

Article

A Comparative Analysis of Spatial Resolution Sentinel-2 and Pleiades Imagery for Mapping Urban Tree Species

Fabio Recanatesi ¹, Antonietta De Santis ¹, Lorenzo Gatti ¹, Alessio Patriarca ^{1,*}, Eros Caputi ²,
Giulia Mancini ¹, Chiara Iavarone ², Carlo Maria Rossi ¹, Gabriele Delogu ², Miriam Perretta ³,
Lorenzo Boccia ³ and Maria Nicolina Ripa ¹

- ¹ Department of Agricultural and Forestry Sciences (DAFNE), University of Tuscia, Via S. Camillo de Lellis, 8, 01100 Viterbo, Italy; fabio.rec@unitus.it (F.R.); antonietta.desantis@studenti.unitus.it (A.D.S.); gatti@unitus.it (L.G.); giulia.mancini@unitus.it (G.M.); carlomariarossivt@gmail.com (C.M.R.); nripa@unitus.it (M.N.R.)
- ² Department of Economics, Engineering, Society and Business Organization (DEIM), University of Tuscia, Via 6 del Paradiso, 47, 01100 Viterbo, Italy; eros.caputi@unitus.it (E.C.); chiara.iavarone@unitus.it (C.I.); gabriele.delogu@unitus.it (G.D.)
- ³ Department of Architecture, University of Naples Federico II, Via Forno Vecchio, 36, 80134 Naples, Italy; miriam.perretta@unina.it (M.P.); lorenzo.boccia@unina.it (L.B.)
- * Correspondence: alessio.patriarca@unitus.it

Abstract: Urbanization poses significant challenges to ecosystems, resources, and human well-being, necessitating sustainable planning. Urban vegetation, particularly trees, provides critical ecosystem services such as carbon sequestration, air quality improvement, and biodiversity conservation. Traditional tree assessments are resource-intensive and time-consuming. Recent advances in remote sensing, especially high-resolution multispectral imagery and object-based image analysis (OBIA), offer efficient alternatives for mapping urban vegetation. This study evaluates and compares the efficacy of Sentinel-2 and Pléiades satellite imagery in classifying tree species within historic urban parks in Rome—Villa Borghese, Villa Ada Savoia, and Villa Doria Pamphilj. Pléiades imagery demonstrated superior classification accuracy, achieving an overall accuracy (OA) of 89% and a Kappa index of 0.84 in Villa Ada Savoia, compared to Sentinel-2's OA of 66% and Kappa index of 0.47. Specific tree species, such as *Pinus pinea* (Stone Pine), reached a user accuracy (UA) of 84% with Pléiades versus 53% with Sentinel-2. These insights underscore the potential of integrating high-resolution remote sensing data into urban forestry practices to support sustainable urban management and planning.

Keywords: urban forest; Sentinel-2; Pleiades; object-based image analysis



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1. Introduction

The twenty-first century is witnessing an unprecedented wave of urbanization, marked by significant landscape transformations and a profound reshaping of human experiences on a global scale. Rapid population growth, driven by improved healthcare, urban job opportunities, and changing lifestyles, has propelled rural communities to migrate to urban areas, leading to the accelerated expansion of cities and the emergence of mega-cities with populations exceeding millions [1–4]. As urban areas continue to develop as vibrant centers of economic, social, and cultural activities, their environmental impact becomes increasingly evident. The consequences of this urban revolution extend far beyond city limits, affecting ecosystems, altering natural habitats, and depleting natural resources. The conversion

of previously forested or agricultural lands into urban areas results in biodiversity loss, disruption of ecological processes, and habitat fragmentation for numerous species [5].

Moreover, intensified human activities in urban areas significantly affect air and water quality. The concentration of industries, transportation systems, and the sheer density of the human population contribute to increased pollution levels, including air pollutants and water contaminants, which have detrimental effects on human health, ecosystem well-being, and the quality of natural resources [6,7]. The urbanization process also exerts immense pressure on water and energy resources, with rising demand for freshwater coupled with inadequate infrastructure and inefficient management practices leading to water scarcity and compromised water quality. Additionally, the energy requirements of densely populated cities contribute to increased carbon emissions, exacerbating the global climate crisis and its associated impacts [8].

It is crucial to recognize that the consequences of this urban revolution extend beyond the environment [9]. The social fabric of communities undergoes significant changes as traditional lifestyles and cultural practices are reshaped or lost, potentially widening social disparities [10]. Urbanization introduces challenges related to housing, transportation, healthcare, education, and social cohesion, necessitating comprehensive planning and sustainable development approaches to ensure equitable and inclusive urban environments [11]. Considering these profound changes, adopting a holistic perspective that considers the interconnections between urbanization, the environment, and human well-being is imperative. Sustainable urban planning, resource-efficient infrastructure, green spaces, and innovative technologies are some of the tools that can mitigate the negative impacts of urbanization and pave the way for environmentally conscious and resilient cities [5,12].

Vegetation plays a crucial role in mitigating the environmental challenges posed by urbanization. Urban green spaces such as parks, gardens, and urban forests provide habitats for diverse plant and animal species, supporting biodiversity and counteracting habitat loss [13,14]. They also improve air quality by acting as natural air filters, absorbing pollutants like nitrogen dioxide, carbon monoxide, and particulate matter while releasing oxygen through photosynthesis [15,16]. Furthermore, vegetation contributes to carbon sequestration by capturing atmospheric carbon dioxide, thereby reducing greenhouse gas emissions and mitigating climate change [17]. Urban greenery helps regulate stormwater by absorbing rainwater, reducing flood risks, and filtering pollutants, which enhances water quality [18,19]. It also regulates urban microclimates by mitigating the heat island effect, providing shade, and cooling the environment through evapotranspiration [20,21]. Beyond environmental benefits, urban vegetation enhances the mental and physical well-being of residents by offering aesthetic value, recreational opportunities, and spaces for community engagement. This holistic set of ecosystem services underscores the necessity of integrating vegetation into urban planning and design for sustainable urban development [22].

In summary, urban vegetation is critical in addressing the environmental challenges of urbanization. Preserving and enhancing urban green spaces contribute to biodiversity conservation, improved air and water quality, carbon sequestration, stormwater management, microclimate regulation, and the well-being of urban residents. Incorporating vegetation into urban planning and design is essential for creating sustainable and resilient cities.

Given the numerous ecosystem services provided by urban forestry, it is evident that specific supervised classification systems for individual tree species should be developed [23,24]. This facilitates the creation of a digital cadastre of urban trees at the species level. This need arises from several factors:

- i Phytosanitary Management: Urban environments predispose vegetation to phytosanitary issues that must be promptly managed. Pollution, soil compaction, and limited

rooting space stress trees, making them more susceptible to pests and diseases. Accurate identification and monitoring of tree species are essential for early detection and management of these issues [25,26].

- ii Remote Sensing Methodologies: A remote sensing-based methodology capable of surveying tree species is indispensable for the proper planning and management of urban vegetation. Remote sensing techniques provide cost-effective and efficient means of collecting large-scale spatial data, allowing comprehensive assessments of urban tree populations. Accurate mapping of tree species distribution and abundance enables prioritization of conservation efforts, identification of areas for tree planting initiatives, and monitoring of changes in tree cover over time [27,28].

The integration of multispectral data from Sentinel-2 and Pléiades satellites into supervised classification systems represents a transformative approach to urban tree census and management. High-resolution remote sensing technologies allow researchers to overcome the challenges posed by traditional field-based surveys, such as high costs and limited spatial coverage [29]. Sentinel-2, with its medium resolution and frequent revisit times, is particularly effective for monitoring vegetation dynamics at broader spatial scales, while Pléiades' very high-resolution imagery enables detailed analysis of tree species distribution and health. This dual capacity bridges the gap between regional assessments and localized precision, making these satellites invaluable for urban forestry.

Studies have demonstrated the efficacy of high-resolution satellite data for tree species classification in urban settings. For example, [30] utilized bi-temporal Pléiades imagery to classify tree species and study ecological interactions, highlighting its potential for urban biodiversity studies. Similarly, [31] leveraged advanced techniques like superpixel-enhanced neural forests to detect urban tree canopies with unprecedented accuracy. These methodologies underscore how remote sensing not only provides detailed vegetation maps but also supports the development of digital green cadastres, which are critical for sustainable urban planning [32,33].

Furthermore, the integration of these satellite datasets into supervised classification algorithms, such as Random Forest (RF) and Object-Based Image Analysis (OBIA), has proven effective in differentiating tree species and assessing vegetation health. High-resolution imagery, when combined with ground truth data, enhances the accuracy of vegetation mapping, as demonstrated in multiple urban contexts [34,35]. These methods are particularly important in densely populated areas, where urban trees provide critical ecosystem services, including air quality improvement, heat island mitigation, and carbon sequestration [36].

As urbanization intensifies, the application of remote sensing for urban forestry will become even more crucial.

Future efforts should aim to refine algorithms for species-specific classification and explore the synergistic use of AI-driven models and other data sources such as LiDAR [37] or hyperspectral data [38–40]. The ability to monitor urban trees efficiently and accurately using Sentinel-2 and Pléiades will enable city planners and ecologists to prioritize conservation efforts, optimize tree planting strategies, and enhance urban resilience. This reinforces the indispensable role of remote sensing in shaping sustainable, biodiverse, and livable cities [41,42].

In light of the critical role played by urban vegetation, particularly trees, it is essential to develop rapid and efficient methods for the census of individual trees, whether standing alone or in groups. While urban tree inventories were previously feasible only through labor-intensive surveys requiring substantial time and resources, advancements in multi-spectral satellite data now enable precise and expedient classification of tree species. These methodologies leverage high-resolution remote sensing technologies, overcoming the limi-

tations of traditional field-based approaches and providing an invaluable tool for urban forest management. This shift underscores the importance of quantitative methods as a cornerstone for creating digital tree cadastres, thereby supporting informed decision-making in urban planning and biodiversity conservation.

This study introduces a novel experimental framework for urban tree species mapping that integrates and compares the capabilities of high-resolution (Sentinel-2, from the European Space Agency’s Copernicus program) and very high-resolution (Pléiades, from the French Space Agency—CNES and Airbus Defence and Space Consortium) multispectral satellite imagery, combined with advanced supervised classification techniques such as OBIA and Random Forest (RF), to achieve species-level identification in complex urban environments like Rome’s historic villas (Villa Borghese, Villa Ada Savoia, and Villa Doria Pamphilj), addressing challenges such as mixed pixels and spectral overlap, while setting a new benchmark for accuracy and efficiency in urban forestry research and supporting the creation of digital green cadastres for biodiversity conservation and sustainable urban planning.

2. Materials and Methods

2.1. Study Area

The study focuses on three prominent urban green spaces in Rome: Villa Borghese, Villa Ada Savoia, and Villa Doria Pamphilj, covering 80, 182, and 180 hectares, respectively (Figure 1). According to the Land Use Cover Map [43], these areas comprise 28.7% of the city’s urban parks.

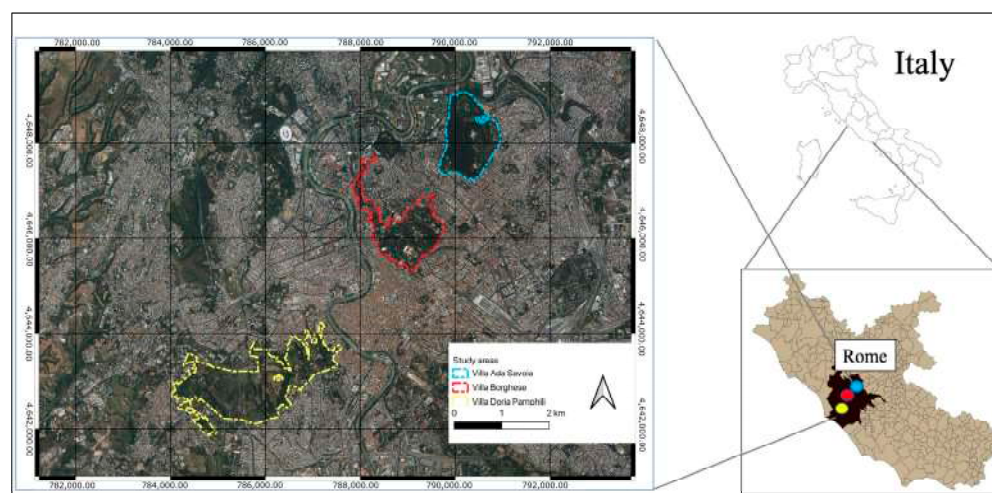


Figure 1. Italy, Municipality of Rome, and study areas: Villa Borghese, Villa Ada Savoia, and Villa Doria Pamphilj.

Moreover, the selection of these three study areas is motivated by the presence of the main tree species commonly used in urban parks across Italian and European cities in the Mediterranean basin, making these case studies paradigmatic examples for understanding and managing urban vegetation in similar contexts.

These historic parks are renowned for their rich vegetation and serve as vital ecological and recreational resources. Each park offers a unique composition of tree species, diverse habitats, aesthetic appeal, and valuable ecosystem services.

Villa Borghese, centrally located, boasts rich arboreal vegetation ideal for ecological and botanical studies. It hosts a variety of tree species, including Italian stone pines (*Pinus pinea*) with umbrella-like crowns, Mediterranean cypress trees (*Cupressus* spp.), majestic

oak trees (*Quercus* spp.), plane trees (*Platanus* spp.), and poplars (*Populus alba*), enhancing its biodiversity [44].

Villa Ada Savoia, in Rome's northeast, features a diverse mix of tree species that enrich its ecological and recreational value. It includes towering holm oaks (*Quercus ilex*) providing shade and grandeur, ash trees (*Fraxinus excelsior*) contributing to diversity, and various pine species (*Pinus* spp.) for Mediterranean charm.

Villa Doria Pamphilj, Rome's largest park, showcases a wide array of arboreal vegetation, including majestic oak trees (*Quercus* spp.) offering shade and grandeur, chestnut trees (*Castanea sativa*) adding to its allure, and pine trees (*Pinus* spp.) enhancing both aesthetic appeal and ecological significance [45].

2.2. Data Set

2.2.1. Satellite Images

The Pleiades satellite imagery (Airbus Defence and Space, France), acquired on 29 July 2021, is distributed in Italy by Planetek Italia <https://www.planetek.it> (accessed on 8 February 2024) and had an average off-nadir view angle of 29.4°. Pleiades is a very high-resolution commercial satellite featuring four multispectral bands (MS) with a spatial resolution of 0.5 m and a swath width of 20 km. The satellite also includes a panchromatic sensor (Pan, 480–830 nm) with similar spatial resolution. These bands are selected to support diverse applications such as resource management, coastal mapping, environmental monitoring, and infrastructure mapping (Airbus Defence and Space, 2012). Acquisition dates were chosen based on optimal conditions for cloud-free skies during mid-summer.

Sentinel-2 satellite imagery from 21 July 2021 was acquired as part of the Copernicus program by the European Space Agency (ESA). Sentinel-2 is a high-resolution satellite and operates in a sun-synchronous orbit, providing imagery with a revisit time of 5 days at the equator. The satellite's multispectral imaging instrument (MSI) comprises 13 bands covering visible to shortwave infrared (SWIR) wavelengths. Spatial resolution varies between 10 m for visible bands (443–695 nm) and 20 m for SWIR bands (740–2190 nm), with a swath width of 290 km, ensuring extensive coverage of large areas.

2.2.2. Ground Locating Tree Species

The preliminary identification of land use and tree species was conducted through the photointerpretation of Google Earth Pro images from the year 2022, supplemented by information available in the specialized literature and a field survey campaign carried out from March 2021 to September 2022. The tree inventory in the urban park was conducted using the QField® (<https://qfield.org>) app, with data collected based on a predefined grid to guide fieldwork. The gathered information was then processed in QGIS and used as training sites, or Regions of Interest (ROIs), during the algorithm classification training phase.

2.3. Methodology

Figure 2 illustrates the workflow for the classification of tree and shrub species using Pléiades and Sentinel-2 multispectral data.

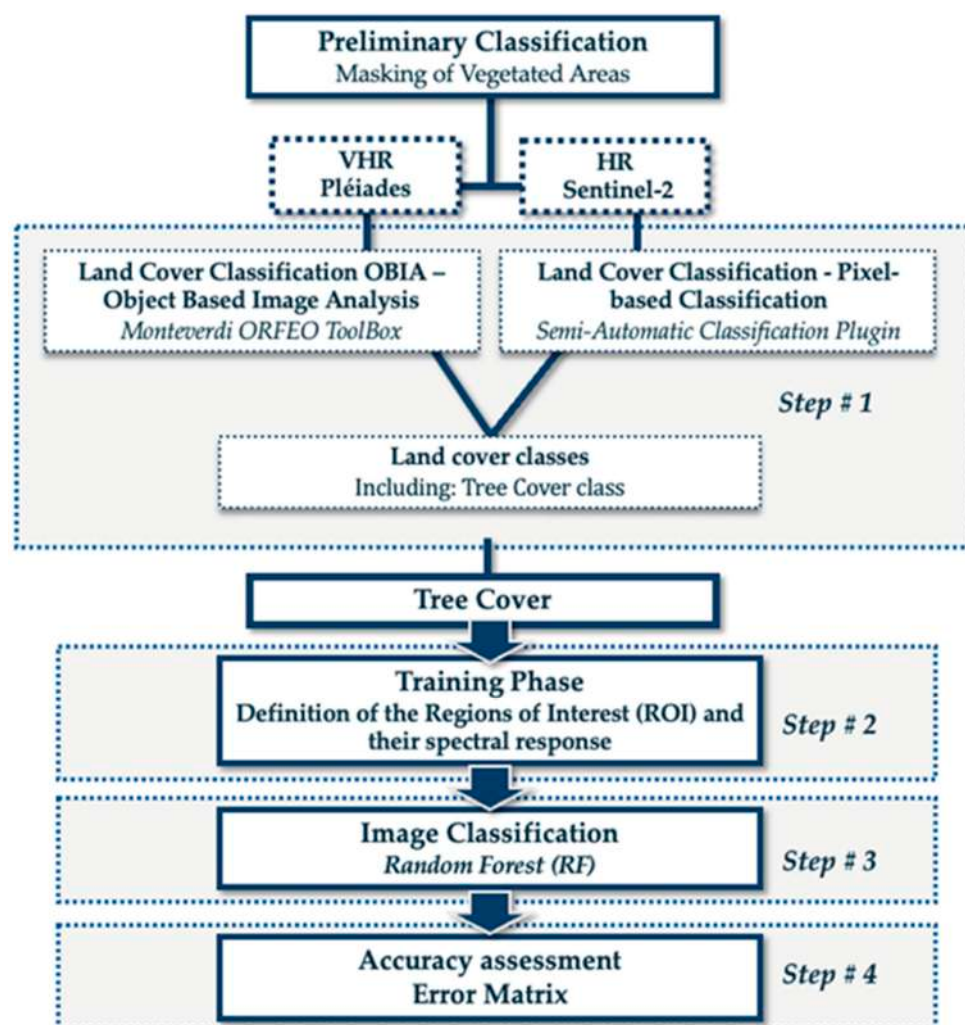


Figure 2. Workflow diagram of the operations performed for the identification and mapping of tree and shrub species using Pléiades and Sentinel-2 multispectral data.

The data were analyzed using the open-source software QGIS 3.16 [46] with algorithms from SAGA GIS due to its efficiency in processing raster data quickly and offering numerous customization options [47]. SAGA GIS was then employed to optimize the classification in the post-processing phase, particularly using the “Majority Filter” command for cell filtering to reduce “noise” and “smooth” the areas once categorized.

The geographic information system was configured with the WGS84 UTM 33 N reference system (EPSG: 32633). The Orfeo Toolbox-Monteverdi (OTB) [48] and Semi-Automatic-Classification (SCP) [49] plugin routines were used in the pre-processing phase for preliminary classification and in mapping tree and/or shrub species at level 3.

The analysis utilized semi-automatic (supervised) classification methods and object-oriented approaches, specifically OBIA. The methodological steps are described as follows:

- Step #1: In the first level (Level 1), a preliminary classification for land cover mapping was performed to reduce spatial heterogeneity within the three study areas. This approach allowed for the discrimination of tree cover only, on which tree species identification and mapping were subsequently carried out;
- Step #2: Identification of the main tree species present in the three study areas and definition of ROI to train the mapping algorithm;
- Step #3: Mapping of tree species using the RF algorithm;
- Step #4: Evaluation of the accuracy of the result through validation points and the elaboration of an error matrix.

2.3.1. Step #1: Preliminary Classification for Masking Vegetated Areas in VHR Images

To reduce the spatial heterogeneity of the objects represented in the images and to subject only tree cover to the classification algorithm for species identification, a gradual process was followed, with a diversified approach based on the spatial resolution of the initial data. For the very high-resolution multispectral data from Pléiades, a more advanced, object-oriented approach was employed [50]. The Pléiades images were segmented using the OTB Monteverdi plugin, which provides various algorithms, including watershed, mean-shift, connected components, and morphological profiles [48]. A mean-shift algorithm was employed in this study, resulting in a vector file composed of segments.

Subsequently, using the “Zonal Statistics” routine within the OTB suite, the Pléiades multispectral image was computed as input for the three study areas and the segmentation vector previously obtained. Statistics such as mean, minimum, maximum, and standard deviation were computed for each previously identified segment. A spatial union of the attribute point vector containing land cover classes and segmentation statistics was then performed. Following this, the “Train Vector Classifier” routine in OTB was used to train the classifier on labeled segments and selected features (in this case, mean and standard deviation). The LibSVM (Library for Support Vector Machine) classifier was employed for this classification.

Finally, using the “Vector Classifier” routine, the image was classified into land cover classes, using as input the segmentation vector with statistics and a previously created model text file for each study area.

Instead, for the high-resolution multispectral data from Sentinel-2, the OBIA classification was not used because the efficiency of segmentation based on object similarity strongly depends on the image’s spatial resolution. Therefore, a more traditional, pixel-oriented approach was adopted, using semi-automatic supervised classification with the SCP and the RF classification algorithm for this first level as well.

In Table 1, the list of land cover classes used in this initial classification process is provided for Pleiades and Sentinel-2 data.

Table 1. List of land cover classes for the preliminary classification of the Pléiades multispectral image.

Id Class	Class Name	Description
1	Grass	Areas covered with grass and other low-lying vegetation typically found in urban parks, lawns, and green spaces.
2	Water	Bodies of water, including rivers, lakes, ponds, and artificial water features within the urban environment.
3	Road network	The network of roads and streets that facilitate transportation within the urban area.
4	Buildings	Structures used for residential, commercial, industrial, and other urban purposes.
5	Trees	Urban tree vegetation, including individual trees and groups of trees in parks, along streets, and in other urban settings.
6	Projected shadows on the ground ^(*)	Shadows cast by buildings, trees, and other structures onto the ground surface.

^(*) Class detected only for the Pleiades data.

2.3.2. Step #2: Training and Validation Sites

The training and validation sites for the six classes listed in Table 1 were acquired through photointerpretation in the QGIS 3.16 environment of a set of color images from Google Earth©, dated 7 July 2022, which includes three visible bands (blue, green, and red) at a spatial resolution of 0.3 m, and a ground truth campaign conducted from March 2021 to September 2022.

During the training phase of the algorithms, a significantly different number of ROIs were used among the different study areas and between the two types of multispectral data. The number of ROIs, points/pixels, used for each land use class is reported in the following table (Table 2). A larger number of pixels and points were employed for the categories “trees/shrubs” and “grassland” to ensure effective discrimination between the two covers, especially for the Sentinel-2 data.

Table 2. Land use training and validation points for Pleiades and Sentinel-2 for the study areas.

		Training Data for PLEIADES						Validation Data for PLEIADES					
Id Class	Class Name	Villa Doria Pamphilj		Villa Borghese		Villa Ada		Villa Doria Pamphilj		Villa Borghese		Villa Ada	
		[# of Point]	[%]	[# of Point]	[%]	[# of Point]	[%]	[# of Point]	[%]	[# of Point]	[%]	[# of Point]	[%]
1	Grassland	226	17.7	211	18.0	162	19.7	421	24.7	273	18.2	186	17.3
2	Water	17	1.3	15	1.3	4	0.5	25	1.5	32	2.1	8	0.7
3	Road	97	7.6	172	14.7	106	12.9	174	10.2	260	17.3	170	15.8
4	Building	46	3.6	122	10.4	60	7.3	74	4.3	186	12.4	87	8.1
5	Tree vegetation	727	56.8	557	47.5	413	50.2	787	46.2	601	40.0	506	47.0
6	Ground shadow	167	13.0	95	8.1	77	9.4	224	13.1	149	9.9	119	11.1
Total		1280	100	1172	100	822	100.0	1705	100	1501	100	1076	100
		Training data for SENTINEL-2						Validation data for SENTINEL-2					
# Class	Class Name	Villa Doria Pamphilj		Villa Borghese		Villa Ada		Villa Doria Pamphilj		Villa Borghese		Villa Ada	
		[# of Point]	# Pixel	[# of Point]	# Pixel	[# of Point]	# Pixel	[# of Point]	[%]	[# of Point]	[%]	[# of Point]	[%]
1	Grassland	20	662	13	75	10	172	421	28.1	273	20.1	186	19.4
2	Water	1	69	4	36	2	14	25	2.4	32	2.3	8	0.8
3	Road	6	212	20	155	8	45	174	11.5	260	19.2	170	17.8
4	Building	6	140	12	77	7	111	74	5.0	186	13.7	87	9.1
5	Tree vegetation	12	868	23	222	8	854	787	53.0	601	44.4	506	52.9
Total		45	1951	72	565	35	1196	1481	100.0	1352	100	957	100

In the second classification level (Level 2), shown in Step #3, concerning tree classification, a new training phase of the RF algorithm was carried out for the census of tree species, using a similar approach for all the input tree cover scenarios. The training phase for the recognition of tree individuals involved the use of data collected from direct sampling, photointerpretation of high-resolution satellite images, and 3D views from Google Earth, as well as Google StreetView. In this phase, approximately 70% of the same ROIs

were used for the classification of tree cover discriminated from Sentinel-2 and Pléiades satellite images. Table 3 shows the number of ROIs used in each study area. Species and ROIs were selected based on the most representative areas of the three historical villas, considering the number of individuals present and favoring those with sufficiently large and defined canopies to characterize the spectral signature. Some tree species were chosen for their historical and landscape importance, and they are commonly found in all three study areas. Additionally, care was taken to select surface portions with acceptable shadow and light conditions and, in the case of mapping the same species, similar values in the spectral response. The RF algorithm was trained to map and identify fourteen classes, including ten tree species, two shrub species, two genera, and two categories encompassing all unidentified or non-representative species in the study areas.

Table 3. ROIs used for the training and validation phase aimed at the census of tree species.

# Class	Species	Common Name/ Description	Training			Validation					
			Sentinel-2 and Pleiades			Sentinel-2		Pleiades			
			# of Polygons			# of Points					
			Villa Doria Pamphilj	Villa Ada Savoia	Villa Borghese	Villa Doria Pamphilj	Villa Ada Savoia	Villa Borghese	Villa Doria Pamphilj	Villa Ada Savoia	Villa Borghese
1	<i>Pinus pinea</i>	Stone Pine	429	202	70	206	396	214	150	189	243
2	<i>Quercus ilex</i>	Holm Oak		67	46	138	251	305	103	131	366
3	<i>Platanus acerifolia</i>	London Plane	30		31	56		95	52		65
4	<i>Celtis australis</i>	European Nettle Tree	23		24	25		18	2		29
5	<i>Magnolia grandiflora</i>	Southern Magnolia			8						19
6	Other Plant Species	Other Plant Species	324	173	54	531	236	368	578	545	278
7	Altre conifere	Other Conifers	41						25		
8	<i>Aesculus hippocastanum</i>	Horse Chestnut	18			8			1		
9	<i>Populus alba</i>	White Poplar	49			12			14		
10	<i>Cedrus</i> spp. (Libani and Deodara)	Cedars (Lebanon and Deodar Cedar)	138	58		24	31		71	90	
11	<i>Ulmus minor</i>	Field Elm	13						1		
12	<i>Nerium oleander</i>	Oleander	8						3		
13	<i>Quercus suber</i>	Cork Oak	92	38			86			45	
Total			1165	538	233	1000	1000	1000	1000	1000	1000

2.3.3. Step #3: Image Classification

At the third level of the analysis, the classification of tree species was performed, resulting in two classifications for the study area: one based on Sentinel-2 data and the other on Pléiades data. The RF algorithm was configured with 100 decision trees and

utilized the “balanced class weight” parameter to manage potential class imbalances due to varying class representativity. A limited number of predictors were used for each class, considering the significant variability in reflectance values in the Pléiades data. The number of ROIs was increased only when strictly necessary to identify smaller canopies, based on the context, to improve mapping accuracy for specific tree species classes. This approach was particularly targeted at the species Stone pine (*Pinus pinea*) and Holm oak (*Quercus ilex*).

2.3.4. Step #4: Accuracy Assessment

At the end of the classification process, the accuracy was evaluated using an error matrix (also known as a confusion matrix). To ensure independence, this matrix was constructed using validation points selected for each class in proportion to the percentage of the area classified relative to the total area. A total of 1000 validation points were used for each classification produced.

Similarly to the accuracy assessment process in OBIA classification, the Overall Accuracy (OA) parameter, the Kappa index, as well as the Producer’s Accuracy (PA), the User’s Accuracy (UA), and the Standard Deviation of User Accuracy (σ UA) were calculated. These latter metrics indicate the precision with which pixels are correctly assigned to classes. Together, these indices provide a comprehensive assessment of the classifier’s performance. The following section provides a detailed analysis of these parameters.

Overall Accuracy (OA) provides a global measure of how well the classifier performs across all classes, representing the percentage of correctly classified pixels in relation to the total number of pixels classified, calculated using the Formula (1):

$$OA = \frac{\sum_{i=1}^n M_{ii}}{\sum_{i=1}^n \sum_{j=1}^n M_{ij}} \quad (1)$$

where

M_{ii} is the number of true positives for class i ;

$\sum_{i=1}^n \sum_{j=1}^n M_{ij}$ is the total number of all pixels classified, regardless of the class.

Kappa Index Accuracy (K) is a statistical measure used to assess the agreement between two sets of categorical data, such as classifications made by different observers or methods. It takes into account the agreement that could occur by chance alone, calculating using the Formula (2):

$$K = \frac{P_0 - P_e}{1 - P_e} \quad (2)$$

where

P_0 is the proportion of observed agreement between two classifiers;

P_e is the proportion of agreement expected by chance.

Producer’s Accuracy (PA) is a metric that measures the proportion of correctly classified pixels among all pixels that actually belong to a specific class. It indicates the ability of the classifier to identify pixels of the target class, calculated using the Formula (3):

$$PA_i = \frac{M_{ii}}{\sum_{j=1}^n M_{ij}} \quad (3)$$

where

M_{ii} is the number of true positives, representing the pixels correctly classified as belonging to class i ;

$\sum_{j=1}^n M_{ij}$ is the total number of pixels that actually belong to class i , which includes true positives (M_{ii}) and false negatives (pixels of class i misclassified as other classes).

User's Accuracy (UA) is a metric in classification accuracy assessment that evaluates the proportion of correctly classified pixels among all pixels assigned to a specific class. It indicates how accurately the classifier identifies pixels belonging to the target class. UA is calculated using the Formula (4):

$$UA_i = \frac{M_{jj}}{\sum_{i=1}^n M_{ji}} \quad (4)$$

where

M_{jj} represents true positive (correctly classified pixels of class j);

$\sum_{i=1}^n M_{ji}$ is the total number of pixels that actually belong to class j , including both true positive and false positive (pixels of other classes misclassified as class j).

Standard Deviation of User Accuracy (σUA) quantifies how the estimated user accuracy varies across different iterations or samples.

$$\sigma UA = \sqrt{\frac{\sum_{j=1}^n (UA_{ij} - \overline{UA}_i)^2}{n - 1}} \quad (5)$$

where

UA_{ij} is the estimated user accuracy for class i in sample j ;

$\overline{UA}_i$ is the mean user accuracy for class i ;

n is the number of samples or iterations.

3. Results

In Figure 3A,B, the land use classifications (Level 1) for the study area of Villa Ada Savoia obtained using Pleiades and Sentinel-2 data, respectively, are presented. Table 4 reports the error matrix and the index values used for the validation of the classifications obtained.

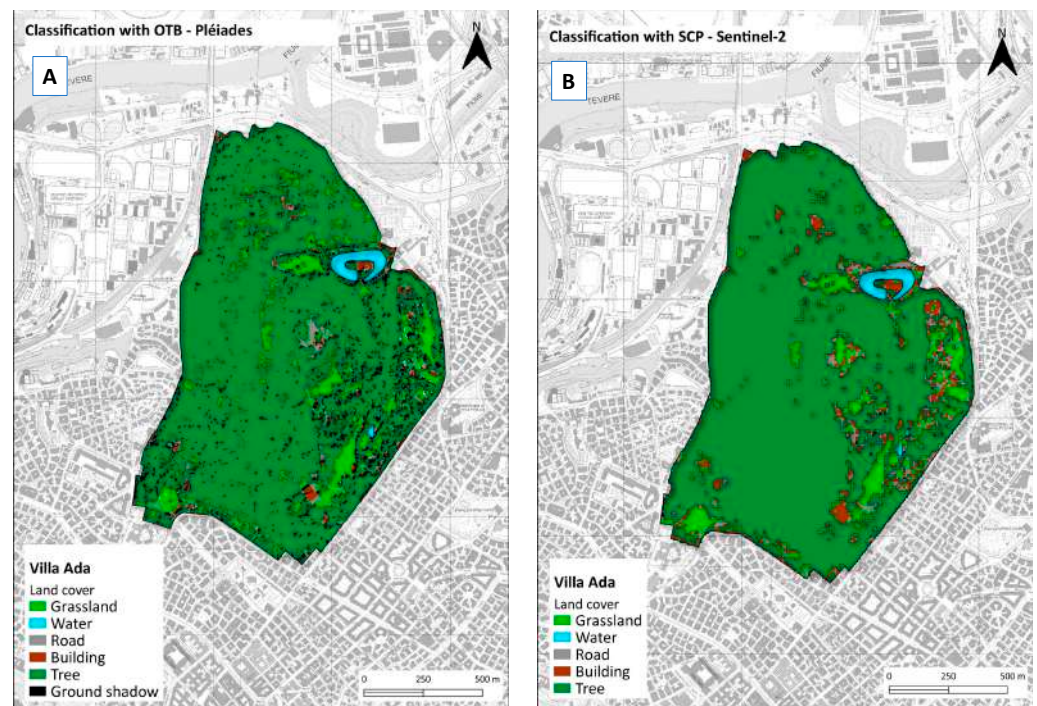


Figure 3. (A) Land use classification (Level 1) for Villa Ada Savoia—Pleiades data; (B) Land use classification (Level 1) for Villa Ada Savoia—Sentinel-2 data.

Table 4. Error matrix e validation indices for land use classification (Level 1) detected in Villa Ada Savoia.

Villa Ada Savoia													
OTB Classified Data-Pléiades							SCP Classified Data-Sentinel-2						
Class		Grass	Water	Road network	Buildings	Trees	Projected shadow	Grass	Water	Road network	Buildings	Trees	
		1	2	3	4	5	6	1	2	3	4	5	
Reference data	Grass	1	172	0	10	1	3	0	94	0	10	18	55
	Water	2	0	8	0	0	0	0	0	6	1	0	0
	Road network	3	10	0	143	16	1	0	40	1	39	49	20
	Buildings	4	9	0	26	50	1	1	17	0	12	45	4
	Trees	5	16	0	1	0	482	7	28	1	18	31	407
	Projected shadows	6	0	0	0	0	21	98	-	-	-	-	-
Validation indices	Kappa	0.84						0.47					
	OA	0.89						0.66					
	Class Comparison	1 vs. <i>all</i>	2 vs. <i>all</i>	3 vs. <i>all</i>	4 vs. <i>all</i>	5 vs. <i>all</i>	6 vs. <i>all</i>	1 vs. <i>all</i>	2 vs. <i>all</i>	3 vs. <i>all</i>	4 vs. <i>all</i>	5 vs. <i>all</i>	
	Accuracy	0.831	1	0.794	0.746	0.949	0.925	0.522	0.750	0.488	0.315	0.837	
	Recall	0.925	1	0.841	0.575	0.953	0.824	0.531	0.857	0.262	0.577	0.839	
	F-score	0.875	1	0.817	0.649	0.951	0.871	0.527	0.8	0.341	0.407	0.838	

Regarding the results obtained from the species classification for the three study areas, Figure 4A,B show the classifications for Villa Borghese obtained using Pleiades and Sentinel-2 data, respectively. Table 5 reports the accuracy values for the two classifications.

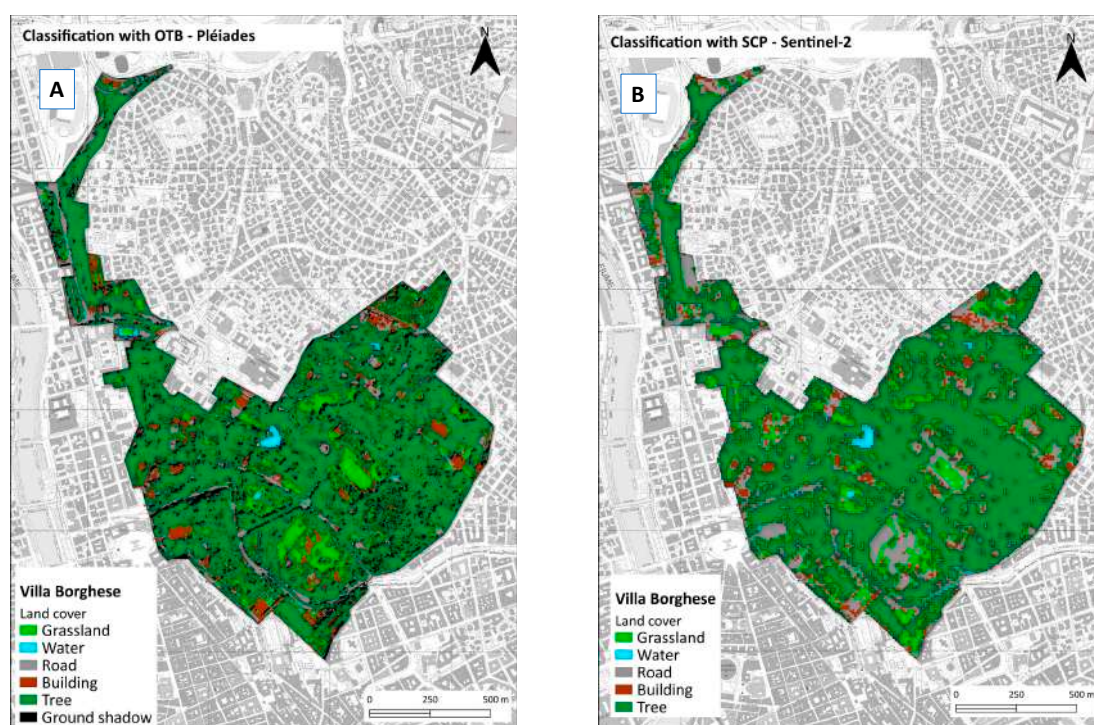
**Figure 4.** (A) Land use classification (Level 1) for Villa Borghese—Pleiades data; (B) Land use classification (Level 1) for Villa Borghese—Sentinel-2 data.

Table 5. Error matrix e validation indices for classification Level 1 detected in Villa Borghese.

Villa Borghese													
OTB Classified Data-Pléiades							OTB Classified Data-Sentinel-2						
Class		Grass	Water	Road network	Buildings	Trees	Projected shadow	Grass	Water	Road network	Buildings	Trees	
		1	2	3	4	5	6	1	2	3	4	5	
Reference data	Grass	1	225	11	7	13	17	0	126	1	38	21	66
	Water	2	0	31	0	0	1	0	3	15	7	0	0
	Road network	3	42	1	145	70	1	1	46	0	140	32	21
	Buildings	4	20	1	54	107	3	1	24	0	59	74	5
	Trees	5	36	0	1	1	560	3	78	3	26	11	478
	Projected shadows	6	0	0	0	0	18	131	-	-	-	-	-
Validation indices	Kappa				0.73				0.50				
	OA				0.80				0.65				
	Class Comparison	1 vs. <i>all</i>	2 vs. <i>all</i>	3 vs. <i>all</i>	4 vs. <i>all</i>	5 vs. <i>all</i>	6 vs. <i>all</i>	1 vs. <i>all</i>	2 vs. <i>all</i>	3 vs. <i>all</i>	4 vs. <i>all</i>	5 vs. <i>all</i>	
	Accuracy	0.697	0.705	0.700	0.560	0.933	0.963	0.455	0.789	0.519	0.536	0.839	
	Recall	0.824	0.969	0.558	0.575	0.932	0.879	0.500	0.600	0.586	0.457	0.802	
	F-score	0.755	0.816	0.621	0.568	0.933	0.919	0.476	0.682	0.550	0.493	0.820	

The classification results for the study area of Villa Doria Pamphilj are presented in Figure 5A,B, and the accuracy values obtained are shown in Table 6.

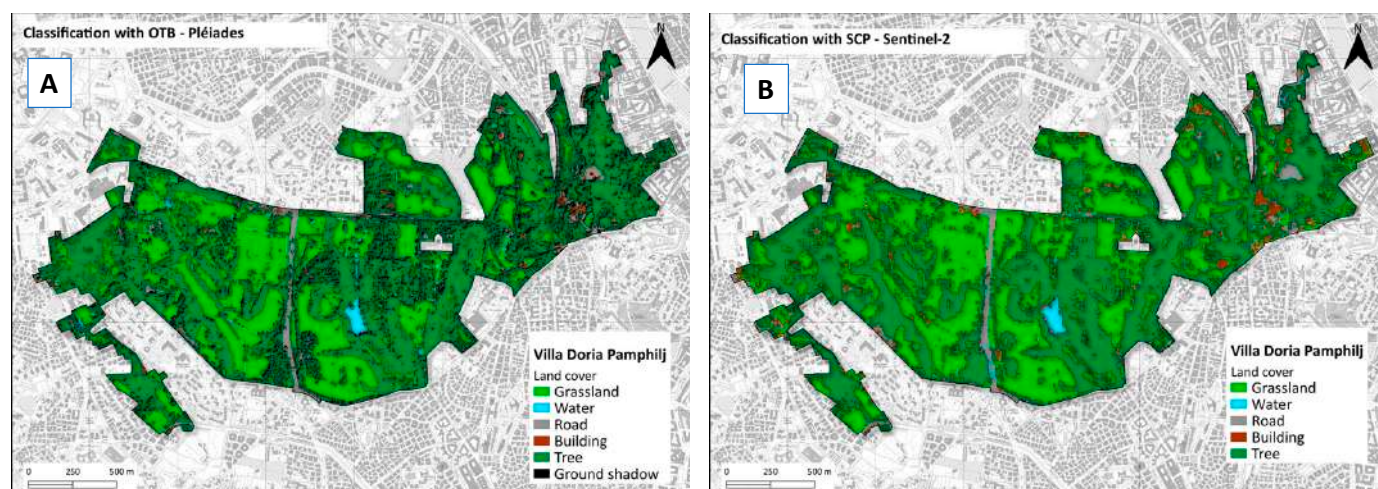


Figure 5. (A) Land use classification (Level 1) for Villa Doria Pamphilj—Pleiades data; (B) Land use classification (Level 1) for Villa Doria Pamphilj—Sentinel-2 data.

Table 6. Error matrix e validation indices for land use classification (Level 1) detected in Villa Doria Pamphilj.

Villa Doria Pamphilj													
OTB Classified Data-Pléiades								OTB Classified Data-Sentinel-2					
Class		Grass	Water	Road network	Buildings	Trees	Projected shadow	Grass	Water	Road network	Buildings	Trees	
		1	2	3	4	5	6	1	2	3	4	5	
Reference data	Grass	1	397	3	3	1	16	0	347	0	5	27	5
	Water	2	2	22	1	0	0	0	7	9	5	1	0
	Road network	3	16	0	140	9	8	1	66	3	53	33	8
	Buildings	4	17	3	20	28	3	3	31	0	16	22	0
	Trees	5	22	0	3	0	748	13	129	4	23	29	583
	Projected shadows	6	0	0	2	0	24	198					
Validation indices	Kappa				0.86				0.54				
	OA				0.90				0.71				
	Class Comparison	1 vs. all	2 vs. all	3 vs. all	4 vs. all	5 vs. all	6 vs. all	1 vs. all	2 vs. all	3 vs. all	4 vs. all	5 vs. all	
	Accuracy	0.874	0.786	0.828	0.737	0.936	0.921	0.598	0.563	0.520	0.196	0.936	
	Recall	0.945	0.880	0.805	0.378	0.952	0.884	0.844	0.409	0.325	0.319	0.759	
	F-score	0.908	0.830	0.816	0.500	0.944	0.902	0.700	0.474	0.400	0.243	0.838	

Regarding the results obtained from the vegetation species classifications, the classifications for the study area of Villa Ada Savoia are shown in Figure 6A,B, while the accuracy values are presented in Table 7.

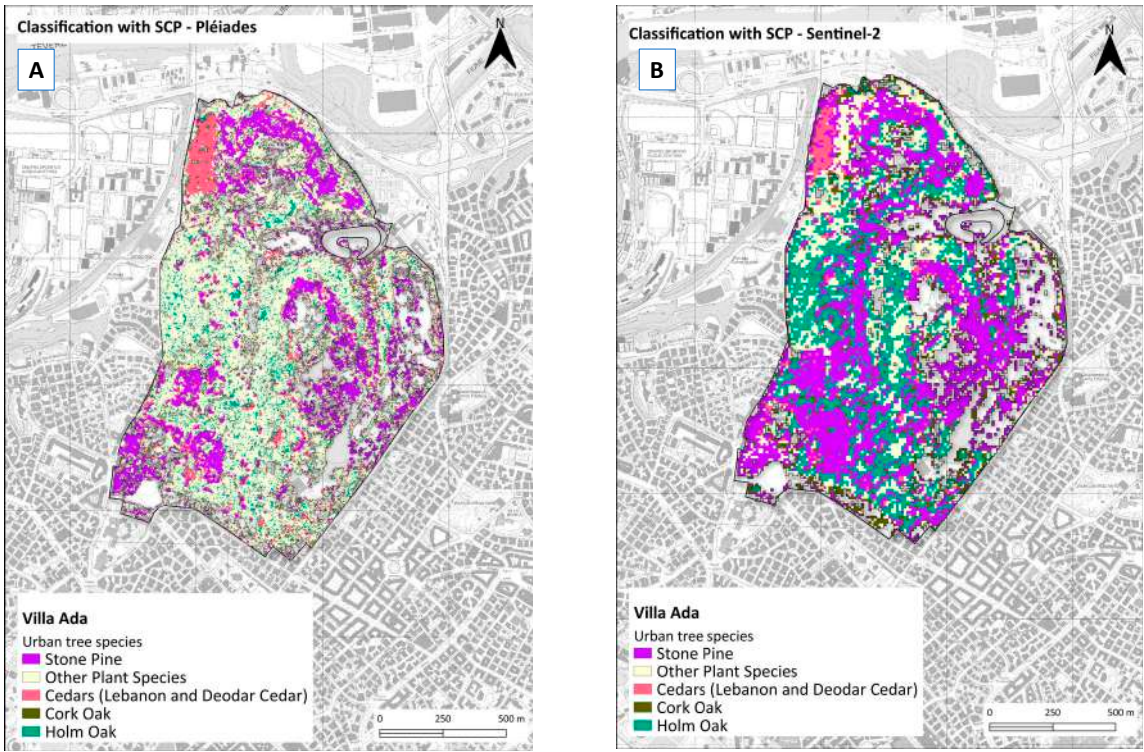
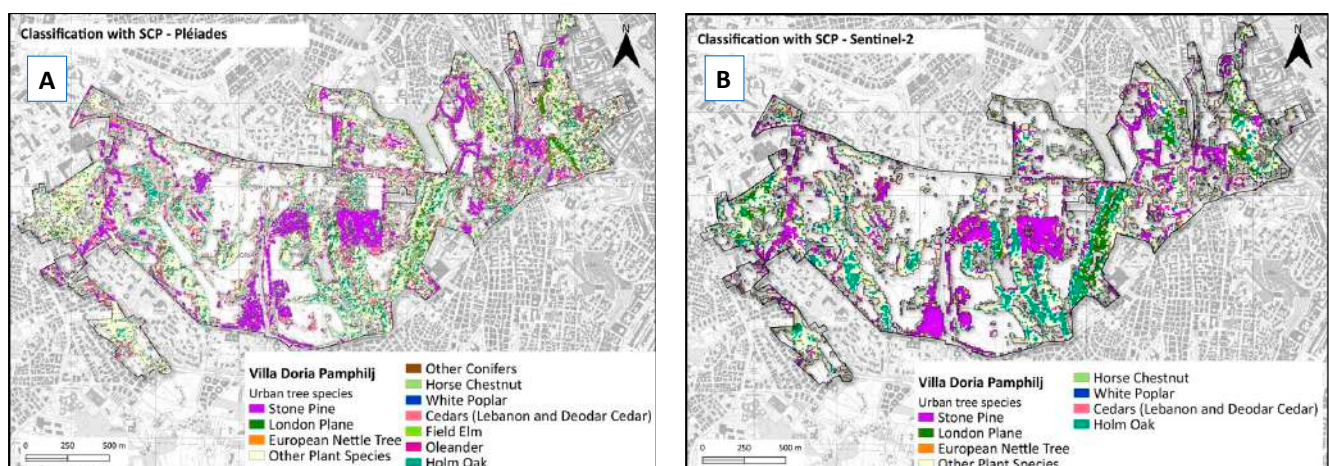


Figure 6. (A) Tree classification (Level 2) for Villa Ada Savoia—Pleiades data; (B) Tree classification (Level 2) for Villa Ada Savoia—Sentinel-2 data.

Table 7. Error matrix e validation indices for tree classification (Level 2) detected in Villa Doria Pamphili.

Sentinel-2 Villa Ada Savoia										Pleiades Villa Ada Savoia								
Class		Reference Data						Total	UA (%)	σ UA (%)	Reference Data					Total	UA (%)	σ UA (%)
		Stone Pine	Other Plant Species	Libani and Deodara Cedrus	Cork Oak	Holm Oak	Stone Pine				Other Plant Species	Libani and Deodara Cedrus	Cork Oak	Holm Oak				
															1			
SCP Classified data	Stone Pine	1	208	131	19	12	26	396	53	50	158	21	4	4	2	189	84	37
	Other Plant Species	6	49	159	13	5	10	236	67	47	37	378	12	20	98	545	69	46
	Libani and Deodara Cedrus	10	14	3	13	1	0	31	42	49	22	23	37	0	9	91	41	49
	Cork Oak	13	13	56	3	3	11	86	3	18	1	33	0	3	8	45	7	25
	Holm Oak	14	19	158	4	5	65	251	26	44	1	96	1	1	32	131	24	43
	Total		303	507	52	26	112	1.000				219	551	54	28	149	1.001	
PA (%)			69	31	25	12	58				0	69	69	11	21			
OA									0.45									0.61
Kappa									0.24									0.38

For the study area of Villa Doria Pamphili, the obtained classifications are shown in Figure 7A,B, and the accuracy values are presented in Tables 8 and 9.

**Figure 7.** (A) Tree classification (Level 2) for Villa Doria Pamphili—Pleiades data; (B) Tree classification (Level 2) for Villa Doria Pamphili—Sentinel-2 data.

For the third study area, Villa Borghese, the classifications obtained from the Pleiades and Sentinel-2 data are shown in Figure 8A and 8B, respectively, while the accuracy values for this area are presented in Tables 10 and 11.

Table 8. Error matrix e validation indices for tree classification (Level 2) detected in Villa Doria Pamphilj using Sentinel-2.

Sentinel-2 Villa Doria Pamphilj																
Class		Reference Data												Total	UA (%)	σ UA (%)
		Stone Pine	London Plane	European Nettle Tree	Other Plant Species	Other Conifers	Horse Chestnut	White Poplar	Lebanon and Deodar Cedar	Field Elm	Oleander	Cork Oak				
SCP Classified data	Stone Pine	1	113	1	0	61	8	0	0	11	0	0	12	206	55	50
	London Plane	3	0	3	0	49	0	0	0	0	0	0	4	56	5	23
	European Nettle Tree	4	5	0	2	10	2	1	0	0	0	0	5	25	8	27
	Other Plant Species	6	30	10	1	375	15	5	5	7	2	0	81	531	71	46
	Other Conifers	7	0	0	0	0	0	0	0	0	0	0	0	0	-	-
	Horse Chestnut	8	2	0	0	1	1	0	1	2	0	1	0	8	0	0
	White Poplar	9	0	0	0	5	0	1	1	2	0	0	3	12	8	28
	Lebanon and Deodar Cedar	10	8	0	1	8	2	0	0	5	0	0	0	24	21	41
	Field Elm	11	0	0	0	0	0	0	0	0	0	0	0	0	-	-
	Oleander	12	0	0	0	0	0	0	0	0	0	0	0	0	-	-
	Cork Oak	14	10	1	0	74	3	0	2	2	0	0	46	138	33	47
	Total		168	15	4	583	31	7	9	29	2	1	151	1000		
PA (%)		67	20	50	64	0	0	11	17	0	0	30				
OA																0.55
Kappa																0.28



Figure 8. (A) Tree classification (Level 2) for Villa Borghese—Pleiades data; (B) Tree classification (Level 2) for Villa Doria Pamphilj—Sentinel-2 data.

Table 9. Error matrix e validation indices for tree classification (Level 2) detected in Villa Doria Pamphilj using Pléiades.

Pléiades Villa Doria Pamphilj																
Reference Data													Total	UA (%)	σ UA (%)	
Class																
	Stone Pine	London Plane	European Nettle Tree	Other Plant Species	Other Conifers	Horse Chestnut	White Poplar	Lebanon and Deodar Cedar	Field Elm	Oleander	Cork Oak					
	1	3	4	6	7	8	9	10	11	12	14					
SCP Classified data	Stone Pine	1	110	1	0	24	3	0	3	7	0	0	2	150	73	44
	London Plane	3	0	16	0	32	0	0	0	0	0	0	4	52	31	46
	European Nettle Tree	4	0	0	0	2	0	0	0	0	0	0	0	2	0	0
	Other Plant Species	6	7	10	3	437	26	5	6	9	2	2	73	580	75	43
	Other Conifers	7	1	0	0	7	7	0	0	0	0	0	10	25	28	45
	Horse Chestnut	8	0	0	0	1	0	0	0	0	0	0	0	1	0	0
	White Poplar	9	2	0	0	2	2	0	3	1	0	0	2	12	25	43
	Lebanon and Deodar Cedar	10	10	1	0	34	4	1	0	17	0	0	4	71	24	43
	Field Elm	11	0	0	0	1	0	0	0	0	0	0	0	1	-	-
	Oleander	12	0	0	0	3	0	0	0	0	0	0	0	3	-	-
	Cork Oak	14	3	1	0	60	1	0	0	3	0	0	35	103	34	47
	Total		133	29	3	603	43	6	12	37	2	2	130	1000		
PA (%)		83%	55%	0%	72	16	0	25	46	0	0	27				
OA															0.63	
Kappa															0.44	

Table 10. Error matrix e validation indices for tree classification (Level 2) detected in Villa Borghese using Sentinel-2.

Sentinel-2 Villa Borghese										
Reference Data								Total	UA (%)	σ UA (%)
Class			<i>Stone Pine</i>	<i>Holm Oak</i>	<i>London Plane</i>	<i>European Nettle Tree</i>	<i>Other Plant Species</i>			
			1	14	3	4	6			
SCP Classified data	<i>Stone Pine</i>	1	96	35	2	3	79	215	45	50
	<i>Holm Oak</i>	14	16	130	17	3	138	304	43	49
	<i>London Plane</i>	3	2	7	24	1	61	95	25	43
	<i>European Nettle Tree</i>	4	0	3	2	2	11	18	11	31
	<i>Other plant species</i>	6	40	116	19	9	184	368	50	50
Total			154	291	64	18	473	1000		
PA (%)			62	45	38	11	39			
OA										0.44
Kappa										0.19

Table 11. Error matrix e validation indices for tree classification (Level 2) detected in Villa Borghese using Pléiades.

Pléiades-Villa Borghese											
		Reference Data							Total	UA (%)	σ UA (%)
Class			<i>Stone Pine</i>	<i>Holm Oak</i>	<i>London Plane</i>	<i>European Nettle Tree</i>	<i>Other Plant Species</i>	<i>Southern Magnolia</i>			
			1	14	3	4	6	5			
SCP Classification	<i>Stone Pine</i>	1	127	44	2	2	68	0	243	52	50
	<i>Holm Oak</i>	14	8	182	12	5	157	2	366	50	50
	<i>London Plane</i>	3	1	0	27	2	35	0	65	42	49
	<i>European Nettle Tree</i>	4	0	2	6	6	15	0	29	21	41
	<i>Other plant species</i>	6	17	44	17	3	195	2	278	70	46
	<i>Southern Magnolia</i>	5	0	3	1	0	11	4	19	21	41
	Total		153	275	65	18	481	8	1000		
PA (%)			83	66	42	33	41	50			
OA											0.54
Kappa											0.37

4. Discussion

The findings of this study highlight the advantages and limitations of utilizing Sentinel-2 and Pléiades imagery for urban tree species detection and classification. By integrating remote sensing technologies with advanced classification algorithms, we provide an effective framework for mapping urban vegetation, a critical step toward sustainable urban planning and biodiversity conservation. The following discussion synthesizes these results with existing literature to contextualize our contributions. The land cover classification was first used to detect broad classes, including trees, while subsequent classification focused on defining specific tree species. Our approach provided an in-depth analysis of the differences between Pléiades and Sentinel-2 imagery. In this context, tree detection played a crucial role in the overall accuracy of our study, benefiting from the higher spatial resolution of Pléiades compared to Sentinel-2.

Land Cover Classification (Level 1):

In the first land cover classification, Pléiades imagery, with its higher spatial resolution, consistently outperformed Sentinel-2 across all study areas. For instance, in Villa Ada Savoia, Pléiades achieved an OA of 89% and a Kappa index of 0.84, compared to 66% OA and 0.47 Kappa for Sentinel-2 (Table 4). These findings align with the observations of Le Zhang et al. [51], who noted the utility of high-resolution Pléiades imagery for detailed urban ecological studies, emphasizing its ability to capture fine spatial details. Similarly, Kang and Cai [52] highlighted the advantages of very high-resolution data in improving classification accuracy for urban vegetation. This trend was also observed in Villa Borghese (80% OA and 0.73 Kappa for Pléiades vs. 65% OA and 0.50 Kappa for Sentinel-2, Table 5) and Villa Doria Pamphilj (90% OA and 0.86 Kappa for Pléiades vs. 71% OA and 0.54 Kappa for Sentinel-2, Table 6).

The superior performance of Pléiades can be attributed to its higher spatial resolution, which enhances its ability to capture detailed features and reduce spatial heterogeneity. This

is particularly beneficial in complex urban areas where mixed land cover types are prevalent. For example, in Villa Ada Savoia, Pléiades carried out high classification accuracy for grass (83%), water (100%), and tree vegetation (95%), significantly outperforming Sentinel-2, which struggled particularly with grass (52%) and road network (49%) classifications.

Tree Species Classification (Level 2):

For the tree species classification, the advantages of Pléiades imagery become even more pronounced. In Villa Ada Savoia, Pléiades achieved an OA of 61% and a Kappa index of 0.38, compared to 45% OA and 0.24 Kappa for Sentinel-2. Specific tree species such as *Pinus pinea* (Stone pine) and *Quercus ilex* (Holm oak) were classified with higher UA and PA using Pléiades. For instance, the UA for Stone Pine was 84% with Pléiades, significantly higher than the 53% achieved with Sentinel-2. Regarding the Cedrus class (*Cedrus libani* and *Cedrus deodara*), the accuracy values are as follows: Sentinel-2 UA = 42% and PA = 25%, while Pleiades UA = 41% and PA = 69%. For the Holm Oak in Villa Ada, the UA values are not very high in both classifications; specifically, Sentinel-2 shows a UA value of 26% and PA = 58%, while Pleiades reports a UA value of 24% and PA = 21% (Table 7). These findings are consistent with the work of Arabi Aliabad et al. [53], who demonstrated the potential of high-resolution imagery to enhance species-level mapping by capturing finer spectral and structural details of tree canopies.

Similar trends were observed in Villa Doria Pamphilj and Villa Borghese. In Villa Doria Pamphilj, Pléiades achieved 63% OA and 0.44 Kappa, whereas Sentinel-2 reached only 55% OA and 0.28 Kappa (Tables 8 and 9). The ability to accurately classify species like *Pinus pinea* and *Platanus acerifolia* (London plane) further underscores the importance of high-resolution data. In Villa Borghese, Pléiades demonstrated higher classification accuracy for Stone Pine (52% UA) and Holm Oak (83% UA) compared to Sentinel-2, which managed only 44% and 62%, respectively (Tables 10 and 11).

The differences in classification performance between Pléiades and Sentinel-2 can be explained by their spatial resolutions and the consequent effects on image interpretation. Pléiades' higher resolution reduces the occurrence of mixed pixels, where a single pixel represents multiple land cover types or species. This results in clearer, more precise boundaries between different land cover types and better differentiation among tree species. Sentinel-2, with its coarser resolution, tends to aggregate diverse land cover types within single pixels, leading to confusion and misclassification, as previously noted by [54,55].

The high resolution of Pléiades also allows for better capture of the spectral and structural characteristics unique to each tree species, such as leaf shape, canopy structure, and spectral reflectance properties; this aspect, which has moreover already been observed by [56,57]. This capability is particularly important in urban environments where tree species diversity and density are high, and accurate species identification is critical for urban planning and biodiversity conservation.

5. Conclusions

The study demonstrates the effectiveness of using high and very high-resolution multispectral satellite data for urban tree species classification. The higher spatial resolution of Pléiades imagery provided more detailed and accurate land cover and tree species classifications compared to Sentinel-2 data. This is reflected in the higher OA and Kappa indices for classifications derived from Pléiades imagery.

The superior performance of Pléiades data can be attributed to its finer spatial resolution, which enables better discrimination of small features and reduces mixed pixel effects. This was particularly evident in the classification of complex urban environments, where the heterogeneity of land cover types and tree species can challenge coarser resolution imagery like Sentinel-2.

The disparity in classification accuracy between different tree species when using Pléiades versus Sentinel-2 data can be attributed to several factors related to spatial resolution, spectral characteristics, and the inherent properties of the species themselves.

1. Spatial Resolution

Pléiades data provides higher spatial resolution, enabling detailed capture of canopy structure, leaf arrangement, and tree crown delineation. This level of detail is crucial for distinguishing species with similar spectral characteristics but differing morphological features, such as *Quercus ilex* (Holm oak) and *Pinus pinea* (Stone pine), whose distinct crown shapes and canopy structures are better resolved with Pléiades, enhancing both User's and Producer's Accuracy.

2. In contrast, Sentinel-2 data's coarser spatial resolution results in mixed pixels, particularly in heterogeneous urban environments. This blending of spectral signatures from different species and land cover types poses challenges in accurately classifying species like *Ulmus minor* (Field maple) and *Platanus acerifolia* (London plane), which exhibit subtle differences in spectral and structural properties.

3. Spectral Characteristics

Quercus ilex and *Pinus pinea*: these species likely have distinct spectral signatures in the bands captured by Pléiades, which aids in their accurate classification. The higher resolution allows for better discrimination of their unique spectral responses, especially in the near-infrared and red-edge bands, which are sensitive to vegetation health and type.

Acer campestre and *Platanus acerifolia*: These species may have spectral signatures that overlap more significantly with other species or land cover types, making them harder to distinguish using Sentinel-2's broader spectral bands. The reduced ability to capture fine spectral differences exacerbates this issue, leading to lower classification accuracies.

4. Urban Environment Complexity

Urban areas are characterized by a complex mosaic of different land covers, including buildings, roads, and various vegetation types. The higher resolution of Pléiades reduces the problem of mixed pixels, enabling more precise identification of tree species within this heterogeneous landscape.

In contrast, Sentinel-2's lower resolution means that pixels often contain a mix of multiple land cover types, complicating the classification process. This is particularly problematic for species like *Ulmus minor* and *Platanus acerifolia*, which might be interspersed with other vegetation types or non-vegetative surfaces.

5. Tree Morphology and Canopy Structure

The physical characteristics of trees, such as canopy density, leaf size, and tree height, play a significant role in their spectral signatures. *Quercus ilex* and *Pinus pinea* have distinct morphological traits that are more easily captured with high-resolution imagery, aiding in their accurate classification.

On the other hand, *Ulmus minor* and *Platanus acerifolia* may have more variable canopy structures or similarities with other urban tree species, making them harder to classify accurately with lower-resolution data.

In summary, the higher spatial resolution of Pléiades imagery provides a more detailed representation of tree species, reducing the effects of mixed pixels and improving the ability to distinguish between species with subtle spectral and morphological differences. This results in higher classification accuracies for species like *Quercus ilex* and *Pinus pinea*, whereas the coarser resolution of Sentinel-2 struggles with accurately classifying species like *Ulmus minor* and *Platanus acerifolia* in complex urban environments.

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