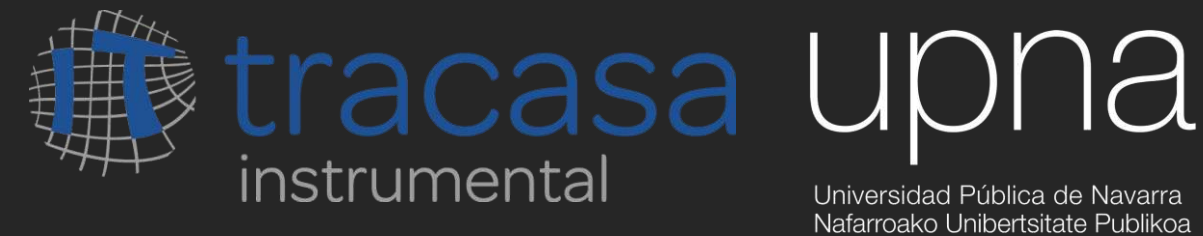


Super-Resolution of Sentinel2 Images Using the Second-order Attention Network and Geosat Images as Real Ground Truth Data

R. Sesma¹, C. Ayala¹, M. Galar²

¹ Tracasa Instrumental, Sarriguren, Spain

² Institute of Smart Cities (ISC), Public University of Navarre (UPNA),
Pamplona, Spain



1. Introduction
2. Related work
3. Motivation
4. Methodology
 - 4.1 Dataset
 - 4.2 Experimental framework
5. Results
6. Conclusions and future work

Sentinel2

- Open multispectral data
- Maximum resolution **10 meter** in RGB and NIR bands
- **NOT SUFFICIENT** for some use cases

Deep learning for super-resolution

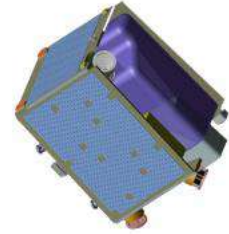
- Avoid using GAN or Diffusion methods as they can produce **unwanted visual artifacts**
- **CNNs** tend to generate more consistent results

Main problem to be solved

- Use data from another sensor with similar spectral characteristics as a ground truth
- **Preserve radiometry**



2. Related work



Reference sensor	<i>RapidEye</i> 5 m	<i>PlanetScope</i> 3.125 m	<i>Geosat</i> 0.75 m (Deimos2)
Image registration	No	Small shifts in HR	Optical flow estimation
Architecture	EDSR	EDSR	SAN
SR Bands	RGB x2 (8 bits)	RGBN x4 (16 bits)	RGBN x4 (16 bits)
Presented	ISPRS 2019 Munich <i>[Galar2019]</i>	MDPI Remote Sensing 2020 SENX4 <i>[Galar2020]</i>	SUREDOS24

[Galar2019] M. Galar, R. Sesma, C. Ayala, and C. Aranda, "Super-resolution for Sentinel-2 images", *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Sep. 17, 2019.

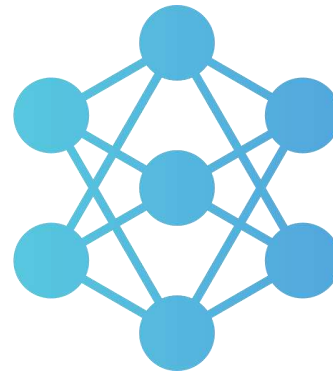
[Galar2020] M. Galar, R. Sesma, C. Ayala, L. Albizua, and C. Aranda, "Super-Resolution of Sentinel-2 Images Using Convolutional Neural Networks and Real Ground Truth Data", *Remote. Sens.*, vol. 12. *Remote. Sens.*, p. 2941, Sep. 10, 2020.

3. Motivation

Enhance our SENX4. Already helps to improve many tasks

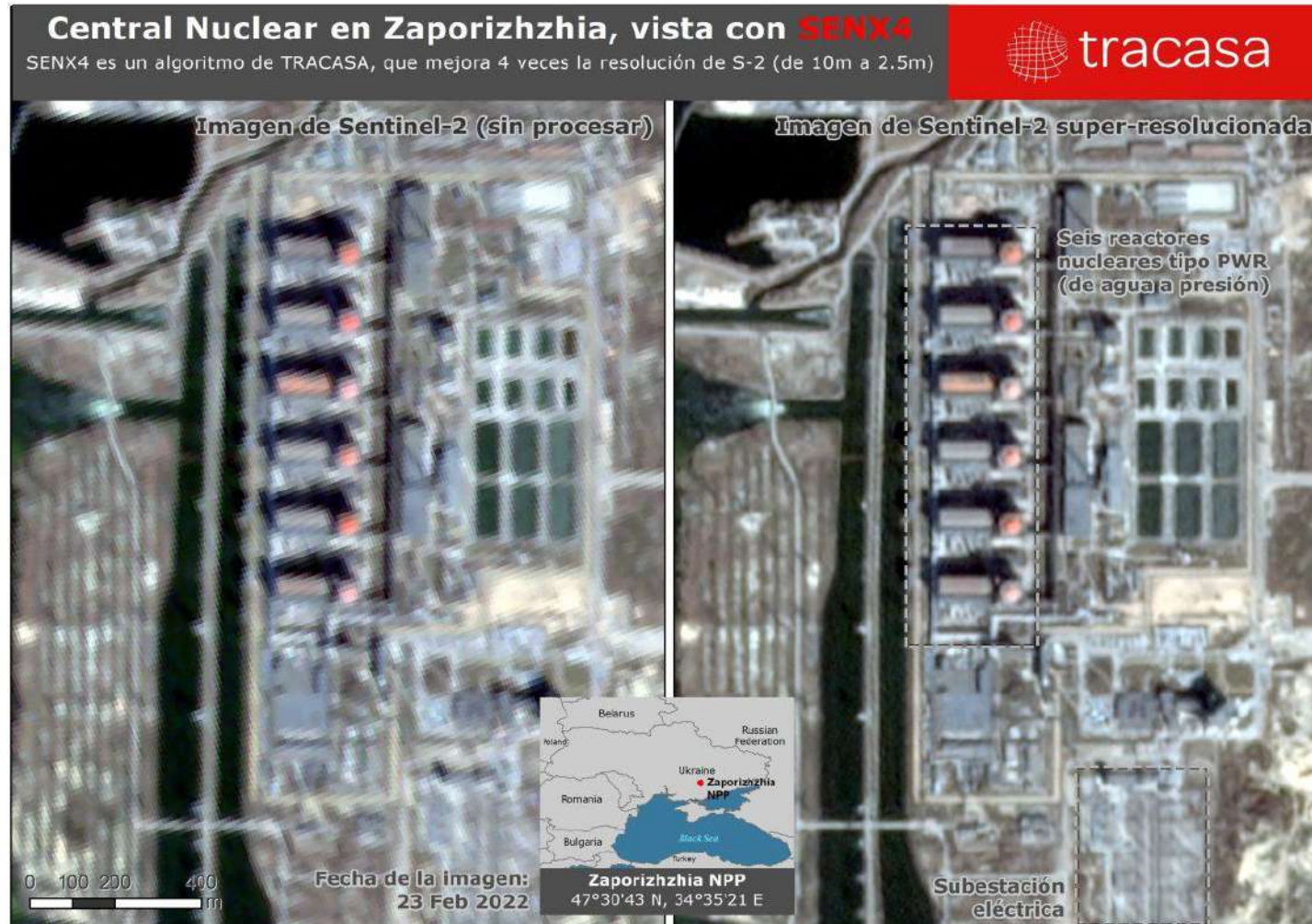
- Roads, paths or building segmentation, object detection, crop fields delimitation,...

Maintain a cutting-edge SR tool with the latest advances on deep learning



3. Motivation

Tracasa has already provided 50,000 km2 of super-resolution Sentinel-2 satellite images of the Ukrainian area



4.1 Dataset

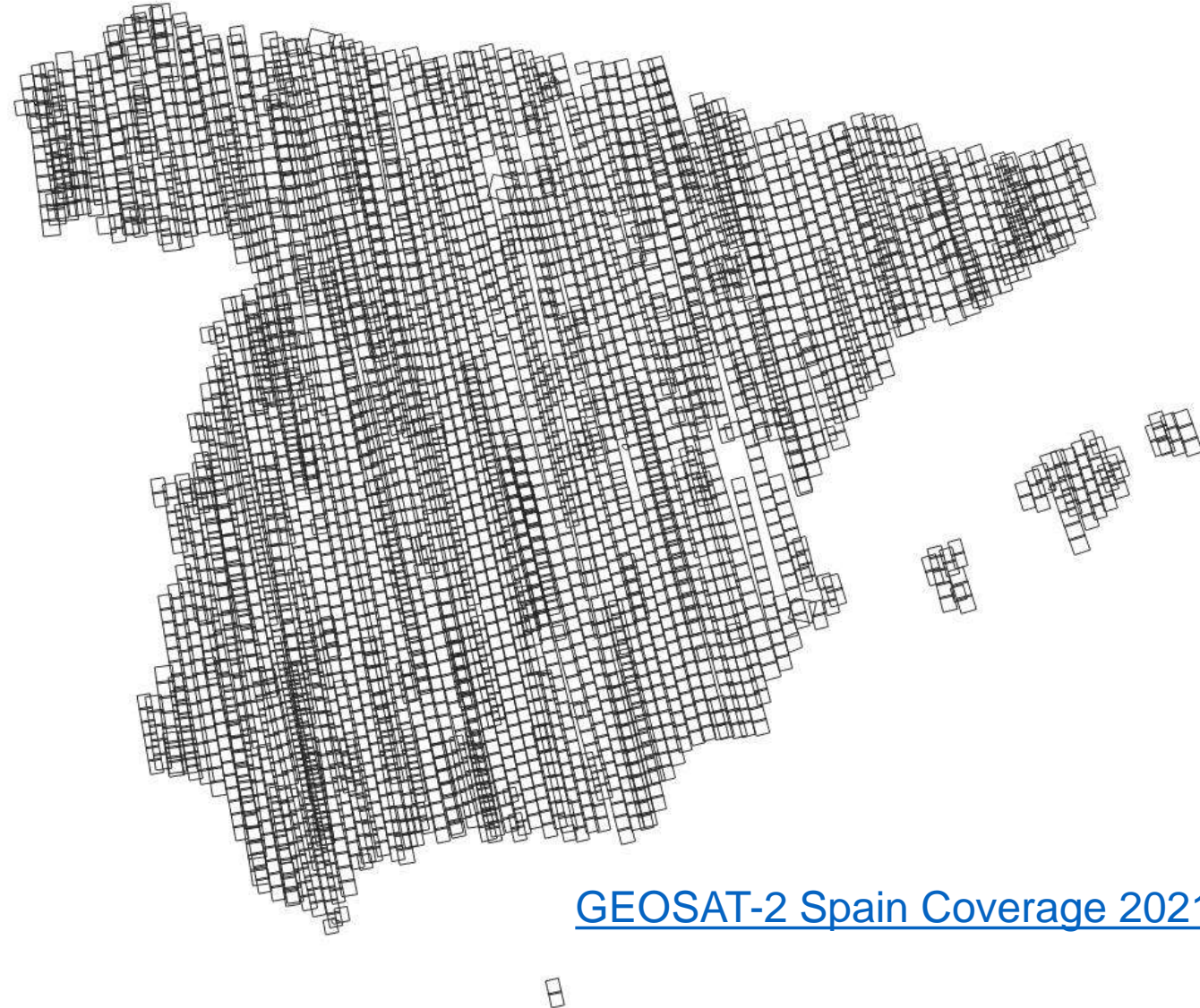
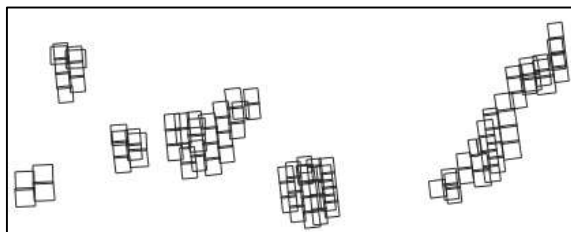
- Optimal Sentinel2-Geosat pairs search
- Co-registration Sentinel2-Geosat
- Patch validation
- Dataset split

4.2 Experimental framework

4.1 Dataset

Search for Sentinel2-Geosat image pairs

- Same date
- Geosat
 - Within Sentinel2
 - Acquisition angle [-15, 15]
 - Cloud coverage 0%
- Sentinel2
 - Cloud coverage between 0% and 5%
- Handmade selection by region/province

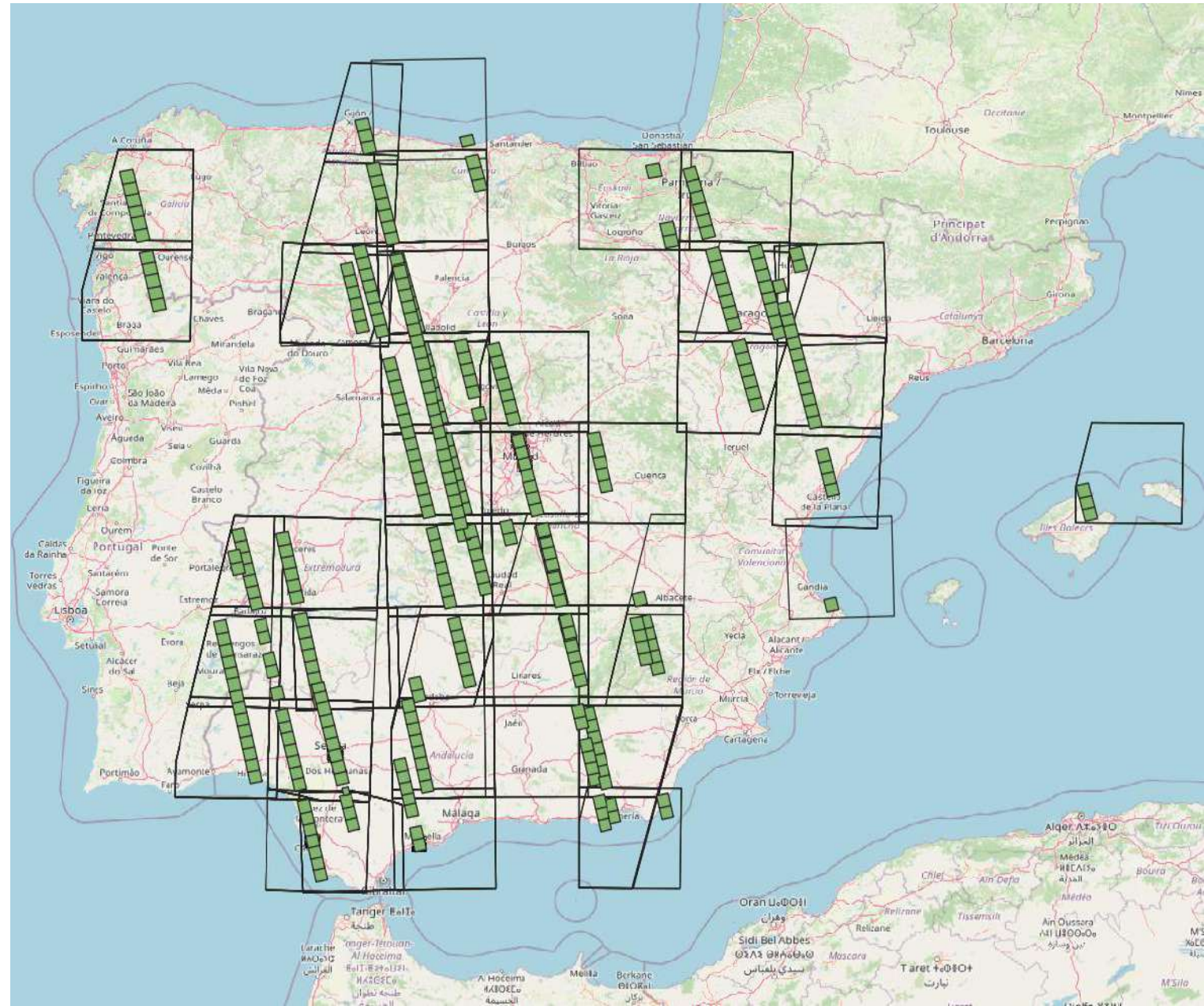


4.1 Dataset

Search for Sentinel2-Geosat image pairs

- **Same date**
- **Geosat**
 - **Within Sentinel2**
 - **Acquisition angle [-15, 15]**
 - **Cloud coverage 0%**
- **Sentinel2**
 - **Cloud coverage between 0% and 5%**
- **Handmade selection by region/province**

Total: 337 pairs



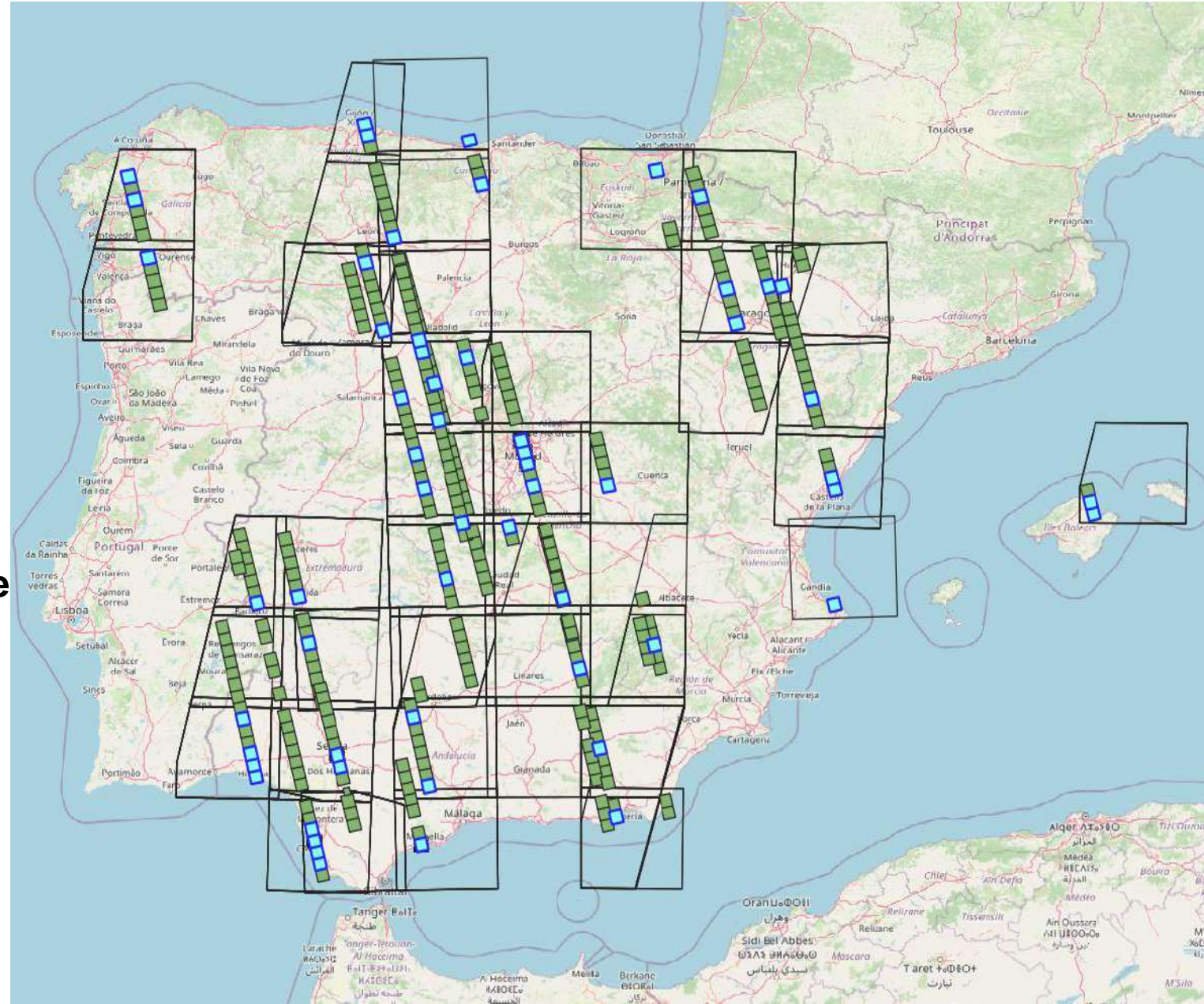
4.1 Dataset

Search for Sentinel2-Geosat image pairs

- Same date
- Geosat
 - Within Sentinel2
 - Acquisition angle $[-15, 15]$
 - Cloud coverage 0%
- Sentinel2
 - Cloud coverage between 0% and 5%
- **Handmade selection by region/province**

Total: 337 pairs

Selected: 60 pairs

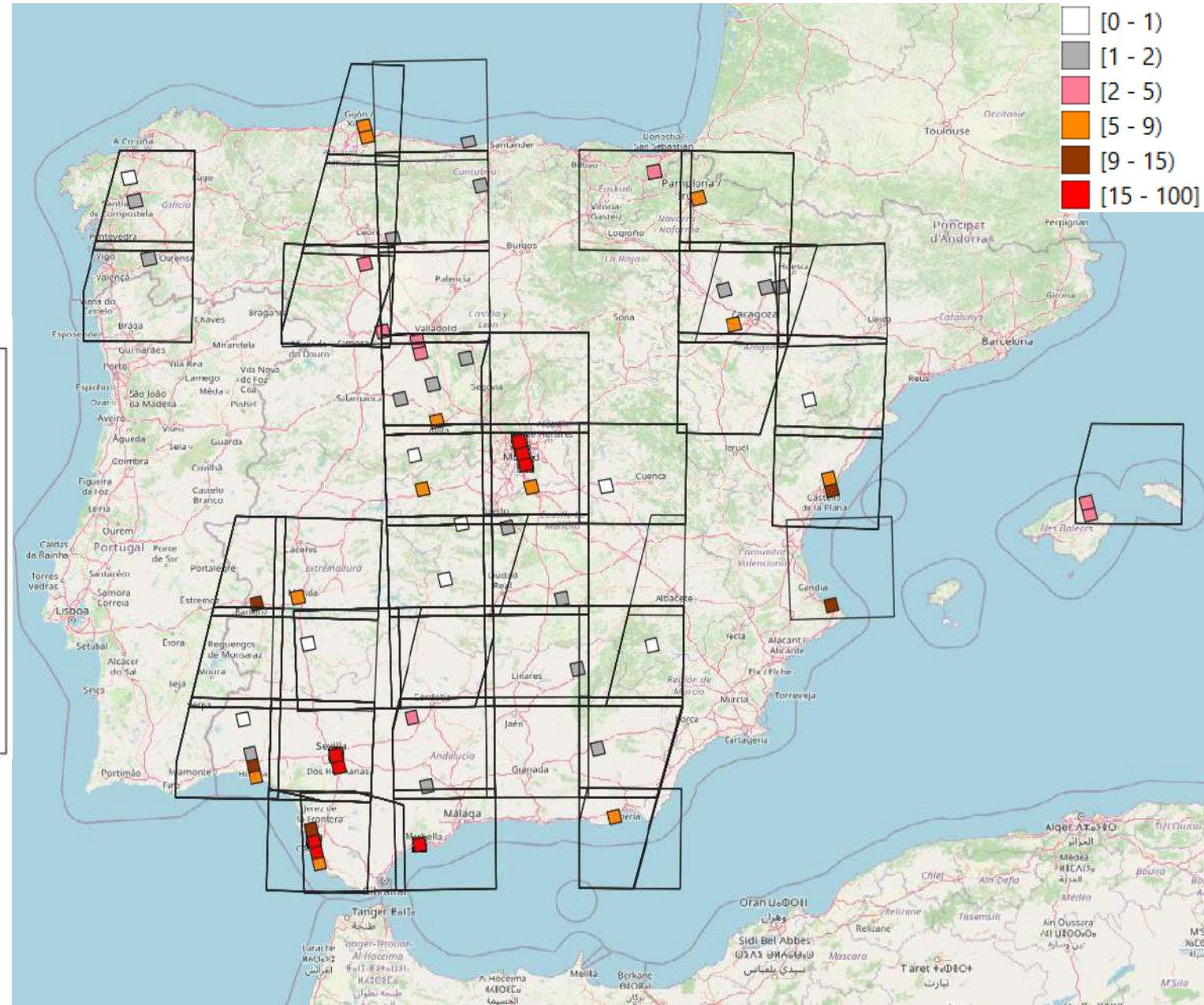
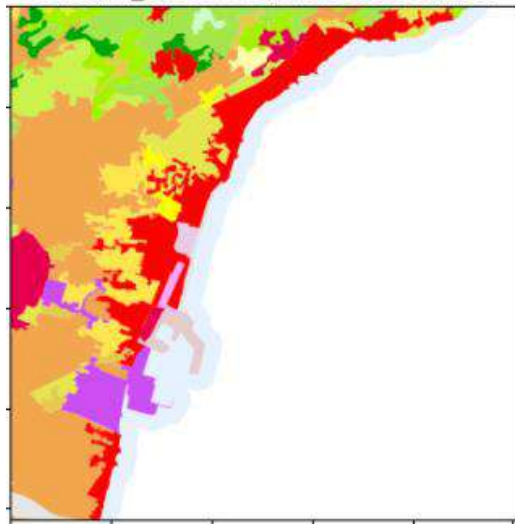


4.1 Dataset

Selected pairs categorization CORINE Urban level percent of each pair based on CORINE LC.LandCoverSurfaces

- 111-Continuous urban fabric
- 112-Discontinuous urban fabric
- 121-Industrial or commercial units
- 122-Road and rail networks and associated land
- 123-Port areas
- 124-Airports
- 133-Construction sites
- 141-Green urban areas
- 142-Sport and leisure facilities

Castelló_Castellón LandCoverSurfaces



4.1 Dataset

Top 6 pairs with highest urban level

Madrid 1

S2A_MSIL2A_20210806T105621_N0301_R094_T30TVK_20210806T140713

DE2_PSH_L1C_000000_20210806T103532_20210806T103535_DE2_38647_794B

Madrid 2

S2A_MSIL2A_20210806T105621_N0301_R094_T30TVK_20210806T140713

DE2_PSH_L1C_000000_20210806T103530_20210806T103533_DE2_38647_57EA

Madrid 3

S2A_MSIL2A_20210806T105621_N0301_R094_T30TVK_20210806T140713

DE2_PSH_L1C_000000_20210806T103529_20210806T103531_DE2_38647_BCF5

Sevilla

S2B_MSIL2A_20210317T110709_N0214_R137_T29SQB_20210317T130544

DE2_PSH_L1C_000000_20210317T105014_20210317T105016_DE2_36540_095E

Cádiz

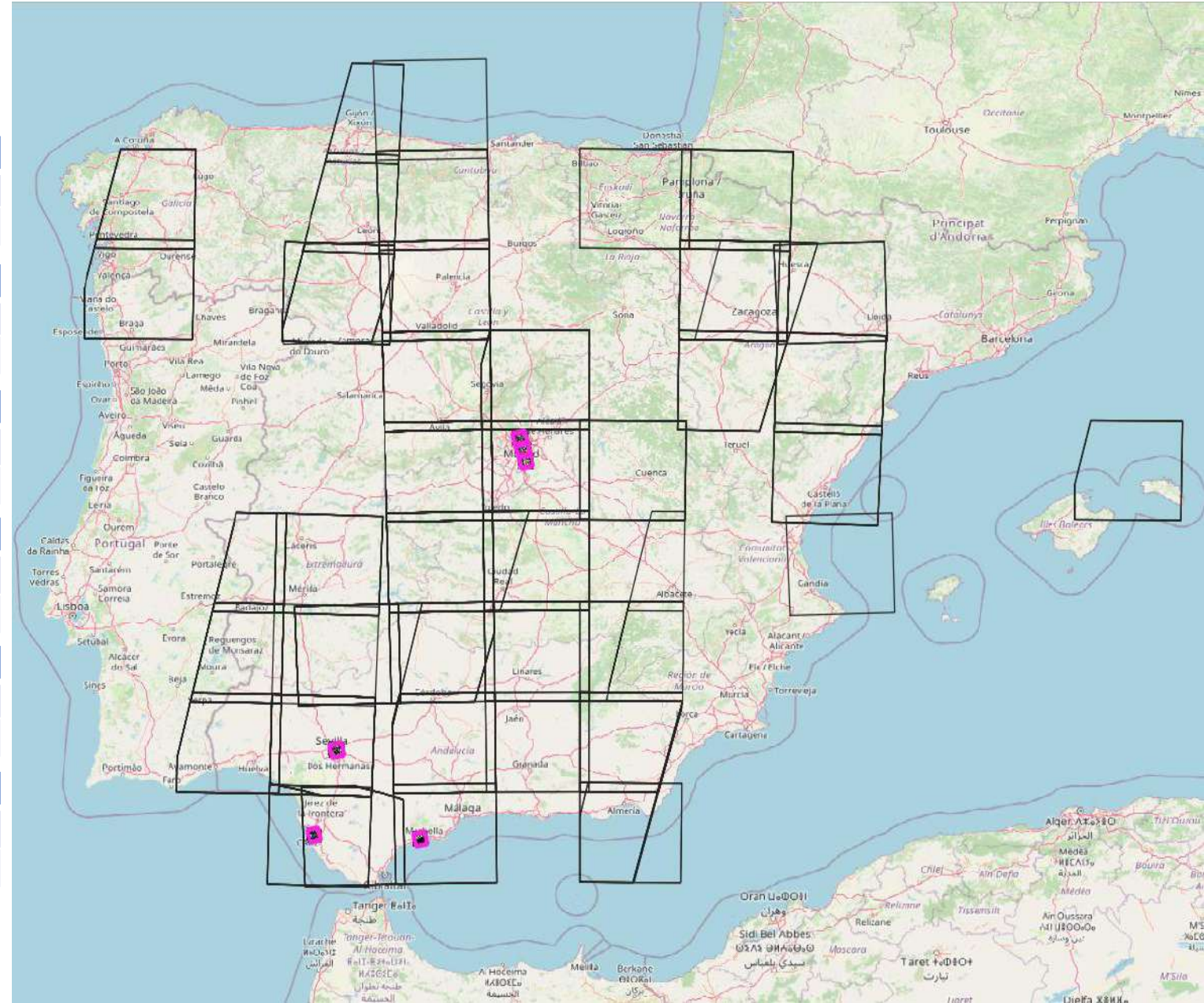
S2B_MSIL2A_20210506T110619_N0300_R137_T30STF_20210506T143112

DE2_PSH_L1C_000000_20210506T105513_20210506T105515_DE2_37282_3781

Málaga

S2B_MSIL2A_20210612T105619_N0300_R094_T30SUF_20210612T124340

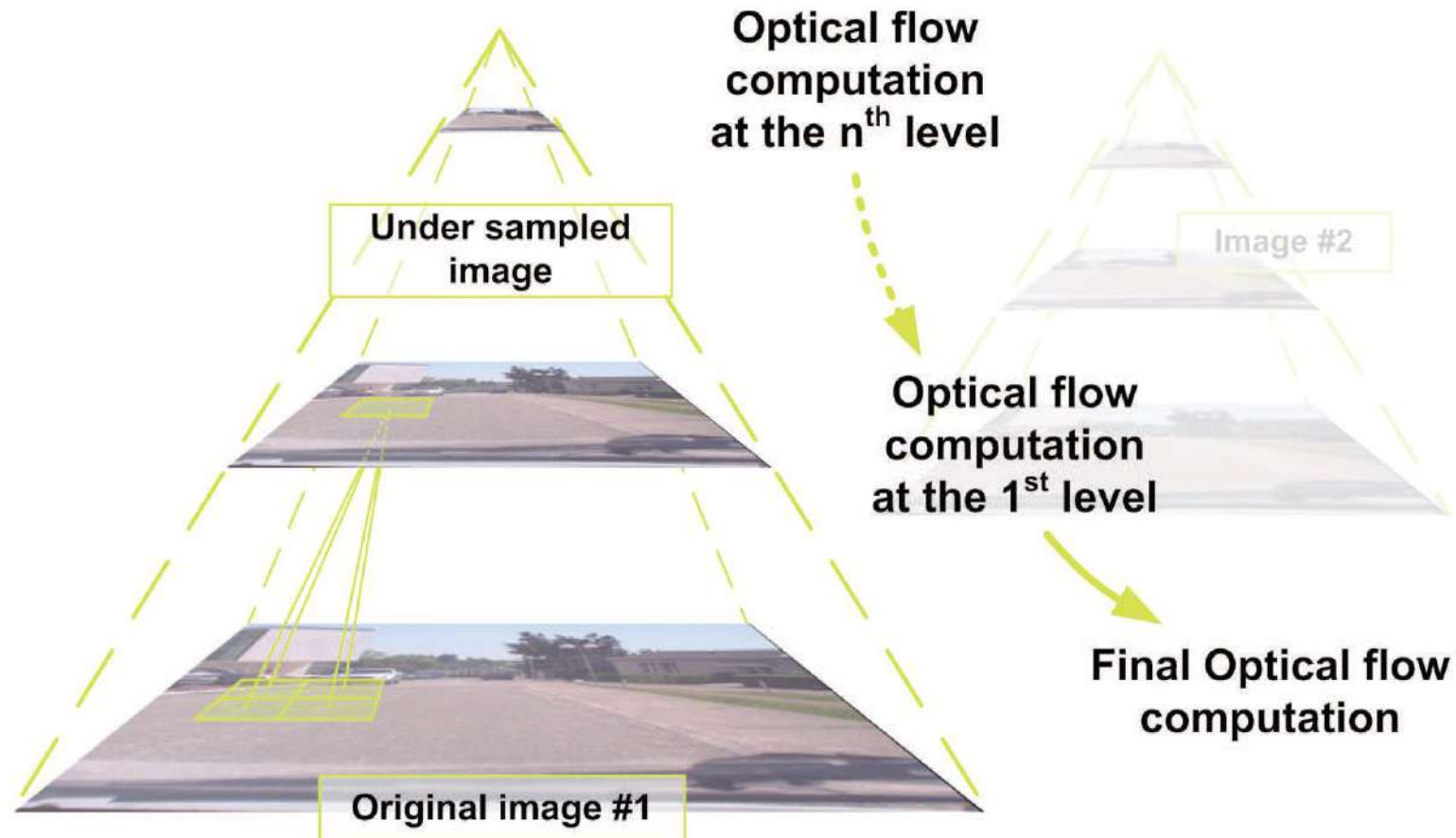
DE2_PSH_L1C_000000_20210612T105028_20210612T105031_DE2_37831_86FF



4.1 Dataset

Image co-registration based on Lucas-Kanade Optical Flow method

For each pixel of the image, establishes the **translation** that allows to find the **corresponding pixel** in the other image



4.1 Dataset

Patch validation

Sentinel2-Geosat RGBN patches

- Spitted images into cell grid
- Sentinel-2 40x40
- Geosat 160x160

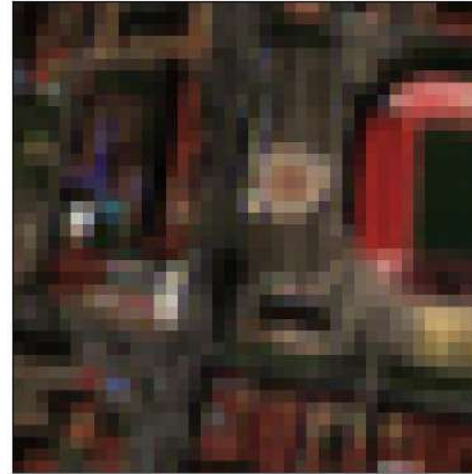
Color correction

- Histogram matching [González2008]

Discarding unwanted patches

- Accept PSNR between 18 and 29
- Automatic validation
- Clouds, flat surfaces, water,...

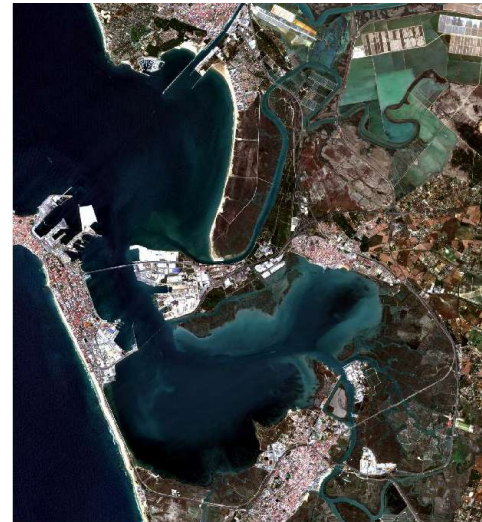
LR Sentinel2



HR Geosat



Histogram matching



Sentinel2



Geosat

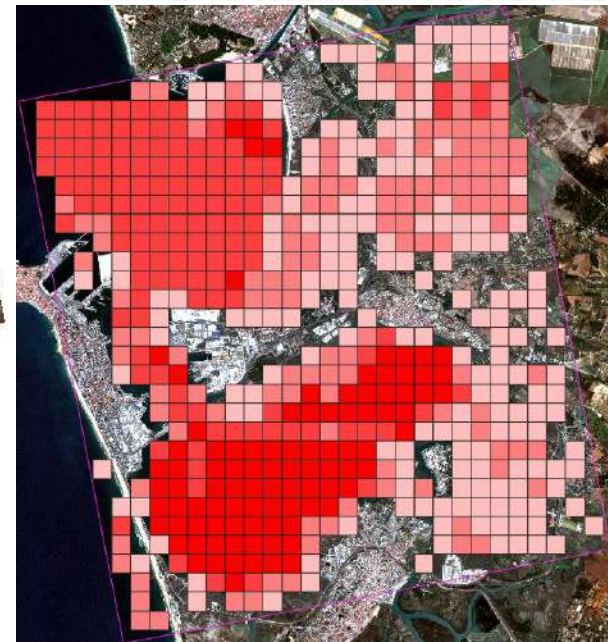
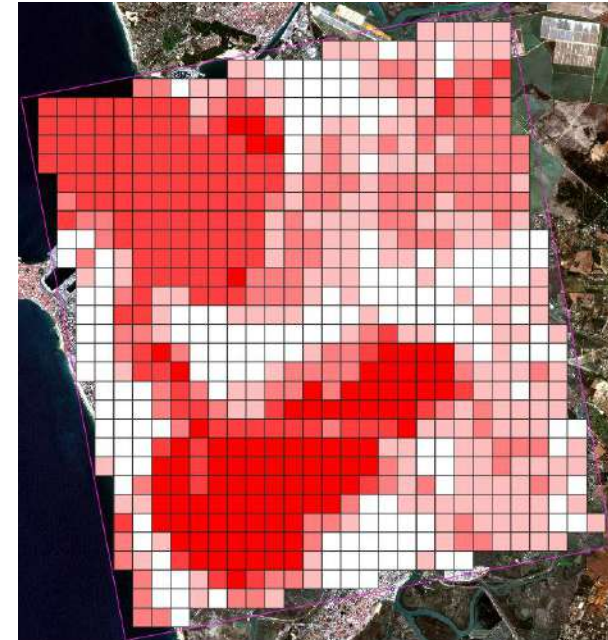


Validation grid cell

[González2008] González, R. C., Woods, R. E., (3rd). 2008. *Digital Image Processing*. Prentice Hall.

4.1 Dataset

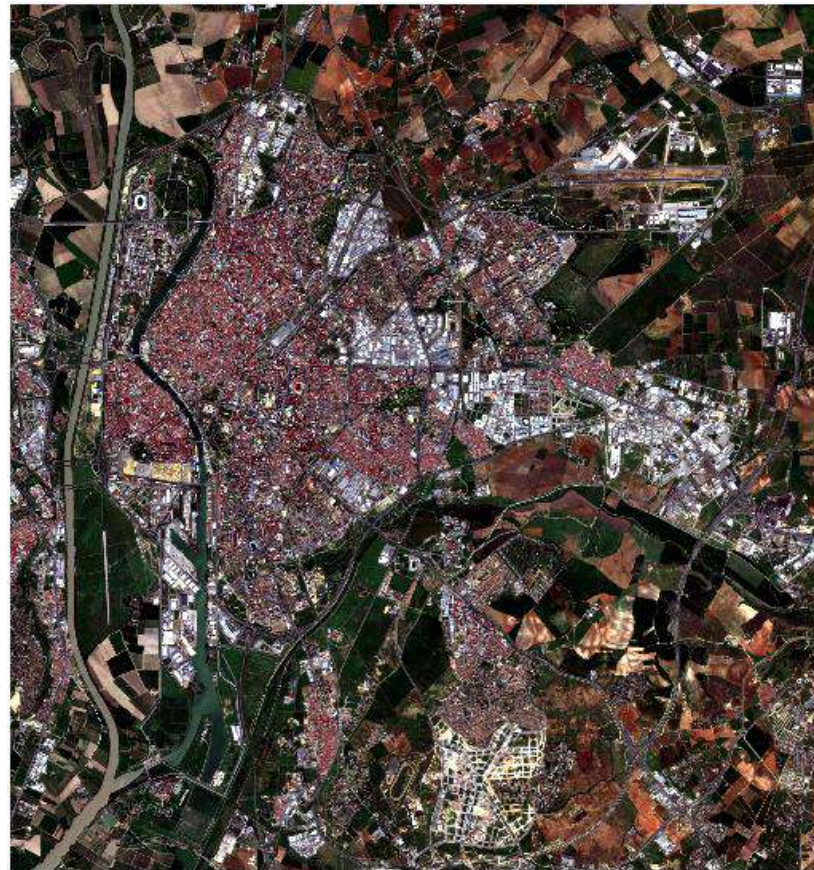
Patch validation PSNR RGBN between [18, 29)
Cádiz



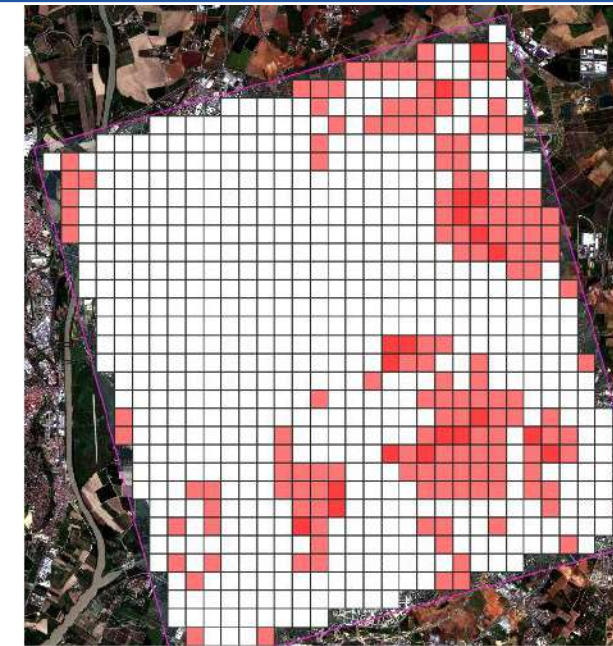
- [22 - 29)
- [29 - 33)
- [33 - 39)
- [39 - 44)
- [44 - 51]





4.1 Dataset

Patch validation PSNR RGBN between [18, 29)



Sevilla

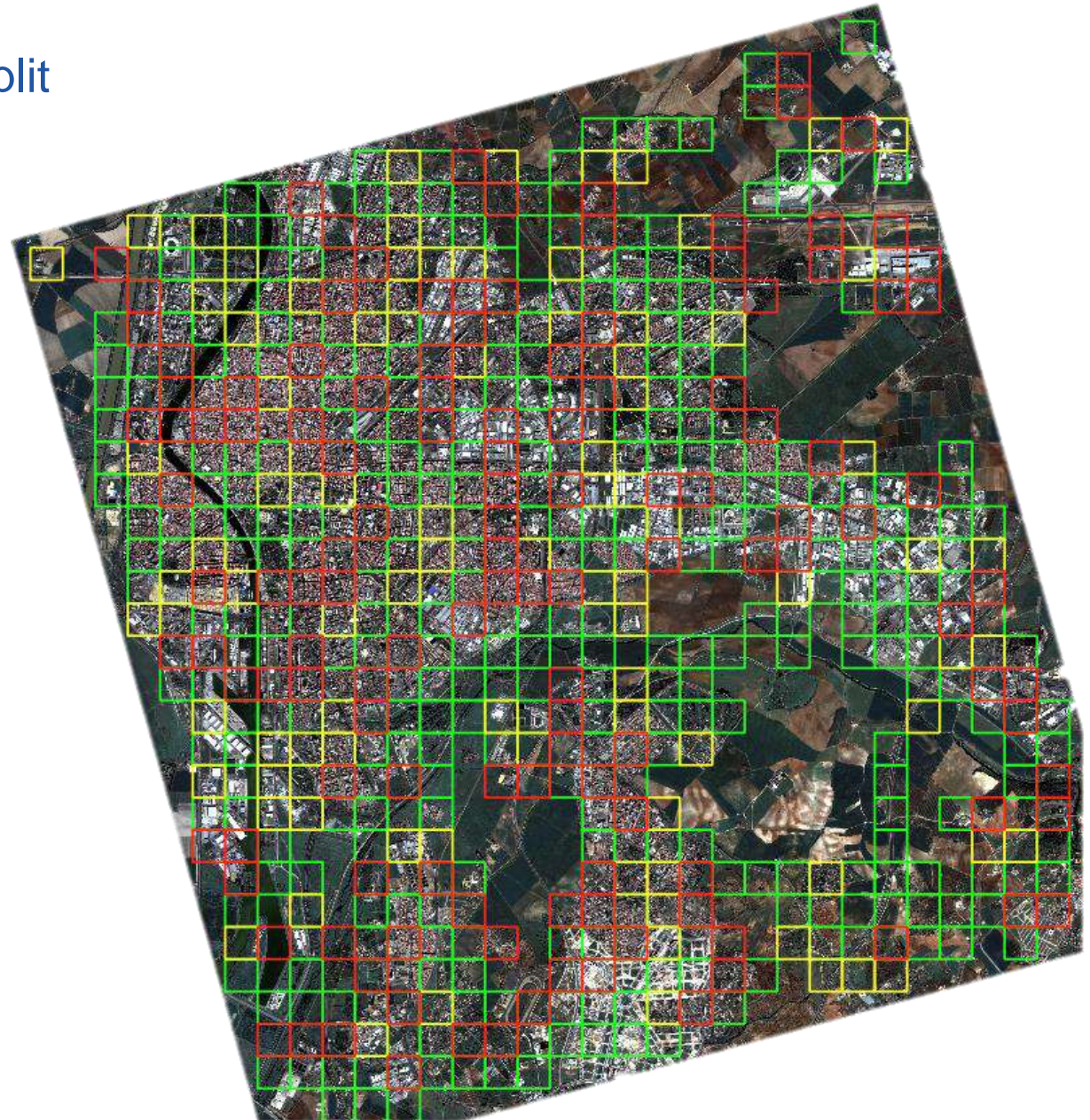


-  [15 - 18)
-  [18 - 29)
-  [29 - 34)
-  [34 - 40]

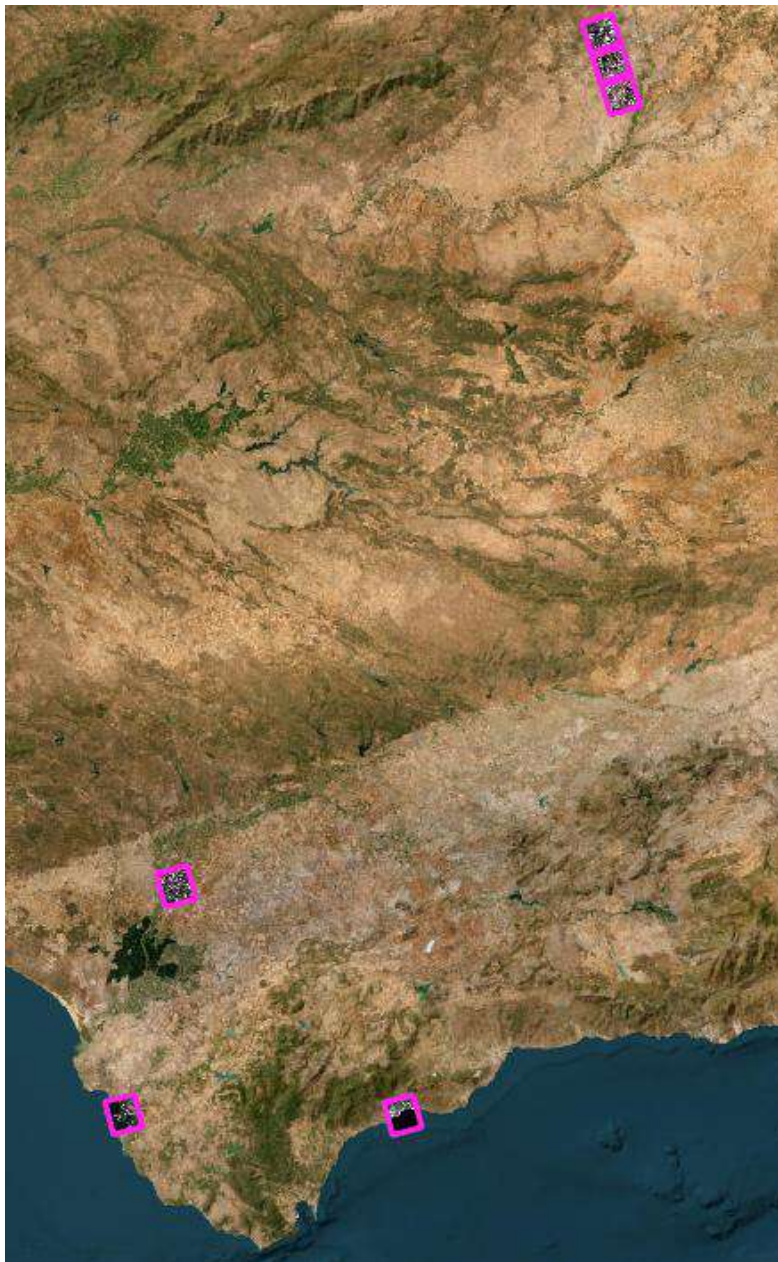
4.1 Dataset

Dataset summary and train/validation test split

Set	Train	Valid	Test	Total
Madrid 1	389	87	121	597
Madrid 2	393	119	128	640
Madrid 3	302	68	82	452
Sevilla	361	89	133	583
Cádiz	115	25	25	165
Málaga	160	42	49	251
Total	1720	430	538	2688
Pct.	64%	16%	20%	100%



4.1 Dataset



4.2 Experimental framework

SENX4, EDSR [Lim2017] vs. SAN [Dai2019]

- 4 channels: Input and output RGB+NIR
- BatchNorm in ResBlocks
- Upsampling blocks with ICNR [Aitken2017]
- Blur with AvgPooling layer [Sugawara2018]

Loss function

- *Pixel + Feature + Style* [Johnson2016]
- Adapted to NIR band
- Weighted loss function RGB+NIR

Training

- Learning rate finder
- *Early stopping* validation set
- Dihedral transform
- Hardware: NVIDIA RTX 2080Ti RAM 11GB0

Normalization

- 12 bit range to [0, 1]

Performance

- PSNR (*Peak Signal-to-Noise Ratio*)
- SSIM (*Structural Similarity*)

Parameter	Value
VGG16 layers in loss	First 3 max-pool layers
Feature and style weights	0.75, 0.25, 0.05 / 100, 25000, 100
RGB / NIR loss	0.75 / 0.25
Optimizer	Adam
Learning strategy	One cycle policy <i>pct_start=0,7</i>
Weight decay	$1e^{-5}$
Batch size	32

[Lim2017] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee, "Enhanced Deep Residual Networks for Single Image Super-Resolution", *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 1132–1140, Jul. 10, 2017.

[Dai2019] T. Dai, J. Cai, Y. Zhang, S. Xia, and L. Zhang, "Second-Order Attention Network for Single Image Super-Resolution", *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 11057–11066, Jun. 01, 2019.

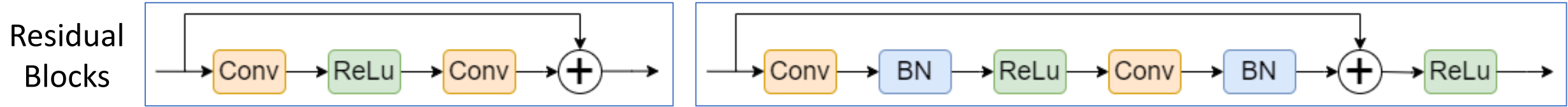
[Aitken2017] A. P. Aitken, C. Ledig, L. Theis, J. Caballero, Z. Wang, and W. Shi, "Checkerboard artifact free sub-pixel convolution: A note on sub-pixel convolution, resize convolution and convolution resize", *ArXiv*, vol. abs/1707.02937. *ArXiv*, Jul. 10, 2017

[Sugawara2018] Y. Sugawara, S. Shiota, and H. Kiya, "Super-Resolution Using Convolutional Neural Networks Without Any Checkerboard Artifacts", *2018 25th IEEE International Conference on Image Processing (ICIP)*, pp. 66–70, Jun. 07, 2018.

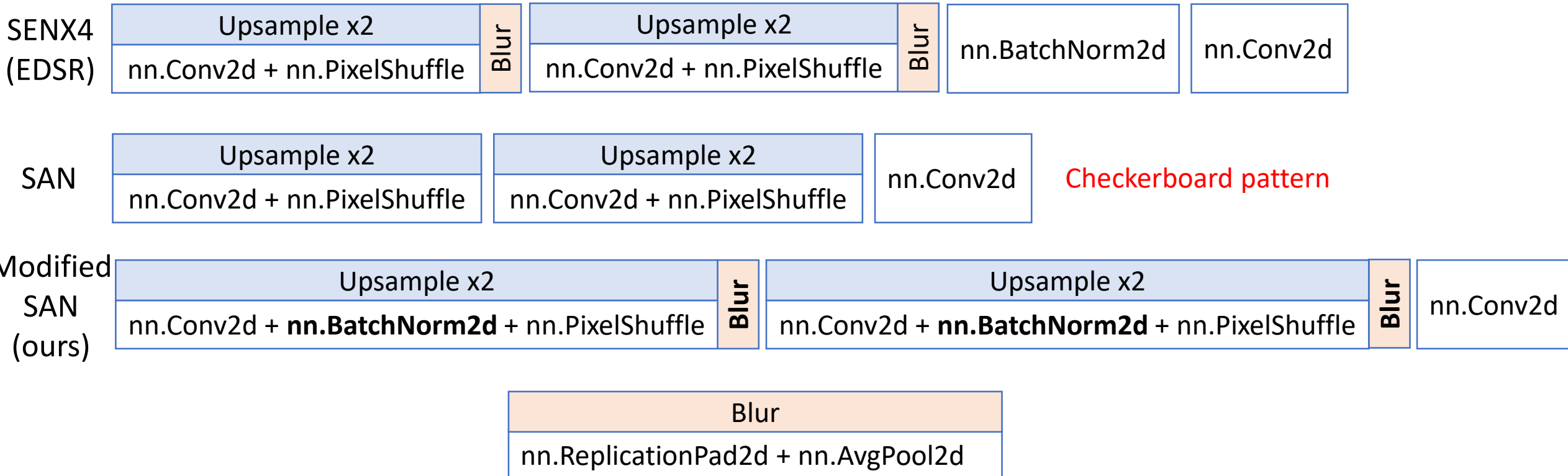
[Johnson2016] J. Johnson, A. Alahi, and L. Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution"– *Computer Vision - ECCV 2016*, pp. 694-711

4.2 Experimental framework

Adjustments in SAN Residual Blocks



Adjustments in Upsampling Blocks + ICNR initialization



5. Results

PSNR			
Method	Train	Valid	Test
Bicubic	24.98	24.83	24.86
SENX4 (PS)	25.64	25.49	25.52
EDSR	26.03	25.87	25.91
SAN	26.46	26.27	26.30
SAN (ours)	27.21	26.86	26.88

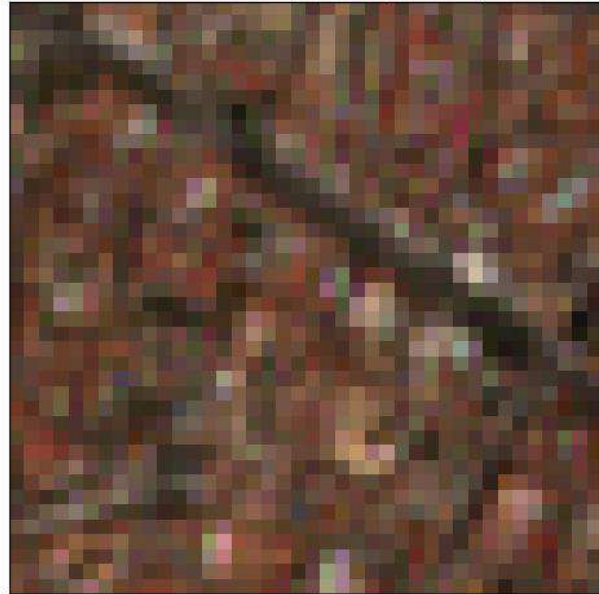
- Improvements with respect to the SENX4 and Bicubic
1.36 PSNR
0.0618 SSIM

SSIM			
Method	Train	Valid	Test
Bicubic	0.6137	0.6073	0.6059
SENX4 (PS)	0.6655	0.6595	0.6576
EDSR	0.6757	0.6698	0.6683
SAN	0.6926	0.6858	0.6831
SAN (ours)	0.7356	0.7220	0.7194

- Adjustments to the SAN architecture have improved results

5. Results

Sentinel2 (PSNR/SSIM)



Bicubic (22.71db/0.4841)



SENX4 (23.82db/0.5929)



Geosat



EDSR (23.75db/0.5839)



SAN (24.43db/0.599)



SAN Ours (25.26db/0.6689)

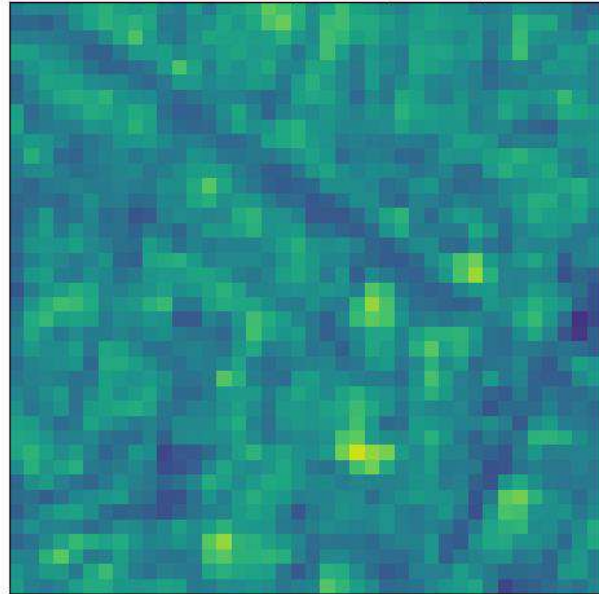


Urban scene RGB

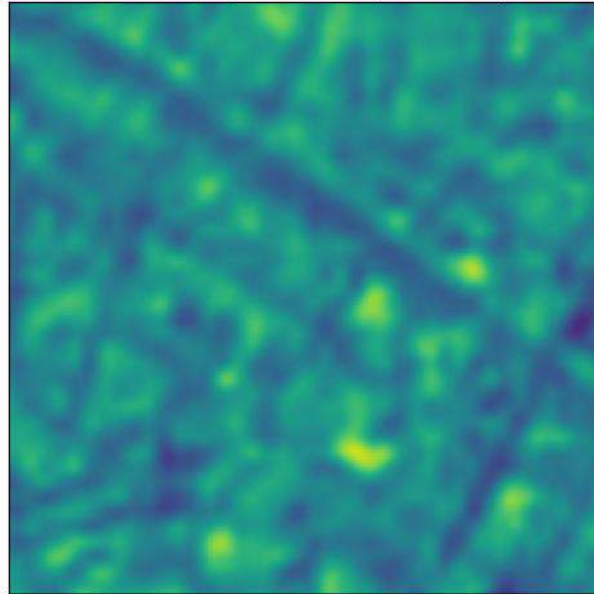
- The blur effect is decreasing
- Fixed checkerboard pattern in SAN

5. Results

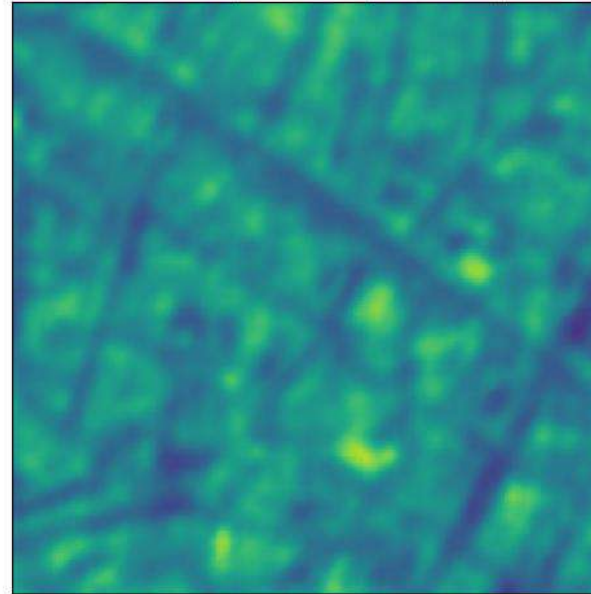
Sentinel2 (PSNR/SSIM)



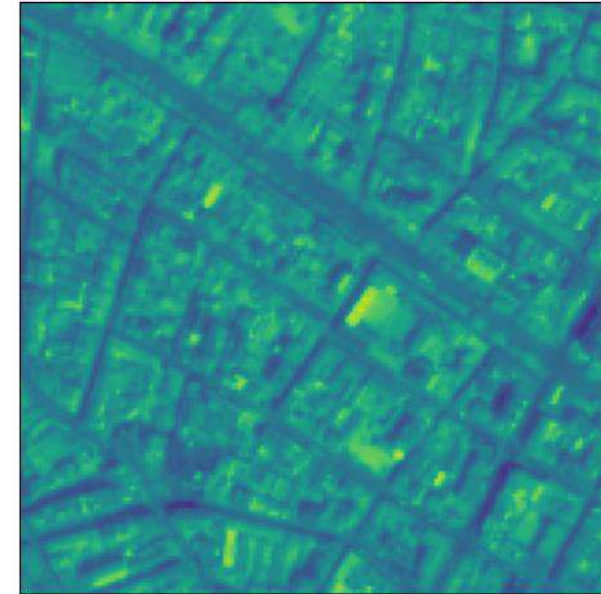
Bicubic (22.71db/0.4841)



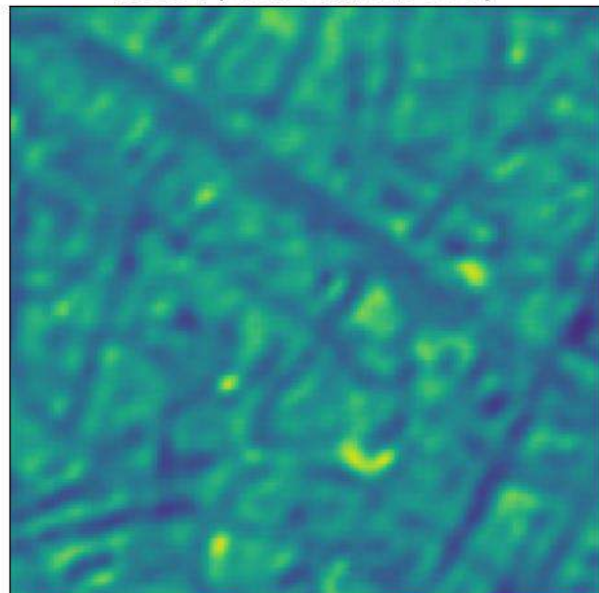
SENX4 (23.82db/0.5929)



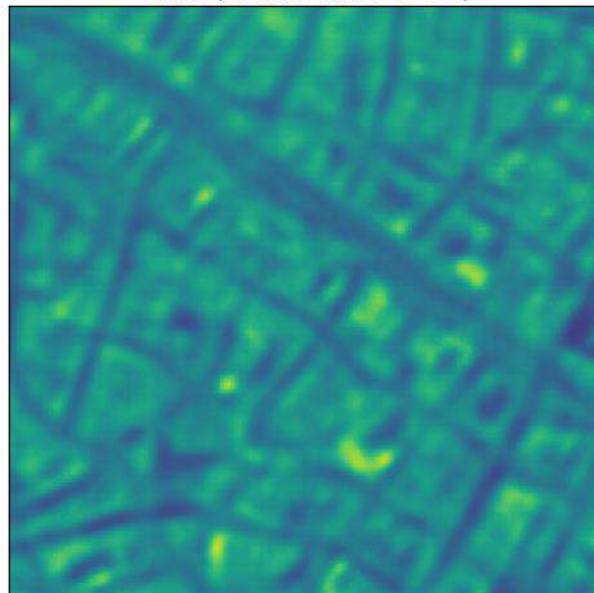
Geosat



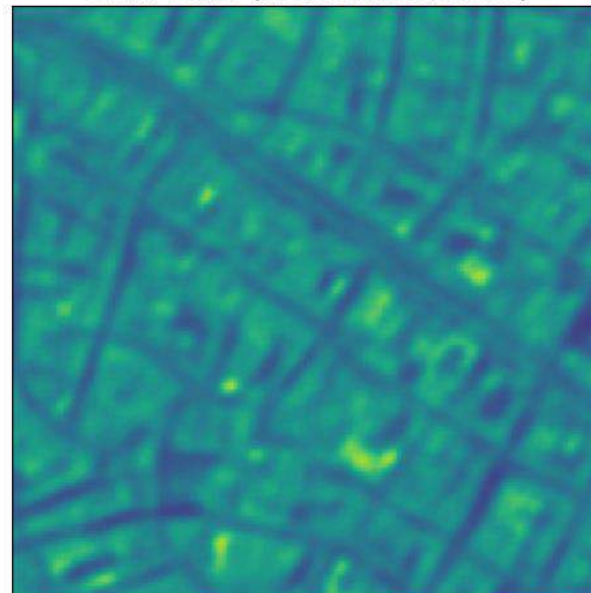
EDSR (23.75db/0.5839)



SAN (24.43db/0.599)



SAN Ours (25.26db/0.6689)

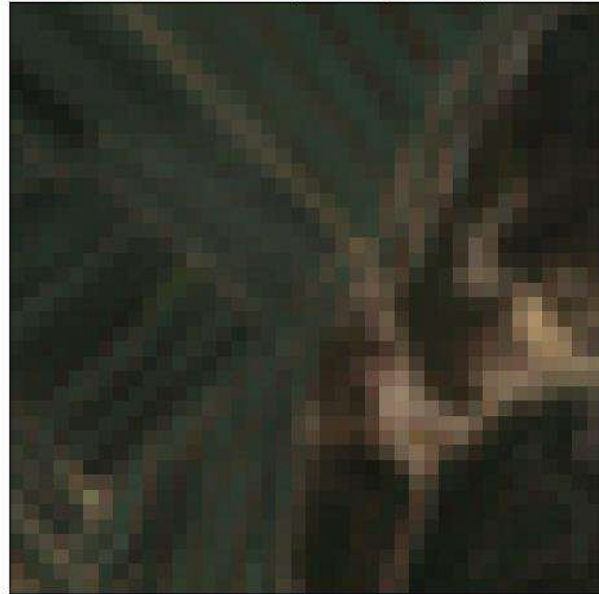


Urban scene NIR

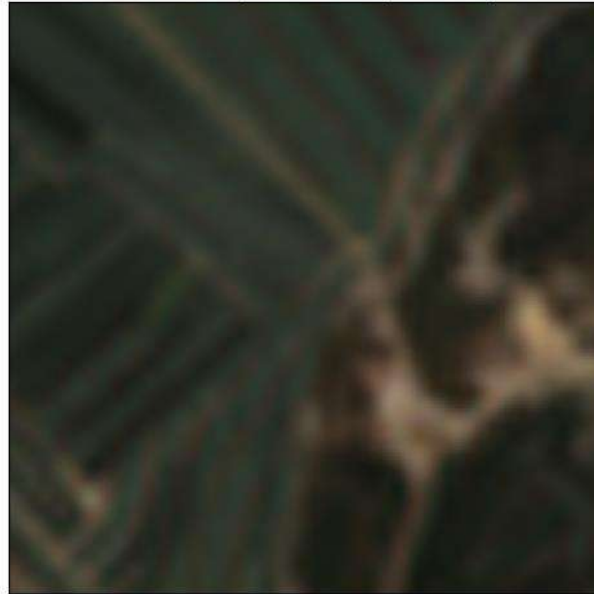
- The blur effect is decreasing
- Fixed checkerboard pattern in SAN

5. Results

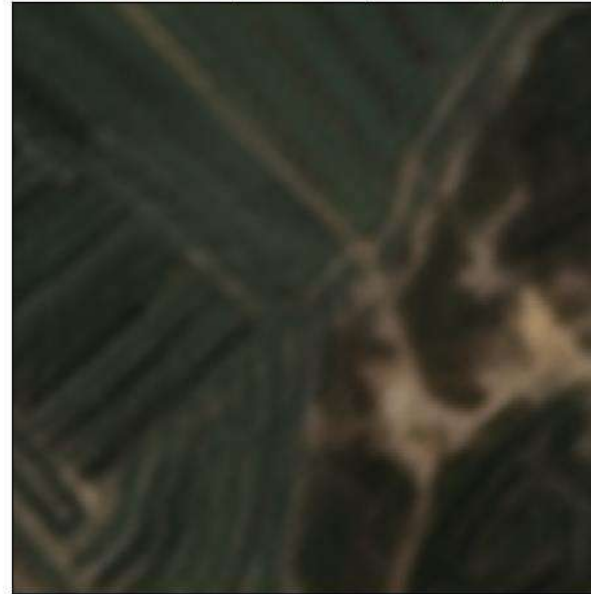
Sentinel2 (PSNR/SSIM)



Bicubic (26.88db/0.618)



SENX4 (27.31db/0.6599)



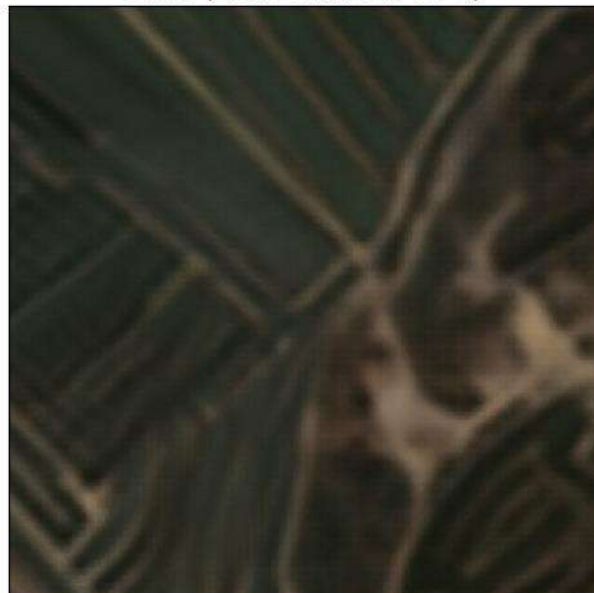
Geosat



EDSR (27.75db/0.6737)



SAN (28.38db/0.7051)



SAN Ours (29.63db/0.7998)

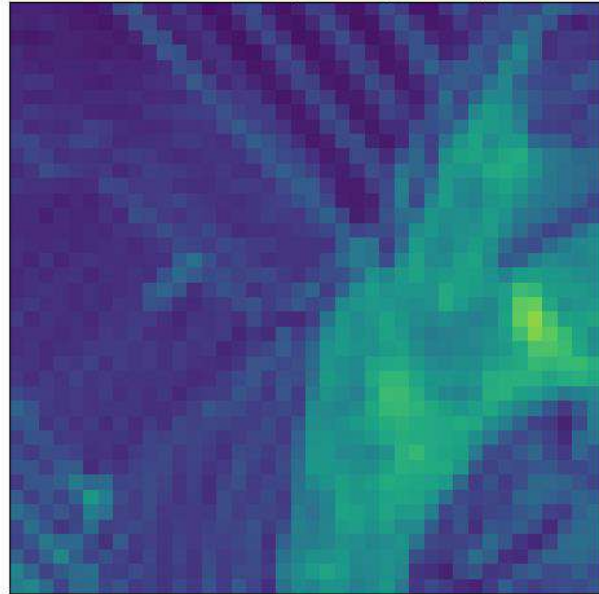


Crops scene RGB

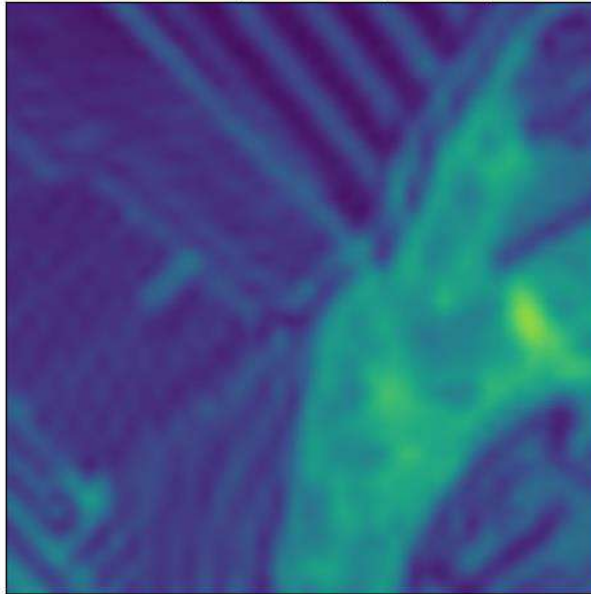
- Enhancements crop boundaries

5. Results

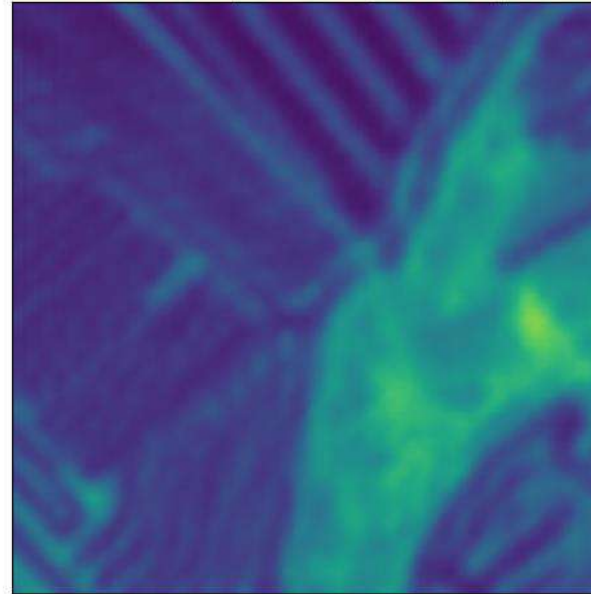
Sentinel2 (PSNR/SSIM)



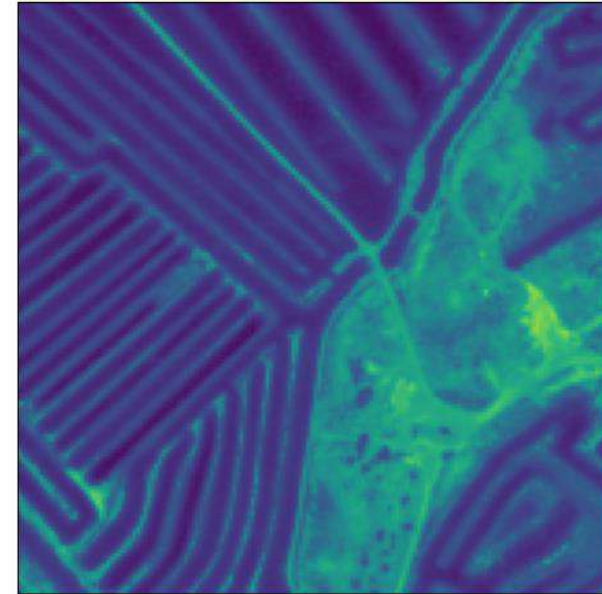
Bicubic (26.88db/0.618)



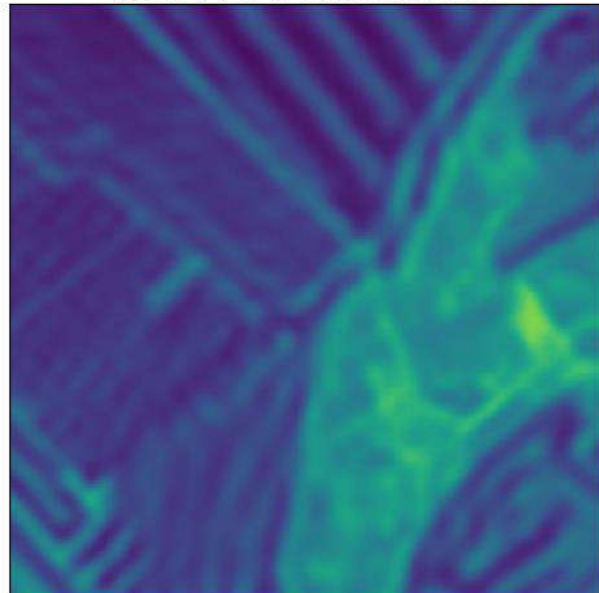
SENX4 (27.31db/0.6599)



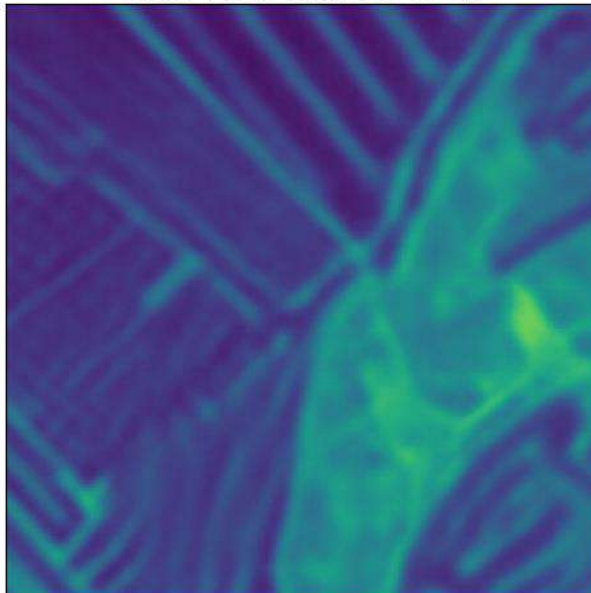
Geosat



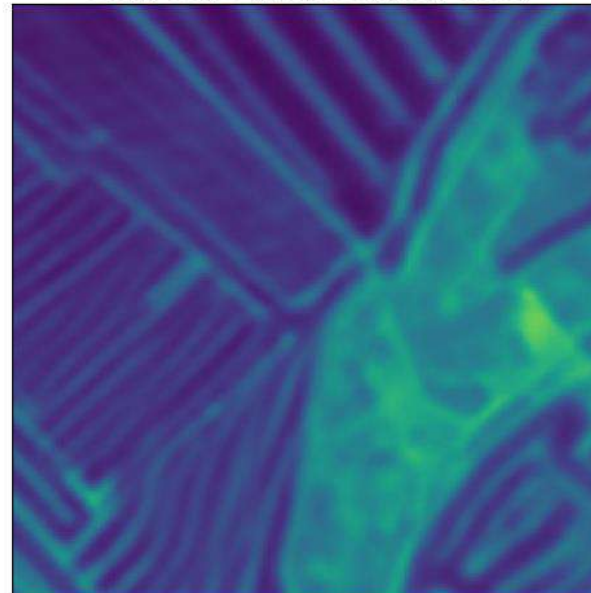
EDSR (27.75db/0.6737)



SAN (28.38db/0.7051)



SAN Ours (29.63db/0.7998)

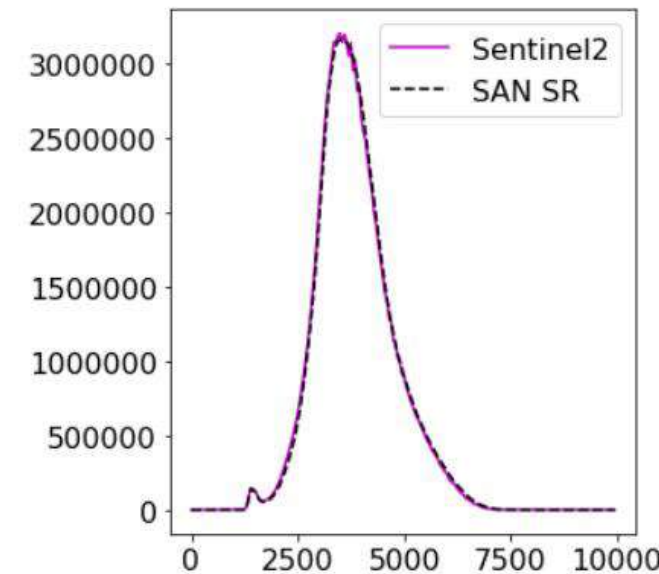
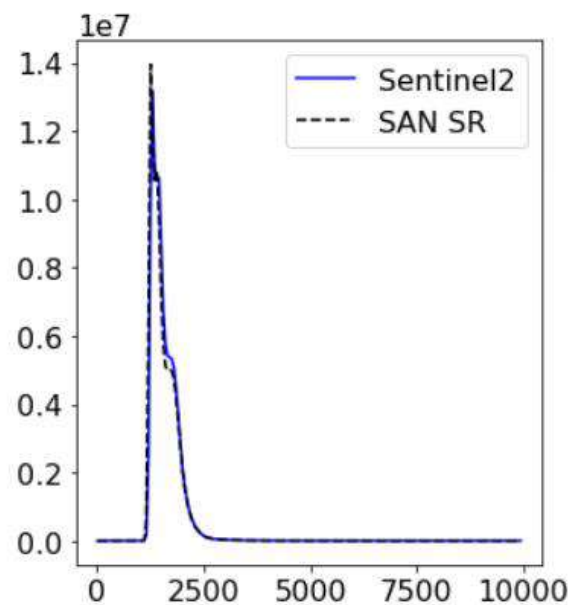
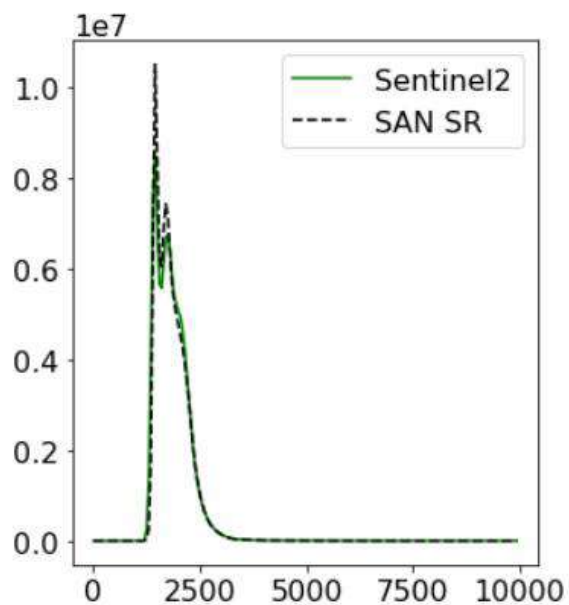
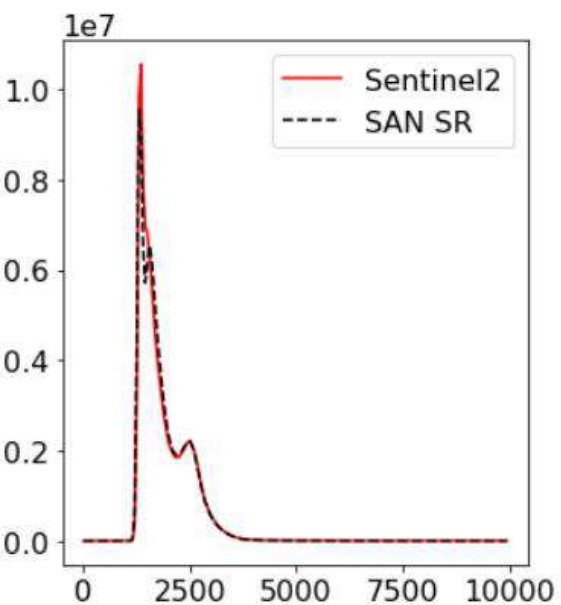
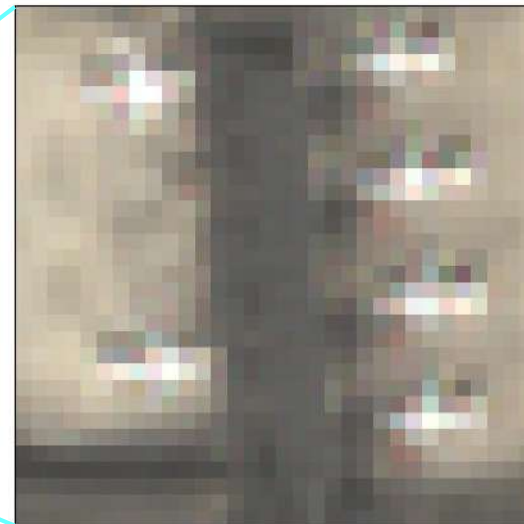
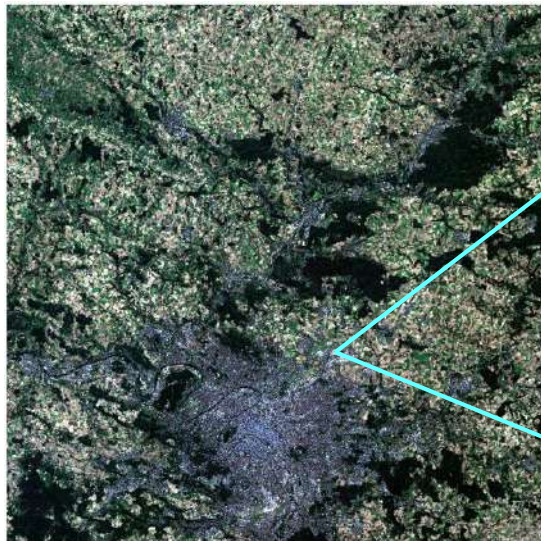
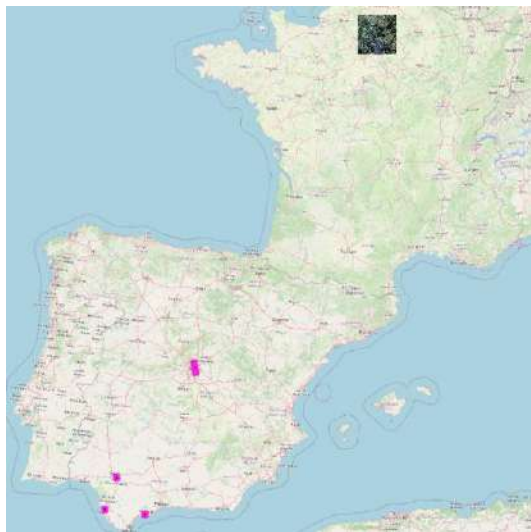


Crops scene NIR

- Enhancements crop boundaries

5. Results

Radiometric validation S2B_MSIL2A_20231007T104829_N0509_R051_T31UDQ_20231007T135731 (Paris)



Conclusions

- **Improvements at each step** of the process demonstrate the advantage of the proposal
- **Histogram matching** for patch validation
- **Adjustments in CNNs** help to avoid the checkerboard pattern
- Reference data from **Geosat** with a resolution greater than 2.5m
- **Radiometric validation**

Future work

- Expand the dataset (number of images, locations, and variety of scenarios)
- Compare with **other architectures**
- Improve the super-resolution of the NIR band
- **Validate results on other tasks** such as semantic segmentation, object detection...

Current status...

Tracasa R&D lab SR current status



S2A_MSIL2A_20240514T100031_N0510_R122_T33TTG_20240514T141750 (St. Peter's Square and Coliseum)



Super-Resolution of Sentinel-2 Images Using the Second-order Attention Network and Geosat Images as Real Ground Truth Data

R. Sesma¹, C. Ayala¹, M. Galar²



Rubén Sesma Redín



Tracasa Instrumental



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upna

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