EARSeL | EUROPEAN ASSOCIATION OF REMOTE SENSING LABORATORIES

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The ALCEO Project: Machine Learning and Remote Sensing for Looting Detection

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The ALCEO Project

Alceo

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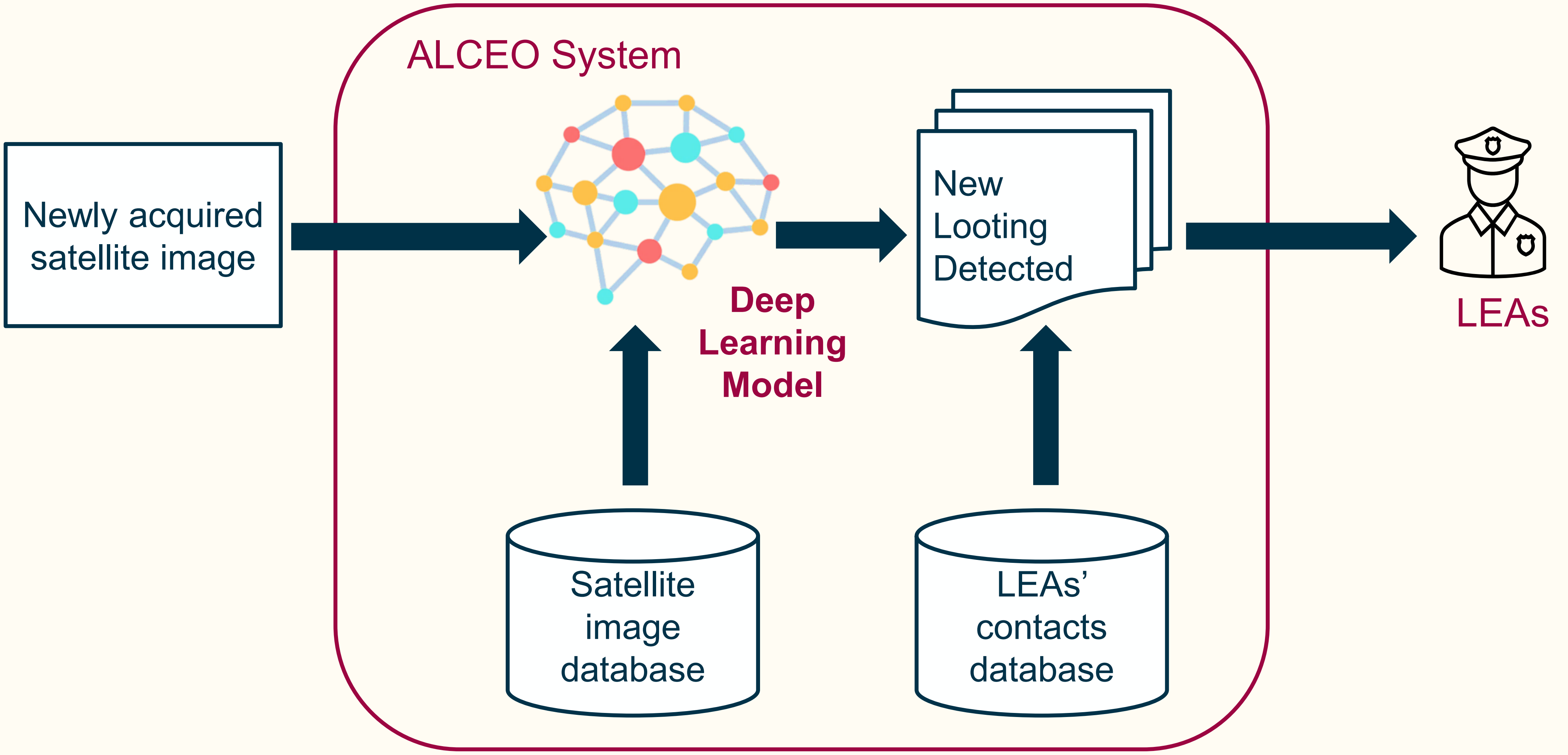
Automatic Looting Classification from Earth Observation

Objectives:

- Analysing the looting phenomenon through Earth Observation
- Automate the analysis of looting on endangered archaeological sites
- Design a proof of concept for an AI-based platform to counter looting

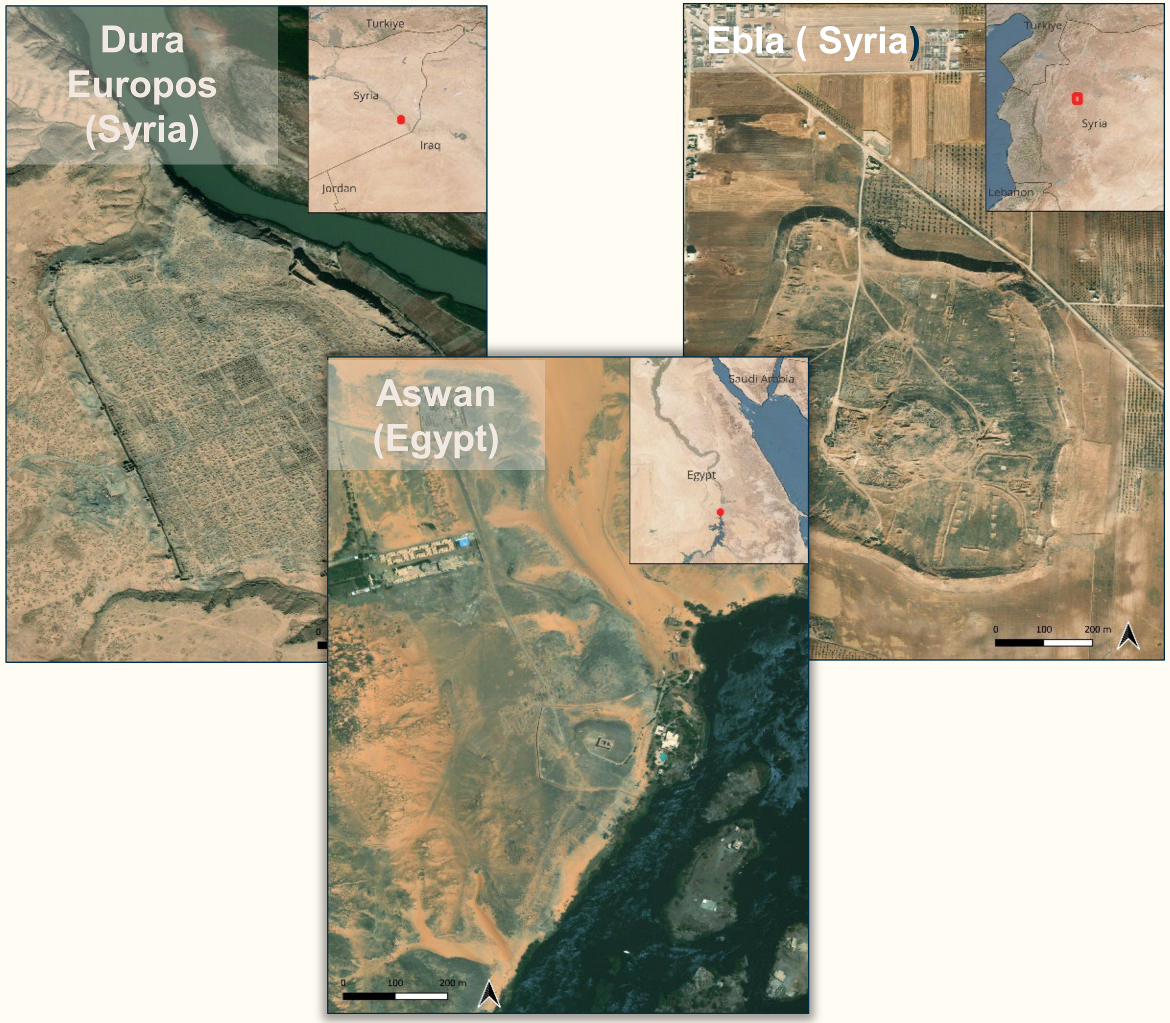
Funded by European Space Agency

An AI-based system to counter looting



Case studies

MENA region



Italy

Case studies

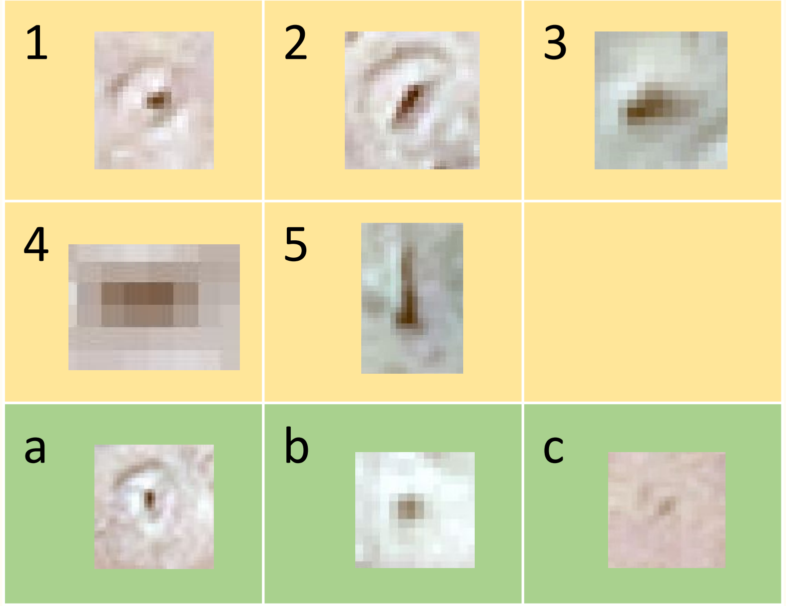
Very high-resolution (30-50 cm GSD) multispectral images from **ESA Contributing Missions**:

Dura Europos		
26/04/2013	Pléiades	1019 features
19/09/2014	Pléiades	3843 features
Aswan		
04/08/2005	Quickbird	187 features
05/10/2015	Pléiades	332 features
20/03/2018	Pléiades	517 features
Ebla		
01/09/2004	Quickbird	30 features
03/04/2014	Pléiades	172 features
13/04/2018	WorldView-2	250 features
07/07/2022	WorldView-2	154 features
Total		6054 looting traces

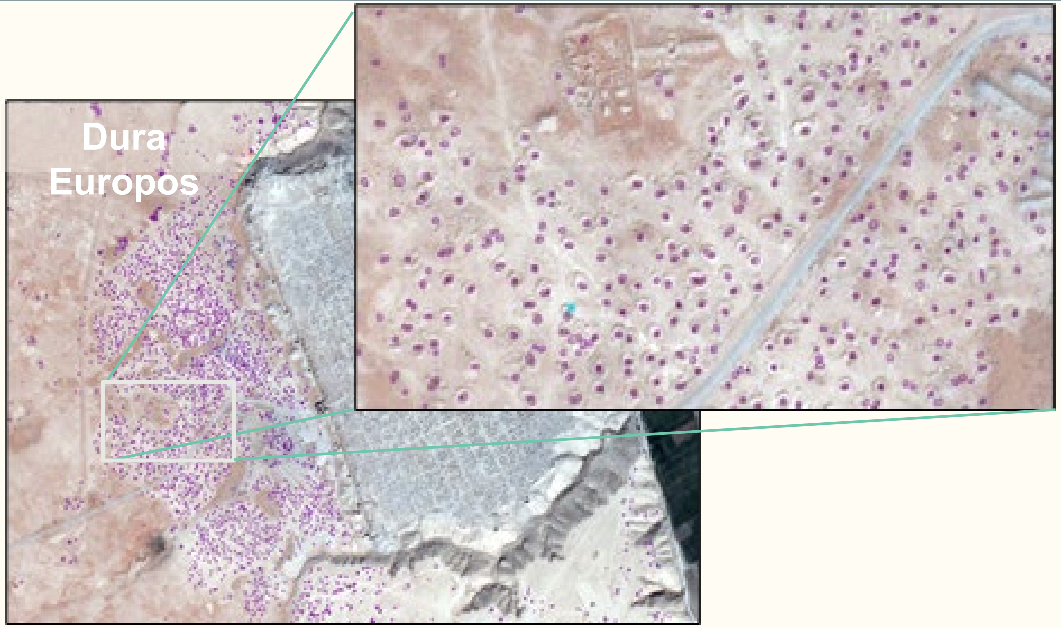
Arpinova		
15 July 2009	Quickbird	55 features
30 April 2010	WorldView-2	65 features
15 February 2011	WorldView-2	11 features
15 June 2016	Pléiades	3 features
Cerveteri		
9 July 2008	Quickbird	15 features
31 May 2015	Geoeye-1	42 features
24 August 2018	WorldView-2	46 features
15 August 2021	WorldView-2	49 features
Total		**328 looting traces**

Building a training dataset for looting

- Date of acquisition
- Site name
- Pit appearance
  - 1)Pit
  - 2)Elongated Pit
  - 3)Extended Pit
  - 4)Trench
  - 5)Excavation
- Confidence Level
  - a)Highly likely
  - b)Likely
  - c)Uncertain
- Date of detection
- Operator



1-5: Pit appearance
a-c: Confidence level



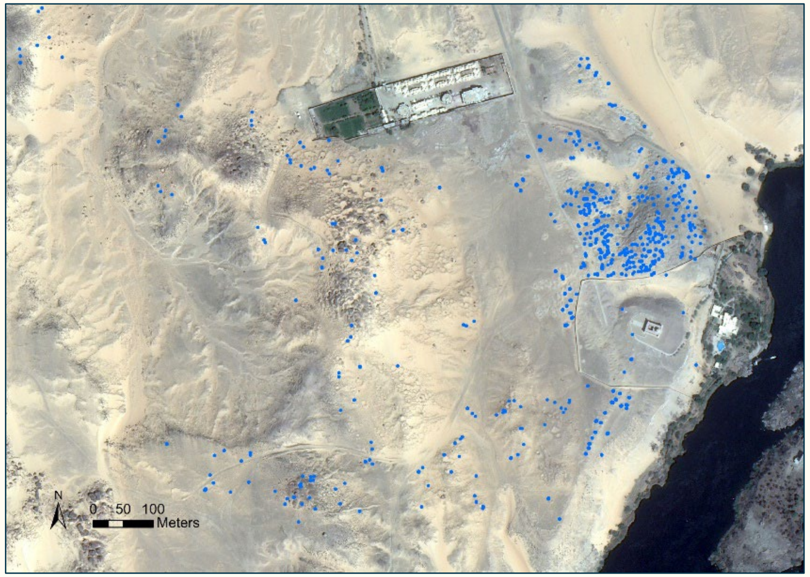
	OBJECTID *	SHAPE *	Day_Month_Year	Archaeological_name	Pit_appearance	Looting_activity	Date_of_detection	Shape_Length
1	1	Polygon Z	26/05/2013	Dura Europos	Extended Pit	Uncertain	18/01/2023	0.00011
2	2	Polygon Z	26/05/2013	Dura Europos	Extended Pit	Likely	18/01/2023	0.000113
3	3	Polygon Z	26/05/2013	Dura Europos	Extended Pit	Likely	18/01/2023	0.000123
4	4	Polygon Z	26/05/2013	Dura Europos	Extended Pit	Likely	18/01/2023	0.000115
5	5	Polygon Z	26/05/2013	Dura Europos	Pit	Uncertain	18/01/2023	0.000082
6	8	Polygon Z	26/05/2013	Dura Europos	Pit	Likely	18/01/2023	0.000074
7	9	Polygon Z	26/05/2013	Dura Europos	Pit	Uncertain	18/01/2023	0.000122
8	13	Polygon Z	26/05/2013	Dura Europos	Pit	Uncertain	18/01/2023	0.000068
9	16	Polygon Z	26/05/2013	Dura Europos	Pit	Uncertain	18/01/2023	0.000067
10	17	Polygon Z	26/05/2013	Dura Europos	Elongated Pit	Uncertain	18/01/2023	0.000092
11	18	Polygon Z	26/05/2013	Dura Europos	Pit	Uncertain	18/01/2023	0.000087
12	19	Polygon Z	26/05/2013	Dura Europos	Pit	Uncertain	18/01/2023	0.000105

The looting phenomenon

Looting intensity varies among case studies.

Dimension of the pits may indicate different excavation techniques.

Sparse looting in Cerveteri (Italy)
49 pits
15/08/2021 (Worldview-2)



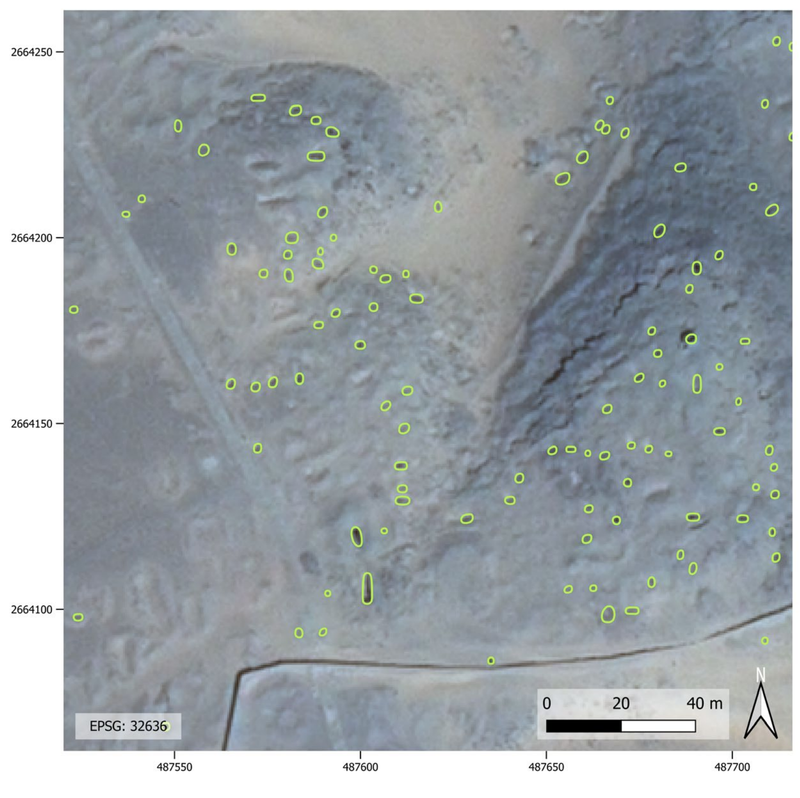
Clustered looting in Aswan (Egypt)
517 pits
20/04/2018 (Quick Bird)

Dense looting in Dura Europos (Syria)
3843 pits
19/09/2014 (Pléiades)

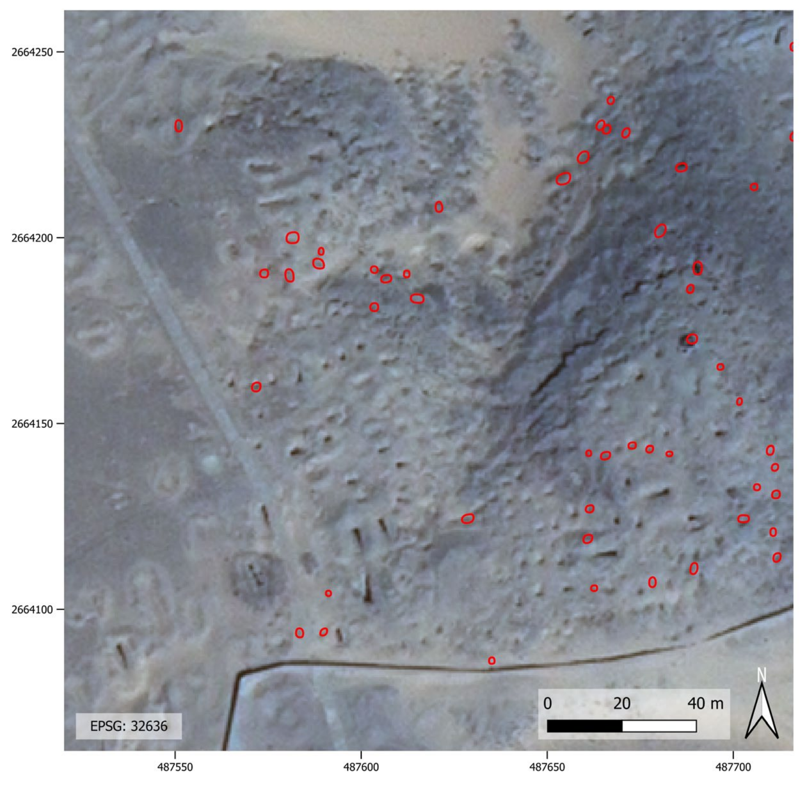
The looting phenomenon

Pits get filled in time, especially in desert areas

Pits can get re-digged



Pits in Aswan (Egypt)
05/10/2015 (Quick Bird)



Disappeared pits
20/03/2018 (Pléiades)

Looting detection as a change detection problem

- Dis/Appearance of a looting pit as a change between two dates.
- Change Detection is the task of comparing two or a sequence of co-registered images to detect specific types of changes between the acquisitions (vegetation changes, urban expansion, polar ice melting, etc.)
- Change Detection was selected to better account for variations on existing pits over time

Model Architecture

FULLY CONVOLUTIONAL SIAMESE NETWORKS FOR CHANGE DETECTION

Rodrigo Caye Daudt[1,2], Bertrand Le Saux[1], Alexandre Boulch[1]

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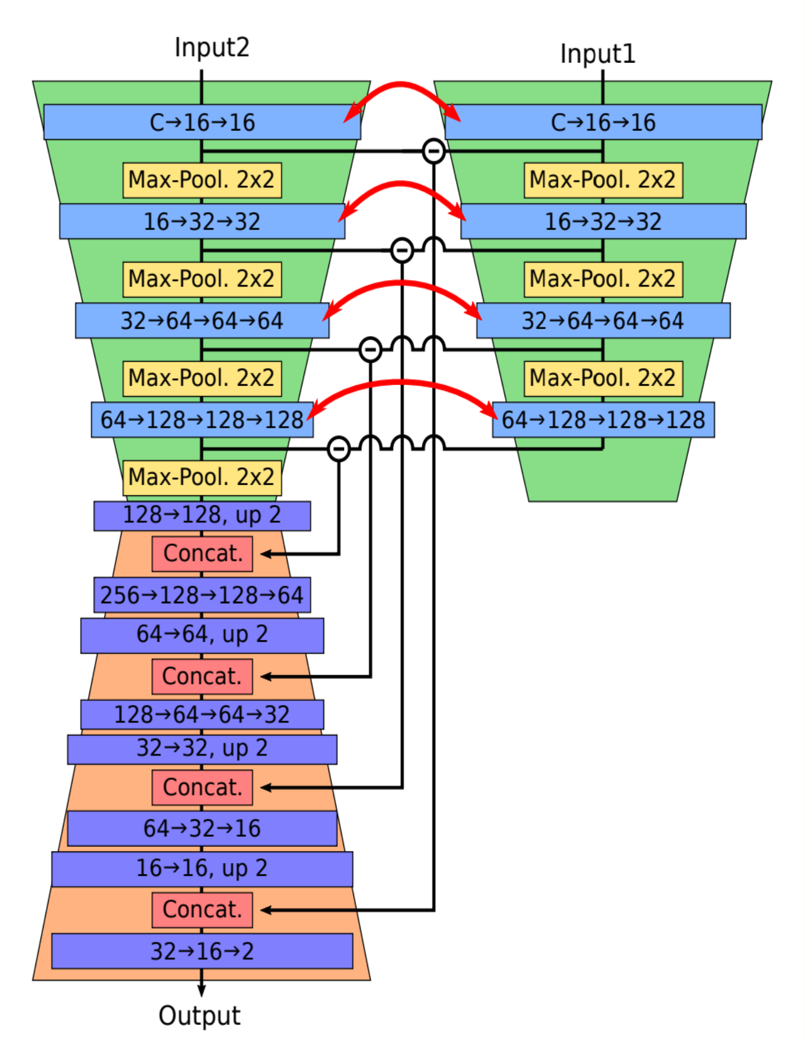
[2]LTCI, Télécom ParisTech, FR-75013 Paris, France

ABSTRACT

This paper presents three fully convolutional neural network architectures which perform change detection using a pair of coregistered images. Most notably, we propose two Siamese extensions of fully convolutional networks which use heuristics about the current problem to achieve the best results in our tests on two open change detection datasets, using both RGB and multispectral images. We show that our system is able to learn from scratch using annotated change detection images. Our architectures achieve better performance than previously proposed methods, while being at least 500 times faster than related systems. This work is a step towards efficient processing of data from large scale Earth observation systems such as Copernicus or Landsat.

can be used. Nevertheless, there are available pixelwise annotated change detection datasets available that can be used to train supervised machine learning systems that detect changes in image pairs, such as the Onera Satellite Change Detection dataset[1] presented in [3] and the Air Change dataset [4].

In this paper we present three Fully Convolutional Neural Network (FCNN) architectures that perform change detection on multi-temporal pairs of images Earth observation images. These architectures are trained end-to-end from scratch using only the available change detection datasets. The networks are tested in both the RGB and multispectral cases when possible. They are extensions of the ones presented in [3], which was the first CD method to be trained end-to-end, to a fully convolutional paradigm. This improves both the accuracy and the inference speed of the networks without increasing



Trained end-to-end from scratch

Fast training (5h on our dataset) and inference

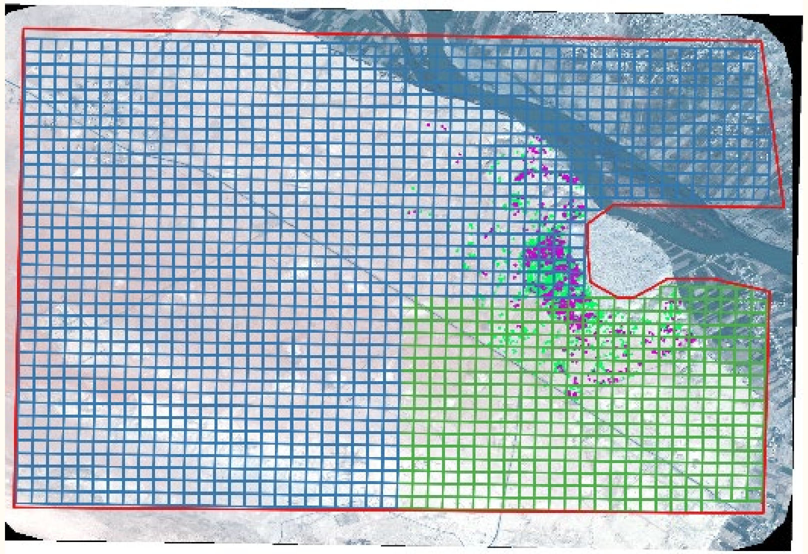
Daudt, Rodrigo Caye, Bertr Le Saux, and Alexandre Boulch. "**Fully convolutional siamese networks for change detection.**" *2018 25th IEEE international conference on image processing (ICIP)*. IEEE, 2018.

Imagery and dataset pre-processing

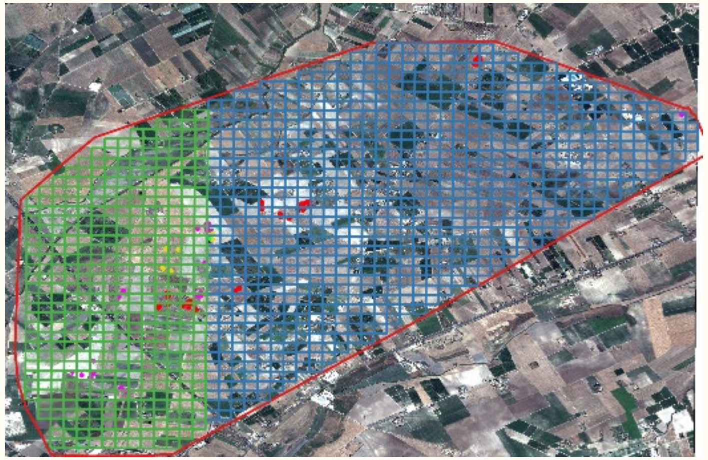
- Geospatial split in training and validation areas for each site
- Tiles of 256x256 pixels

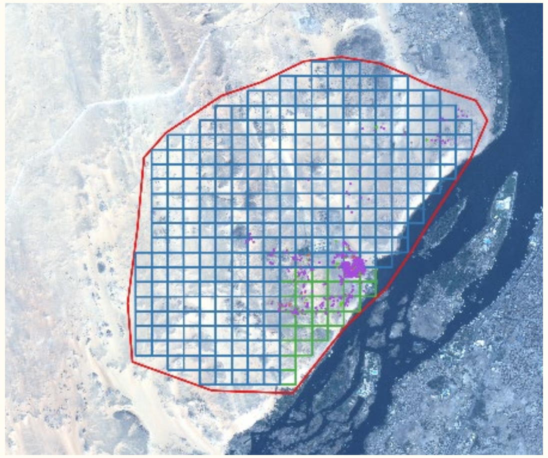
EBLA

DURA EUROPOS



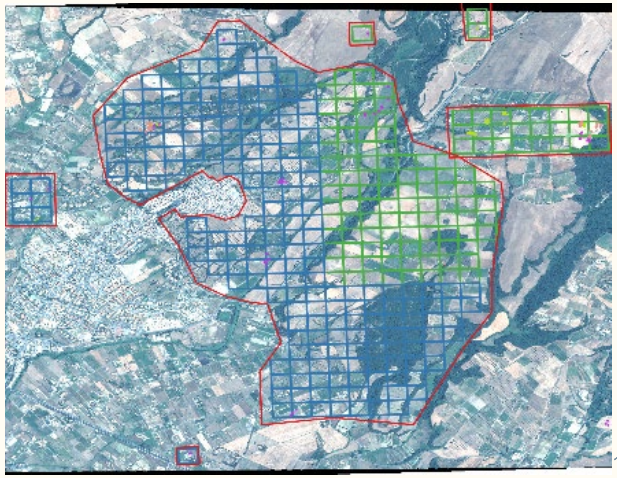
ARPINOVA





ASWAN

CERVETERI



Balancing data for ML

Sampling:

- Approx. 93% of the tiles were with no looting features
- Sampling technique with weights in training to achieve 50% probability of events

Site	% tiles with events	Weight for positive tile
ARPINOVA	0.8%	125
ASWAN	15.2%	6.6
CERVETERI	3.6%	27.8
DURA EUROPOS	9.8%	10.2
EBLA	7.9%	12.6

Loss-function:

- ***Focal Loss*** to learn more from tiles with few positive pixels

Data augmentation to improve generalisation:

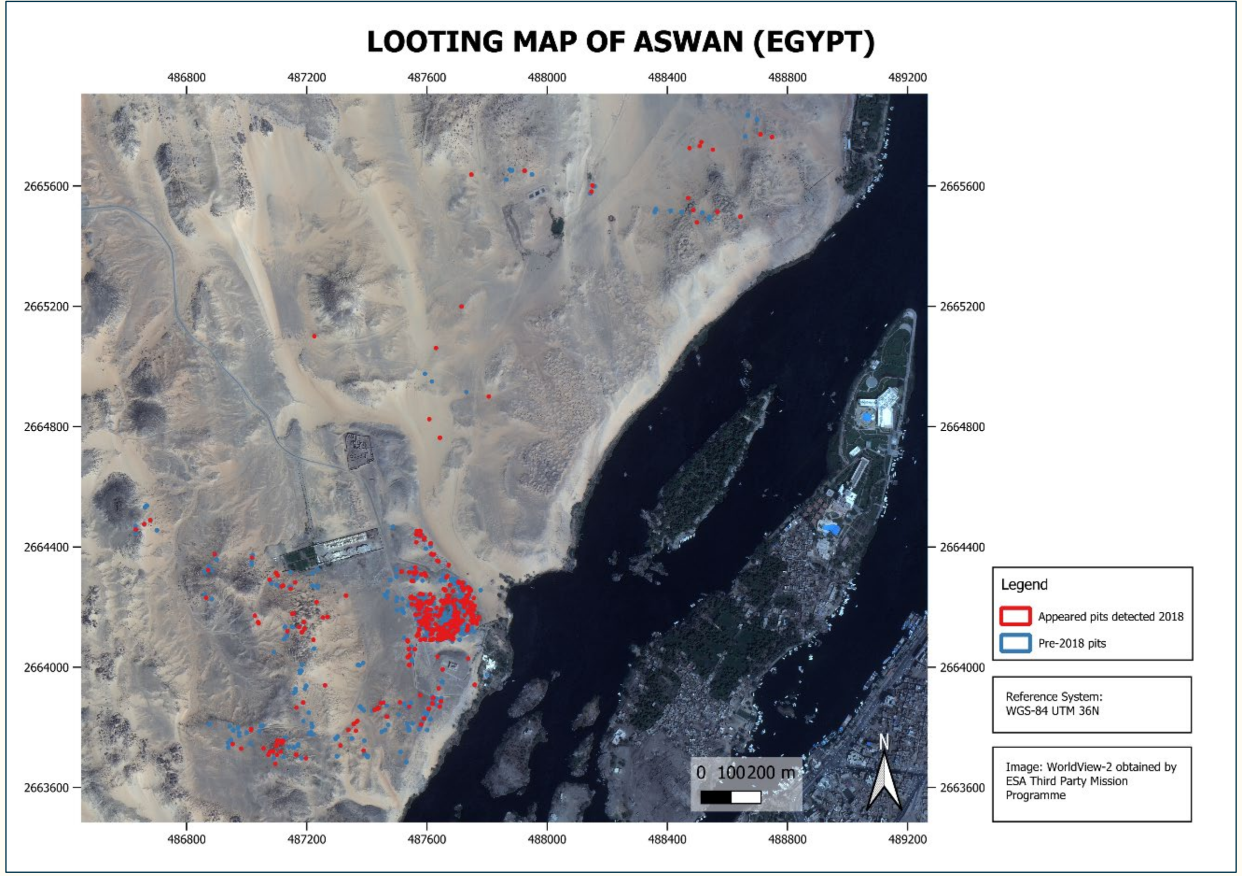
- Rotation
- Horizontal flip
- Vertical flip

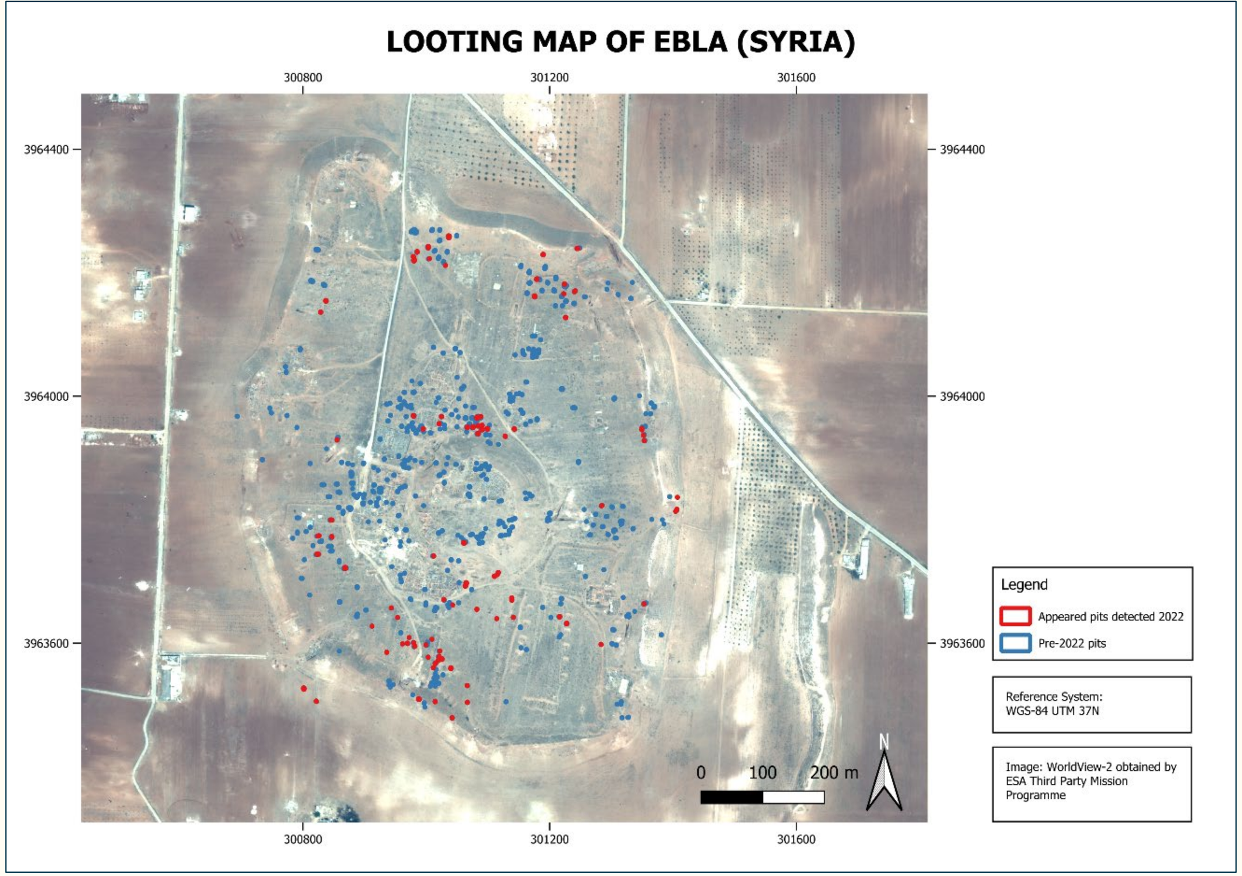
Results

Metric/Site	ARPINOVA	ASWAN	CERVETERI	DURA EUROPOS	EBLA	Overall
IoU	0.5317	0.8346	0.5951	0.6910	0.8631	**0.7145**
F1	0.4910	0.6423	0.4049	0.5492	0.7022	**0.6580**
Precision	0.5155	0.5951	0.5897	0.4906	0.8411	**0.5271**
Recall	0.6913	0.9348	0.6144	0.8439	0.9205	**0.8782**

Inference on new images

Inference on unseen images from dates not used in training

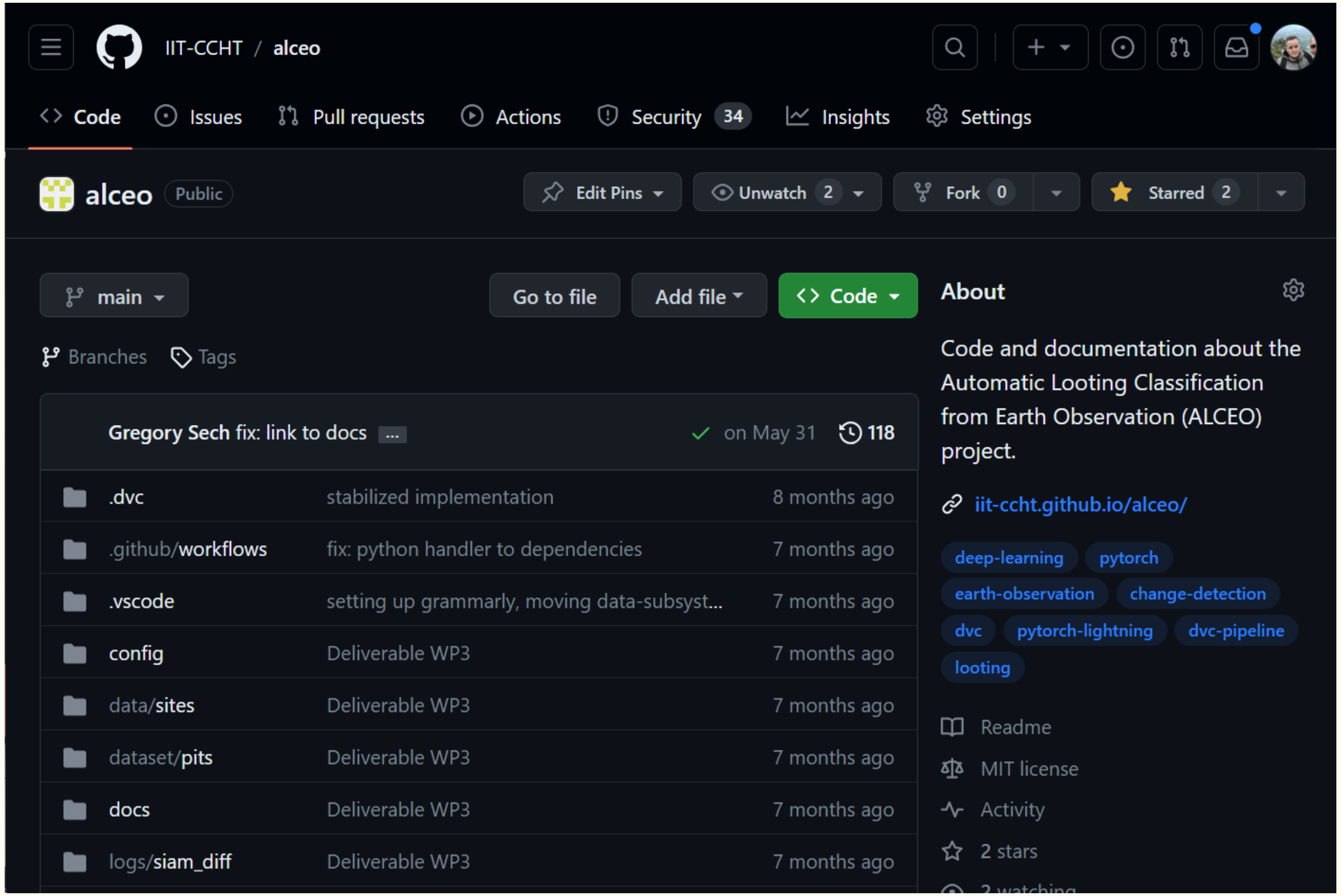




Ground- truth campaign

- Ground truth campaign in 2023 in Aswan
- **129 features** were verified (24 false positives) from the training dataset and a new inference
- Qfield app to collect ground truthing information
- This step is important to re-train the model adding or removing misidentified looting pits to improve performance

GitHub for code and documentation



https://github.com/IIT-CCHT/alceo

Future perspective

- Improve the data management system
- Provide smoother integration of labelling data into the modelling system
- Reducing the number of labelled images using more efficient detection methods
- Developing QGIS plugin to facilitate the usability of the model

Credits

Thank you for your attention!

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