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Beyond super-resolution: virtual sensing

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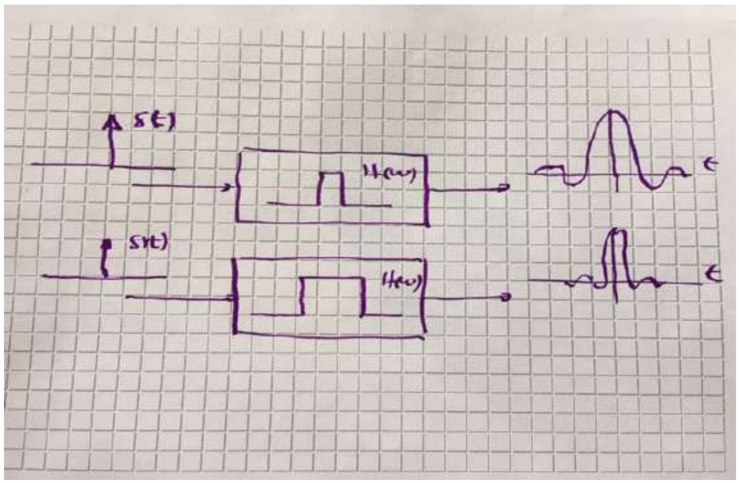
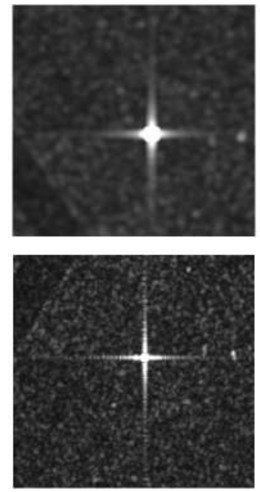
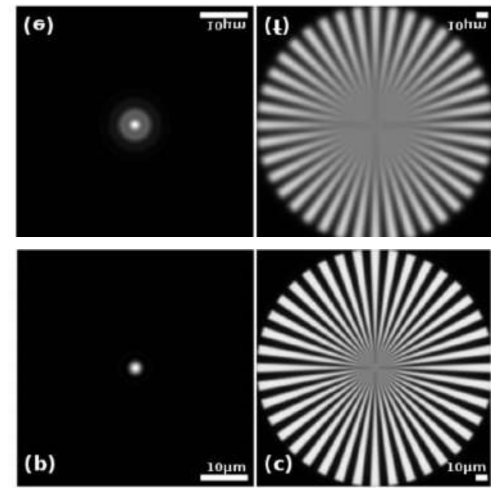
Resolution is a property of the imaging system

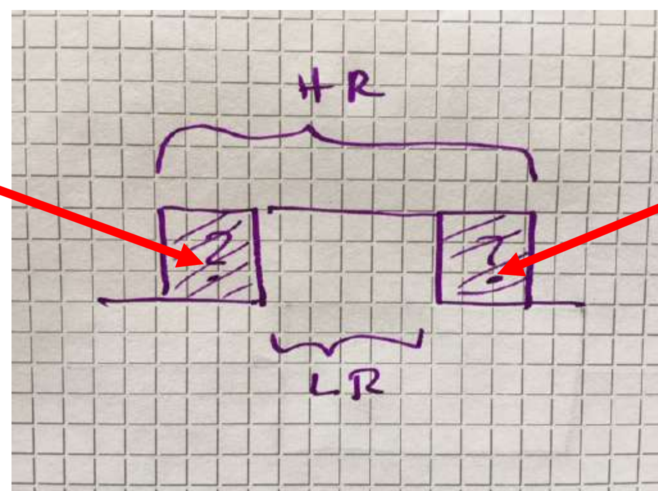






Super-resolution

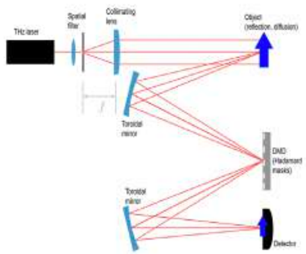
How to add **new** info



How to add **new** info

Many types of super-resolution

Single Pixel Camera (SPC)



Measurements acquisition with a THz laser as a source of illumination.

SPC Point Spread Function h

$$h = h_o * c$$

DMD cell

Optical system PSF

$$h_o = h_{Airy} * h_{aberr}$$

Diffraction limited PSF

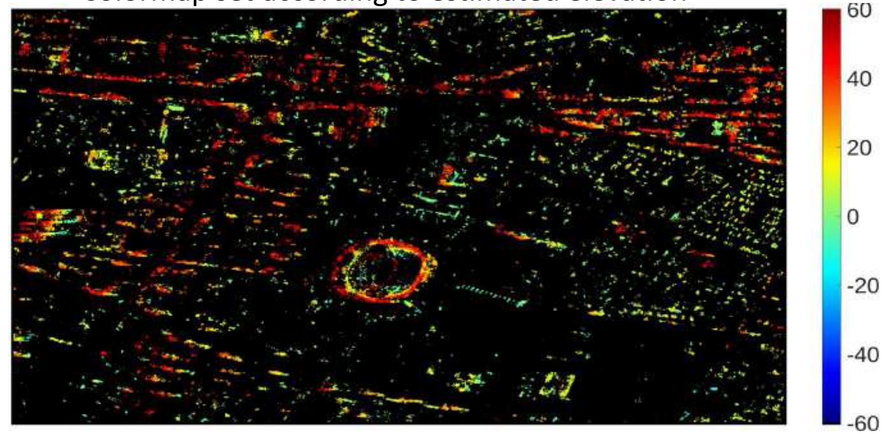
$$h_{aberr} = rect\left(\frac{z \cdot r}{w \cdot \Delta z}\right)$$

when defocus is the main lens aberration

z distance to the optical system
r PSF radius
w camera aperture
Δz distance from the real image to the PSF

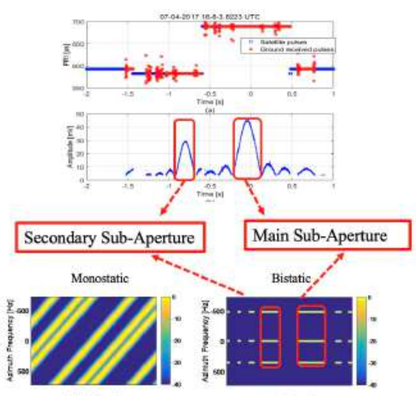
Damian, C., Garoi, F., Udrea, C., & Coltuc, D. (2019). The evaluation of single-pixel camera resolution. *IEEE Transactions on Circuits and Systems for Video Technology*, *30*(8)

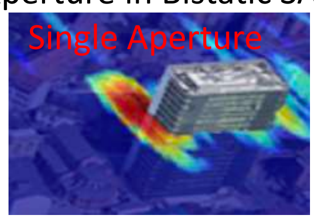
Spatial distribution of detected double scatterers.
Colormap set according to estimated elevation



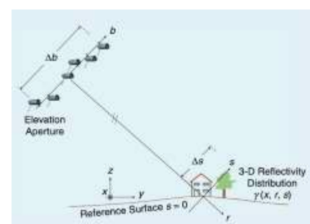
C. Danisor, G. Fornaro, A. Pauciullo, D. Reale, and M. Datcu, (2018) Super-resolution multi-look detection in SAR tomography, Remote Sensing, vol. 10

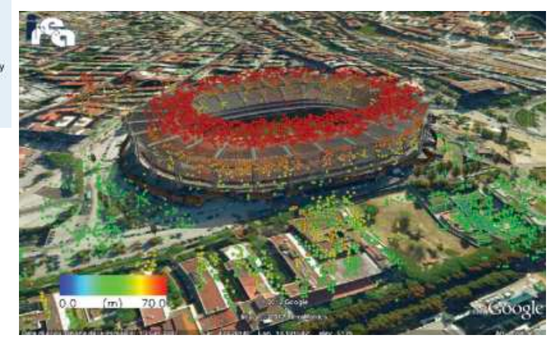
Super-resolution with Multi-Aperture in Bistatic SAR





F. Rosu, A. Anghel, R. Cacoveanu, B. Rommen and M. Datcu, (202) Multiaperture Focusing for Spaceborne Transmitter/Ground-Based Receiver Bistatic SAR, IEEE JSTARS, vol. 13





Fornaro, Gianfranco et al, (2012) *SAR Tomography: an advanced tool for spaceborne 4D radar scanning with application to imaging and monitoring of cities and single buildings.* IEEE Geoscience and Remote Sensing Newsletter

Super resolution: an overview

Cal/val		N/A		
Hypothesis Constrains	GMR, TV No. of targets, Scene Imaging	MaxEnt	S/N vs resolution No change	No change
Method	Inverse problem Wave number shift	Unmixing End members	Multi-Looking	TomoSAR Time Series Video
Parameter resolved	Spatial	Spectral	Radiometric	Temporal

Deep Learning & AI: predictive and generative models

Super resolution: prediction of missing/un-observed signatures

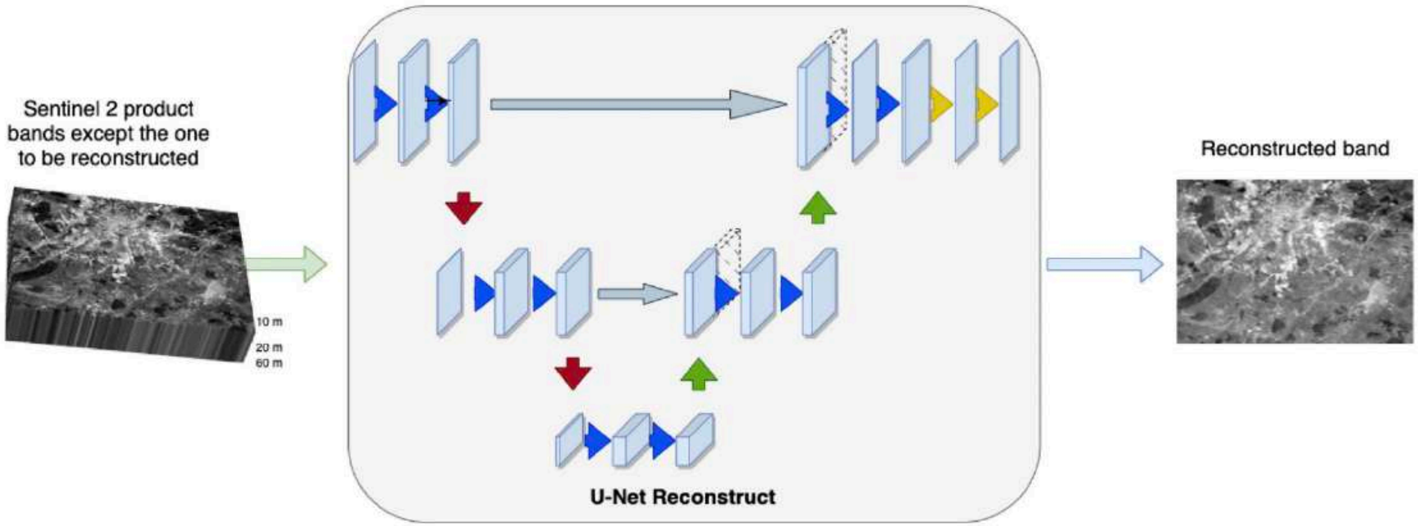
Predictive models: are trained with existing datasets and applied to new data to forecast the likelihood of a particular outcome

Generative models: models that learn the underlying patterns or distributions of data in order to generate new, similar data

No hypotheses, no constrains

But, EO is differnet from CV

S-2 Band Reconstruction Using a Modified UNet

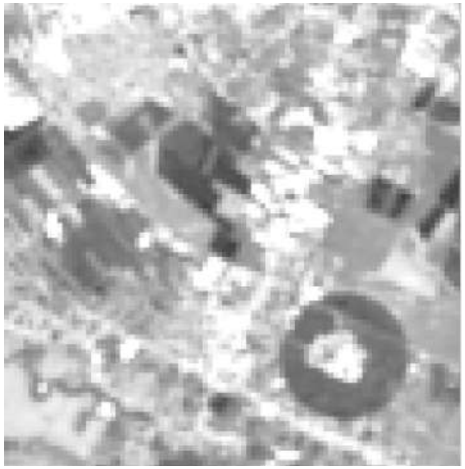


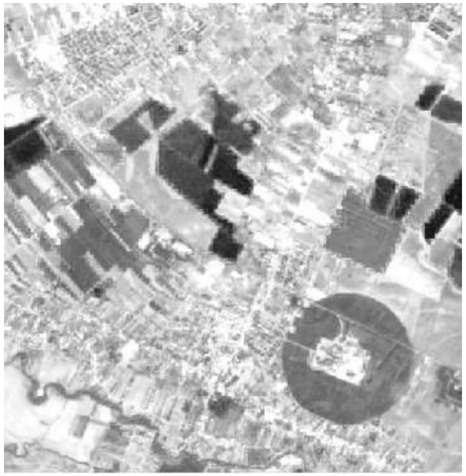
- Valorizing the spectral information available in the bands to predict missing observations
- We considered the worst case scenario, the lack of any information relative to the missing band
- Super-resolution is included
- It does not require additional information from other sensors
- It is an unsupervised method
- The corrupt band is not used based on the assumption that it was not observed

S-2 Band Reconstruction Using a Modified UNet

Reconstruction of spectral bands affected by artefacts

Prediction of un-observed data, i.e. missing spectral bands and super-resolution





Neagoe, I. C., Vaduva, C., and Datcu, M. (2022) Band reconstruction using a modified UNet for Sentinel-2 images. IEEE JSTARS

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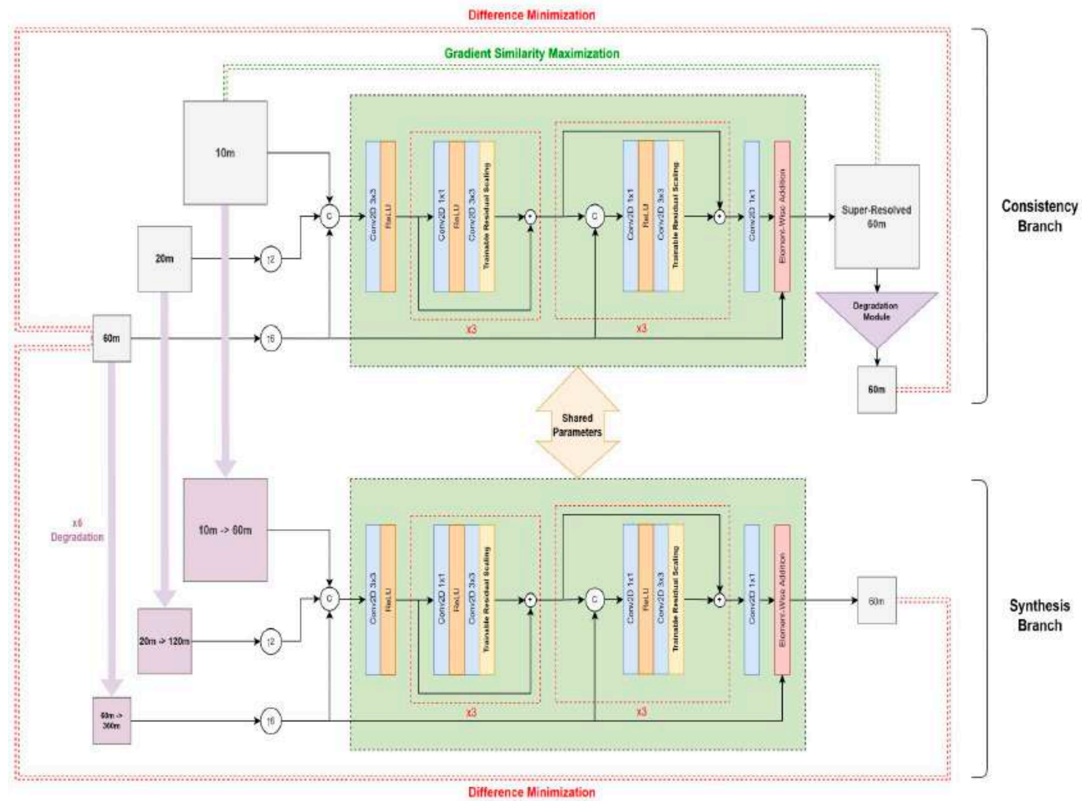
S-2 Image Super-Resolution: Multi-objective Training

- Implement the synthesis evaluation, the Wald's protocol, and use of sensor's modulation transfer function (MTF) to learn an inverse mapping from LR to HR images, for achieving a good consistency value
- Implement a multi-objective loss for training the architectures, including an MTF-based forward model
- Use a direct input–output mapping using synthetically degraded data, with direct similarity measures between high-frequency details from the 10-m bands, and super-resolved images.



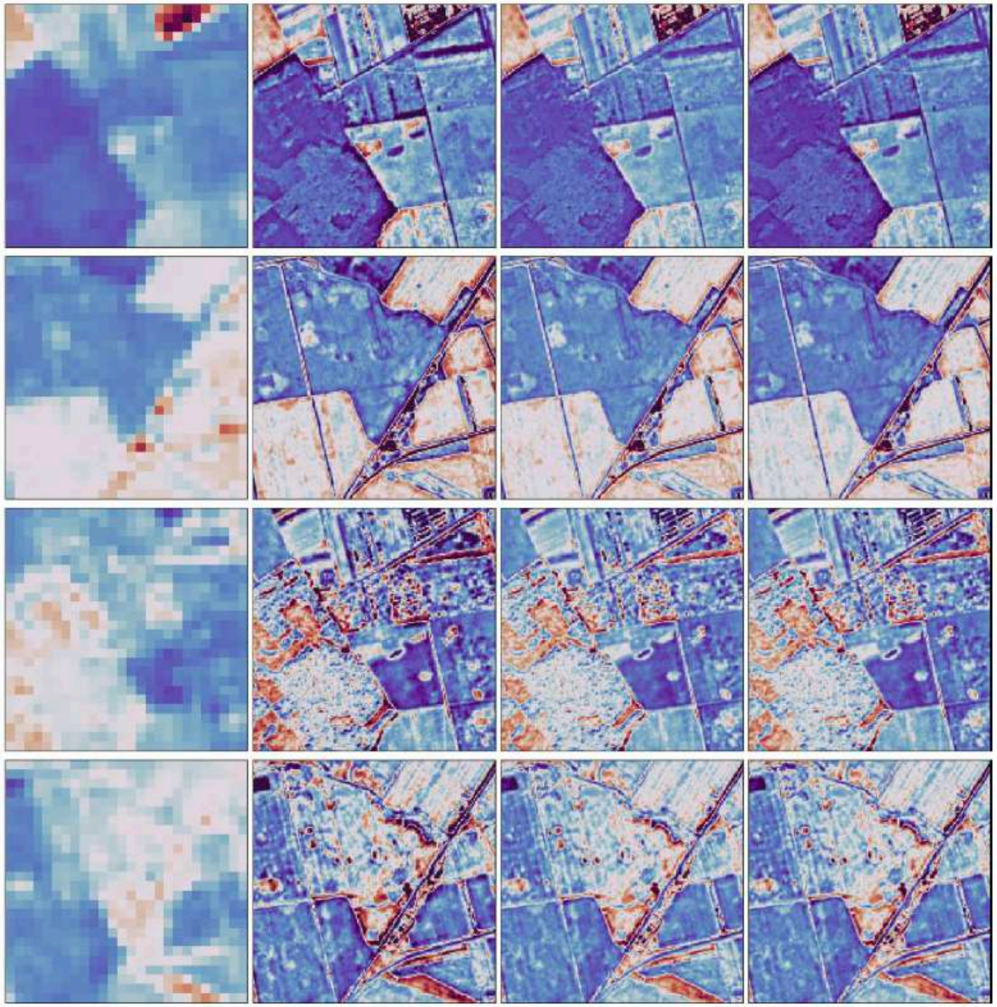
V. Vasilescu, M. Datcu, D. Faur, "A CNN-Based Sentinel-2 Image Super-Resolution Method Using Multiobjective Training," in IEEE TGRS, 2023

Single-pass Bistatic SAR Tomography (TomoSAR-1B)

$$\mathcal{L} = \alpha \mathcal{L}_{\text{consistency}} + \beta \mathcal{L}_{\text{sym}} + \gamma \mathcal{L}_{\text{synthesis}}$$

From left to right: Original, (1, 1, 1), (1, 0.1, 1), and (1, 0.1, 0).

B1 on the first two rows and B9 on the last two rows.



Dialectical GAN for SAR image translation: from TerraSAR-X to Sentinel-1

Hegel

A formula for the explanation of change

There is a triad in the system of dialectics, thesis, antithesis and synthesis

(1) a beginning proposition called a thesis
(2) a negation of that thesis called the antithesis
(3) a synthesis whereby the two conflicting ideas are reconciled to form a new proposition

Ao, D.; Dumitru, C.-O.; Schwarz, G.; Datcu, M.; Dialectical GAN for SAR Image Translation: From Sentinel-1 to TerraSAR-X, *Remote Sensing*, vol. 10, no. 10, pp. 1-24, Multidisciplinary Digital Publishing Institute (MDPI), 2018

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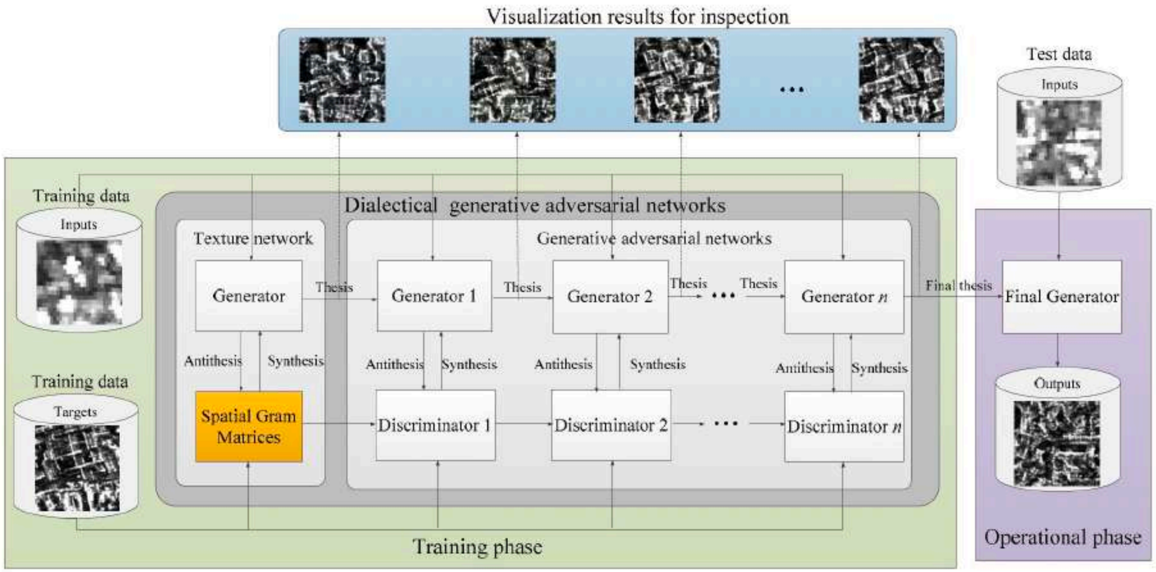
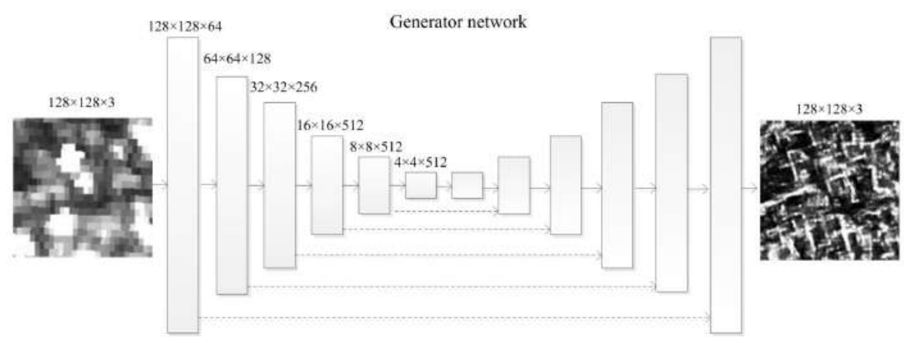
Dialectical GAN for SAR image translation: from TerraSAR-X to Sentinel-1

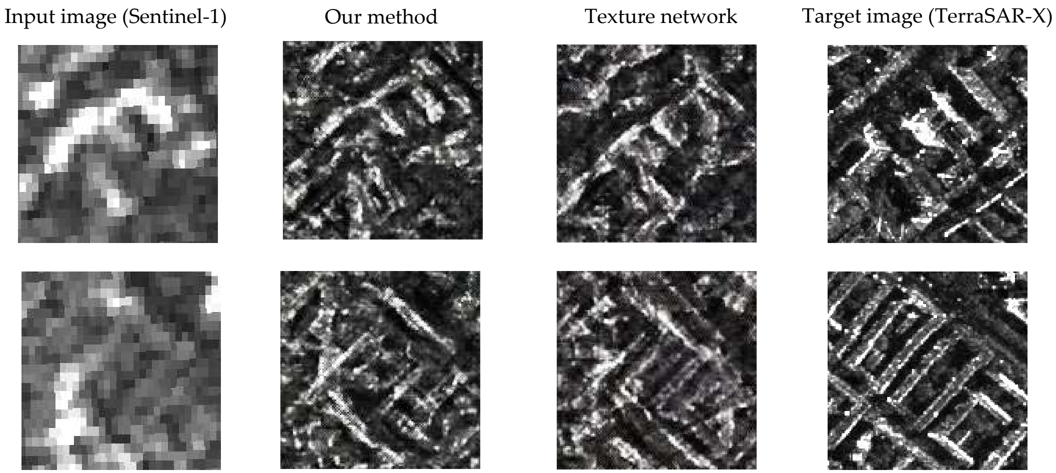


Dialectical GAN: the workflow



U-Net Generator

Dialectical GAN vs. Texture network



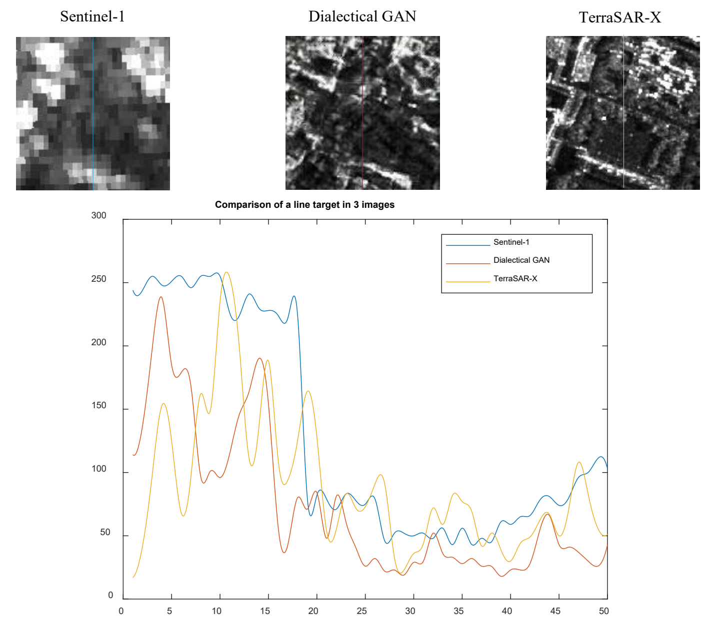


Image pairs	Methods	MSE	SSIM	ENL
1	Texture network	0.3264	0.0614	**1.3933**
	Dialectical GAN	**0.3291**	**0.0884**	1.5885
2	Texture network	0.3396	**0.0766**	**1.6270**
	Dialectical GAN	**0.3310**	0.0505	1.8147
Test set	Texture network	0.3544	0.0596	**1.7005**
	Dialectical GAN	**0.3383**	**0.0769**	1.8804

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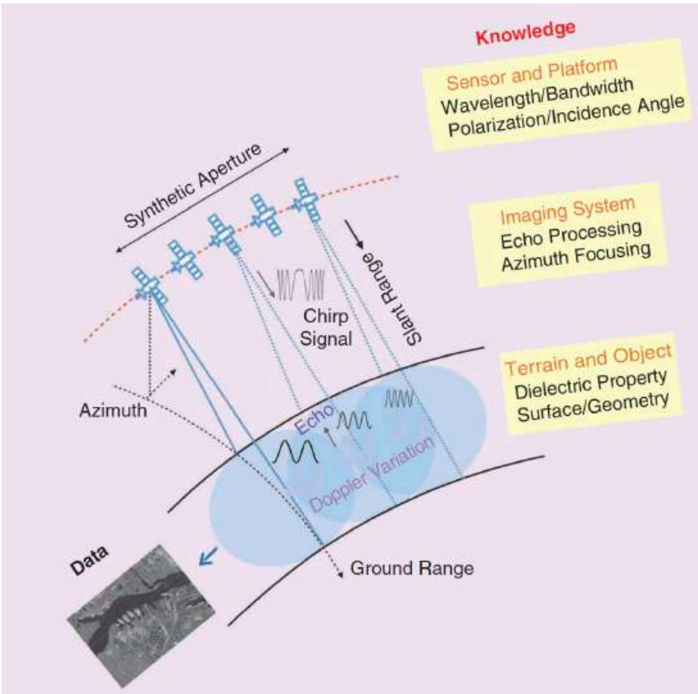
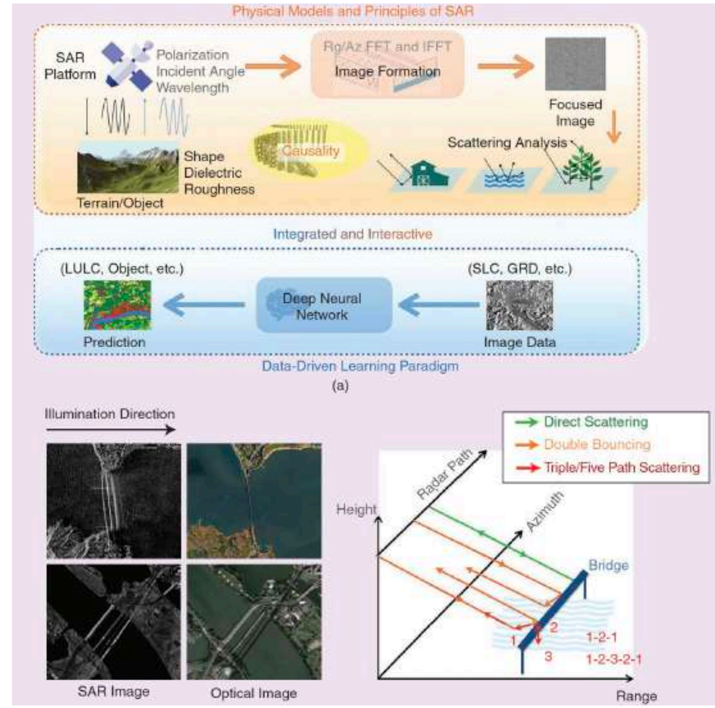
Explainable, Physics-Aware, Trustworthy AI4EO



- Imaging sensors generate an **isomorphic representation** of the observed scene
- For EO, the observations are a **doppelgänger of the scattered** field, an **indirect signature of the imaged object.**
- EO images in addition to the spatial information, are sensing **physical parameters**



The proposed paradigm shift integrated and interacting with physical models of SAR imaging process

M. Datcu, Z. Huang, A. Anghel, J. Zhao and R. Cacoveanu, "Explainable, Physics-Aware, Trustworthy Artificial Intelligence: A paradigm shift for synthetic aperture radar," in *IEEE Geoscience and Remote Sensing Magazine*, vol. 11, no. 1, pp. 8-25, March 2023

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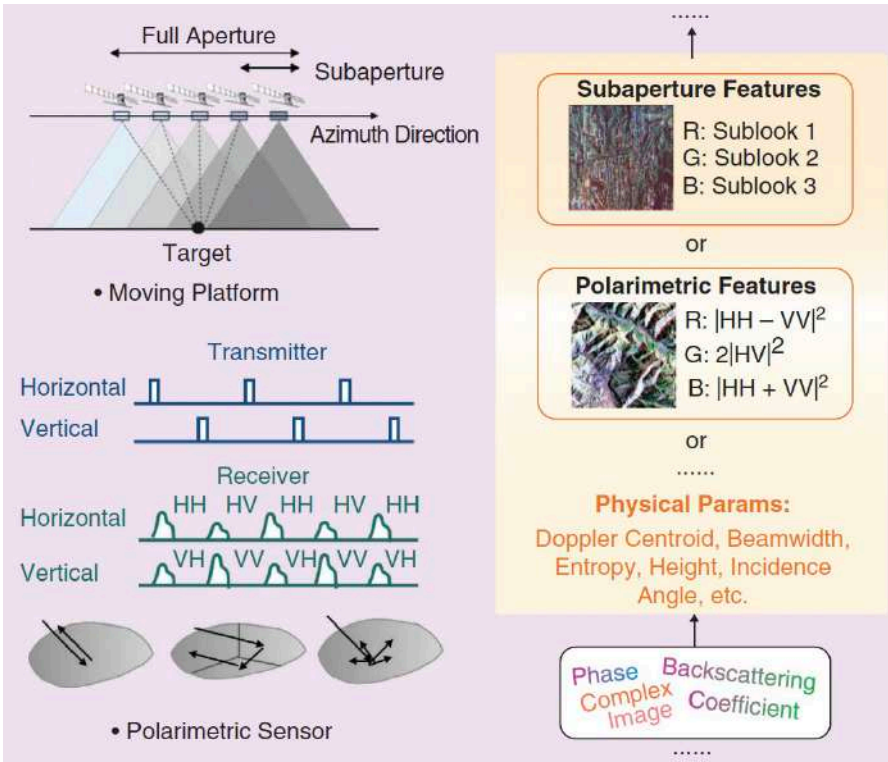
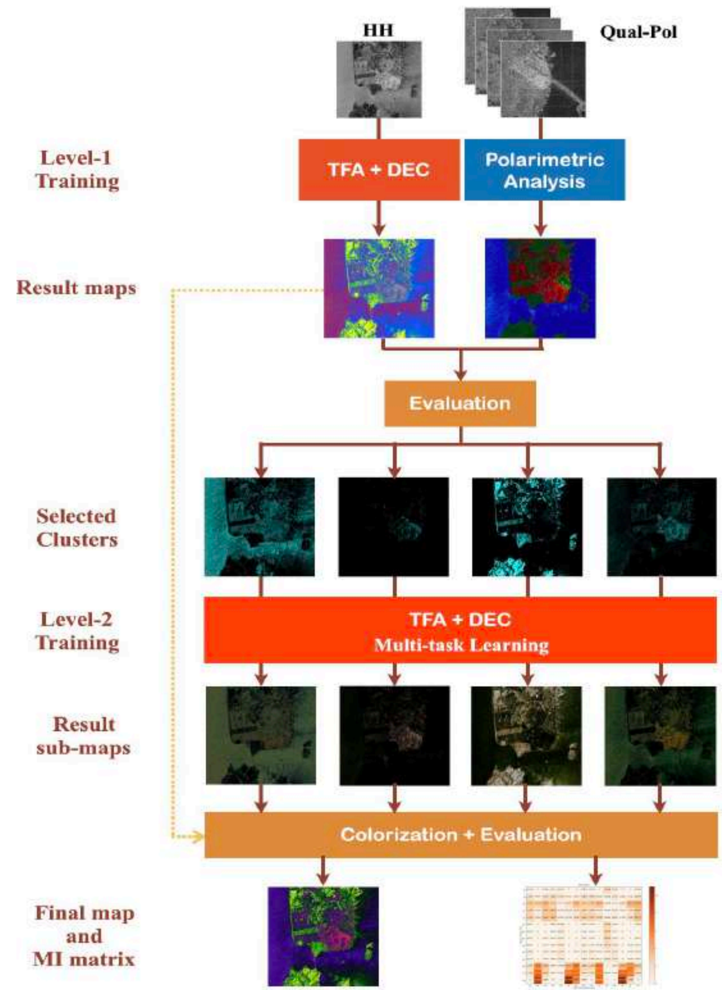
From single-PolSAR to quad-PolSAR





Physical layer The moving platform creates Doppler variations and synthesizes a large virtual aperture; PolSAR transmits and receives diverse polarized waves, and SAR polarimetric characteristics are depicted.

Huang, Z.; Datcu, M.; Zongxu P., Qiu, X.; Lei, B., (2021), HDEC-TFA: An Unsupervised Learning Approach for Discovering Physical Scattering Properties of Single-Polarized SAR Image, IEEE Transactions on Geoscience and Remote Sensing,

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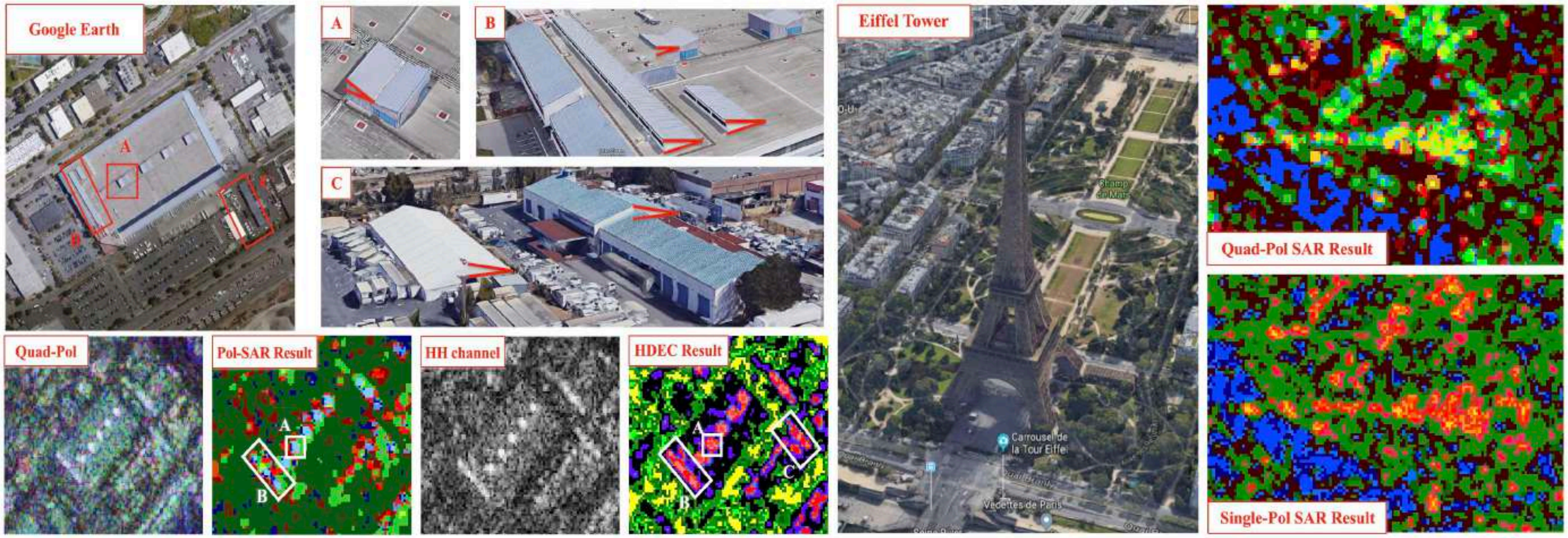
From single-PolSAR to quad-PolSAR



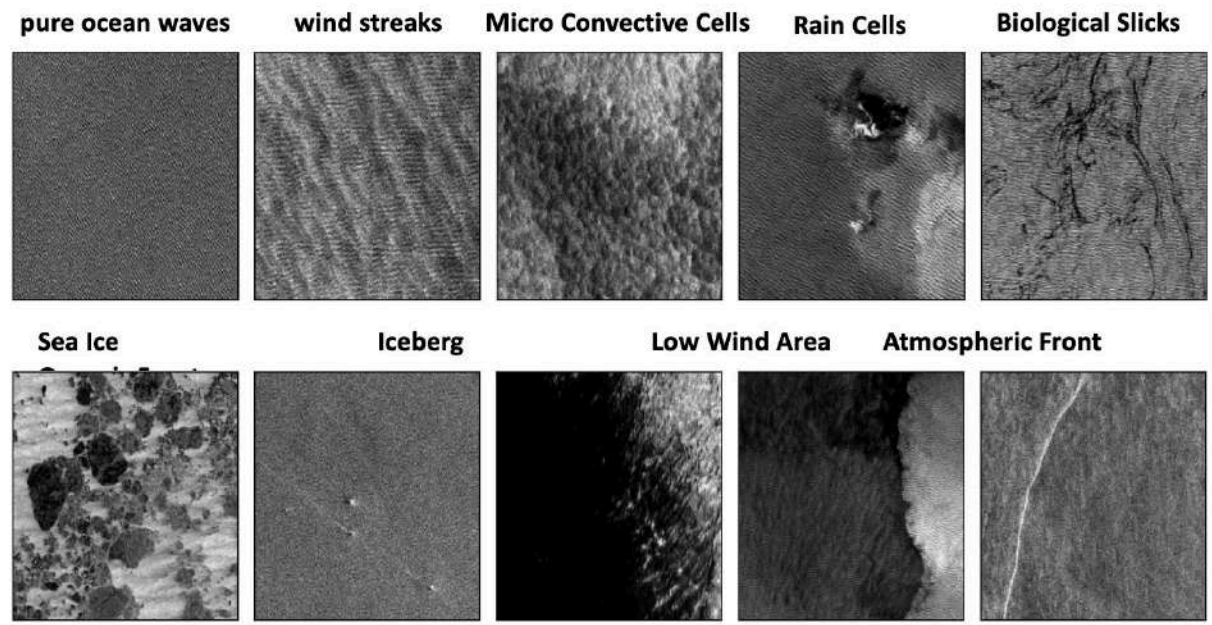
Physical scattering maps in Paris area.

- Polarimetric analysis result with GD-Wishart algorithm, using quad-polarimetric SAR images.
- Single-polarization SAR data result with the proposed HDEC-TFA method.

Physics Aware Generative Models

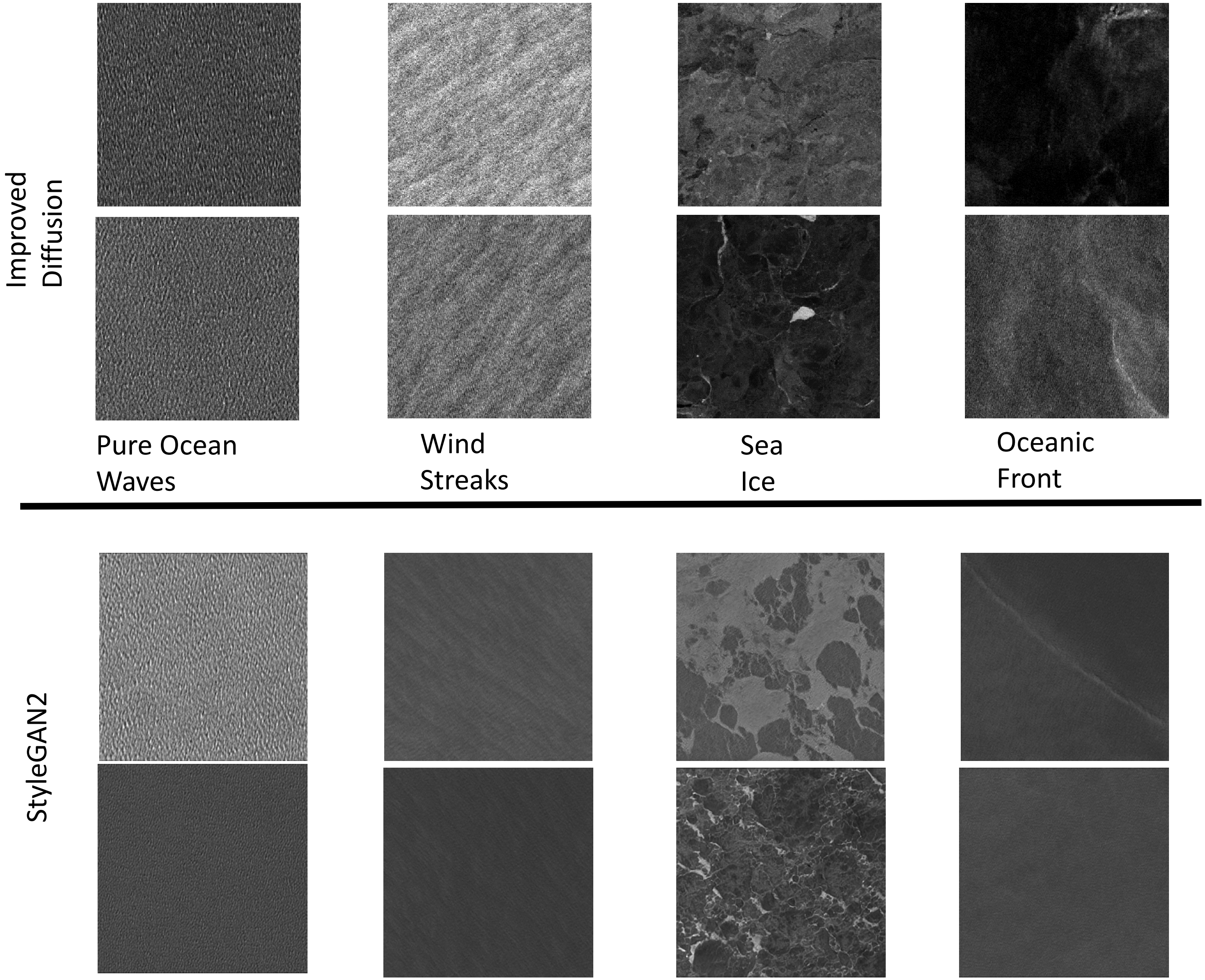
A labelled ocean SAR imagery dataset of ten geophysical phenomena from Sentinel-1 wave mode

Classes	# sample
F: Pure Ocean Waves	4900
G: Wind Streaks	4797
H: Micro Convective Cells	4598
I: Rain Cells	4740
J: Biological Slicks	4709
K: Sea Ice	4370
L: Iceberg	1980
M: Low Wind Area	2160
N: Atmospheric Front	4100
O: Oceanic Front	1199



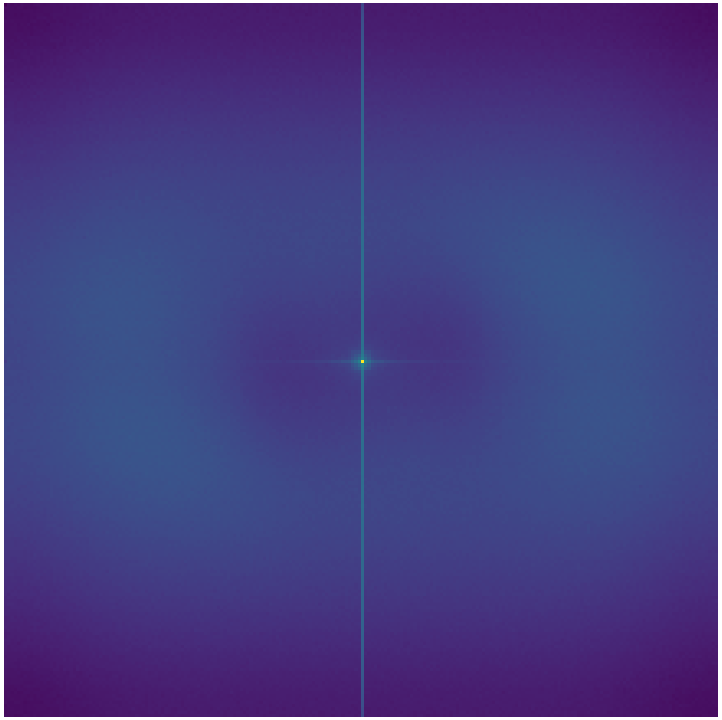
Wang Chen, Mouche Alexis, Tandeo Pierre, Stopa Justin, Longépé Nicolas, Erhard Guillaume, Foster Ralph, Vandemark Douglas, Chapron Bertrand (2018). Labeled SAR imagery dataset of ten geophysical phenomena from Sentinel-1 wave mode (TenGeoP-SARwv). SEANOE. https://doi.org/10.17882/56796

Two example of generated images for different categories by DPM and GAN

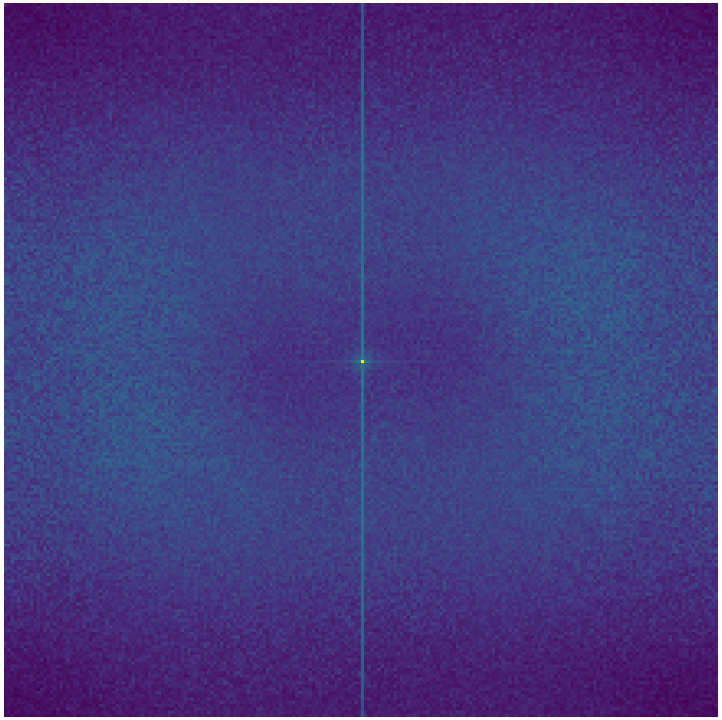


Pure Ocean Waves

Average Fourier Spectrum Real Images

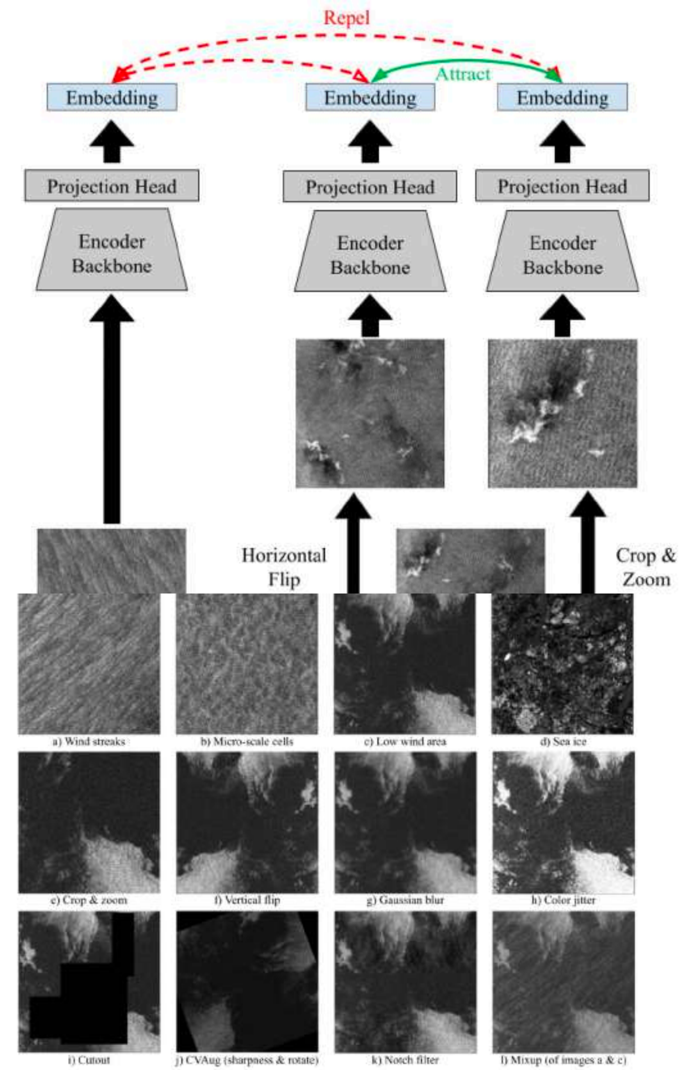


Average Fourier Spectrum Generated Images



SAR Ocean Patterns Augumenation

The SimCLR algorithm, images are randomly augmented to create several views of the same image. An encoder network — consisting of a backbone and a smaller projection head — learns to produce an embedding that is similar to embedded views from the same original image and dissimilar to embedded views from all other images. Only the encoder backbone is used for transfer learning.



Yannik Glaser, Bertrand Chapron et al, 2024, WV-Net: A foundation model for SAR WV-mode satellite imagery trained using contrastive self-supervised learning on 10 million images

Image Retrieval instead of Image Synthesis

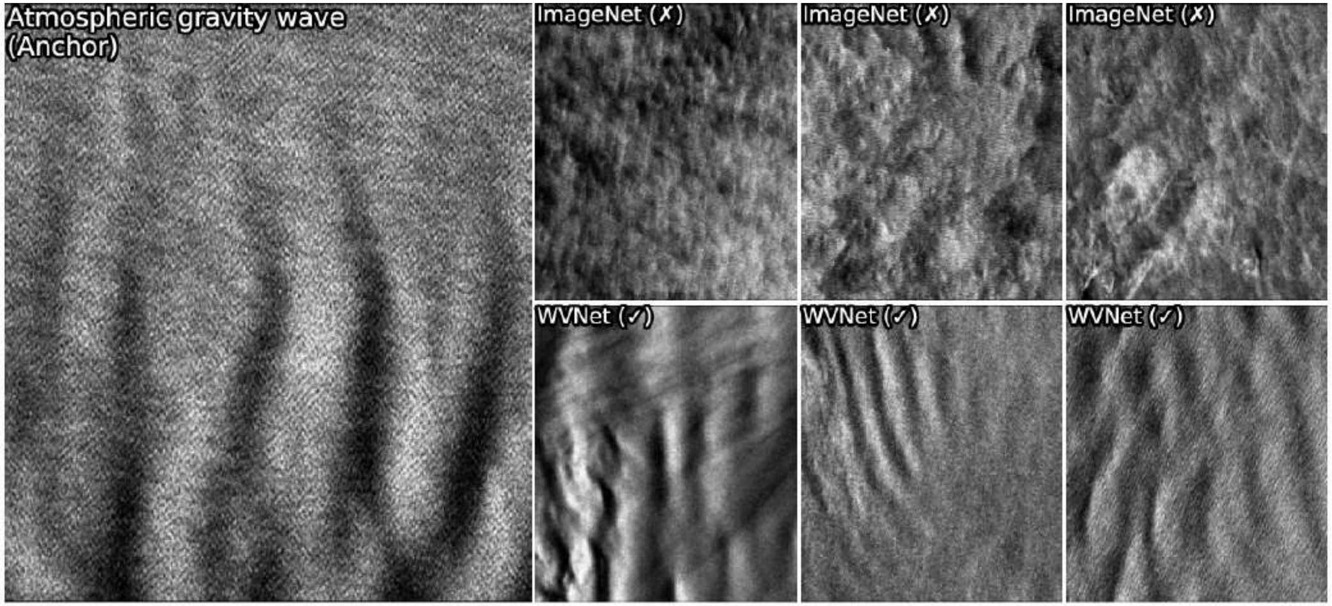


Image retrieval example for atmospheric gravity wave class. Anchor image (left column) is the query for kNN retrieval and the six images to the right are top-3 neighbors from ImageNet and WV-Net embeddings. This example shows successful image retrieval with the class present in the lower half of the anchor image.

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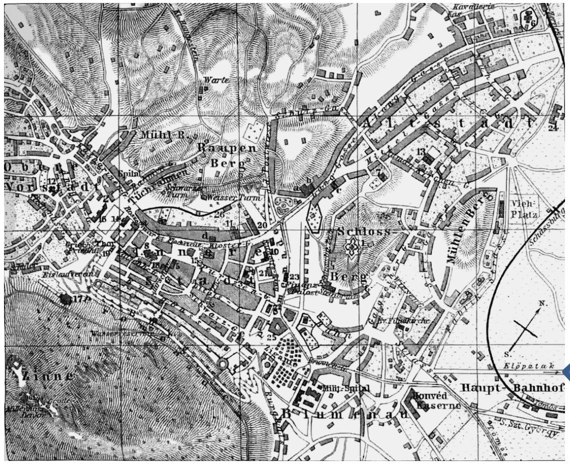
Back in time: virtual satellite images of 19th century

Image generation from historical maps based on DALL-E

Map XIX Century



RS XIX Century

RS XXI Century

Conclusions

A change of paradigm: Explainable, Physics-Aware, Trustworthy AI4EO

- From super-rezolution to prediction
- The Virtual Sensing – prediction and generation of observed:
  - Images
  - Scene physical signatures
- Physics aware generative models:
  - Realistic synthetic data
  - Simulations
- From Big EO Data to Small [Smart] Data:
- Synthetic data
- Image retrieval