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UNIVERSITÀ DEGLI STUDI DI PADOVA

Satellite data analysis for monitoring of territory, infrastructure and mobility

Anselmo Bettio - 37th Cycle

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PhD Admission to the Final Procedure - 17/09/2024

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Framework

The research has been carried out in collaboration with Stellar Project, a start-up company founded in 2015 focusing on the development of optical communication technologies and started to expand their activities on data analytics both for terrestrial applications and the space environment

Motivations

According to the European Association of Remote Sensing Companies (EARSC), the Earth Observation (**EO**) **sector** continues to grow at a good rate of **10% per year**.

In the next future, the capability of produce more and more data of the Earth should be supported by a capability to download and processing all this data as fast as possible.

Just providing raw data isn't enough, the sector needs to develop **new algorithms and tools** to turn Big EO data into **information for users**

EO satellites increasing

↓

Big EO Data

↓

Need of new EO methods and tools to exploit Big EO Data

Objective

The main objective of this research work is to develop new **methodologies** and **algorithms** for the analysis of EO images that can contribute to turn EO data into actionable **insights for users**. The proposed methods are designed to be **scalable** in prospective of the next **future** development of EO infrastructure.

Outputs

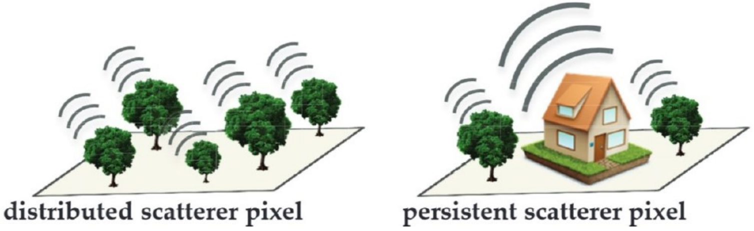
Novel Proposed Methodologies	Produced Scientific Papers
Synthetic Aperture Radar (SAR) EO Images → **Context-Based InSAR Prediction System (CIPS)** → Territory vertical movements predictions	[1] A. Bettio, F. Sansone , A. Francesconi, «Artificial Neural Network for Prediction of Land Subsidence in Mudslides Region Through InSAR and Rain Data,» The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-1/W2-2023 ISPRS Geospatial Week 2023, 2–7 September 2023, Cairo, Egypt
Optical/SAR EO Images → **Space Edge Computing Workflow (SEC-W)** → Near Real Time Change Detection and Monitoring	[2] Bettio, A., Sansone, F., Francesconi, A (2024, May). Automated Neural Network Dataset Creation through a Probabilistic Texture Classification Algorithm for Space Edge Computing Purpose, 4S Symposium poster presentations. [3] Bettio, A., Sansone, F., Francesconi, A (2024, October). Probabilistic Change Detection on Satellite Images through a Novel GLCM-PCA-SFCM Workflow, IAC 2024. [4] Bettio, A., Sansone, F., Francesconi, A (2024, October). Space Edge Computing Change Detection through an Unsupervised Trained U-Net, IAC 2024.

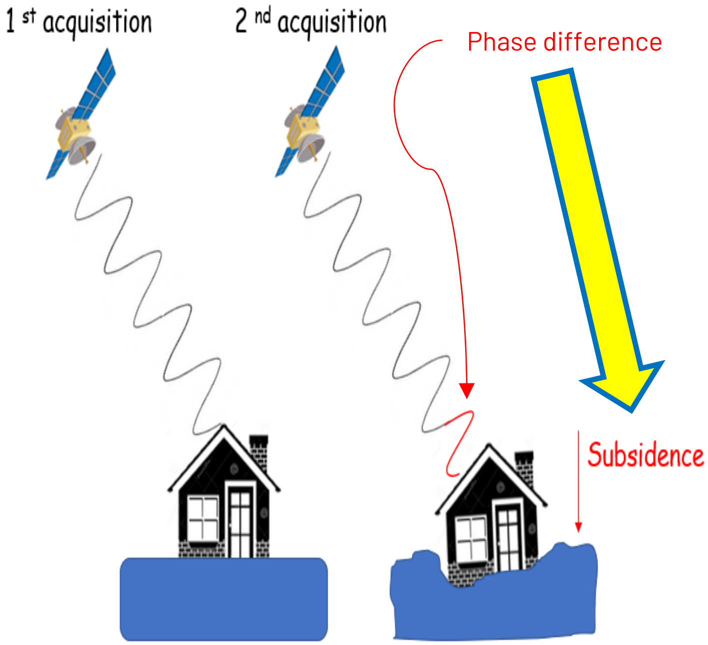
Context-Based InSAR Prediction System

InSAR PSI

InSAR PSI is an advanced technique used for monitoring and measuring ground deformation with **millimeter-level accuracy** by analyzing a time series of SAR images.

This technique exploits the backscattered radar signals from **persistent scatterers** (PS), which are characterized by stable and long-lasting reflectivity properties.





Predict future InSAR PSI data

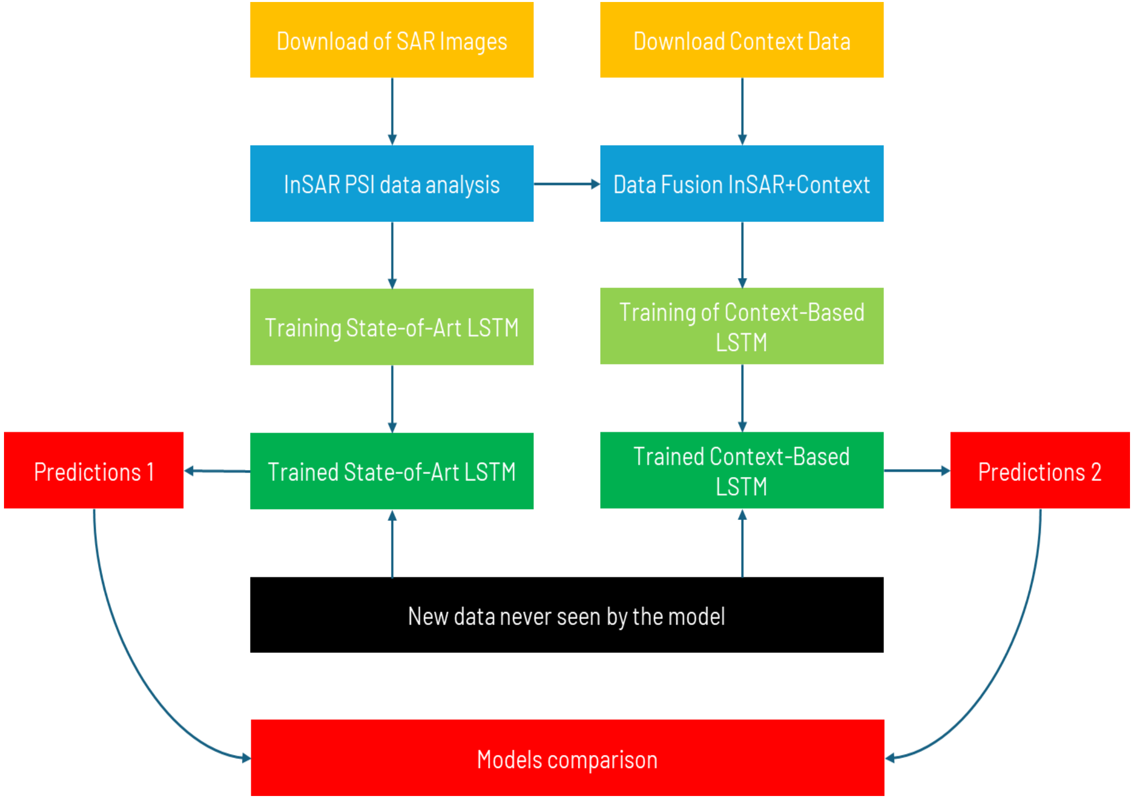
Analytical Models	Black Box Models
Some scientific works present the potentiality of analytical methods to make prediction on future movements of the territory based on InSAR data	Long-Short Term Memory Recurrent Neural Networks (LSTM RNN) architecture has proven to be highly effective in modeling complex sequential patterns. Some recent works have trained them with InSAR data.
Interpretability of the entire process	The internal process is not known
Easy to find and correct errors	Difficult to correct errors
Could not be able to model complex phenomena	Able to model complex phenomena
Often this model are very time consuming	Once trained the model provide results near real time

Black box models do not replace analytical models. Indeed, black box model can provide new insights to improve analytical models

Methodology

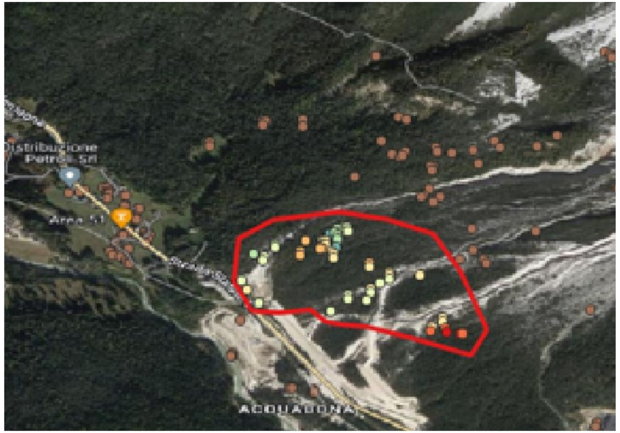
Context-Based InSAR Prediction System (CIPS) aims to improve the prediction results with respect to current state-of-art by adding to the **LSTM model** a context data **related** to the moving phenomena.

Mudslides movements phenomena. Rain data could be added as context data because the mudslides depends in someway, not known analytically, by the **quantity of water** absorbed by the terrain.



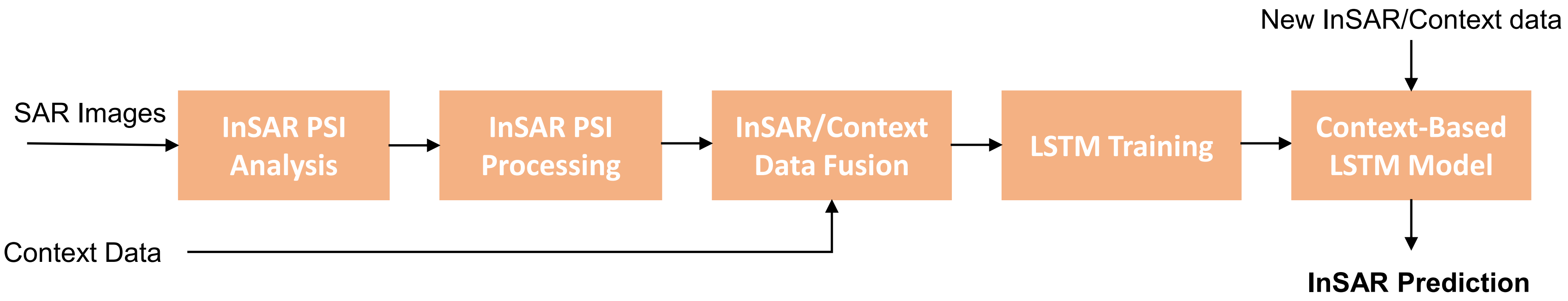
Case study: Acquabona 2015-2018 (Belluno, Italy)

Mudslides Risk Area

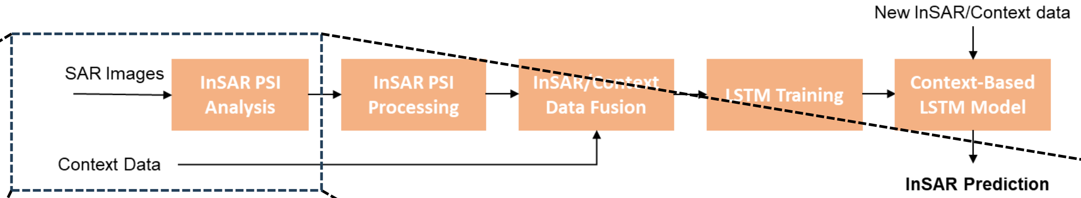


Persistent scatterers (PS) obtained after the snap2stamps + stamps workflow in Acquabona site. The PS time series within the red circled area are used in the proposed workflow

CIPS Blocks Diagram

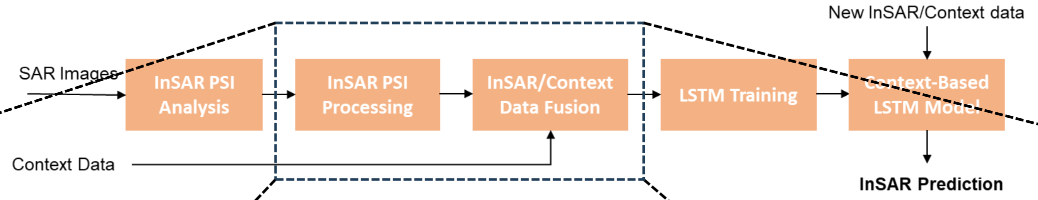


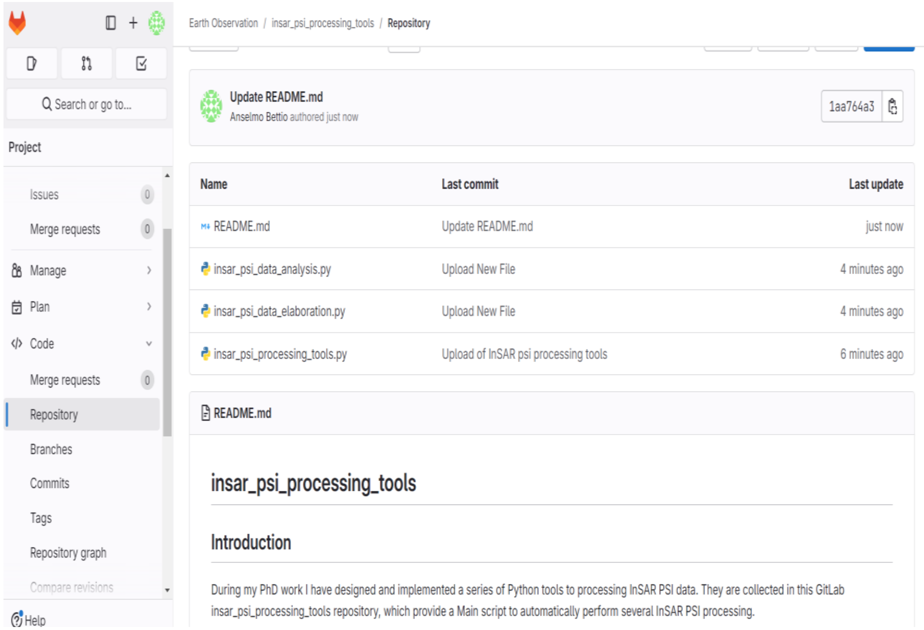
InSAR PSI Analysis



- **Sentinel-1 SAR data** downloaded from the Copernicus Open Access Hub
- Processing through **snap2stamps** processing Python script (Delgado Blasco, Michael Foumelis)
- **Persistent Scatterers** calculation (StaMPS Andy Hooper)
- **Rain data** downloaded from Regional Agency for Environmental Prevention and Protection of the Veneto (ARPAV) website

InSAR PSI Processing Tools

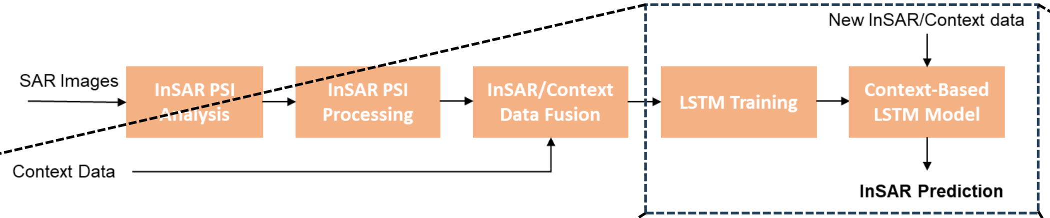




insar_psi_processing_tools has been exploited to perform the CIPS processing and data fusion steps:

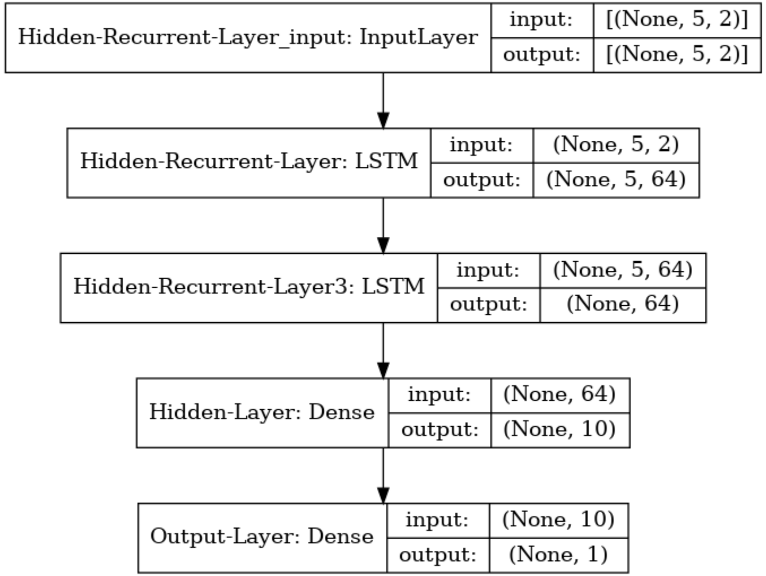
- **Normalization** of InSAR PSI data (StaMPS2Standard)
- **Spatial Cropping** of InSAR PSI data according to an input Geojson mask (SpatialFilter)
- Computing **moving average measurement** over all the InSAR PSI data (MovingWindowMeasurament)
- **Data Fusion** of InSAR data with context data to form the dataset to train the LSTM Neural Network (DataFusion)

Context-Based LSTM

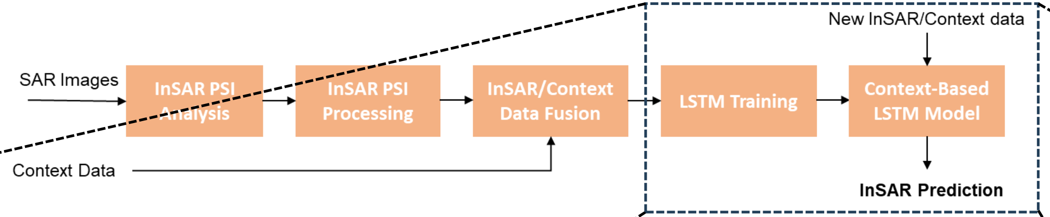


- Design and implementation of a parametric LSTM (#LSTM layers, #units) by means Python Keras and Tensorflow libraries

Configuration ID	LSTM layers	LSTM units
1	1	16
2	1	32
3	1	64
4	2	16
5	2	32
6	2	64



Context-Based LSTM



- Training

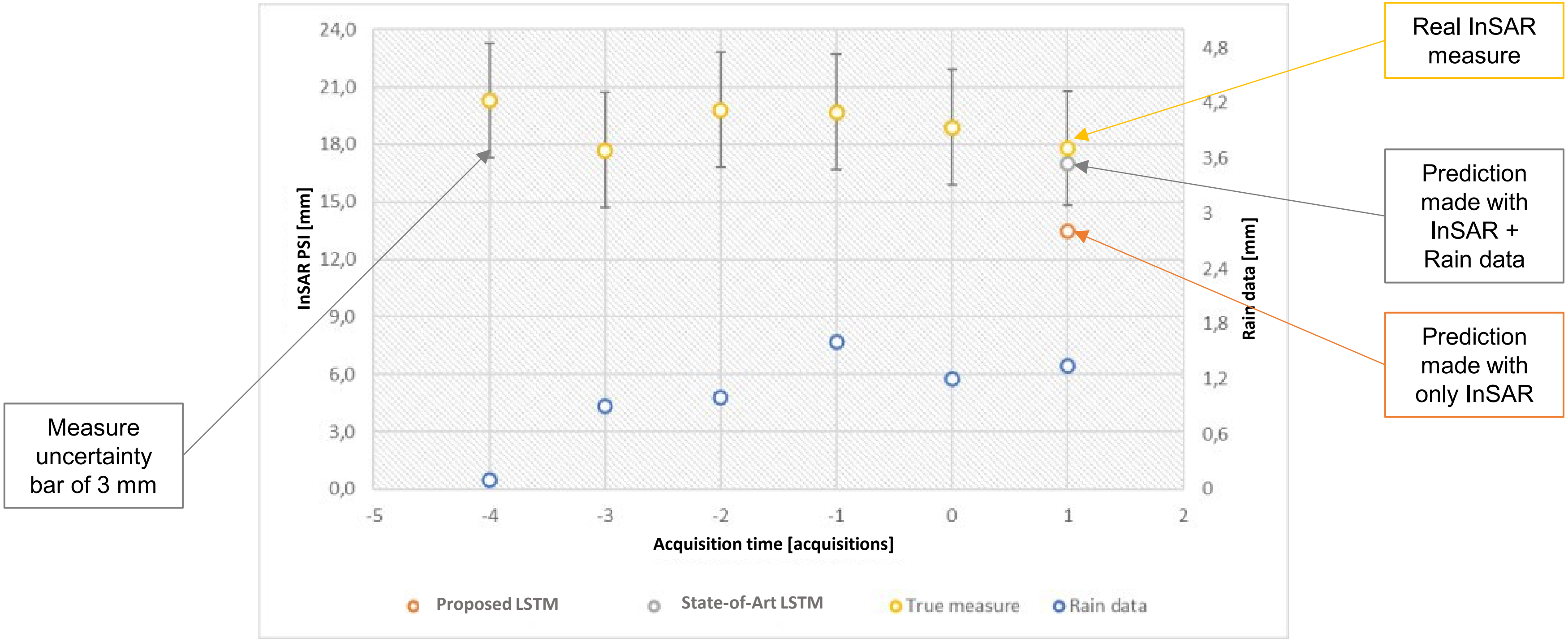
$$([[A_{-4}, R_{-4}], [A_{-3}, R_{-3}], [A_{-2}, R_{-2}], [A_{-1}, R_{-1}], [A_0, R_0]], [A_1])$$

$A_{-n} = InSAR\ PSI\ measure\ at\ time\ -n$; n = 0 is present time, n = 1 is the prediction

$R_{-n} = Rain\ measure\ at\ time\ -n$; n = 0 is present time

- Test with new data never seen by the model

Results



Predictions comparison between proposed Context-Based LSTM and State-of-Art LSTM models

Conclusions

- The proposed Context-Based InSAR Prediction System trained with the data fusion of InSAR PSI and meteorological data **improves the forecast performances of the 12% in terms of MSE** and of the **27% in terms of MAE** with respect to the State-of-Art LSTM trained with only InSAR PSI data.

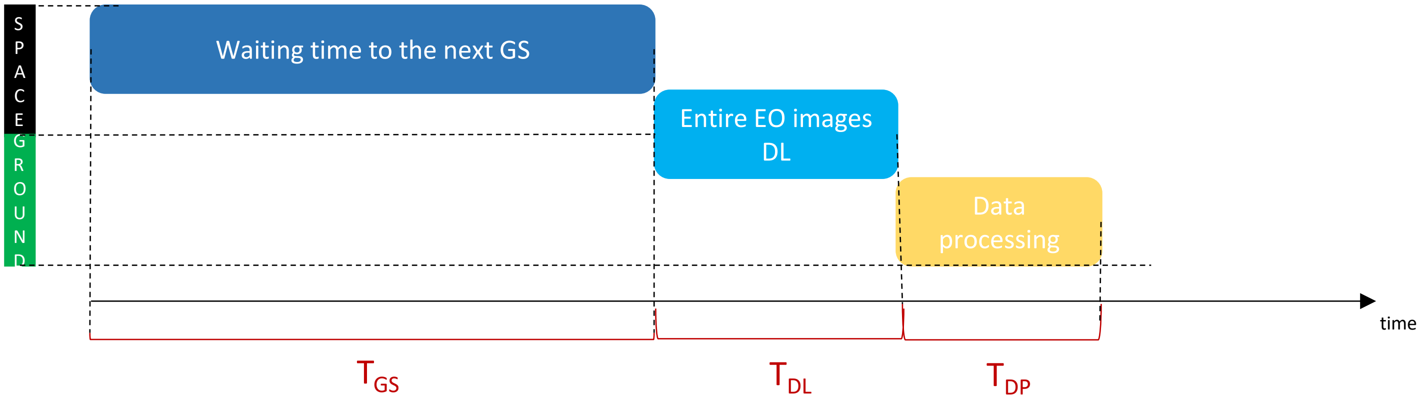
- The present research demonstrates how the data fusion of InSAR data with data which defines the measurement context (e.g., Rain Data for Mudslide Area) can improve the InSAR prediction precision.
  - The methodology can be applied to other applications such as predictions of InSAR road movements by integrating in the model the traffic data

A. Bettio, F. Sansone , A. Francesconi, «Artificial Neural Network for Prediction of Land Subsidence in Mudslides Region Through InSAR and Rain Data,» The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-1/W2-2023
ISPRS Geospatial Week 2023, 2–7 September 2023, Cairo, Egypt

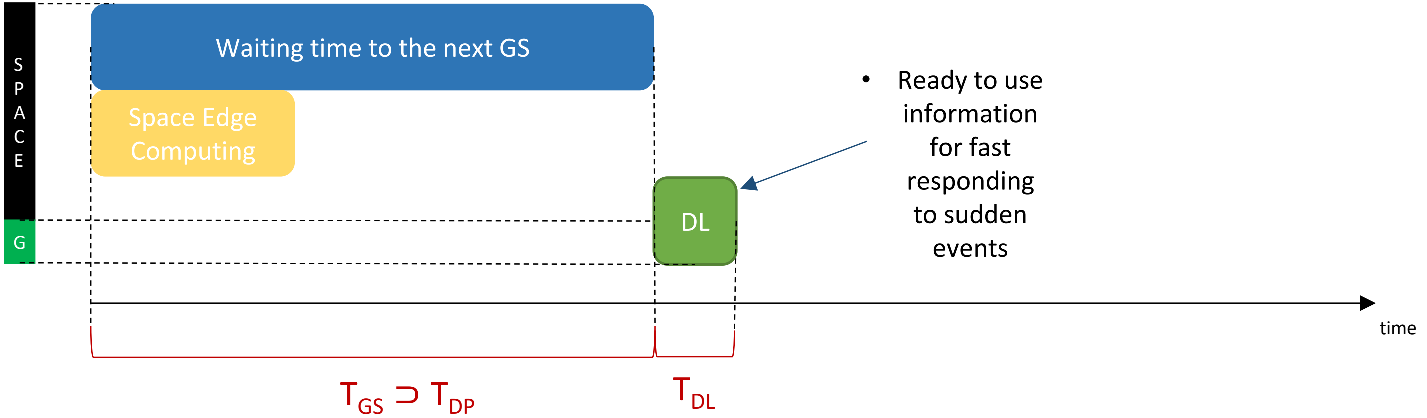
Space Edge Computing System

Timing

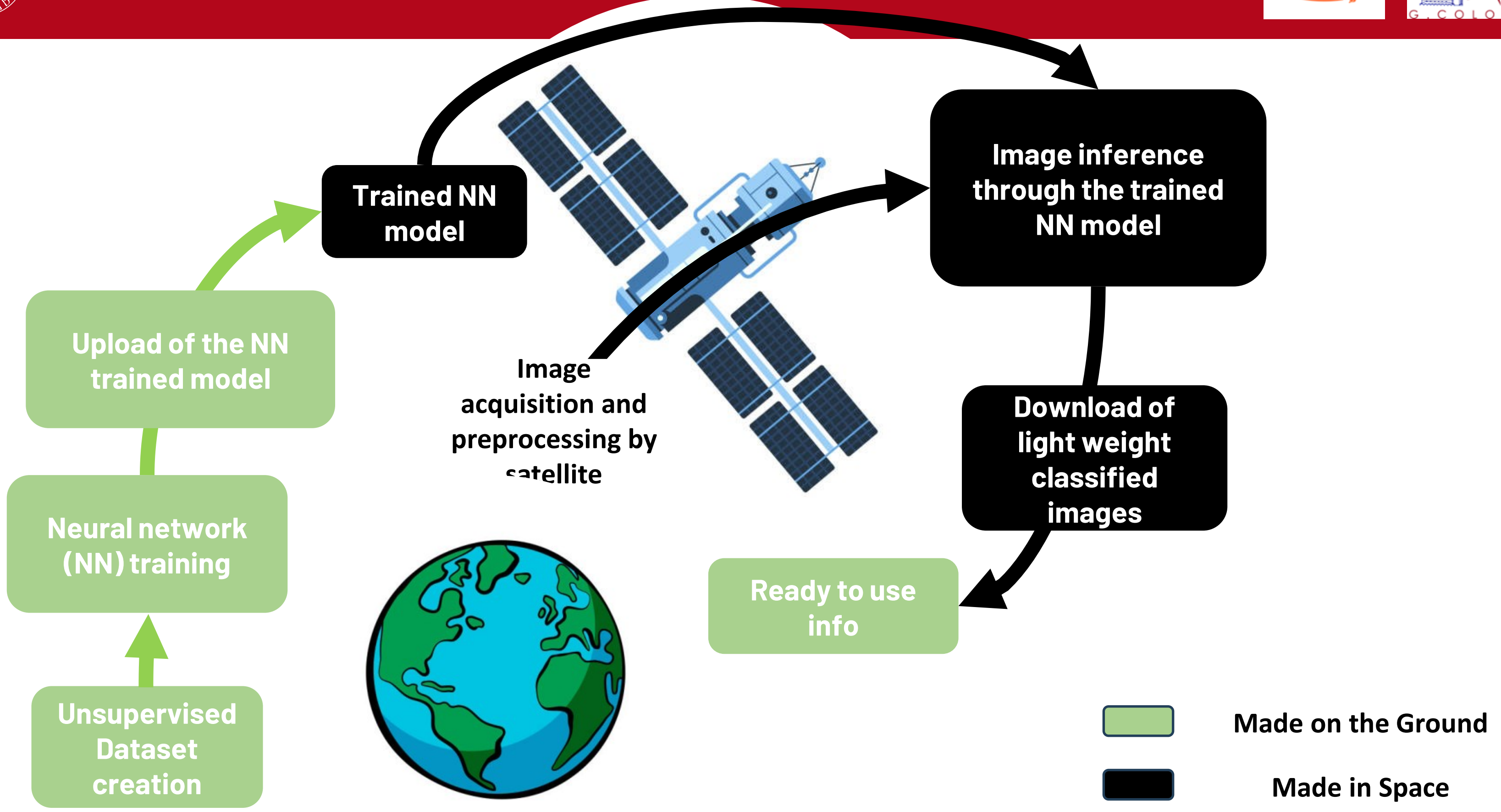
Ground-Based Centralized Computing



Space Edge Computing System



Overview

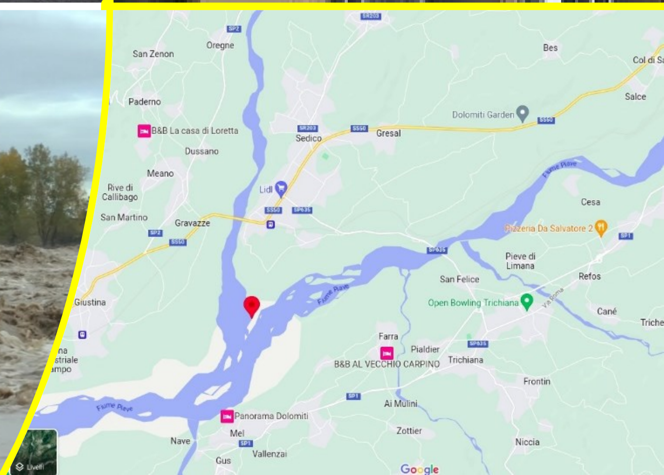


Unsupervised Dataset creation
Neural network (NN) training
Upload of the NN trained model
Trained NN model
Image acquisition and preprocessing by satellite
Image inference through the trained NN model
Download of light weight classified images
Ready to use info
Made on the Ground
Made in Space

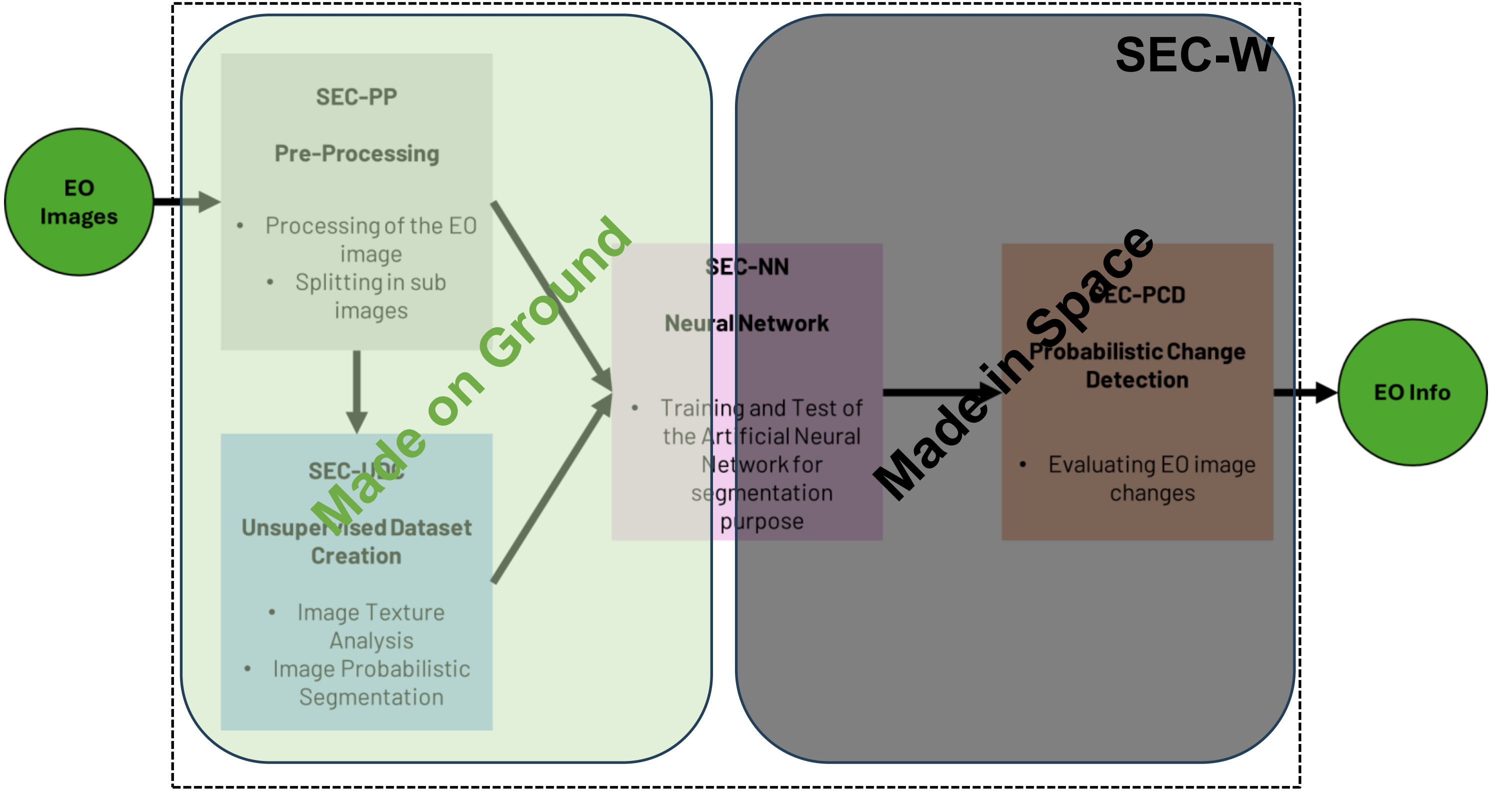
Case Study: Piave Flood (30/10/2018)

- **Goal**: Apply the implemented SEC-W to evaluate the the impact of Piave flood

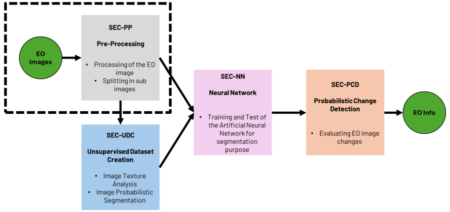
- One image before the flood – 11/07/2018
- One image after the flood – 02/11/2018
- Focusing on **the area of interest** shown in bottom right Figure

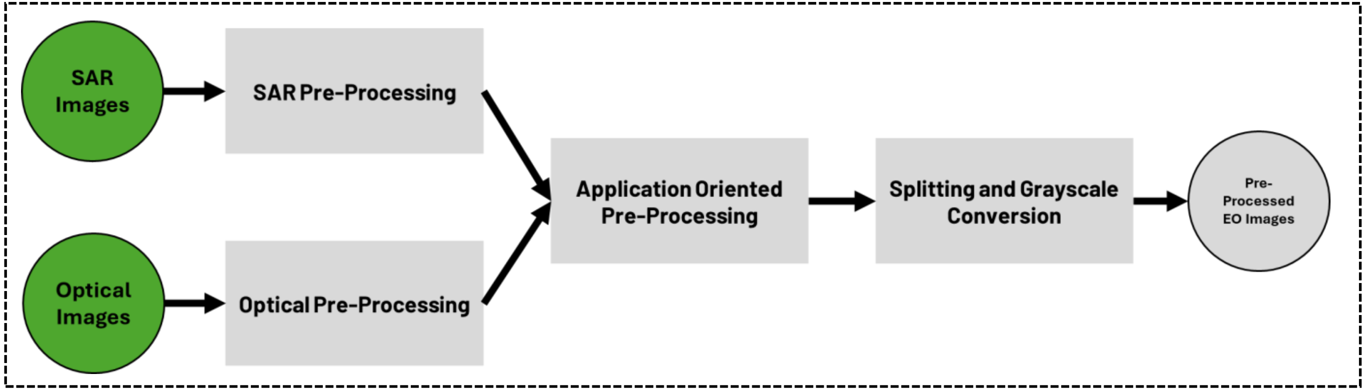


Space Edge Computing Workflow (SEC-W)

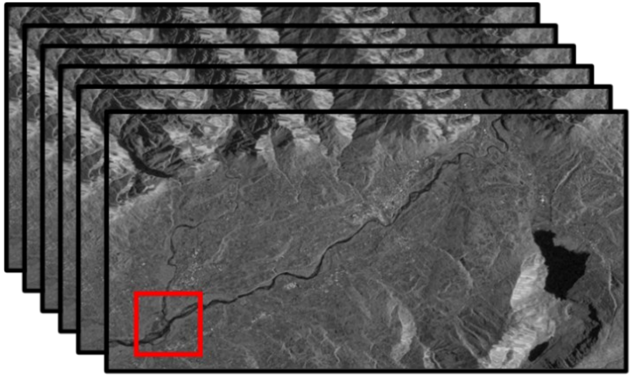


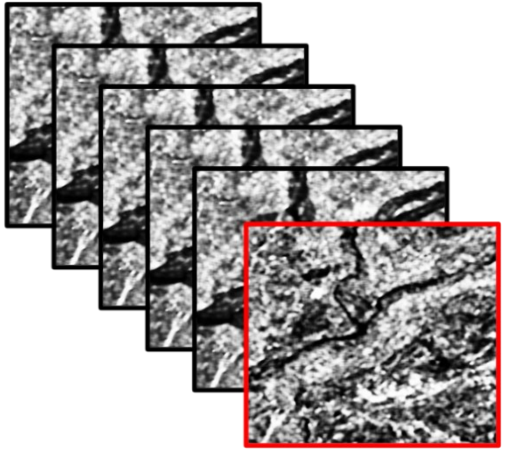
Pre-Processing (SEC-PP)



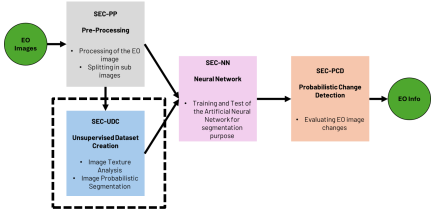


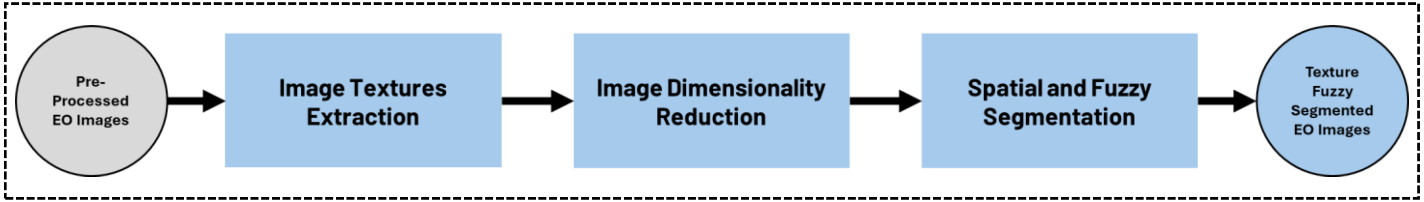
- **Goal**: To prepare EO images (both SAR and optical) to the subsequent data creation step



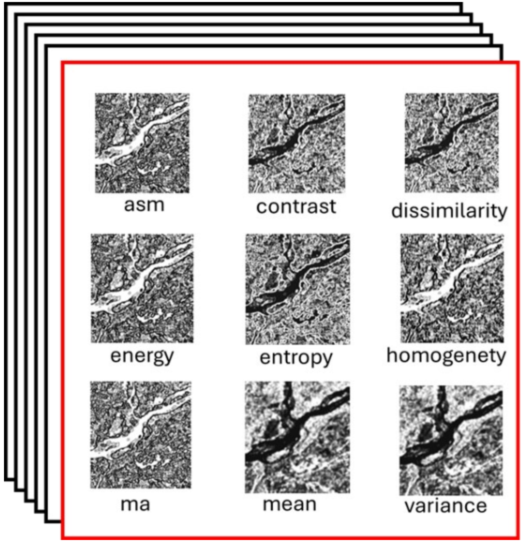


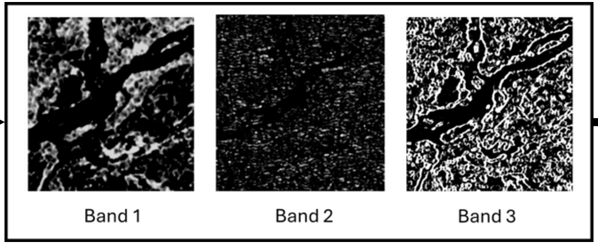
Unsupervised Dataset Creation (SEC-UDC)

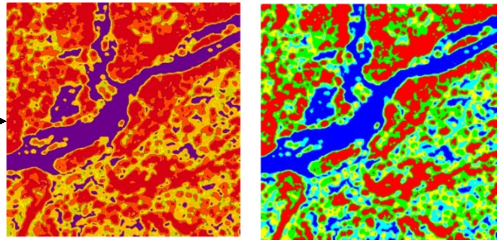




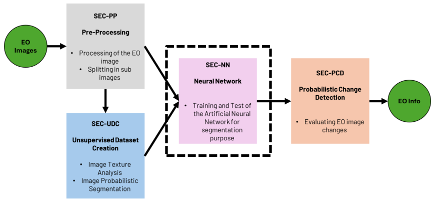
- **Goal**: To create in unsupervised manner a dataset of segmented images able to discriminate land cover features





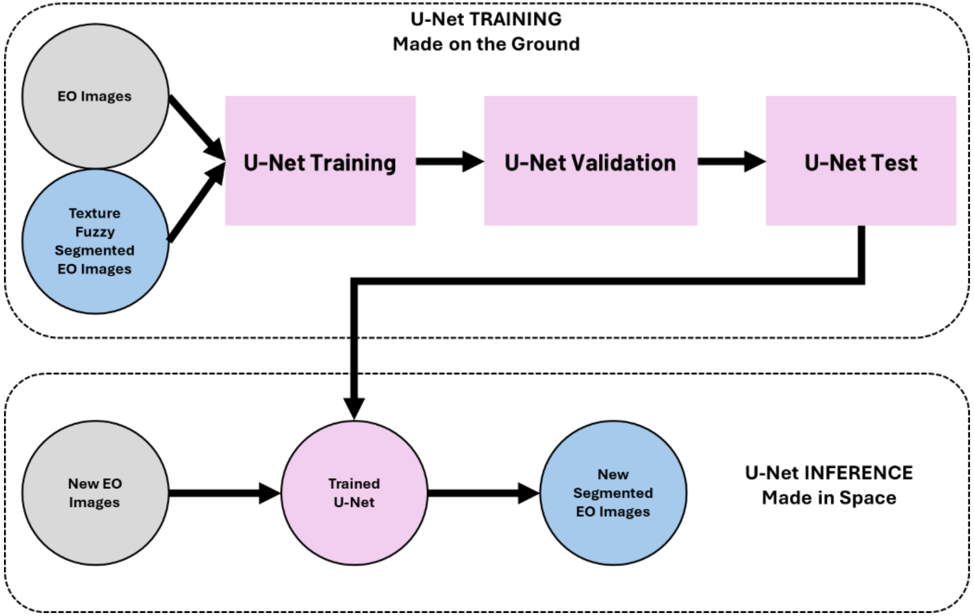


Neural Network (SEC-NN)

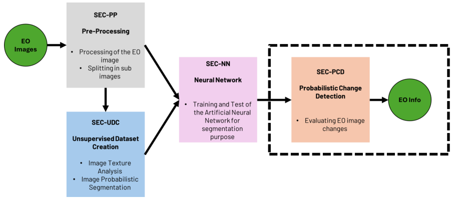


- **Goals**:

(1) Train a U-Net by using the dataset created at the previous step
(2) Test U-Net in compatible nano satellite hardware



Pre-Processing (SEC-PCD)



- **Goals**:

Find changes between two segmented images and the related change probability

Segmented EO Image at time t1 S(t1)

1	2	4	3	1	5	6	8
4	3	4	4	2	6	8	10
5	4	4	3	2	7	8	11
1	1	1	2	7	8	8	12
6	7	8	2	7	8	8	13
6	8	3	1	3	14	13	16
8	5	1	1	2	16	15	14
5	4	1	1	11	11	9	10

Segmented EO Image at time t2 S(t2)

1	2	4	3	1	2	6	8
4	3	4	4	2	3	8	10
4	4	4	3	2	4	8	11
1	1	1	2	4	4	8	12
2	3	4	2	2	1	8	13
6	8	3	1	3	14	13	16
8	5	1	1	2	16	15	14
5	4	1	1	11	11	9	10

ProbMembership[S(t1)]

0.44	0.63	1	0.82	0.44	0.44	0.63	1
1	0.82	1	1	0.63	0.63	1	0.63
0.44	1	1	0.82	0.63	0.82	1	0.82
0.44	0.44	0.44	0.63	0.82	1	1	1
0.63	0.82	1	0.63	0.82	1	1	0.44
0.63	1	0.82	0.44	0.82	0.63	0.44	1
1	0.44	0.44	0.44	0.63	1	0.82	0.63
0.44	1	0.44	0.44	0.82	0.82	0.44	0.63

ProbMembership[S(t2)]

0.44	0.63	1	0.82	0.44	0.63	0.63	1
1	0.82	1	1	0.63	0.82	1	0.63
1	1	1	0.82	0.63	1	1	0.82
0.44	0.44	0.44	0.63	1	1	1	1
0.63	0.82	1	0.63	0.63	0.44	1	0.44
0.63	1	0.82	0.44	0.82	0.63	0.44	1
1	0.44	0.44	0.44	0.63	1	0.82	0.63
0.44	1	0.44	0.44	1	1	0.44	0.63

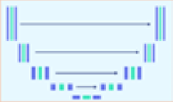
ProbChangedPixels(t1.t2)

0.19	0.40	1.00	0.67	0.19	0.28	0.40	1.00
1.00	0.67	1.00	1.00	0.40	0.52	1.00	0.40
0.44	1.00	1.00	0.67	0.40	0.82	1.00	0.67
0.19	0.19	0.19	0.40	0.82	1.00	1.00	1.00
0.40	0.67	1.00	0.40	0.52	0.44	1.00	0.19
0.40	1.00	0.67	0.19	0.67	0.40	0.19	1.00
1.00	0.19	0.19	0.19	0.40	1.00	0.67	0.40
0.19	1.00	0.19	0.19	0.82	0.82	0.19	0.40

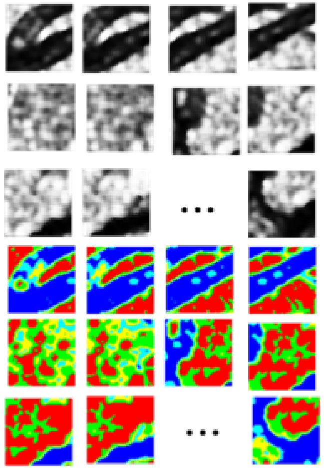
Results

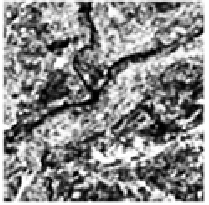
Training of a UNET neural network model

Trained UNET neural network

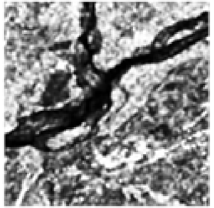


Created LargeDataset

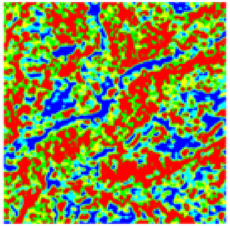




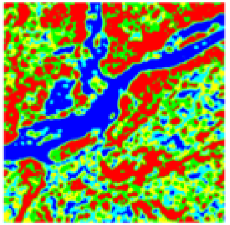
SAR image Piave **before** the flood



SAR image Piave **after** the flood

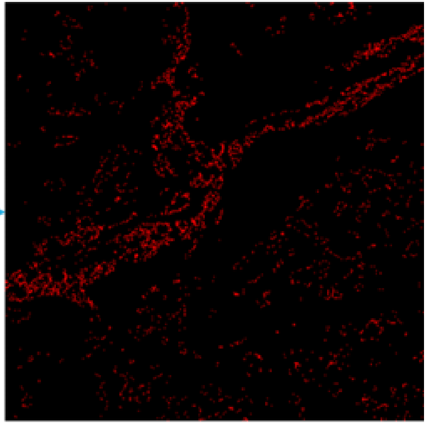


Classified image Piave **before** the flood



Classified image Piave **after** the flood

The probabilistic information derived from the two classified images is used to create a **probabilistic change detection map** (on the right).



The red pixels in the above probabilistic change detection map are changed from **not-water** to **water** with a probability higher than 60% as consequence of the flood.

Conclusions

- The proposed Space Edge Computing Workflow has been used to detect changes during a flood with nanosatellite compatible hardware
- The results in terms of accuracy are between 80% and 90%
- The data volume of the output segmented image results to be 87% less than the input image. This makes it possible to downlink a ready to use information to the ground in few seconds, allowing a faster response to sudden events

[2] Bettio, A., Sansone, F., Francesconi, A (2024, May). Automated Neural Network Dataset Creation through a Probabilistic Texture Classification Algorithm for Space Edge Computing Purpose, 4S Symposium poster presentations.
[3] Bettio, A., Sansone, F., Francesconi, A (2024, October). Probabilistic Change Detection on Satellite Images through a Novel GLCM-PCA-SFCM Workflow, IAC 2024.
[4] Bettio, A., Sansone, F., Francesconi, A (2024, October). Space Edge Computing Change Detection through an Unsupervised Trained U-Net, IAC 2024.

Università degli Studi di Padova

Gantt Chart

PHD STUDENT	Anselmo Bettio	DATE	01/09/2024
PHD THESIS	Analisi di dati satellitari per il monitoraggio del territorio, delle infrastrutture e della mobilità	ADMISSION TO	Final Exam

WBS NUMBER	TASK TITLE	% OF TASK COMPLETE	FIRST YEAR												SECOND YEAR												THIRD YEAR											
			T1			T2			T3			T4			T1			T2			T3			T4			T1			T2			T3			T4		
			O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S
1	Analysis of applications, study and training																																					
1.1	Analysis of applications	100%	X	X	X																																	
1.2	State of the art of SAR satellite images	100%		X	X	X	X	X	X																													
1.3	Educational activities	100%				X	X	X	X	X	X																											
1.4	Acquisition of practical skills on SAR image analysis	100%				X	X	X	X	X	X	X	X	X																								
2	Algorithms definition and implementation																																					
2.1	Ideation and development of the algorithms	100%													X	X	X	X	X	X	X	X	X															
2.1.1	Definition of algorithms for monitoring and prediction of Territory Movements	100%													X	X	X	X	X																			
2.1.2	Definition of Edge Computing territory classification and segmentation algorithms	100%																	X	X	X	X	X															
2.2	Educational activities	100%																X	X	X	X	X	X															
2.3	Design Implementation of the algorithms for InSAR movements prediction	100%																X	X	X	X	X	X	X	X													
2.3.1	Implementation of a Recurrent Neural Network 1 (InSAR data)	100%																X	X	X	X	X																
2.3.2	Implementation of Recurrent Neural Network 2 (InSAR + Rain data)	100%																		X	X	X	X	X	X													
2.3.3	Writing of the paper	100%																							X													
2.4	Implementation of the algorithms for edge computing change detection	100%																				X	X	X	X	X	X	X	X									
2.4.1	Implementation of SAR pre-processing algorithms	100%																				X	X	X	X													
2.4.2	Design and Implementation of the SFCM library in Python	100%																					X	X	X	X												
2.4.3	Design and implementation of SECS-NN and its training-test procedure	100%																							X	X	X	X	X									
3	Implementation and validation																																					
3.1	Validation of the Edge Computing algorithms in small satellite hardware	100%																								X	X	X	X	X	X	X				
3.1.1	Test of Myriad 2 VPU	100%																								X	X	X								
3.1.2	Test of SECS-NN in the Myriad 2 VPU	100%																										X	X	X	X	X				
3.2	Educational activities	100%																										X	X	X	X	X	X			
3.3	Final thesis and documentation writing	100%																												X	X	X	X	X	X	X

Thanks for the Attention

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Comparison Metrics

- The Mean Square Error **(MSE)** is defined as:

$$MSE = \frac{1}{n}\sum_{k=0}^{n}\left(Y_k - \hat{Y}_k\right)^2 \quad [mm\hat{}2]$$

Where, Y_k is the observed measurement and $\hat{Y}_k$ is the predicted measurement.

- The Mean Absolute Error **(MAE)** is defined as:

$$MAE = \frac{1}{n}\sum_{k=0}^{n}\left(Y_k - \hat{Y}_k\right) \quad [mm]$$

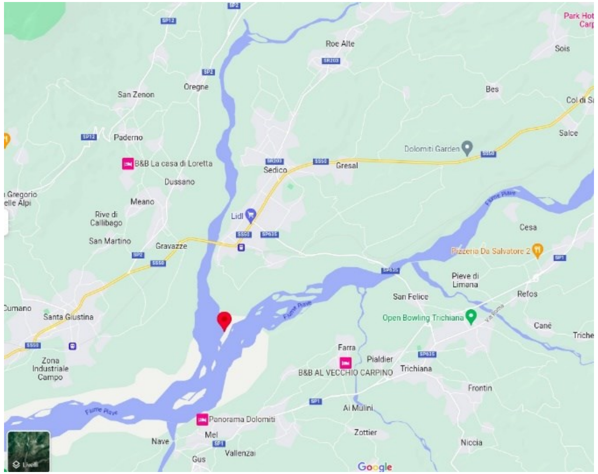
Where, Y_k is the observed measurement and $\hat{Y}_k$ is the predicted measurement.

Results

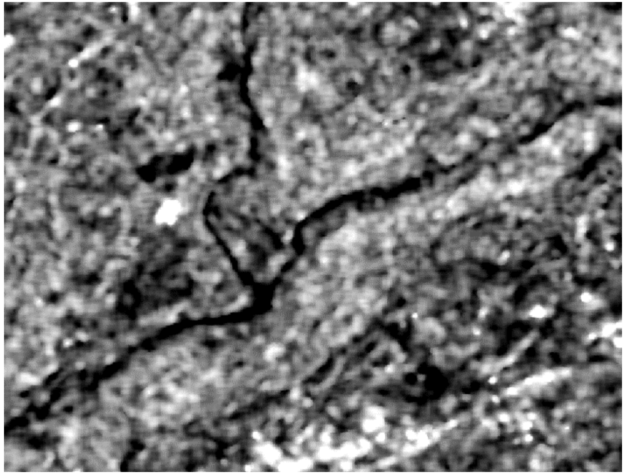
Conf. ID	LSTM Layers	LSTM Units	Context-Based InSAR Prediction System (InSAR + Rain data)				State-Of_art InSAR LSTM prediction (only InSAR data)			
			Evaluation with training set		Evaluation with test set		Evaluation with training set		Evaluation with test set	
			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
1	1	16	2.4	0.9	9.7	1.9	8.5	2.4	7.2	2.2
2	1	32	2.1	0.8	9.7	1.8	7.5	2.2	5	1.8
3	1	64	1.8	0.7	9.9	1.9	7.3	2.2	7.7	2.3
4	2	16	2.6	0.9	6.8	2.4	8.5	2.4	6.5	2
5	2	32	1.8	0.7	8	1.6	7.3	2.2	8.1	2.2
6	2	64	2	0.7	4.4	1.3	6.7	2	7.6	2.2

SAR Pre-processing

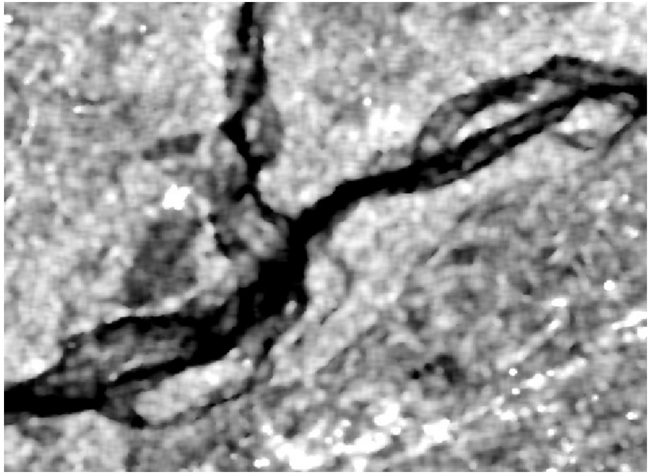
SAR GRD → Orbit File → Terrain Correction → Calibration → Speckle Noise Filtering → SAR Pre-processed



(a) Area of Interest

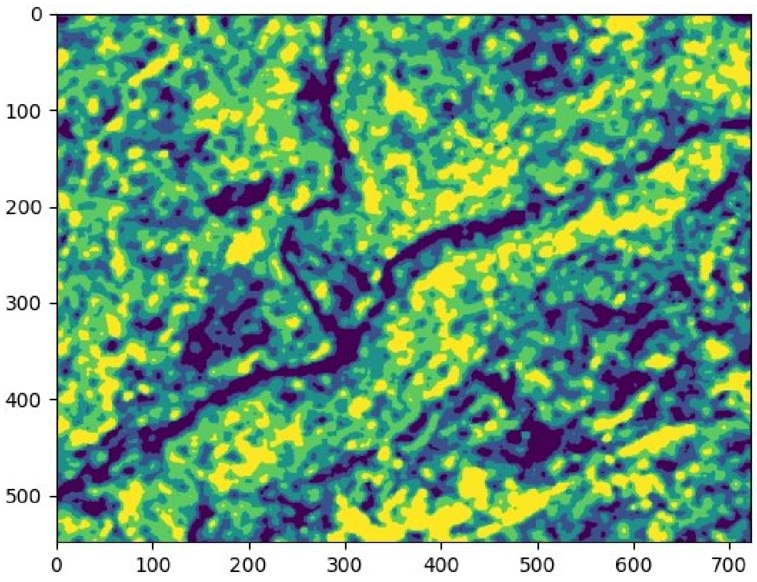


(b) Pre-processed SAR image (Before Piave flood, 11/07/2018)

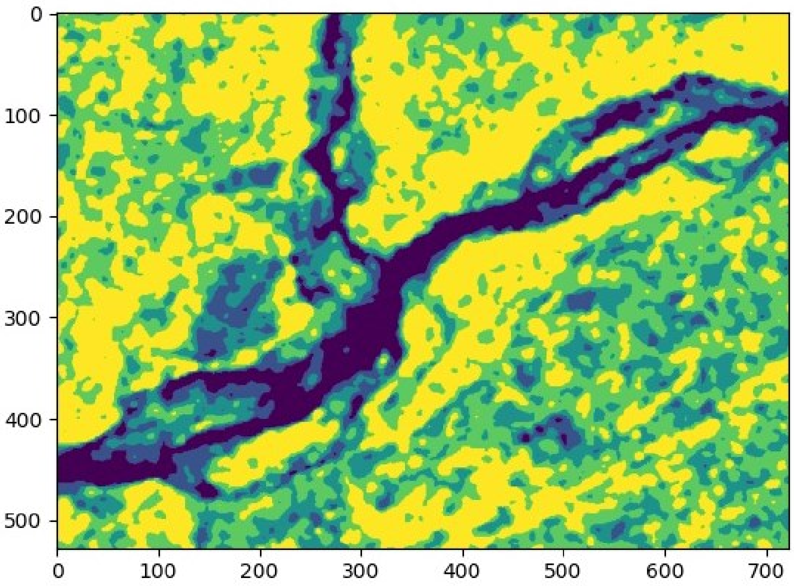


(c) Pre-processed SAR image (After Piave flood, 02/11/2018)

SFCM



(a) SFCM image (Before Piave flood, 11/07/2018)



(b) SFCM image (After Piave flood, 02/11/2018)

Motivation of Space Edge Computing

Two motivations behind the research on new methods and technologies on Space edge computing are the following:

- Need to have **faster decision processes and responses** during critical scenarios such as floods, oil spills, fires, or other sudden changes in territory → **Near Real Time Monitoring**

- Need to perform **preliminary image analysis** on board of the satellite since the increasing quantity of EO satellite will produce more and more EO images, which could create a congestion in the downloading process to the ground