# Deep Transformers machine learning method to improve spatial coverage of InSAR

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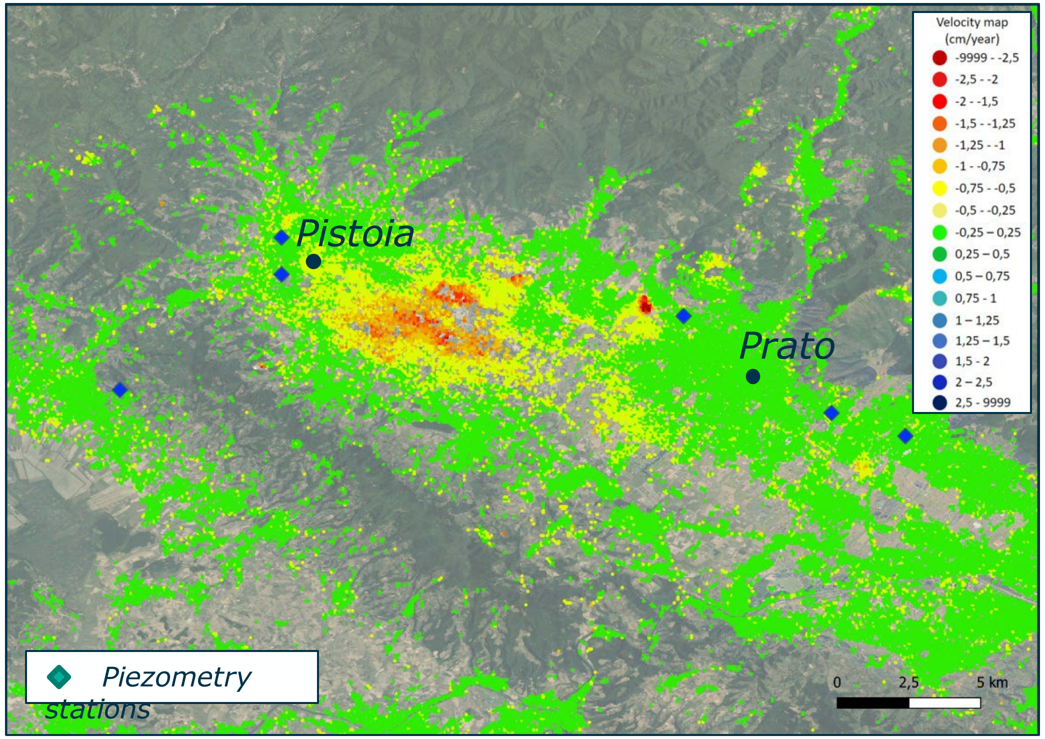
# To apply AI methods to environmental hydrogeological problems and deliver simple tools for the local monitoring agencies

Application to subsidence

Traditionally studied with levelling => spatially limited

Recently with InSAR



**Land subsidence: «A gentle lowering or a sudden sinking of the ground surface» (Galloway and Burbey, 2011)**

**Can be caused by**

**Natural events: volcanic eruptions, earthquakes, sinkholes**

**Anthropogenic events: groundwater pumping, surface loading, underground mining**

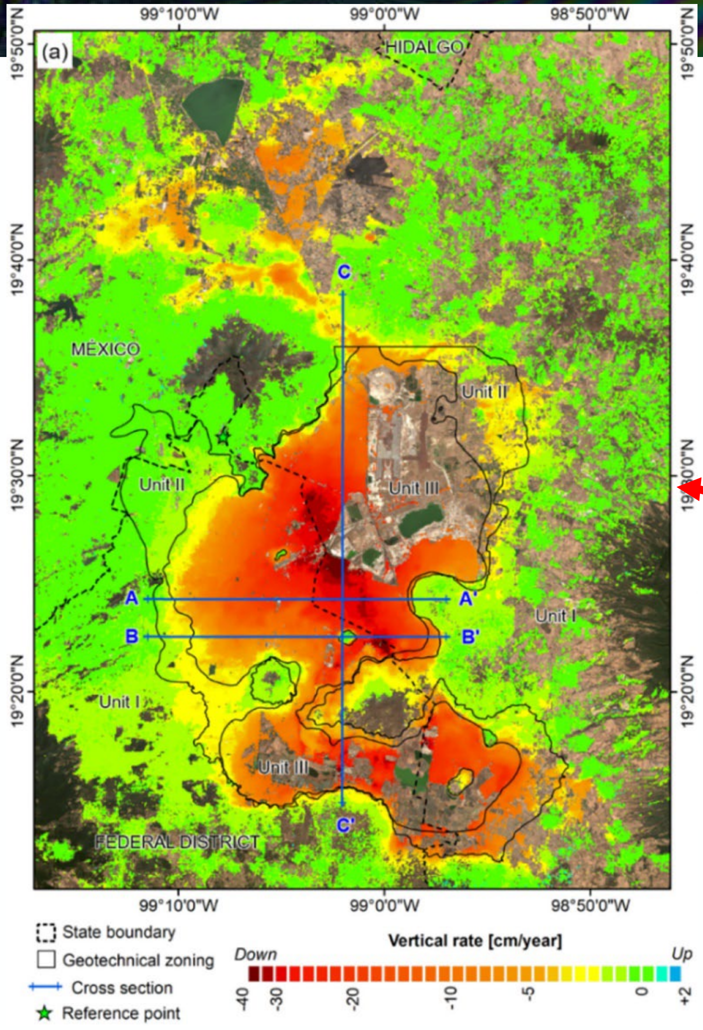
**Impacts on infrastructure in urban areas**


(Osmanoğlu B. et al., 2011)

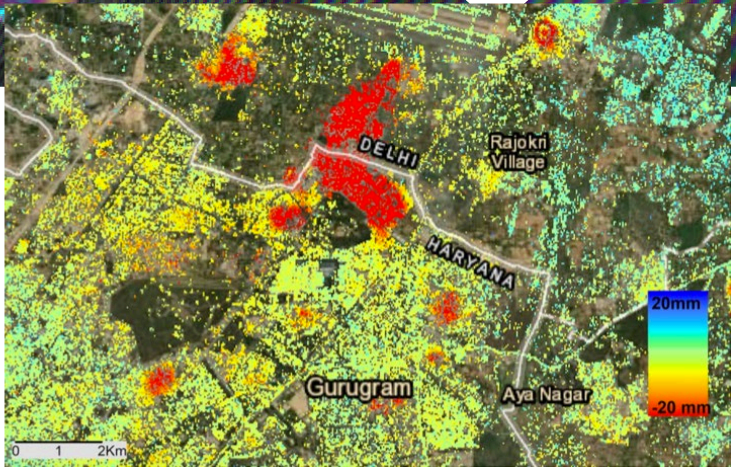

(Brunori C. A. et al., 2015)


(Fryksten J. and Nilfouroushan F., 2019)

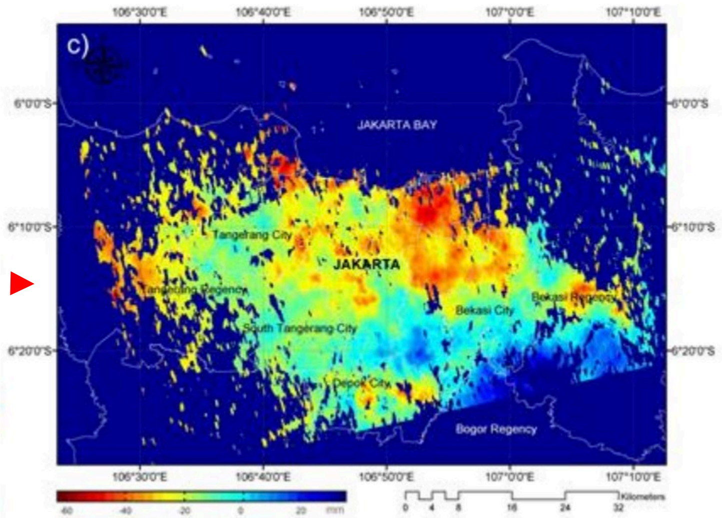
# Examples of subsidence monitoring



Cigna F. & Tapete D., 2021



Garg S., et al., 2022



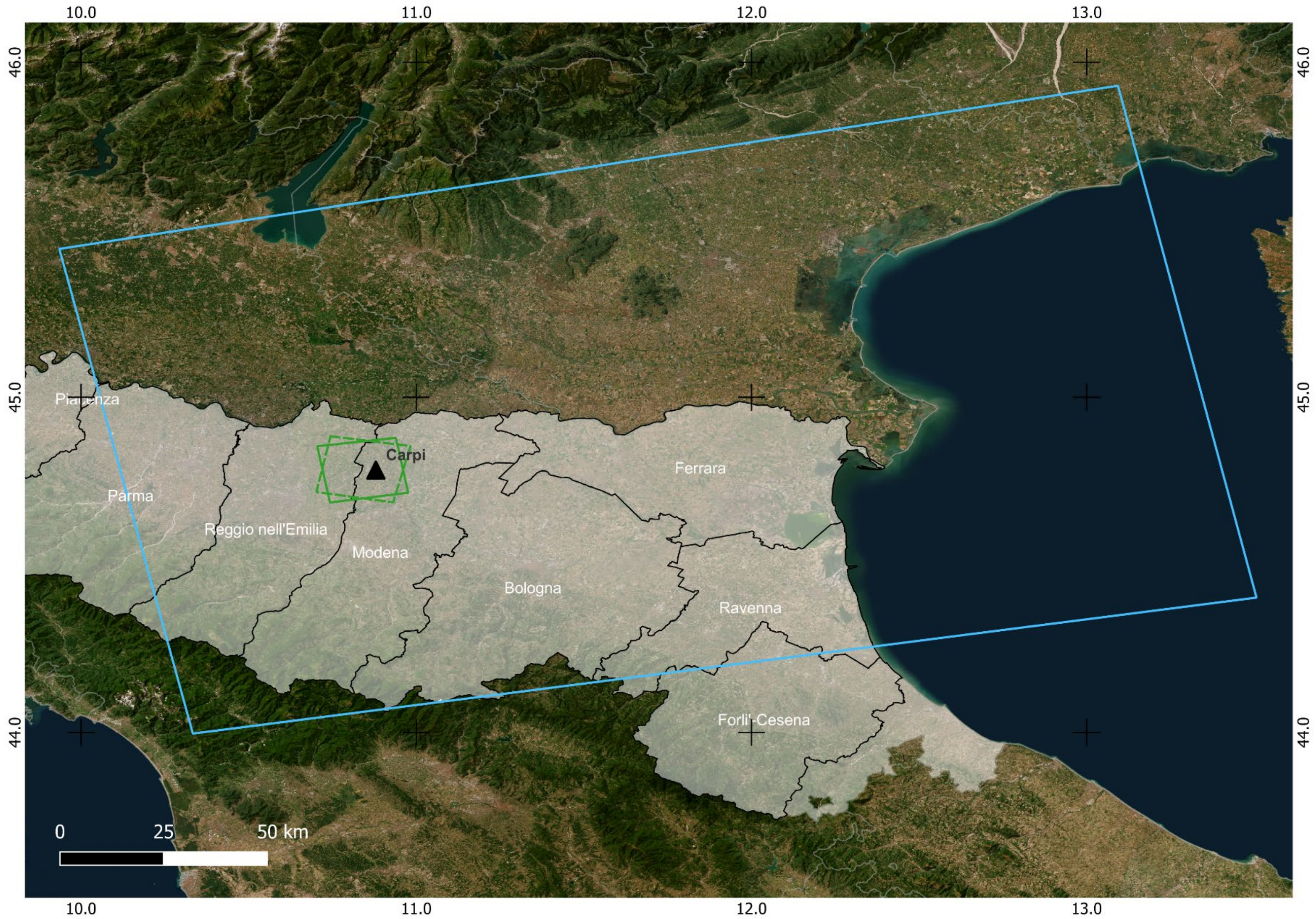
Widodo et al., 2019

# Study area: Carpi zone

The city of Carpi is located in northern Italy, in the Po alluvial plain (Emilia-Romagna region), and together with other sites (Valli di Comacchio, Bologna) experiences subsidence due to groundwater extraction for industrial usage

The Carpi area is farmed, unrbanized and industrialized

We used SBAS (TEP Geohazards) and StaMPS to measure the subsidence



# InSAR SBAS

**Satellite: Sentinel-1A**

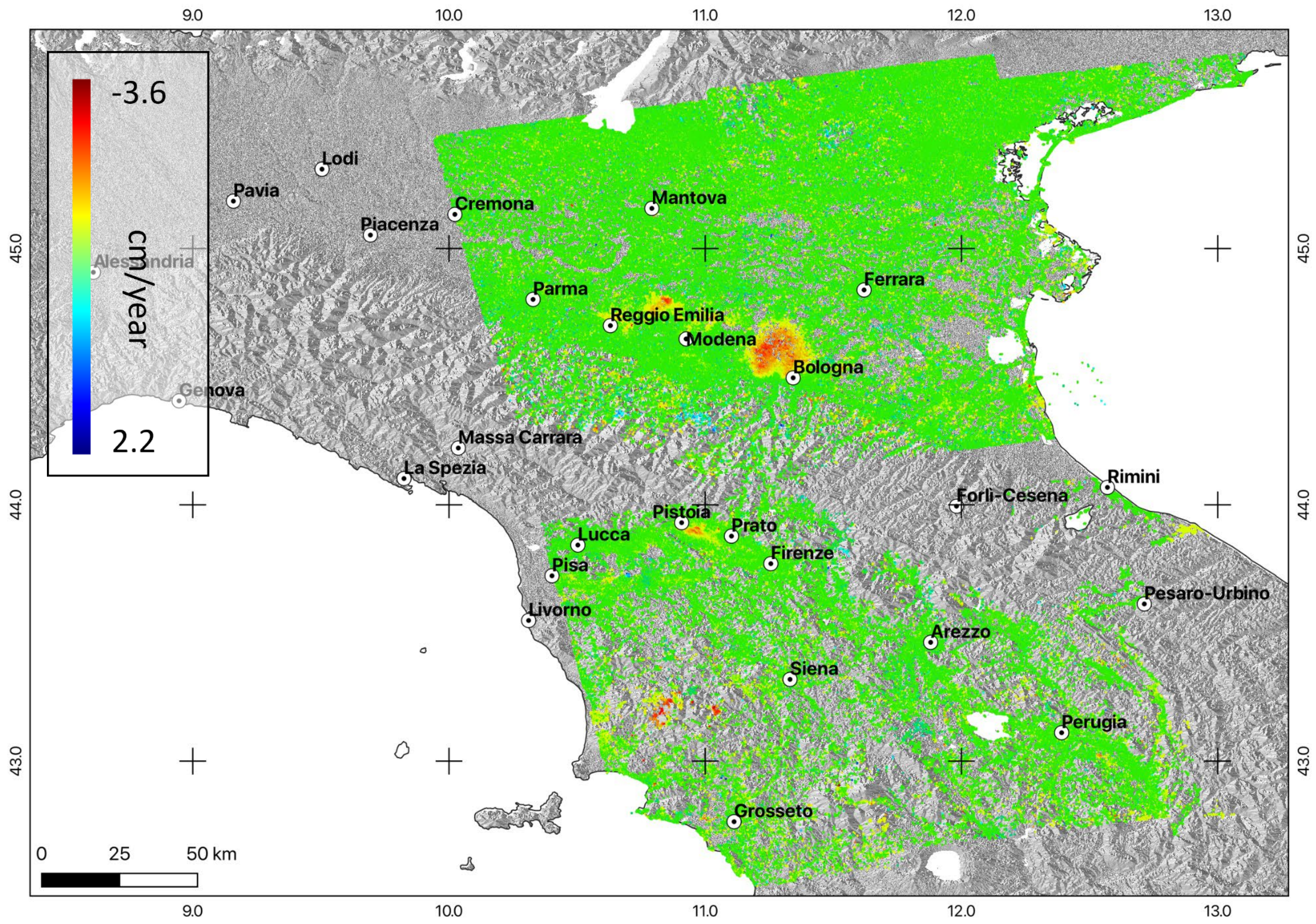
**Period of analysis: 04/2017-**

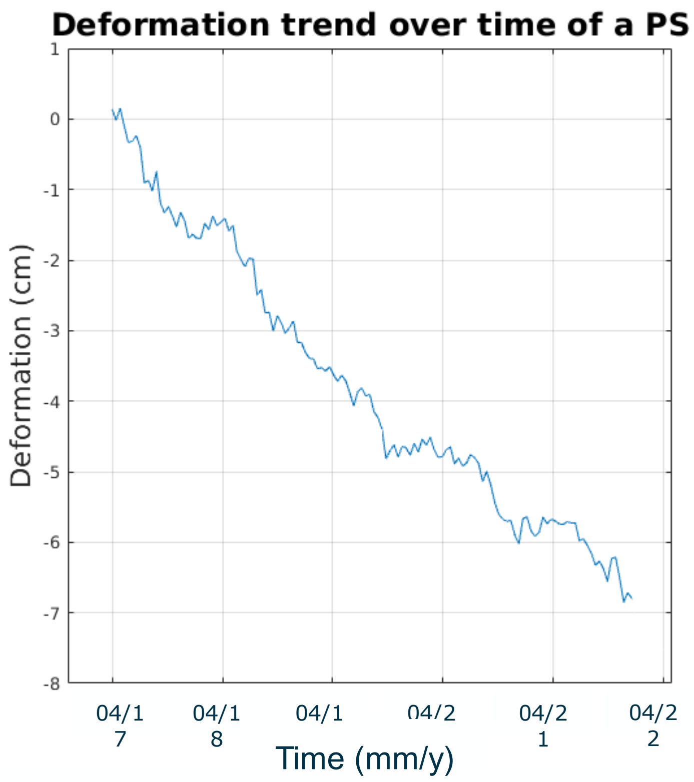
**140 SAR acquisitions**

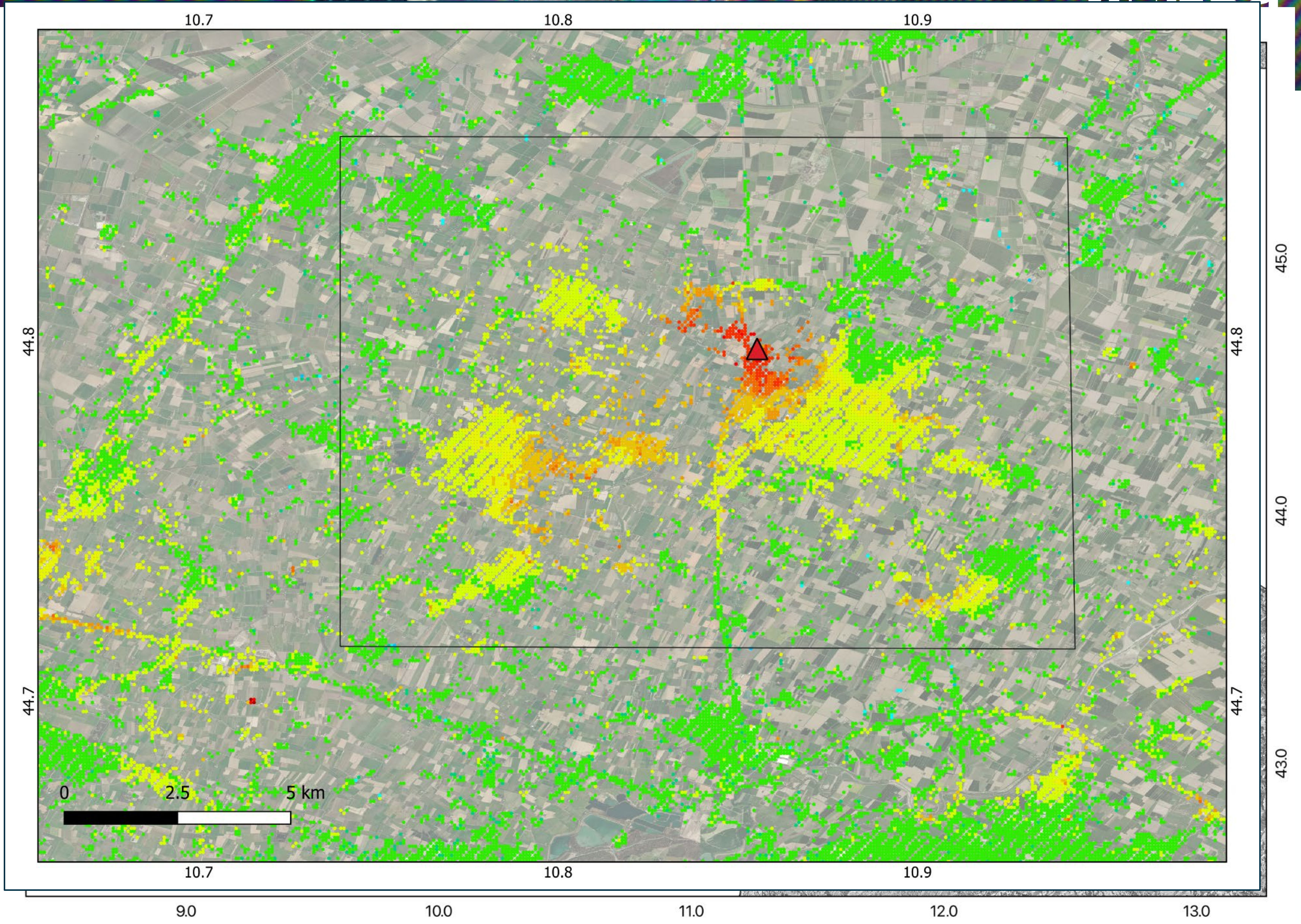
**Coherence threshold 0.75**

**SRTM DEM 30 m x 30 m**

**Orbit: Ascending**



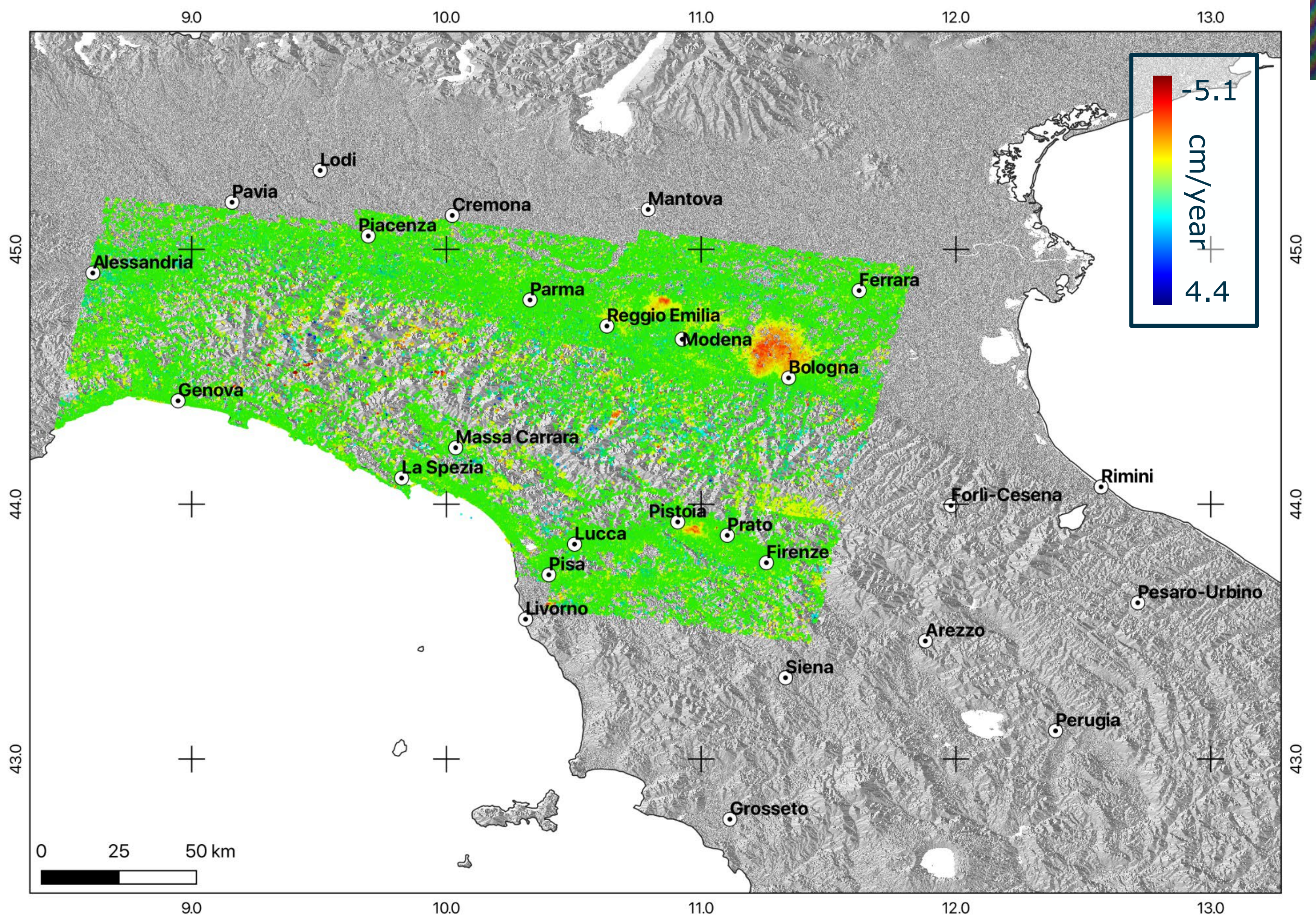

Deformation trend over time of a PS
Deformation (cm)
Time (mm/y)
1
0
-1
-2
-3
-4
-5
-6
-7
-8
04/17
04/18
04/1
04/2
04/21
04/22


10.7
10.8
10.9
44.8
44.7
45.0
44.0
43.0
9.0
10.0
11.0
12.0
13.0
0
2.5
5 km

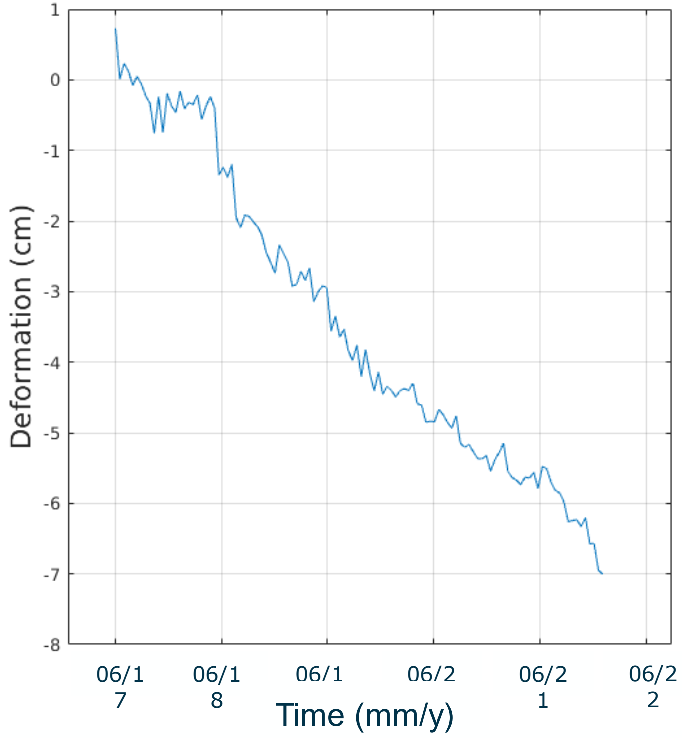
**Satellite:**
**Sentinel-1A**

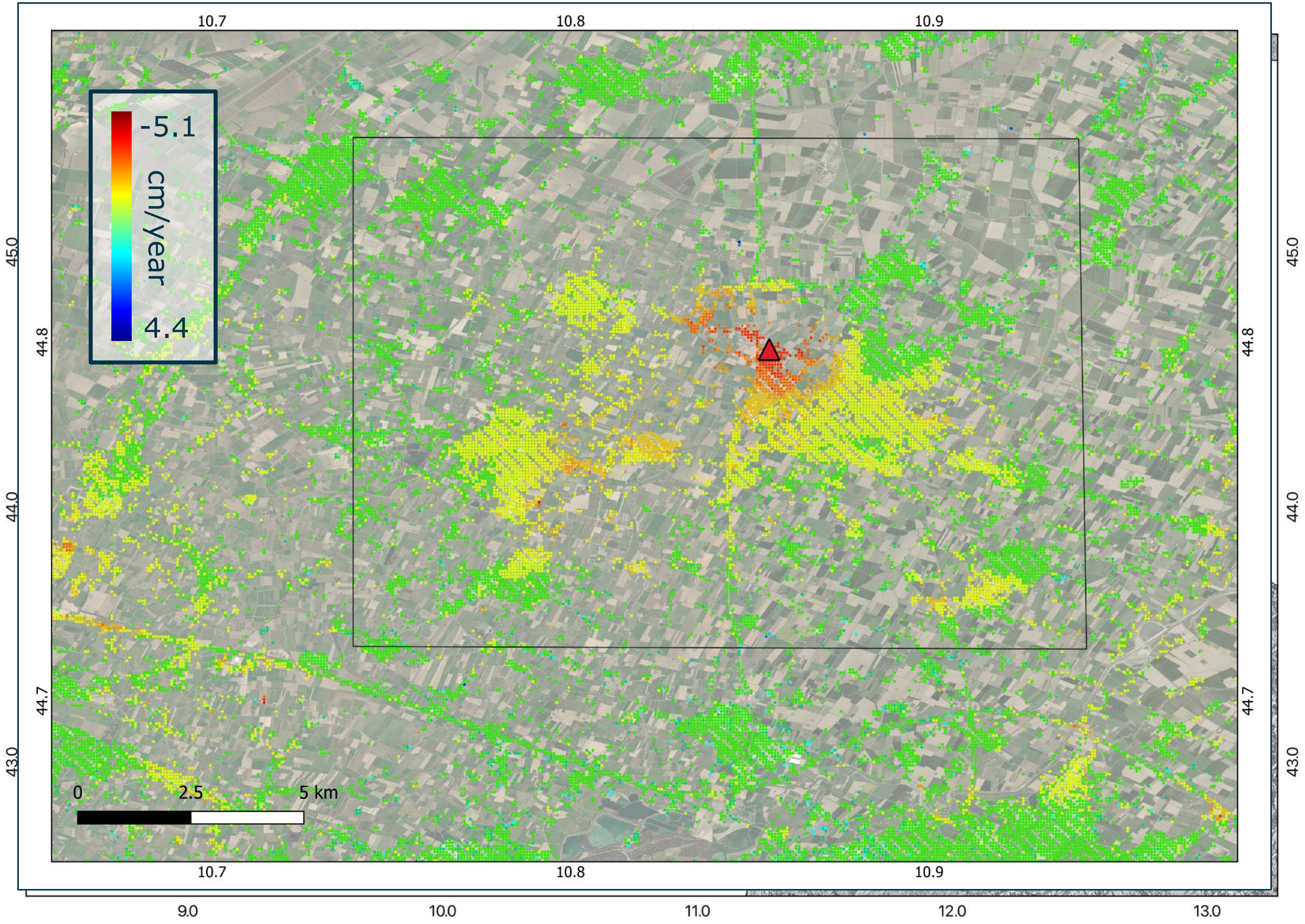
**Period of analysis:**
**06/2017-**
**12/2021**

**Orbit:**
**Descending**



Deformation trend over time of a PS



# InSAR Persistent Scatterer Interferometry with StaMPS

esa

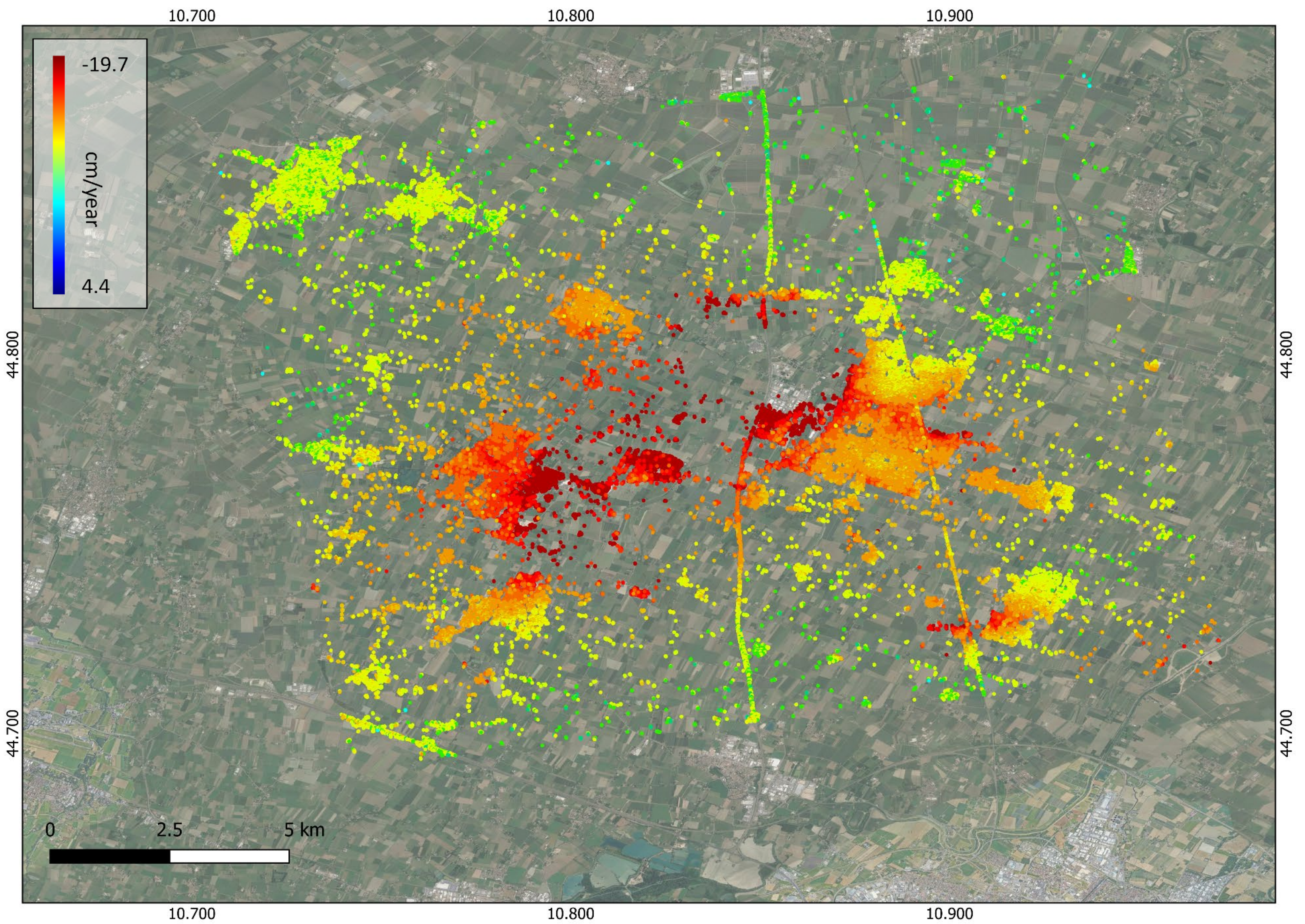
**Satellite: Sentinel-1A**

**Period of analysis: 12/2017-11/2021**

**Master image: 26/01/2020**

**Orbit: Ascending**

**Stable pixels: 116273**



# InSAR Persistent Scatterer Interferometry with StaMPS

esa

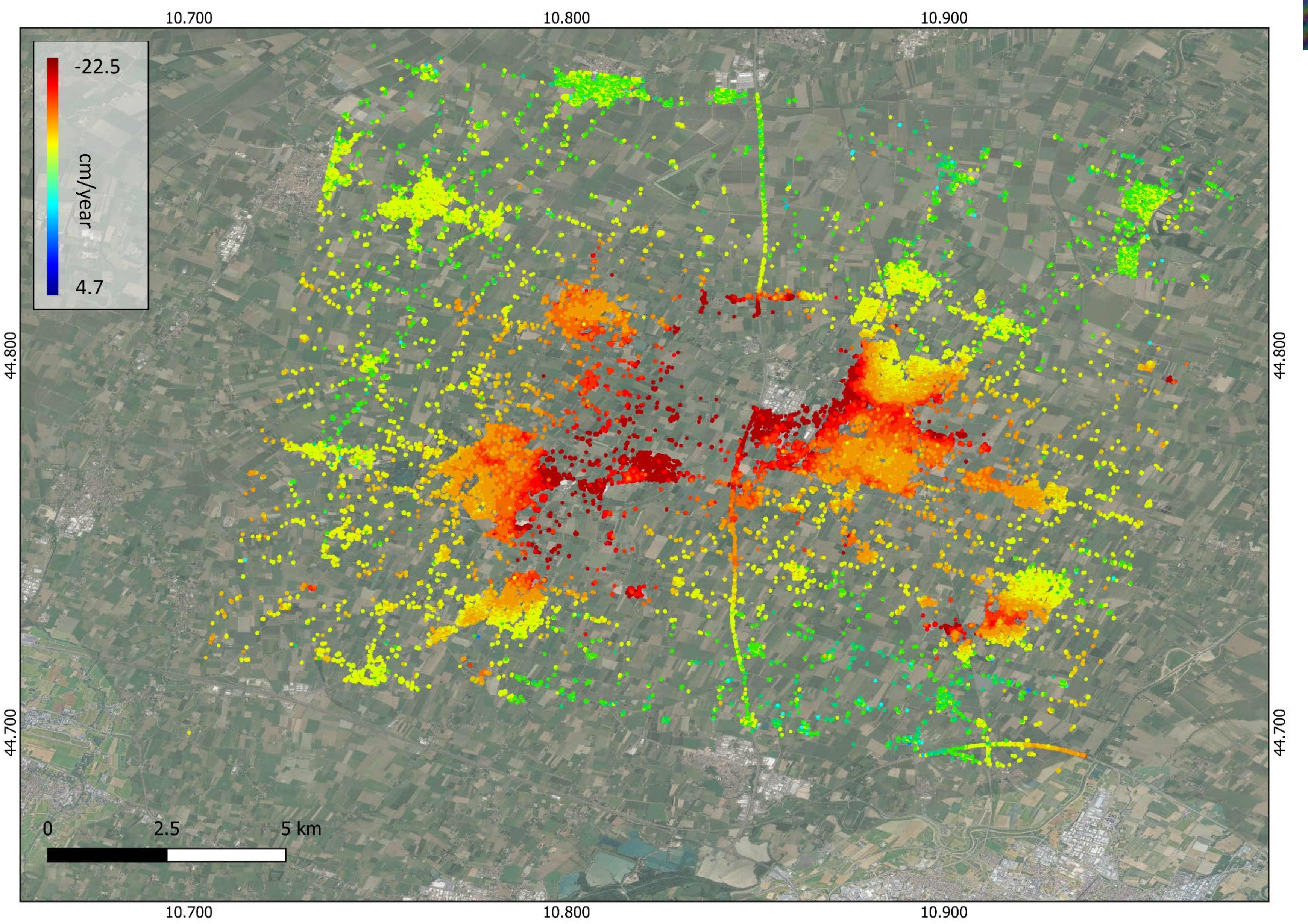
Satellite: Sentinel-1A

Period of analysis: 11/2017-12/2021

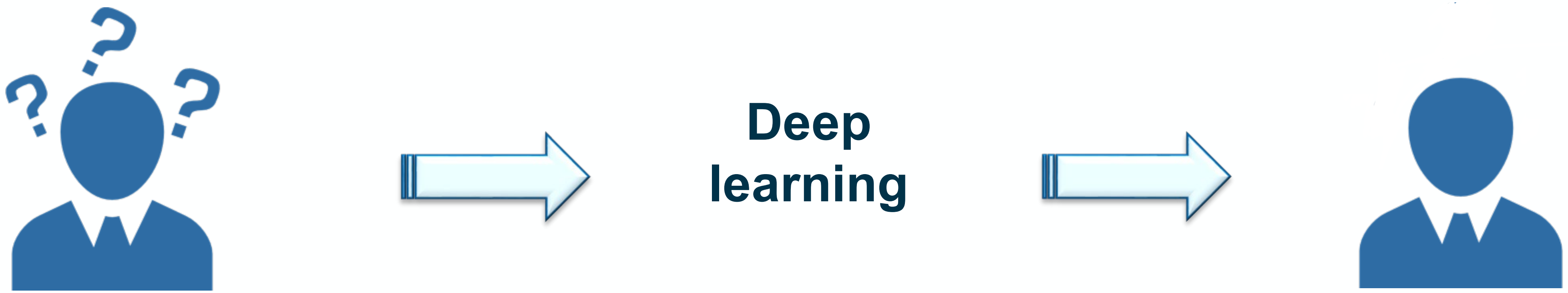
Master image: 27/10/2019

Orbit: Descending

Stable pixels: 101950



# Rationale



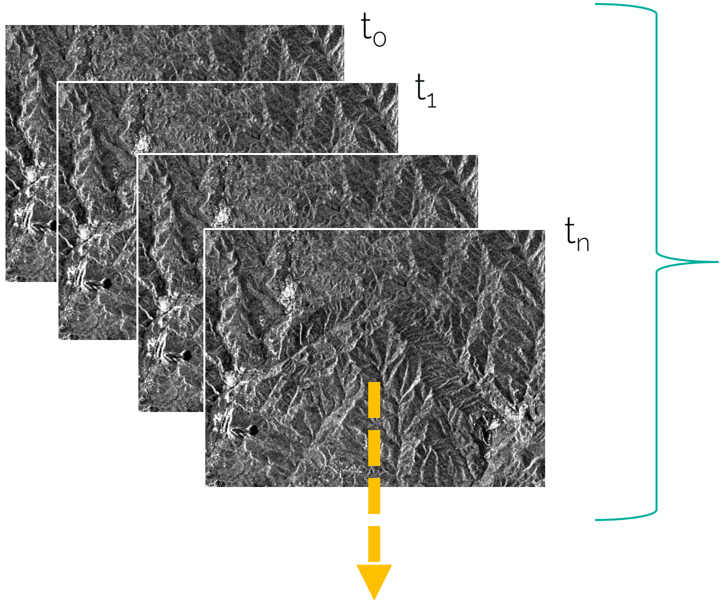

**Transformers:**

InSAR subsidence signal in Carpi is incoherent

Use Deep Learning method for sequential data with 'self-attention mechanism', weighting the significance of an input in the sequence

Obtaining more coherence in the InSAR maps

# Generation of the Machine Learning dataset




ML dataset is the InSAR time-series of the Carpi region from PS-SBAS

For each epoch $t_i$:

Resample the InSAR displacement map using cell size of 100 m × 100 m

Data aggregation -> created a mask by adding all $t_j$ cell values that are non-null -> used for ML as reliable values

# Pre-processing steps

Given the collection of sparse matrices {St}, the ML dataset is created as follows:

Random selection

- Random Selection of a submatrix of 20×20 cells, $S_t^{20x20}$ (2 km x 2 km)
- if $S_t^{20x20}$ has non-null pixels > 100 → generation of a **submatrix vectorial record**

Batch limit

- If $S_t^{20x20}$ has > 300 non-null pixels, only 300 are selected to limit the batch of **submatrix vectorial records**

Vectorial transform

- A vectorial record is made by the sequence of **coordinates** $(x_i, y_i)$ followed by the respective **subsidence** values $z_i$:

$$\mathbf{v} = [x_1, y_1, x_2, y_2, \dots x_i, y_i][z_1, z_2, \dots z_i]$$

ML set definition

- *Collection of vectorial records generated from the available matrices.*
- The training and the testing sets are created by randomly extracting 80% and 20% of the vectorial records, respectively

# Transformers architecture: Causal Language Modeling

**The ML task** to **predict** the next value of the sequence, $z_i$ , by using the previous elements of the vectorial record (or tokens) is a regression

$$x_1,\ y_1,\ x_2,\ y_2,\ \dots\ x_i,\ y_i, z_1,\ \dots\ z_{i-1} \rightarrow z_i$$

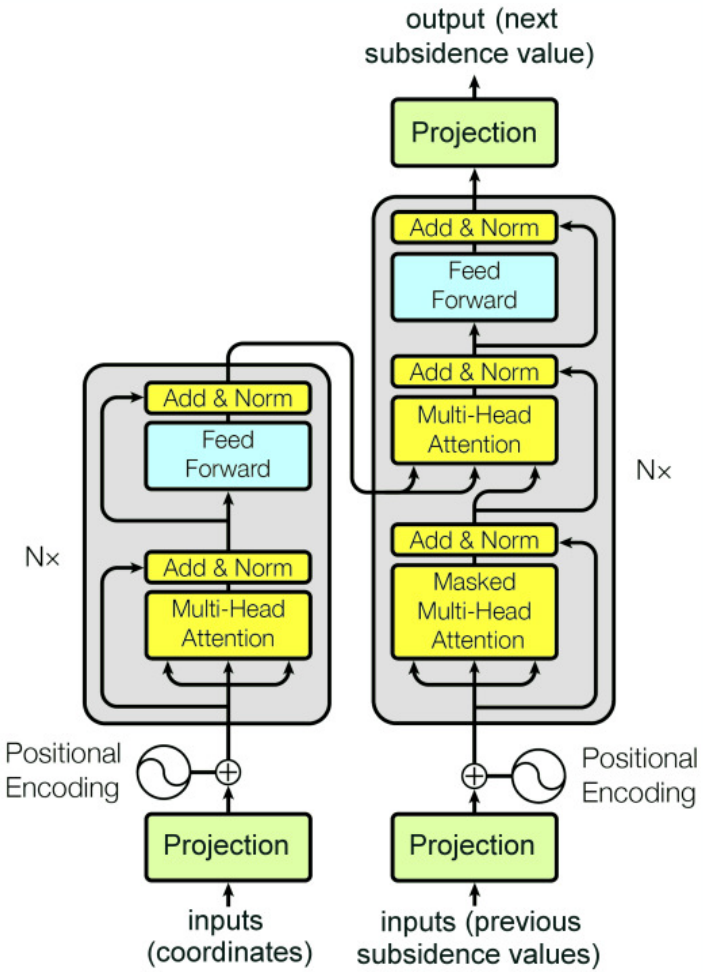
**CLM** works *forcefully mask all the subsequent tokens in the attention matrix and then to predict the next token given all the previous ones*.

Transformer does not contain recurrence or convolution to allow the model to make use of the order of the sequence, **so information about the position of the tokens in the sequence is provided by the *Encoder-Decoder architecture***

The attention function is the function mapping the query and a set of key-values to the output

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}(\mathbf{Q}\mathbf{K}^{\mathbf{T}} / \sqrt{d_k})\mathbf{V}$$

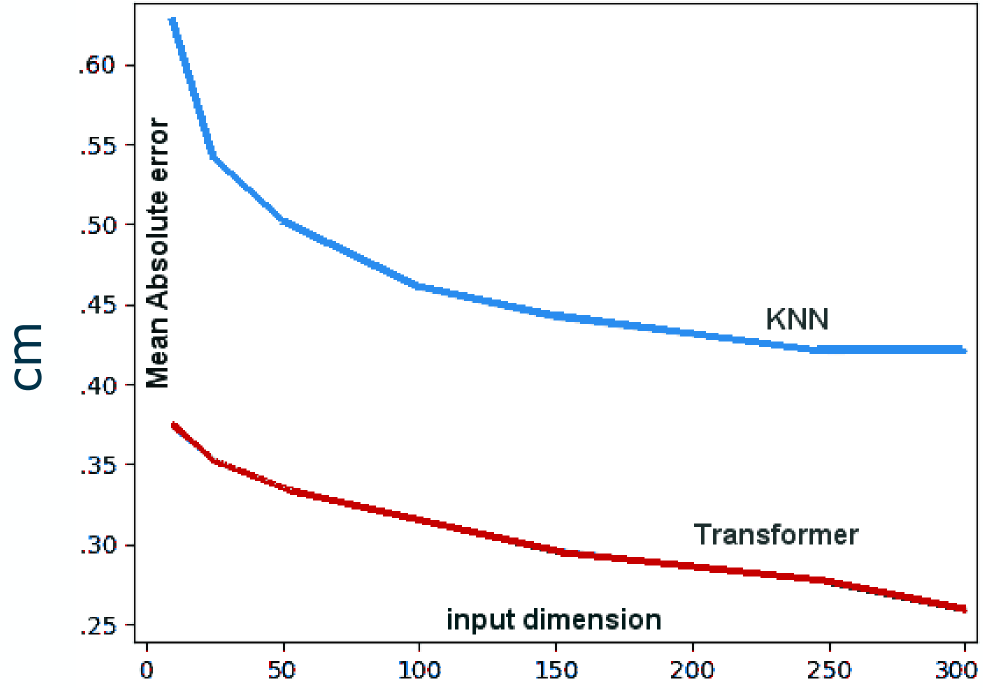
**Q** query, **K** keys, **V** values, $d_K$ input dimension



# Fit calculated on the testing dataset

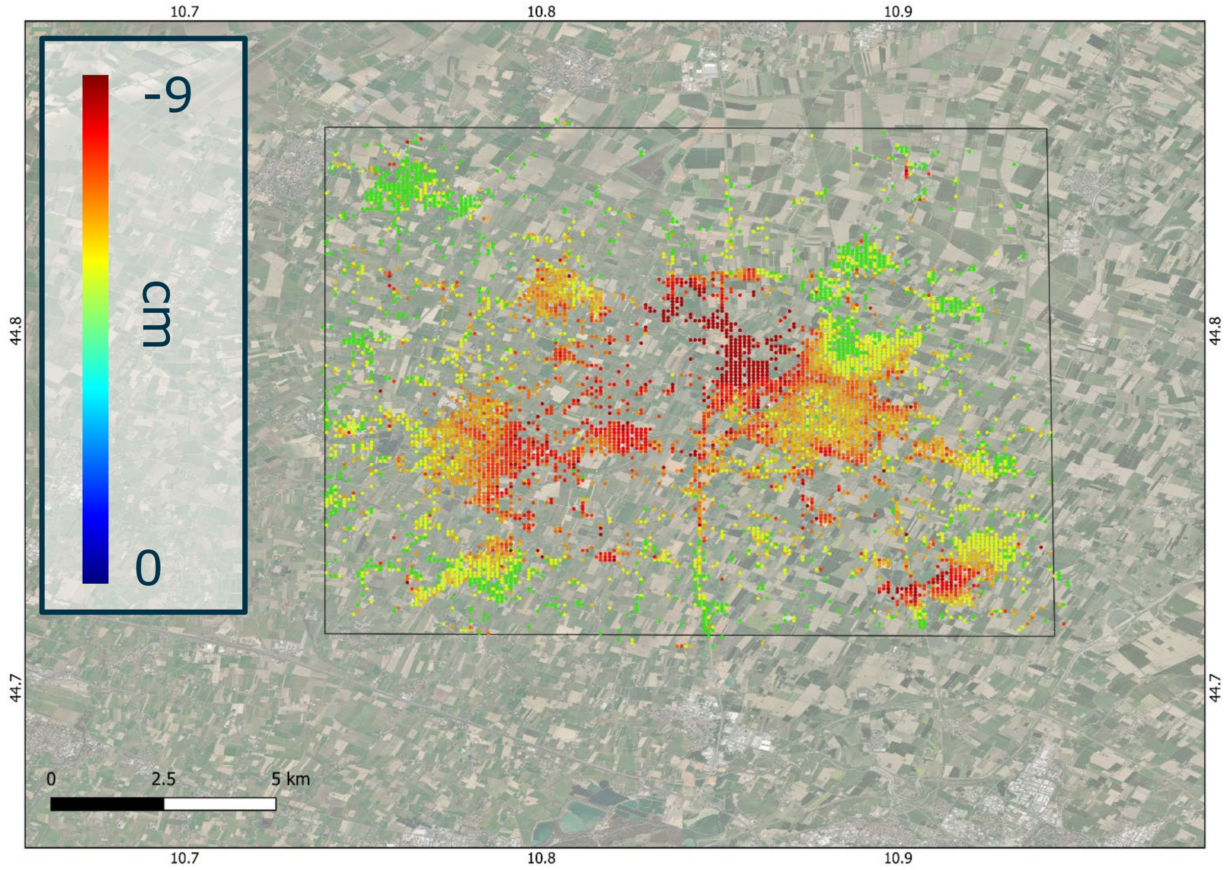
The **transformer encoder-decoder has been compared with KNN regression**, a non-parametric method that predicts the output value by using the average (weighted by distance) among the neighborhoods

The size of the neighborhood has been set to the 25% of the training set, using cross-validation, as the size that minimizes error

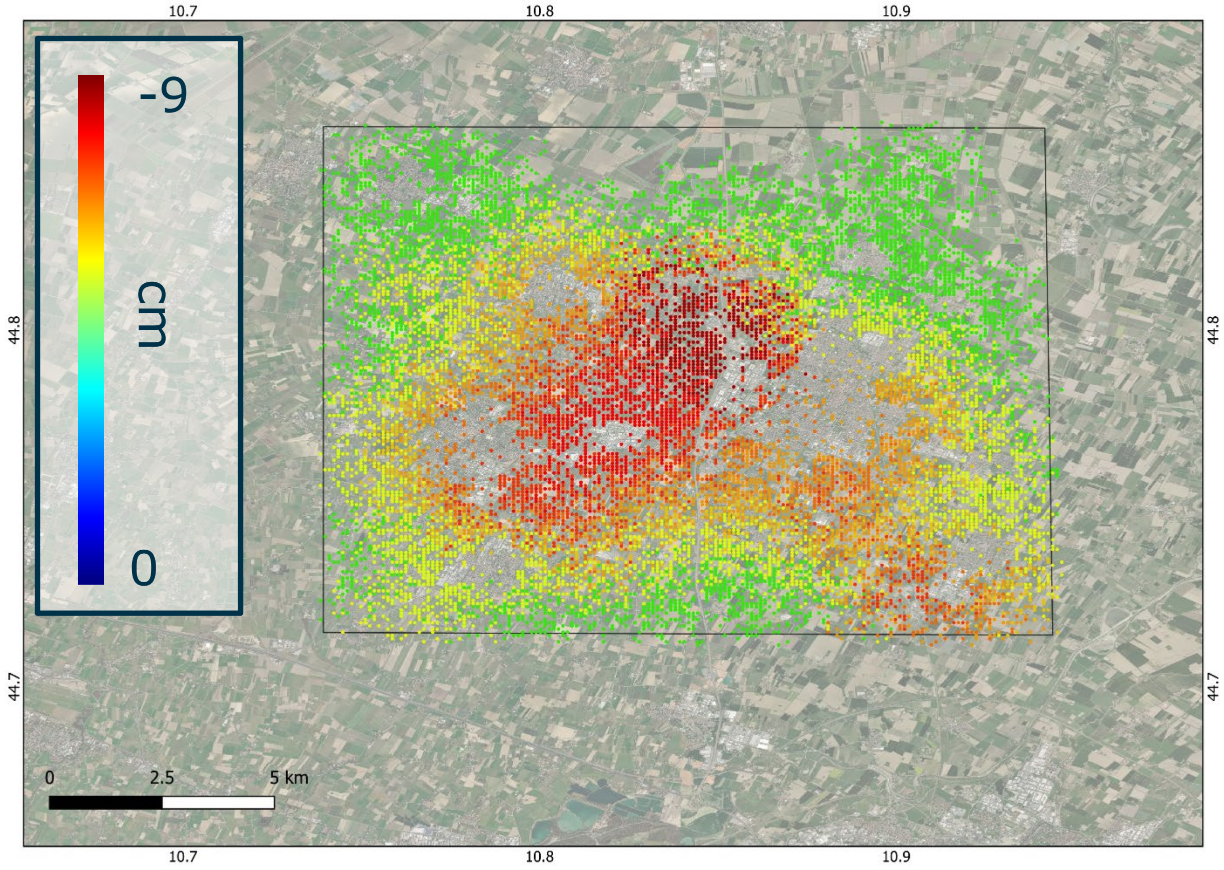


# Carpi original and predicted interferogram at epoch 01/06/2019 (Ascending)

*ORIGINAL*

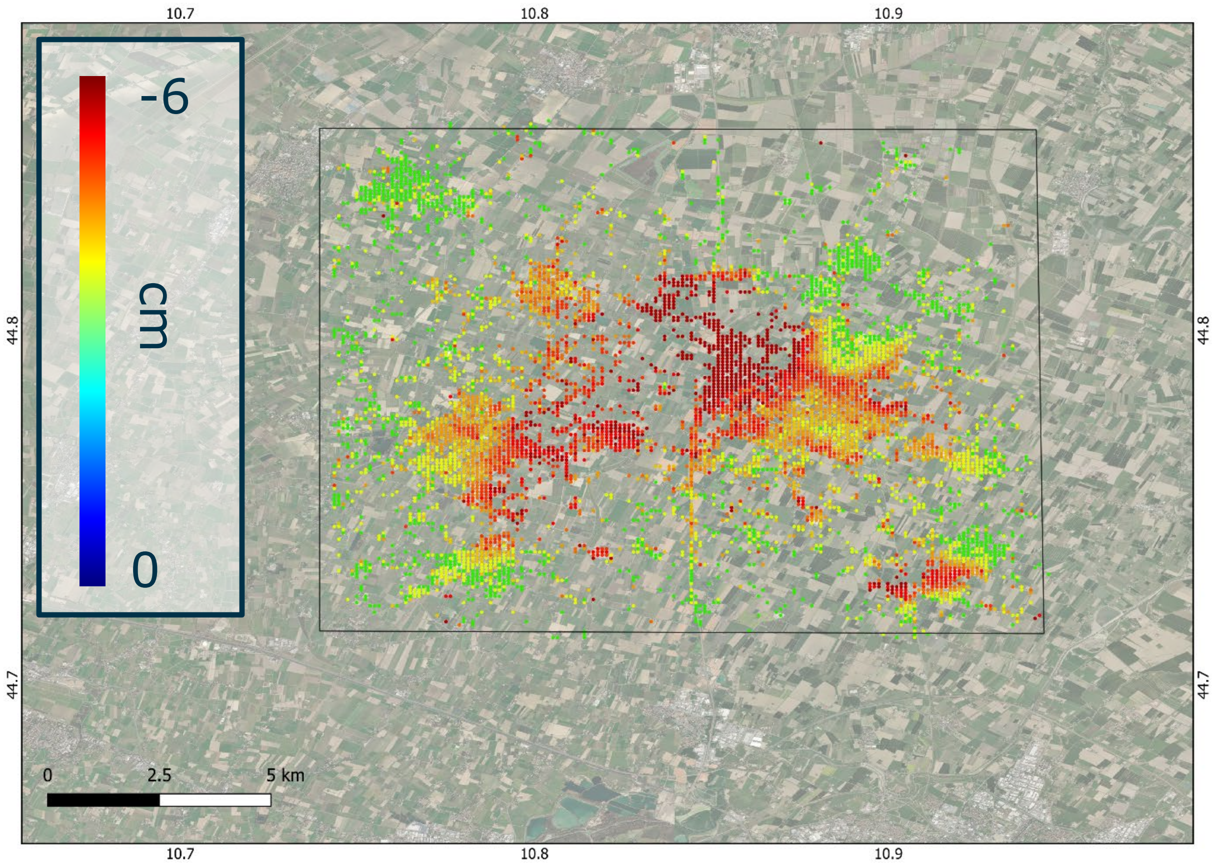



*PREDICTED*

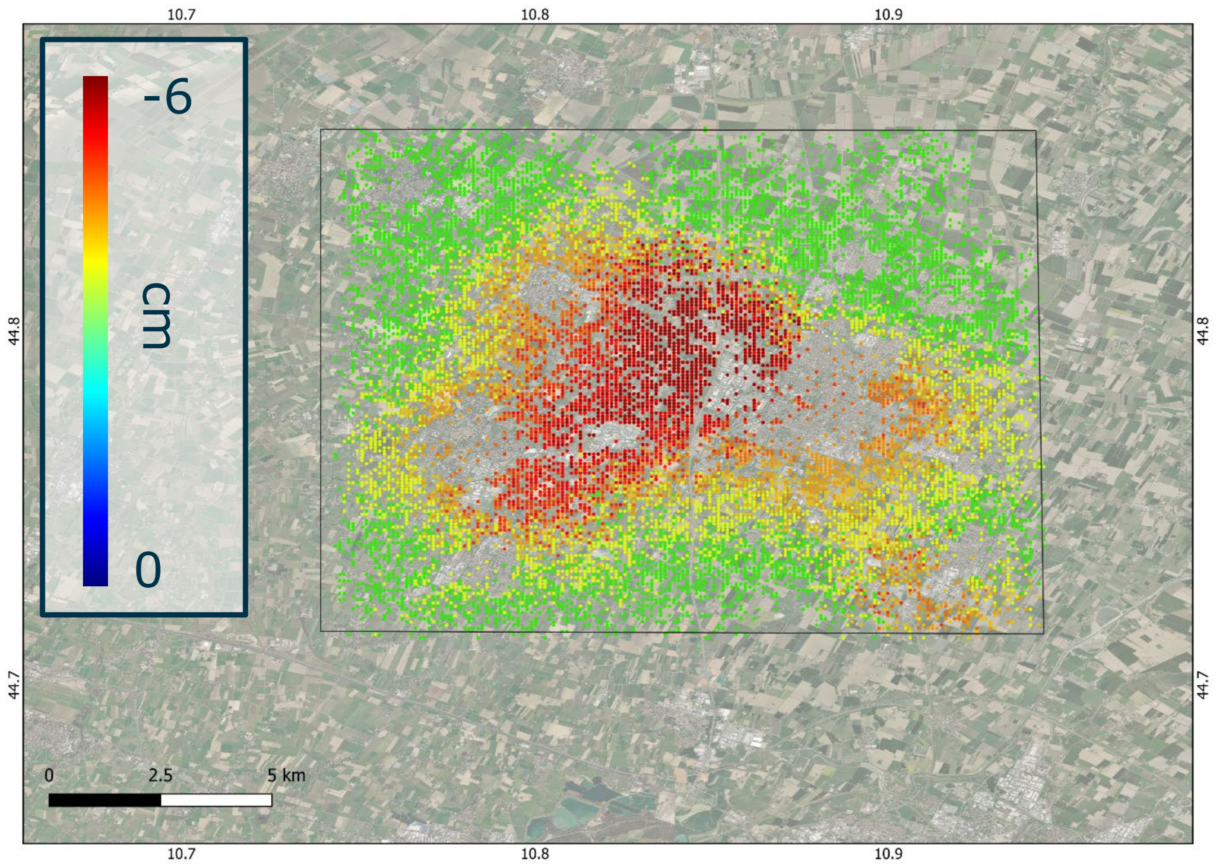


# Carpi original and predicted interferogram at epoch 18/05/2020 (Descending)

*ORIGINAL*




*PREDICTED*



# Conclusions and Potential improvements

ML Transformers can fill in ‘missing tokens’ overcoming InSAR incoherence

ML Transformers could be trained using incremental time-series to maximize the observations on pixels

ML Transformers can also be trained on different time-periods to reproduce signals evolving in a non linear manner

ML Transformers, differently form Neural Networks, can work with missing tokens and have a self-attention mechanism to estimate weights

Comparing with other satellite techniques (e.g. GPS) can provide validation for the subsidence in the areas of incoherence

The approach can be useful when using InSAR time-series from open platforms with limited freedom to tune the time-series parameters to improve coherence

Software available at Github repository Cogsima2022: https://github.com/galatolofederico/cogsima2022/

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