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Automatic classification of bridges and continental water bodies from 3D point clouds (aerial LiDAR)

EuroSDR

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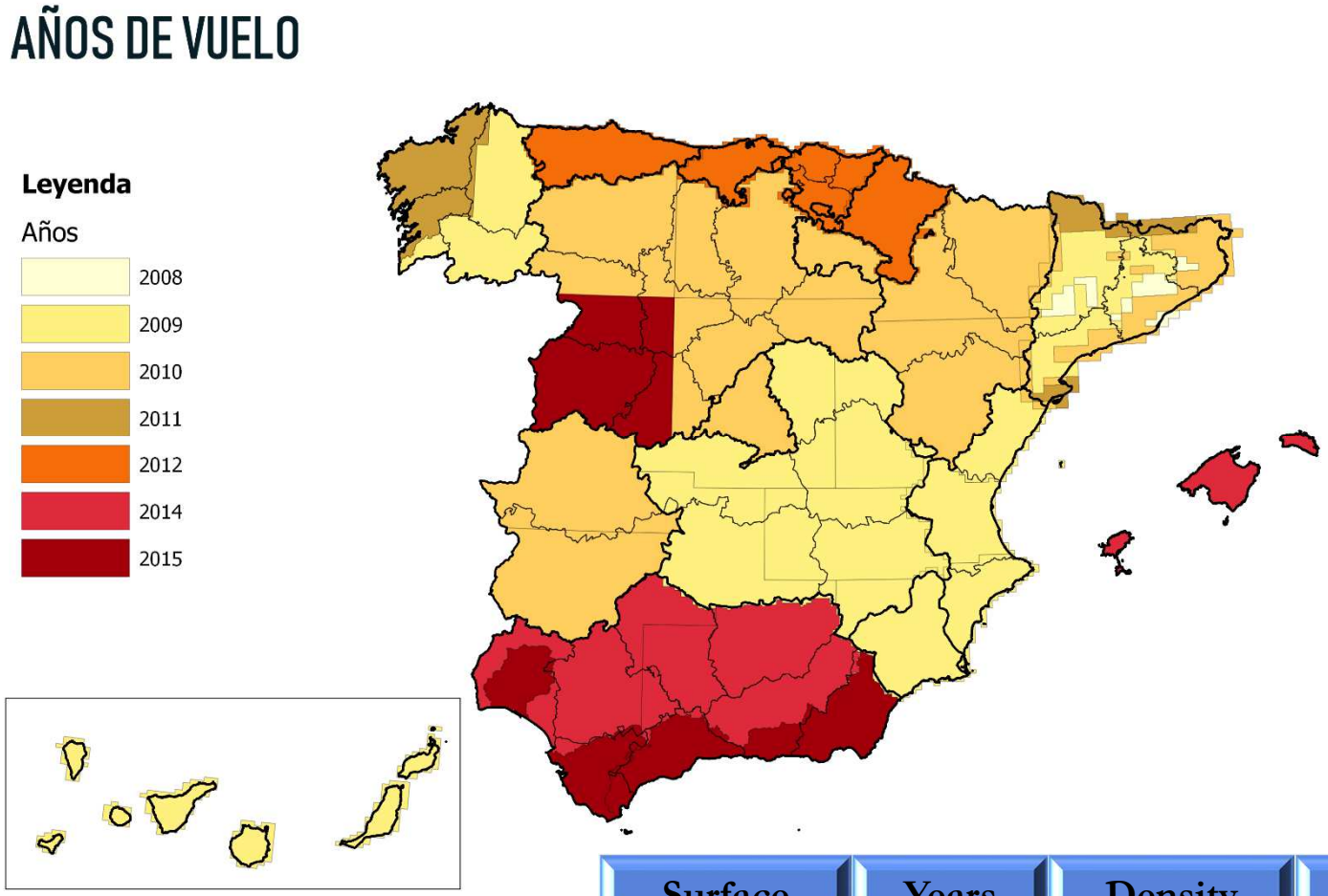
1. PNOA-LiDAR project

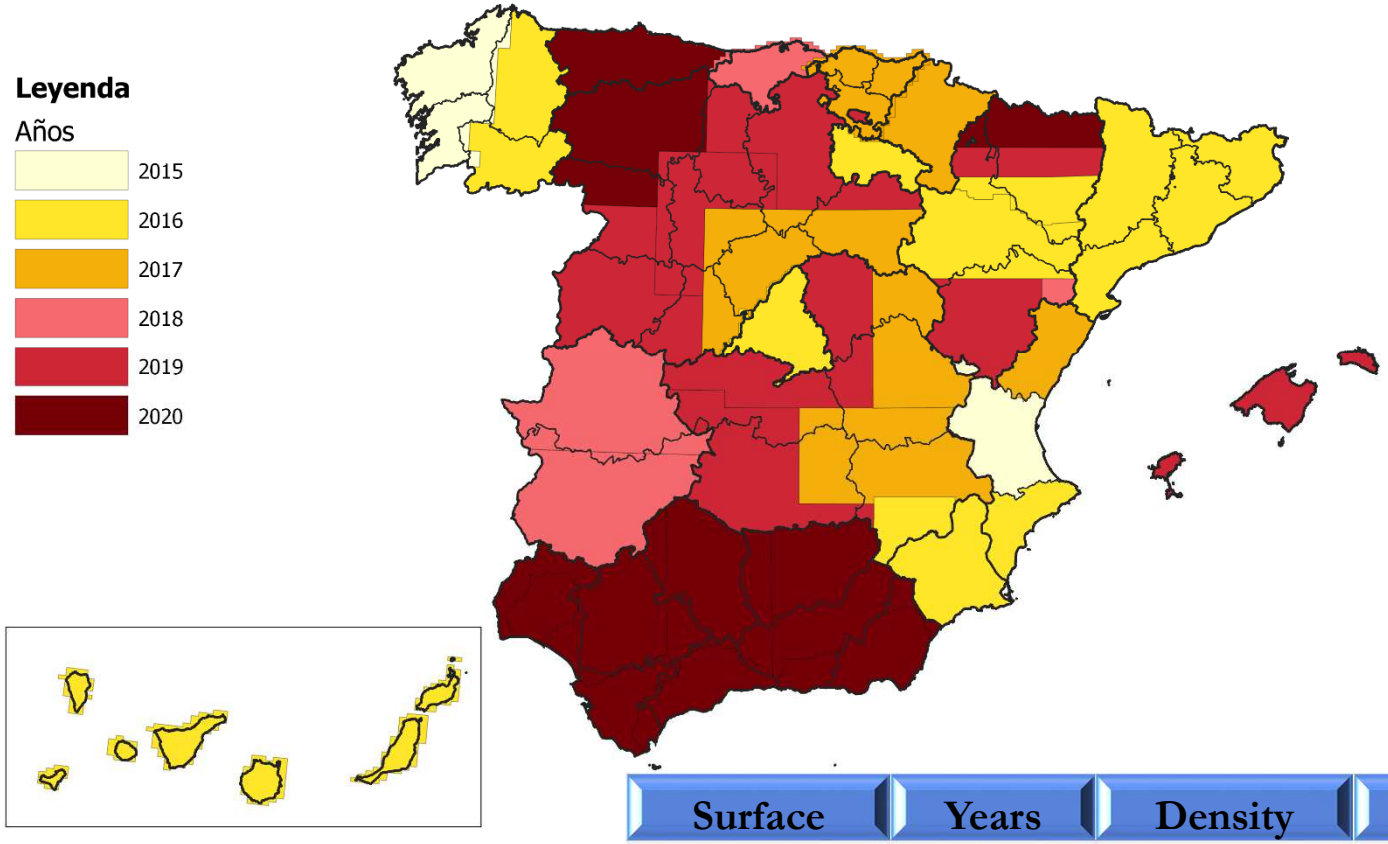
First Coverage: 2009 – 2015



Surface	Years	Density	RMSE	DTM
505.000 km^2	2009-2015	0,5 p/m^2	Z: 20 cm	5m

Second coverage: 2015 – 2020

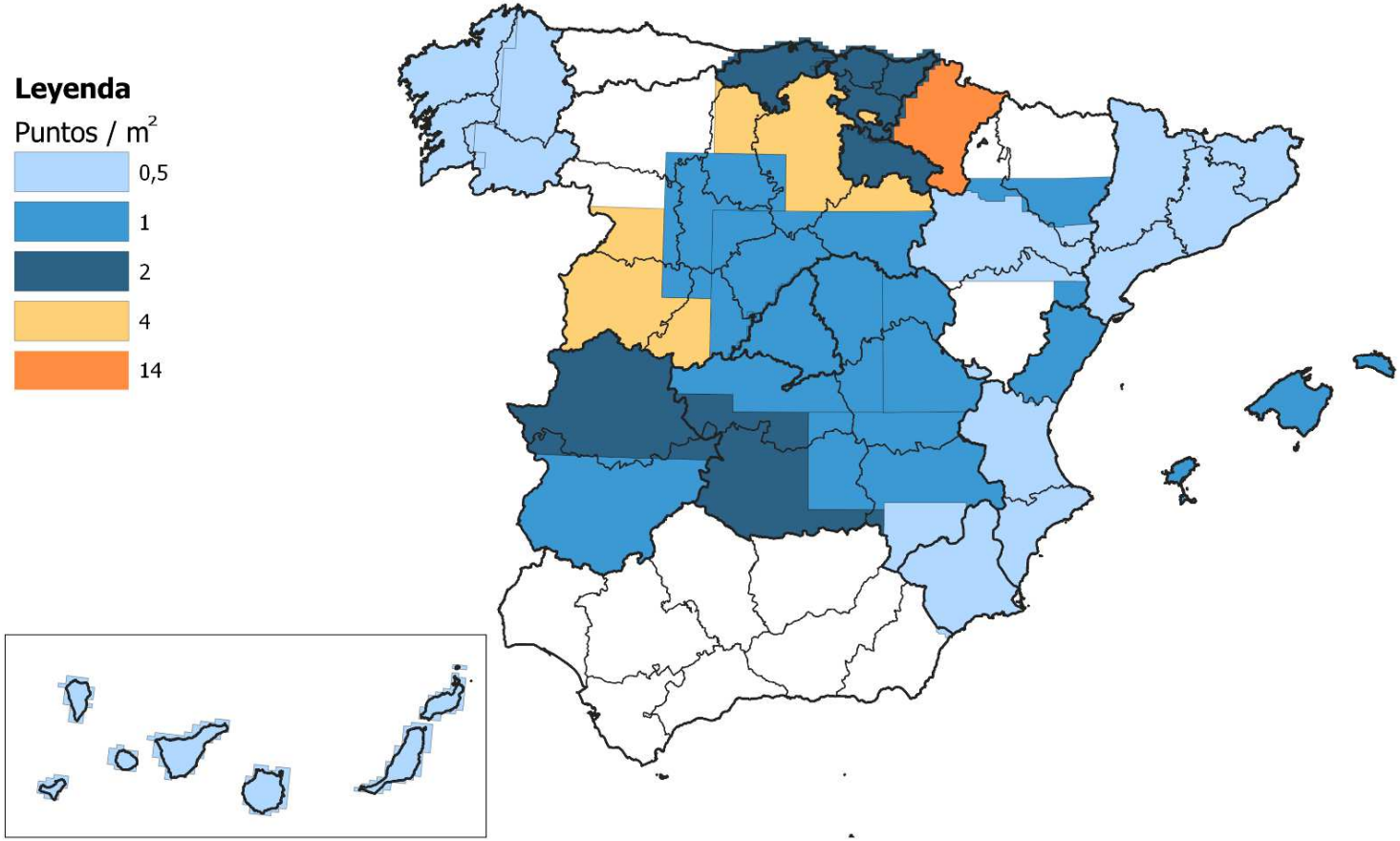
AÑOS DE INICIO DE VUELO



Surface	Years	Density	RMSE	DTM
505.000 km^2	2015-2020	0,5 to 4 p/m^2	Z: 15cm	2m

Second Coverage: density

DENSIDAD DE PUNTOS



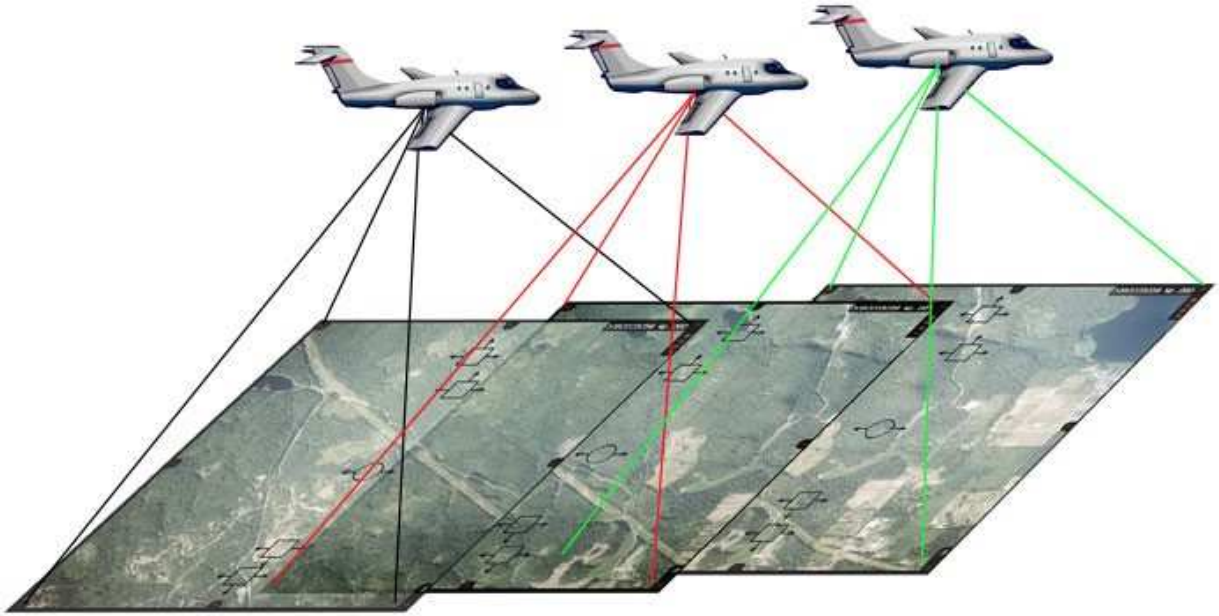
Third coverage: ¿2021?-¿?

- Planning to continue with a 3rd coverage after 2021

Integration of photogrammetric camera

Since 2015 we are acquiring imagery simultaneously with LiDAR, since 2017 is mandatory

Medium format camera are used, acquiring RGB and infrarred information.



Download Center

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2. Classification PNOA-LiDAR

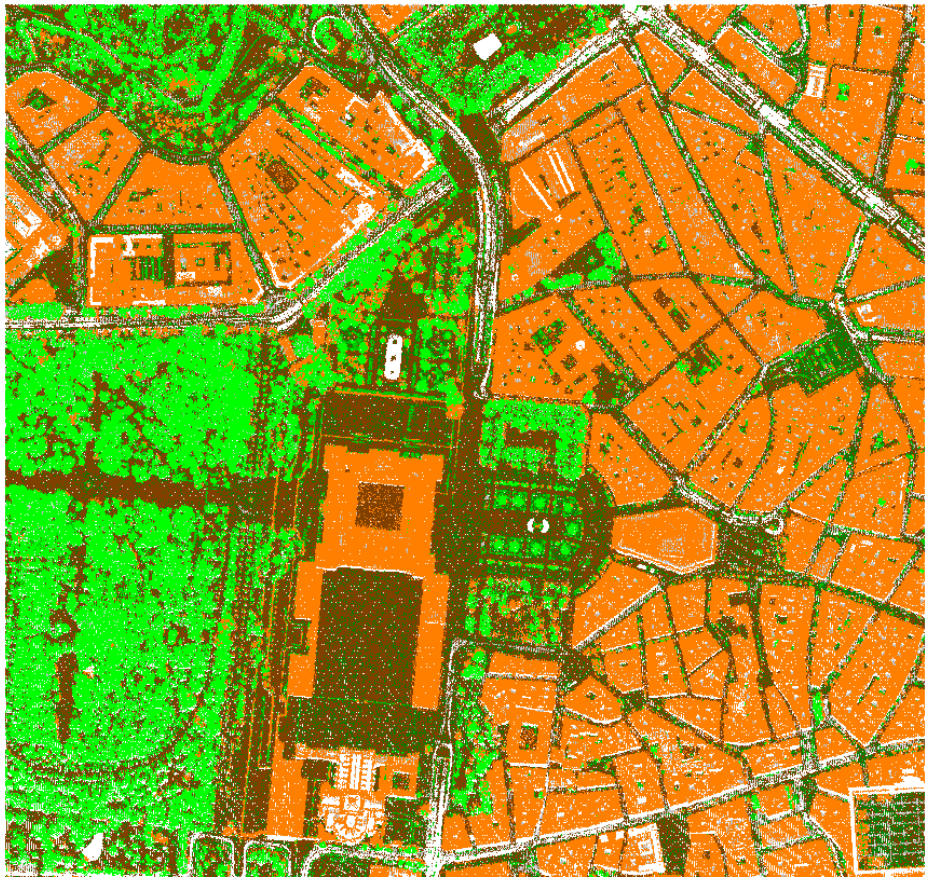
❖ 2. Classification PNOA-LiDAR

1. Colorization

RGB

Infrarred

2. Automatic classification (Terrasolid)

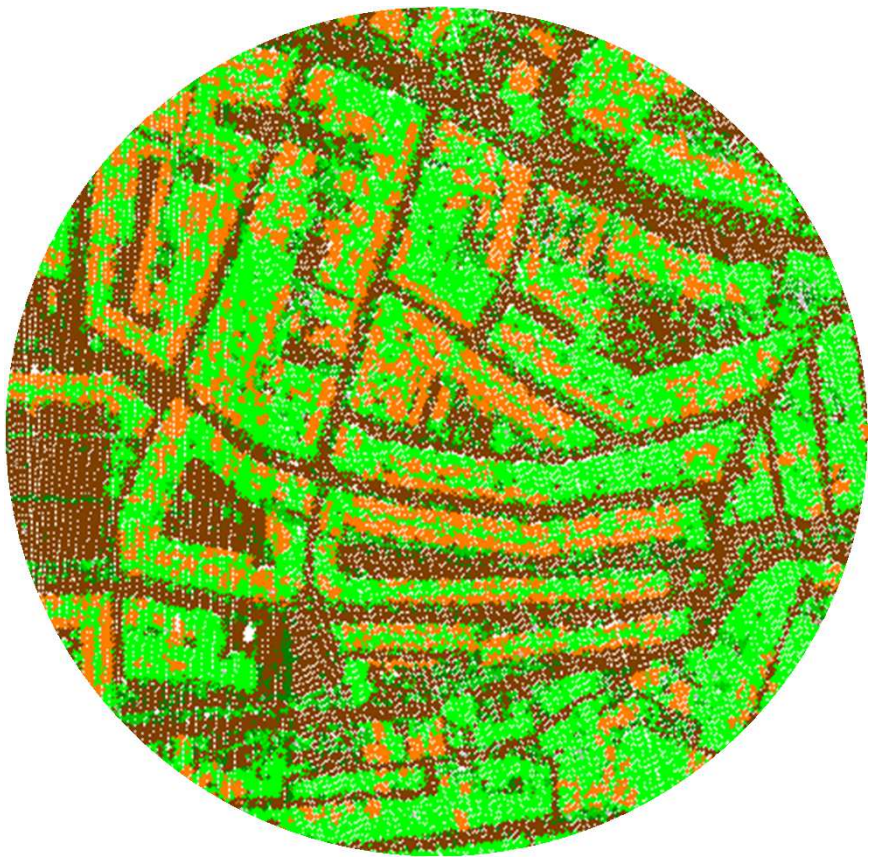


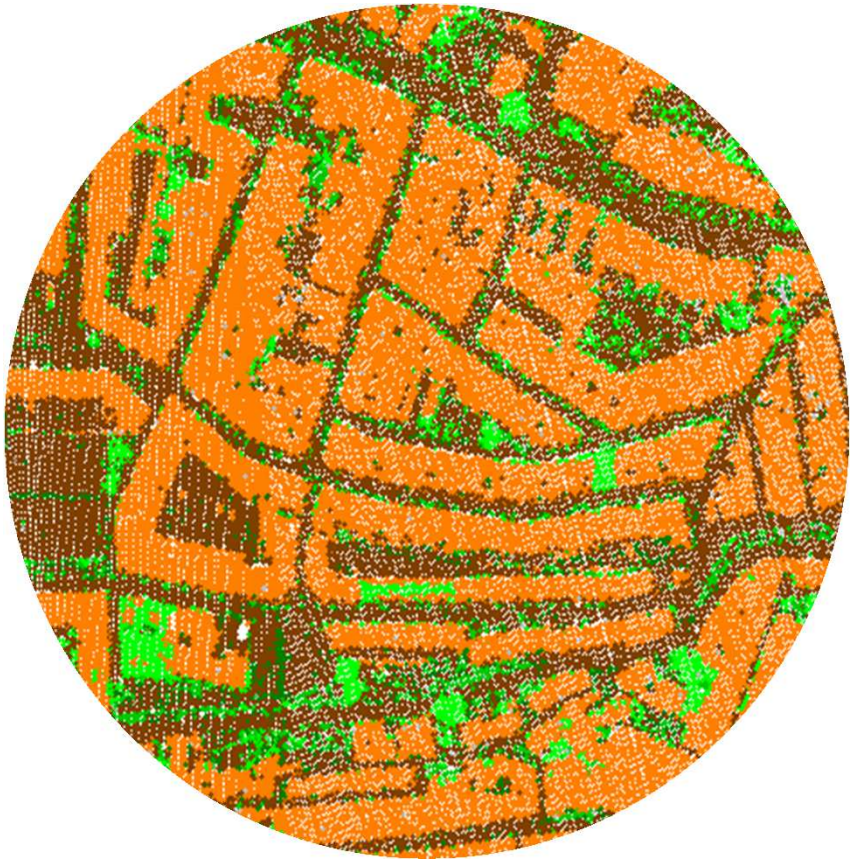
Ground

Buildings

Vegetation (low, medium, high)

3. Buildings improvement

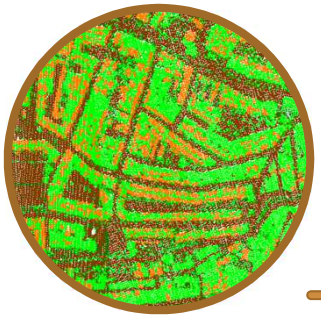


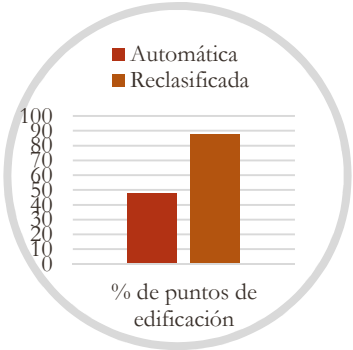


3. Buildings improvement

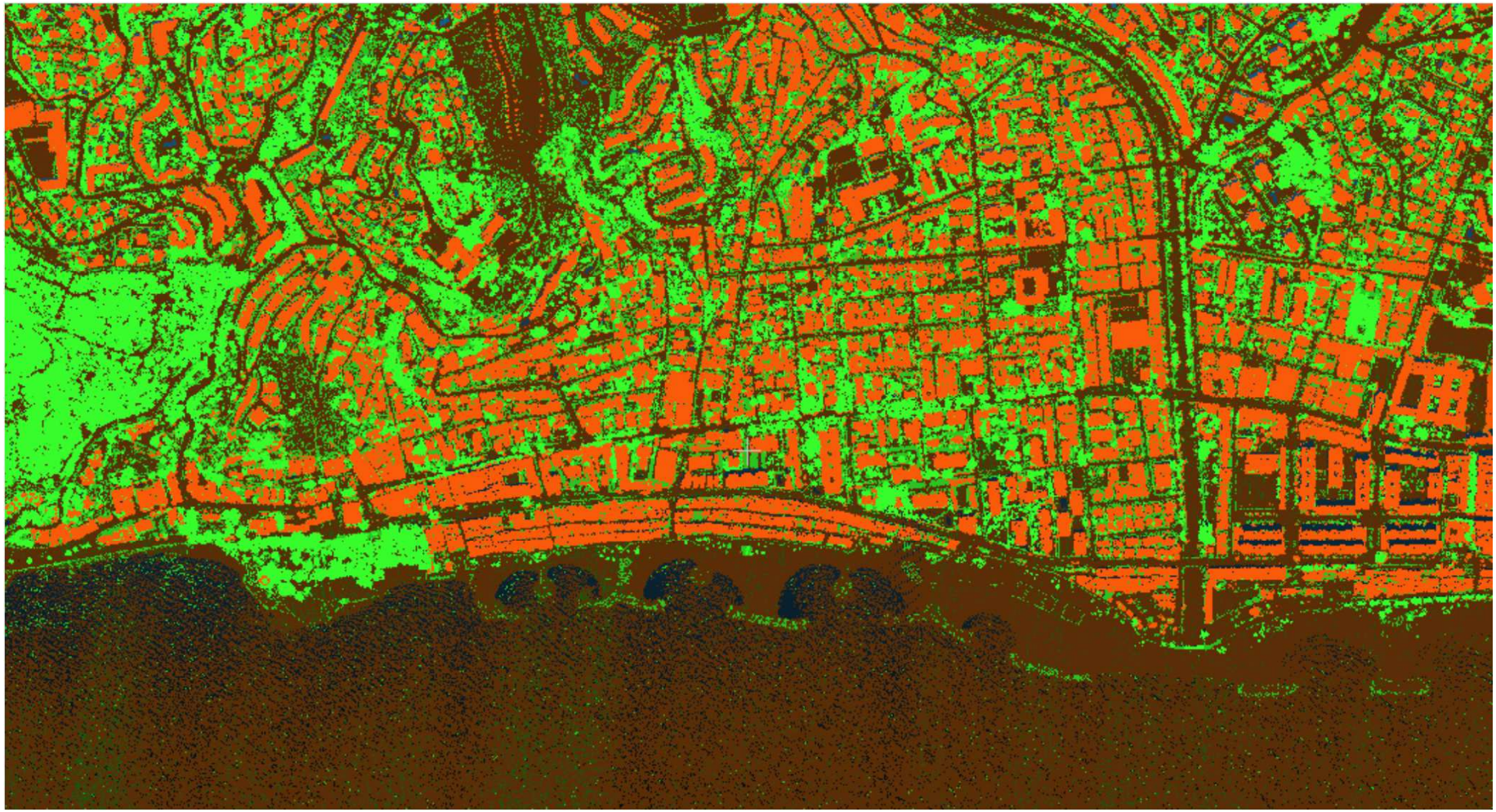
Radiometry + Cartographic information

- NDVI
- Cadaster information





4. Sea water classification



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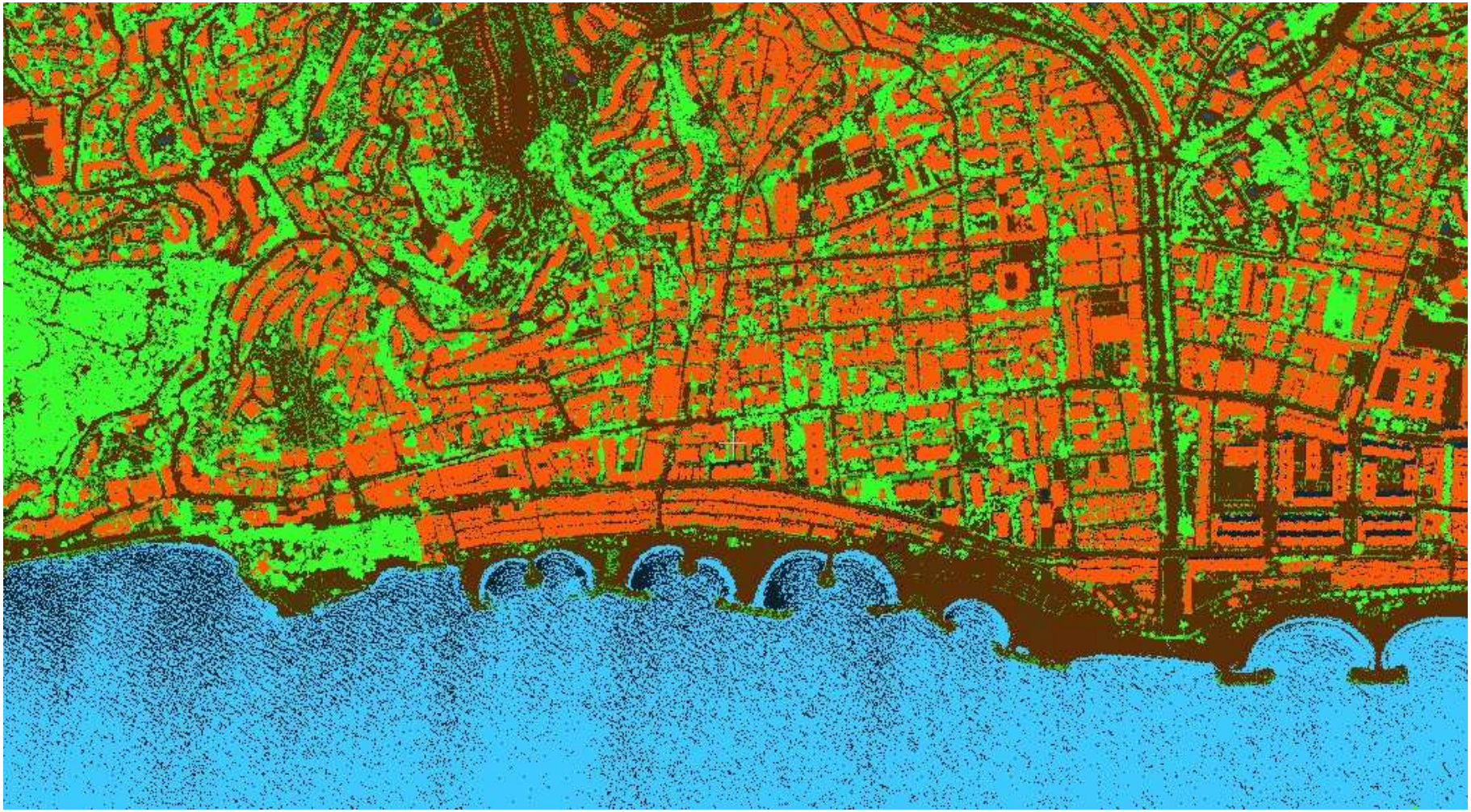
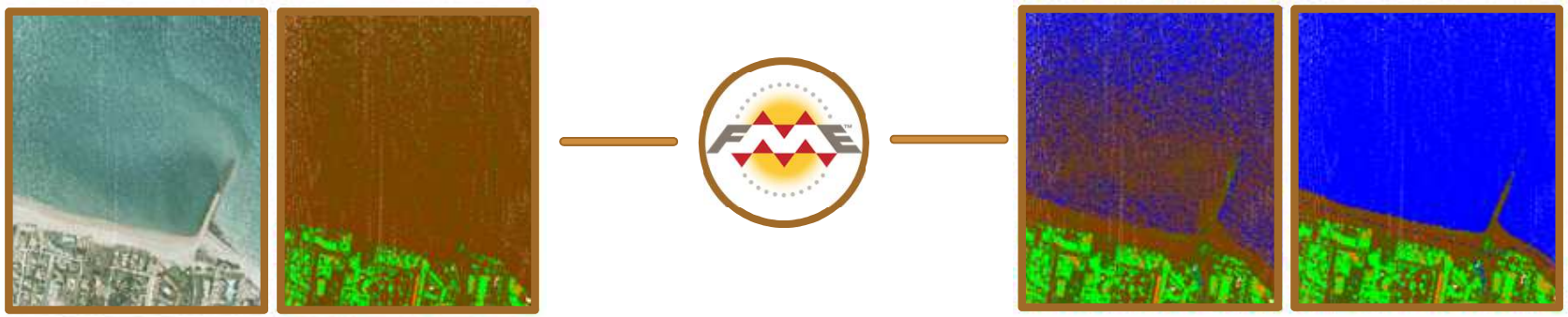


4. Sea water classification

Radiometry + cartographic information + geometry

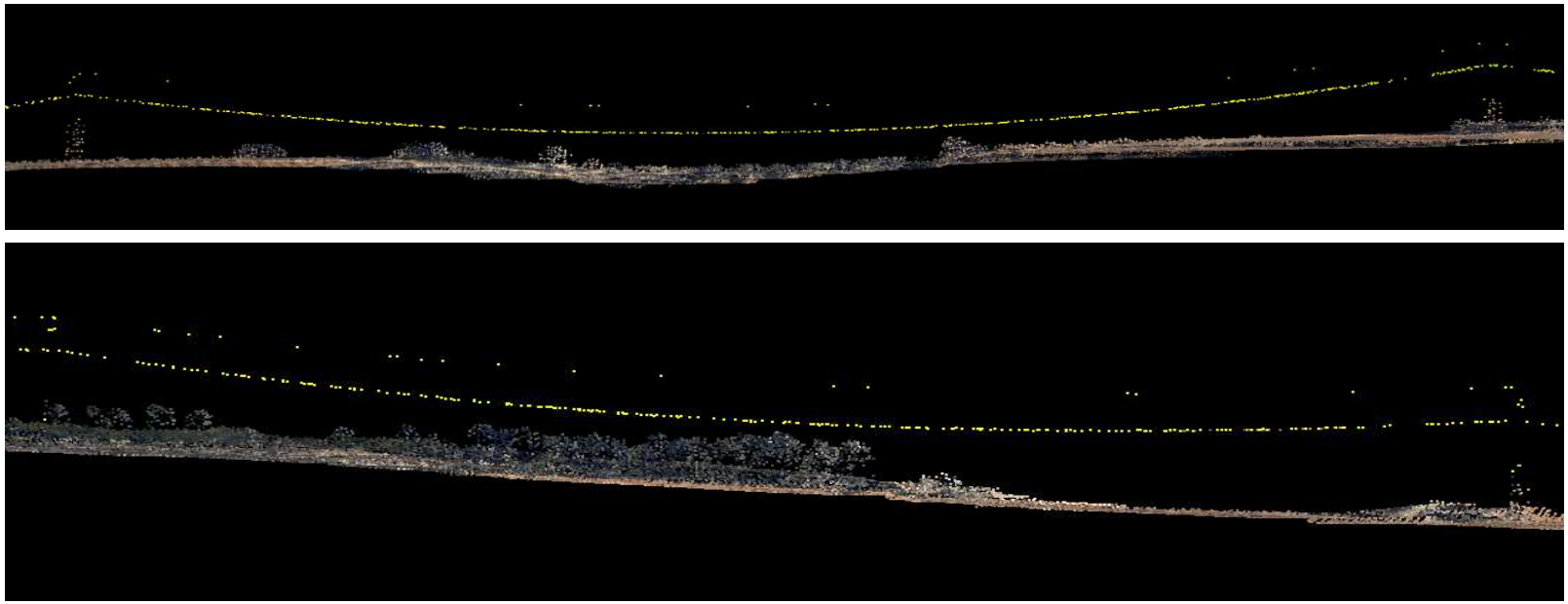
- HUE from the RGB information
- Density
- Height
- Other external information



5. Powerline classification

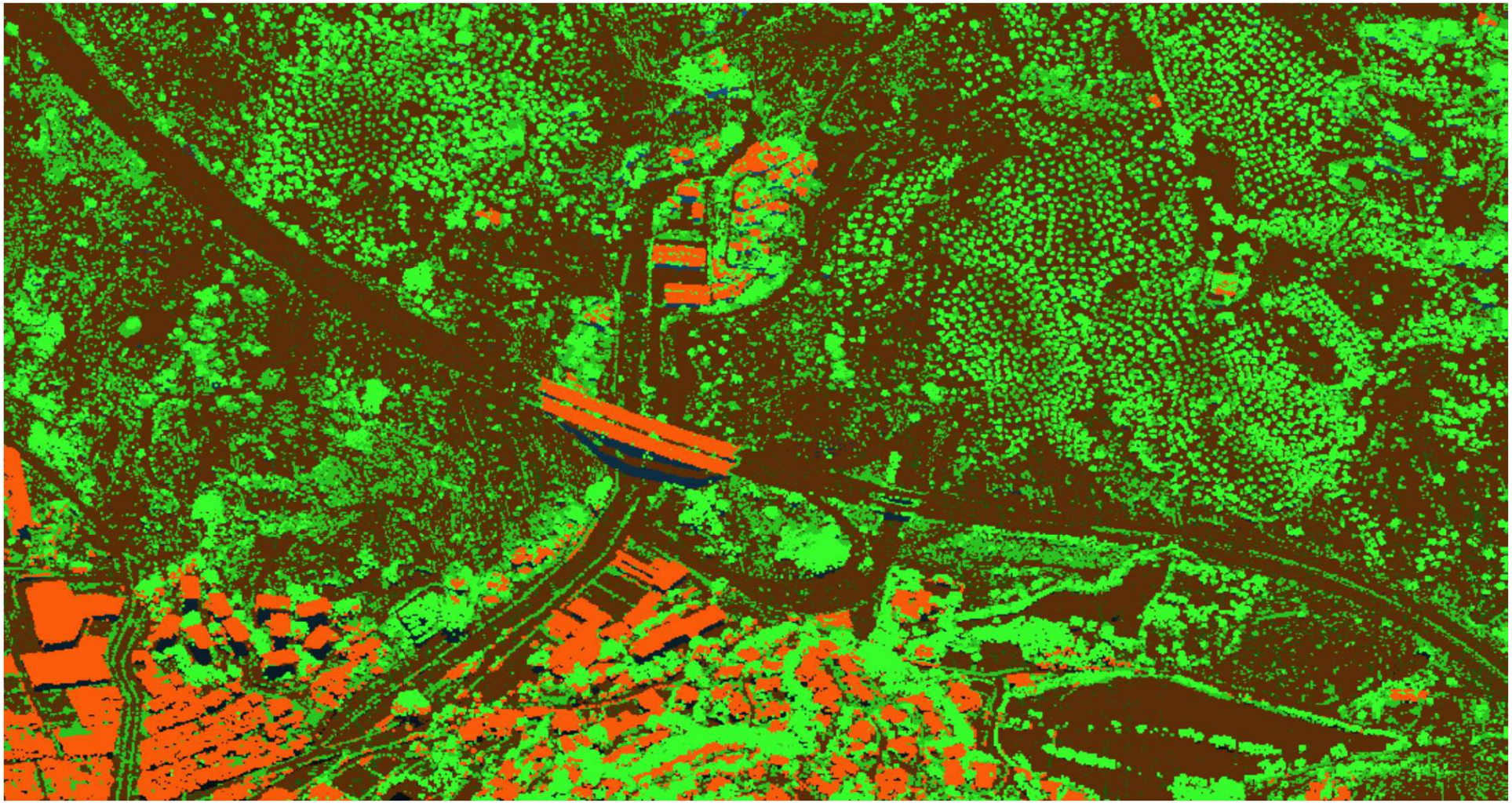
Geometry + intensity

- **Density**: points per m^3 around the point evaluated
- **Roughness**: distance between the point evaluated to and adjusted plane
- **Intensity**

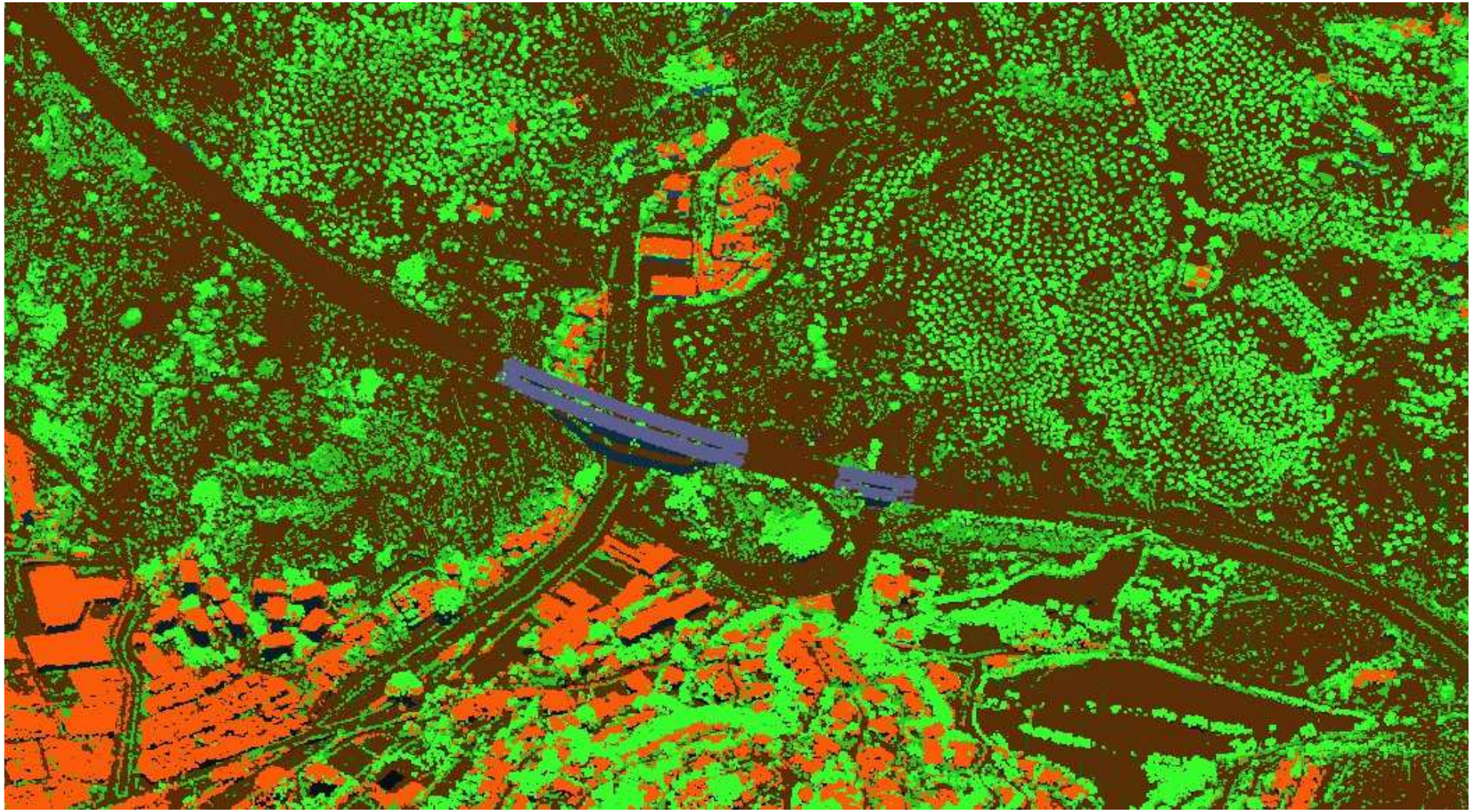


3. Classification bridges

❖ 3. Classification bridges



❖ 3. Classification bridges



1. Introduction

- Automatically misclassified as ground or buildings
- Need of a good classification for DTM (removal of bridges).

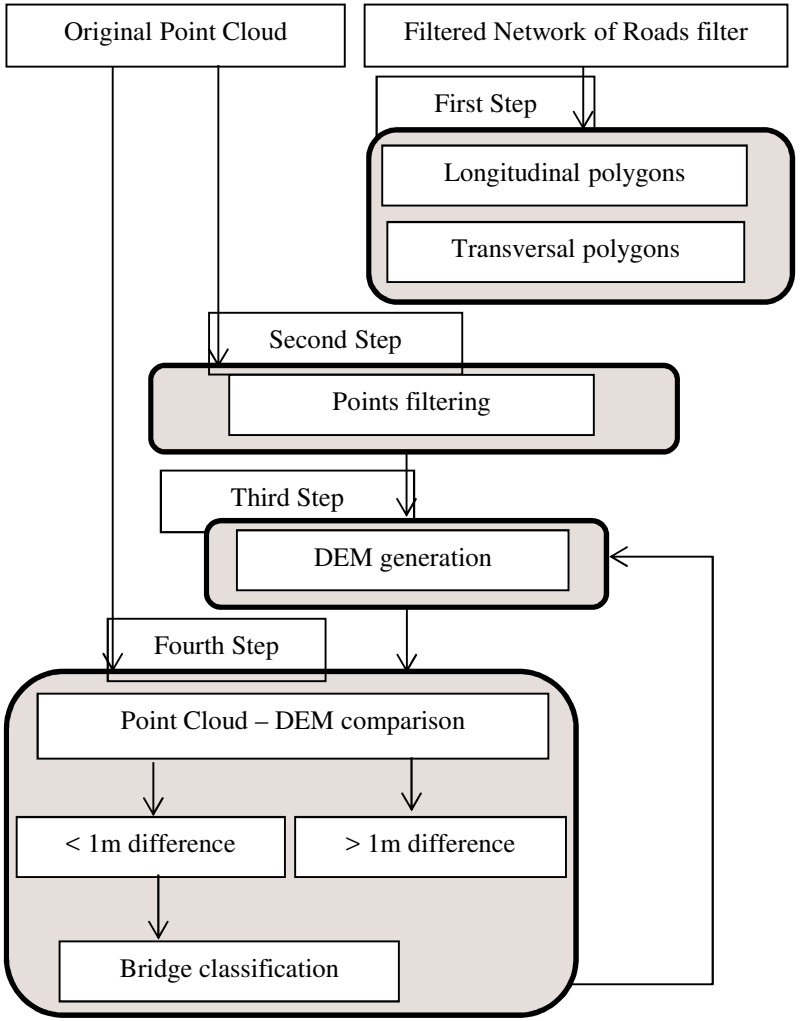
↓

- Geospatial Reference Information on Transport Network (GRI-TN) in IGN

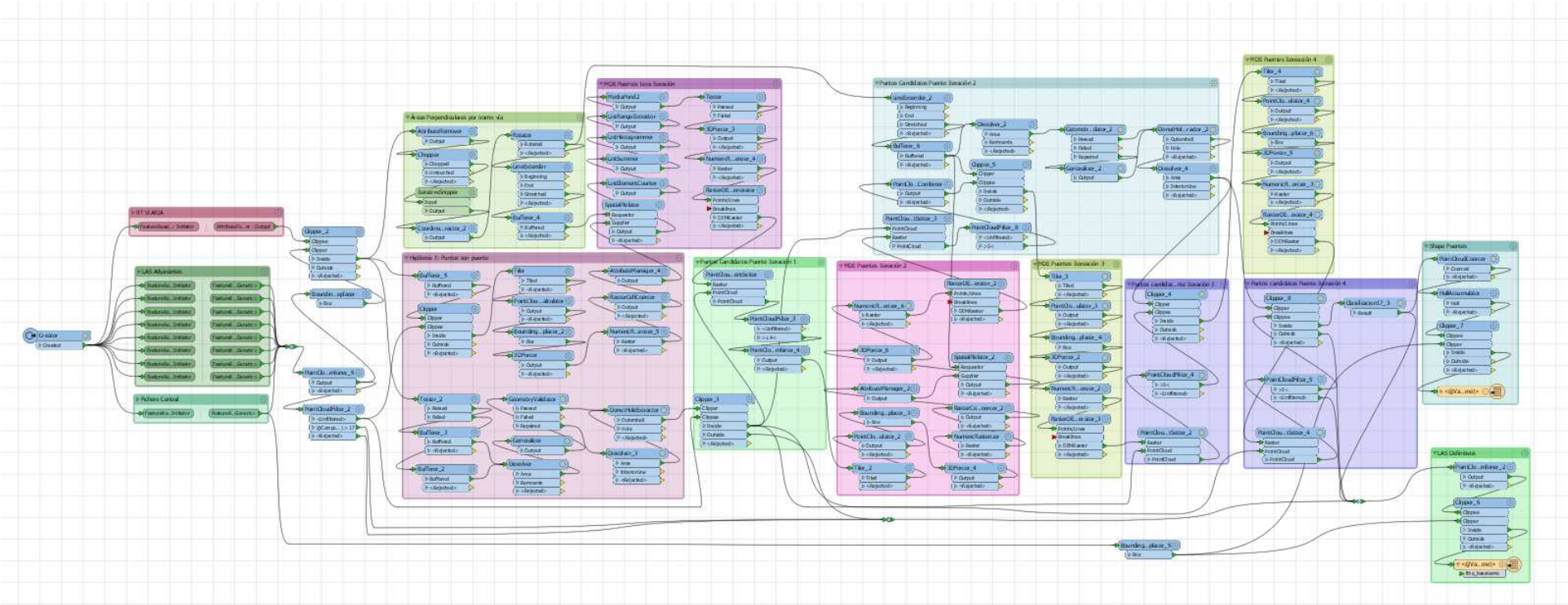
2. GRI Transport Network

3. Methodology

- Cartographic information + geometry



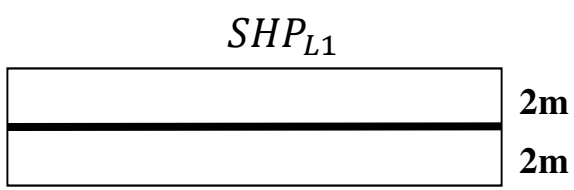
3. Methodology

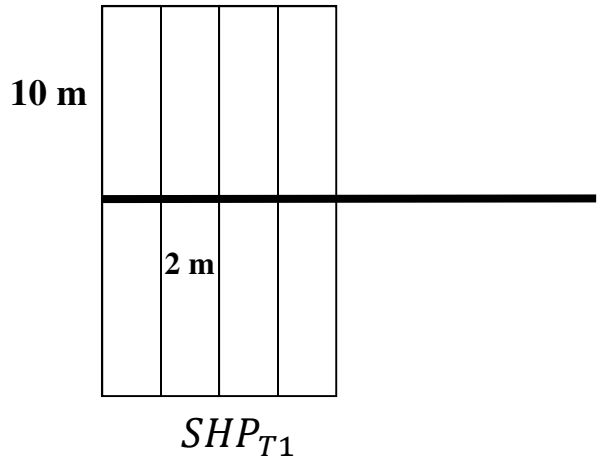


3. Methodology

1st TN filtering (main roads bridges)

(axis)



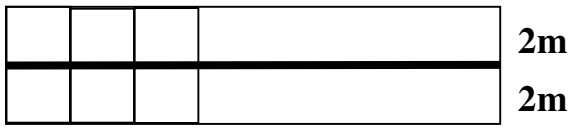


2nd Point cloud intersection

- Classified point cloud (PC_1) intersects SHP_{L1}.
- **Result**: PC_2 where all the points inside SHP_{L1} are considered bridge.

3rd DEM generation

- Generation of a DEM_1 2x2m with PC_2 using average height.



3. Methodology

4th

- SHP_{T1} intersects DEM_1
- **Result**: a SHP_{T2} with an average height assigned per section.

5th End of first loop

- PC_1 intersects SHP_{T2} → points with a difference lower than 1m are considered bridge.
- **Result**: PC_3 with the first iteration of points classified as bridge.

6th Beginning of second loop

- Back to 3rd step and generation of DEM_2 2x2m with PC_3
- Repeat steps 4th and 5th
- 3 Loops are implemented

4. Results

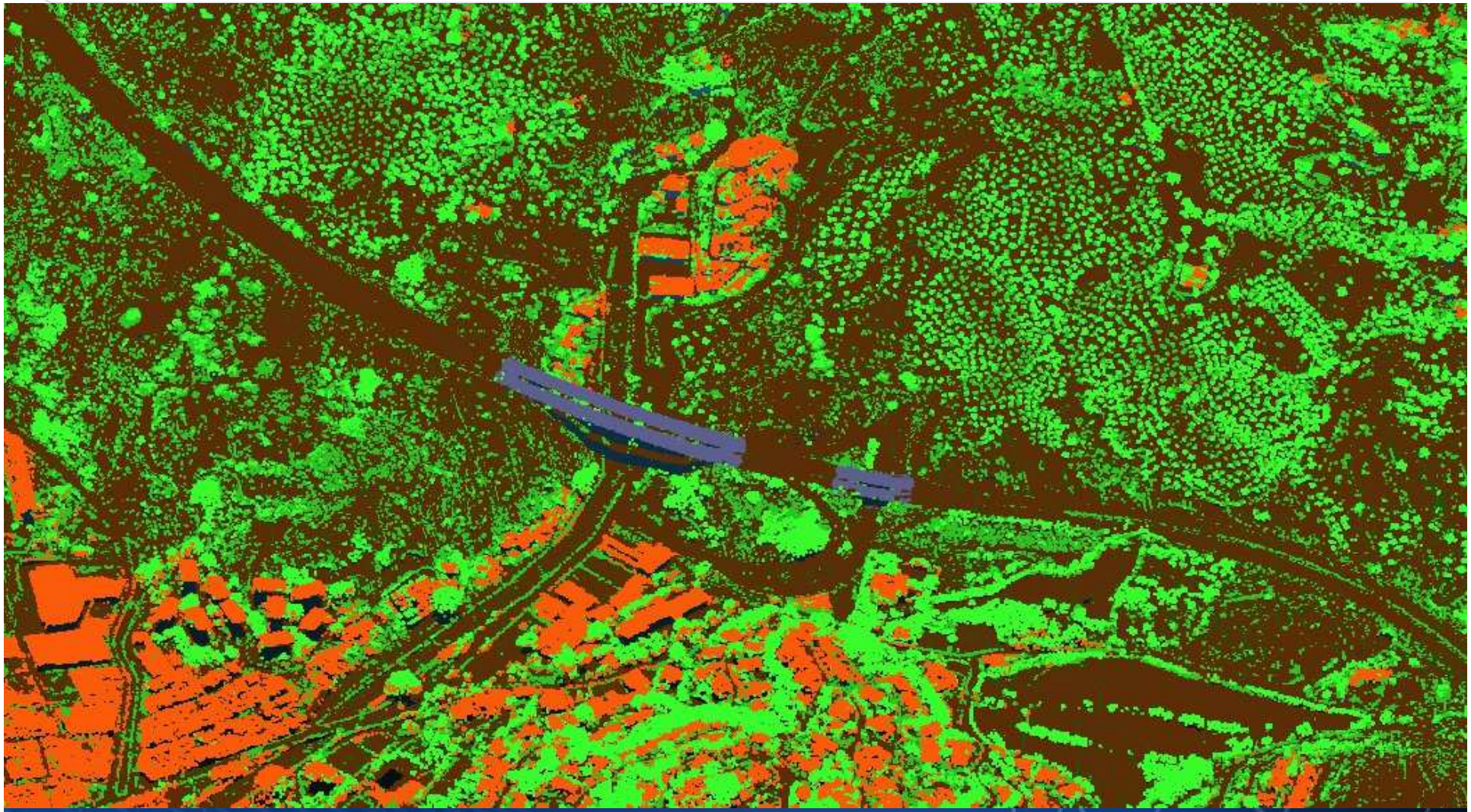
- Test Area of 1.000 km2

- Visual review: ortophoto acquired simultaneously with LiDAR used as ground truth.

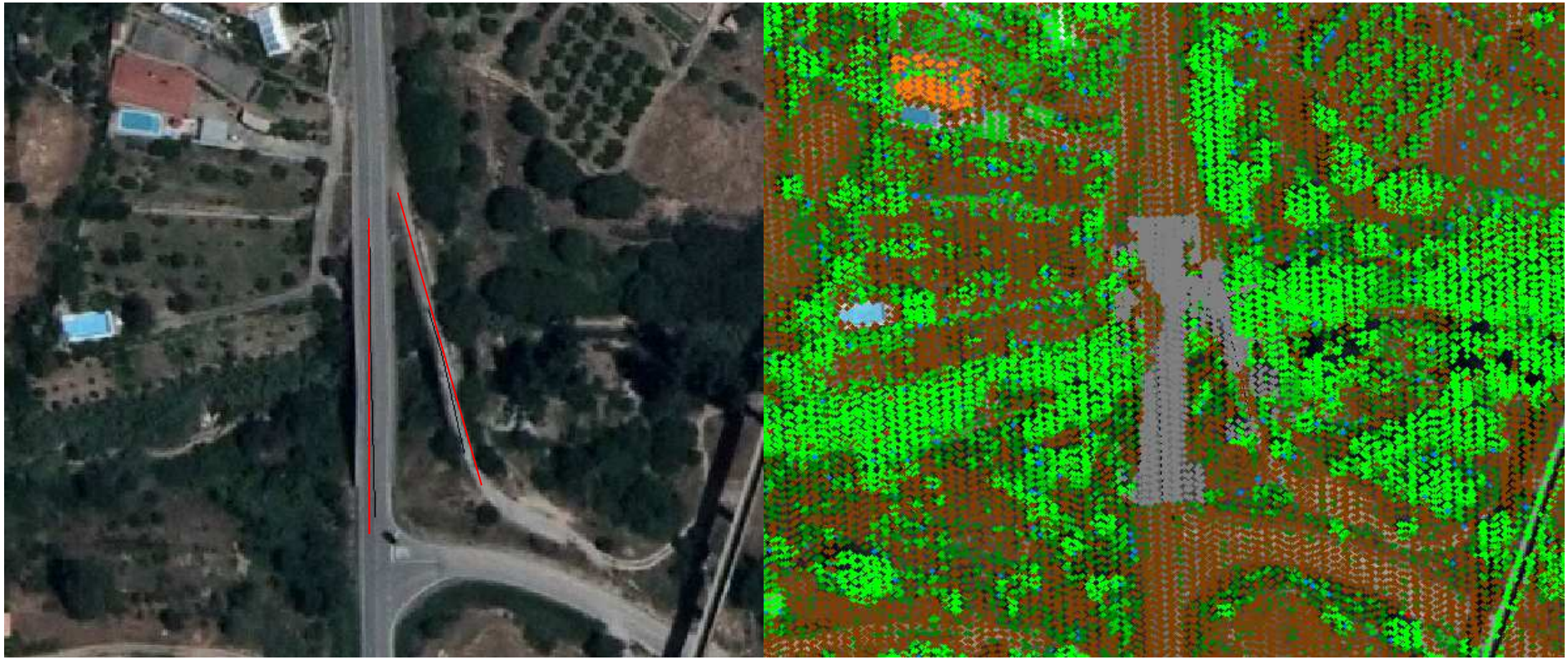
Type of detection	Number of bridges	Percentage
Omissions	9	21%
Commissions	0	0%
Partial detections	4	10%
Full detections	29	69%
Total	42	100%

- 18.838 points classified as brigdes
- 80% accuracy between full and partial detection.

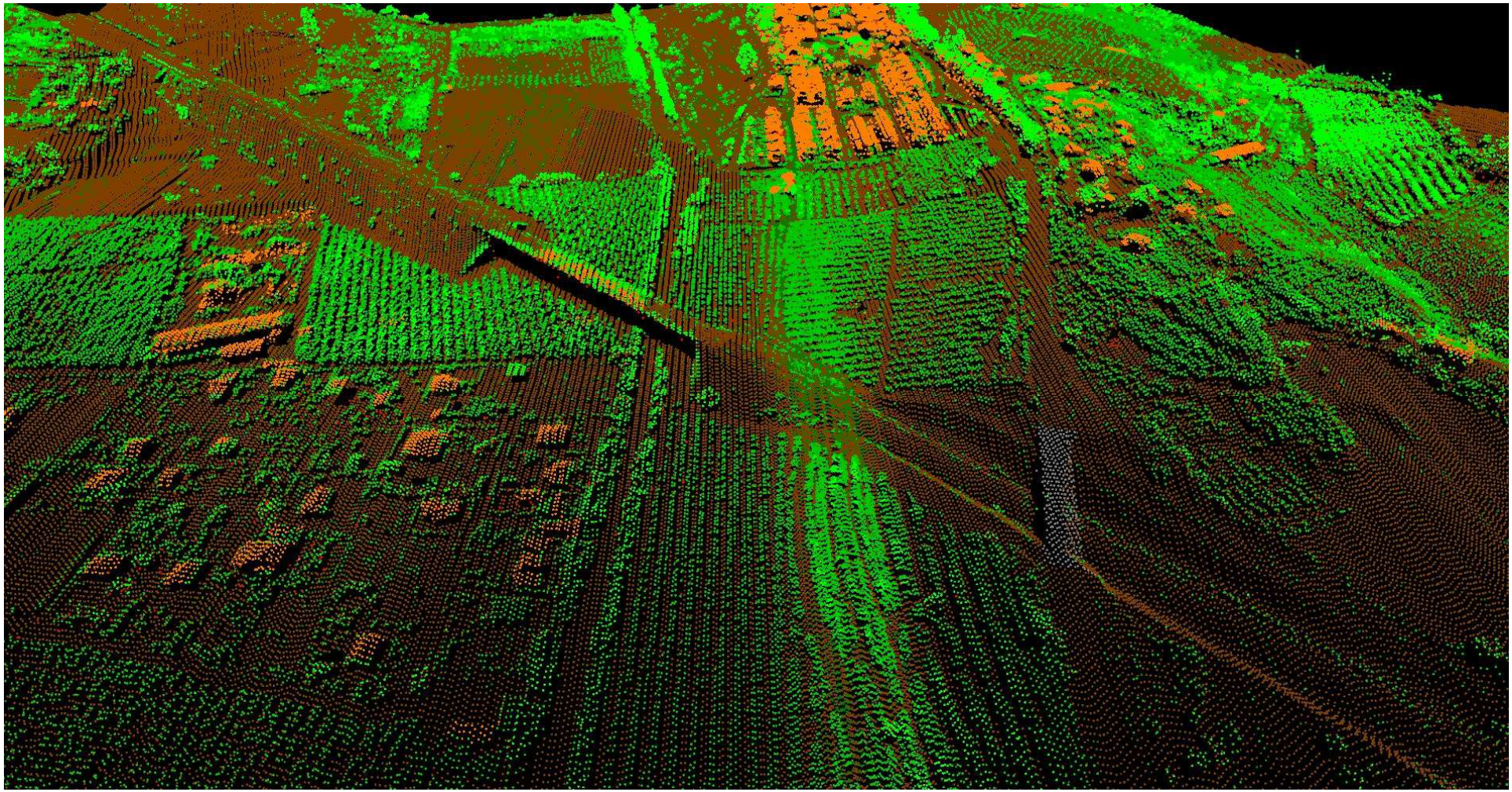
4. Results: Full detection



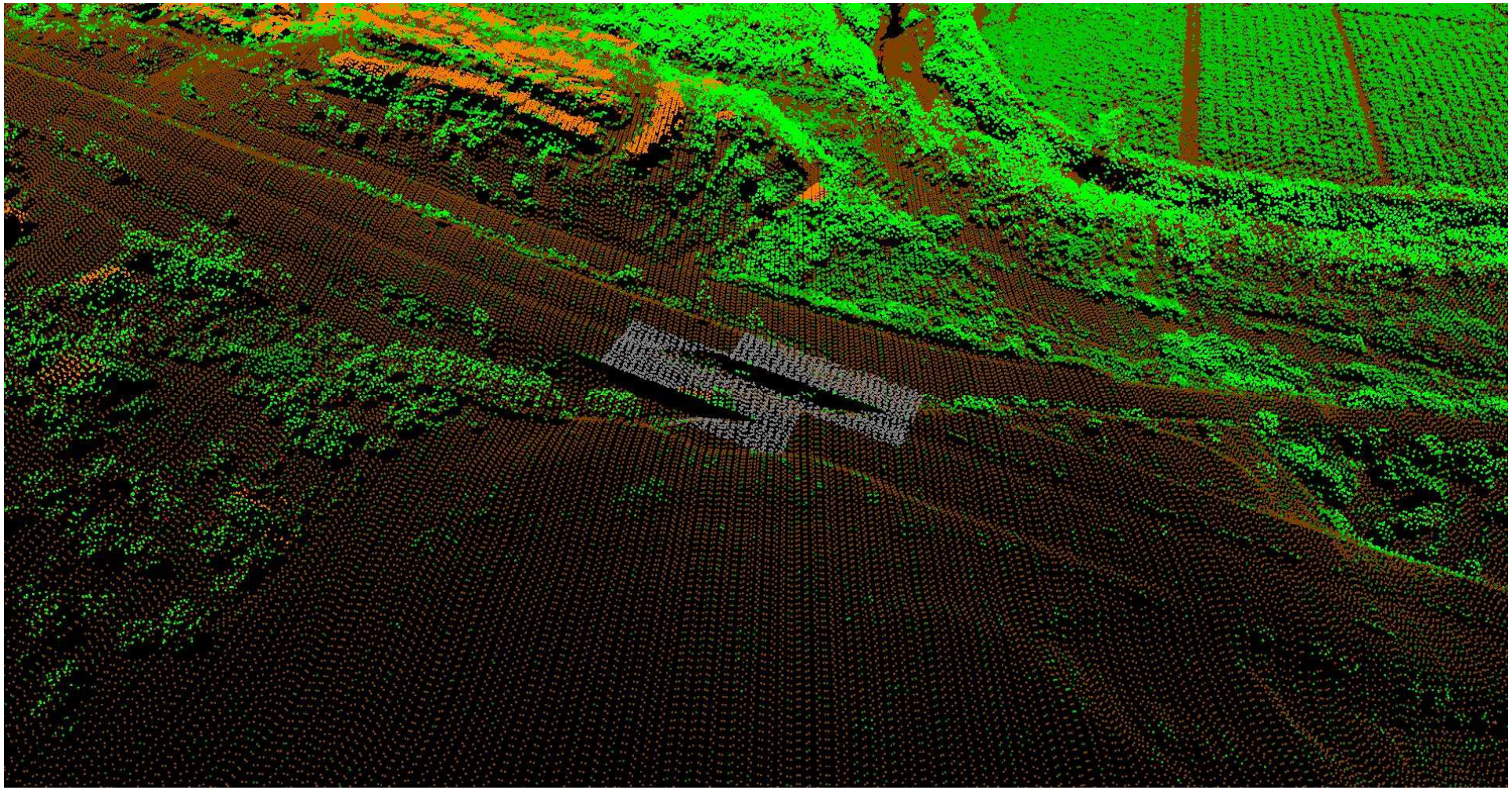
4. Results: Partial detection



4. Results: Omission



4. Results: Error



5. Conclusions

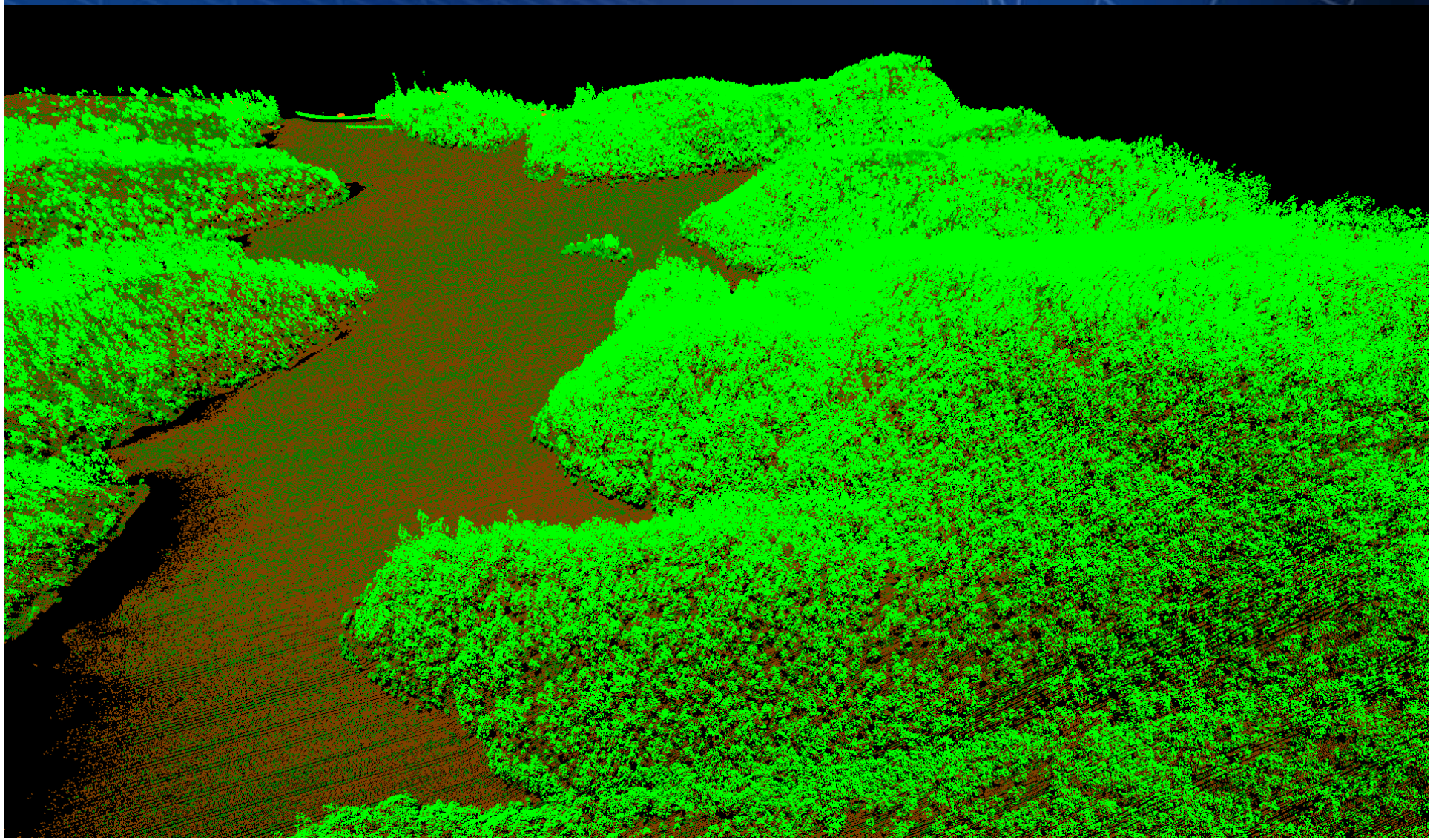
- **Highly dependent on TN**

- Feedback with TN needed (already in motion) → detect errors in the TN and report → loop where every project help each other.

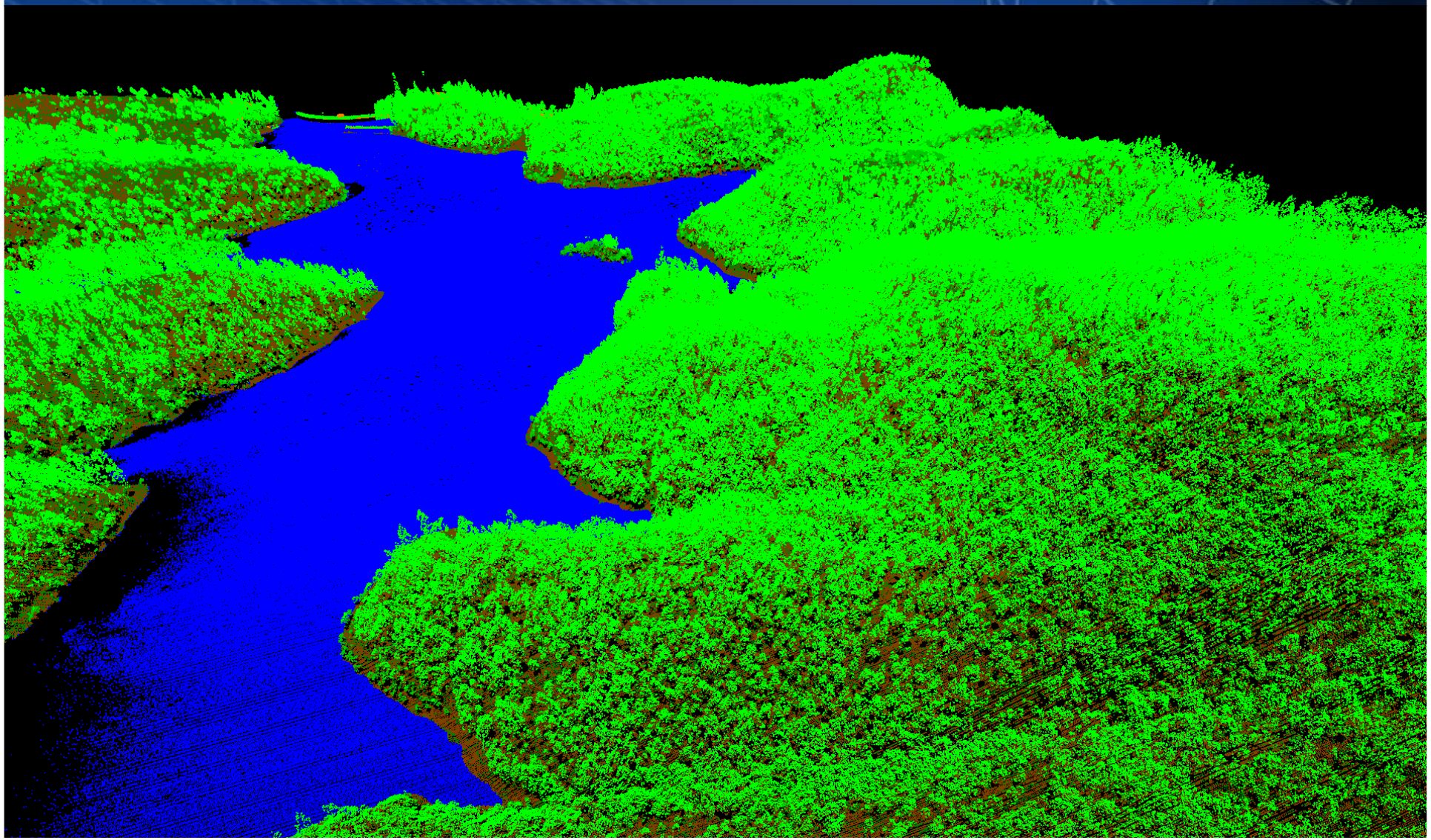
- **Satisfactory results** (as a first approximation) → it improves previous classification, although more improvement is needed.
  - Already part of the workflow
  - Not main bridges.
  - Manual edition still needed

4. Classification continental water bodies

❖ 4. Classification continental water bodies



❖ 4. Classification continental water bodies



1. Introduction

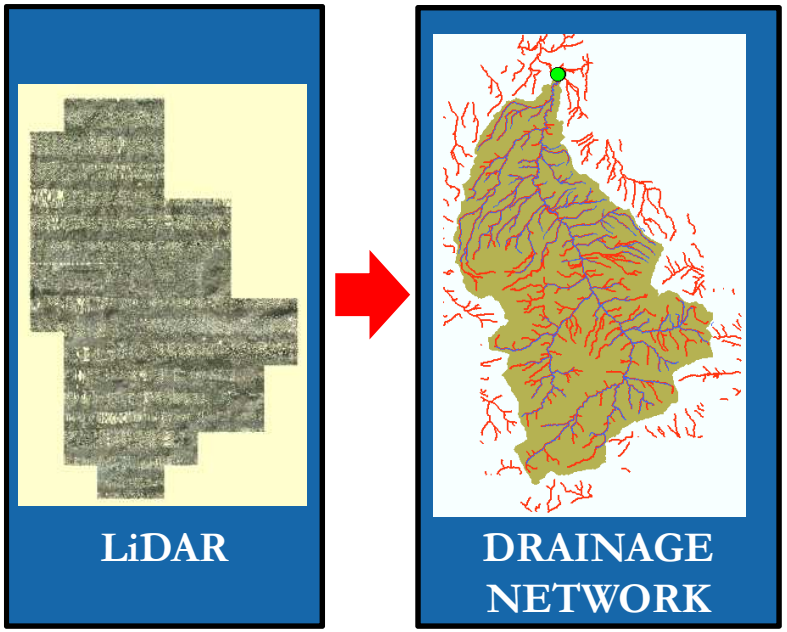
- Automatically not classified (or misclassified as ground or vegetation.
- Need of a good classification for DTM (hydro flattening)

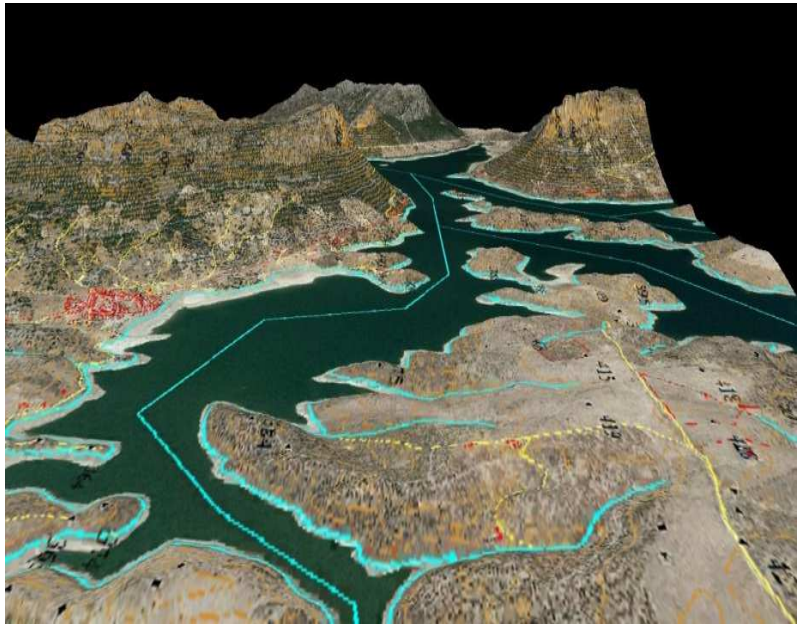
↓

- Geospatial Reference Information on Hydrography (GRI-H) in IGN

2. GRI Hydrography

- Accurate (XYZ) and Update automatic river extraction from LiDAR data





3. Methodology: indexes

- Radiometry + geometry + cartographic information

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \qquad NDWI = \frac{(G - NIR)}{(G + NIR)}$$

$$Normalized\ False\ Colour = \frac{(NIR * R * G)}{2^{bits}}$$

Probability	NDVI	NDWI	NFC
High	< -0.10	> 0.20	>0.03
High	< -0.20	-	-
Medium	< 0.15	(-0.15, 0.40)	<0.03

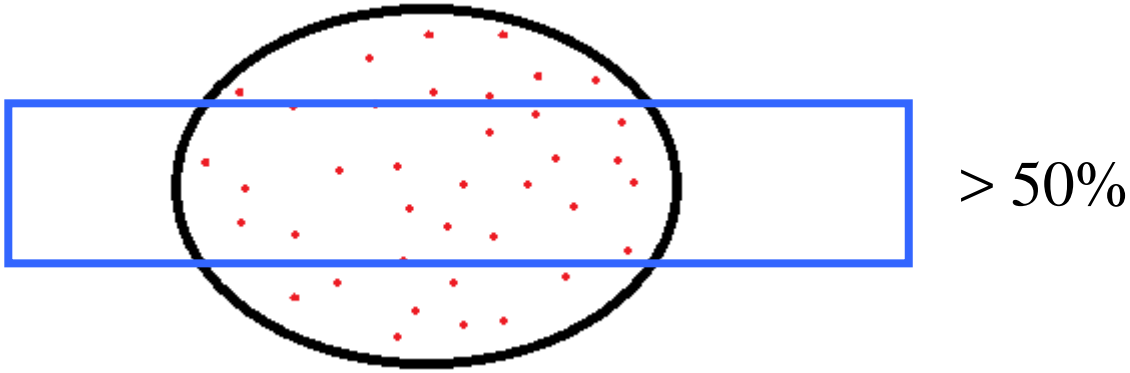
3. Methodology: filtering

- **Point cloud classified**: all ground or low vegetation are considered, discarding the rest.

- **Slope**
  - Value in points selected as water must no differ on 0.5m of Z mean value in an area of 2x2m
  - In this way we eliminate shadows.

3. Methodology: filtering

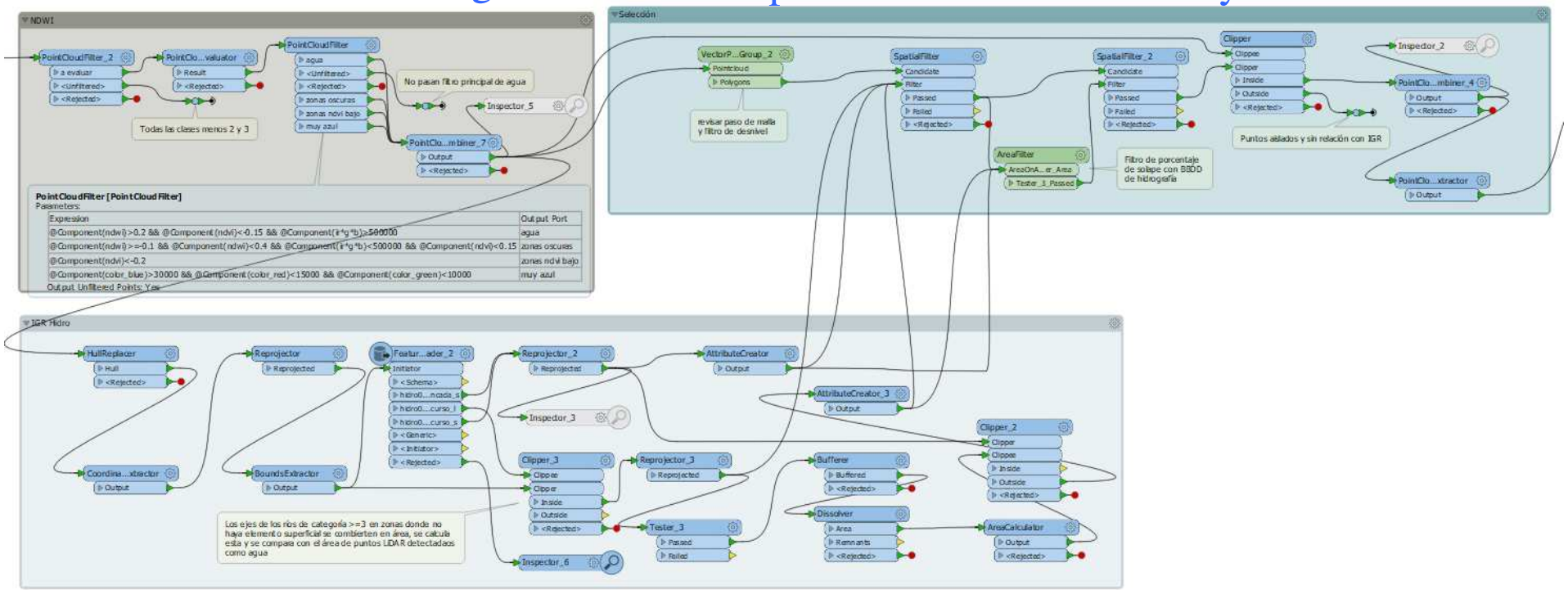
- **Hydrographic Network**
  - If the convex hull polygon to near points radiometrically selected as water intersects in a percentage of surface greater tan 50% with a polygon of the hydrographic model, those points are considered to have more probabilities to belong to a water body



3. Methodology:

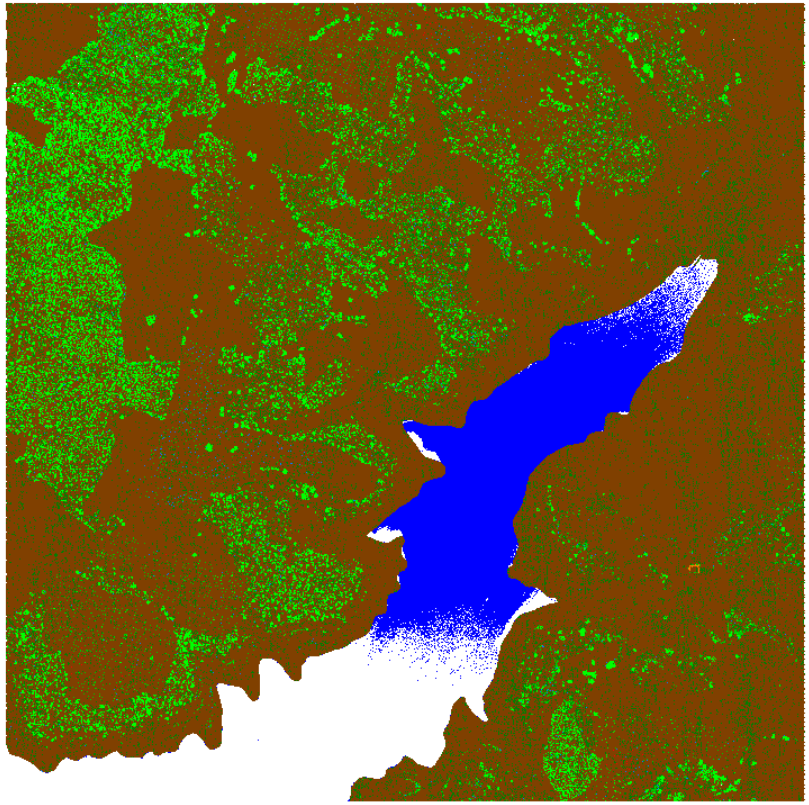
Indexes and filtering

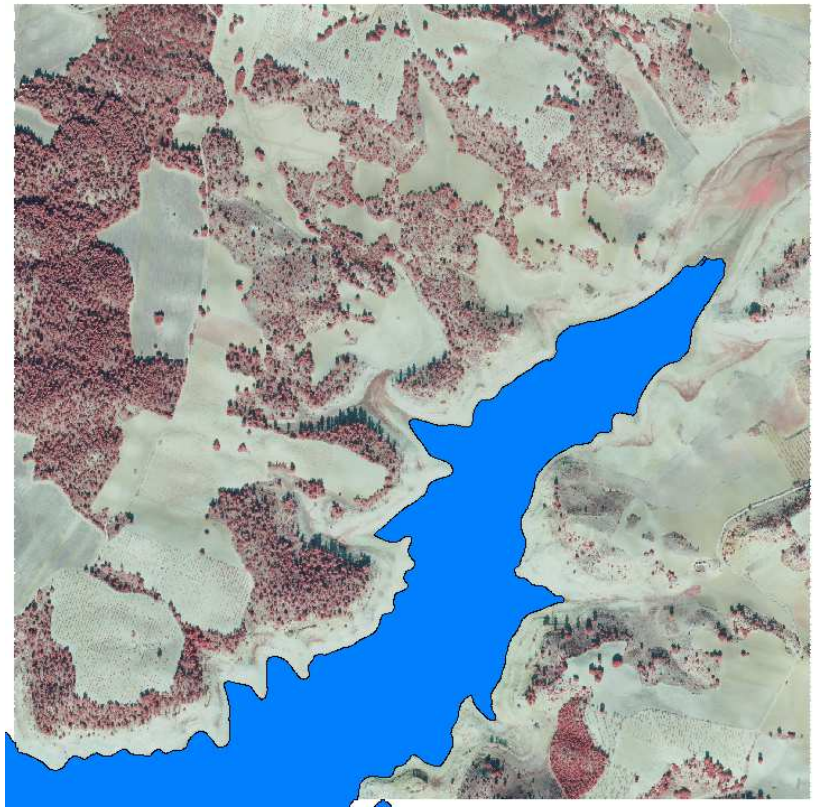
Slope and intersection with hydro model



Filtering of hydro model

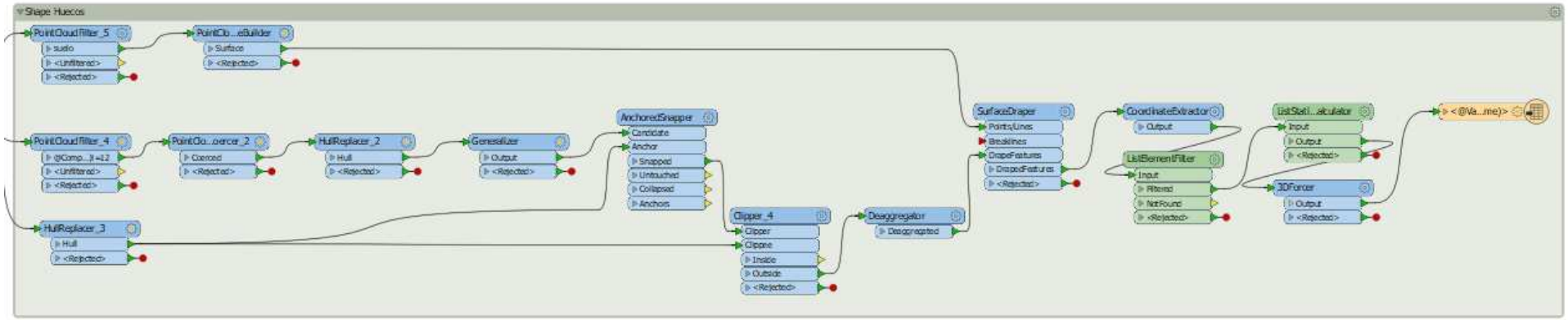
3. Methodology: water bodies

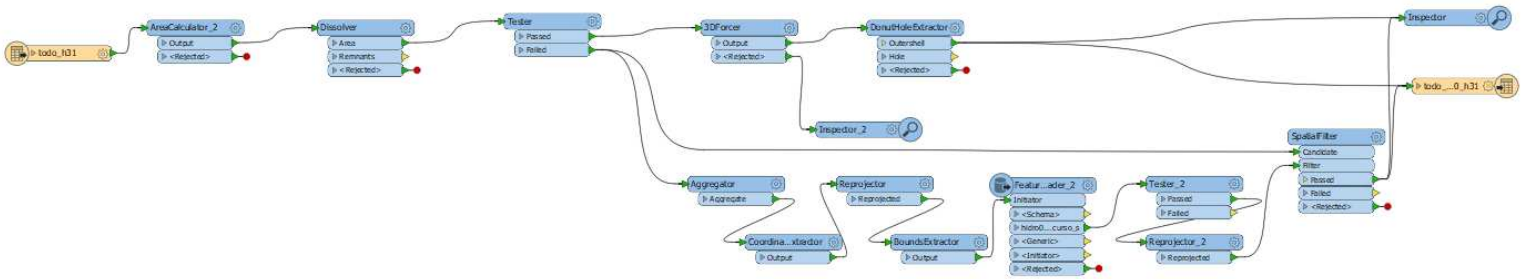




3. Methodology: water bodies

- Removal of points classified as water.
- Vectorization of empty areas where there was water
- Fusion of different areas





4. Results:

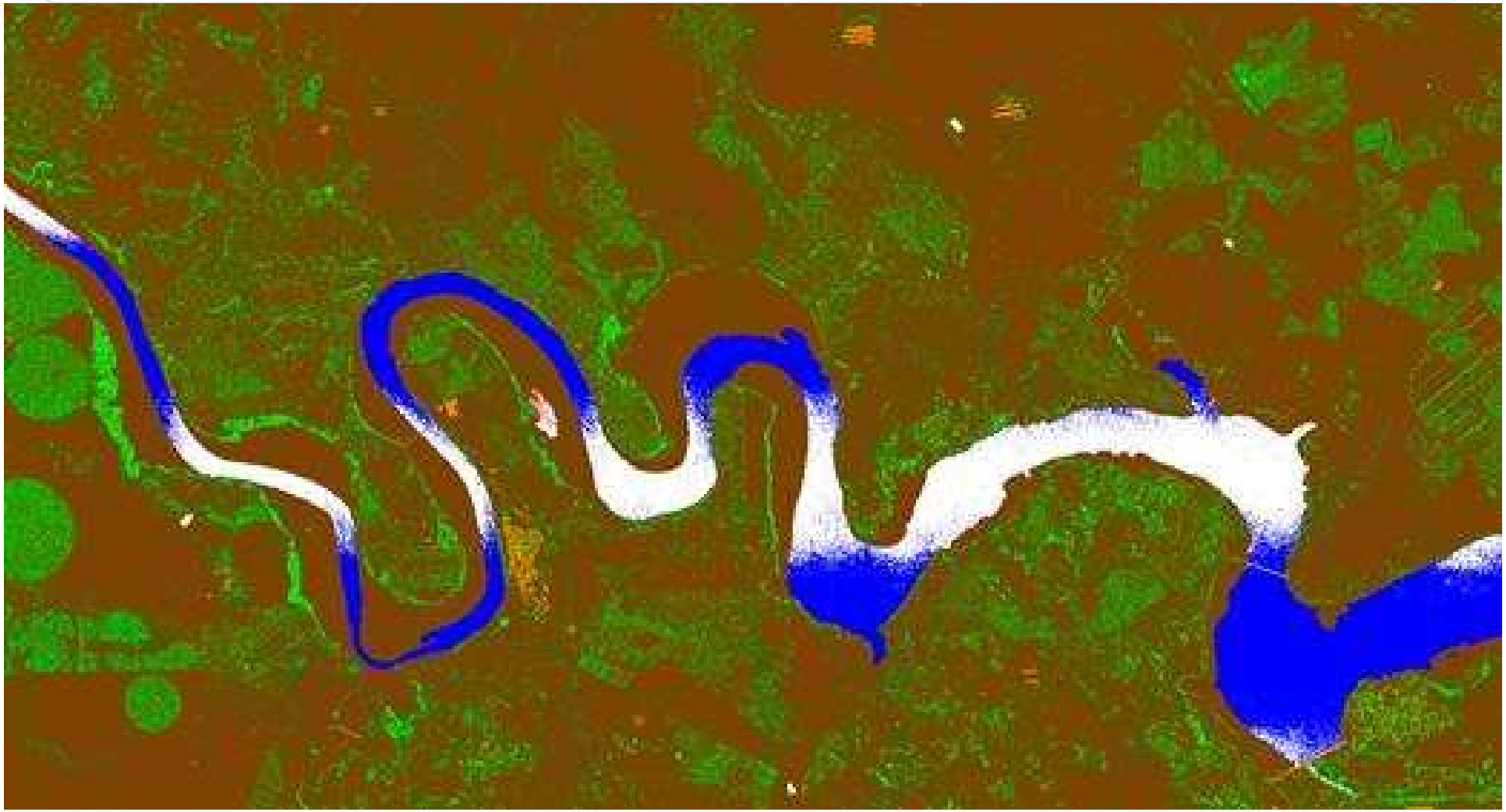
- Test Area of 1.000 km2
- Visual review: ortophoto acquired simultaneously with LiDAR used as ground truth.
- Rivers have been considered as a unique element, with some exceptions.

4. Results:

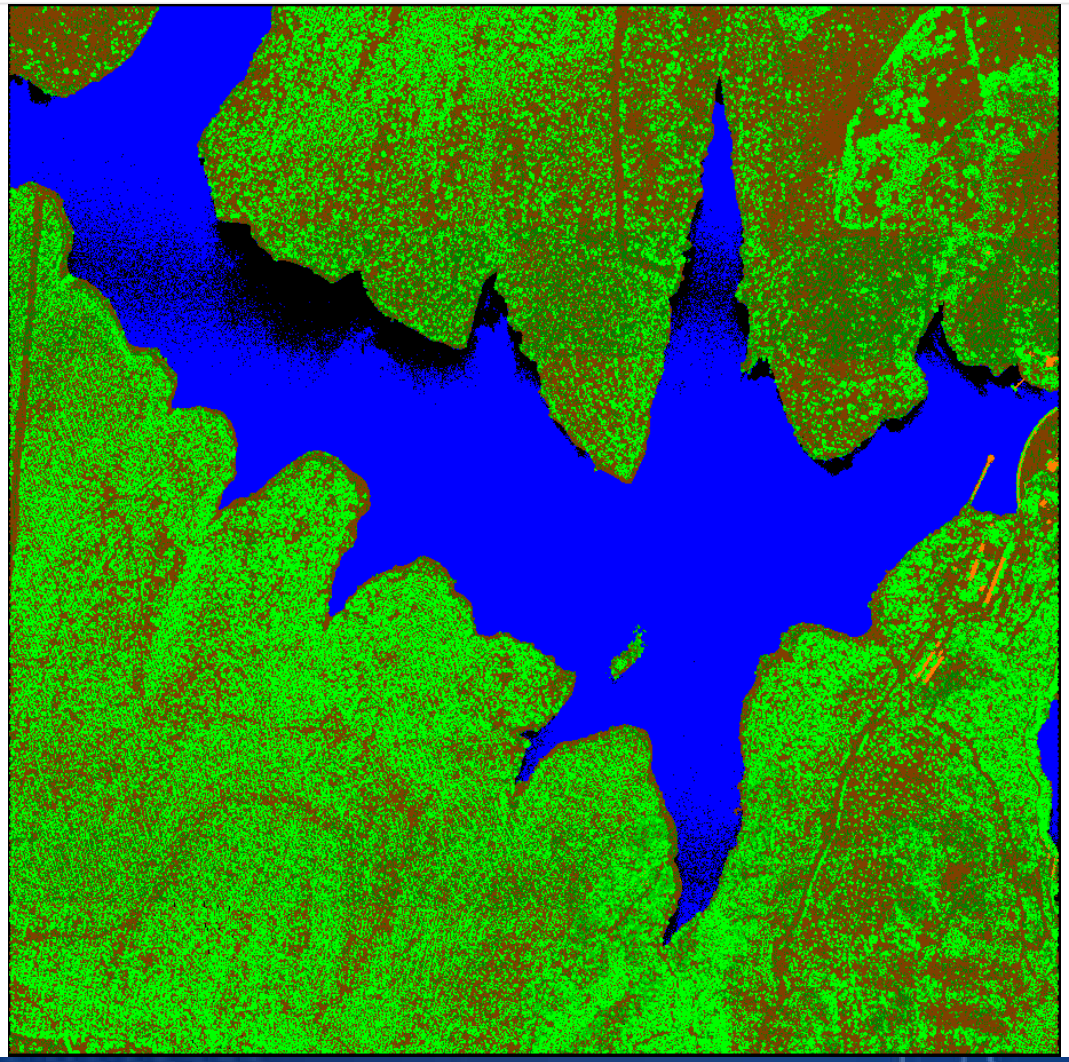
Type of detection	Number of water bodies	Percentage
Omissions	5	16%
Commissions	2	6%
Partial detections	5	16%
Full detections	20	63%
Total	32	100%

- 356.168 points have been classified as water
- 79% accuracy between full and partial detection

4. Results: Full detection

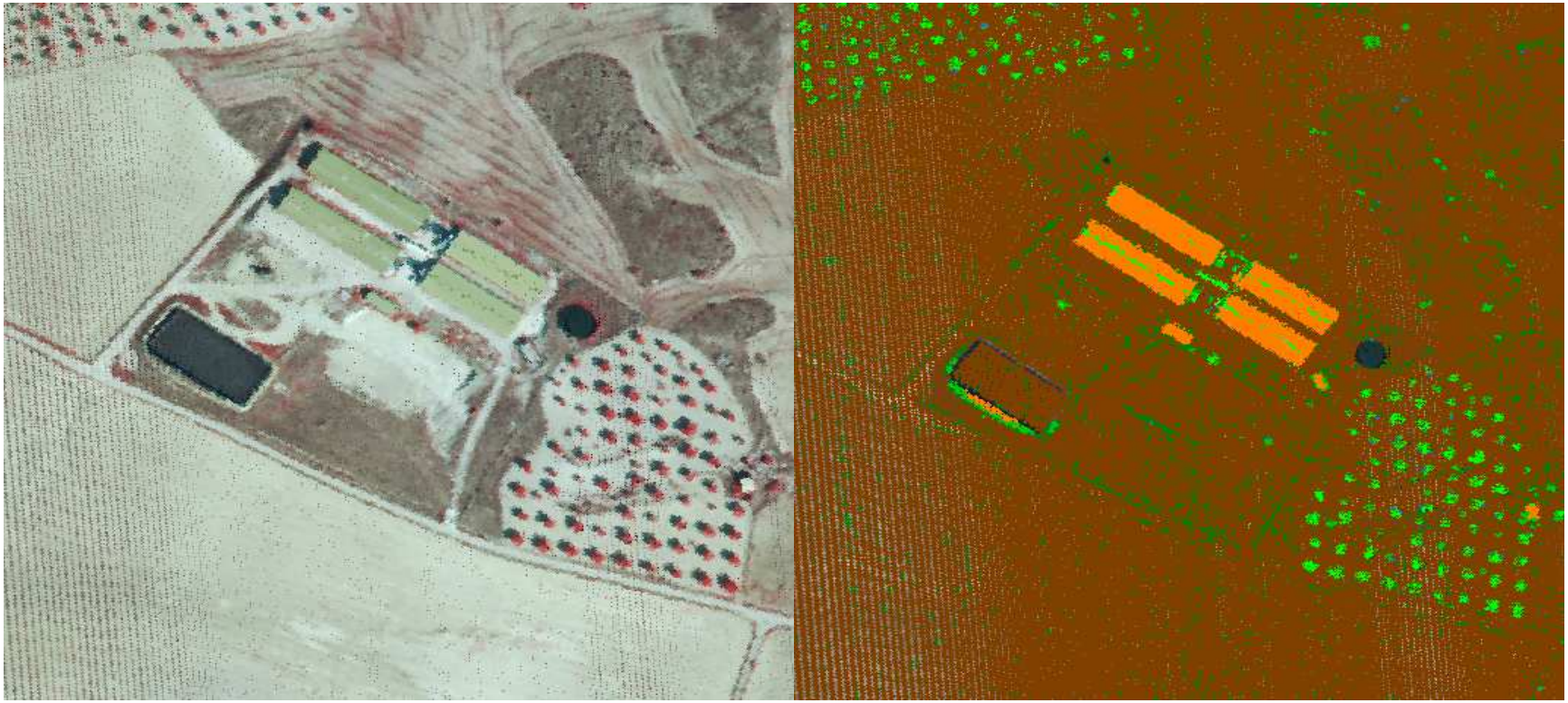


4. Results: Full detection



4. Results: Partial detection

4. Results: Omission



5. Conclusions:

- Low dependent on GRI-Hydro
- Automatic DTM hydro flattening from the water bodies generated.
- GRI-Hydro will use the water bodies generated for their model.
- Not able to classify water not seeing in the imagery (below trees) (obviously!!).
- Not working well in complicated rivers, as shown in the partial detection example.
- **Satisfactory results**, it is already part of the standard workflow → improves previous classification, small improvements are needed

5. Conclusions

❖ 5. Conclusions

- Improvement of LiDAR classification.

- Error reporter for the products used → future results will be more accurate.

<u>Future ideas</u>

- Implementation in CAD for manual edition.

- Data collected for the whole country in different years, conditions etc etc makes difficult the automatization → The algorithms would need some parameter of machine learning.

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National Geographic Institute

Thank you for your attention

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