EARSeL | EUROPEAN ASSOCIATION OF REMOTE SENSING LABORATORIES

esa

EO for Cultural and Natural Heritage Workshop 2024

15-16 October 2024 | ESA/ESRIN

Detecting and Analysing Looting Activities using LiDAR and Machine Learning: the OPTIMAL Project

Marco Fiorucci[1], Peter Nayor[2], Arianna Traviglia[1]

[1] Center for Cultural Heritage Technology, Istituto Italiano di Tecnologia[2]
[2] ESA, Φ-lab

This project is funded by the European Union's Horizon 2020 *Research and Innovation* programme, GA 101027956

Looting

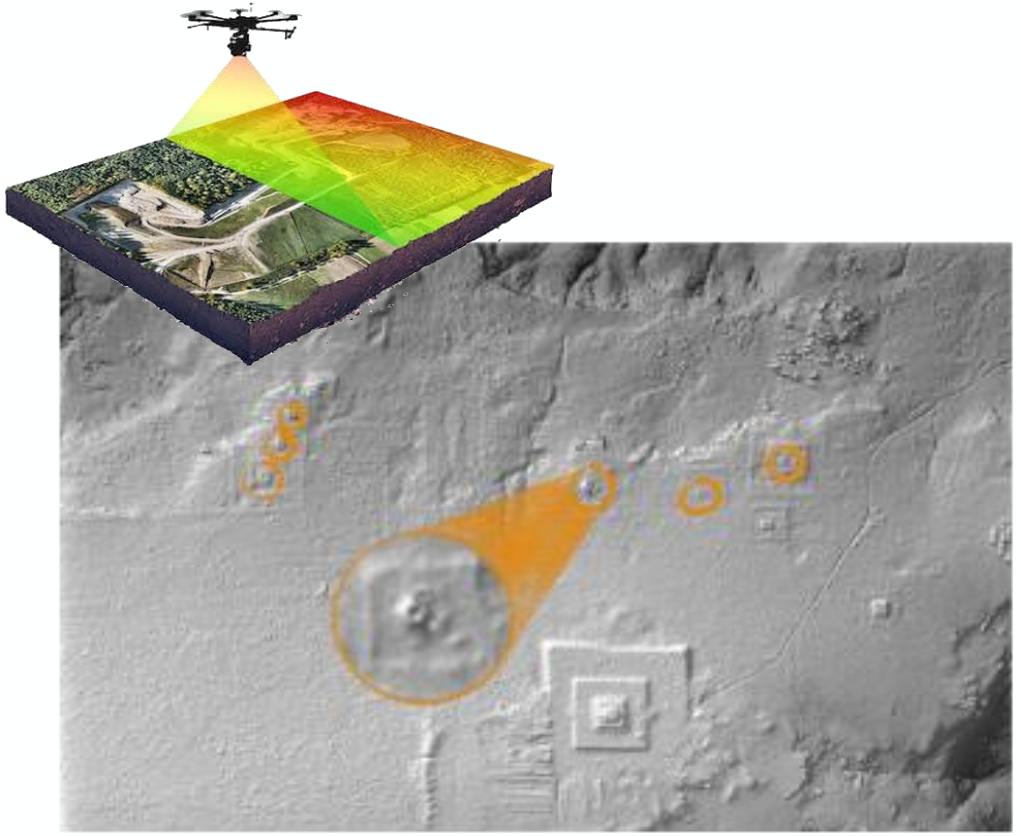
The **illegal excavation** of archaeological sites to collect historical material culture ("looting").

It is a pressing problem for two crucial reasons:

1. The **destruction** of our cultural heritage.
2. Stolen artifacts are sold on the black market to fund **terrorism**.

We need efficient ways to automatically detect looting on remote sensing data.

The OPTIMAL project

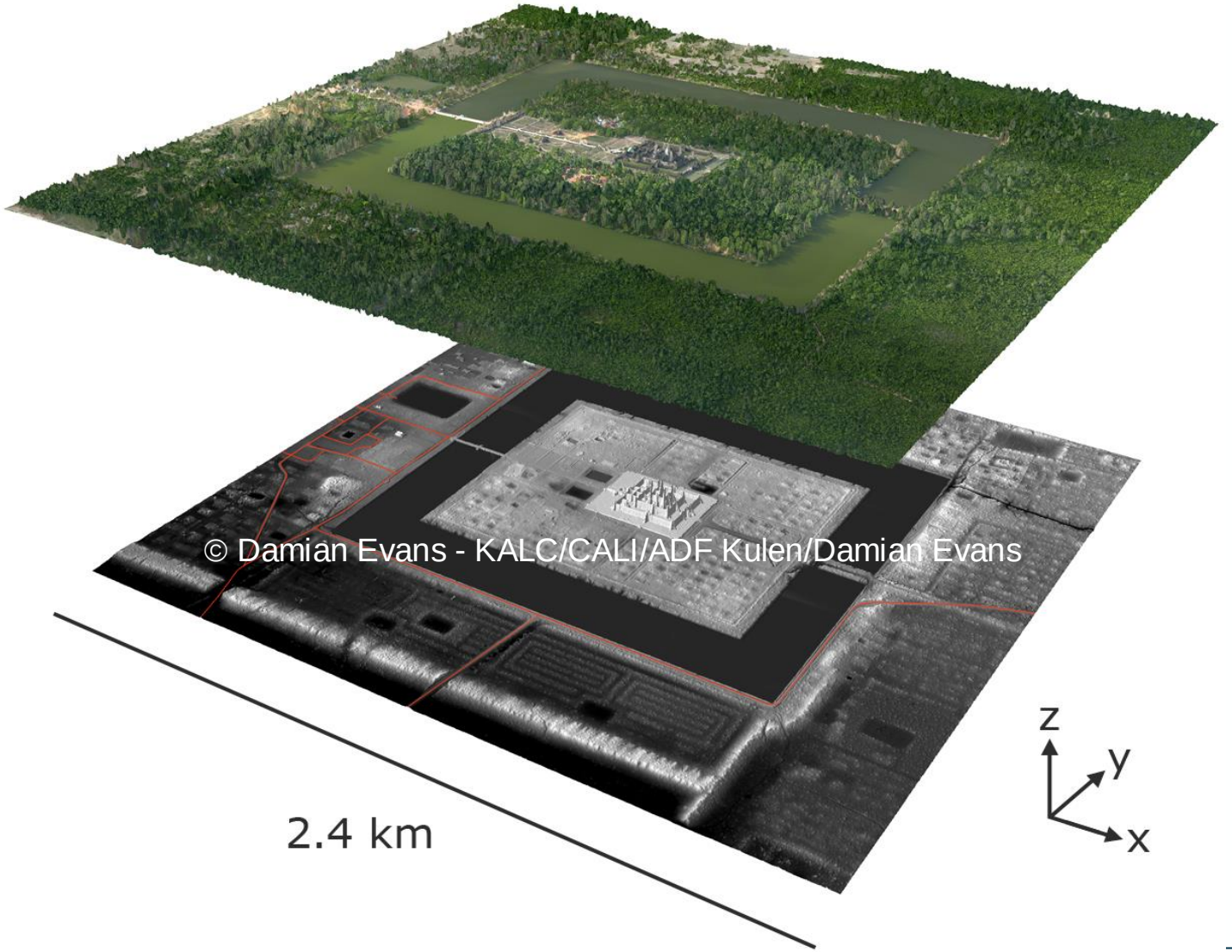


OPTIMAL

OPtimal Transport for Identifying Marauder Activities on LiDAR
(Light Detection and Ranging)

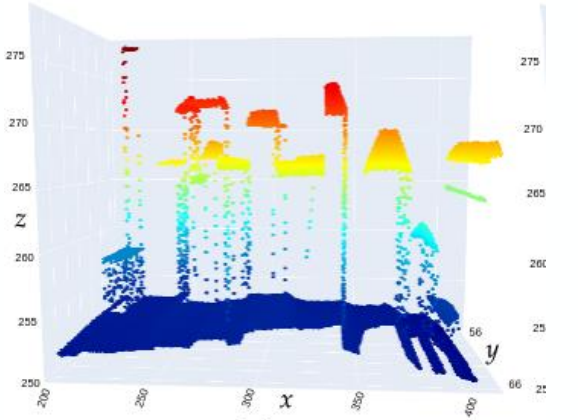
This project is funded by the European Union's Horizon 2020 *Research and Innovation* programme, GA 101027956.

Why LiDAR?

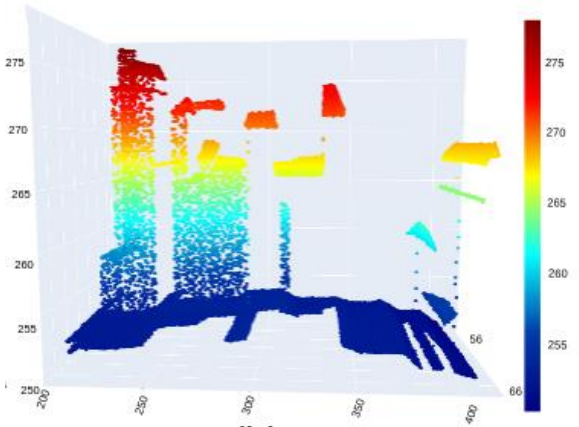


Change detection on LiDAR Point Clouds

CD aims to identify **relevant differences in altitude** on a pair of LiDAR point clouds collected over the same geographical location.



(a) pc_0

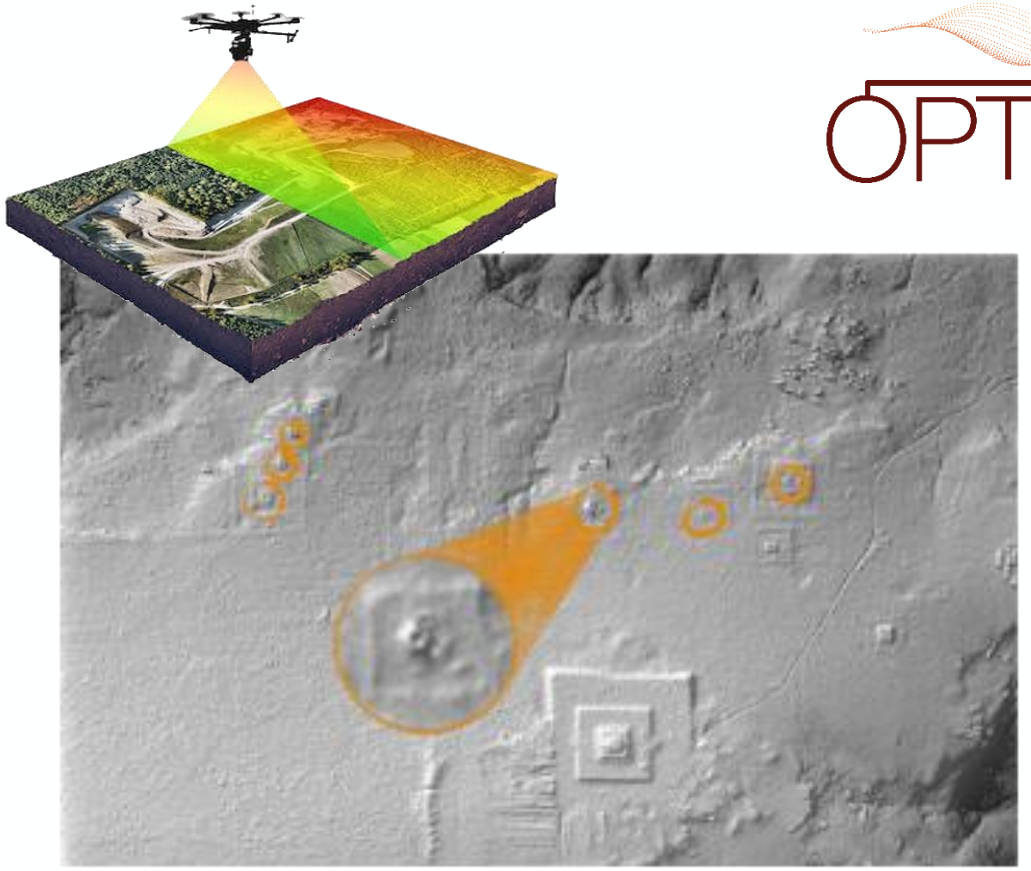

(b) pc_1

Challenging:

1) unmatching spatial supports and point density variations.

2) prohibitive cost of collecting and labelling training sets

The OPTIMAL project

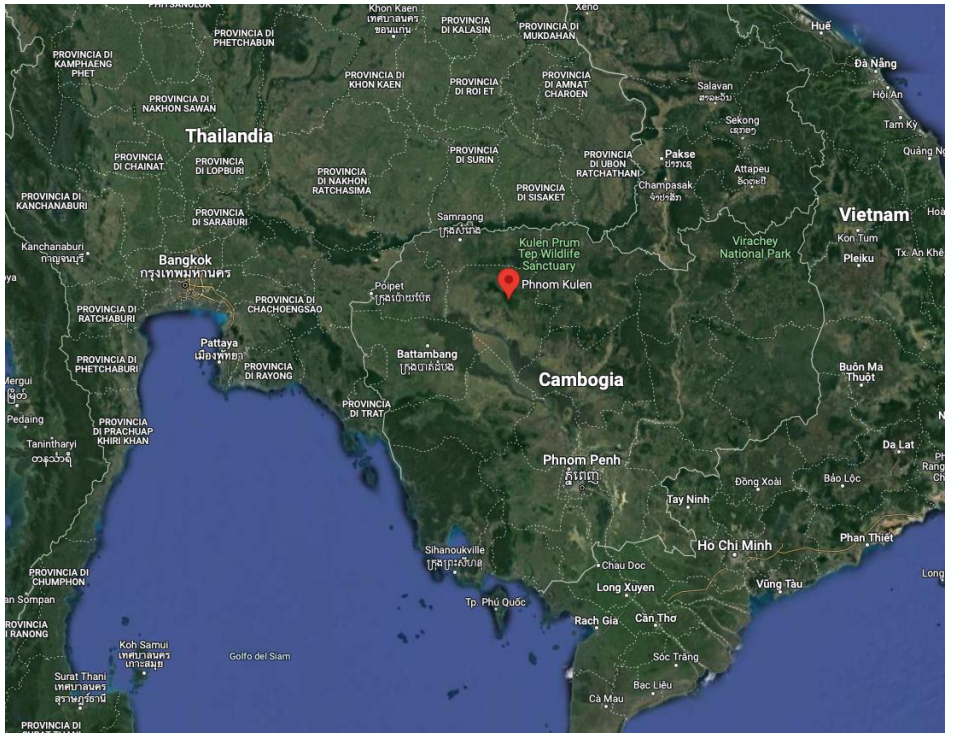


To identify looting activites on **LiDAR point clouds** we developed

Two unsupervised change detection (CD) methods based on:

i) Optimal trasport (OT)
ii) Implicit neural representation (INR)

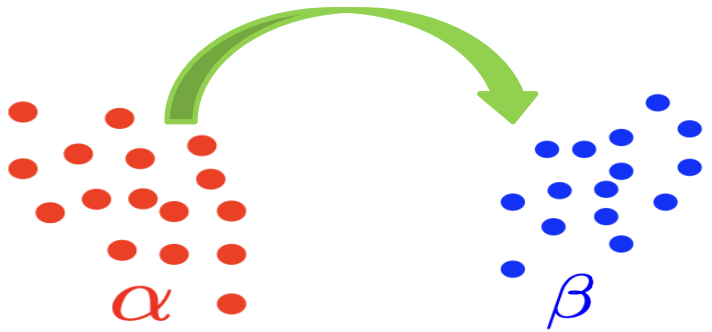
Study area



© Photo courtsey of Damian Evans (EFEO). Looting in Cambodia highlighted by Lidar

Optimal transport for change detection

Optimal Transport



Input

$$\alpha = \sum_{i}^{n} a_i \delta_{x_i} \qquad \beta = \sum_{j}^{m} b_j \delta_{y_j}$$

$$\delta x_i(x) \ = 1 \ if \ x = x_i \ else \ 0$$

Cost Function

$$C : X \times Y \rightarrow \mathbb{R}$$

Output

Finding **matches** between the supports

Kantorovitch's Formulation

$$\min_{\Pi \in U(\mu,\nu)} \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij} c(\boldsymbol{x}_i, \boldsymbol{y}_j)$$

$$U(a,b) = \{ \Pi \in \mathbb{R}_{+}^{\{n \times m\}} \; ; \; P\, 1_m = a \; ; \; P^T 1_n = b \}$$

Mass Conservation

Kantorovitch's Formulation

$$\min_{\boldsymbol{\Pi} \in \boldsymbol{U}(\mu,\nu)} \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij} c(\boldsymbol{x}_i, \boldsymbol{y}_j)$$

Amount of mass transported from x_i to y_j

Kantorovitch's Formulation

$$\min_{\boldsymbol{\Pi} \in \boldsymbol{U}(\mu,\nu)} \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij} c(\boldsymbol{x}_i, \boldsymbol{y}_j)$$

Cost of transporting a **unit of mass** from x_i to y_j arial

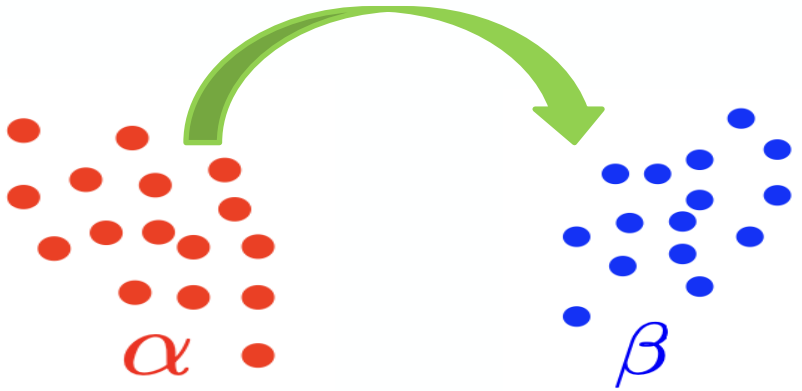
Kantorovitch's Formulation

$$\min_{\boldsymbol{\Pi} \in \boldsymbol{U}(\mu,\nu)} \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij} c(\boldsymbol{x}_i, \boldsymbol{y}_j)$$

The **cost** of transporting the whole mass from x_i to y_i arial

Optimal Transportation Plan

$$\min_{\boldsymbol{\Pi}\in\boldsymbol{U}(\mu,\nu)} \sum_{i=1}^{n}\sum_{j=1}^{m} \pi_{ij} c(\boldsymbol{x}_i, \boldsymbol{y}_j)$$



The **total cost** of transporting the total mass from the point cloud α to the point cloud β

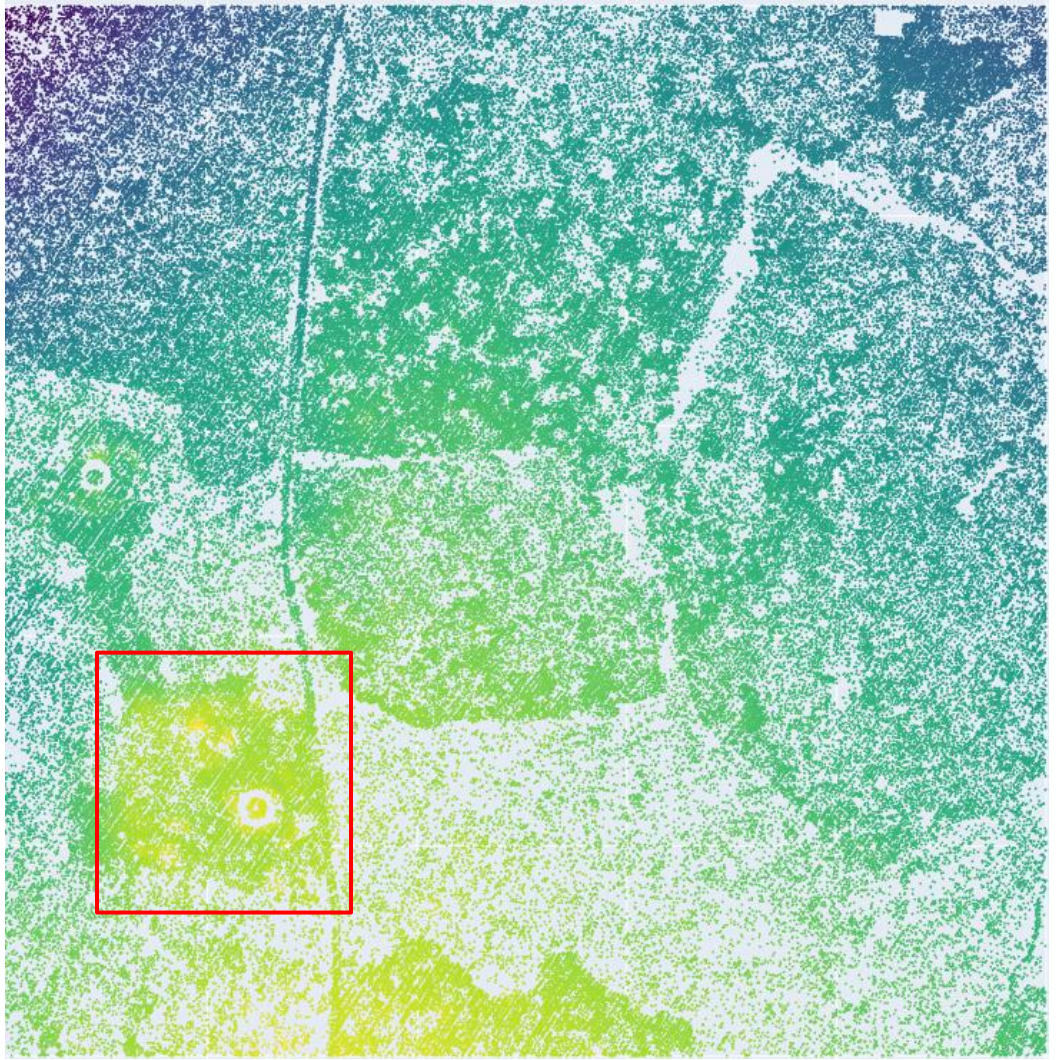
Optimal Transport for Change Detection

1. Compute the **optimal transport plan** Π^* with $c(x_i, y_j) = ||x_i - y_j||_2^2$

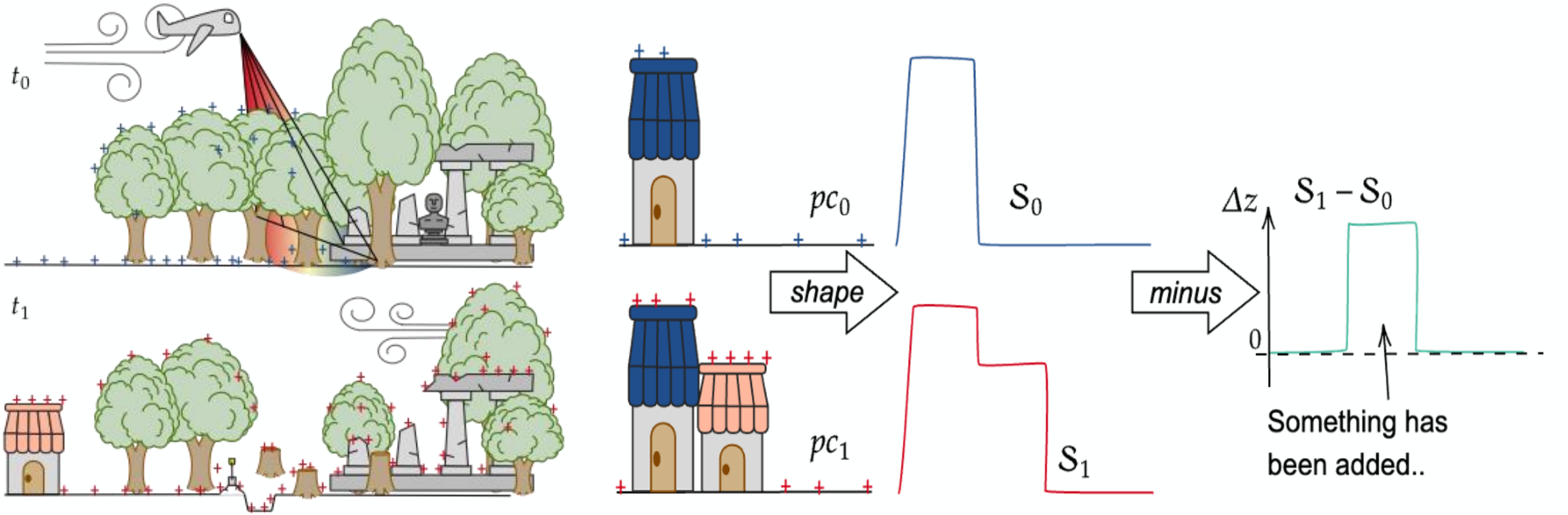
2. **Project** all the points of support X onto support Y (displacement interpolation: $\hat{Y} = m\,\Pi^{*T}X$): **co-registration** the two supports

3. Compute the **intensity of changes** for each of the original points Y w.r.t. $\hat{Y}$: $||Y - \hat{Y}||_2^2$

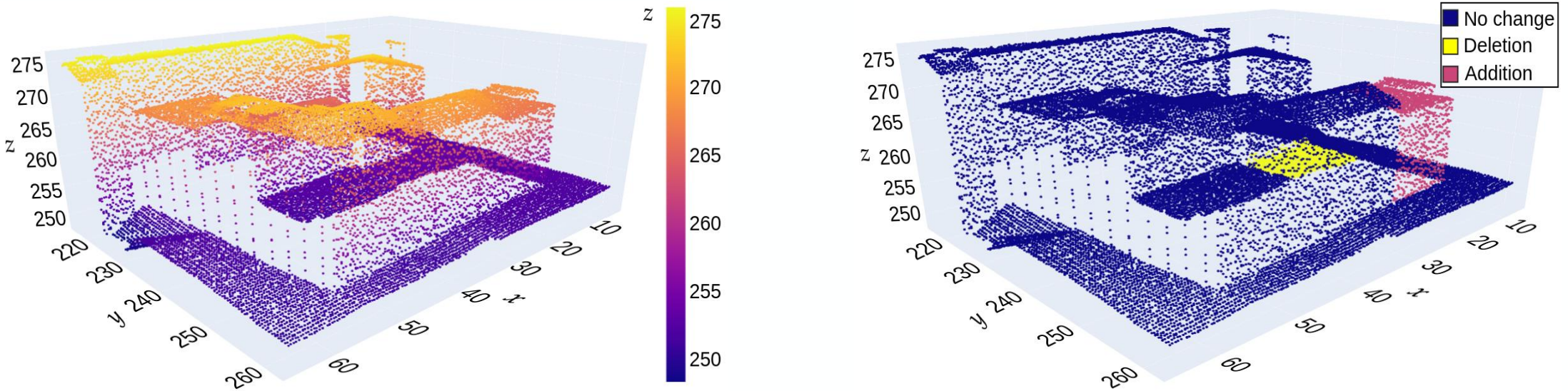
Optimal Transport for Looting Detection



Implicit Neural Representation for CD



A test bench dataset



Simulated airborne LiDAR point clouds for change detection

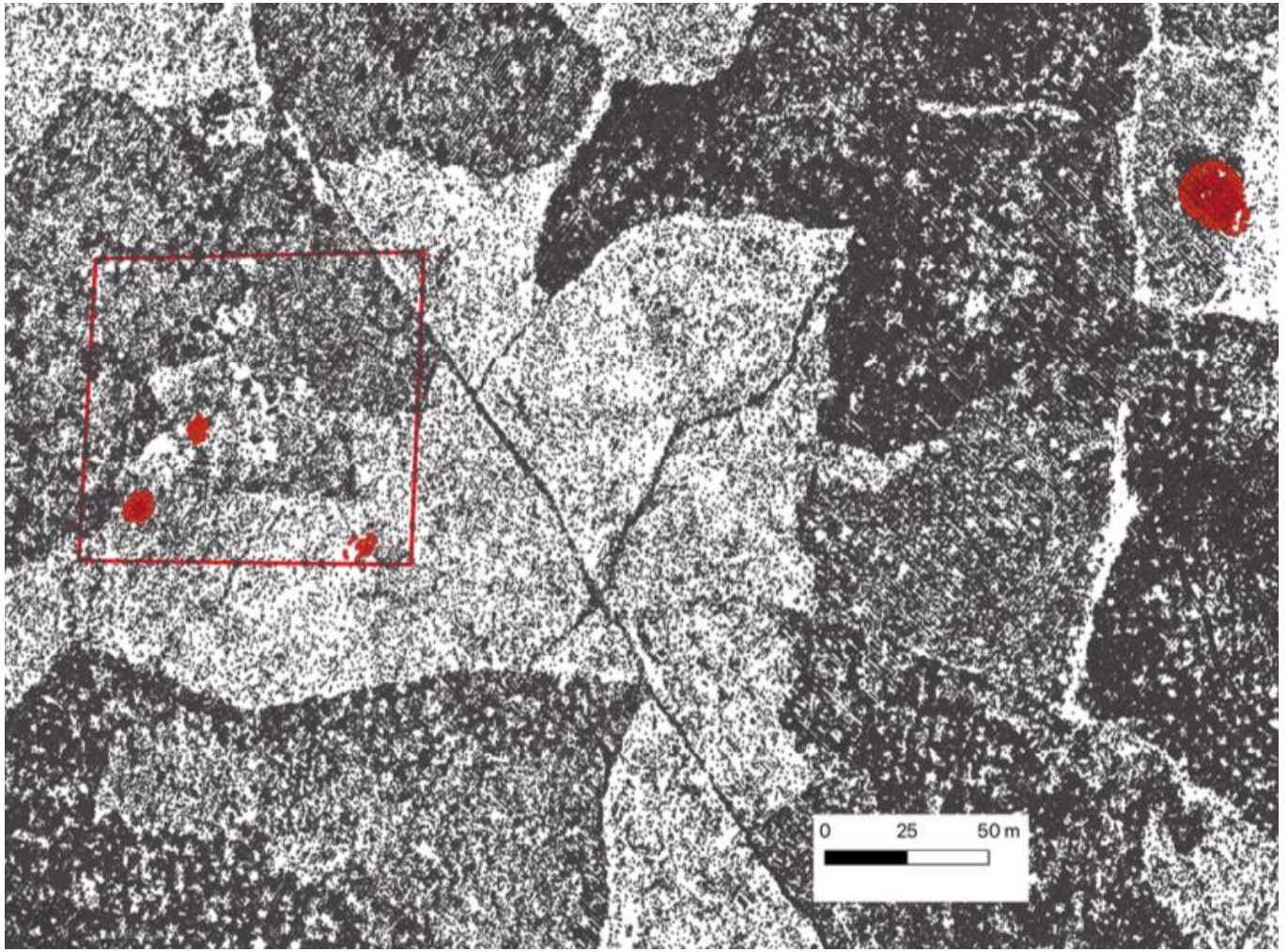
de Gélis, I.; Lefèvre, S.; Corpetti, T. Change Detection in Urban Point Clouds: An Experimental Comparison with Simulated 3D Datasets. *Remote Sens.* **2021**, *13*, 2629. https://doi.org/10.3390/rs13132629

Experimental results

Data	M3C2 [25]	OT [17]	None	SIREN	RFF (Proposed Method)					
			S+TVN	S	D	D+TVN	S	S+TVN	S+TD	S+TVN+TD
(1)	29.87	40.65	37.22	40.14	50.13	44.68	52.49	**55.87**	54.73	49.68
(2)	53.73	55.20	45.22	53.98	57.39	59.33	56.45	**61.17**	60.34	59.52
(3)	38.72	39.26	33.11	38.57	46.54	43.17	51.87	46.94	**54.00**	53.33
(4)	35.01	39.89	33.54	39.01	48.62	49.70	51.38	51.10	53.40	**53.99**
(5)	37.78	**48.17**	37.97	40.48	42.55	43.16	42.95	43.26	40.55	47.17
Avg	39.02	44.63	37.41	42.43	49.04	48.00	51.02	51.67	52.60	**52.74**

Comparaison to state-of-the-art on the IoU metric (in %), we only report the best configuration

Looting detection



Conclusions

Two unsupervised change detection methods on point clouds:
- optimal transport
- implicit neural representation.

Our methods can automatically detect looting in an unsupervised manner.

We plan to combine optimal transport and implicit neural representation to improve the looting detection accuracy.

Thank you

Contacts:
Marco Fiorucci
marco.fiorucci@iit.it

References

M. Fiorucci, P. Naylor and M. Yamada, "Optimal Transport for Change Detection on Lidar Point Clouds," *IGARSS 2023.*

P. Naylor, D. Di Carlo, A. Traviglia, M. Yamada and M. Fiorucci, "Implicit neural representation for change detection," *WACV*, 2024.