



Characterizing ligneous resources by using remote sensing

From trees outside forests to forest stands

04/06/2020 – Corentin Bolyn

Interreg

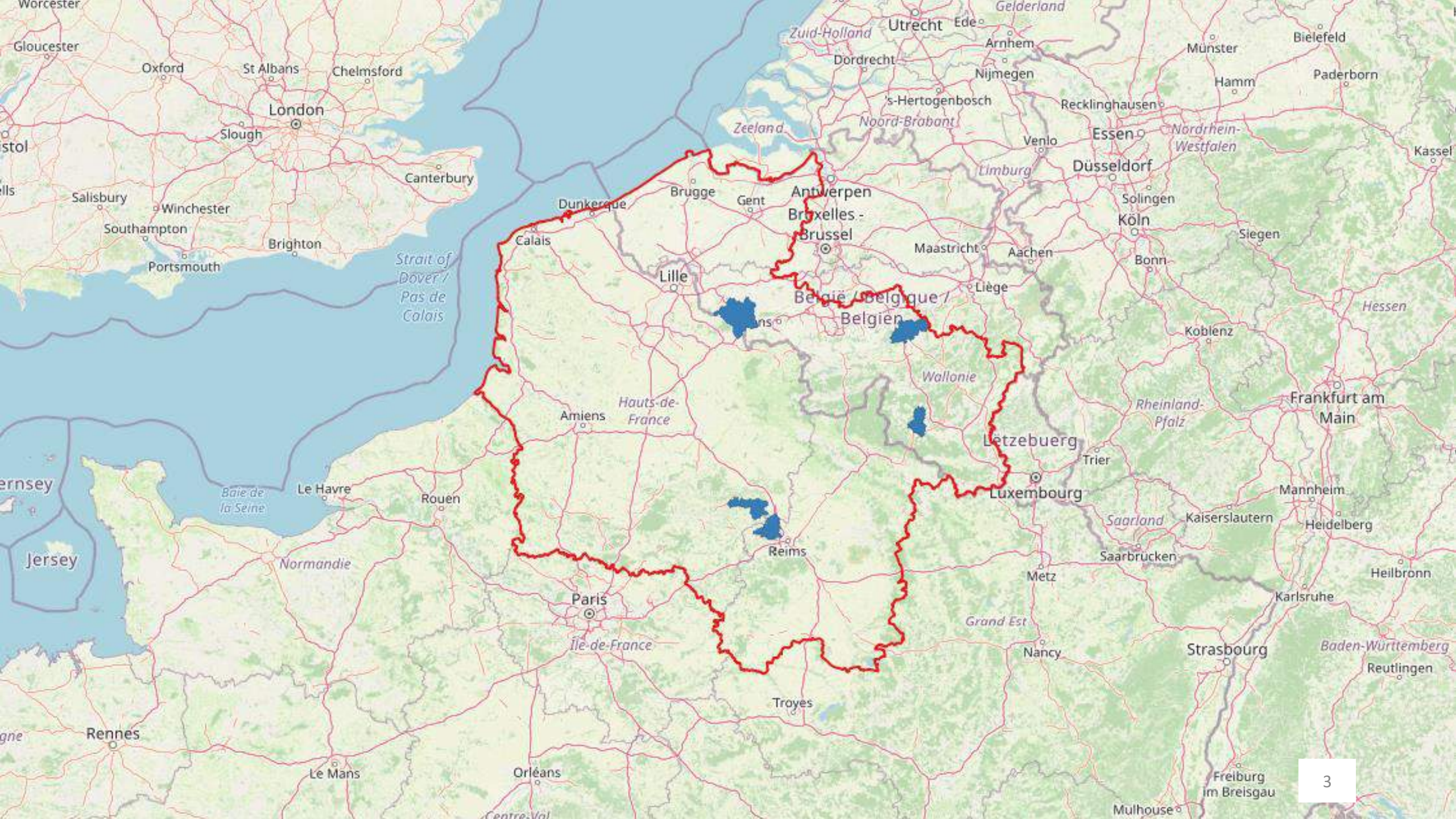
France-Wallonie-Vlaanderen



UNION EUROPÉENNE
EUROPESE UNIE

Feel Wood

Forêt Pro Bos



Forêt Pro Bos – remote sensing as a tool for the good management of our territories

- Improve our knowledge about the distribution and evolution of timber resources located in the Interreg project area
- Three development goals related to remote sensing :
 - Mapping main timber resources forest species
 - Mapping ligneous elements outside forests
 - Characterizing the development stages of poplar stands

Ligneous elements in the landscape
From trees outside forests ...



... to forest stands



According to their development stage, forestry plantations can belong to both categories

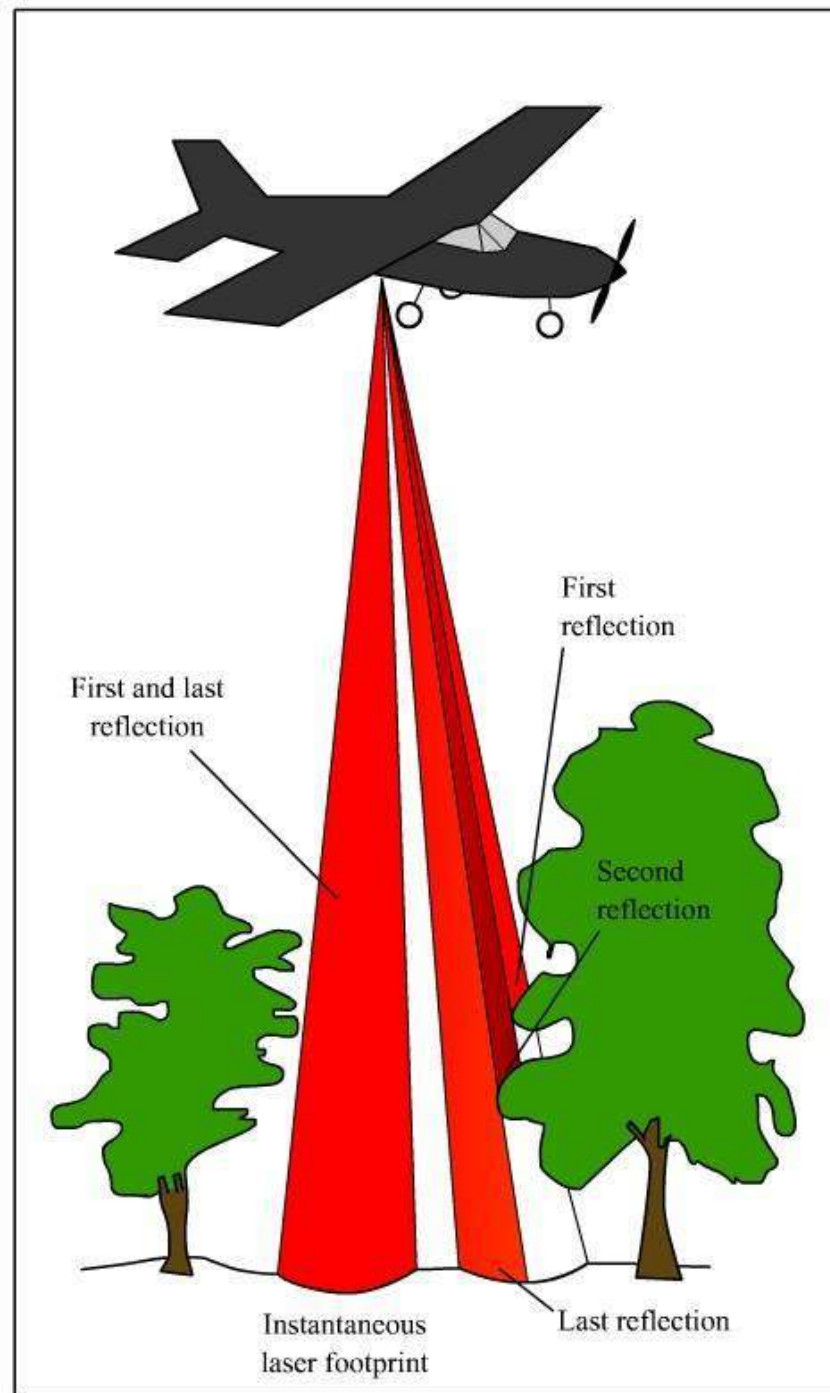


Mapping and characterizing trees outside forests by using the LiDAR technology

- Requires very high spatial resolution data
 - Delineating small ligneous elements
 - Differentiating immediate environment : herbaceous vegetation, man-made elements.

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- Mapping method exclusively based on aerial LiDAR

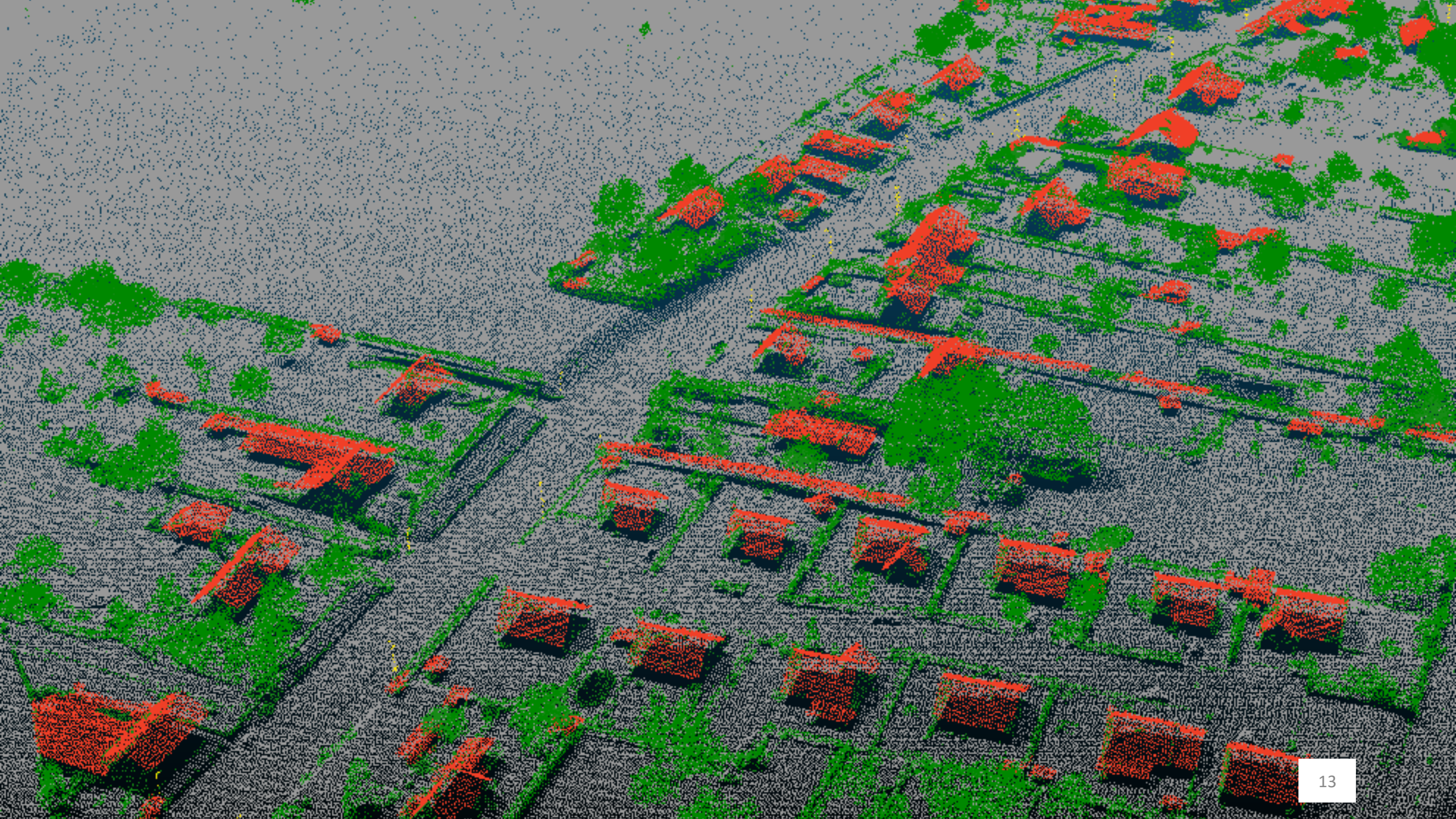


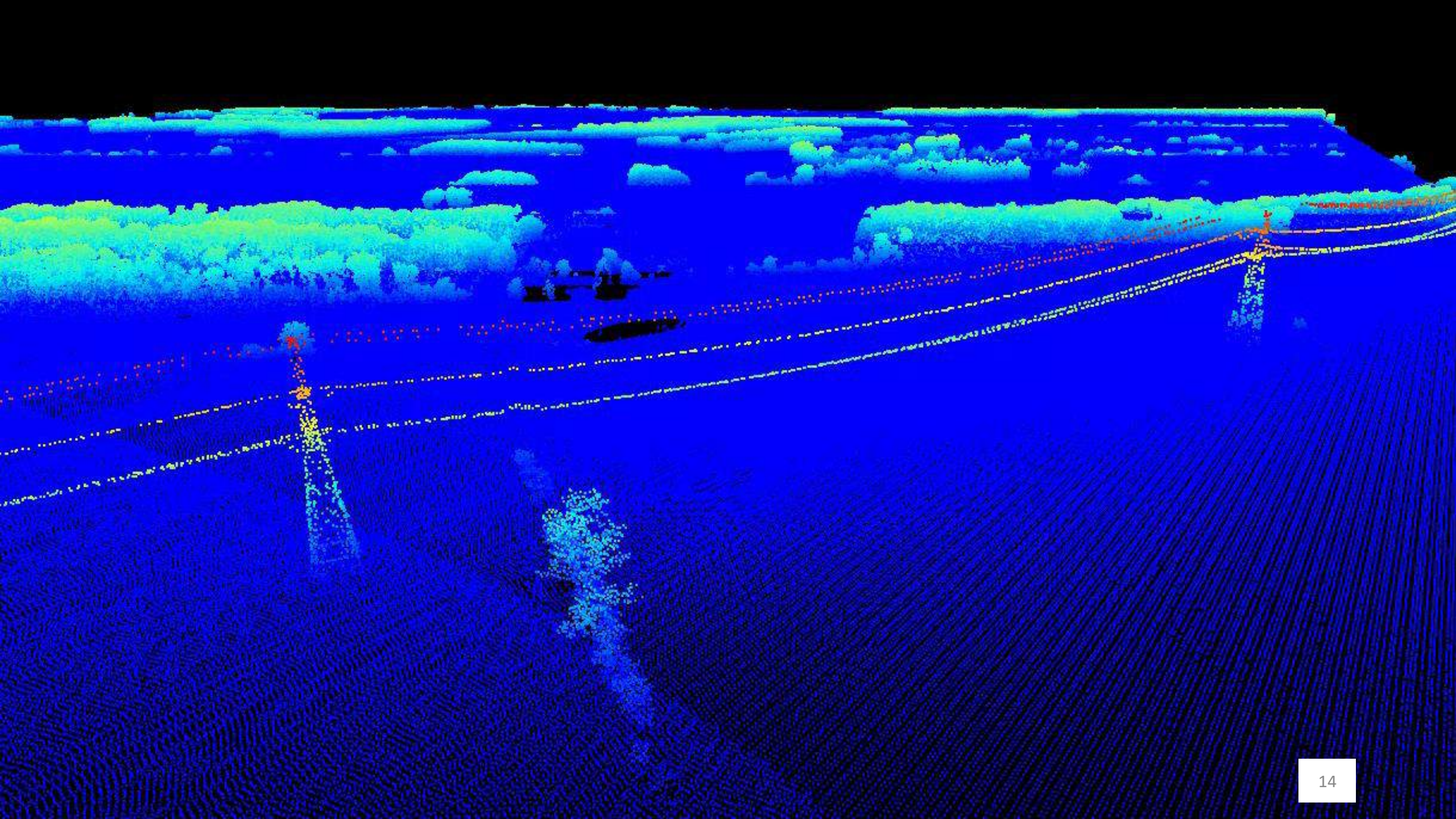
4 steps methodology

1. Identify « ground » points and normalize the point cloud

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2. Identify all the points corresponding to ligneous elements
3. Make the distinction between forest stands and trees outside forests

Definition of a forest

- FAO definition
 - *Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ*



4 steps methodology

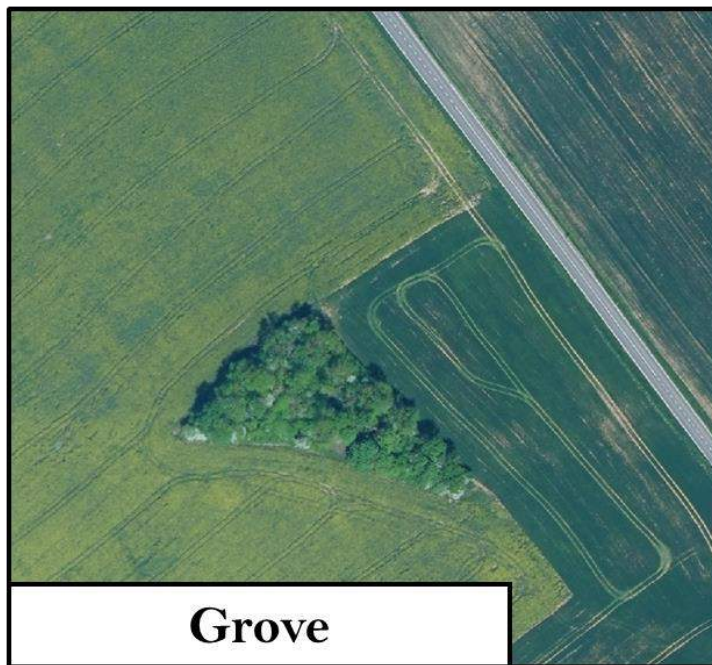
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3. Make the distinction between forest stands and trees outside forests
4. Classification of ligneous elements located outside forests

Typology of trees outside forests

- **Grove** : continuous and non-linear element spanning more than 400 m²
- **Agglomerated trees** : a group of ligneous elements standing less than 10 m apart and that are not aligned (e.g. orchards) ;
- **Aligned trees** : an alignment comprised of at least 5 ligneous elements standing less than 10 m apart ;
- **Hedges** : continuous and linear element being at least 10 m long and not exceeding 20 m in width. The length/width ratio is above 3. The hedge sections standing less than 5 m apart are considered as part of the same hedge ;
- **Isolated trees** : ligneous elements comprising only one tree, standing more than 5 m away from any other mapped element. The corona projected on the ground spans at least 12,6 m², corresponding to a 4 m diameter disk ;
- **Shrub** : isolated ligneous elements, standing more than 5 m away from a grove, a hedge or a forest and more than 10 m away from another ligneous element. This category includes shrubs, bushes and groves not exceeding a surface of 400 m² ;
- **Others** : comprises elements of over 2 m which are not meeting the above-mentioned criteria



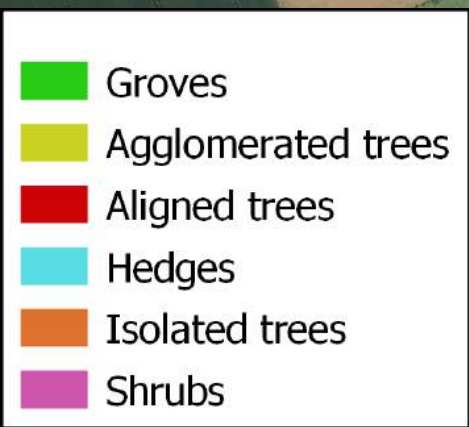
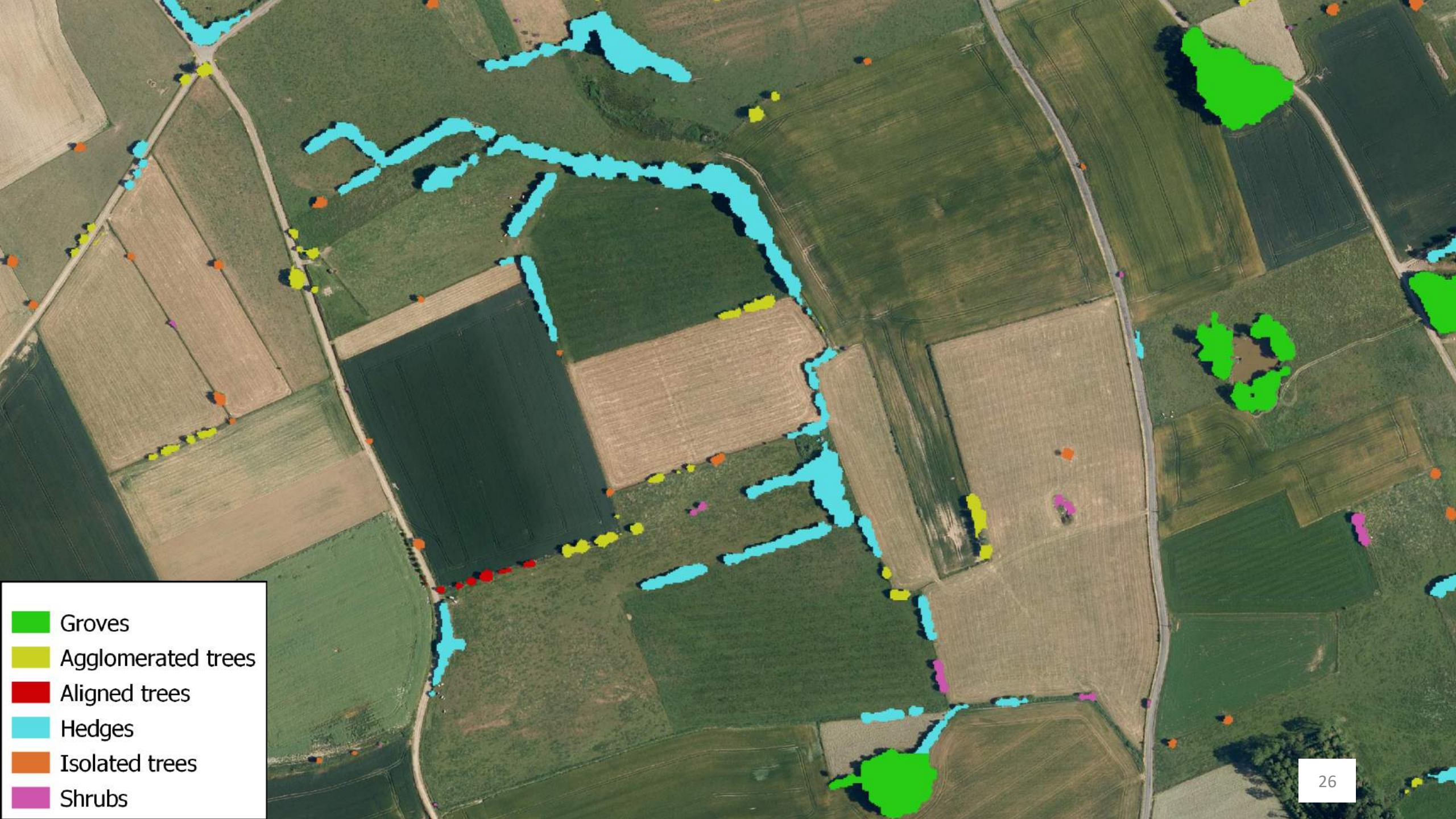
Classifying ligneous elements located outside the forest

- 1st step : classifying the various elements into three classes :
 - Small size ligneous elements
 - Groves (surface area $> 400 \text{ m}^2$)
 - Linear elements (minimum length : 10 m, maximum width : 20 m, (length/width) > 3)

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 - Groves (surface area $> 400 \text{ m}^2$)
 - Linear elements (minimum length : 10 m, maximum width : 20 m, (length/width) > 3)
- 2d step : algorithm comprising proximity criteria in order to achieve the final classification into 6 categories





Accuracy, strengths and weaknesses

- Strength: automated processing chain that can be applied to any other LiDAR data set

Accuracy, strengths and weaknesses

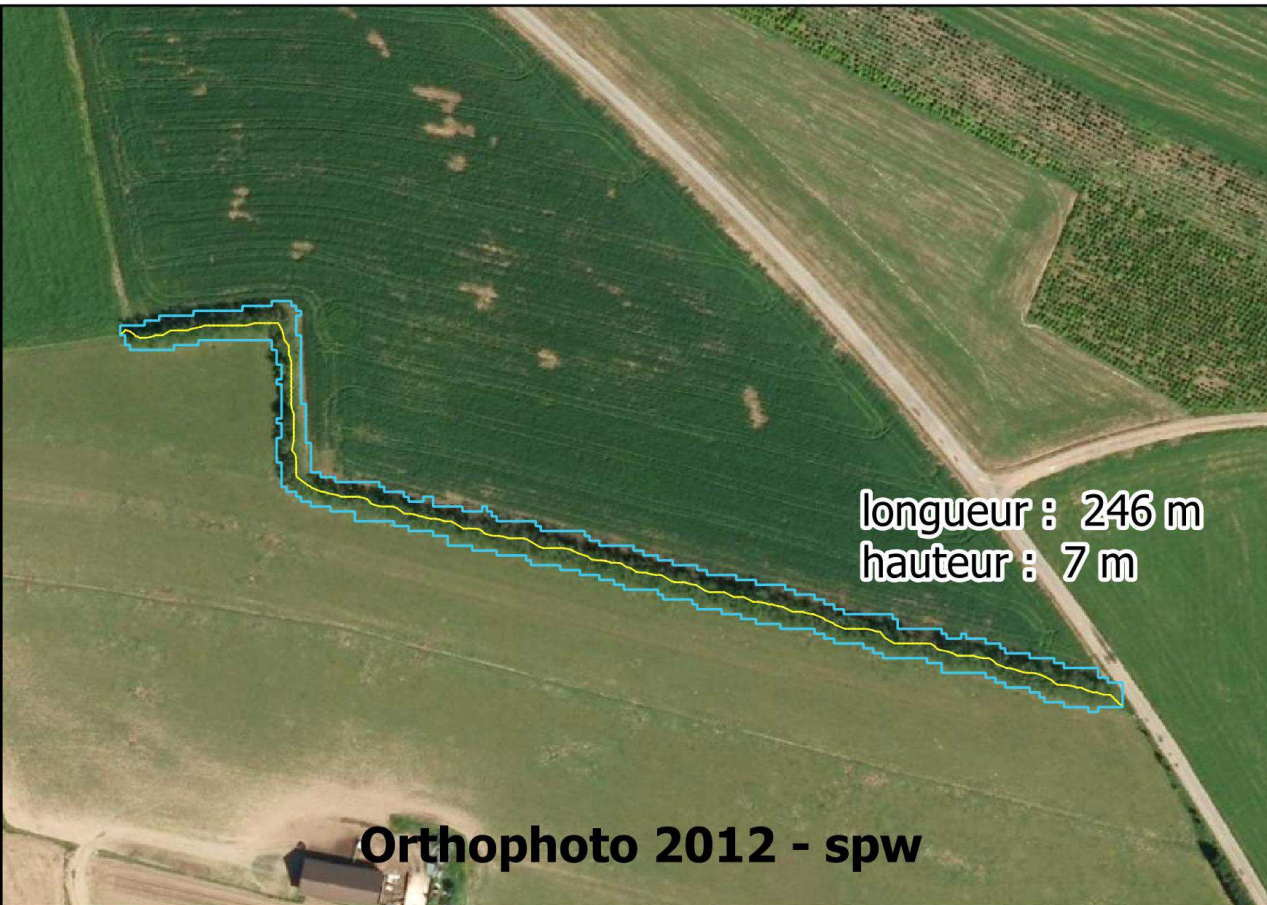
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- Source of error : confusion between ligneous elements and non-ligneous elements exceeding 2 m
- Using photointerpretation in order to assess the classification of ligneous elements in agricultural areas : 93 % accuracy

Further analyses

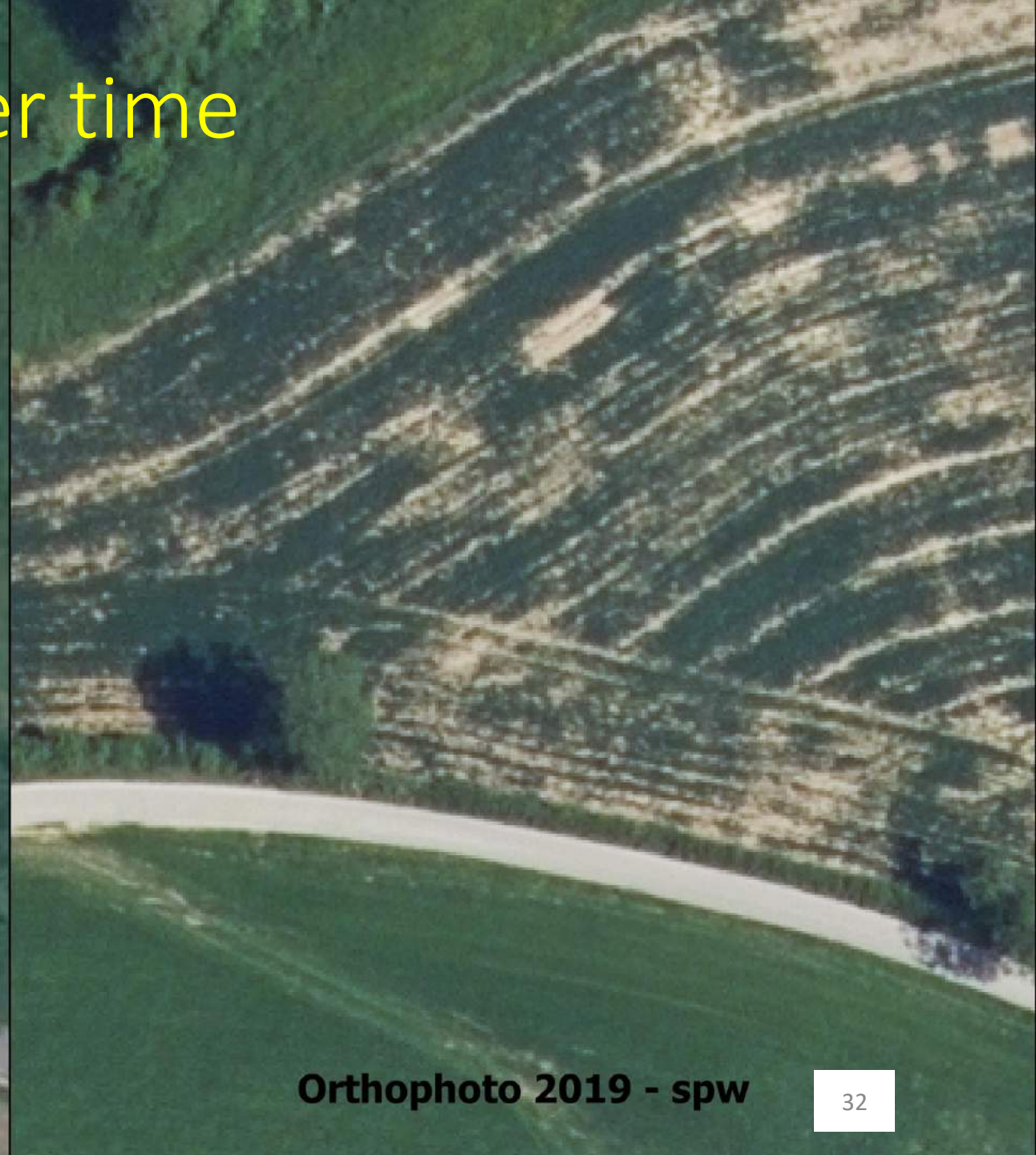
Detection of changes over time



Detection of changes over time

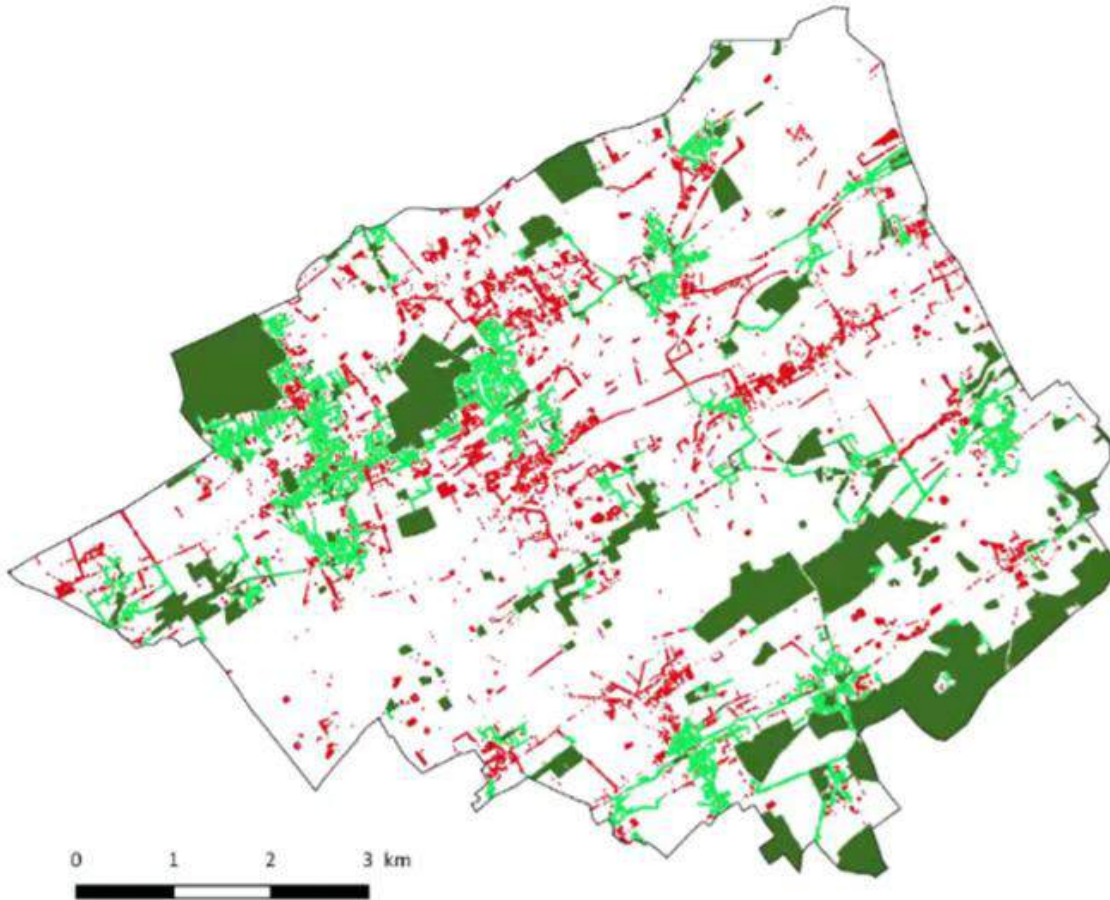


Orthophoto 2012 - spw

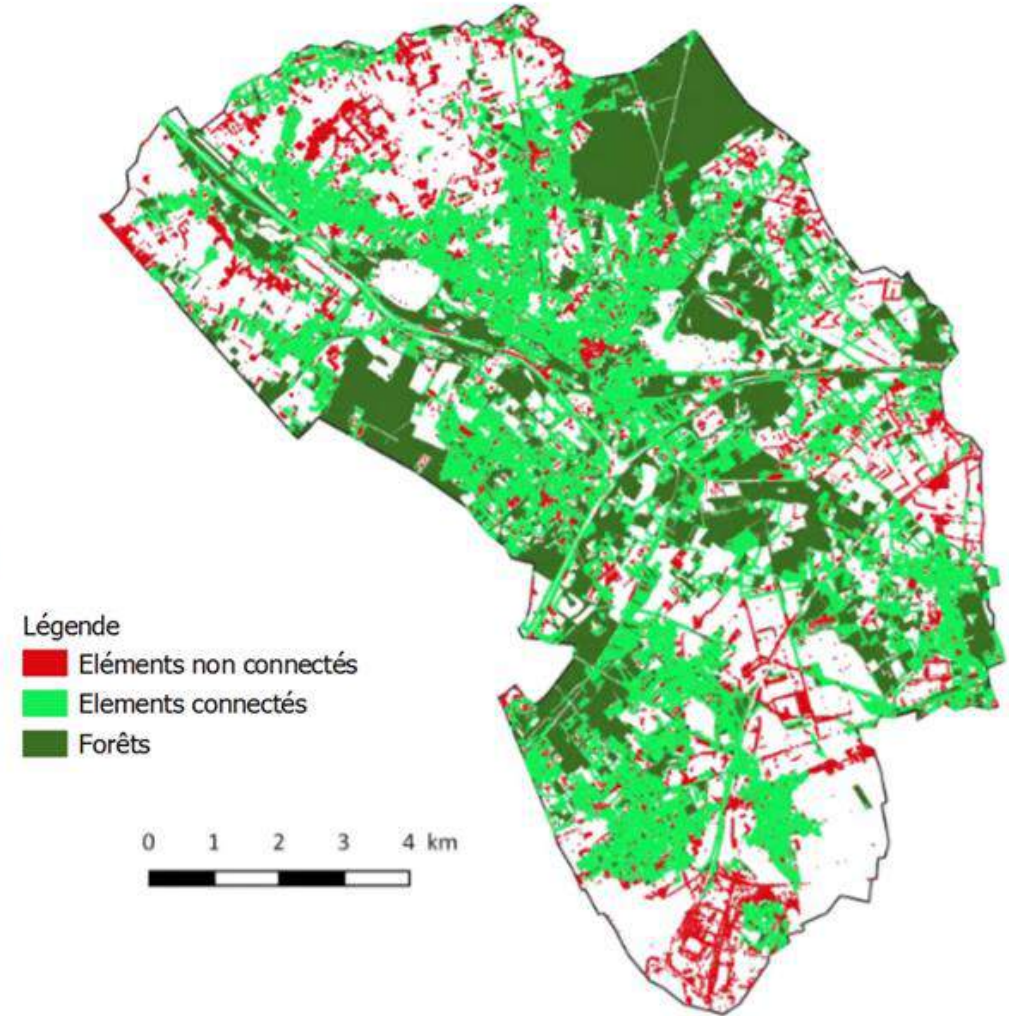


Orthophoto 2019 - spw

Connectivity analysis



Ohey municipality : 55 %



Condé sur l'escaut area : 84 %

Results in young plantations ?



Sensing of poplar plantations

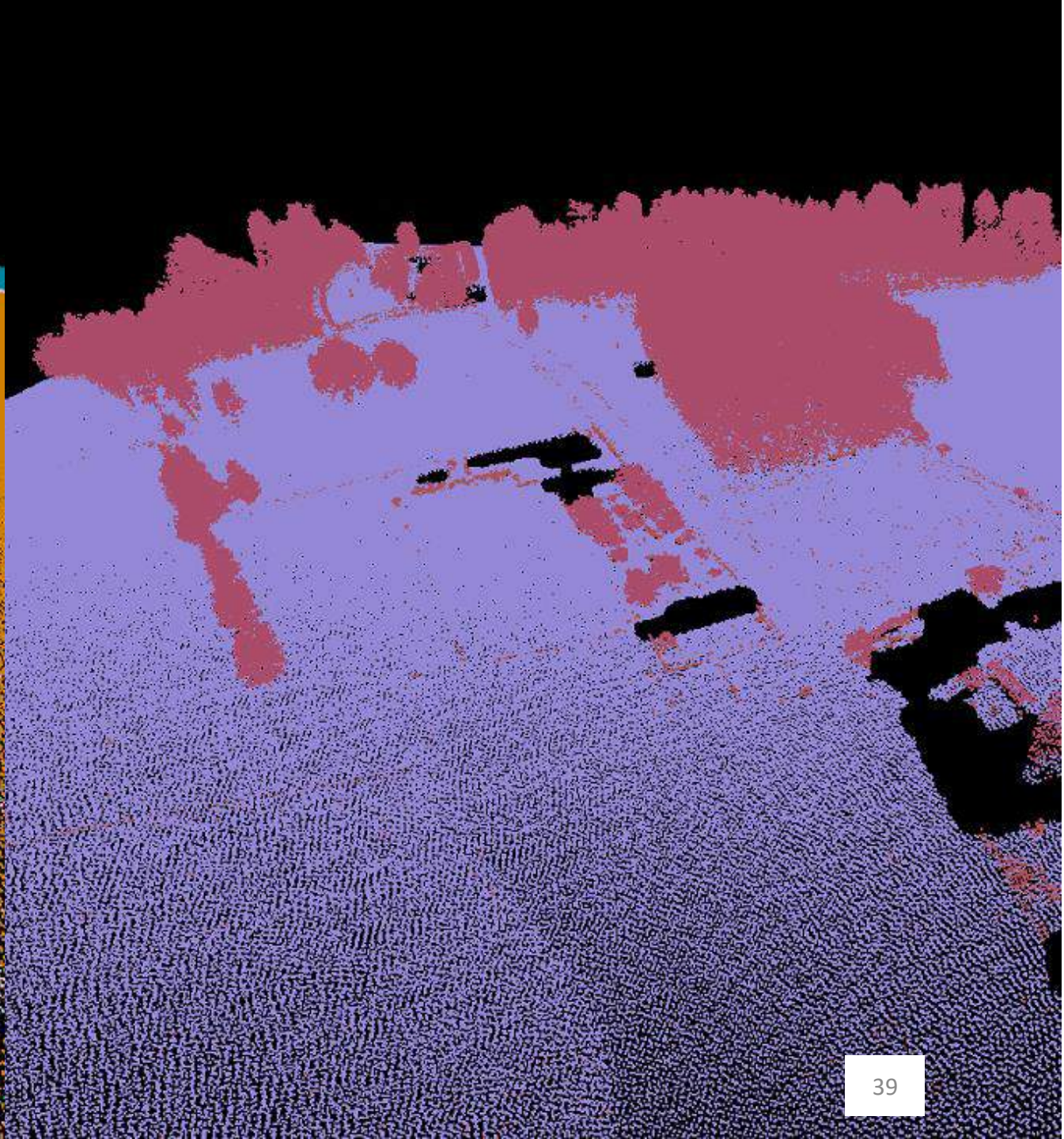
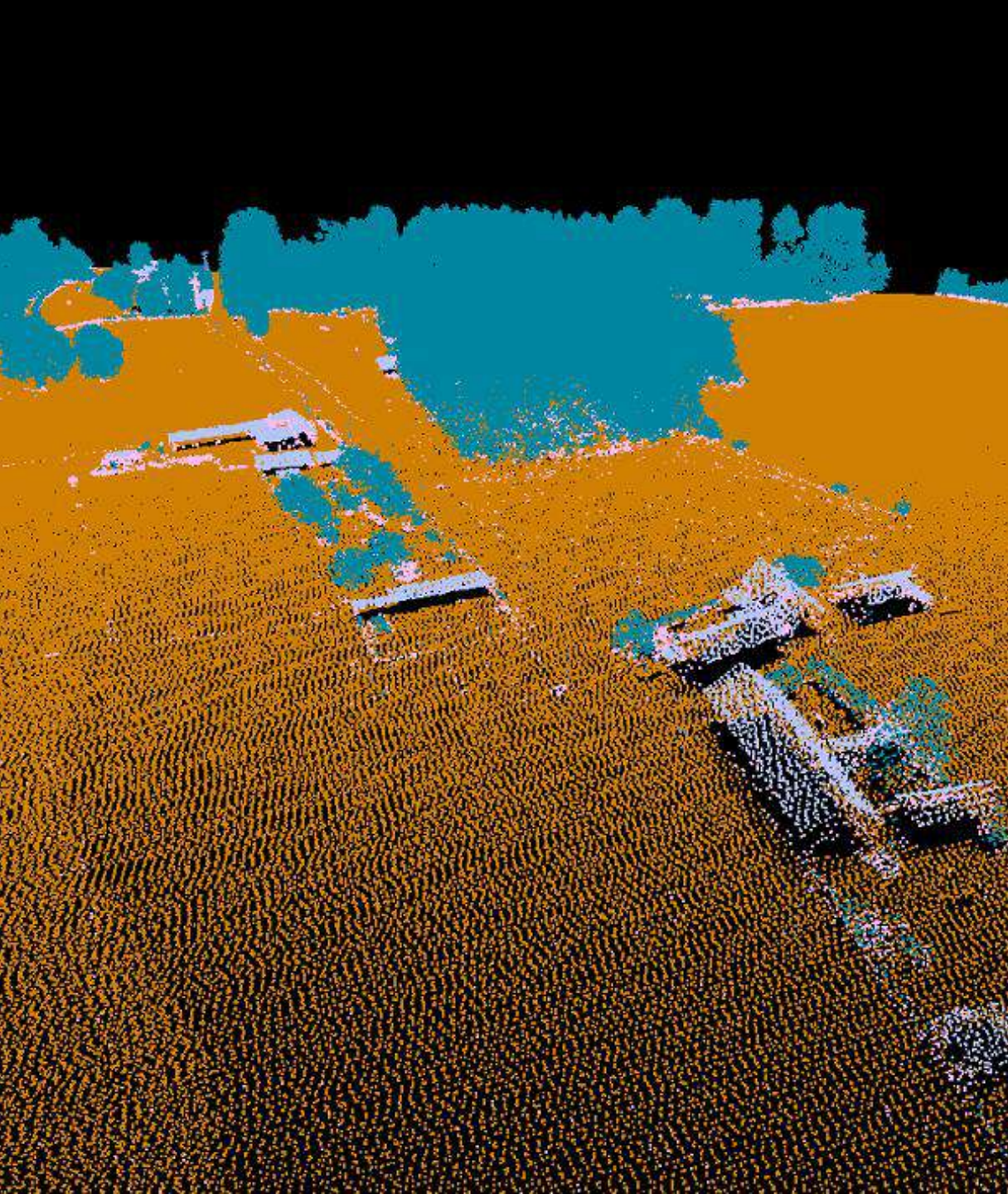
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 - Accurate positioning of trees inside the plantation
 - Detecting plants that have a small crown
 - Differentiating the immediate environment : regrows

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Methodology

1. Identify « ground » points and normalize the point cloud
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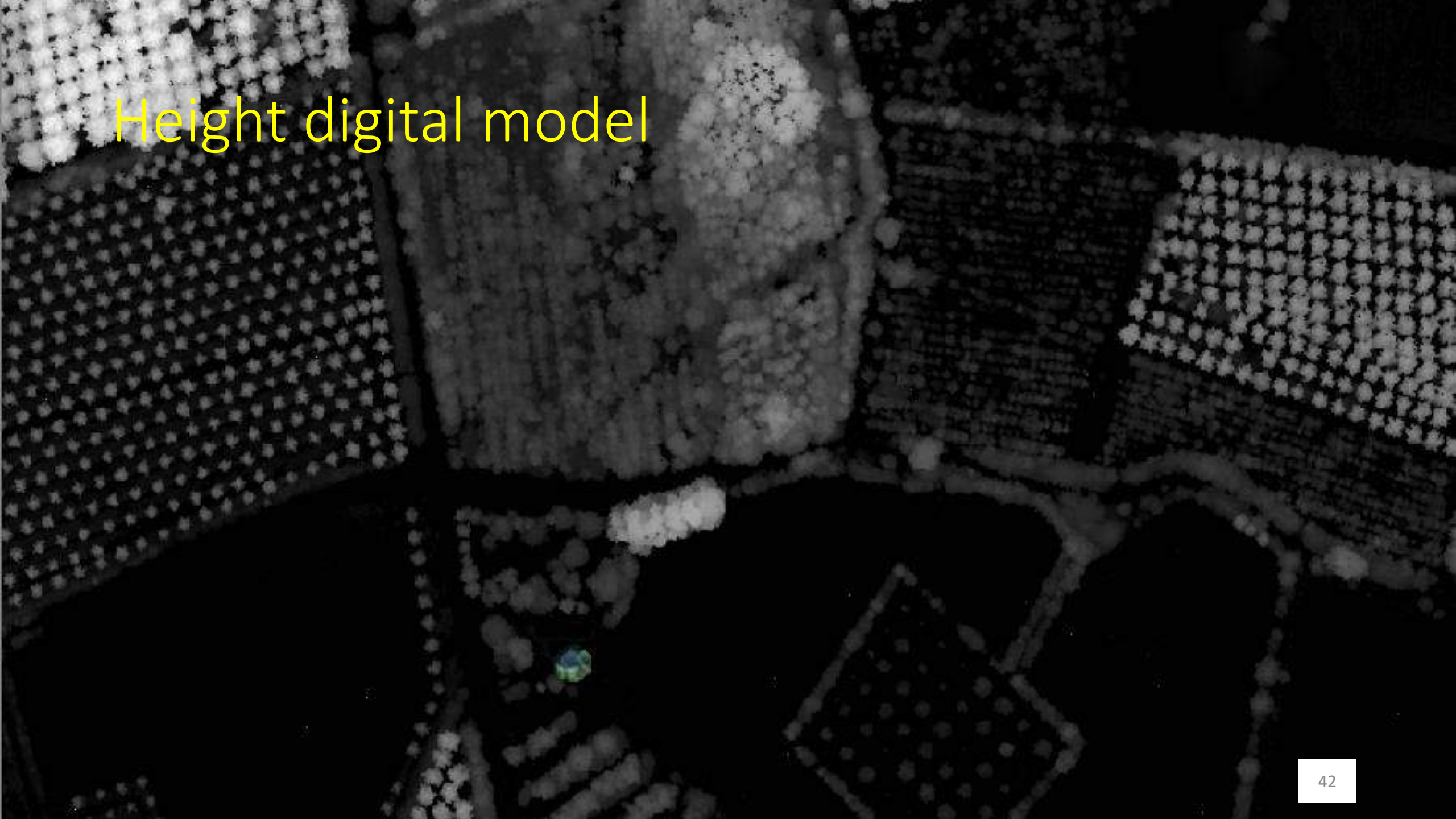


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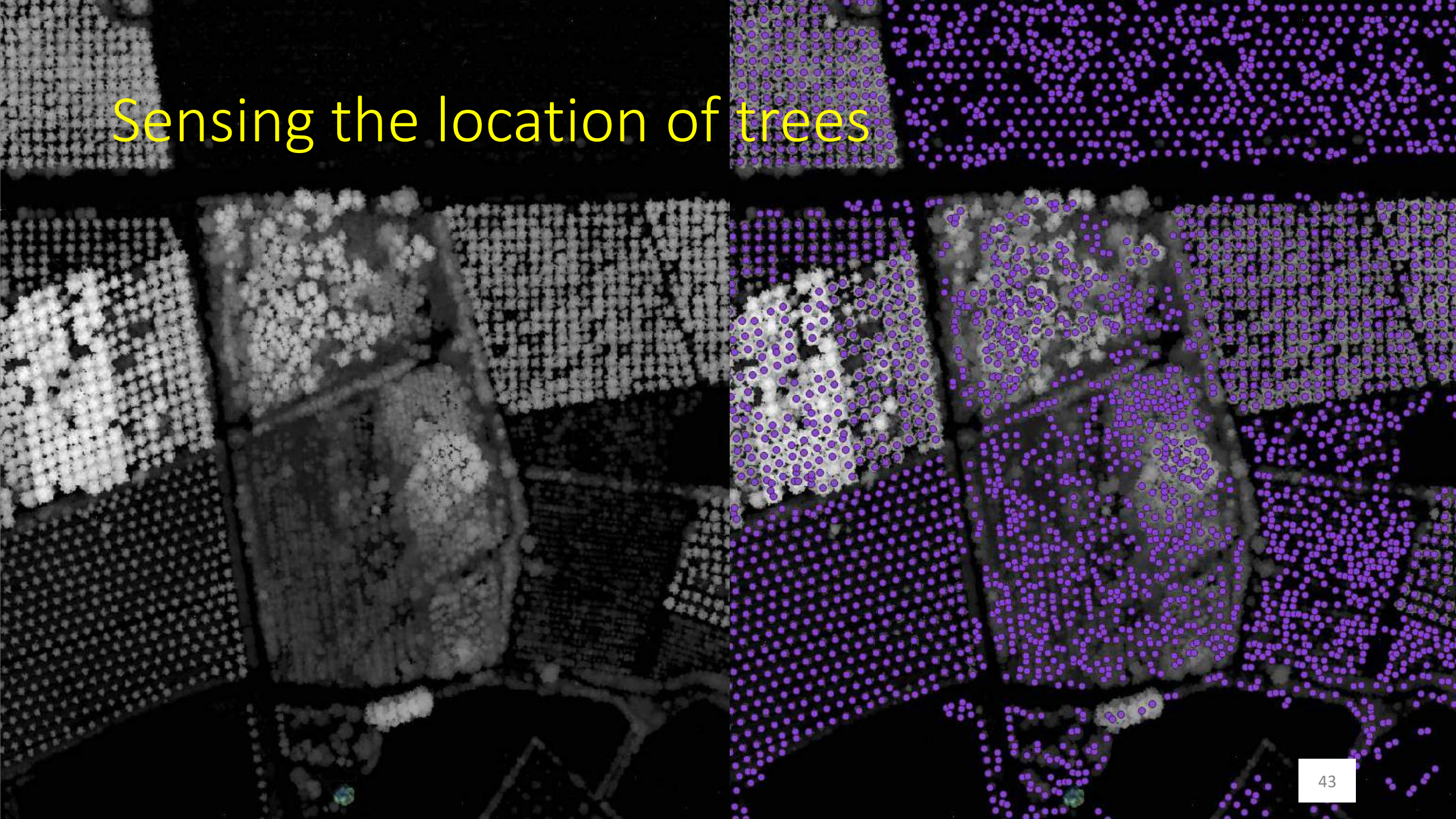
Methodology

1. Identify « ground » points and normalize the point cloud
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3. Sensing the location of trees and per stratum clustering
 - Geographic proximity (x, y, z)
 - Proximity of texture indexes measured around the tree

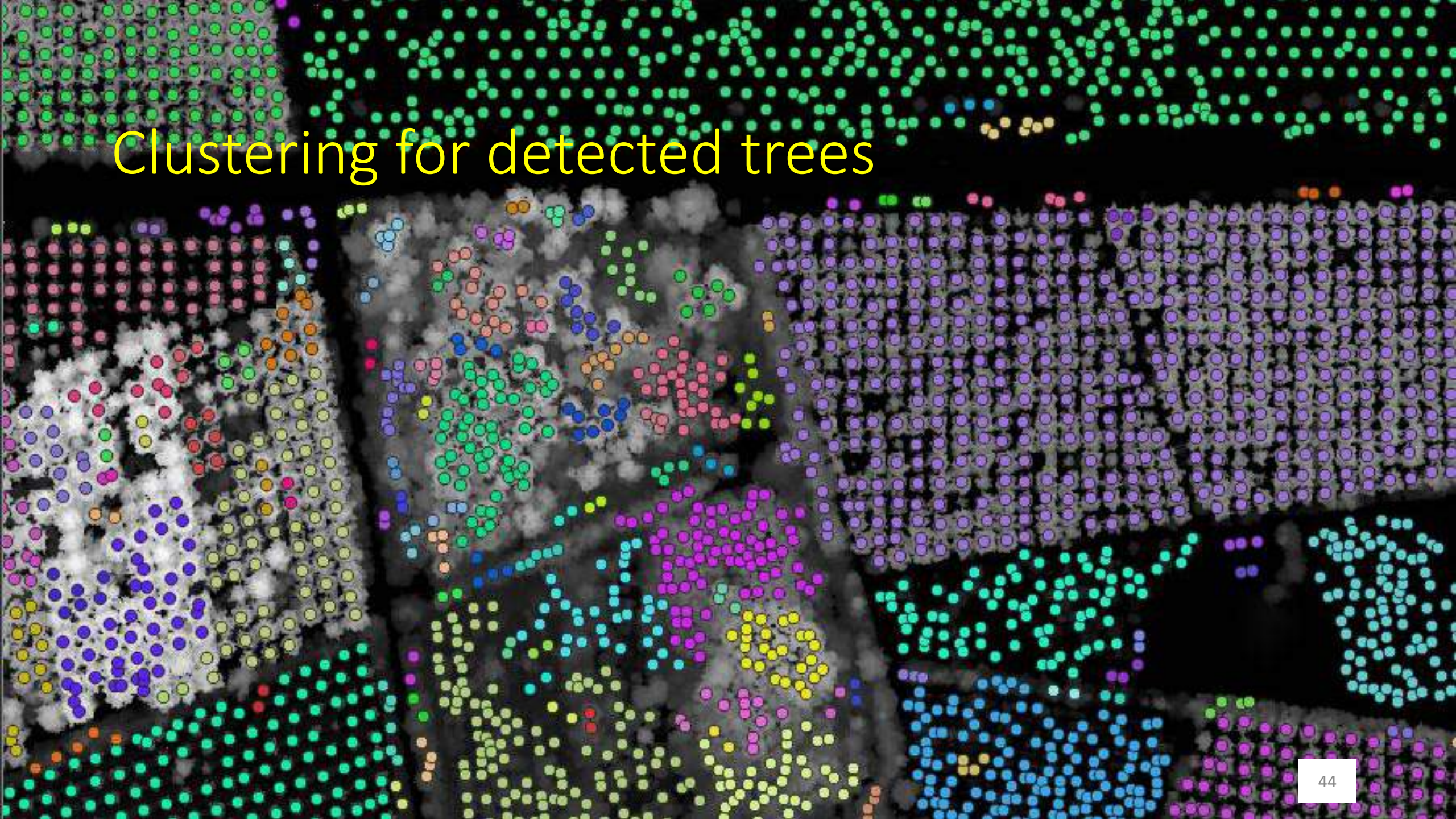


Height digital model

Sensing the location of trees



Clustering for detected trees

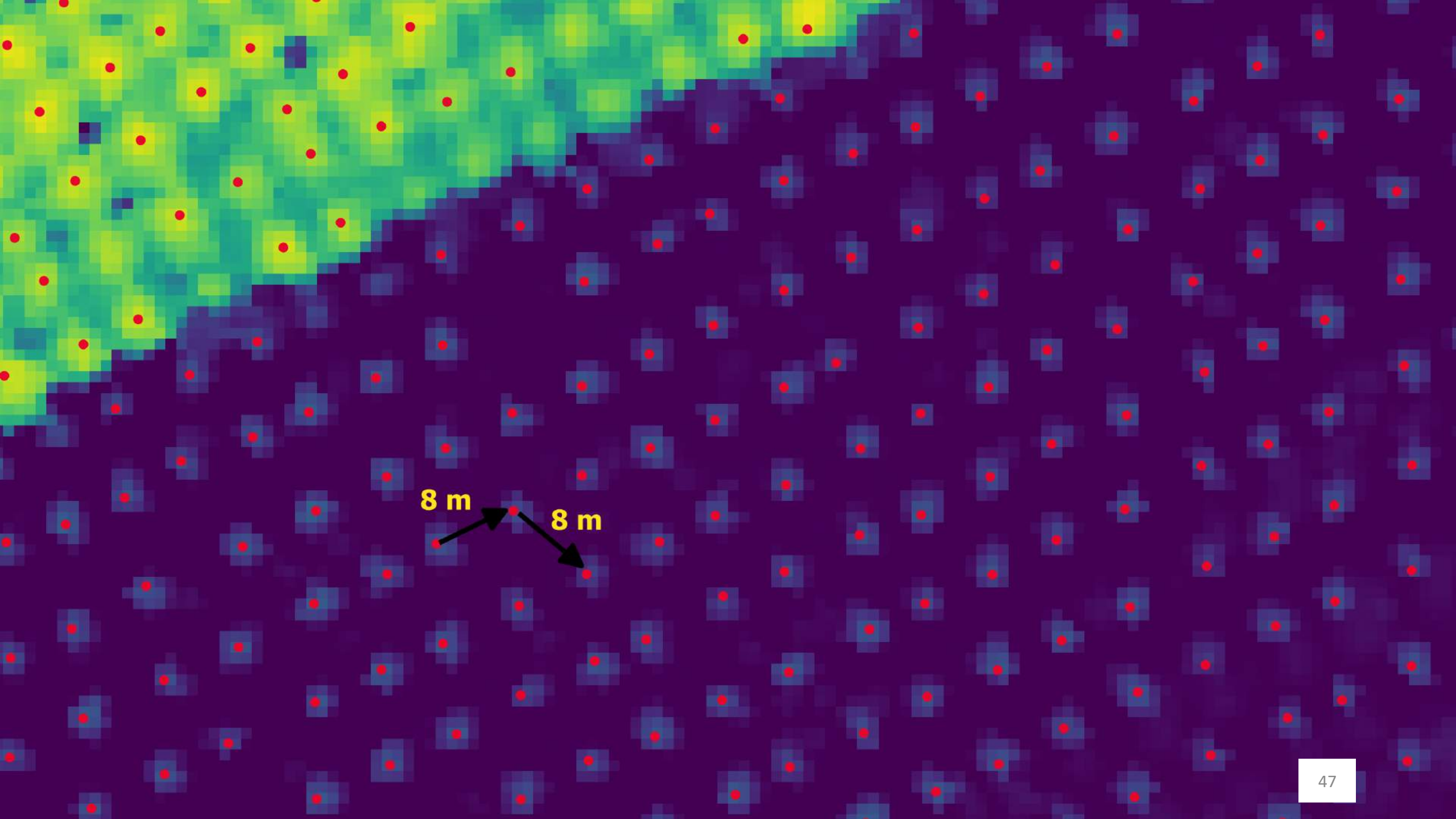


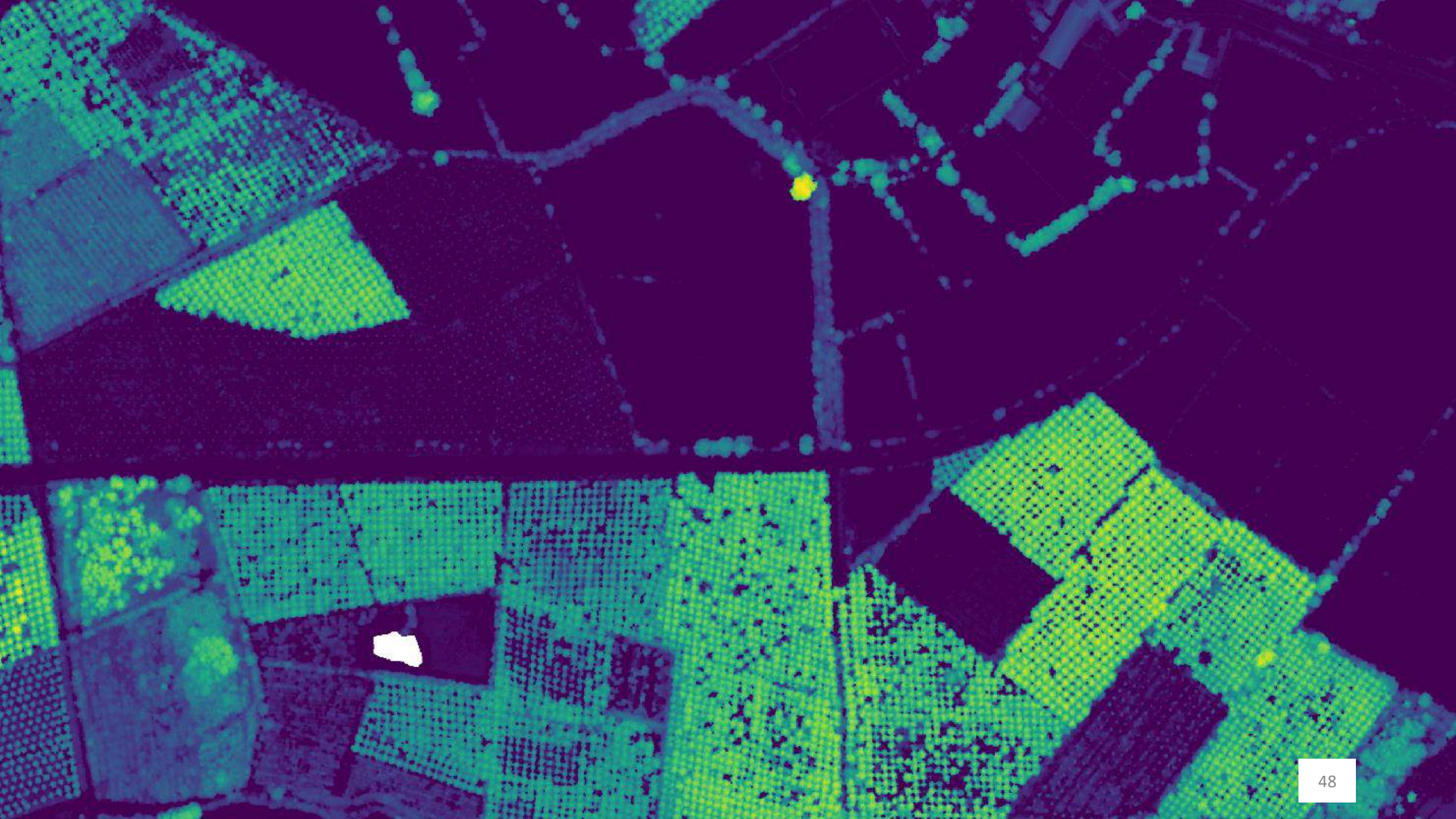
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3. Sensing the location of trees and per stratum clustering
4. Sensing the « plantation » pattern (8 X 8 m)
 - Algorithm comprising distance matrices
 - Tree group index representing the proportion of points laid out in a 8 X 8 m grid

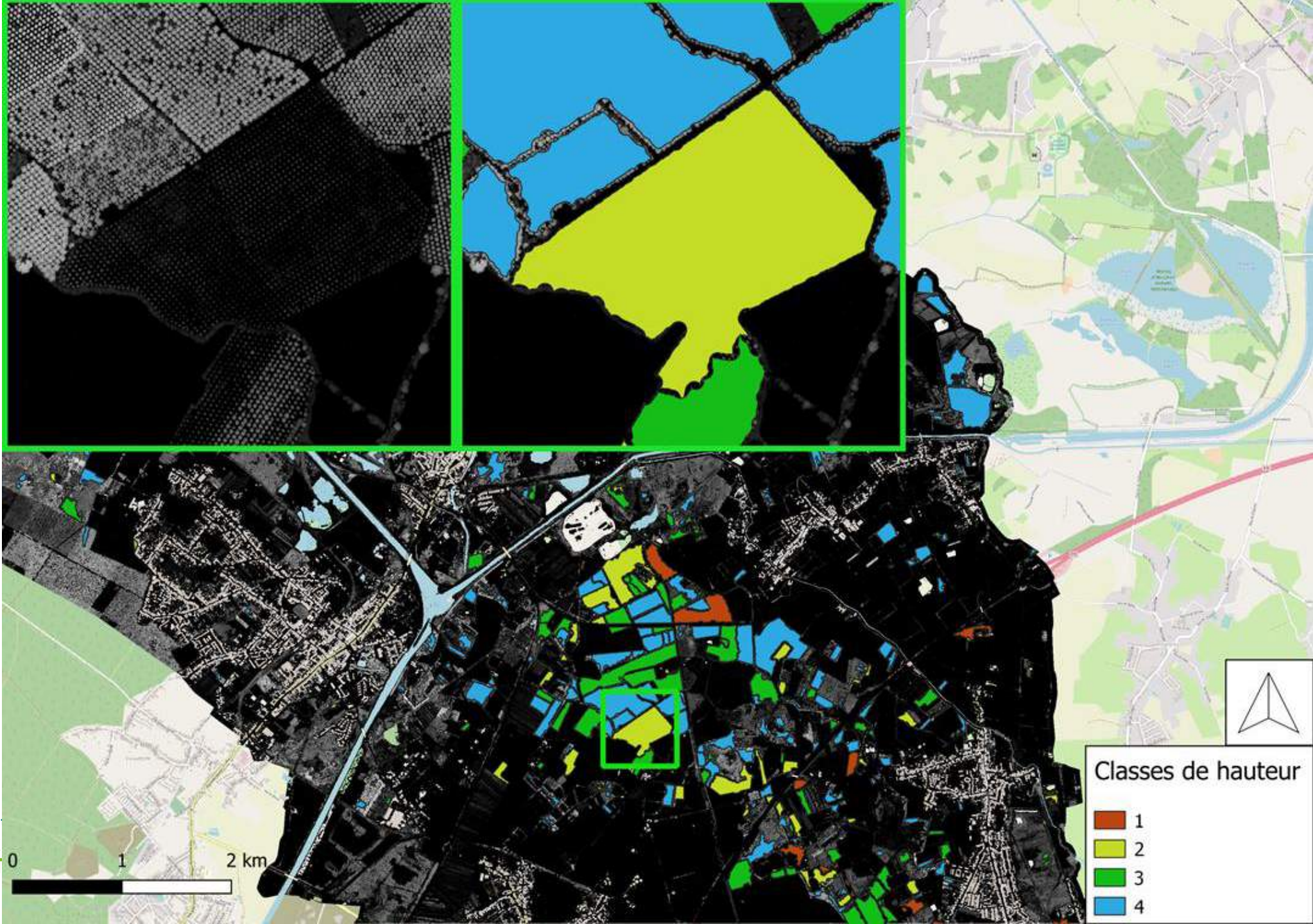








- $< 4 \text{ m}$
- $[4 \text{ m} , 12 \text{ m} [$
- $[12 \text{ m} , 20 \text{ m} [$
- $> 20 \text{ m}$



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- Weakness: solely based on the trees layout, noise-sensitive
- Accuracy analysis: based on MNH LiDAR photointerpretation and knowledge of the ground

- Grid 100 x 100 m
- Sensing accuracy for the plantations by height categories

Class	Nord	Marne	Aisne
1	0.996	1.000	0.999
2	0.976	0.986	0.966
3	0.970	0.963	0.927
4	0.884	0.946	0.926

Results in mature forest plants ?



- $< 4 \text{ m}$
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Results in mature forest plants ?

- Complementary approach combined with the mapping of timber species through satellite imagery

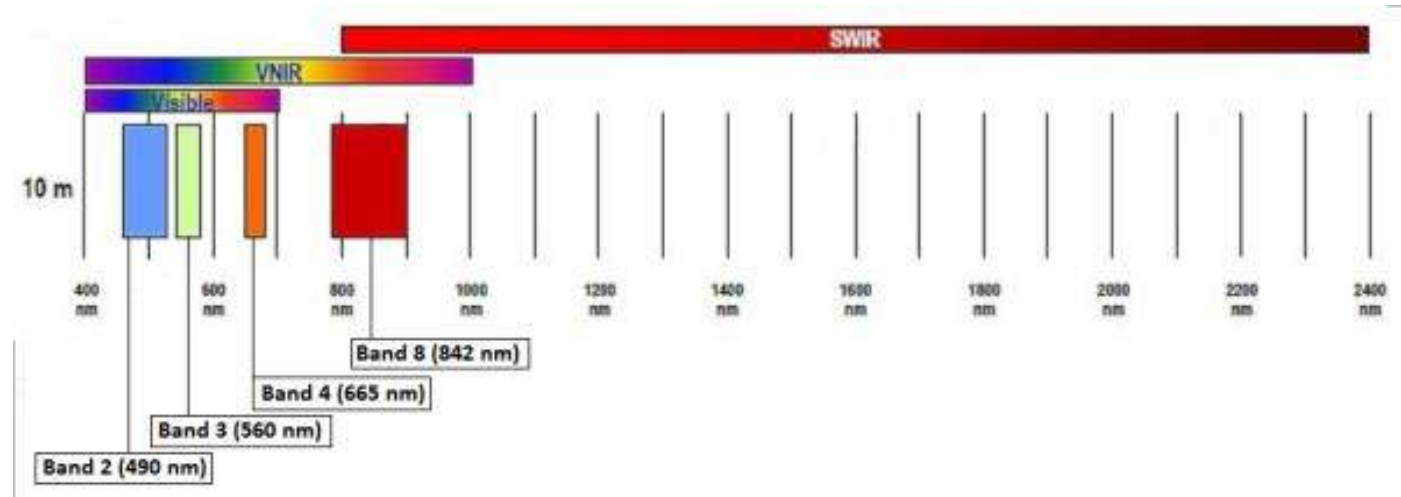
Mapping of timber species through the use of Sentinel-2 satellite imagery

- Mapping of forest stands
 - Less constraining spatial resolution
 - Work undertaken at the Interreg territory level

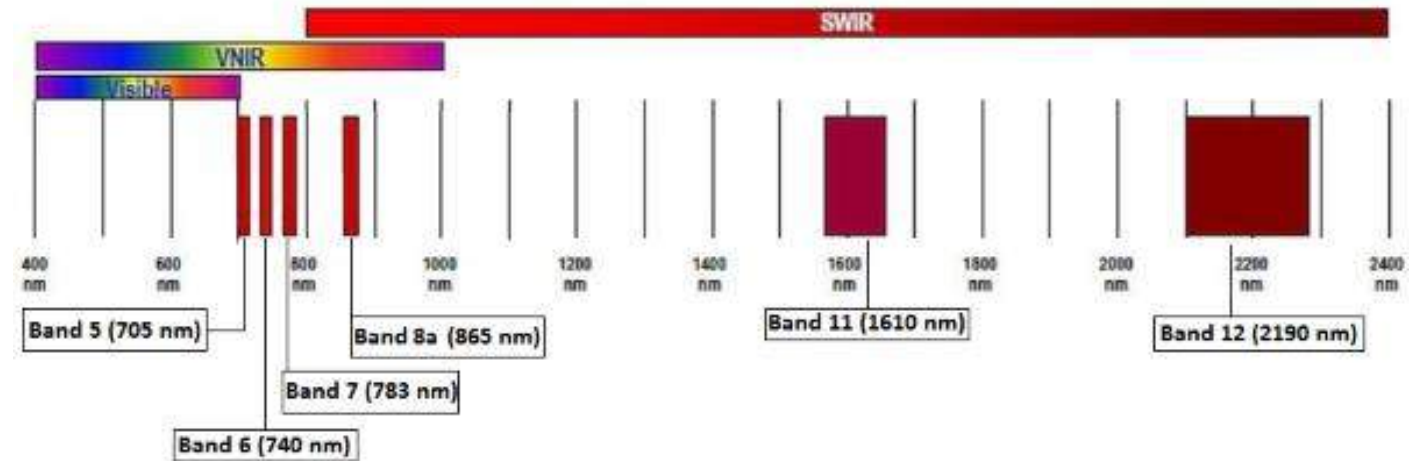
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- Sentinel-2 imagery
 - Available for the entire area
 - Continuous acquisition, return time : 5 days
 - High spectral resolution for 10 bands

- 10 m bands



- 20 m bands



Technical constraint related to satellite imagery

- At the Interreg project level
 - Impossible to have no clouds for a definite period
 - Use the available images without a cloud?
 - Poorly reproducible approach



Technical constraint related to satellite imagery

- Developing a S2 mosaic without a cloud for the vegetation period (from 2018-05-01 to 2018-09-30)

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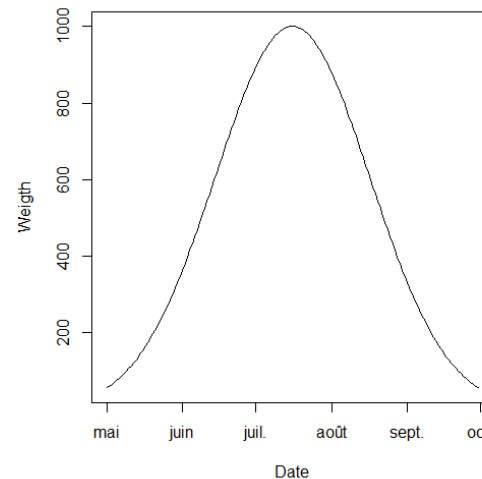
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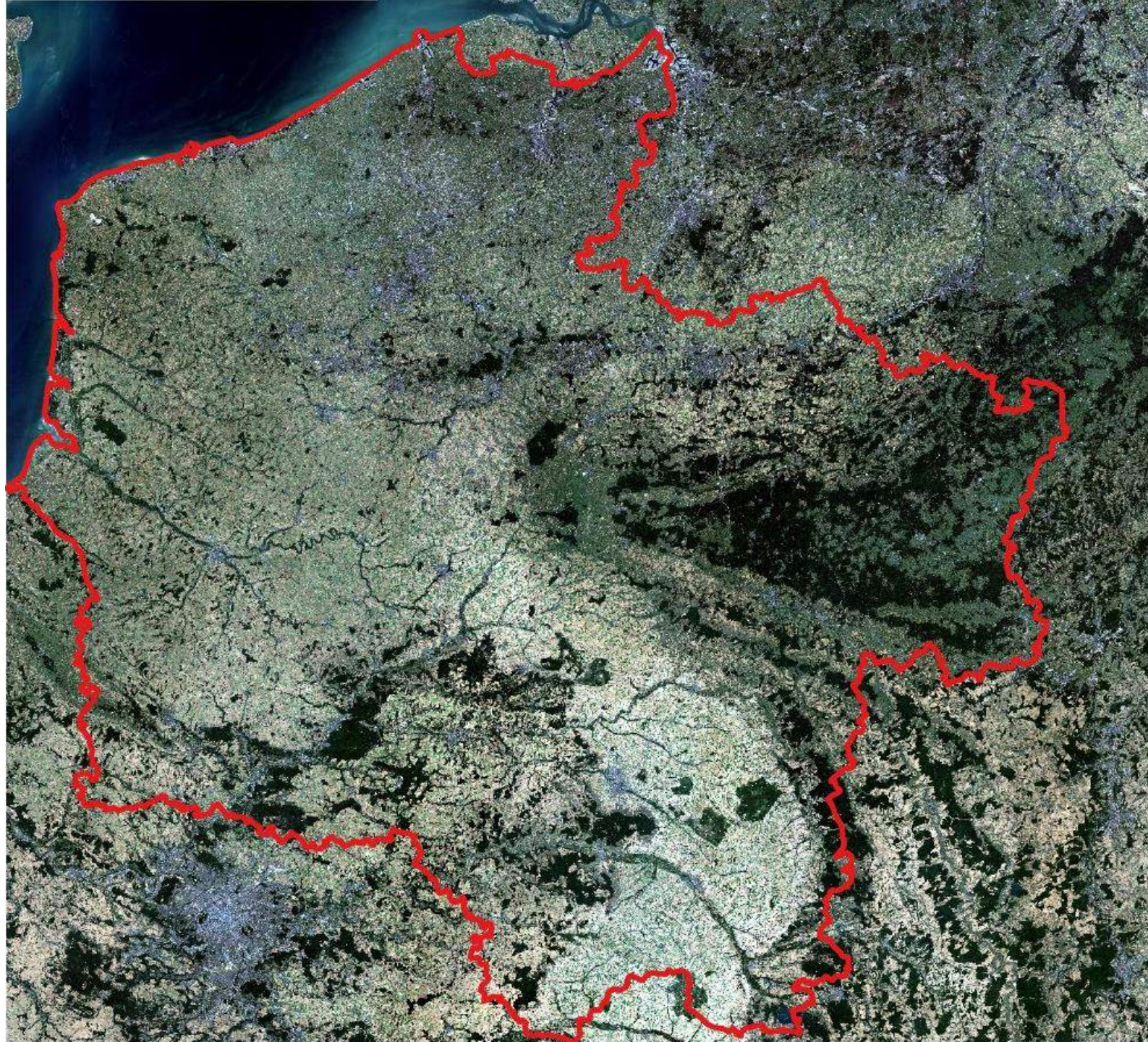
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$$brightness = mean(bands)$$

$$Normalized\ band = \frac{Band - brightness}{Band + brightness}$$

Mosaic S2
RGB



Mosaic S2
Nir SWIR SWIR



Supervised per pixel classification

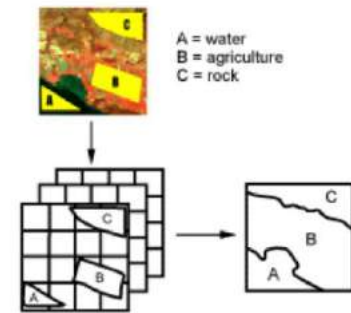
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- Training data :
 - Geodatabase of the Department of Nature and Forests (Public Service of Wallonia)
 - Data from the Interreg Transpop project
 - Digitalized data from the project's partners

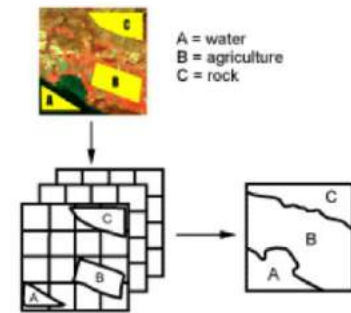
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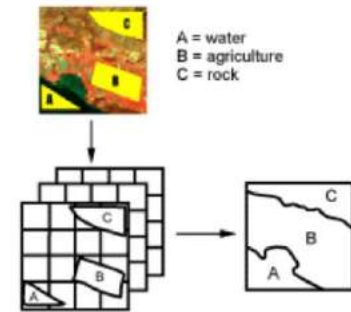
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- Random forest model

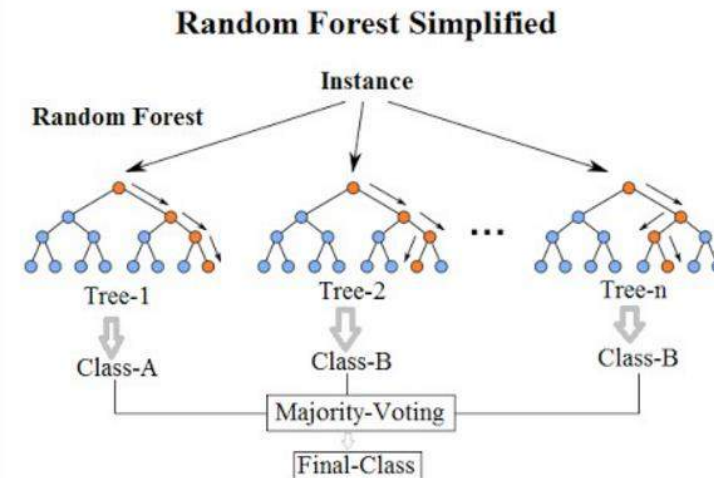


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Method

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2. 1 model per timber species to be mapped:
 - Deciduous trees: oak, beech, poplar, other deciduous trees
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3. Produce maps showing the presence probability according to random forest model

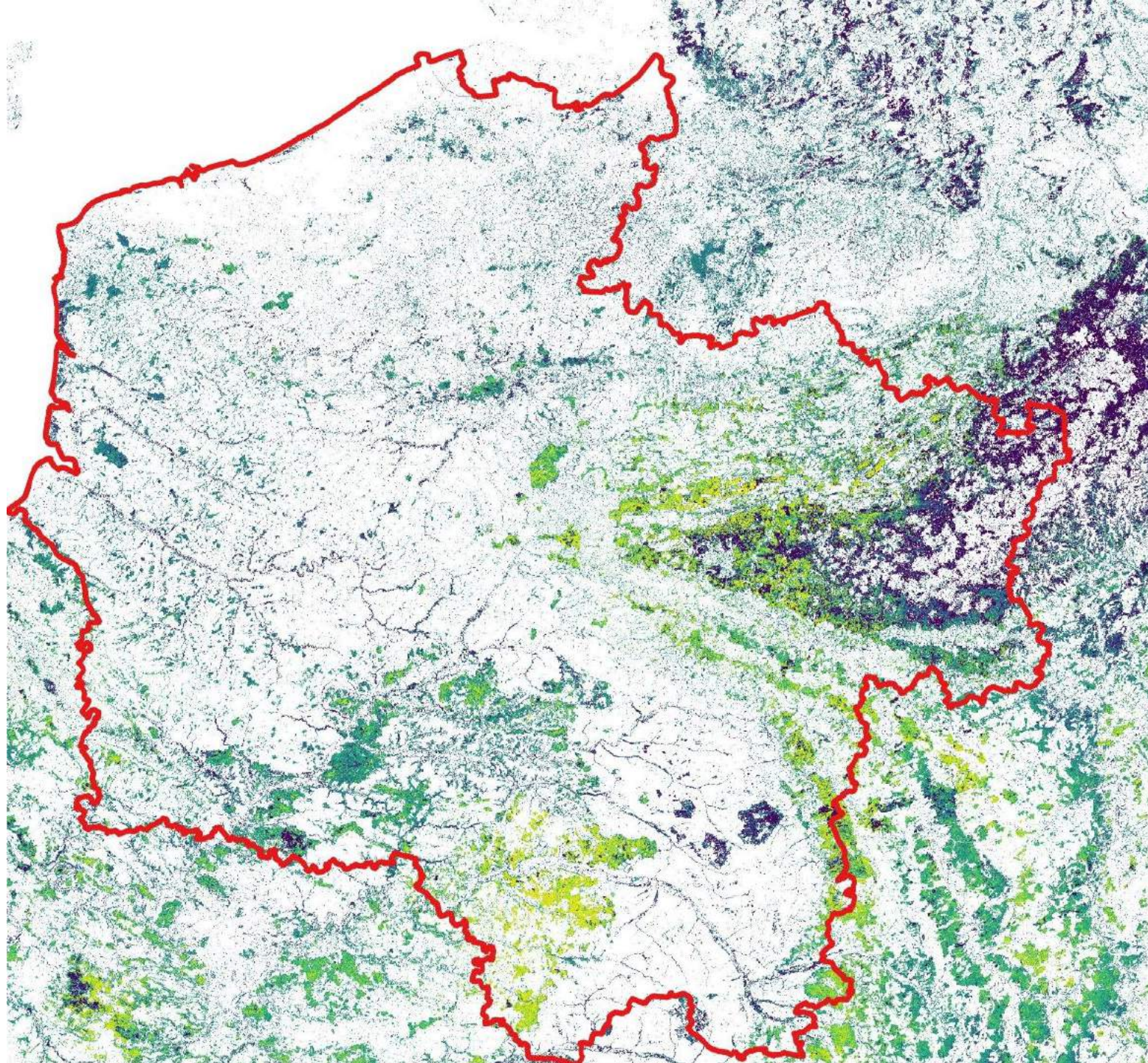
Mosaic S2
Nir SWIR SWIR



Result:
Ligneous mask

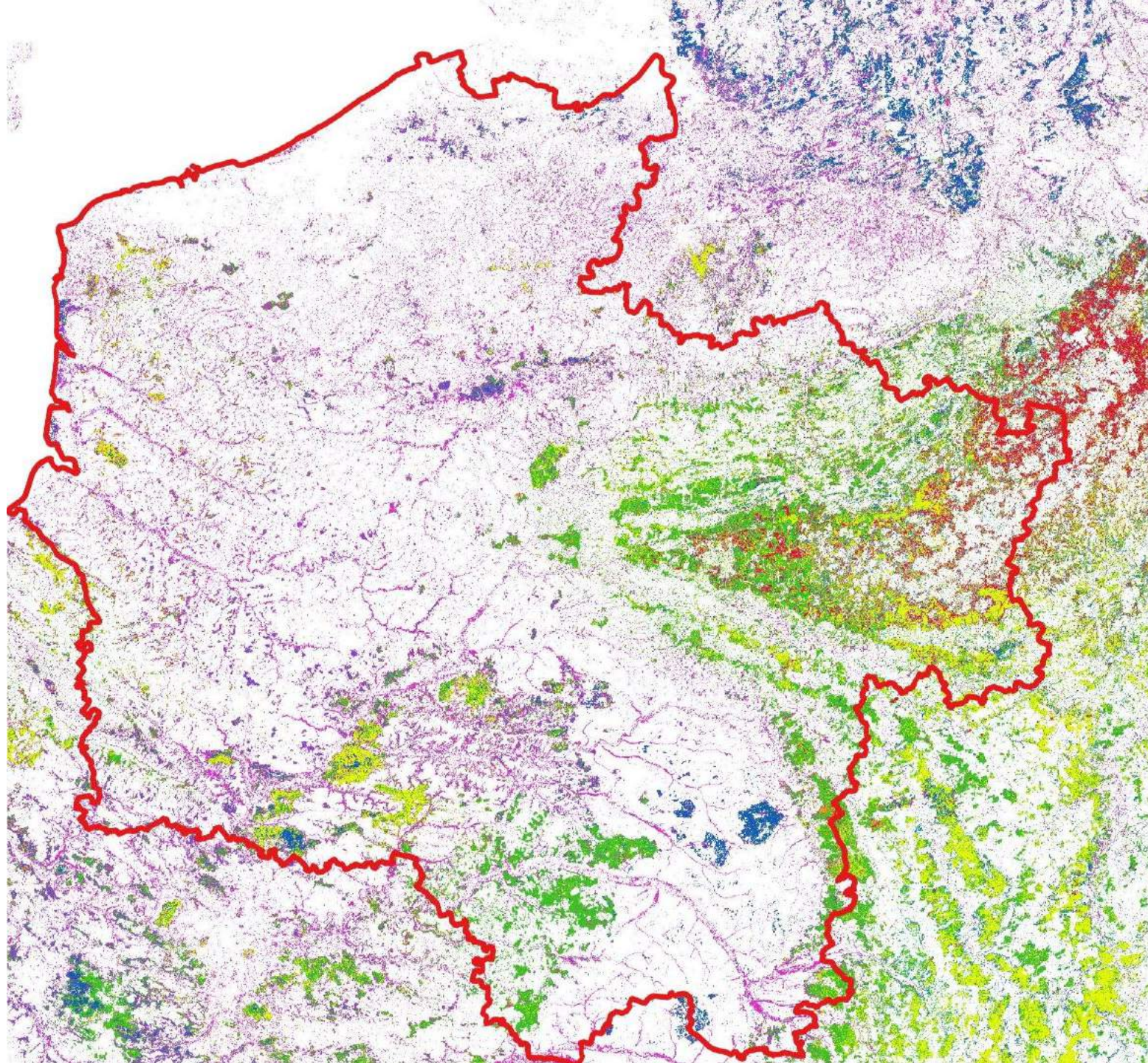


Result:
Presence probability
of oak



Result:
Combination of the
probability maps

- Quercus sp
- Pseudotsuga menziesii
- Picea sp
- other broad-leaved
- Fagus sylvatica
- Larix sp
- Populus sp
- Pinus sp
- Other needle-leaved



Accuracy, strengths and weaknesses

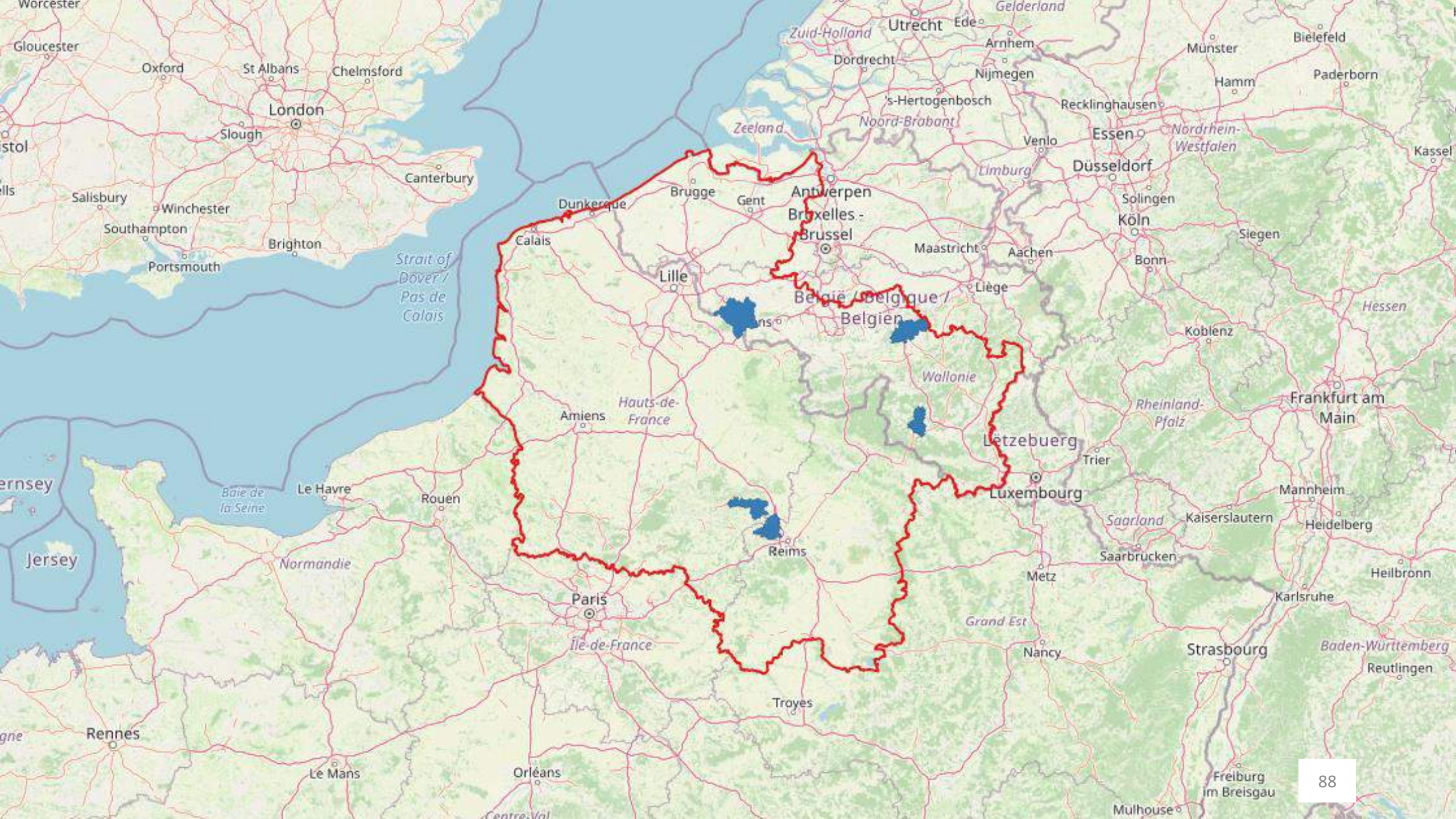
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 - Workable for large study areas (whole Interreg area)

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- Strengths :
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 - Workable for large study areas (whole Interreg area)
- Weaknesses :
 - Training data for the models
 - Ligneous mask solely defined on the basis of satellite imagery
 - Possible confusion with other types of soil occupation

Accuracy, strengths and weaknesses

- Assessment of the accuracy :
 - Field inventory undertaken in the framework of the project for 5 pilot areas
 - 751 plots inventoried in the field by the task officers and forest technicians for the Pro Bos Forest project



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Accuracy, strengths and weaknesses

- Detection of the most dominant species
- Detection of one of the dominant species

Accuracy, strengths and weaknesses

- Detection of the most dominant species

	Reference									
Prediction	CH	DO	EP	FE	HE	MZ	PE	PI	RE	
CH	167	0	1	70	10	1	3	3	0	
DO	0	31	12	0	0	0	0	0	1	
EP	0	6	62	0	2	1	0	0	0	
FE	65	0	1	115	4	1	4	0	0	
HE	52	1	4	59	111	1	0	2	0	
MZ	6	4	5	14	5	25	1	7	1	
PE	27	0	1	100	2	0	48	2	1	
PI	16	10	14	37	12	6	5	40	16	
RE	4	3	34	1	4	1	0	1	6	

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Accuracy, strengths and weaknesses

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PE	27	0	1	100	2	0	48	2	1	
PI	16	10	14	37	12	6	5	40	16	
RE	4	3	34	1	4	1	0	1	6	

Class	UA	PA
CH	0.6549020	0.4955490
DO	0.7045455	0.5636364
EP	0.8732394	0.4626866
FE	0.6052632	0.2904040
HE	0.4826087	0.7400000
MZ	0.3676471	0.6944444
PE	0.2651934	0.7868852
PI	0.2564103	0.7272727
RE	0.1111111	0.2400000

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Accuracy, strengths and weaknesses

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FE	65	0	1	115	4	1	4	0	0		FE	0.6052632	0.2904040
HE	52	1	4	59	111	1	0	2	0		HE	0.4826087	0.7400000
MZ	6	4	5	14	5	25	1	7	1		MZ	0.3676471	0.6944444
PE	27	0	1	100	2	0	48	2	1		PE	0.2651934	0.7868852
PI	16	10	14	37	12	6	5	40	16		PI	0.2564103	0.7272727
RE	4	3	34	1	4	1	0	1	6		RE	0.1111111	0.2400000

- Detection of one of the dominant species

Class	UA	PA
CH	0.827	0.754
DO	0.773	0.673
EP	0.887	0.567
FE	0.916	0.465
HE	0.670	0.813
MZ	0.456	0.694
PE	0.309	0.787
PI	0.410	0.764
RE	0.222	0.44

Conclusion

- Developments made in the framework of the Pro Bos Forest project show the potential of existing remote sensing data in order to map and characterize timber resources in all their forms
- The acquisition of aerial LiDAR data is a major asset in order to characterize the territory and monitor the evolution of our resources in the future
- All of the three topics addressed here show concrete ways for improvement. One of the biggest challenges is the improvement of the training database used for generating forest species mapping models.

An aerial photograph of a rural landscape. A winding river flows through the center of the image. To the left of the river are green agricultural fields. To the right, there is a small village with several buildings and a church spire. The background shows more fields and a line of trees.

Thank you

Bolyn Corentin

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Bolyn, C., Michez, A., Gaucher, P., Lejeune, P., Bonnet, S., 2018. Forest mapping and species composition using supervised per pixel classification of Sentinel-2 imagery. *Biotechnol. Agron. Soc. Environ.* 16.

Bolyn, C.; Lejeune, P.; Michez, A.; Latte, N. Automated Classification of Trees outside Forest for Supporting Operational Management in Rural Landscapes. *Remote Sens.* 2019, 11, 1146.