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TAKING THE PULSE OF OUR PLANET FROM SPACE

Multimodal InSAR Reliability Prediction using Graph Neural Networks

H2020 Deep Cube project

Federico Ricciuti[1], Alessio Rucci[1], Chiara Gervasi[1], Ioannis Papoutsis[2], Roberto Acerbis[3]

[1] Tre Altamira, [2] Institute of Astronomy, Astrophysics, Space Applications & Remote Sensing, National Observatory of Athens, [3] Tecne Gruppo Autostrade

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DeepCube

DeepCube – “Explainable AI pipelines for big Copernicus data” – is a three-year project, funded by the Horizon 2020 programme of the European Union under the topic “Big data technologies and Artificial Intelligence for Copernicus”. The project aims to unlock the potential of Copernicus data, leveraging on advances in the fields of Artificial Intelligence and Semantic Web.

The DeepCube technologies will be showcased in six Use Cases (UCs):

- Forecasting of localized extreme drought and heat impacts in Africa (UC1)
- Climate induced migration in Africa (UC2)
- Fire hazard short-term forecasting in the Mediterranean (UC3)
- Global volcanic unrest detection and alerting (UC4a)
- **Deformation trend change detection for critical infrastructure monitoring (UC4b)**
- Copernicus services for sustainable and environmentally-friendly tourism (UC5)

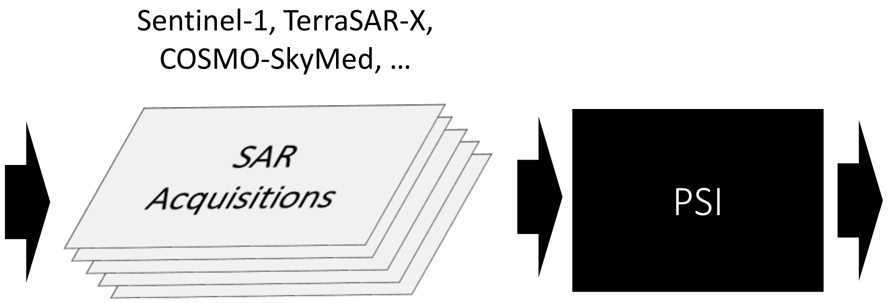
PSI point cloud reliability map is one of the products

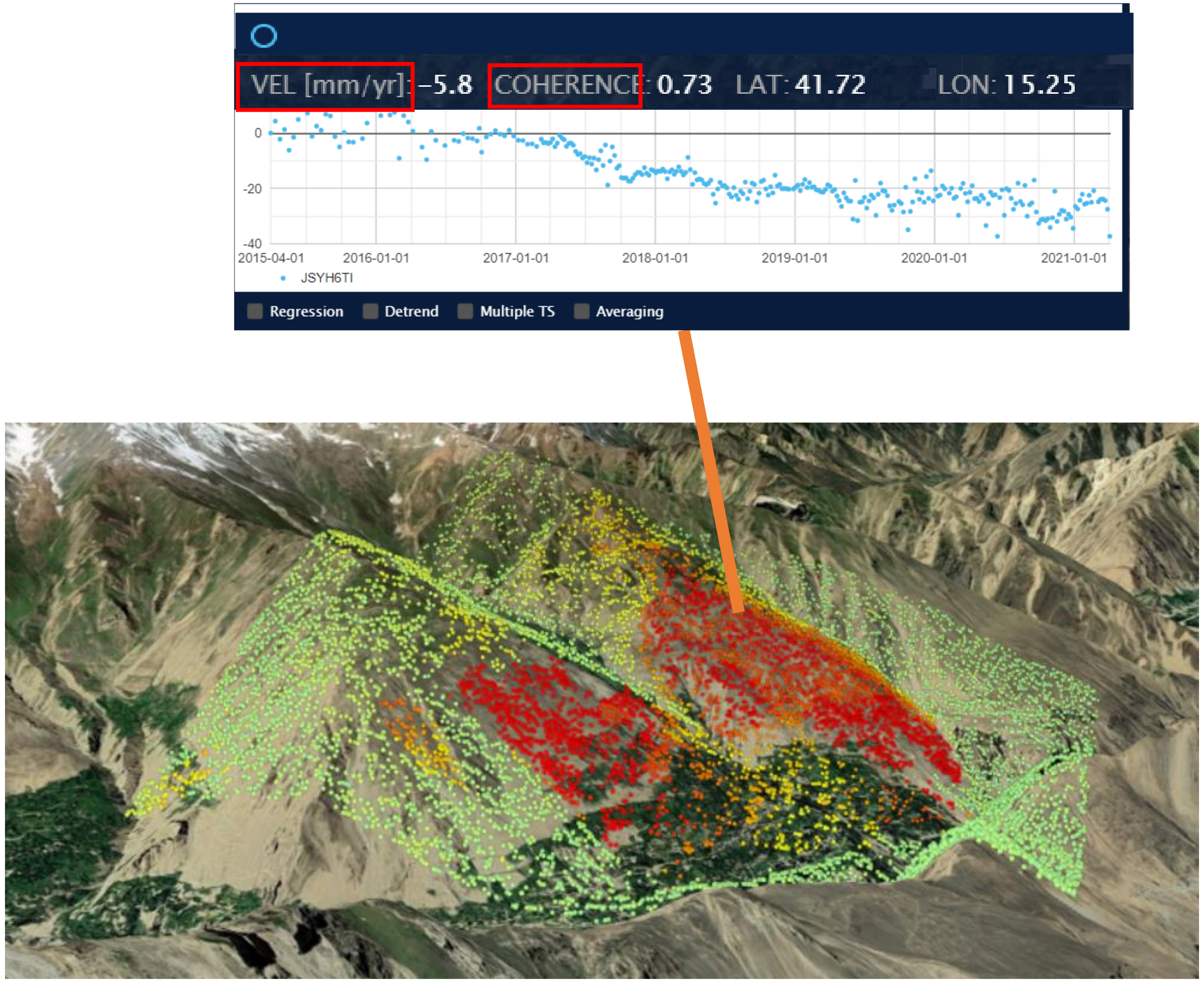
https://deepcube-h2020.eu

Persistent Scatterer Interferometry - PSI

PSI is a multitemporal InSAR technology that makes it possible to identify radar targets exhibiting a very stable return, allowing one to measure surface displacement with very high precision

- Area of Interest
- Temporal Span





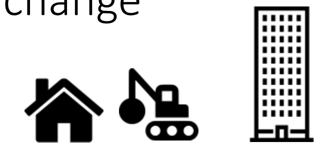
VELOCITY MAP

PSI

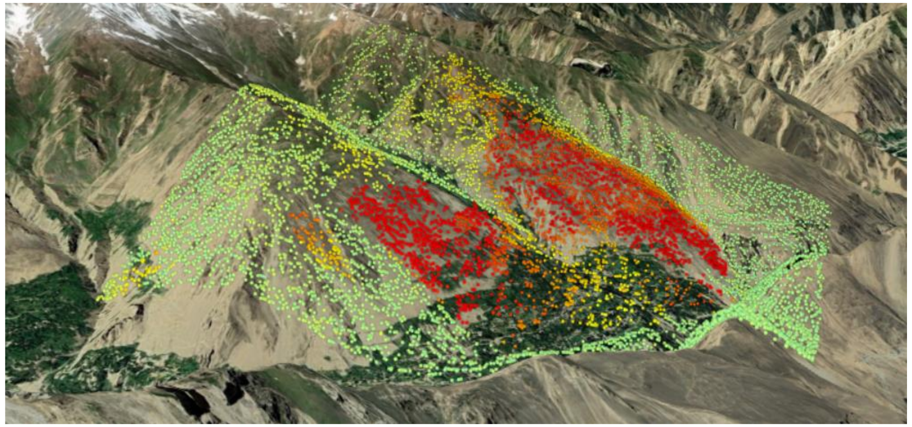
The quality of PSI point clouds can be negatively influenced by:

- Decorrelation due to weather conditions (e.g. rain, snow)

- Target change



- Signal not related to an actual deformation (e.g. growing vegetation, penetration depending on the level of moisture)

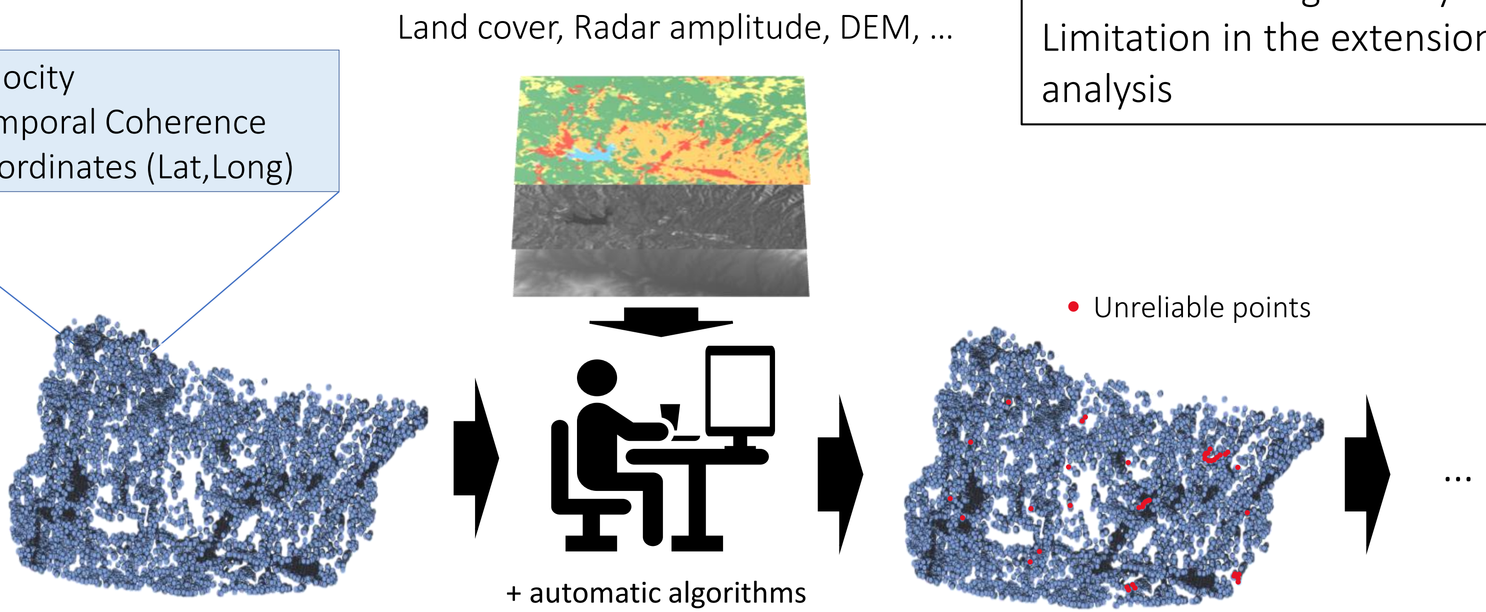


VELOCITY MAP

Data Screening – As-is

Time consuming activity
Limitation in the extension of the analysis

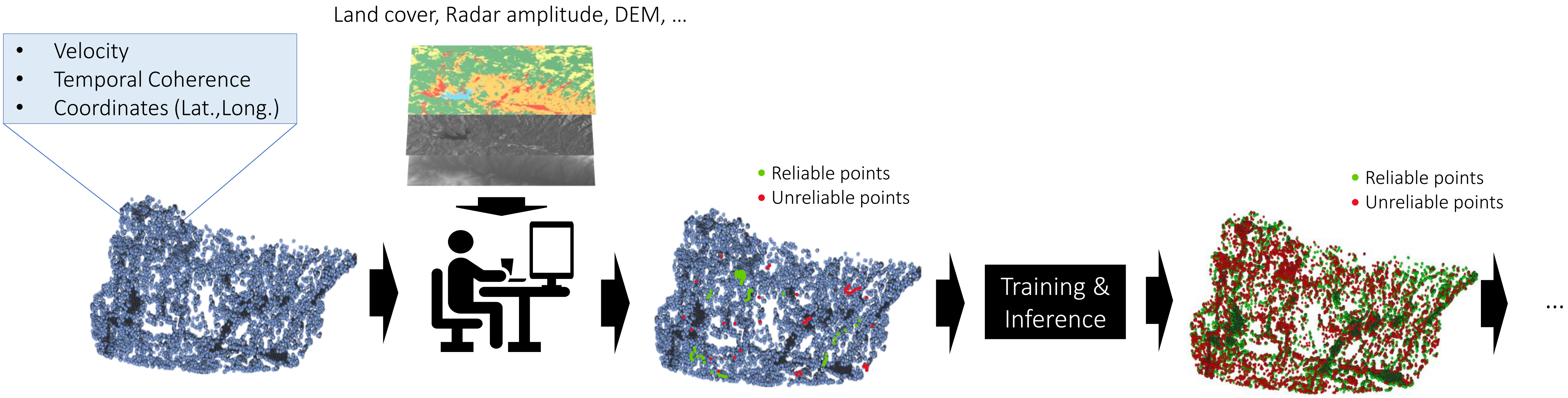
- Velocity
- Temporal Coherence
- Coordinates (Lat,Long)



The operator identify and remove noisy and unreliable points from the original point cloud, depending on:

- the likelihood of the physical phenomena associated to the measurements with respect to the terrain properties and land type
- scattering characteristics
- spatial consistency with respect to the pointwise properties (e.g. coherence, amplitude, velocity, ...)

Data Screening – to-be



1. The operator labels a subset of random points as “Reliable” and “Not Reliable”
2. A model is trained on the set of points labelled by the operator
3. The trained model is applied over the entire point cloud

Assumptions

Pointwise properties

- The reliability of a point strongly depends on coherence
- The land type positively (e.g. build areas) or negatively (e.g. vegetative areas) influences the reliability
- …

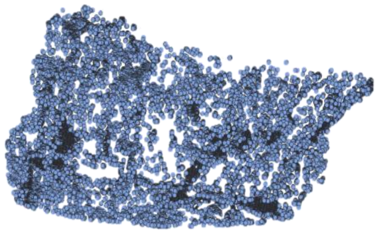
Spatial correlation

- Neighbors generally share the same class (high homophily)
- Pointwise properties very different from the neighborhood can determine the unreliability of a point
- …

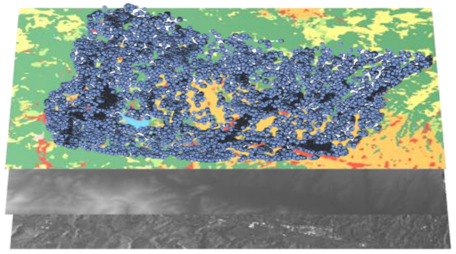
Multimodal model able to jointly consider pointwise information and the spatial correlations between points

<u>In this work we explored the application of Graph Neural Network models to meet these requirements</u>

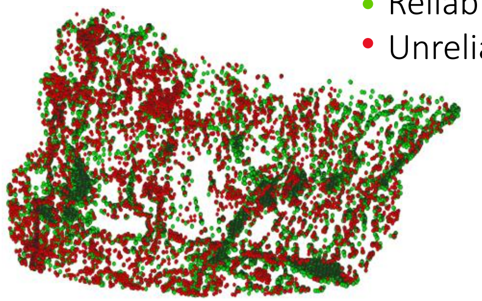
Data Labelling – Case Study



> 40.000 points

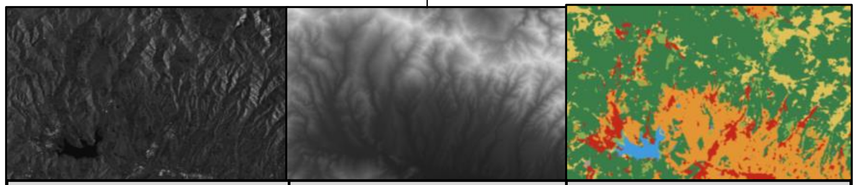


Hand-labelling



- Reliable points (84%)
- Unreliable points (16%)

class imbalance



	Mean SAR amplitude	**TinItaly DEM**	**ESRI Land Cover**
Resolution	5x20m	10x10m	10x10m

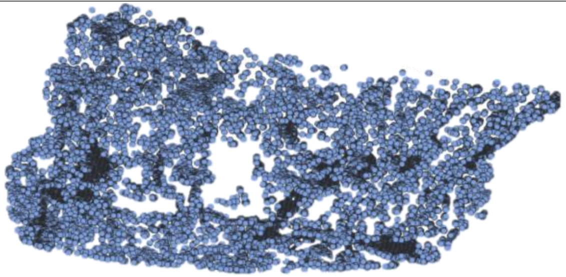
https://tinitaly.pi.ingv.it/
https://www.arcgis.com/home/item.html?id=d6642f8a4f6d4685a24ae2dc0c73d4ac

Transductive Setting

stratified split: 8/2/90
(same as ogbn-products)

The features used during the labelling are the same used for training of the model

Graph and Feature Construction



Hand Labeled Point Cloud

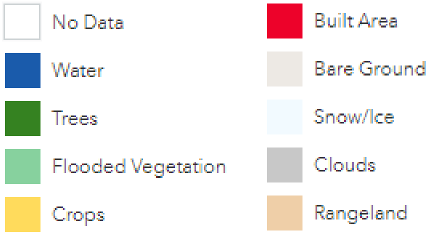
Graph Construction

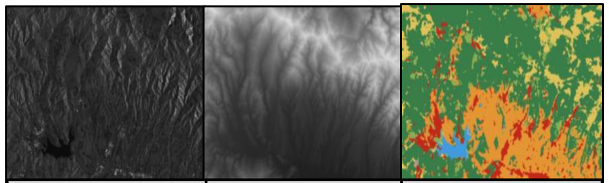
KNN – Graph (k: 20)
Distance – Haversine

$$e_{i,j} = p_i - p_j$$

$p_i = (lon_i, lat_i)$

$e_{i,j}$: edge feature
p_i : node position

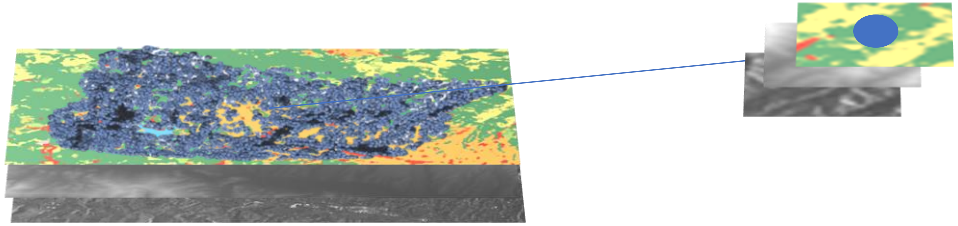




Mean SAR amplitude	TinItaly DEM	ESRI Land Cover
5x20m	10x10m	10x10m

upsampled (5m)

Pointwise Feature Construction

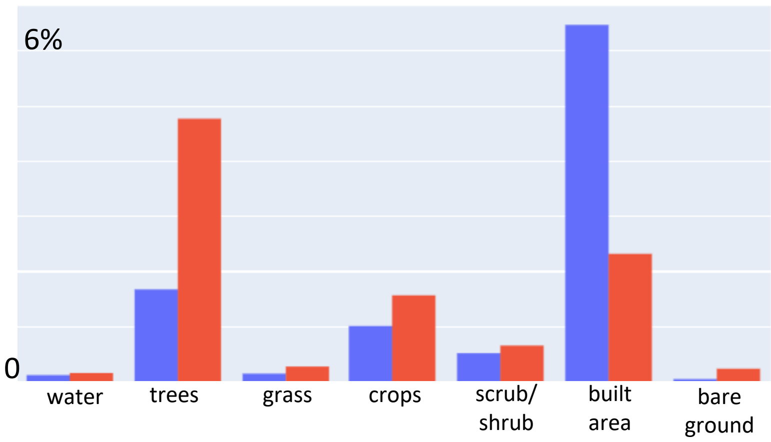


Amplitude $\in \mathbb{R}_{\geq 0}^{80x80}$
DEM $\in \mathbb{R}^{80x80}$
Surface Type $\in \{1, \ldots, 10\}^{80x80}$
Velocity $\in \mathbb{R}$
Coherence $\in [0, 1] \subset \mathbb{R}$

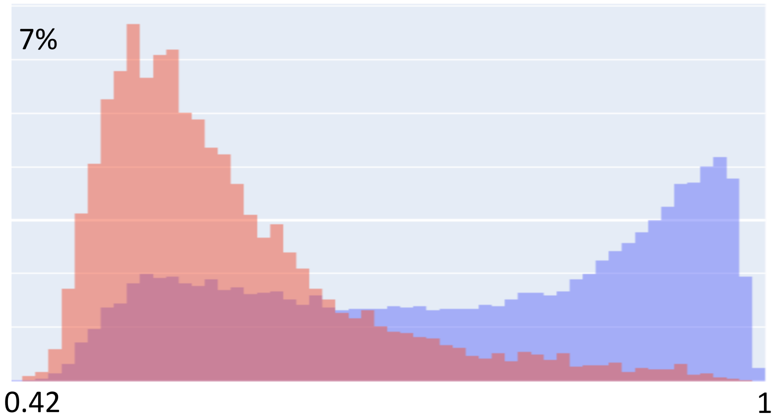
Correlation

Reliable
Unreliable

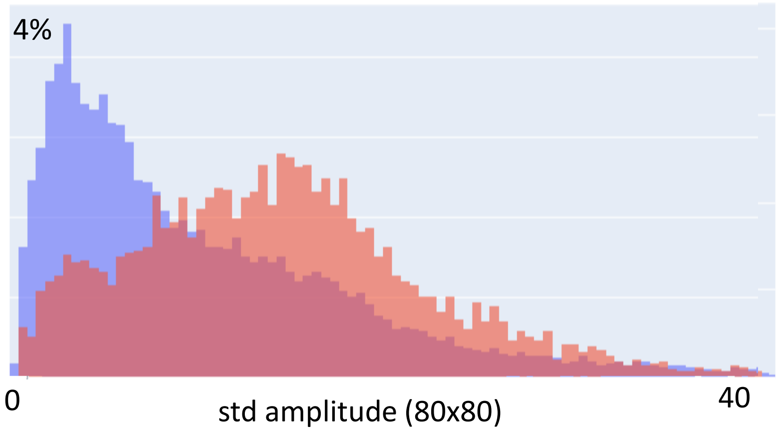
land cover/use



coherence

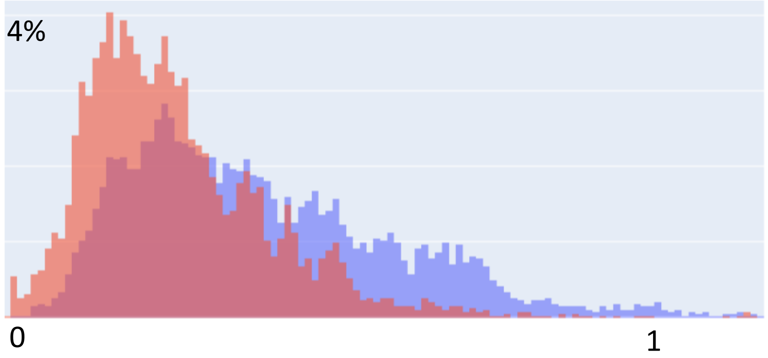


std dem (80x80)



...

std amplitude (80x80)



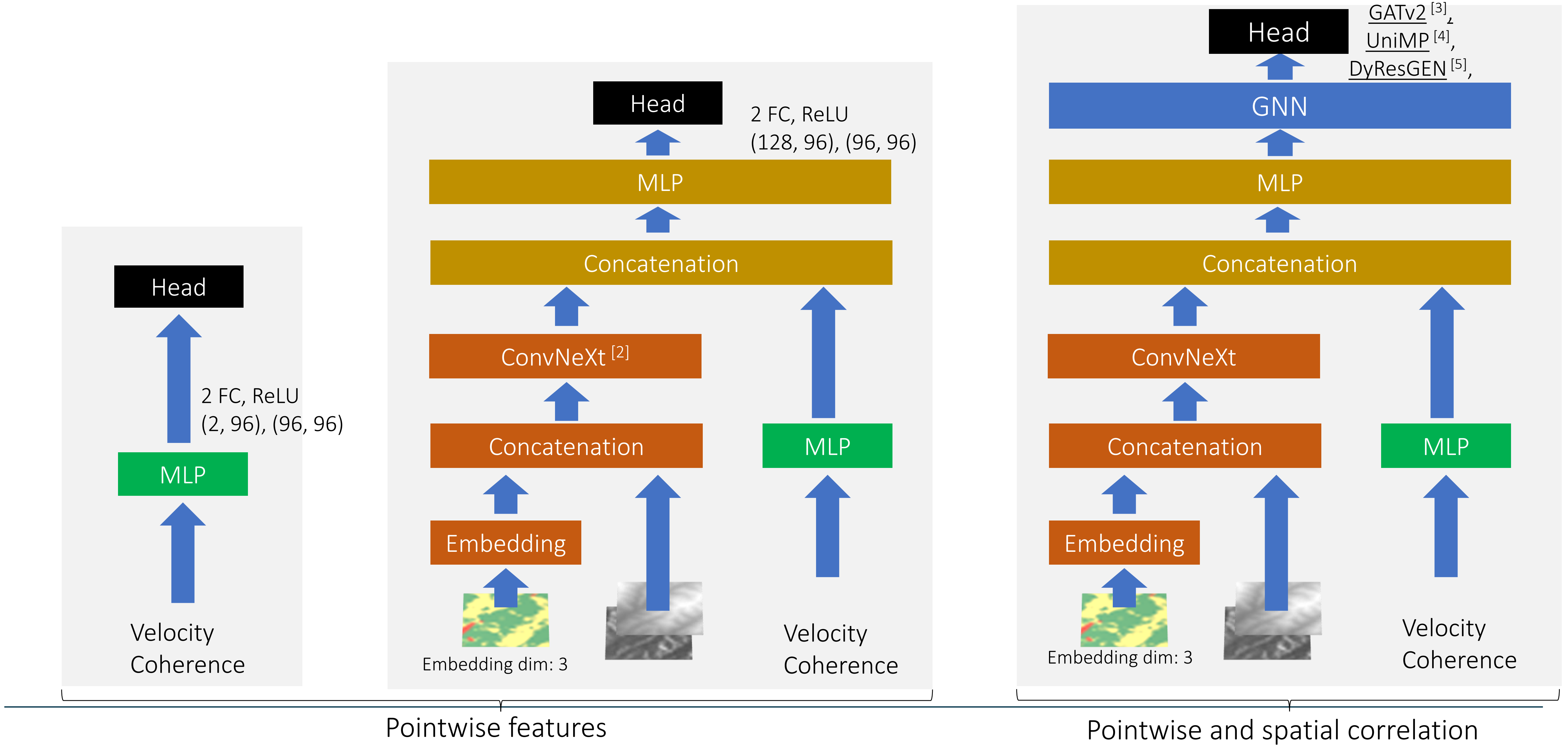
#nodes	#edges	#cc	homophily	homophily (reliable)	homophily (unreliable)
42309	846180	1	0.809	0.894	0.374

$$\frac{|\{(u,v):(u,v)\in E\ ,\mathrm{y_u}=\mathrm{y_v}=\mathrm{class}\}|}{|\{(u,v):\ \mathrm{y_u}=\mathrm{class}\}|}$$

$$\frac{|\{(u,v):(u,v)\in E\ ,\mathrm{y_u}=\mathrm{y_v}\}|}{|E|}$$

“class-wise” homophily

Experiments

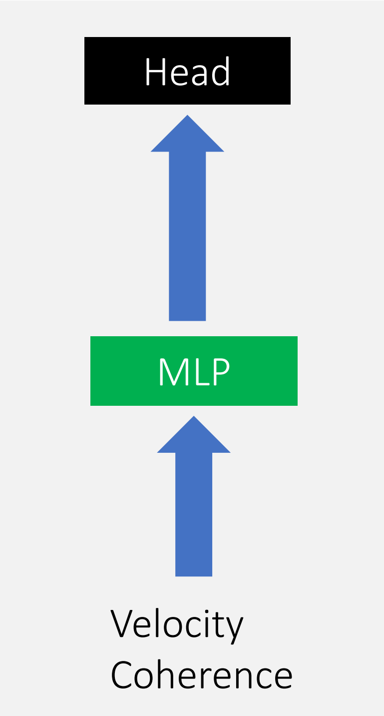


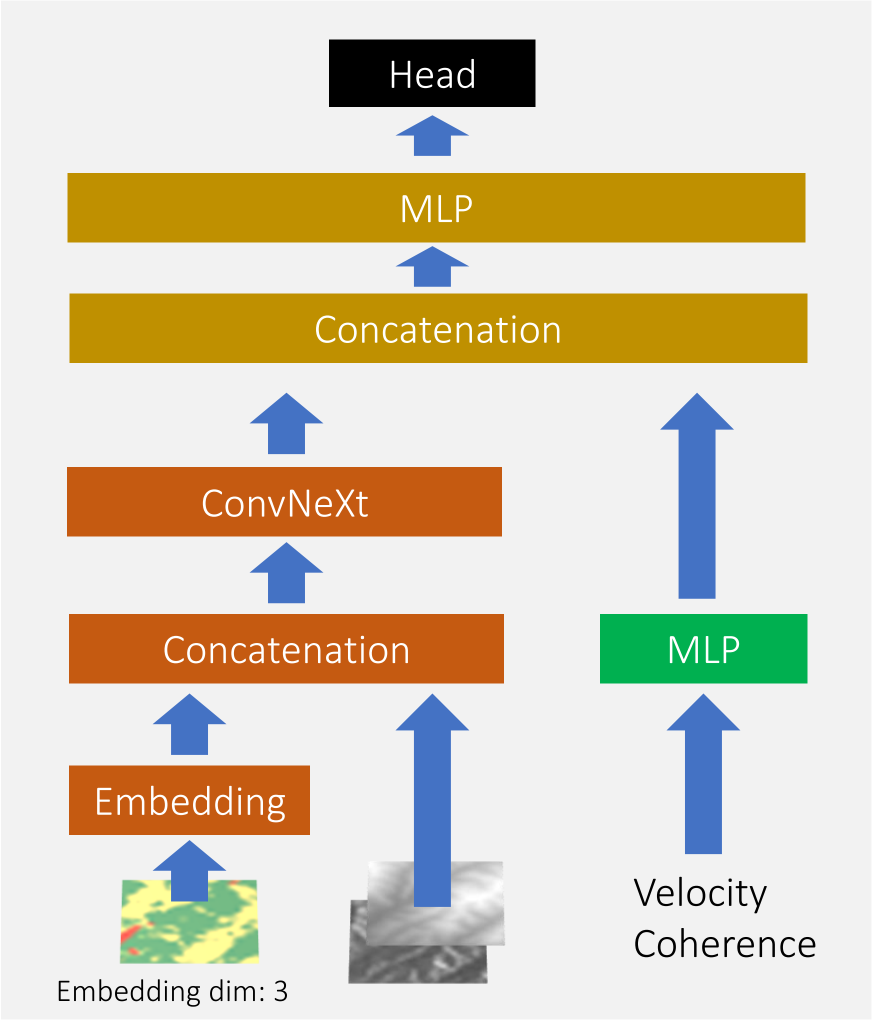
Pointwise properties

	Validation F1 Score
*Baseline	0.785±0.025
+ Layers	0.803±0.013

Mean results over six different splits and runs of each model.
***Similar results were obtained using also simpler models (e.g. SVM:** 0.754 ±0.027**)**

The introduction of external layers improve the performance of the model

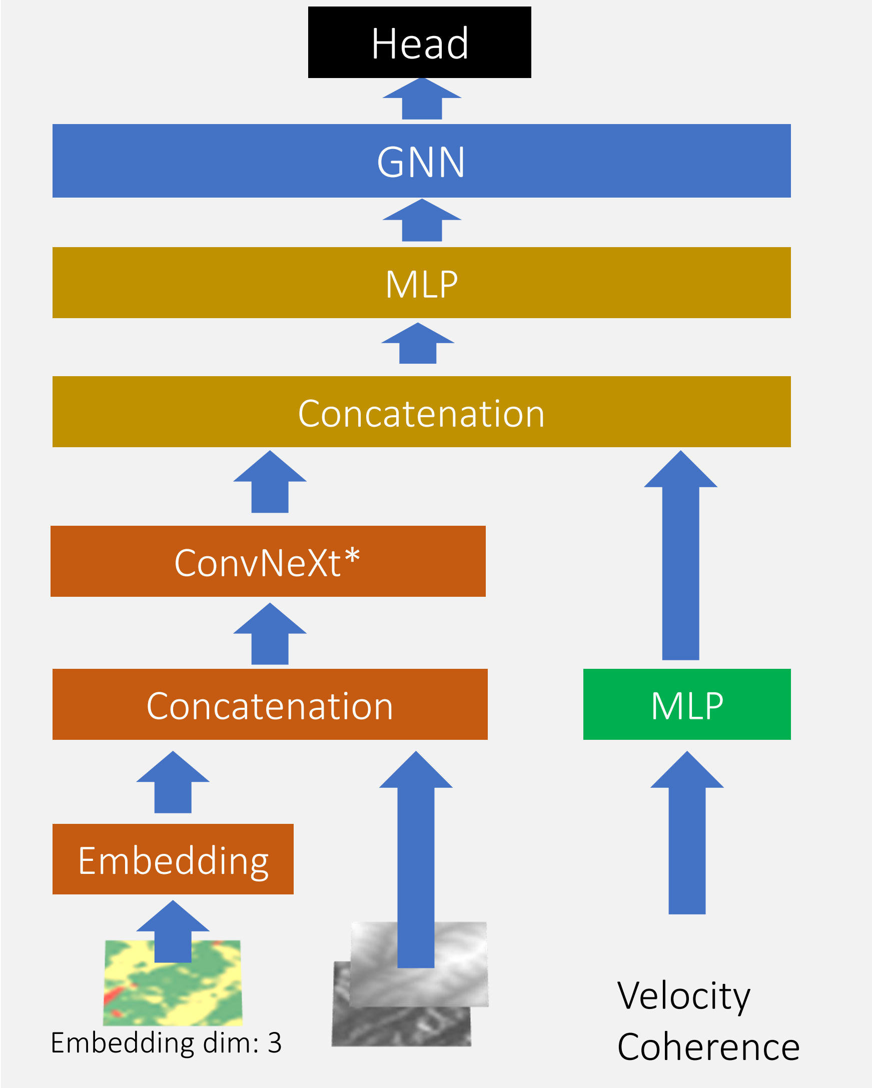




Pointwise and spatial properties

Model	Validation F1 Score
Baseline	0.785±0.025
+ Layers	0.803±0.013
GATv2 (1 Layer)	0.825±0.014
UniMP (1 Layer)	0.824±0.013
DyResGEN (1 Layer)	**0.829**±0.011

Mean results over six different splits and runs of each model.



Scaling up - GNN

Model	Validation F1 Score	Test F1 Score	Training/Inference time*
Baseline	0.785±0.025	0.755±0.011	
+ Layers	0.803±0.013	0.788±0.003	
DyResGEN (1 Layer)	0.829±0.011	0.812±0.007	0h 20m / 8s
DyResGEN (2 Layer)	0.841±0.012	0.822±0.006	0h 50m /10s
DyResGEN (3 Layer)	**0.843**±0.007	**0.823**±0.008	1h 30m /12s

Mean results over six different splits and runs of each model.
*** AWS Instance: g4dn.xlarge (T4 NVIDIA GPU, 16GB GPU Memory), 0,736 USD/h**

Scaling up the network increases the performances of the models, but the improvements slow down after the introduction of two layers

Scaling down – Training set

Training size	Validation F1 Score	Test F1 Score
8%	0.843±0.007	0.823±0.008
4%	0.796±0.011	0.778±0.014
2%	0.769±0.014	0.739±0.013

Mean results over six different splits and runs of each model.
Results are obtained using the DyResGEN (3 layer) model

It is possible to obtain meaningful results with only 4% of the point cloud (~800), containing approximately 130 unreliable points

Conclusions

- We presented one of the first works showing an application of Graph Neural Networks for the analysis of PSI point clouds
- External layers improve the accuracies of the models
- It is possible to achieve reasonable accuracies using few data points during the training
- Graph Neural Network are valuable architectures to combine spatial and pointwise properties in PSI applications

Next Steps

- Creation of additional hand-labelled PSI point clouds and exploration of the inductive setting*
- Comparison of GNN to other methods
- Improve the construction of the Graph
- Identification of other PSI supervised task that could be used for the validation of the approach

*We have already created two additional hand-labelled point clouds and we are testing the model in an inductive setting

References

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Thank you for your attention

MILANO

Ripa di Porta Ticinese, 79
20143 Milano - ITALY
Tel: +39 02 4343 121

BARCELONA

Carrer de Còrsega, 381-387
08037 Barcelona - SPAIN
Tel: +34 93 183 57 50

VANCOUVER

Suite 410, 475 West Georgia Street
Vancouver, BC V6B 4M9 - CANADA
Tel: +1 604 331 2512

TRE ALTAMIRA
A CLS Group Company

sales@tre-altamira.com

Regional offices

FRANCE

Parc Technologique du Canal
11, Rue Hermès
F-31520 Ramonville St Agne
Tel: +33 561 39 47 19

PERU

Av. Angamos Oeste 537
Miraflores, Lima
Tel: +51 1 4402717

AUSTRALIA

Suite 207 – 122 Toorak Road | South Yarra
Melbourne
Tel: +61 455 154552

Training parameters

Training Config	
Optimizer	AdamW
Base learning rate	4e-3
Weight decay	0.1
Optimizer momentum	β_1, β_2=0.9, 0.999
Batch size	32
GNN Config	
Sampling method	Neighbor Sampling
Normalization	Layer Normalization

ConvNeXt Config	
Stochastic depth	0.5
Layer scale	1e-6
Depths	[2 2 4 2]
Hidden sizes	[12 24 48 96]
Patch size	80x80
Normalization	Layer Normalization