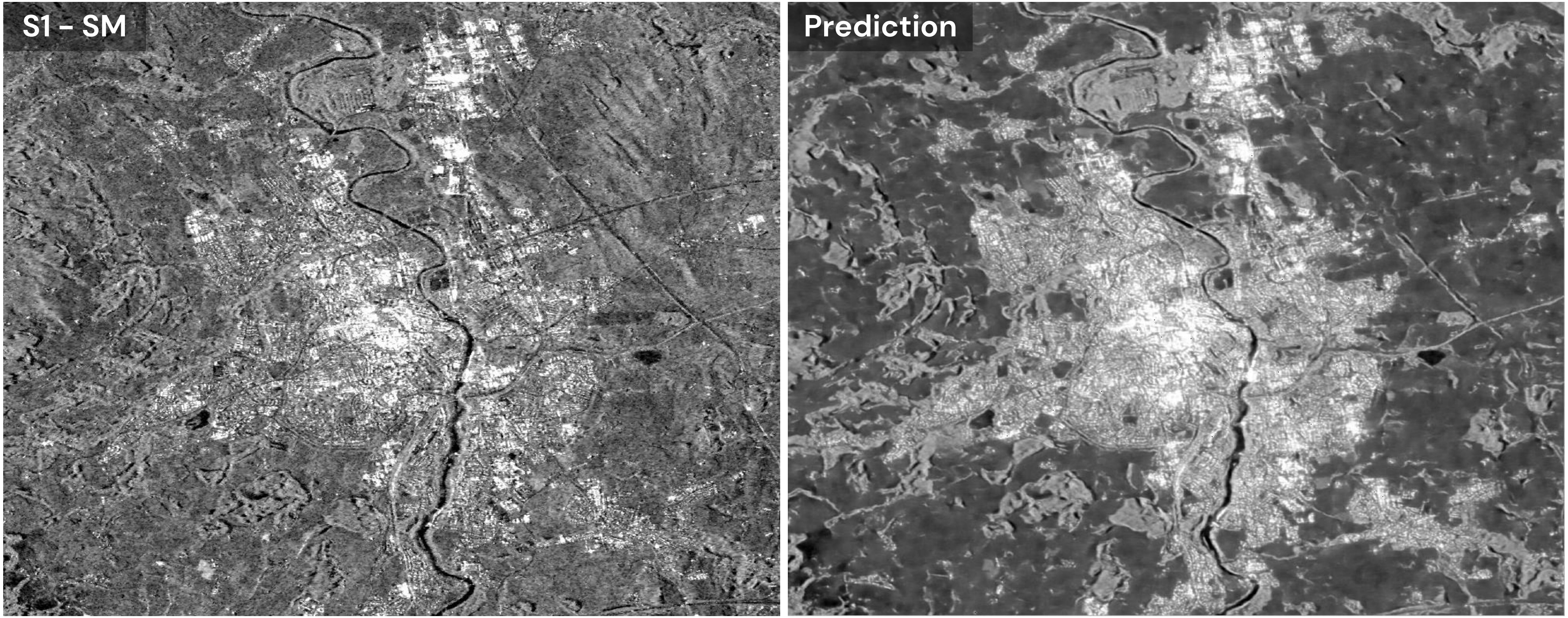


More visual examples





More visual examples



Conclusions and future work

What have we achieved? What are the next steps?

Enhancing the Details, Removing Speckle, and Preserving the Radiometry

Lines of Future Work

- **4x Scale Factor** (using a GT with higher resolution).
- Improve the quantitative evaluation by incorporating **more appropriate metrics**.
- Experiment with **different network architectures**.
- **Increase the dataset size** by including different locations, possibly avoiding pre-training phase.
- Apply this technique to **raw complex data (SLC)** to enable further applications.

Thank you!

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