IUFRO FOREST ENVIRONMENT DIV8 CONFERENCE 2023

Canopy-based Classification of Urban Vegetation from Very High-Resolution Satellite Imagery

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AIRFRESH : Air pollution removal by urban forests for a better human well-being
www.life-airfresh.eu

Major public health issue in the EU where the annual O_3-related number of premature deaths increased (+ 0.55 deaths per 10^6 inhabitants).

Urban and Peri-urban reforestation should help **meet clean air standards** in cities.

- ✓ To provide **suitable selection** of tree species to reduce AP in cities (e.g., for city planners).
- ✓ To provide a **quantitative assessment of the role of urban trees** in affecting air quality.

AIRFRESH: 2 Front Runners Cities

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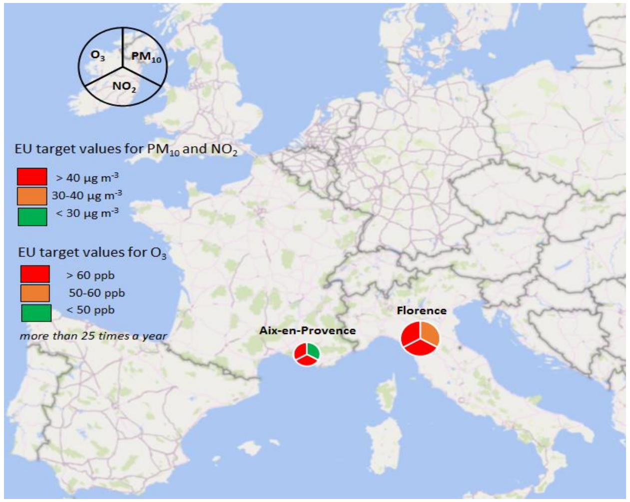
- Aix-en-Provence

- Firenze

Aix-en-Provence (143,000 people) **& Florence** (380,000 people): human exposure regularly exceeds the WHO protection limits (PM_{10}, NO_2, O_3).



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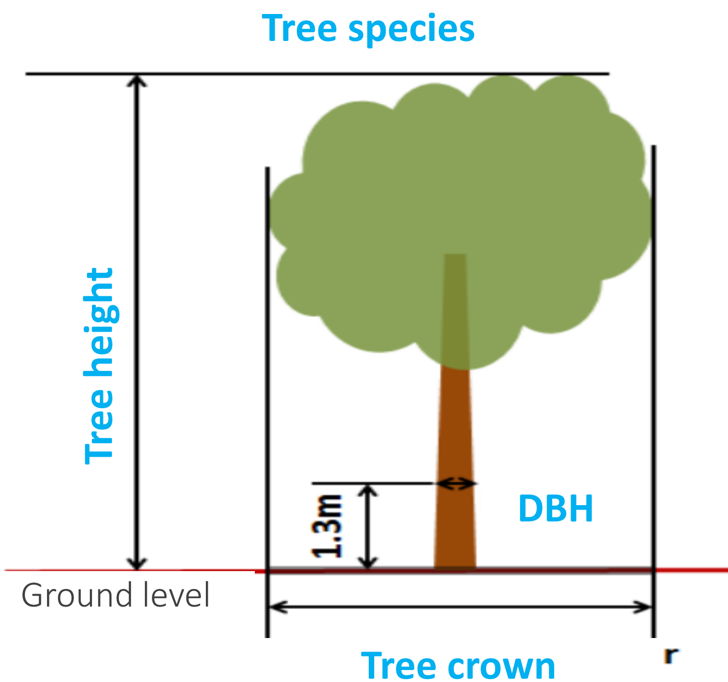
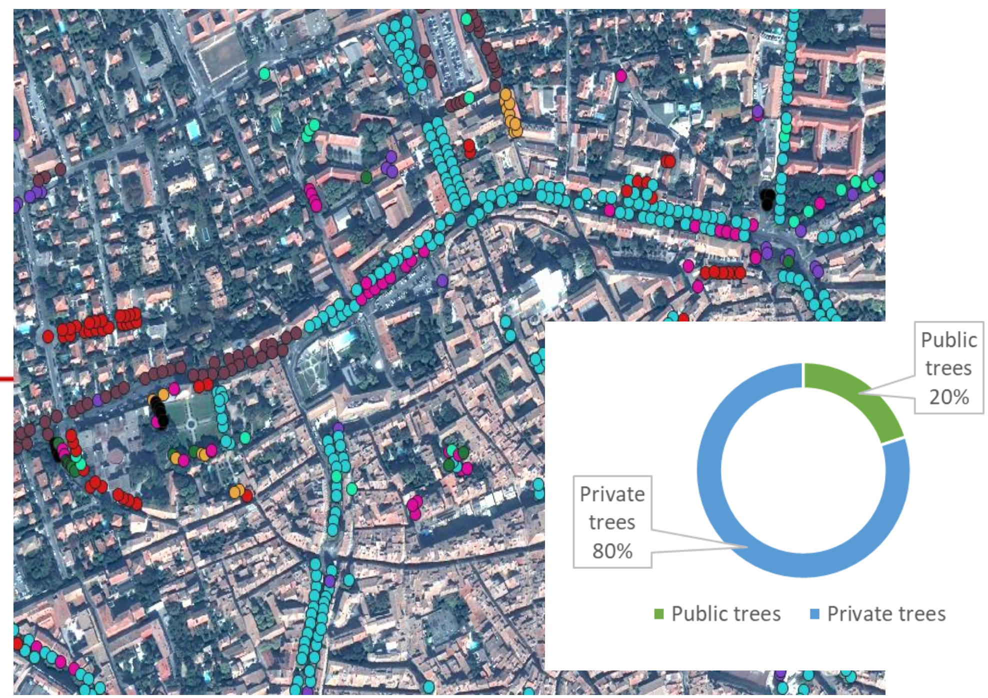
- ✓ To provide a **quantitative assessment of the role of urban trees** in affecting air quality.
- ✓ To avoid a **large underestimation** of the AP removal capacity:



Public trees inventory from municipality service Aix-en-Provence(France)



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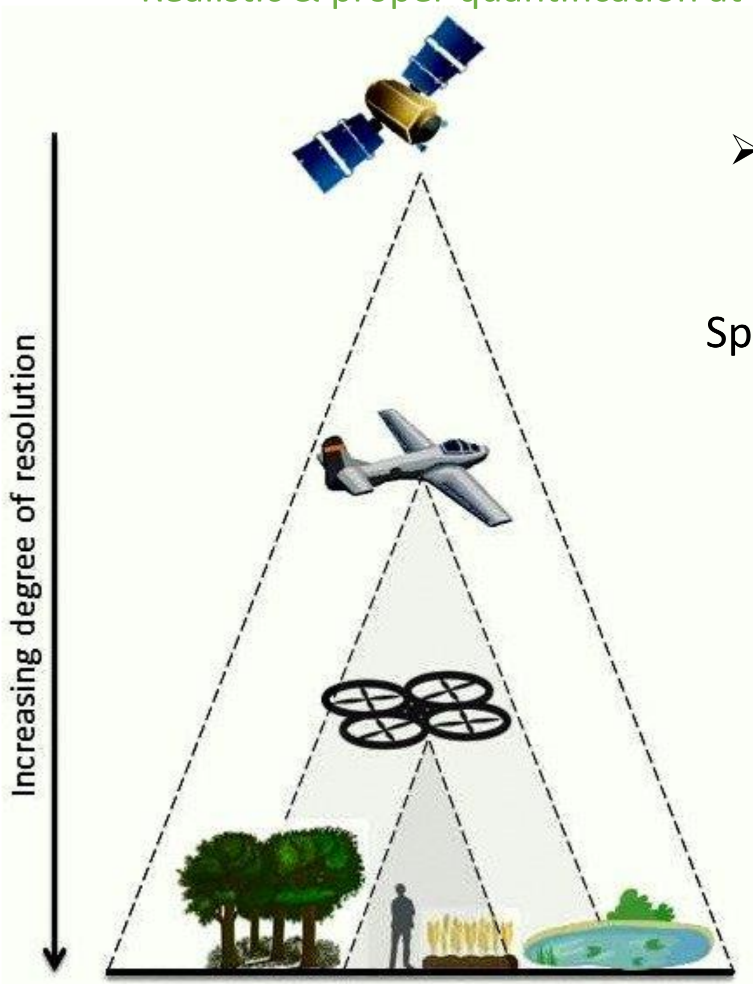
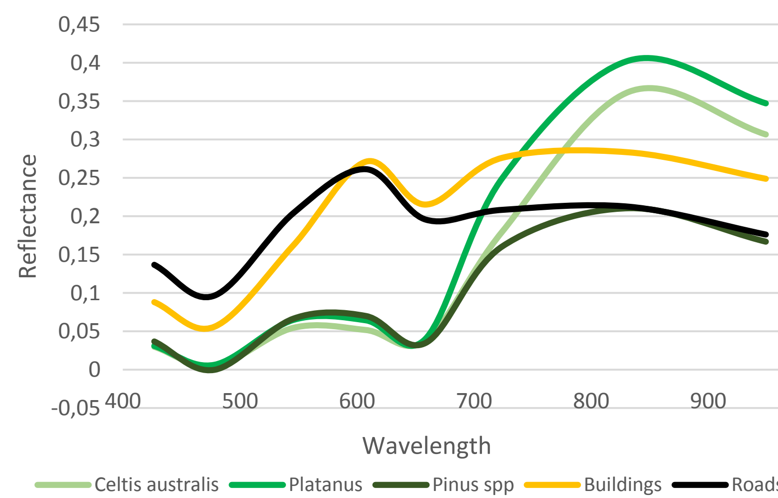
Public + private urban trees distribution & classification

Realistic & proper quantification at city scale = **consistent tree inventory** is needed.



- new generations of optical satellites allow an access to finer information and the study urban areas

Spectral differentiation -> **Detection & Classification**



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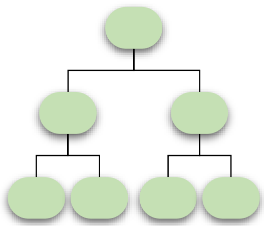
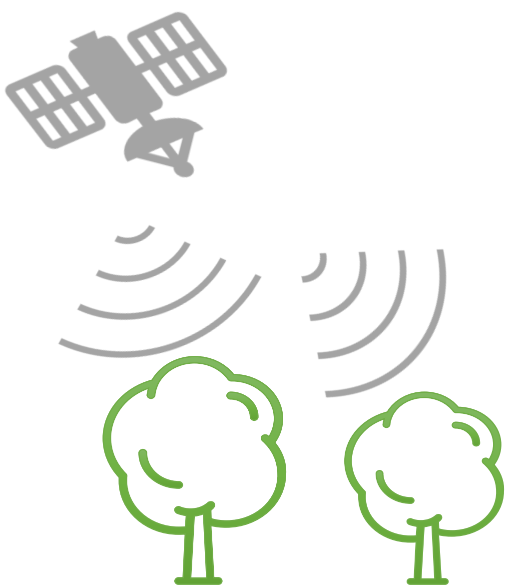
Objectives of the presentation



Process

Results



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Object-based classification of urban plant species from very high-resolution satellite imagery

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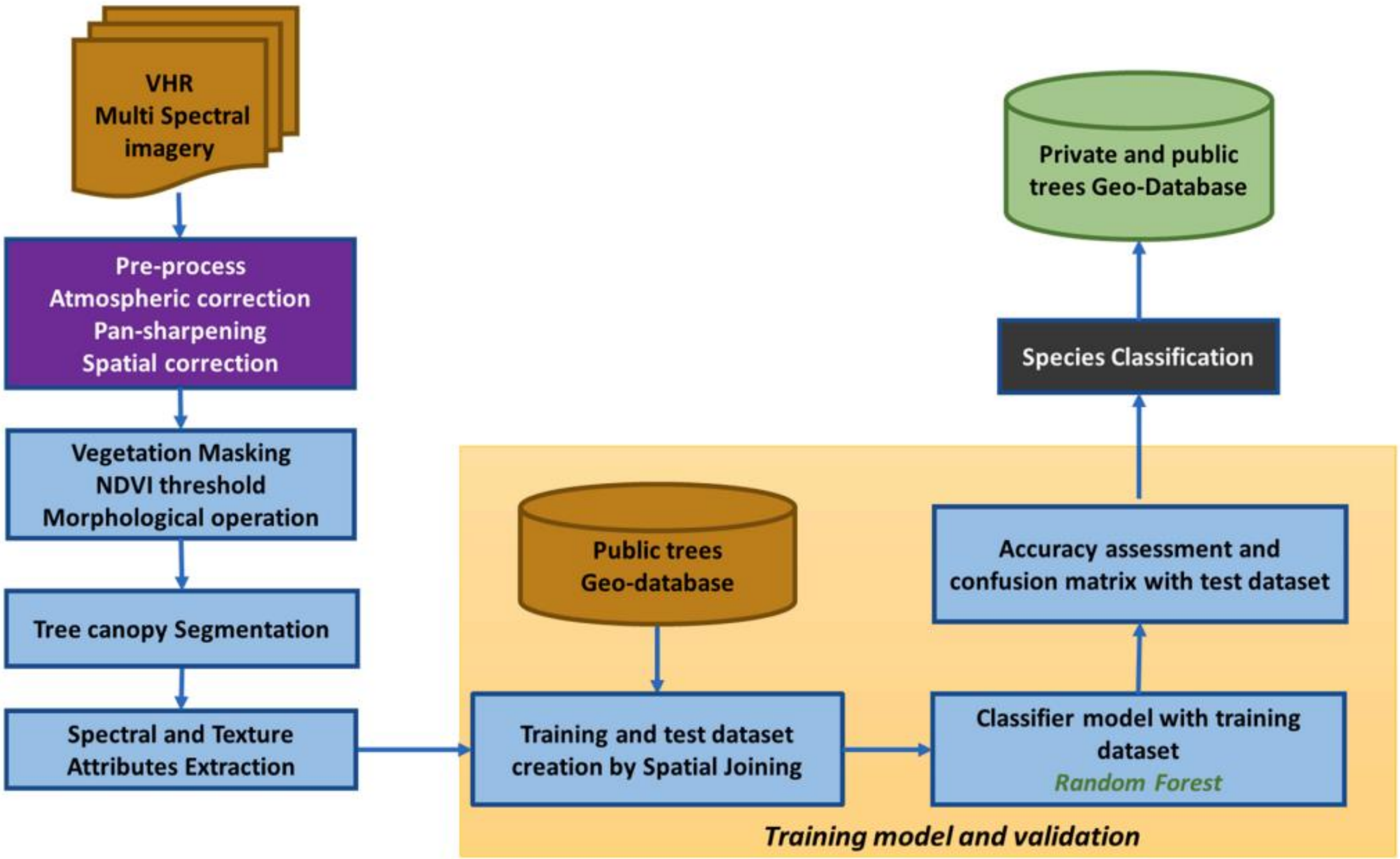
ABSTRACT

Cities are facing too many challenges. Urban vegetation, in particular trees, are essential as they provide services in terms of air pollution mitigation, freshness, biodiversity, and citizens' well-being. Accurate data on location, species, and structural characteristics are essential for quantifying their benefits. However, the cost of measuring thousands of individual trees through field campaigns can be prohibitive and reliable information on domestic gardens is lacking due to difficulties in acquiring systematic data. The main objective of this study was to investigate the suitability of very-high resolution satellite imagery, e.g., WorldView-2, for detecting, delineating, and classifying the urban plant species in both public and private areas. The characterization of urban vegetation is difficult due to the complexity of the urban environment (buildings, shadows, open courtyards), the diversity of species and the spatial proximity between trees. To overcome these constraints, an object-based classification was developed with the selection of new relevant spectral and texture-based features for each plant species. Four spectral bands (blue, green, yellow, red) and four texture features (i.e., energy, entropy, inverse difference moment, Haralick correlation) were found to be the most efficient attributes for object-based classification from WV-2 images. Then, a classification of plant species, by using a Random Forest classifier, and ground validation were performed. In the two study areas, Aix-en-Provence (France) and Florence (Italy), 22 and 20 dominant plant species, and grassland, were identified and classified with an overall accuracy of 84% and 83%, respectively. The highest classification accuracy was obtained for *Pinus* spp. and *Platanus acerifolia* in Aix-en-Provence, and for *Celtis australis* and *Cupressus sempervirens* in Florence. The lowest classification accuracy was obtained for *Quercus* spp. in Aix-en-Provence, and *Magnolia grandiflora* in Florence.

Our workflow



Our resources

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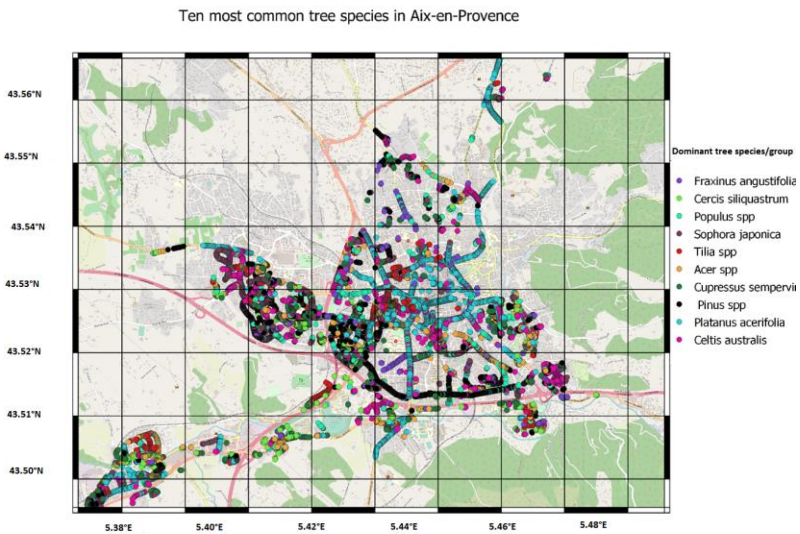
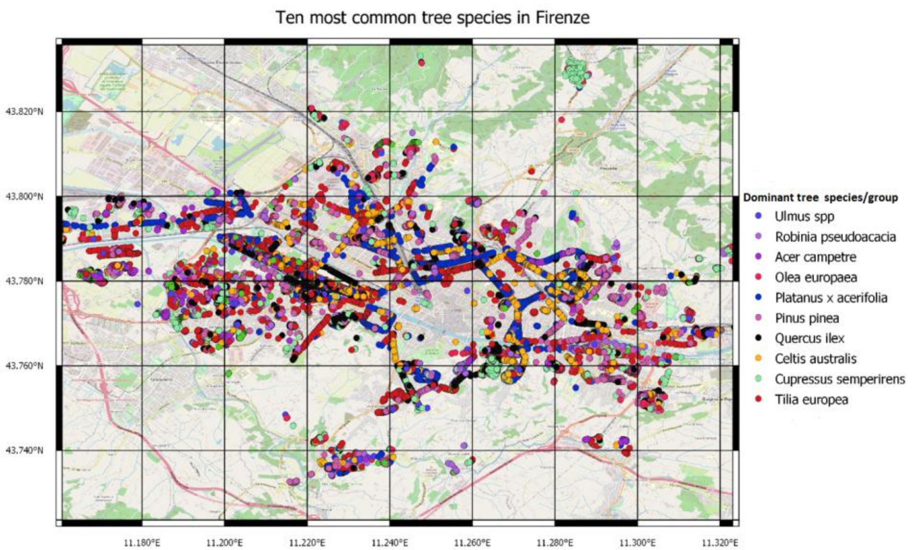
Public trees inventories by municipalities

~ 31 000 trees geolocated

~ 75 700 trees geolocated





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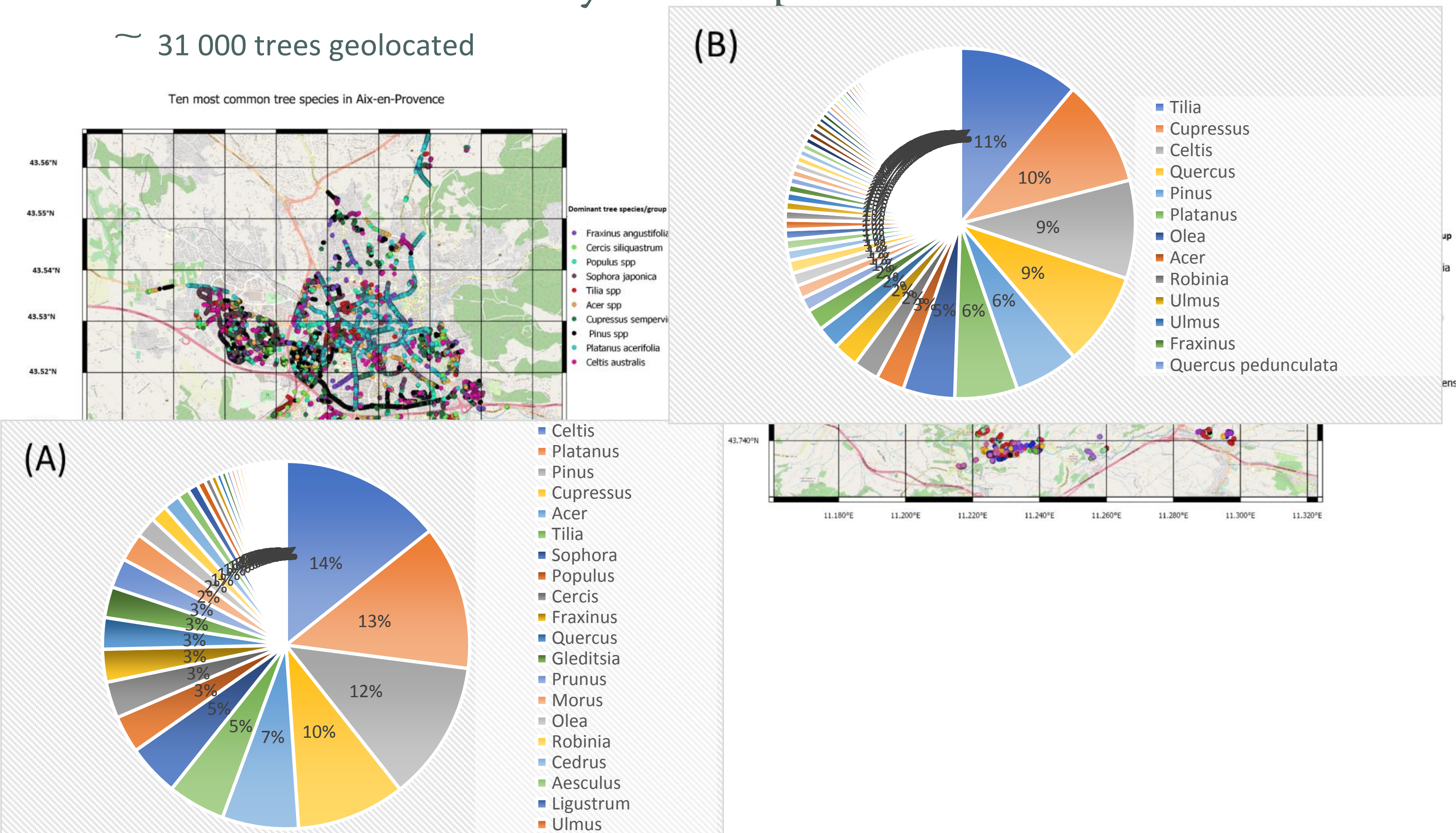

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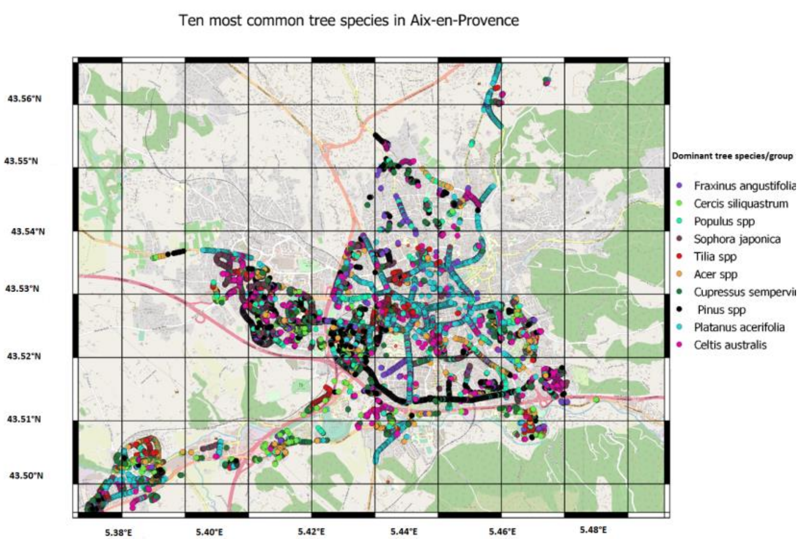

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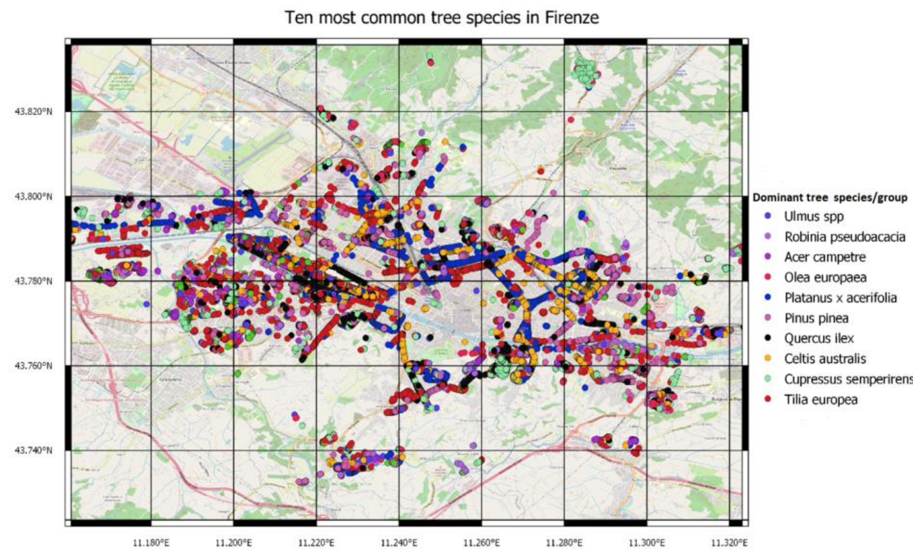

Multi-spectral satellite data with 50cm spatial resolution

Study area	Imagery	Date	Area
Aix	VW-2 (DigitalGlobe)	17/07/2020	50km2
Florence	VW-2 (DigitalGlobe)	30/07/2020	80km2

Some acquisition conditions :

Cloud free

Low incidence angle

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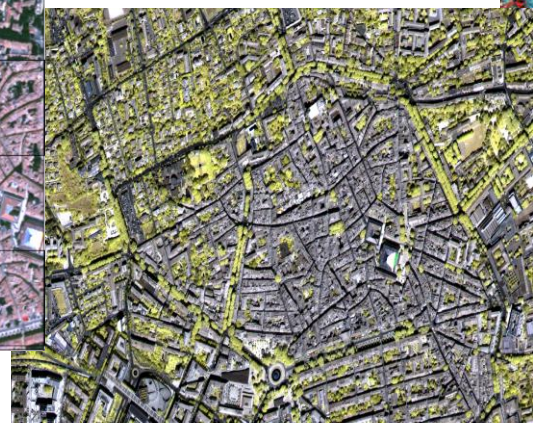
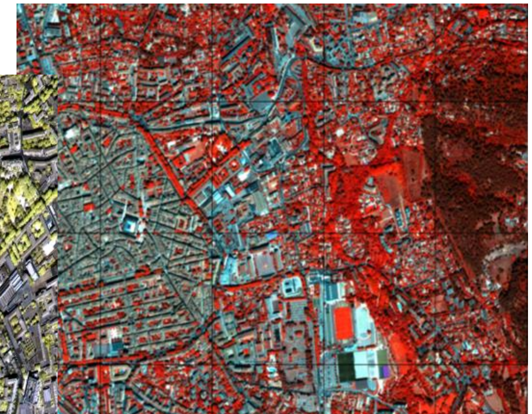
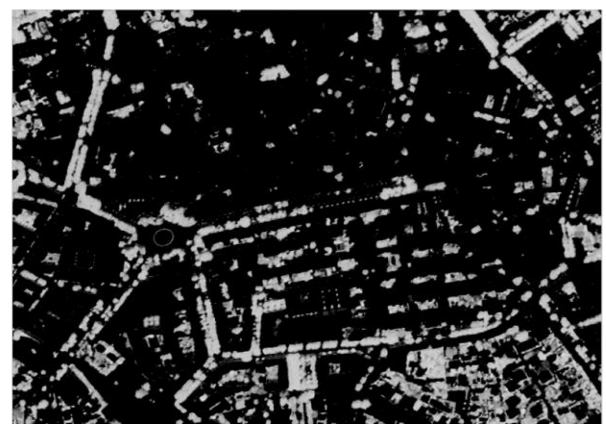
Stepwise masking system of urban vegetation



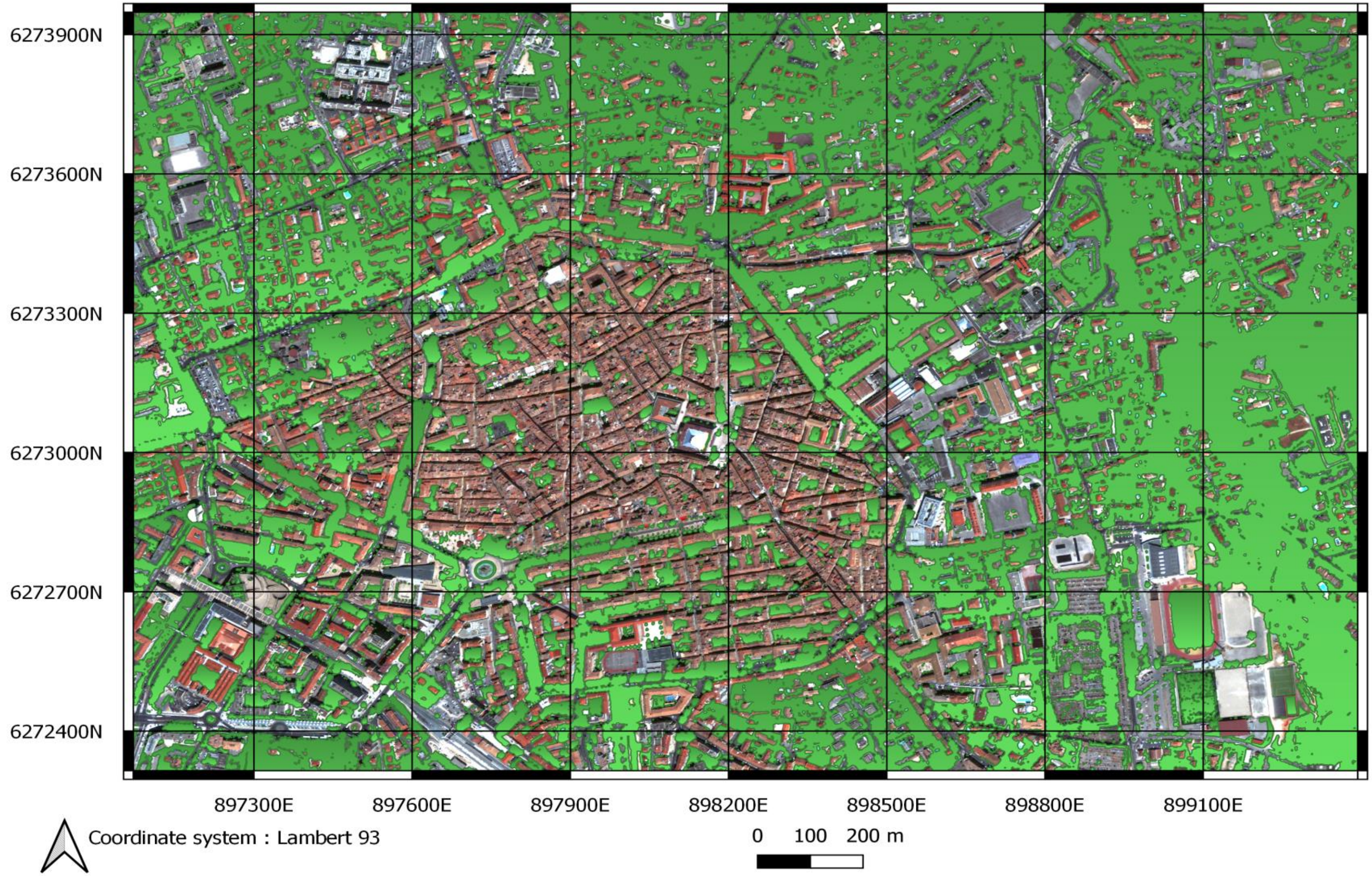


$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{red}}}$$

Normalized Difference Vegetation Index



Urban green cover map



Tree canopy segmentation

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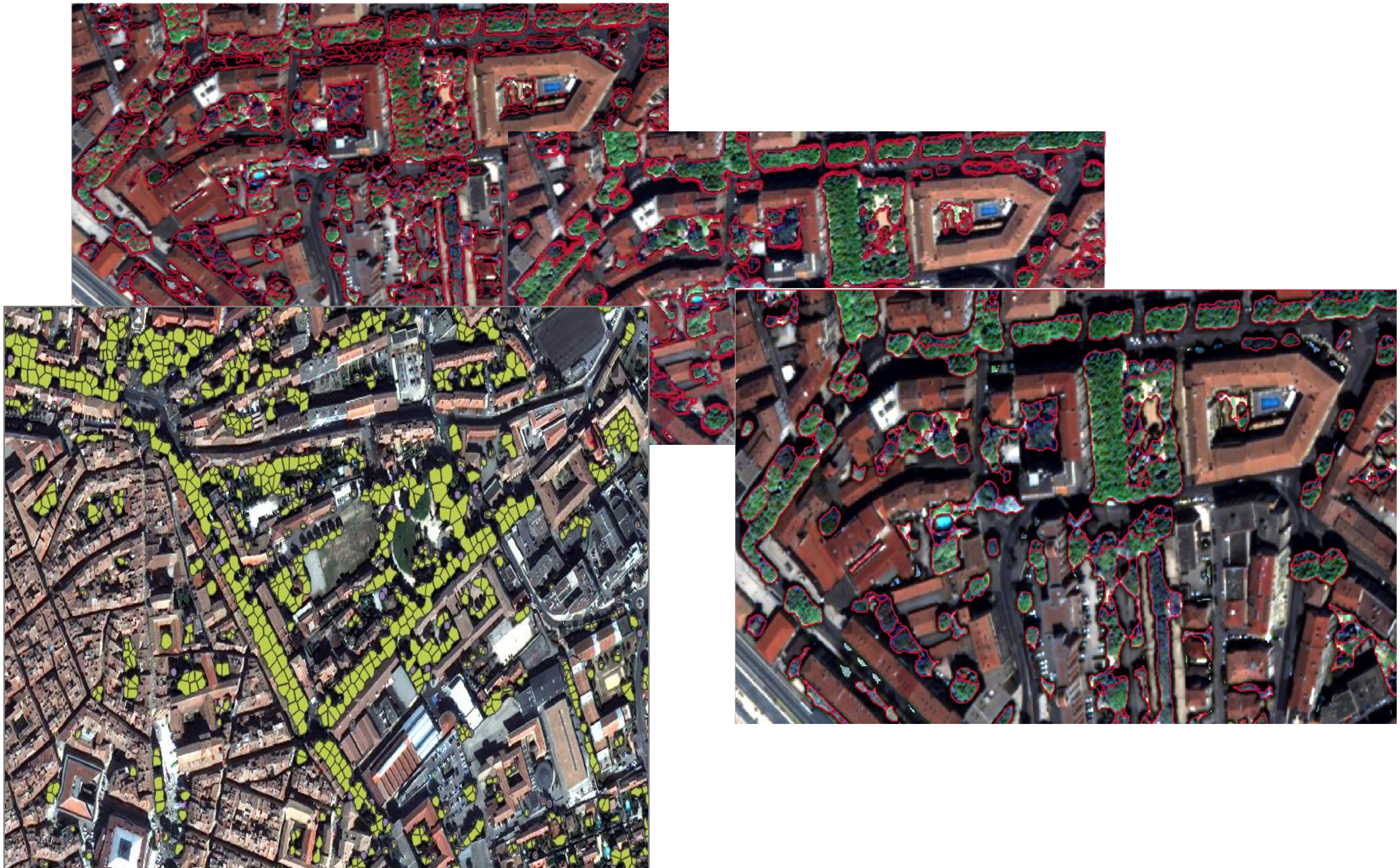

Tree canopy segmentation

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Canopy attributes computation

Haralick features

For each spectral band of the images

The grey level co-occurrence matrix (GLCM) is computed and texture features (descriptors)

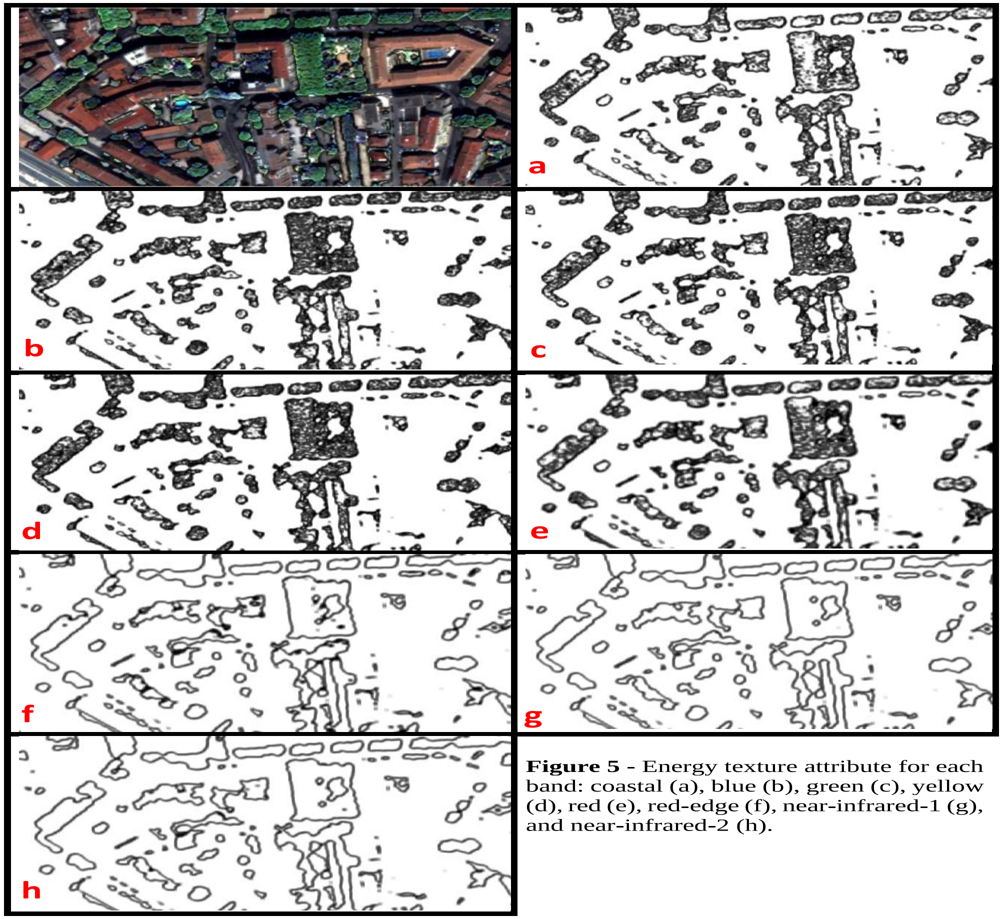

Figure 5 - Energy texture attribute for each band: coastal (a), blue (b), green (c), yellow (d), red (e), red-edge (f), near-infrared-1 (g), and near-infrared-2 (h).

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Training and validation model

- 22 species in Aix-en-Provence and 20 in Florence
- 3,777 and 30,764 training samples in Aix-en-Provence and Florence, respectively.
- 70% of the samples as training and 30% for validation of classification.
- 16 texture-based features were extracted for each training sample

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Training and validation model

The dataset

Plant species	No. of training samples	4 bands + 4 Haralick attributes		8 bands + 10 Haralick attributes	
		PA (%)	UA (%)	PA (%)	UA (%)
Acer spp. [1]	374	76.4	89.1	70.4	81.5
Aesculus hippocastanum	50	87.8	81.8	84.0	76.4
Ailanthus altissima	35	65.7	74.2	63.6	67.8
Cedrus spp. [2]	56	87.3	73.1	83.0	71.6
Celtis australis	395	84.1	81.9	73.6	78.0
Cercis siliquastrum	89	77.5	56.1	72.1	47.7
Cupressus sempervirens	350	81.2	90.0	77.8	87.8
Fraxinus spp. [3]	127	74.9	72.0	74.8	65.1
Gleditsia triacanthos	120	84.2	84.3	82.7	79.3
Laurus nobilis	17	64.7	84.6	62.5	73.9
Ligustrum japonicum	34	82.4	59.2	78.1	51.0
Morus nigra	112	73.2	85.0	70.1	75.0
Pinus spp. [4]	566	78.7	94.5	76.1	92.1
Platanus acerifolia	811	89.0	93.6	86.2	90.2
Populus spp. [5]	76	86.8	61.1	86.0	45.4
Prunus cerasifera	60	90.0	64.7	88.9	47.1
Quercus spp. [6]	31	83.9	46.6	76.9	34.5
Robinia pseudoacacia	32	90.6	61.5	88.6	55.8
Sophora japonica	288	84.0	91.8	78.7	86.6
Tamarix tetrandra	18	55.6	83.3	52.9	75.0
Tilia spp. [7]	76	96.1	73.7	90.4	61.6
Ulmus spp. [8]	24	70.8	52.9	66.7	41.2
Grass	96	91.3	92.3	87.5	89.2
Kappa coefficient (k)		**0.82**		**0.72**	
Overall accuracy (%)		**84.9**		**74.1**	

Band	Textural features	*Acer spp.*	*Celtis australis*	*Sophora japonica*	*Pinus spp.*
Blue	Entropy	0.75	0.69	0.74	0.74
	Energy	0.71	0.88	0.80	0.85
	Inverse Difference Moment	0.95	0.94	0.94	0.93
	Haralick Correlation	522.46	400.88	649.88	693.88
Green	Entropy	1.06	0.67	1.62	1.90
	Energy	0.62	0.77	0.43	0.35
	Inverse Difference Moment	0.91	0.94	0.87	0.82
	Haralick Correlation	356.10	298.78	249.92	387.00
Yellow	Entropy	1.30	1.52	1.83	1.86
	Energy	0.55	0.51	0.37	0.39
	Inverse Difference Moment	0.91	0.89	0.86	0.86
	Haralick Correlation	412.42	513.21	260.22	398.23
Red	Entropy	0.99	1.12	0.87	1.83
	Energy	0.66	0.64	0.70	0.36
	Inverse Difference Moment	0.94	0.93	0.94	0.84
	Haralick Correlation	522.46	400.88	649.88	693.88

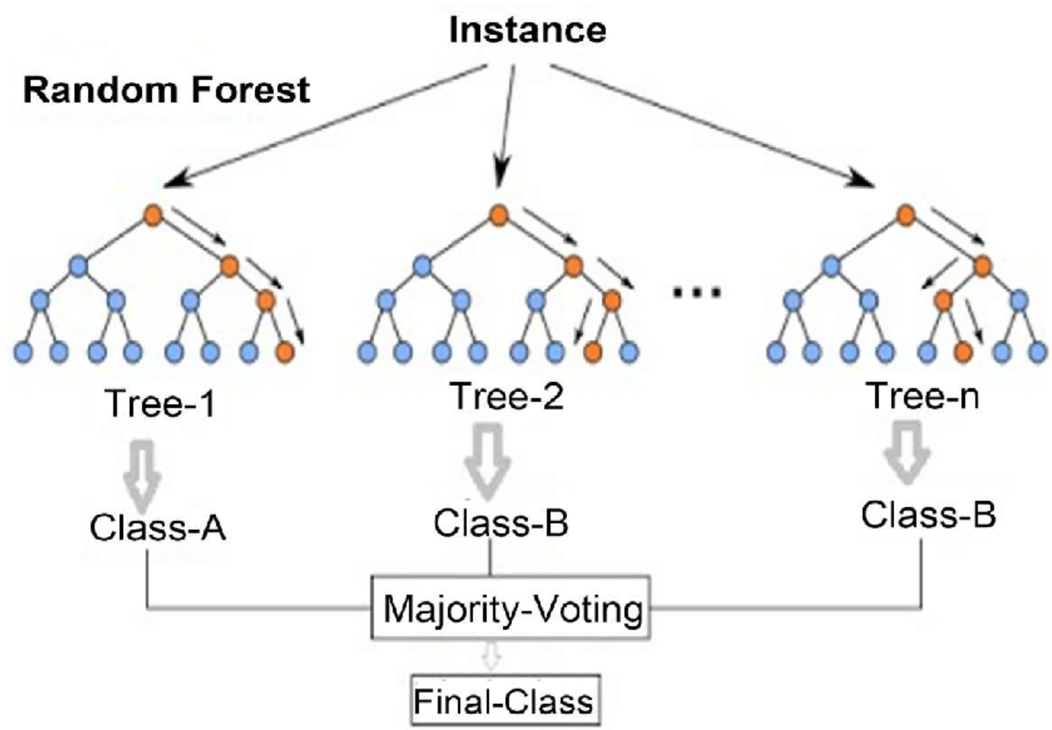
The model

Random forest classification

•The random forest algorithm is significantly more accurate than most of the non-linear classifiers.

•This algorithm is also very robust because it uses multiple decision trees to arrive at its result.

•The random forest classifier doesn't face the overfitting issue because it takes the average of all predictions, canceling out the biases and thus, fixing the overfitting problem.



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Training and validation model

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❖ Aix-en-Provence

Plant species	Number of tree canopies / grass areas	Coverage (ha)	No. of training samples	Producer accuracy (%)	User accuracy (%)
***Acer* spp.** [1]	**53,937**	**264.90**	**374**	**76.4**	89.1
Aesculus hippocastanum	157	3.37	50	87.8	81.8
Ailanthus altissima	70	0.82	35	65.7	74.2
Cedrus spp. [2]	800	7.20	56	87.3	73.1
Celtis australis	**104,625**	**373.73**	**395**	**84.1**	81.9
Cercis siliquastrum	**1,768**	**14.06**	**89**	**77.5**	56.1
Cupressus sempervirens	**38,761**	**124.21**	**350**	**81.2**	90.0
***Fraxinus* spp.** [3]	**2,407**	**40.94**	**127**	**74.9**	72.0
Gleditsia triacanthos	6,283	51.76	120	84.2	84.3
Laurus nobilis	11	0.26	17	64.7	84.6
Ligustrum japonicum	26	0.28	34	82.4	59.2
Morus nigra	801	7.26	112	73.2	85.0
***Pinus* spp.** [4]	**106,835**	**487.25**	**566**	**78.7**	94.5
Platanus acerifolia	**74,088**	**369.87**	**811**	**89.0**	93.6
***Populus* spp.** [5]	**701**	**8.37**	**76**	**86.8**	61.1
Prunus cerasifera	204	4.27	60	90.0	64.7
Quercus spp. [6]	87	5.91	31	83.9	46.6
Robinia pseudoacacia	65	0.75	32	90.6	61.5
Sophora japonica	**18,520**	**54.40**	**288**	**84.0**	91.8
Tamarix tetrandra	184	2.01	18	55.6	83.3
***Tilia* spp.** [7]	**3,370**	**7.14**	**76**	**96.1**	73.7
Ulmus spp. [8]	195	0.78	24	70.8	52.9
Grass	5,438	151.67	96	91.3	92.3
Total	**419,333**	**1981.21**	**3,777**		
Kappa coefficient (k)	**0.82**				
Overall accuracy (%)	**84.9**				
Green cover (%)	**30.6**				

[1] Acer campestre, A. platanoides. [2] Cedrus atlantica, C. deodara, C. libani. [3] Fraxinus angustifolia, F. excelsior. [4] Pinus halepensis, P. pinaster, P. pinea. [5] Populus nigra, P. alba. [6] Quercus ilex, Q. pubescens, Q. cerris. [7] Tilia cordata, T. platyphyllos. [8] Ulmus campestris, U. minor.

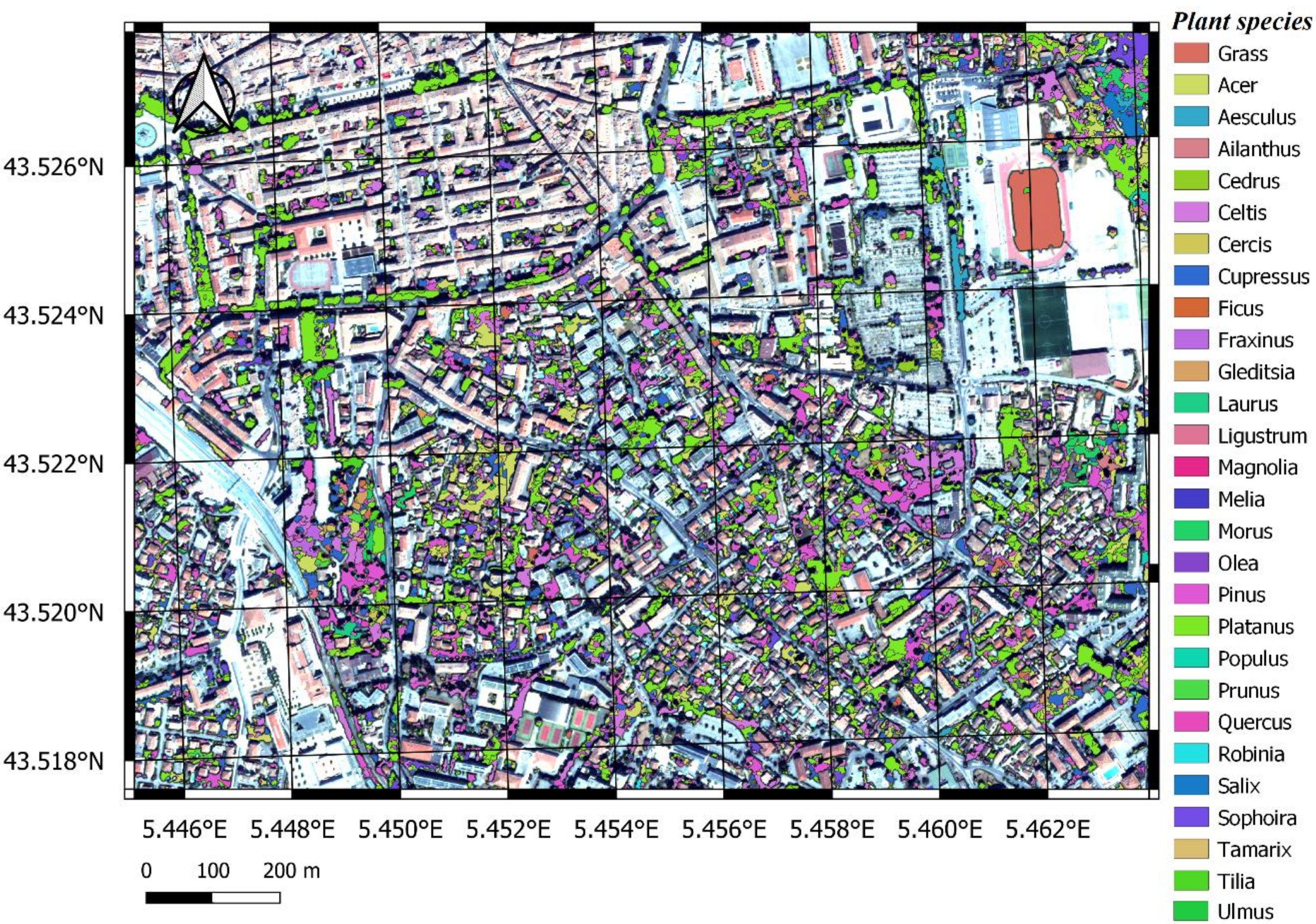
❖ Florence

Plant species	Number of tree canopies / grass areas	Canopy cover (ha)	No. of training samples	Producer accuracy (%)	User accuracy (%)
***Acer* spp.** [1]	**11,018**	**61.53**	**1,239**	**99.0**	**72.6**
Aesculus hippocastanum	774	4.20	324	99.7	67.5
Ailanthus altissima	272	1.01	81	100	66.8
Cedrus spp. [2]	3,768	17.93	726	100	85.6
Celtis australis	**107,677**	**337.93**	**5,242**	**68.1**	**91.4**
Cercis siliquastrum	717	2.94	233	100	76.9
Cupressus sempervirens	**54,403**	**175.75**	**1,828**	**97.8**	**91.5**
Fraxinus spp. [3]	2,652	20.46	672	99.6	72.8
Ligustrum spp.[4]	1,034	3.22	397	99.7	80.3
Magnolia grandiflora	102	0.67	22	100	62.6
Olea europaea	**22,462**	**87.67**	**1,189**	**75.4**	**68.5**
***Pinus* spp.** [5]	**39,723**	**277.70**	**2,033**	**94.7**	**89.6**
Platanus acerifolia	**23,456**	**89.65**	**2,432**	**99.5**	**85.7**
Populus spp. [6]	7,402	43.34	948	99.6	**79.5**
Prunus spp. [7]	1,702	6.63	562	100	66.7
***Quercus* spp.** [8]	**155,019**	**727.94**	**6,294**	**61.4**	**90.4**
Robinia pseudoacacia	**1,106**	**8.65**	**435**	**100**	**67.2**
Tilia europaea	**104,234**	**492.51**	**4,835**	**91.0**	**88.1**
***Ulmus* spp.** [9]	**11,895**	**47.47**	**1,283**	**88.1**	**62.6**
Grass	1,157	1.94	11	100	52.4
Total	**550,573**	**2409.16**	**30,764**		
Kappa coefficient (k)	**0.80**				
Overall accuracy (%)	**82.9**				
Green cover (%)	**30.1**				

[1] Acer campestre, A. negundo, A. platanoides. [2] Cedrus atlantica, C. deodara. [3] Fraxinus angustifolia, F. excelsior. [4] Ligustrum japonicum, L. lucidum. [5] Pinus pinea, P. nigra. [6] Populus canescens, P. nigra, P. alba. [7] Prunus cerasifera, P. avium. [8] Quercus ilex, Q. robur, Q. rubra. [9] Ulmus campestris, U. minor.

Urban trees maps

- Aix-en-Provence



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Urban trees maps

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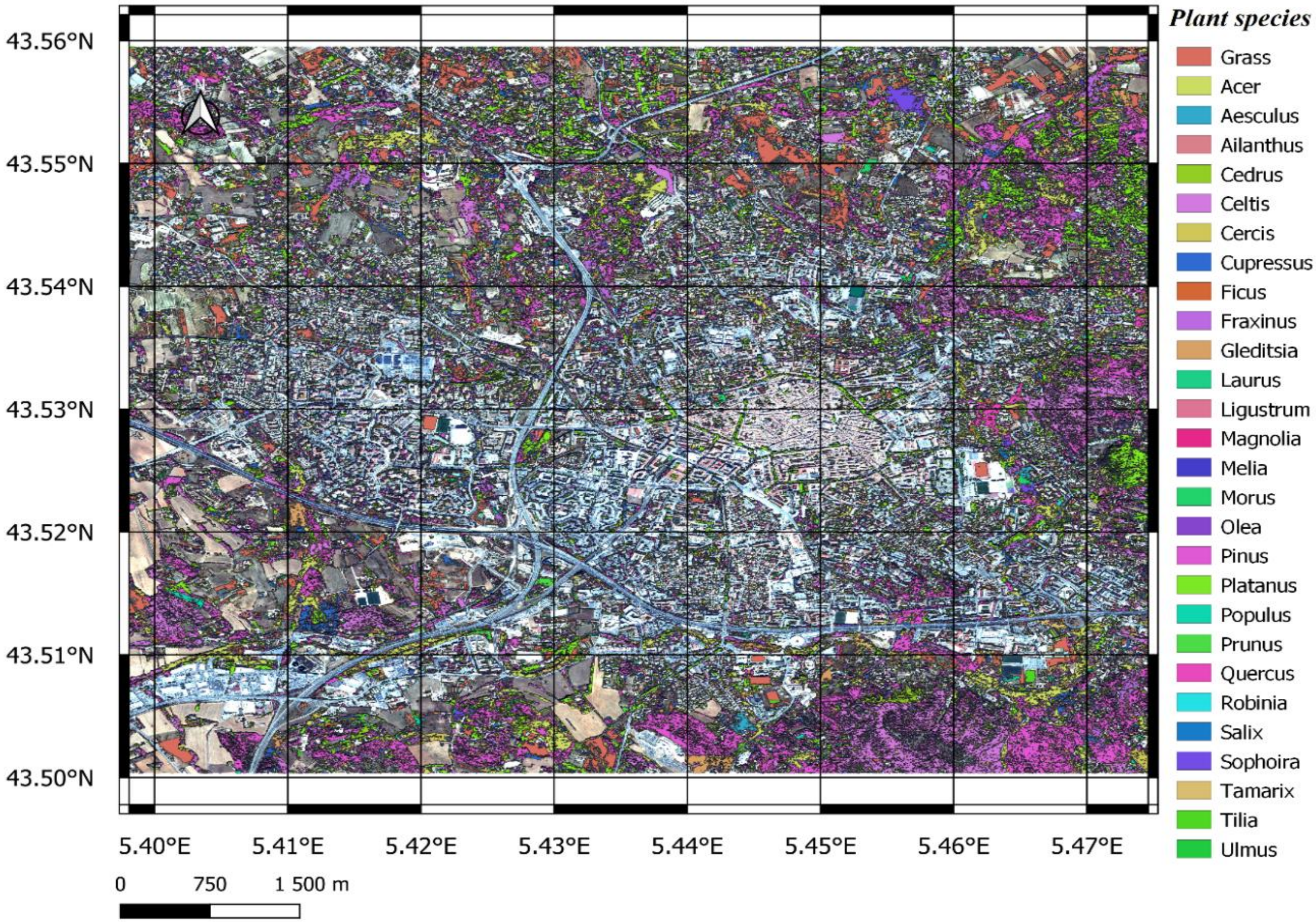

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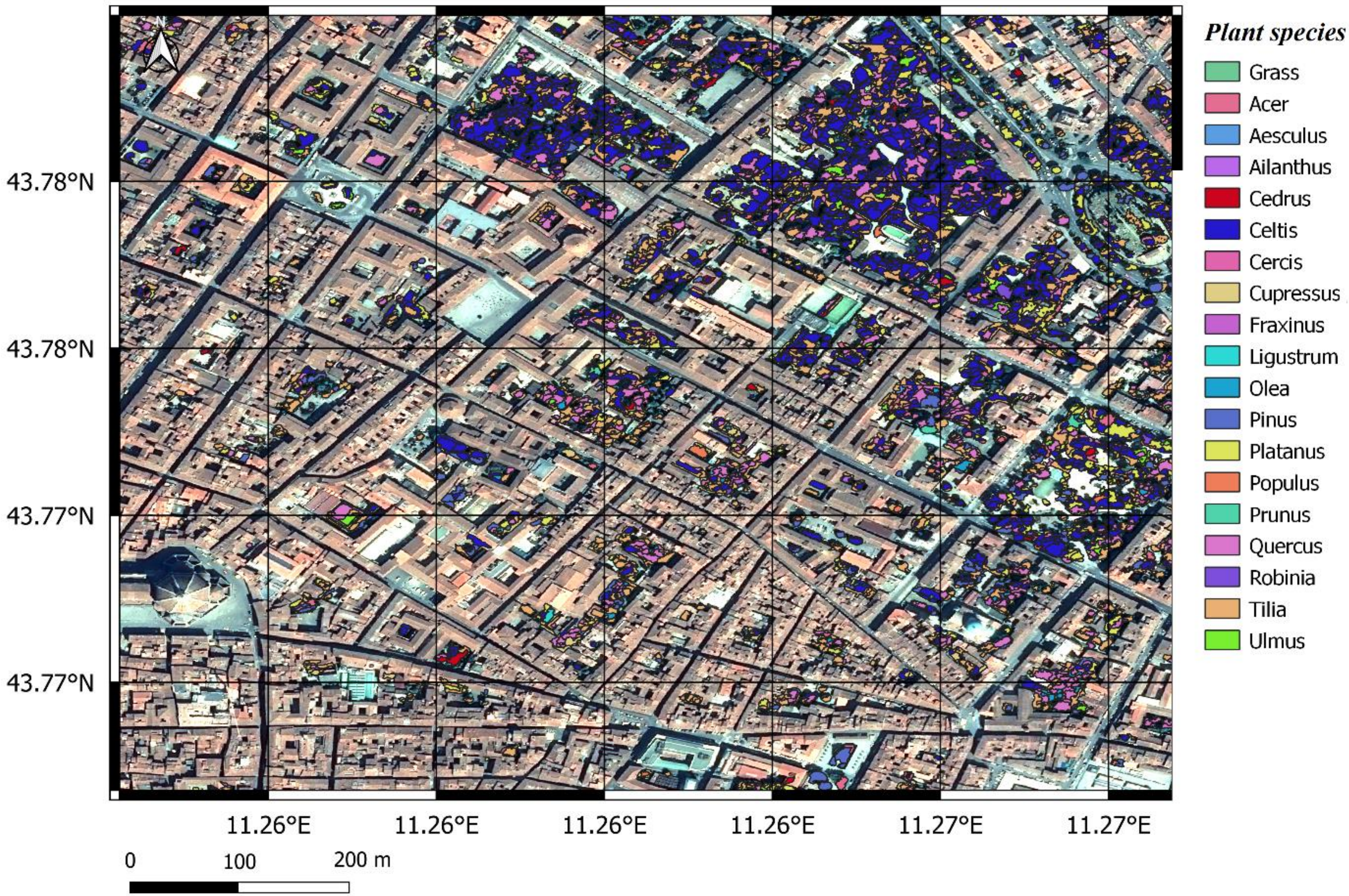
Urban trees maps

- ❖ Florence



Urban trees maps

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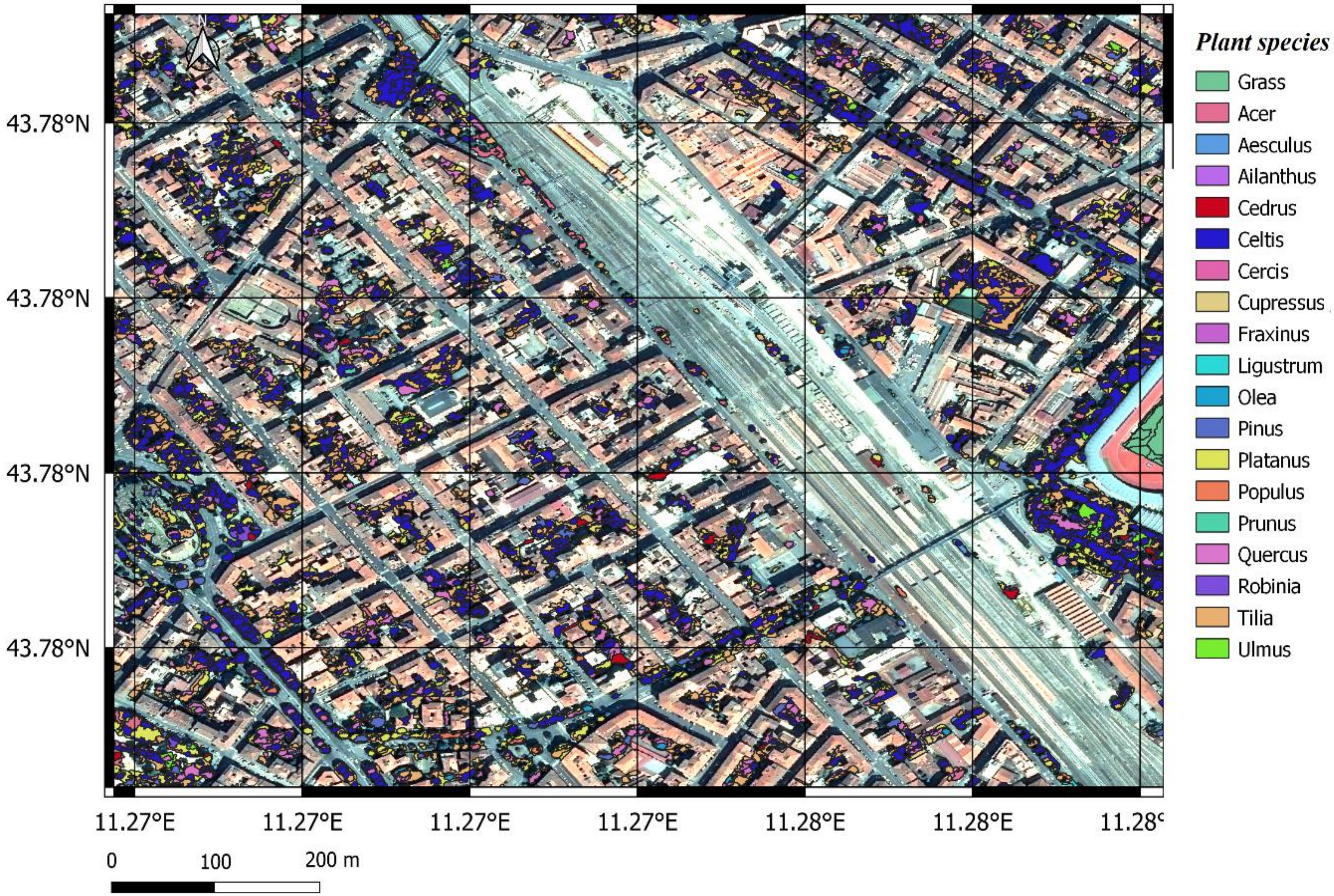

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Map of urban trees with position, species

Reproductible methodology with training dataset

Good advantages for time

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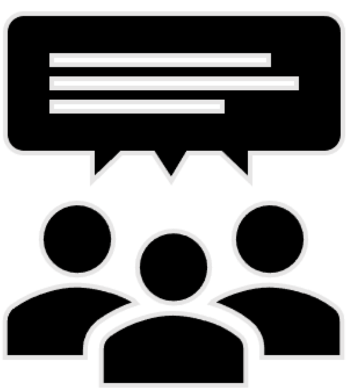
Thank you !



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