UPDATE OF THE LAUSANNE CITY CADASTRE USING DL AND UAV OBLIQUE IMAGES

ANTOINE CARREAUD

ADRIEN GRESSIN

GA - SGPF, JUNE 2023

INTRODUCTION

Goals : Updating automatically the land cover of the official cadastre

Area : 210 ha in the dense urban zone of Lausanne

Project financed by the Direction du cadastre et de la géomatique du canton de Vaud, in association with the City of Lausanne

WHY OBLIQUE IMAGES ?

Ortho image are great !

And allow to extract lot's of information ...

Our result from the Flair #1 challenge, publication to come.

.. but vegetation and building hide many part of the ground !

WHY OBLIQUE IMAGES ?

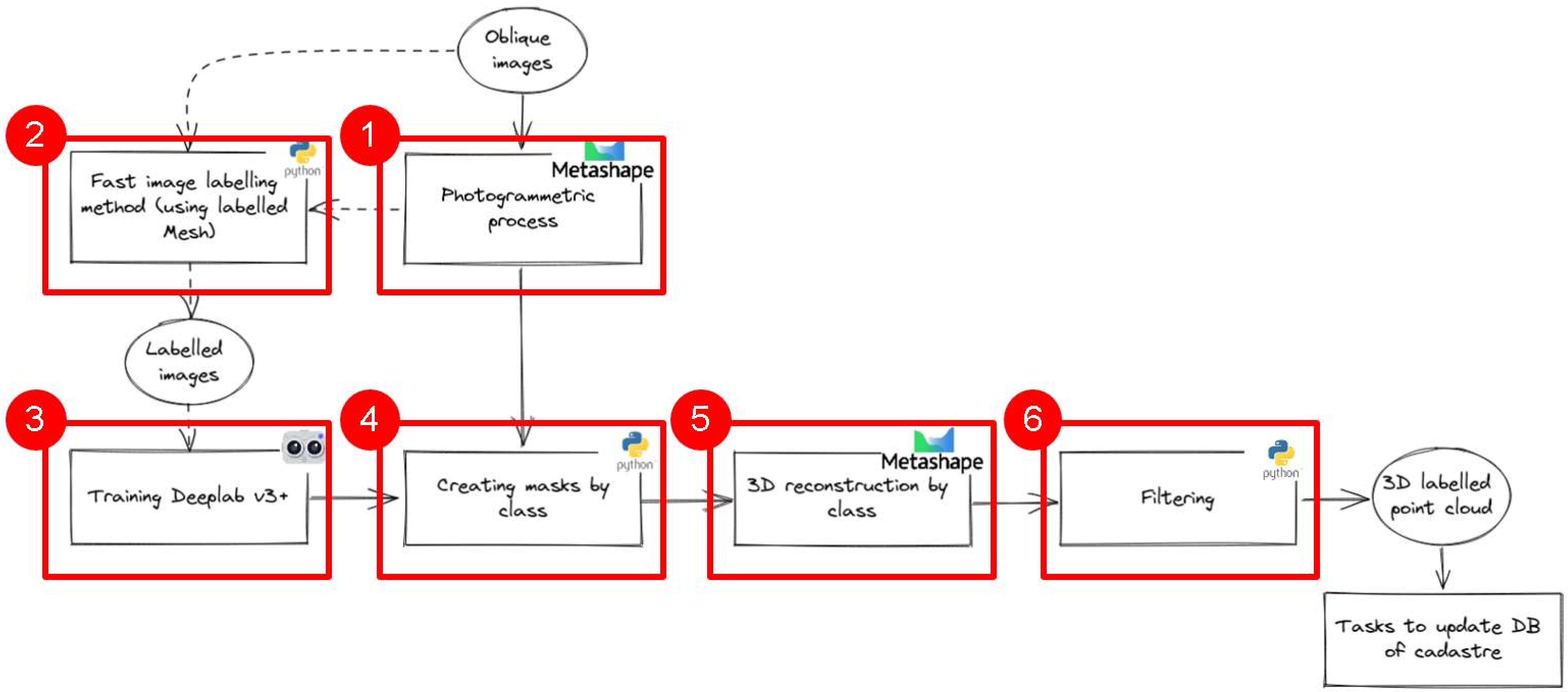
Today, uav allow to acquired easily oblique images

Allowing multiple points of view and reducing hidden areas !

Ortho-image VS oblique images

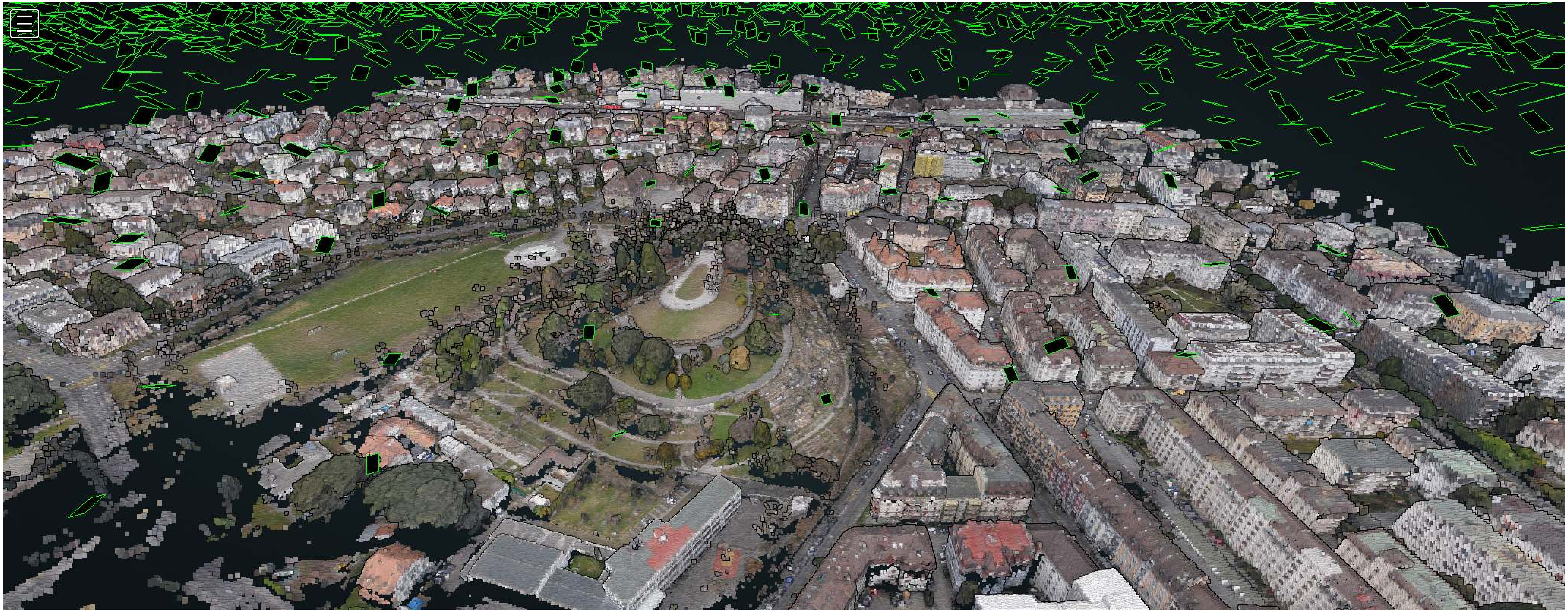
HOW TO DEAL WITH OBLIQUE IMAGES ?

Automated processing chain from training step to 3D classified points cloud.



PHOTOGRAMMETRIC STEP

1700 oriented oblique images and 3D reconstruction

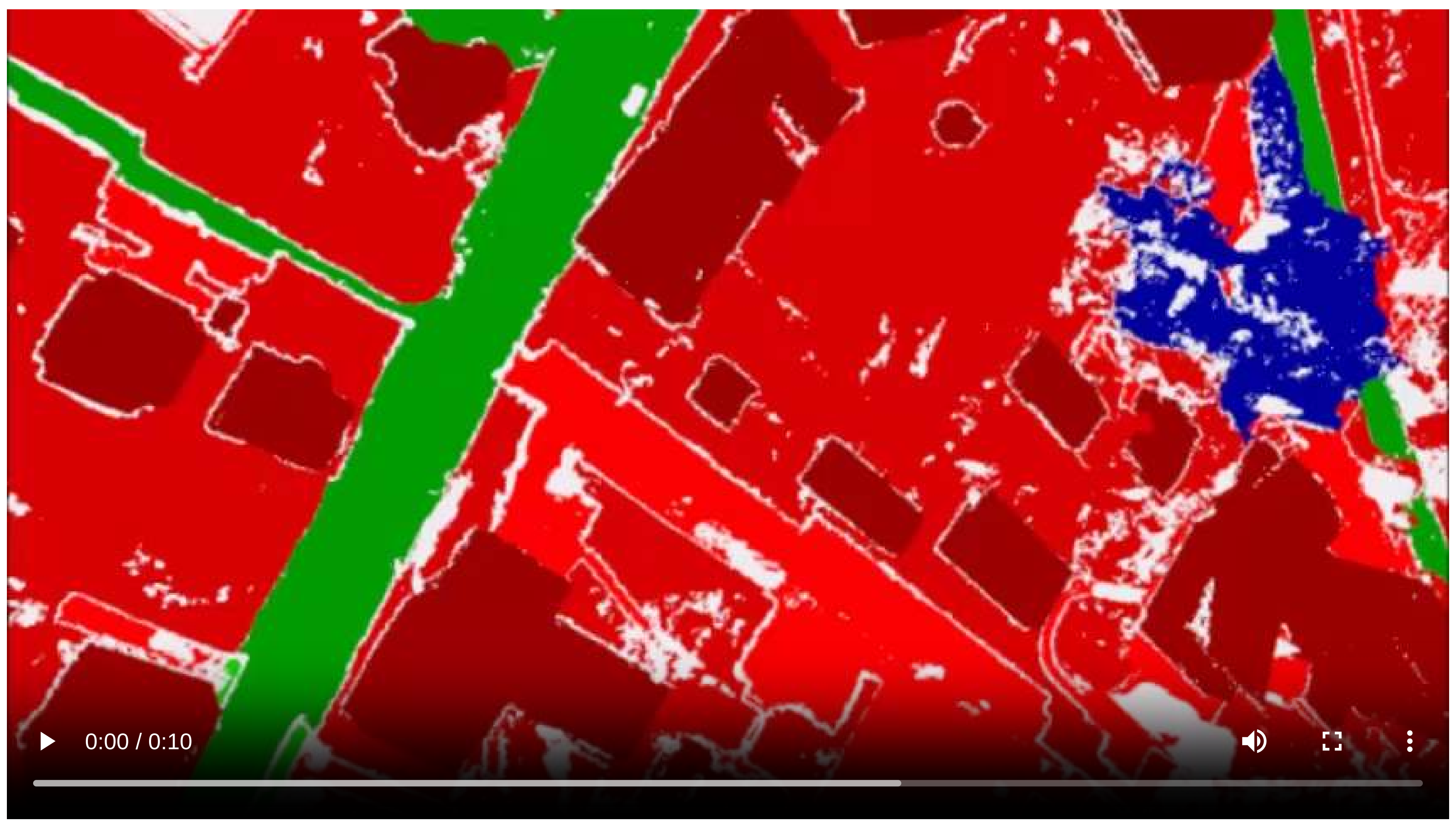


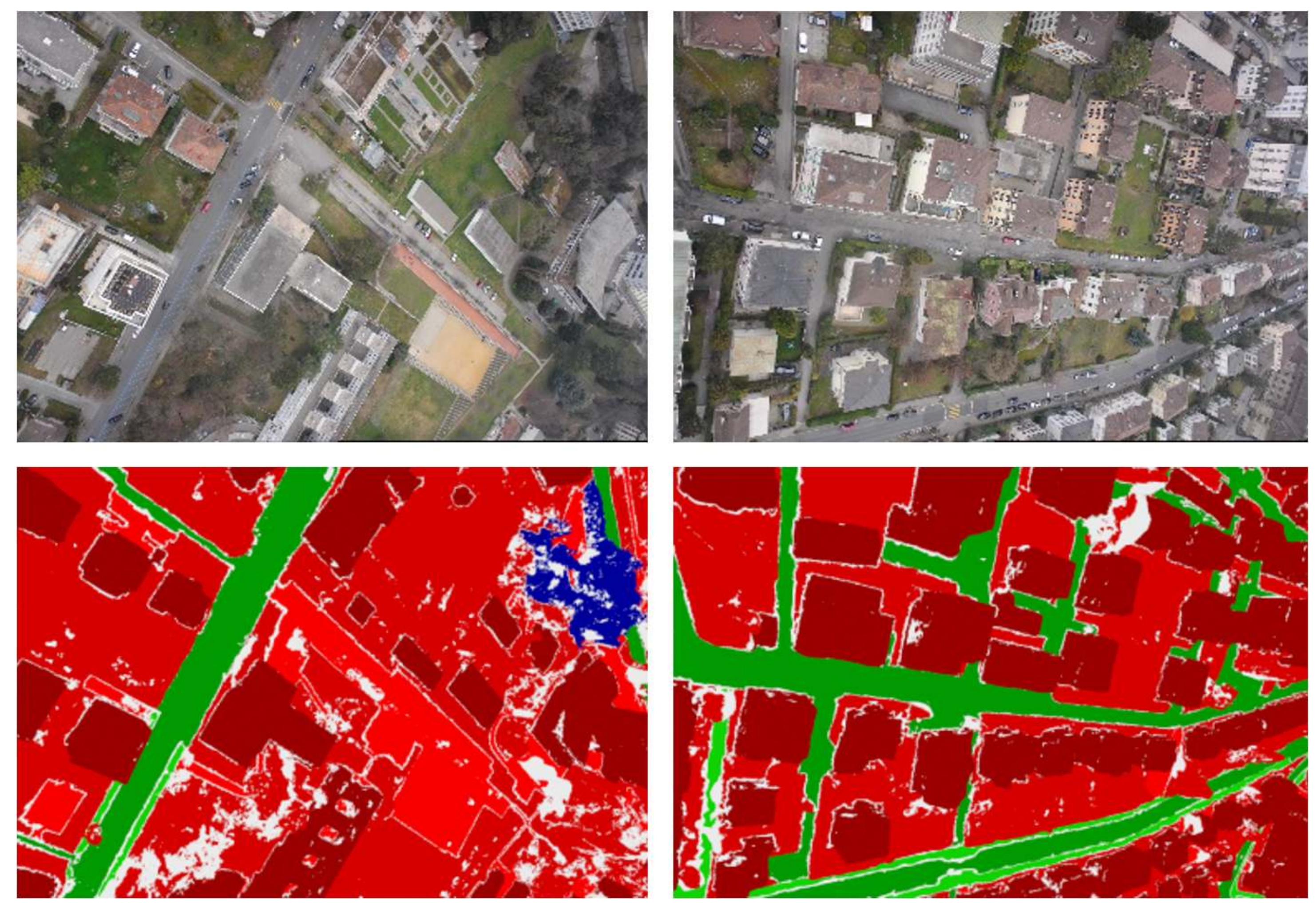
FAST LABELLING STEP

Good label: a key phase for any AI project !

1700 oblique images to label → **35 days of manual work!**

Fully automated for this short project with virtual cameras and labelled mesh





FAST LABELLING STEP

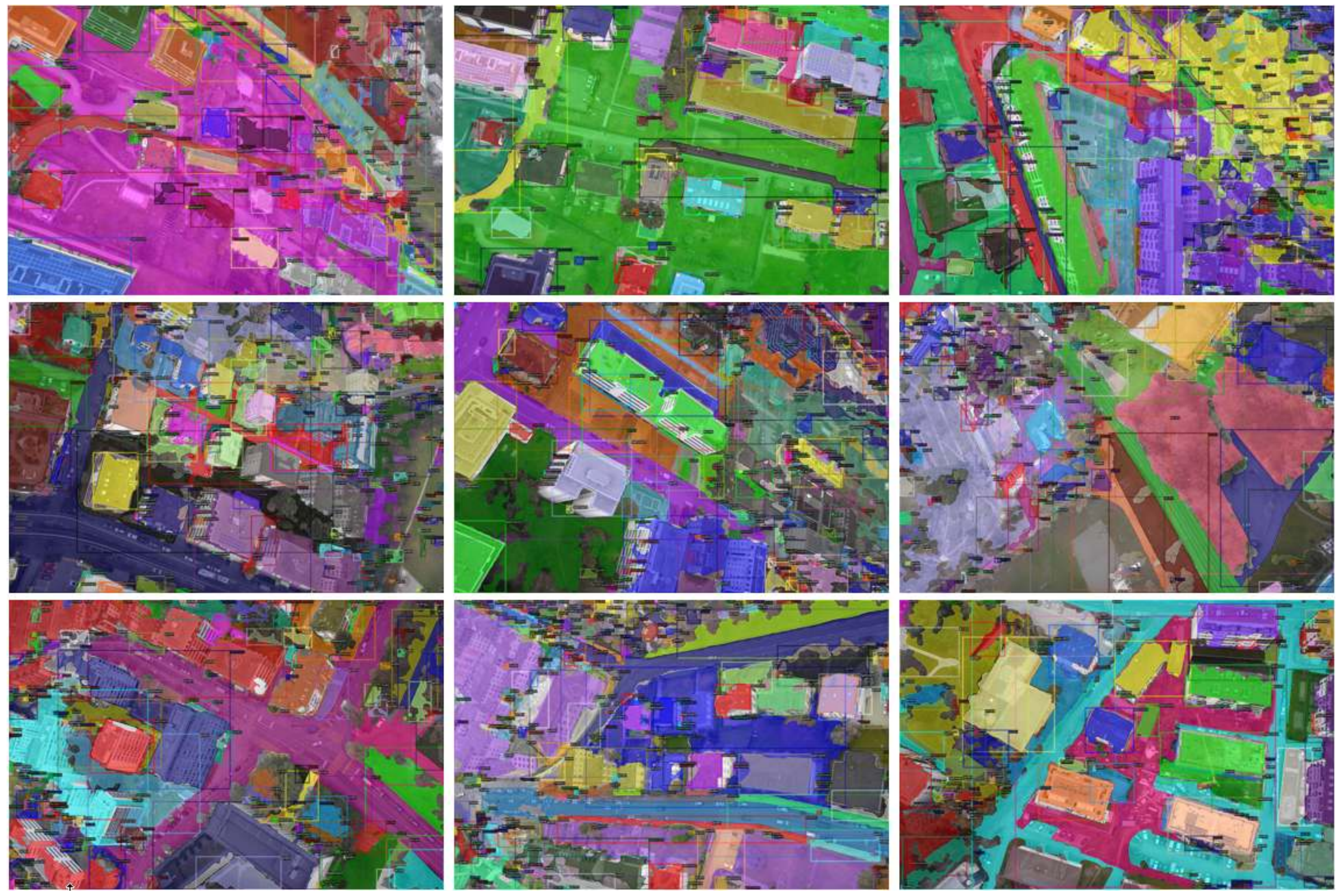
Labelled mesh and point cloud

- Automated projection of 2D polygon to the 3D model
- 1 day of manual corrections

Dataset of 1700 labelled images with 9 specific classes of cadastre (available on demand)

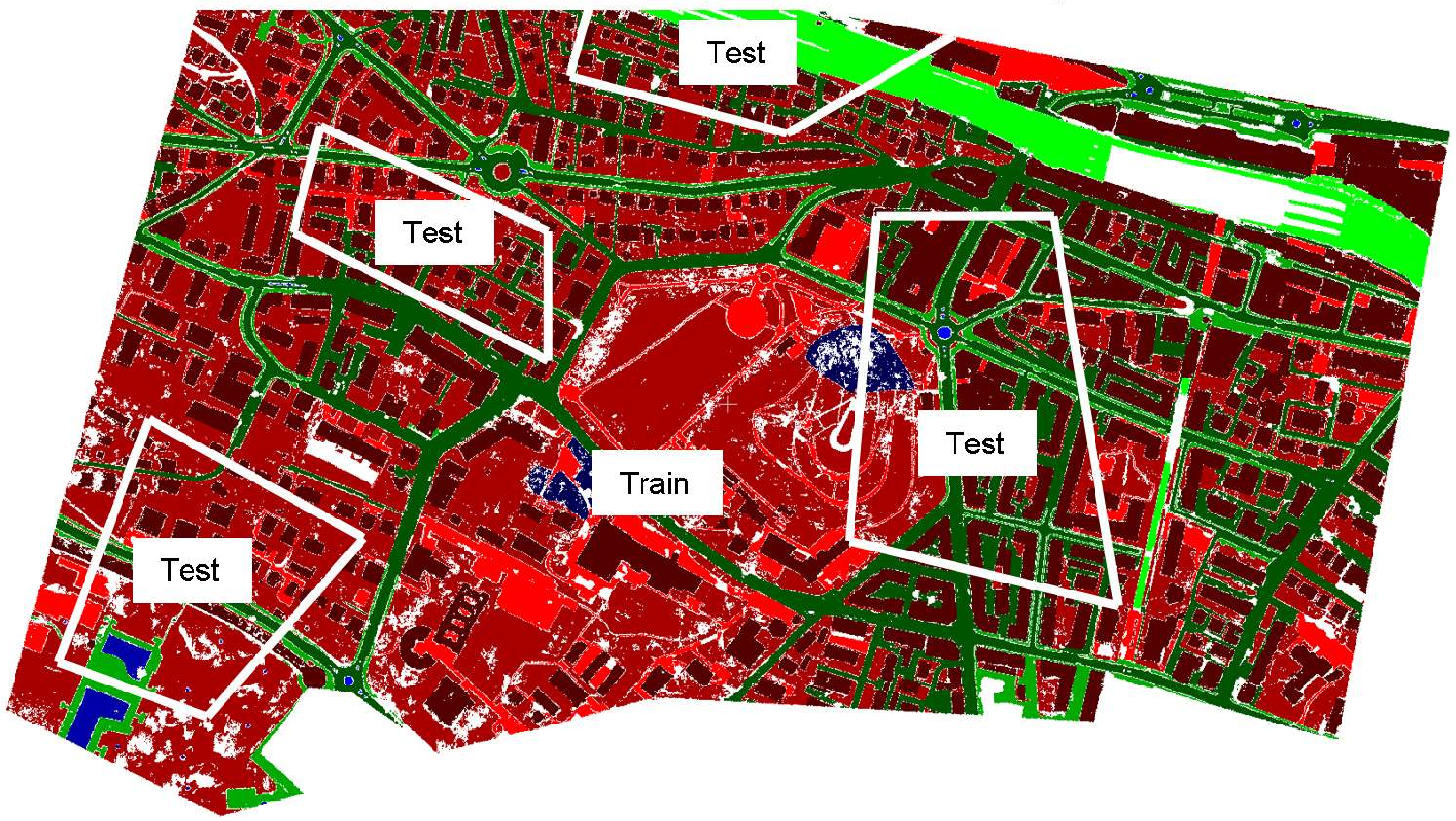
- Obtained automatically

Class	Number of pixels	% of total
Building	11.1 B	36.88
Garden	10.0 B	33.22
Access	1.8 B	5.98
Road	4.9 B	16.28
Pavement	0.95 B	3.16
Railway	0.85 B	2.82
Forest	0.48 B	1.59
Basin	0.008 B	0.03
Road island	0.016 B	0.05



TRAINING STEP

- Split data into 2/3 train and 1/3 test
- Use semantic detection with Deeplab v3+



2D IMAGE LABELLING RESULTS

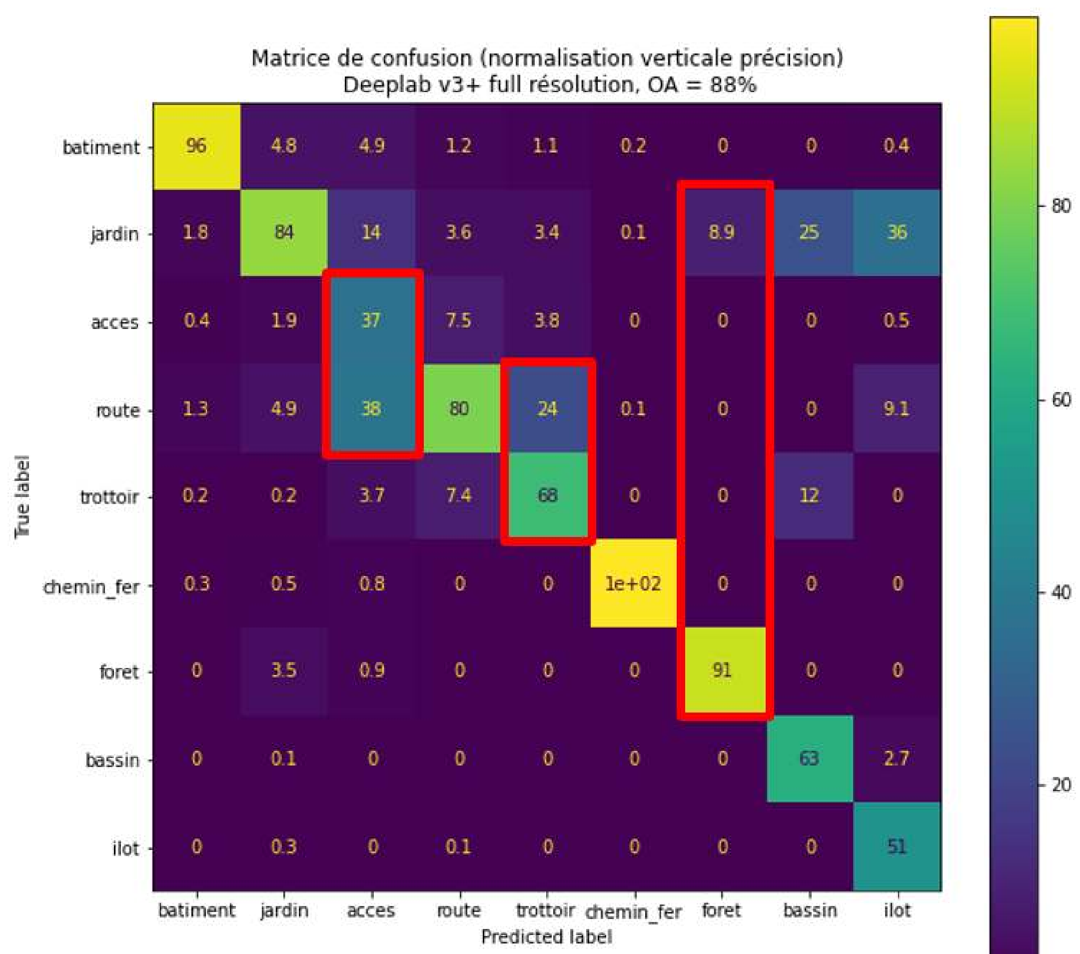
Merging classes to avoid problems with data distribution

and ambiguity between land use and land cover

Class	Number of pixels	% of total
Building	11.1 B	36.88
Garden	10.0 B	33.22
Access	1.8 B	5.98
Road	4.9 B	16.28
Pavement	0.95 B	3.16
Railway	0.85 B	2.82
Forest	0.48 B	1.59
Basin	0.008 B	0.03
Road island	0.016 B	0.05

→

Class	Number of pixels	% of total
Building	11.1 B	36.88
Vegetation	10.5 B	34.81
Hard surface	7.6 B	25.47
Railway	0.85 B	2.82
Basin	0.008 B	0.03



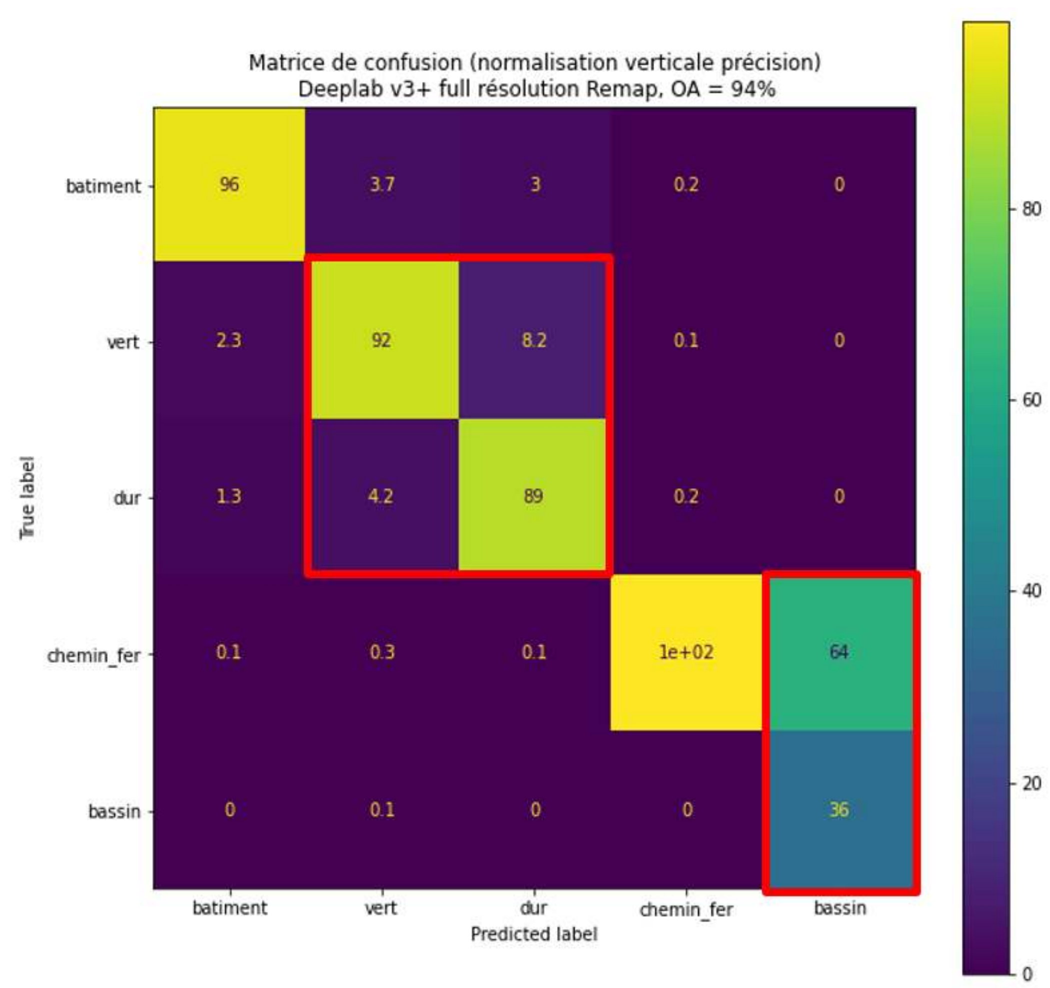
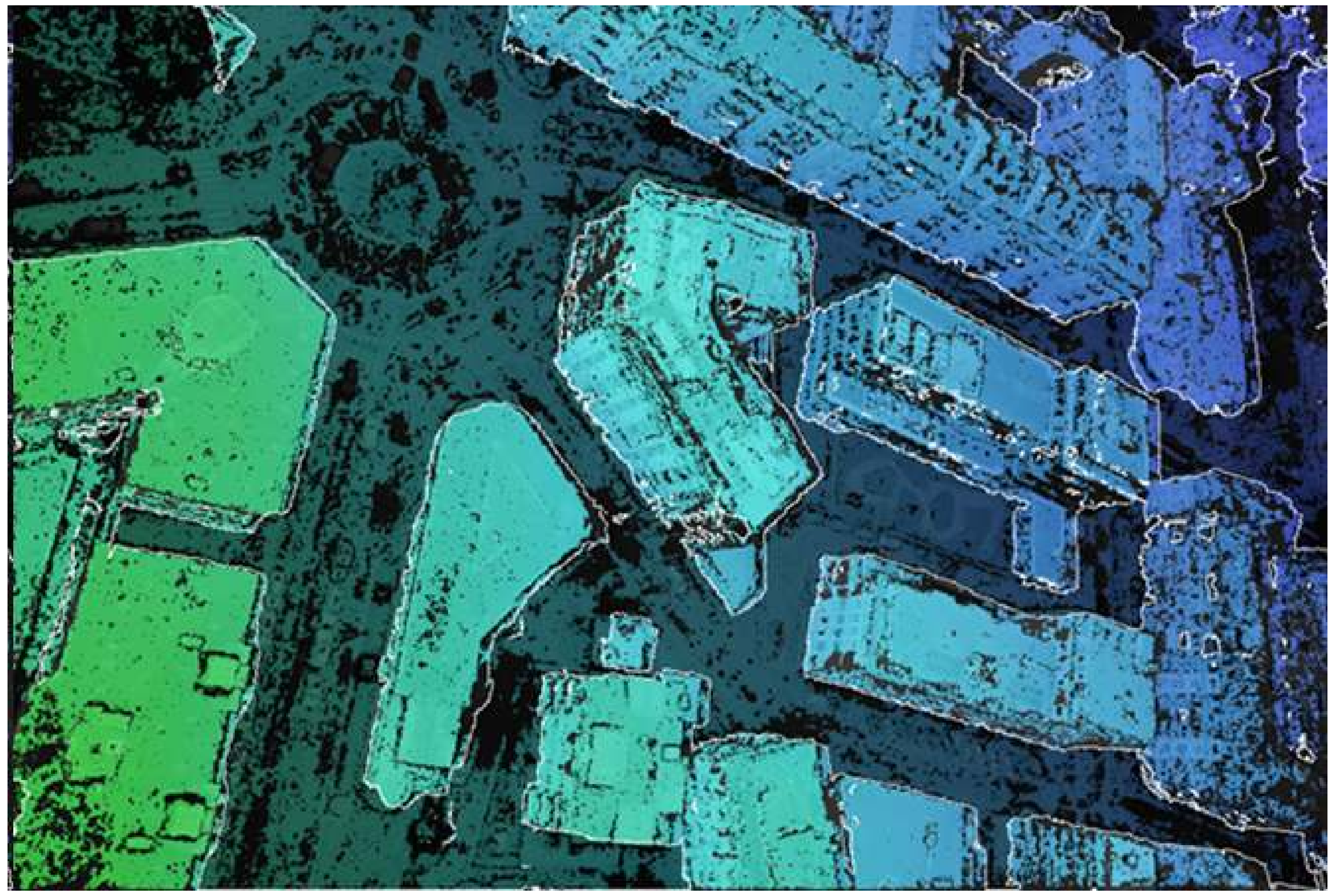
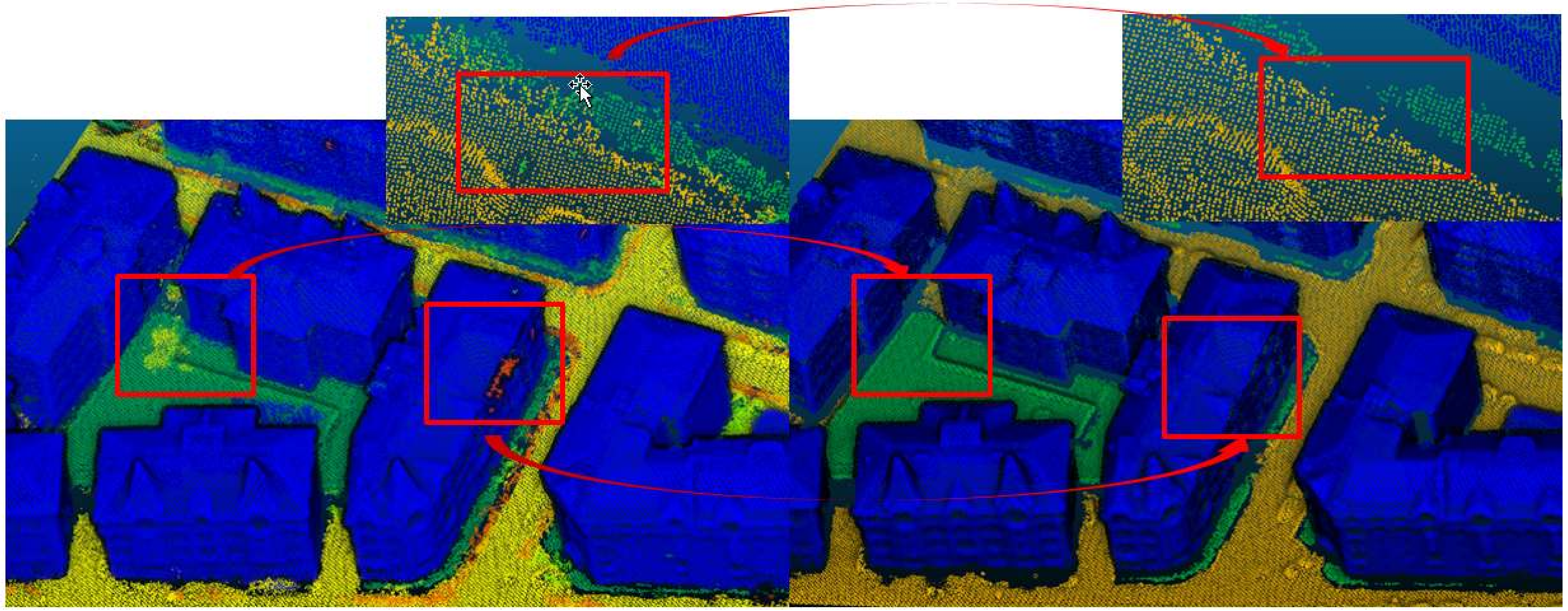


IMAGE TO 3D

- Use masks per class for dense cloud generation
- Filtering by majority class



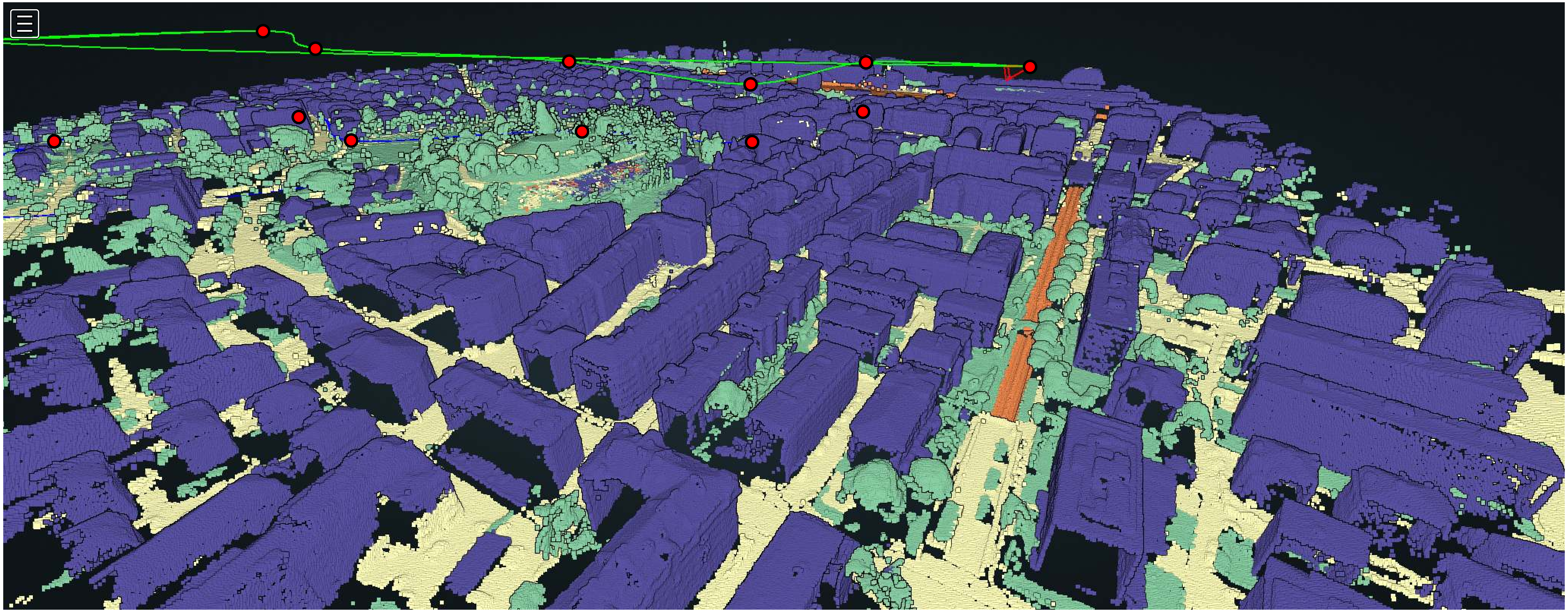


3D POINT CLOUD LABELLING RESULTS

	Recall (%)	Accuracy (%)
Building	95.7	94.8
Vegetation	80.7	81.1
Hard Surface	87.6	87.1
Railway	92.5	86.0

- Hard to compare 2 point cloud, reference not ideal
- Poor quality of the photogrammetric 3D reconstruction

3D POINT CLOUD LABELLING RESULTS



CONCLUSION

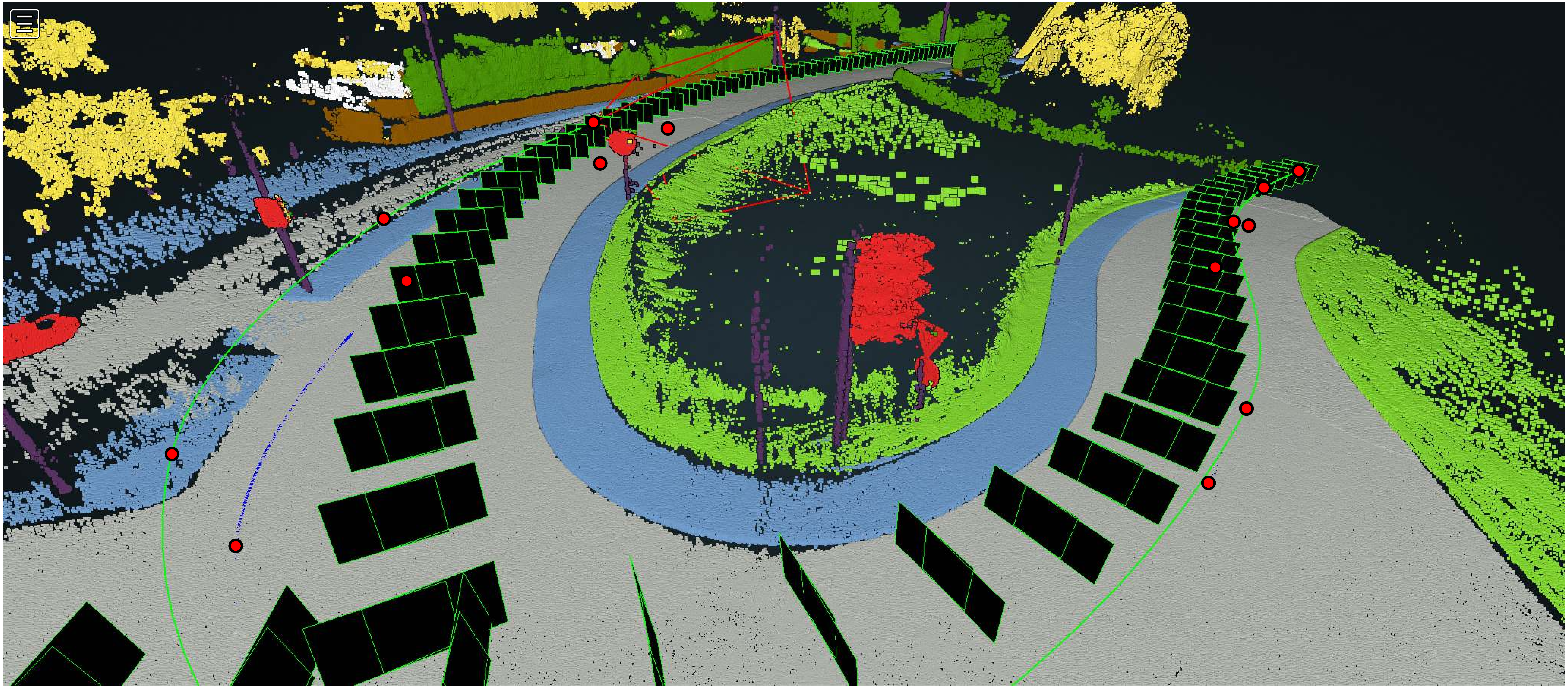
Promising results with few limitations due to several reasons:

- 3D reference created based on 2D data
- Photogrammetric 3D reconstruction method introduce noise
- Ambiguity between land use and land cover classes

Perspectives

- Better and larger training data, for more complex DL architecture ?
- Better geometry from LiDAR data ?
- Merging aerial with terrestrial data ?

Our first results in a new projet, more details coming soon ... follow us ;)



Thank you for your attention !