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Assessing urban forest biodiversity through automatic taxonomic identification of street trees from citizen science applications and remote-sensing imagery

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A R T I C L E I N F O

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A B S T R A C T

The positive impact of urban forests and trees on the well-being of urban residents worldwide is well known. Resistance to pests, diseases, and extreme weather events are among the most critical characteristics of resilient cities, closely related to species richness and, consequently, to the diversity of street trees. However, urban forest inventories are currently scarce worldwide. For this reason, urban trees' biodiversity and capacity to provide these ecosystem services are not developed enough. Three state-of-the-art species identification applications were tested, Plant.id, Pl@ntNet and Seek (iNaturalist) to identify a large number of tree families, genera, and species automatically. Two individual Google Street View images were queried for each tree in the study area, adjusting the Field of View and pitch parameters. The predictive capacity of the three apps was compared, and a biodiversity analysis was performed for different geospatial scales within the study area (i.e., at the whole study area, neighborhood, and street levels, respectively). Notably, our research contributes in an innovative way to the assessment and monitoring of the ecosystem services provided by street trees and sheds light on the great potential of combining remote sensing, citizen science and artificial intelligence for urban forest biodiversity assessments at multiple spatial and temporal scales.

1. Introduction

As the population of cities continues to grow, so does the importance of urban forests and trees due to their ability to provide ecosystem services key to human well-being. Climate change is expected to increase temperatures in built-up areas further, so the cooling effect of trees and their ability to sequester and store carbon becomes relevant concerning human well-being (Ow and Ghosh, 2017; Roebuck et al., 2022; Xing et al., 2021). In addition to these ecosystem services, urban forests also have a positive effect on mental and physiological health (Helbich et al., 2019; Wood et al., 2018), especially in areas with higher biodiversity (Billé et al., 2012; Giacinto et al., 2021).

In this context, tree species diversity and spatial configuration are crucial to the urban forest ecosystem's functioning (Alvey, 2006; Li and Ratti, 2018; Yahiaoui et al., 2012). Higher urban biodiversity, including higher diversity of tree species, can contribute to improved vegetation stability and resilience (Roebuck et al., 2022). In the same vein, urban trees create corridors that connect larger green areas, enabling animal mobility and facilitating the exchange of genetic material through cross-pollination (Caneva et al., 2020). For instance, a study made in the city of McAllen in Texas, United States of America, found that native trees hosted a relatively high number of arthropods (approximately 90 species) in the canopy foliage, thus providing sustenance for a more extensive food web and enhancing biodiversity (Racelis et al., 2013). However, even if the species composition is generally diverse in many cities, they are often planted in a rather monospecific way, especially alongside the roads, predisposing the trees to disease or damage (Kara, 2012).

This information regarding tree location and taxonomic classification is currently found in urban forest inventories. Importantly, this dearth of comprehensive urban forest inventories perpetuates a significant gap in information, hindering an understandable urban forest

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dynamics and impeding targeted conservation efforts (Zhang et al., 2015). Furthermore, identifying tree species can be difficult, time-consuming, and expert-intensive (Jones, 2020; Wäldchen and Mäder, 2018), which increases the challenges regarding biodiversity conservation and plant studies in a situation where both biodiversity and the number of taxonomic experts are declining (Gaston and O'Neill, 2004; Hopkins and Freckleton, 2002; Jones, 2020; Wäldchen et al., 2018). To overcome these constraints, previous research has addressed the mapping and massive identification of urban trees through remote sensing data (Atasoy, 2020; Branson et al., 2018; Fassnacht et al., 2016; Li et al., 2019; Wang et al., 2018). For instance, species identification through Light Detection and Ranging (LiDAR) data (Chi et al., 2020; Sun et al., 2019; Timilsina et al., 2020) or satellite imagery (Hartling et al., 2019; Jiang et al., 2017; Ozkan et al., 2016), as well as tree mapping (Branson et al., 2018; Laumer et al., 2020; Lumnitz et al., 2021), have been the focus of research in recent years. However, previous research has seldom focused on automatic urban forest inventory, especially regarding species identification and mapping. In the few cases available, the research has been modest in scope, or the models have had poor replication (Branson et al., 2018; Seiferling et al., 2017), which has contributed to the current gap in knowledge on the application of new technologies to the assessment of urban tree diversity in a spatially-explicit and automatic way.

Artificial intelligence opens new possibilities to massive tree species identification from ground-sourced images, which can contribute to filling the void arising from the costly field inventories and the lack of experts, especially in urban areas where footage such as the Google Street View (GSV) images already exists and are available over large scales worldwide (Seiferling et al., 2017). GSV has emerged as a viable alternative for analyzing elements on Earth, directly competing with traditional remote sensing sources (Hou and Biljecki, 2022). A contemporary trend in scientific advancement is the emergence of citizen science. Citizen science involves the active participation of the general public, without scientific training, in research projects (Roman et al., 2016). This approach has garnered popularity also in forest research, where citizens contribute through continuous species consultation and corrective identification, thereby facilitating the establishment of an expanding bank of botanical samples (Otter et al, 2012). There are already multiple smartphone applications, such as LeafSnap (Kumar et al., 2017) and Pl@ntNet (Anubha Pearline et al., 2019), which allow any user to identify plant species with photos taken with their phones (Iskrenovic-Momcilovic, 2020; Otter et al., 2021). Some of these applications have been made in cooperation with entrepreneurs, research groups, and botanists. They are mostly citizen science-based leading to a steady increase in the accuracy of these apps, thus providing a tool for species recognition open to the public (Otter et al., 2021). Some research has previously evaluated the performance of these tree-recognition applications (Bilyk et al., 2020; Xing et al., 2021). However, these studies have been conducted with photographs taken directly by the users, which implies moving to the field and the target study area. While facilitating field data collection, tree-to-tree city visits remain arduous (Jones, 2020). Capecchi et al. (2023) studied the performance of Pl@ntNet and Plant.id with massively available ground-sourced data as a cost-effective option to inventory urban street trees.

The main objective of this study is to evaluate the predictive capability of citizen science-based species identification applications in a large-scale setting, using automatically generated individual-tree geo-positioning data from remote sensing data. The paper introduces an approach to provide an individual ground-level images for each tree from multiple viewpoints. Model performance was validated in a selected study area of the city of Lleida, Spain, for which an available field-based urban tree inventory could be used as ground truth for model testing and validation. The second objective was to evaluate tree biodiversity by automatically analyzing biodiversity indices obtained from the best-performing citizen science application and comparing these results with the ground-truth tree inventory information. This study represents a significant step forward in automating the urban forest inventory process and the study of urban tree biodiversity, with the potential to inform urban forest biodiversity at multiple spatial and temporal scales. Furthermore, by addressing the shortcomings of previous research and explicitly comparing with existing global urban forest inventory practices, this study contributes to bridging critical knowledge gaps in the field.

2. Material and methods

2.1. Study area

The study area was located in the western part of the city center of Lleida. Lleida is located alongside the river Segre in Lleida province, Catalonia region, northeastern Spain. The municipality of Lleida covers an area of 212 km^2 (Ajuntament de Lleida, 2022), of which the study area covered 59.12 ha (Fig. 1).

According to the official forest inventory provided by the city council of Lleida, the street trees in the study area consisted of 30 families, 40 genera, and 49 species of trees. According to this field inventory, 52 % of the trees in the study area belong to 4 species: *Morus alba* L. *(20 %)*, *Platanus* × *hispanica* Mill. ex Münch 21.78 *(16 %), Ligustrum japonicum* Thunb *(10 %),* and *Melia azedarach* L *(7 %)*. Most of the individuals of these species are grouped in specific streets, *Morus alba* being mainly located north of the study area, among detached houses and along some important avenues, *Platanus x hispanica* being distributed primarily in the northwest part of the city, while *Ligustrum japonicum* is more widespread but mainly distributed within the western area of the city. Overall, the study area is composed of 37 streets, 22 of which have trees, encompassing three different neighborhoods; Joc de la Bola (1), Universitat (2), and Camp de Esports (3).

2.2. Data

For this study, two different data sources were used, namely, i) the official forest inventory of Lleida, based on field inventory of urban trees and including taxonomic classification at the species level, among other attributes, and ii) remote sensing data on the location of individual urban trees automatically generated by Velasquez-Camacho et al. (2023). The latter relies on a methodology that maps street trees using deep learning algorithms by combining GSV and aerial or satellite images. It returns the following geographic information of each street tree: the distance from the image center to the tree mapped, the area covered by the bounding box delimiting the tree detected in the GSV image, the unique identifier assigned by Google Maps to the images (Google, 2022), the heading value (degree camera rotation $0^{\circ} - 360^{\circ}$), and an individual coordinate. In the study area, information on 968 individual trees was returned, to which the taxonomic classification at the family, genus, and species level from the official urban inventory of the city of Lleida was added to construct the validation database.

2.2.1. Google street View parameters

To query each GSV tree image and obtain the best view of the tree canopy, it was necessary to adjust two additional parameters to the heading: the pitch and the Field Of View (FOV). The FOV refers to the zooming level that provides a broader or narrower view of an image, while the pitch is the camera tilt angle from top to bottom (Fig. 2).

These adjustments were made considering the tree size, determined by the bounding box size and distance between the tree and the image center (Table 1).

The query parameters were constructed by consulting the individual identifier for individual GSV images, which was used in a request in Python 3.10 using the Static Street View API key in Google Maps. On average, two static images per tree were consulted automatically.

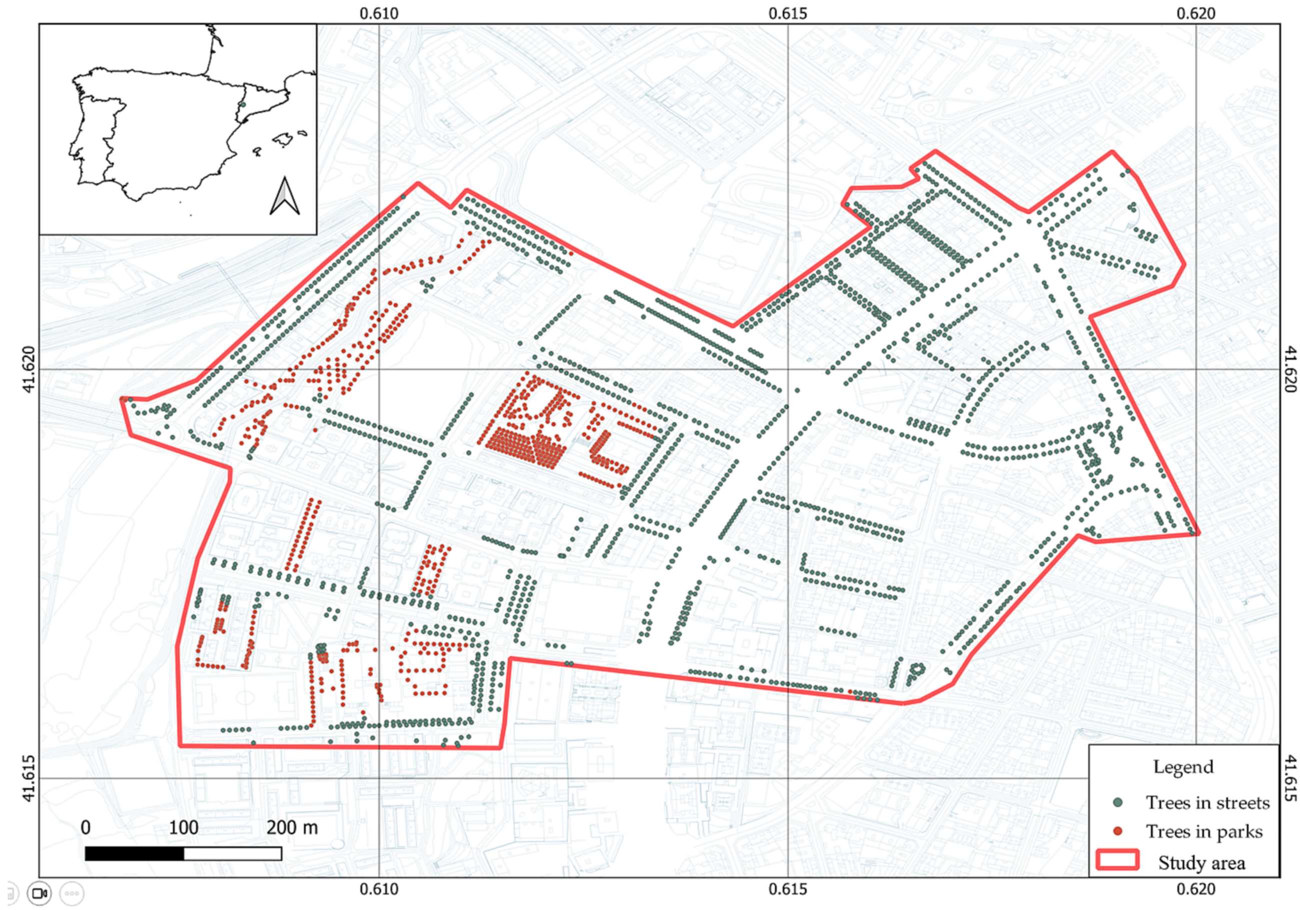

Fig. 1. Study area and tree distribution by the street tree or park tree. Green dots represent the street trees. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.): Red dots represent the trees located in parks.

Fig. 2. Example of request parameters in a panoramic image in Google Street View. Heading. Degree camera rotation. Pitch: Camera tilt angle from top to bottom; FOV: Field of view.

2.3. Methods

2.3.1. Plant species identification applications

After conducting thorough research regarding the state-of-the-art and availability of tree taxa identification applications based on citizen science and artificial intelligence (deep learning algorithms), three of them were selected for this study, namely, Plant.id (Plant.id, 2022), Pl@ntNet (Pl@ntNet, 2022), and Seek from iNaturalist (iNaturalist, 2020). Pl@ntNet and Plant.id, both center around a crowdsourcing approach, where users upload images of plants, and the system, through the analysis of visual features, facilitates the identification of plant species with the contribution of the community (Pl@ntNet, 2022; Plant.id, 2022). Seek, follows a similar paradigm, incorporating image recognition technology to identify not only plants but also animals and fungi. It stands out for its educational orientation (iNaturalist, 2020). While the architectures used are not publicly disclosed, these applications share the purpose of promoting plant identification through the leveraging of deep learning techniques and citizen science (iNaturalist, 2020; Jones, 2022; Plant.id, 2022; Pl@ntNet, 2022). In the selection process of suitable applications for our research aims, we specifically chose these three applications due to their unique feature of providing an API key. This key, essential for developer mode access, enables seamless requests through a web version of each app. These applications predict the probability of a given tree to belong to a specific family,

Table 1
The parameters set for the automatic request of the Google Street View Images. Bounding box area ratio: Relation between the bounding box size and pixel size. Field of view: The smaller the number, the higher the zoom level. Pitch: Defines the angle variance < 0 = tilt down; > 0 = tilt up.

Distance from image to tree (m)	Bounding box area ratio	Field of view (FOV degrees)	Pitch (-90 – 0 – 90 degrees)
<5	<0.5	30	10
<5	0.5 – 0.7	45	15
<5	>0.7	80	40
5–10	<0.25	30	5
5–10	0.25–0.50	30	10
5–10	0.5 – 0.75	40	10
5–10	>0.75	40	30
10–20	<0.25	20	5
10–20	0.25 – 0.50	20	10
10–20	>0.50	45	20

genus, and species through the analysis of pictures obtained from various types of cameras, including mobile or internet images. Upon uploading an image, these applications utilize image classification algorithms to assign a taxonomic category to the tree analyzed. The crucial input information for the successful operation of these applications includes the mandatory API key and the geographical location, ensuring precise and context-specific tree identification. Plant.id and Pl@ntNet provide a confidence score and the predicted taxonomic information.

2.3.2. Analysis of predictive performance of tree taxa

The taxonomic classification yielded by each citizen science application was assessed with a multi-class and multi-labeling method. Multi-class refers to classifying the input (i.e., tree species, genus, or family) into one class out of two non-overlapping classes (correct – incorrect). Data from the official forest inventory of Lleida (validation database) was used to evaluate the accuracy in the predictive performance of each application (Plant.id, Pl@ntNet, and Seek) for each taxonomic level (family, genus, and species).

The total accuracy obtained from each application was calculated as the number of Trees Correctly (TC) identified divided by the total number of tree species, genus, or family in the study area, respectively. The total number of records (samples) for each taxon (Total number) was extracted from the validation database:

(1) Accuracy:

$$Accuracy = \frac{TC(species/genus/family)}{Totalnumber(species/genus/family)}*100$$

Secondly, a multi-labeling method was used to evaluate the performance in predicting the individual label. Thus, this multi-labeling method was used to analyze the result of surveying the taxonomic classification of the same tree separately at the species, genus, and family levels. So that the performance in the identification of different taxonomic levels was studied independently for each taxonomic level using several metrics, namely, precision, recall and F1 (Sokolova and Lapalme, 2009):

(2) Precision:

$$P_M = \frac{\sum_{i=1}^{l} \frac{tp_i}{tp_i + fp_i}}{l}*100$$

(3) Recall:

$$R_M = \frac{\sum_{i=1}^{l} \frac{tp_i}{tp_i + fn_i}}{l}*100$$

(4) F-1 score:

$$F1_M = \frac{Precision_M Recall_M}{Precision_M + Recall_M}*100$$

where:Mmacro averaging, tp_itrue positive for taxonomic level i, tn_itrue negative for taxonomic level i, fp_ifalse positives for taxonomic level i, $l$total number of trees in taxonomic level i in the validation dataset.

In addition to the average precision, recall, and F1 metrics, a macro (M) and weighted average of these metrics were used to evaluate each application's performance in the massive automatic prediction of the family, genus, and species of urban trees from GSV images. The weighted averaging considered the different degrees of importance for each class into which the data were classified based on the number of samples in each category (Patro and Ranjan Patra, 2014). We chose the nine most frequently occurring species/genus/family labels to simplify the resulting plotting. Additionally, we incorporated the "other" category to account for the remaining labels predicted by the apps (for complete results, refer to the Supplementary material).

2.3.3. Biodiversity analysis

A biodiversity analysis was performed at three different spatial scales, namely at the whole study area, neighborhood and street levels, by comparing the results from the citizen science apps with the biodiversity indices calculated from the ground truth (official urban forest inventory). Namely, richness (i.e., number of families, genera, and species), Simpson's index (Simpson, 1949) and Shannon's index (Shannon and Weaver, 1949) were used to evaluate urban tree biodiversity as predicted by each citizen science application. Moreover, Inverse Simpson's index and equitability index based on Shannon's index were calculated to quantify species/genera/families evenness (Fedor and Zvaríková, 2008):

(5) Shannon's index:

$$H = -\sum_{i=1}^{S} P_i \ln P_i$$

(6) Simpson's index:

$$D_1 = 1 - \sum_{i=1}^{S} p_i^2$$

(7) Inverse Simpson's index:

$$IS = \frac{1}{D_1}$$

where p_i represents the proportional number of species/genera/families i, and S was the richness of species/genera/families. IS is the Inverse Simpson's index, where D is the Simpson's index.

(8) Equitability index:

$$E_H = \frac{H}{\ln S}$$

where E_H represents the equitability index, H is the Shannon's index, and S was the number of different species/genera/families (richness). Equation 3 resulted in a value between 0 and 1, with zero indicating low evenness and one indicating high evenness between the species.

2.3.4. Performance in the prediction of biodiversity indices

In order to ascertain the consistency of the results, a comparison was made between the biodiversity indices generated using the validation database and the identifications obtained from the most effective application. In addition, the Shannon's index and Inverse Simpson's index results were normalized between 0 and 1. Normalizing the biodiversity indices facilitates the comparison and interpretation of the predictions and validation data, as well as among different geographic scales. The normalization was computed as follows:

(9) Normalization:

$$z_i = \frac{(x_i - \min(x))}{(\max(x) - \min(x))}$$

where z_i was the normalized biodiversity index value, x_i the ith value of the dataset, min(x) the minimum value of the dataset, and max(x) the maximum value of the dataset. The normalized biodiversity values from the validation database and the biodiversity values from the citizen science apps were then subtracted to obtain the normalized difference

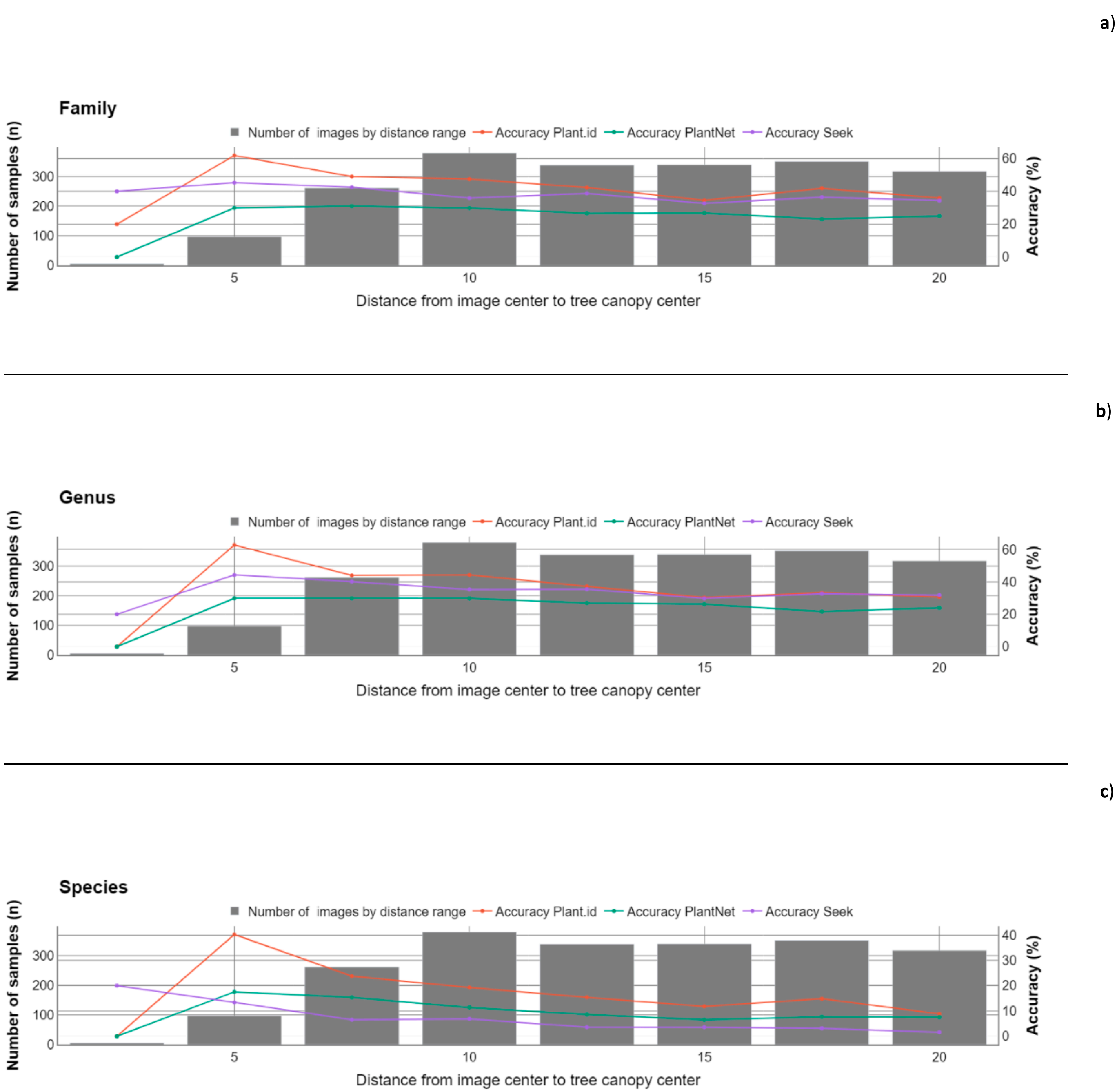

Fig. 3. Number of trees mapped by distance from the image center to the tree in meters (grey bars) and the accuracy of taxonomic classification. The lines show the different accuracies for each taxonomic level (a: Family, b: Genus, c: Species). Red line.: Accuracy forPlant.id app (%);Green line: Accuracy for Pl@ntNet app (%); Purple line: Accuracy for Seek app (%).

between the predicted and the observed biodiversity:

(10) Normalized difference:

$$N = Appresults_{Streeti} - ValidationDb_{Streeti}$$

N indicates the difference index, *Validation* $Db_{Street\ i}$ is the normalized biodiversity index of a street from the validation database, and *App* $results_{Street\ i}$, the normalized biodiversity index of a street as predicted from a given citizen science app.

3. Results

3.1. Predictive performance of citizen science apps

The predictive performance of the tested citizen science apps varied with the distance between the image center and each tree, as well as by taxonomic level (Fig. 3). Out of all the 2087 taxonomic classifications, Plant.id resulted in the highest overall accuracy at all taxonomic levels (family 42.9 %, genus 37.7 %, species 16.6 %), Seek being the second highest at the family and genus levels, still, the worst performing at the species level (family 36.9 %, genus 34.5 %, species 4.6 %), while Pl@ntNet had the lowest accuracy among the tested apps at the family and genus levels (family 26.9 %, genus 26.4 %, species 9.7 %).

Regarding species identification, Plant.id exhibited a significantly higher success rate compared to Seek and Pl@ntNet, particularly for trees located within a maximum distance of 5 m (40.20 %, 13.40 %, and 17.52 % of accuracy, respectively, as shown in Fig. 3c). At the genus level, all the applications showed notable improvements in accuracy compared to the species level (15 % for Plant.id and Pl@ntNet, and 30 % for Seek). At the family level, Plant.id achieved a 12 % higher accuracy compared to the genus level, while Seek exhibited a slight increase (2 %) (Table 2).

The distance between the image capture location and the tree influenced the accuracy of the applications. Among the trees located within a range of 2.5–5 m from the image capture location (95 trees), Plant.id resulted in the highest accuracy at all taxonomic levels (61.85 % at the family level, 62.88 % at the genus level, and 40.20 % at the species level). However, it should be noted that the number of samples at closer distances (0–2.5 m) was lower (5 trees), comprising less than 5 % of the evaluated trees, compared to those located further away. The accuracies with Plant.id app in the family-level analysis at distances greater than 5 m remained relatively constant, with 640 (30.6 %) images captured at 5–10 m, 677 (32.4 %) images at 10–15 m, and 668 (32 %) images at 15–20 m of distance. Indeed, similar trends were observed with the Pl@ntNet and Seek apps, where the accuracies tended to be higher at the lowest distances. This pattern of higher accuracies differed for Pl@ntNet and Seek at the species level as their accuracy was notably lower than Plant.id predictions, even at the closest distance (5 m).

Out of the 34 families identified by Plant.id, only 14 were found in the validation database. Plant.id obtained the best macro-averaging precision, with 16 %, 9 %, and 4 % precision at the family, genus, and species level, respectively. The recall metric was low for all the tested applications being Plant.id the app with the highest recall value (12 %), and consequently, all F-scores were also low.

The results based on the weighted average showed that the majority of families and genera were correctly assigned to their corresponding categories in the validation dataset. Plant.id showed a significant increase in accuracy when comparing the macro average with weighted average metrics, namely, a 23 % increase in accuracy at the family level, a 44 % increase at the genus level, and a 17 % increase at the species level. Similarly, Pl@ntNet and Seek also showed high scores across all categories. Pl@ntNet achieved a 38 % increase in accuracy at the family level and a 42 % increase at the genus level compared to the macro averaging metric. Seek showed a 26 % increase at the family level and a 35 % increase at the genus level.

Across all applications, the best performance in taxonomic classification was observed at the family level (Fig. 4). Upon normalizing the results, it was found that Plant.id showed the highest accuracy in correctly assigning trees to the Moracea family, with only a few misidentifications. On the other hand, Seek showed the best performance in identifying trees of the Platanaceae family, although there were instances where the trees were misidentified as Sapindaceae family or “other” families. Pl@ntNet showed better accuracy detecting Meliacea family trees than the other two applications. However, it is worth noting that Pl@ntNet did not achieve a remarkable detection rate for any specific family, as it frequently misidentified trees from various families as “other” species.

In general, Plant.id exhibited higher accuracy in genus-level classification, but certain genera, such as *Prunus sp.* and *Morus sp.*, were successfully detected by all three applications. On the other hand, Seek performed exceptionally well in identifying *Platanus* sp., the most common genus in the study area, while Plant.id outperformed the other apps in detecting *Celtis sp.* and *Ligustrum sp.* We noted a recurring detection error in Pl@ntNet and Plant.id, where the most ten common genera in the validation data were erroneously identified *Prunus* sp.

At the species level, the most accurately identified trees were *Lagerstroemia indica*, consistently well-detected by all apps. *Ligustrum japonica* was predicted with high accuracy in both Pl@ntNet and Plant.id, while *Acer campestre* was classified better with Plant.id, and *Morus alba* with Seek. However, it is worth noting that the detection accuracy for species is remarkable only in these four cases, as the other species showed lower detection rates.

The results of Plant.id were used to compare the biodiversity indices with the validation database (the 968 trees mapped) since it demonstrated the highest performance in taxa prediction at all taxonomic levels (Table 3).

3.2. Predictive performance of biodiversity indices

The analysis of total identifications from Plant.id revealed an overestimated biodiversity compared to the validation database. At the family level, the richness estimate from the automatic predictions was 160 % higher than the ground truth. Shannon’s index was 18 % higher, Simpson’s index was 6 % higher, and Inverse Simpson’s index was 56 %

Table 2
Evaluation metrics by taxonomic level and application. Macro averaging (macro-avg) precision, recall, and F1 score. Weighted averaging (weighted-avg) precision, recall, and F1 score.

Application	Family (%)			Genus (%)			Species (%)		
	Plant.Id	Pl@ntNet	Seek	Plant.Id	Pl@ntNet	Seek	Plant.Id	Pl@ntNet	Seek
Overall accuracy	42	26	36	38	26	34	16	9	4
macro-avg Precision	16	7	8	11	4	4	6	1	1
macro-avg Recall	13	4	5	8	2	2	5	1	1
macro-avg F1	12	4	5	7	2	2	4	1	1
weighted-avg Precision	65	64	59	74	68	69	33	25	27
weighted-avg Recall	43	27	37	38	26	34	17	10	5
weighted-avg F1	48	36	43	45	36	42	20	13	7

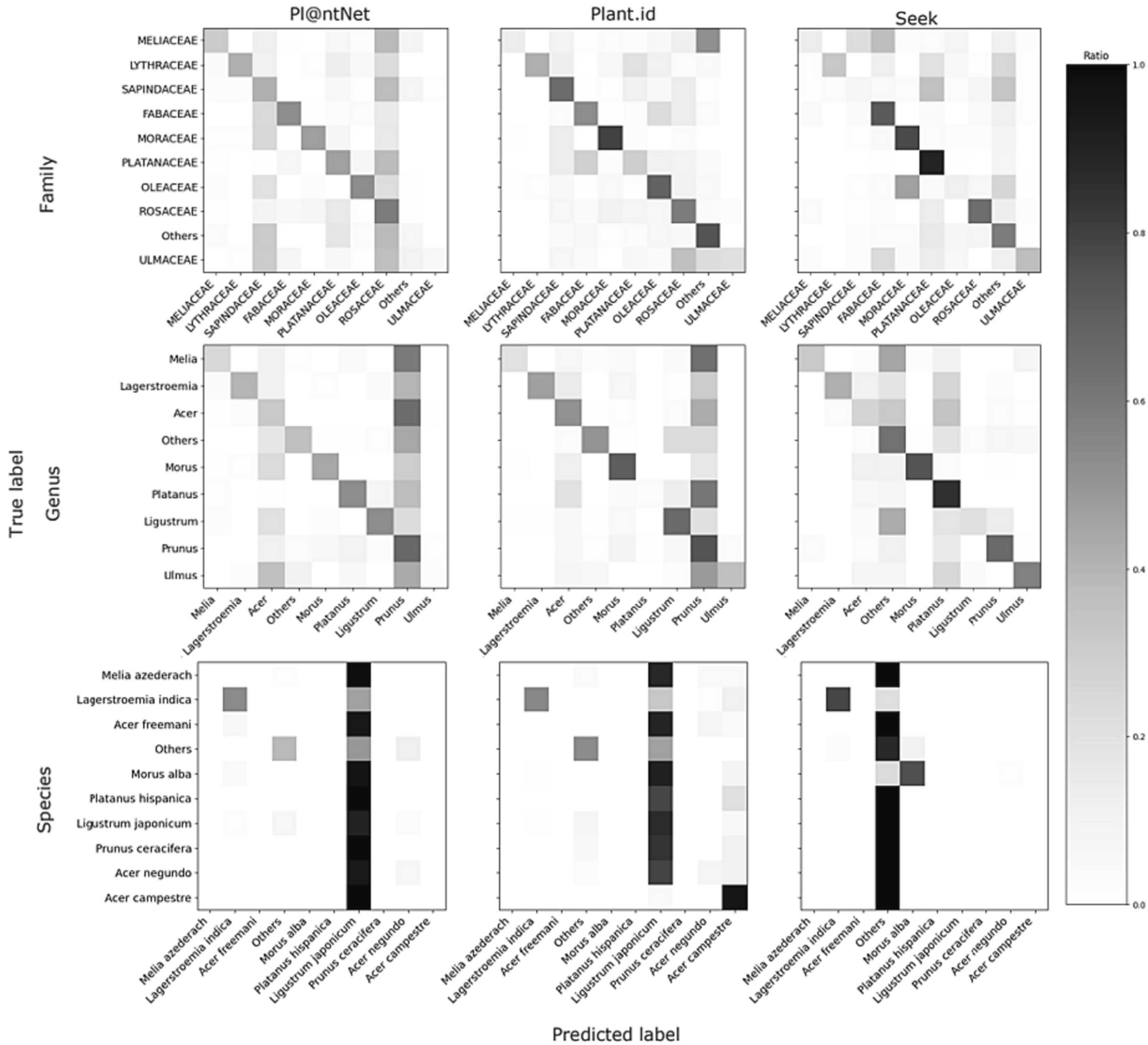

Fig. 4. Associated normalized confusion matrices depicting the performance of the taxonomic classification of each tree by each application at different taxonomic levels (family, genus, and species). The ratios within the matrices indicate the degree of accuracy between categories, with a higher ratio meaning higher accuracy.

Table 3
Richness values at the family, genus, and species level in the validation database and the database resulting from all and correct identifications by Plant.id.

Database	Family	Genus	Species
Validation database	21	30	41
Plant.id – total identifications	34	63	83
Plant.id – correct identifications	14	20	16

higher compared to the validation database. Similarly, at the genus level, the Shannon's index was 19 % higher, and the 7 % in Simpson's and Inverse Simpson's indices were 7 % and 60 % higher, respectively, compared to the validation data. At the species level, the Shannon's, Simpson's, and Inverse Simpson's indices were 11 %, 6 %, and 57 % higher than in the validation database. Both at the genus and species levels, the richness was overestimated by approximately 200 %, as the total identifications from Plant.id resulted in an overestimated count of genera and species compared to the actual biodiversity in the validation database.

At the neighborhood level, the trends suggest that the predicted values tend to overestimate biodiversity (except for Simpson's Index D, where it is underestimated) in all neighborhoods, with varying magnitudes of differences between observed and predicted values. In Neighborhood 1 (Joc de la Bola), the average difference between observed and predicted biodiversity indices was approximately −0.258. Neighborhood 2 (Universitat) showed an average difference of roughly 0.113, indicating slight overestimation, except for Simpson's Index D, which was slightly underestimated by −0.019. However, the average difference in Neighborhood 3 (Camp de Esports) was approximately −0.644, suggesting that the overestimation was higher. The most significant difference in species richness was observed in Neighborhood 1 with a value of −71, followed by Neighborhood 3 with −72, and Neighborhood 2 with −40 (Table 4).

At the street level, the predicted biodiversity indices were generally

Table 4
Biodiversity indices computed at the species taxonomic level at the neighborhood scale. Neighborhood 1: Joc de la Bola; Neighborhood 2: Universitat; Neighborhood 3: Camp de Esports.

Neighborhood	Category	Shannon index		Shannon equitability index		Simpson's index D		Inverse Simpson index (1/D)		Species richness	
		Val	Pred	Val	Pred	Val	Pred	Val	Pred	Val	Pred
1	**Species**	2.247	2.39	0.716	0.883	0.175	0.108	5.70	9.191	23	94
2		2.461	2.193	0.835	0.914	0.107	0.126	9.263	7.912	19	59
3		1.982	2.470	0.608	0.838	0.236	0.119	4.229	8.362	23	95

overestimated compared to the validation dataset, particularly with neighborhood-level predictions. However, there were some exceptions, such as the square within neighborhood 2 (Universitat), where the predicted biodiversity was underestimate in family category in all indices (Table 5).

The normalized difference analysis at the street level unveiled certain shared trends between the validation database and the biodiversity indices calculated using Plant.id identifications (Table 6). Positive values indicate an overestimation of biodiversity indices when utilizing Plant.id identifications, whereas negative values imply underestimations. These findings suggest a correlation between Plant.id identifications and ground truth data, indicating potential reliability in assessing differences in biodiversity levels between streets within urban areas.

Notably, at the family level, streets 6 and 21 consistently exhibited the most congruent biodiversity indices (lower difference values) between the validation database and Plant.id predictions. Conversely, streets 1, 12, and 20 showed the highest differences between predicted and observed biodiversity indices. According to the validation dataset, these three streets harbored two species, resulting in lower biodiversity indices, so that Plant.id predictions resulted in overestimated biodiversity (See complementary material: Difference Index Maps folder).

In 27 % of the streets there was a significant correlation between the predicted and observed Shannon indices, with values ranging from −0.1 to 0.1. About 50 % of the streets exhibited correlation values between 0.1 and 0.5 in absolute value, while 22 % displayed disparities over 0.5 (absolute value). Only two streets (16 and 4) exhibited pronounced underestimations in predictions (values lower than −0.5). Regarding Simpson's index, the minimal difference (lower than 0.1 in absolute value) prevailed in a mere 22 % of streets. Around 54 % of streets displayed differences between 0.1 and 0.5 in absolute value, while 24 % showcased differences over 0.5 in absolute value. Only one street (4) yielded an underestimation of Simpson's difference index, while three streets resulted in overestimation (>0.5). Finally, the inverse Simpson's index at the family level revealed four streets with differences exceeding 0.5 and lower than −0.5, 60 % with values ranging from 0.1 to 0.5 and from −0.5 to −0.1, and 18 % with values oscillating between −0.1 and 0.1, indicating substantial associations.

At the genus level, Plant.id provided the most accurate predictions of Inverse Simpson's index. Approximately 36 % of the streets exhibited difference values ranging from −0.1 to 0.1, while around 45 % displayed values from −0.5 to −0.1 and 0.1 to 0.5. Merely 18 % (4 streets) had differences higher than 0.5 in absolute value.

At the species level, more streets exhibited lower differences (lower than 0.1 in absolute value) regarding Inverse Simpson's index, accounting for 22 % (8 streets). In contrast, only five streets exhibited similar normalized difference to the ground truth for Simpson's and Shannon's indices.

4. Discussion

This study contributes to further improve and expand the growing body of research on the automated taxonomic classification of urban trees by utilizing three different citizen science-based applications combined with ground-sourced GSV images. In contrast to previous studies, which manually selected tree images, our approach utilized the automatic retrieval of tree images from GSV (Bertrand et al., 2018; Bilyk et al., 2020; Otter et al., 2021; Xing et al., 2021) in the same vein as Cappechi et al. (2023), who employed an automatic model to segment urban tree canopies and utilized GSV images for species identification via species identification applications. We selected 59 ha of a representative study area in the city of Lleida (Spain) as detailed in the Methods section (section 2.1. Study area). This enhances the replicability and generalization of our findings, while also providing a comprehensive understanding of the urban tree biodiversity within the geographical context of the study area. The ensuing discussion unfolds across three key sections. The first section delineates the fundamental aspects of our approach, while the second section delves into the factors

Table 5
Average biodiversity indices, equitability index, and species richness on a street level and a city square, on family, genus, and species level, obtained from the validation database and Plant.id's identifications. *The range of indices within all the studied streets.

Results streets/square (mean)	Category	Shannon's index	Shannon's equitability index	Simpson's index (1-D)	Inverse Simpson index (1/D)	Richness
Validation database streets	Family	0.78 (0.15–1.86)*	0.72 (0.22–1)*	0.45 (0.07–0.82)*	2.11 (1.07–5.66)*	3.3 (1–7)*
	Genus	0.81 (0.15–1.86)*	0.73 (0.22–1)*	0.46 (0.07–0.83)*	2.16 (1.07–5.79)*	3.3 (1–7)*
	Species	0.83 (0.15–1.86)*	0.73 (0.22–1)*	0.47 (0.07–0.83)*	2.22 (1.07–5.79)*	3.4 (1–7)*
Plant.id identifications	Family	1.54 (0.41–2.52)*	0.82 (0.44–1)*	0.69 (0.24–0.91)*	4.42 (1.32–11.3)*	7
	Genus	1.6 (0.69–2.68)*	0.83 (0.43–1)*	0.71 (0.32–0.92)*	4.91 (1.46–12.9)*	8
	Species	1.77 (0.69–2.98)*	0.84 (0.46–1)*	0.74 (0.38–0.94)*	5.59 (1.6–17.5)*	8.8
Validation database square	Family	1.598	0.821	0.727	3.662	3
	Genus	1.919	0.923	0.834	6.025	5
	Species	1.919	0.923	0.834	6.025	5
Plant.id identifications square	family	1.381	0.771	0.678	3.11	6
	genus	2.084	0.905	0.844	6.42	10
	species	2.084	0.905	0.844	6.42	9

Table 6
Normalized difference index at the street level illustrates the difference between predicted and observed biodiversity indices in the same street when the normalized biodiversity indices of the validation database and Plant.id's total identifications are compared. Lower value = lower difference in the indices; Dark grey = index < 0.05; Light grey = index 0.05–0.1; No coloring = index > 0.1. See complementary material for the specific index value.

Normalized difference									
Street	Shannon's Index			Simpson's Index			Inverse Simpson's index		
	Family	Genus	Species	Family	Genus	Species	Family	Genus	Species
1	0,60	0,62	0,50	0,43	0,43	0,39	0,81	0,81	0,56
2	0,03	0,03	0,00	0,05	0,05	0,04	0,20	0,24	0,18
3	−0,10	−0,23	−0,24	−0,02	−0,10	−0,19	−0,01	−0,02	−0,05
4	−0,50	−0,45	−0,47	−0,73	−0,51	−0,61	−0,29	−0,25	−0,30
5	0,08	−0,05	0,00	0,19	0,12	0,12	0,06	0,04	0,02
6	0,02	−0,05	0,03	−0,01	−0,07	−0,01	−0,02	−0,03	−0,04
7	0,18	0,07	0,08	0,12	0,05	0,04	0,03	0,02	0,00
8	0,49	0,51	0,42	0,33	0,33	0,29	0,33	0,31	0,19
9	−0,24	−0,26	−0,32	−0,17	−0,19	−0,24	−0,57	−0,61	−0,74
10	0,34	0,44	0,38	0,46	0,72	0,67	0,12	0,26	0,19
11	0,33	0,33	0,34	0,34	0,36	0,35	0,49	0,46	0,41
12	0,64	0,71	0,64	0,63	0,67	0,64	0,55	0,73	0,54
13	0,42	0,36	0,45	0,31	0,29	0,31	0,28	0,23	0,22
14	0,34	0,27	0,20	0,18	0,15	0,13	0,11	0,07	0,00
15	0,31	0,20	0,29	0,38	0,32	0,32	0,11	0,09	0,08
16	−0,54	−0,30	−0,24	−0,35	−0,13	−0,05	−0,79	−0,54	−0,24
17	−0,26	−0,39	−0,32	−0,47	−0,58	−0,59	−0,15	−0,16	−0,18
18	0,00	0,19	0,05	−0,03	0,13	0,07	−0,15	0,08	−0,05
19	0,45	0,46	0,44	0,30	0,31	0,32	0,42	0,46	0,47
20	0,66	0,56	0,48	0,75	0,72	0,67	0,41	0,35	0,25
21	0,00	−0,12	−0,15	0,03	−0,03	−0,10	−0,01	−0,03	−0,08
22	0,20	0,10	0,41	0,24	0,21	0,50	0,22	0,16	0,34

influencing taxonomic classification. The final section offers an analysis of the practical implications in urban forest planning.

4.1. *Factors influencing taxonomic classification*

A comprehensive exploration of factors affecting taxonomic classification follows. Noteworthy insights include the significance of image proximity, the influence of various vegetative parts on identification, and the challenges posed by the structural complexity of urban environments.

We observed that the accuracy of the taxonomic classification increased considerably when the images were taken at closer distances to the trees, particularly within a 5-meter range. This consideration could be incorporated in future versions, wherein the FOV and pitch settings are determined automatically rather than relying solely on predefined rules. This is attributed to the fact that close-up images better capture the distinctive characteristics of the tree foliage, which are crucial for accurate identification. It is worth mentioning that traditional botanical identification typically relies on studying the vegetative parts of the plant, such as leaves and stems (bark), for plant identification (Bilyk et al., 2020). However, species identification often requires the analysis of reproductive organs, such as flowers (Jones, 2020).

On the other hand, Bertrand et al. (2018) discovered that including the bark improves the tree recognition abilities compared to only using the leaf. In our study, the limited accuracy in tree species detection by all applications can be attributed to several factors. Firstly, the tree images available from GSV were captured on different dates and may not always correspond to the spring or flowering season when flowers and leaves are present. Secondly, identifying flowers in the images would require a separate and more specialized process, with specific parameters adjusted accordingly. However, incorporating the bark tree segment could potentially enhance the identification process. Nonetheless, this requires adjusting the image pitch. Additionally, plant identification in urban environments is particularly challenging due to the numerous ornamental elements and diverse plant species visible in GSV images. This further adds to the complexity of accurately identifying and distinguishing individual trees in the cityscape.

Although all applications are citizen science-based, they exhibit differences in their functioning that can influence the accuracy of their predictions. Plant.id's accuracy is generally regarded as high, particularly at the genus level, where it performs better than other plant identification apps. Our results showed this for all taxonomic categories with images taken at closest distances. Its ability to identify a wide range of genera and species may be due to its extensive database, which includes data from the Global Biodiversity Information Facility (GBIF) (Plant.id, 2022). Seek, a plant and animal identification app, generally shows high accuracy, particularly for common and well-documented species. The app's database draws from the vast collection of observations contributed to iNaturalist, one of the largest citizen science platforms for biodiversity data (iNaturalist, 2020). Our study focused solely on the initial automated classification of trees without considering any feedback from users or experts. This approach was taken to evaluate the effectiveness of the automation process itself, which significantly reduces its full potential for improvement through user-contributed feedback that could take from two to eighteen days (iNaturalist, 2020. iNaturalist, 2022).

In contrast, the literature shows that Pl@ntNet has a dataset of 140 million images more evenly distributed worldwide, enabling it to identify approximately 7,000 species in Europe (Pl@ntNet, 2022). However, it is documented that Pl@ntNet's performance is influenced by the quality of the images and the specific organ being used for identification, such as flowers, bark, and leaves (Jones, 2020). In our study, we evaluated the predictive capacity based on all the crowns but without considering other items, such as flowers or bark, which may have contributed to lowering the overall predictive ability.

According to our results, taxonomic identification at different levels was influenced by morphological characteristics. For instance, genera with larger crowns or distinctive colors were better identified. For example, *Prunus sp.*, with a very characteristic color, was correctly identified by all three apps, or *Ligustrum japonicum*, with its well-defined foliage, achieved a good classification rate. This observation aligns with the findings of Capecchi et al. (2023), who reported that tree species with distinct morphological characteristics exhibit higher classification accuracy. However, contrary to our initial expectations and previous reports by Capecchi et al. (2023), Jones (2020) and Nguyen et al. (2018), our study found that the use of geographical location had no significant effect on the prediction accuracy.

4.2. Comparison of taxonomic identification accuracy

Our results can be categorized into two main aspects: first, the overall accuracy, where Plant.id achieved the highest accuracy at 42 %, followed by Seek at 36 %, and Pl@ntNet at 26 % when considering family-level identification. These accuracy values are lower than those reported by Capecchi et al. (2023) and Jones (2022). However, it's important to note that a more appropriate interpretation of our main findings can be obtained by using weighted average metrics, considering the multi-class problem involved in individual classification. It is worth noting that Jones's study (2020) focused solely on species identification, which was achieved with high accuracy due to the availability of flower and fruit images. In our study, we observed that Plant.id achieved an identification rate of 16 % at the species level and 38 % at the genus level. Secondly, when we examined the precision metrics at the family level (65 % for Plant.id, 59 % for Seek, and 64 % for Pl@ntNet), our results indicated higher precision compared to those reported by Jones (2020), who found performance rankings for the applications as follows: 62 % for Plant.id, 51 % for Seek, and 42 % for Pl@ntNet. On the other hand, our results align with those reported by Xing et al. (2021), where Pl@ntNet also achieved the lowest accuracy at the species and genus levels. These findings underscore the potential of Plant.id for accurate automatic taxonomic classification.

The biodiversity assessment using Plant.id predictions resulted in overestimation of richness values at the family level. The normalized biodiversity indices also resulted in overestimation compared to the ground-level values. Despite these discrepancies, the overall trend across all taxonomic levels provides insights into identifying levels of tree biodiversity in urban environments.

4.3. Practical implications for urban planning

Despite the inaccuracies in the species/genera/families predictions, these findings can serve as a foundation for strategically planning street trees to uphold biodiversity at a city-wide scale rather than being confined to specific areas. By considering the general patterns and trends observed, decision-makers can strategically select tree species and locations to promote biodiversity richness across neighborhoods and urban landscapes. This can contribute to creating more ecologically sustainable and resilient urban environments (Alvey, 2006).

Regarding the accessibility to use the different citizen science-based taxonomic classification apps, when this research was conducted Pl@ntNet offered the most accessible option, allowing up to 500 daily image consultations for free, while Plant.id provided a free trial for 100 identifications, and Seek allowed only five identifications without a subscription. For our study, we opted for a paid subscription in Seek and Plant.id, while Pl@ntNet provided us with a research license. It is crucial to acknowledge that restricted access to these applications may impede their widespread use, potentially limiting their impact on urban biodiversity assessments. However, it is worth noting that Pl@ntNet and Seek data can be downloaded to create personalized models. This offers a significant opportunity in the realm of open data practice. Nevertheless, it is essential to acknowledge that this approach demands high computational capacity.

In the broader context, this research underscores the potential of automated species identification technology together with further remote sensing and artificial intelligence, representing a transformative shift in the field of urban forest inventory. The ability of these applications to streamline and enhance species identification processes, even with their current limitations, together with further technological progress in image quality and AI algorithms, holds promise for advancing citizen science initiatives and community-based projects. The democratization of access to these tools fosters inclusivity and empowers individuals and communities to actively participate in biodiversity assessments, thereby contributing to the broader goals of urban forest conservation and management. Future work could entail refining image quality through the implementation of more sophisticated algorithms, especially those designed to query images within the Google platform. Additionally, exploring innovative technologies to address existing challenges related to coverage and access is essential. Moreover, considering the introduction of complementary steps, such as a preliminary classification based on tree morphological characteristics or foliage color, holds promise for enhancing accuracy and bolstering the effectiveness of automatic species identification applications in the realms of urban forestry and biodiversity. Emphasizing the importance of ongoing research into innovative technologies to address existing challenges related to coverage and access remains crucial. These advancements are instrumental in ensuring the continuous evolution and efficacy of automated species identification applications within the fields of urban forestry and biodiversity research.

5. Conclusions

This study highlights the potential of citizen science-based applications for taxonomic classification in automatically recognizing tree taxa and estimating biodiversity based on GSV images, particularly when the trees are located within 5 m from the image capture point. The accuracy in taxonomic classification increases significantly at the genus and family levels compared to the species level. However, it is not enough for the results to be used to create comprehensive databases of trees or to study the level of biodiversity in the city without a significant error when compared to the ground truth. Using all the suggestions obtained from the applications would result in a remarkable overestimation of tree species richness and, in turn, also of other biodiversity metrics. Nevertheless, the predicted taxonomic classification and related biodiversity indices could help to identify the areas with lower or higher biodiversity within cities.

Moreover, the results obtained in this study provide promising first steps to study tree species efficiently, and some species with high accuracy, from ground-level imagery and further assess biodiversity if traditional field-based tree inventories are not available. Future advancements in automatic taxonomic classification and biodiversity assessments of urban forests and trees are promising. Improved image quality and advanced artificial intelligence algorithms will enhance the accuracy of tree identification and classification through the citizen science application as Plant.id, Pl@ntNet or Seek. Certainly, the active participation and observations of citizen scientists have the potential to significantly contribute valuable data to these efforts. As a result, this should promote greater accessibility to information within these applications. Moreover, the integration of identification applications with complementary remote sensing technologies such as LiDAR or photogrammetry has the potential to further enhance the automatic identification process. The synergy of these technologies will ultimately contribute to the broader goals of urban landscape observation and geoinformation, and a deeper understanding of the ecological significance of urban forests and trees.

CRediT authorship contribution statement

Luisa Velasquez-Camacho: Data curation, Formal analysis, Investigation, Methodology, Validation, Writing –original draft, Writing – review & editing. **Esko Merontausta:** Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Maddi Etxegarai:** Investigation, Methodology, Supervision, Validation, Writing – review & editing. **Sergio de-Miguel:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2024.103735.

References

Alvey, A.A., 2006. Promoting and preserving biodiversity in the urban forest. Urban for. Urban Green. 5, 195–201. https://doi.org/10.1016/j.ufug.2006.09.003.
Anubha Pearline, S., Sathiesh Kumar, V., Harini, S., 2019. A study on plant recognition using conventional image processing and deep learning approaches. J. Intell. Fuzzy Syst. 36, 1997–2004. https://doi.org/10.3233/JIFS-169911.
Atasoy, M., 2020. Characterizing spatial structure of urban tree cover (UTC) and impervious surface cover (ISC) density using remotely sensed data in Osmaniye. Turkey. SN Appl. Sci. 2, 1–7. https://doi.org/10.1007/s42452-020-2154-0.
Bertrand, S., Ben Ameur, R., Cerutti, G., Coquin, D., Valet, L., Tougne, L., 2018. Bark and leaf fusion systems to improve automatic tree species recognition. Ecol. Inform. 46, 57–73. https://doi.org/10.1016/j.ecoinf.2018.05.007.
Billé, R., Lapeyre, R., Pirard, R., 2012. Biodiversity conservation and poverty alleviation: a way out of the deadlock? S.a.p.i.en.s 5, 1–15.
Bilyk, Z.I., Shapovalov, Y.B., Shapovalov, V.B., Megalinska, A.P., Andruszkiewicz, F., Dołhańczuk-Śródka, A., 2020. Assessment of mobile phone applications feasibility on plant recognition: Comparison with Google Lens AR-app. CEUR Workshop Proc. 2731, 61–78.
Branson, S., Wegner, J.D., Hall, D., Lang, N., Schindler, K., Perona, P., 2018. From Google Maps to a fine-grained catalog of street trees. ISPRS J. Photogramm. Remote Sens. 135, 13–30. https://doi.org/10.1016/j.isprsjprs.2017.11.008.
Capecchi, I., Borghini, T., Bernetti, I., 2023. Automated urban tree survey using remote sensing data, Google street view images, and plant species recognition apps. Eur. J. Remote Sens. 56 https://doi.org/10.1080/22797254.2022.2162441.
Chi, D., Degerickx, J., Yu, K., Somers, B., 2020. Urban tree health classification across tree species by combining airborne laser scanning and imaging spectroscopy. Remote Sens. 12 https://doi.org/10.3390/RS12152435.
Ajuntament de Lleida, 2022. Informacion general. URL https://www.paeria.es/cas/informacio-general.asp.
Fassnacht, F., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L.T., Straub, C., Ghosh, A., 2016. Review of studies on tree species classification from remotely sensed data. Remote Sens. Environ. 186, 64–87. https://doi.org/10.1016/j.rse.2016.08.013.
Fedor, P., Zvaríková, M., 2008. Encyclopedia of Ecology. In: Fath, B. (Ed.), Encyclopedia of Ecology. Elsevier, Slovakia, p. 337347.
Gaston, K.J., O'Neill, M.A., 2004. Automated species identification: Why not? Philos. Trans. r. Soc. B Biol. Sci. 359, 655–667. https://doi.org/10.1098/rstb.2003.1442.
Giacinto, J.J., Andrew Fricker, G., Ritter, M., Yost, J., Doremus, J., 2021. Urban forest biodiversity and cardiovascular disease: Potential health benefits from California's street trees. PLoS One 16, 1–23. https://doi.org/10.1371/journal.pone.0254973.
Google, 2022. Streetview request and response. URL https://developers.google.com/maps/documentation/streetview/request-streetview.
Hartling, S., Sagan, V., Sidike, P., Maimaitijiang, M., Carron, J., 2019. Urban tree species classification using a worldview-2/3 and liDAR data fusion approach and deep learning. Sensors (switzerland) 19, 1–23. https://doi.org/10.3390/s19061284.
Helbich, M., Yao, Y., Liu, Y., Zhang, J., Liu, P., Wang, R., 2019. Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing. China. Environ. Int. 126, 107–117. https://doi.org/10.1016/j.envint.2019.02.013.

Hopkins, G.W., Freckleton, R.P., 2002. Declines in the numbers of amateur and professional taxonomists: Implications for conservation. Anim. Conserv. 5, 245–249. https://doi.org/10.1017/S1367943002002299.

Hou, Y., Biljecki, F., 2022. A comprehensive framework for evaluating the quality of street view imagery. Int. J. Appl. Earth Obs. Geoinf. 115, 103094 https://doi.org/10.1016/j.jag.2022.103094.

INaturalist, 2022. iNaturalist Computer Vision Explorations. URL https://www.inaturalist.org/pages/computer_vision_demo (accessed 7.15.22).

iNaturalist, 2020. Seek by iNaturalist, user guide. URL https://static.inaturalist.org/wiki_page_attachments/SeekUserGuide2020.pdf.

Iskrenovic-Momcilovic, O., 2020. Contribution of using mobile application on botanical fieldwork in primary school. Interact. Learn. Environ. 1–13. https://doi.org/10.1080/10494820.2020.1826531.

Jiang, B., Deal, B., Pan, H.Z., Larsen, L., Hsieh, C.H., Chang, C.Y., Sullivan, W.C., 2017. Remotely-sensed imagery vs. eye-level photography: evaluating associations among measurements of tree cover density. Landsc. Urban Plan. 157, 270–281. https://doi.org/10.1016/j.landurbplan.2016.07.010.

Jones, H.G., 2020. What plant is that? tests of automated image recognition apps for plant identification on plants from the British flora. AoB Plants 12, 1–9. https://doi.org/10.1093/aobpla/plaa052.

Kara, B., 2012. Assessment of the distribution and diversity of street tree species in Aydin, Turkey. J. Food Agric. Environ. 10, 919–928.

Kumar, N., Barré, P., Stöver, B.C., Müller, K.F., Steinhage, V., 2017. LeafNet: a computer vision system for automatic plant species identification. Ecol. Inform. 40, 50–56. https://doi.org/10.1016/j.ecoinf.2017.05.005.

Laumer, D., Lang, N., van Doorn, N., Mac Aodha, O., Perona, P., Wegner, J.D., 2020. Geocoding of trees from street addresses and street-level images. ISPRS J. Photogramm. Remote Sens. 162, 125–136. https://doi.org/10.1016/j.isprsjprs.2020.02.001.

Li, X., Chen, W.Y., Sanesi, G., Lafortezza, R., 2019. Remote sensing in urban forestry: recent applications and future directions. Remote Sens. 11, 1–20. https://doi.org/10.3390/rs11101144.

Li, X., Ratti, C., 2018. Mapping the spatial distribution of shade provision of street trees in Boston using Google Street View panoramas. Urban for. Urban Green. 31, 109–119. https://doi.org/10.1016/j.ufug.2018.02.013.

Lumnitz, S., Devisscher, T., Mayaud, J.R., Radic, V., Coops, N.C., Griess, V.C., 2021. Mapping trees along urban street networks with deep learning and street-level imagery. ISPRS J. Photogramm. Remote Sens. 175, 144–157. https://doi.org/10.1016/j.isprsjprs.2021.01.016.

Nguyen, T.T.N., Le, T.L., Vu, H., Hoang, V.S., Tran, T.H., 2018. Crowdsourcing for botanical data collection towards to automatic plant identification: a review. Comput. Electron. Agric. 155, 412–425. https://doi.org/10.1016/j.compag.2018.10.042.

Otter, J., Mayer, S., Tomaszewski, C.A., 2021. Swipe right: a comparison of accuracy of plant identification apps for toxic plants. J. Med. Toxicol. 17, 42–47. https://doi.org/10.1007/s13181-020-00803-6.

Ow, L.F., Ghosh, S., 2017. Urban cities and road traffic noise: reduction through vegetation. Appl. Acoust. 120, 15–20. https://doi.org/10.1016/j.apacoust.2017.01.007.

Ozkan, U.Y., Ozdemir, I., Saglam, S., Yesil, A., Demirel, T., 2016. Evaluating the woody species diversity by means of remotely sensed spectral and texture measures in the urban forests. J. Indian Soc. Remote Sens. 44, 687–697. https://doi.org/10.1007/s12524-016-0550-0.

Patro, V.M., Ranjan Patra, M., 2014. Augmenting weighted average with confusion matrix to enhance classification accuracy. Trans. Mach. Learn. Artif. Intell. 2.

Pl@ntNet, 2022. Identify, explore and share your observations of wild plants. URL https://identify.plantnet.org/.

Plant.id, 2022. Identify plants and plant diseases. For free. URL https://plant.id/.

Racelis, A.E., Vacek, A., Goolsby, C., Goolsby, J., 2013. Arthropod abundance and diversity in street trees of south Texas, USA. Subtrop. Plant Sci. 65, 31–37.

Roebuck, A., Hurley, L., Slater, D., 2022. Assessing the species diversity and vulnerability of urban tree populations in the London borough of Westminster. Urban for. Urban Green. 74, 127676 https://doi.org/10.1016/j.ufug.2022.127676.

Seiferling, I., Naik, N., Ratti, C., Proulx, R., 2017. Green streets – Quantifying and mapping urban trees with street-level imagery and computer vision. Landsc. Urban Plan. 165, 93–101. https://doi.org/10.1016/j.landurbplan.2017.05.010.

Shannon, C.E., Weaver, W., 1949. The Theory of Mathematical Communication. Int, Bus, p. 131.

Simpson, 1949. April 30, 1949 vol. 163. Nature 163, 688.

Sokolova, M., Lapalme, G., 2009. A systematic analysis of performance measures for classification tasks. Inf. Process. Manag. 45, 427–437. https://doi.org/10.1016/j.ipm.2009.03.002.

Sun, Y., Xin, Q., Huang, J., Huang, B., Zhang, H., 2019. Characterizing tree species of a tropical wetland in southern china at the individual tree level based on convolutional neural network. IEEE J Sel. Top. Appl. Earth Obs. Remote Sens. 12, 4415–4425. https://doi.org/10.1109/JSTARS.2019.2950721.

Timilsina, S., Aryal, J., Kirkpatrick, J.B., 2020. Mapping urban tree cover changes using object-based convolution neural network (OB-CNN). Remote Sens. 12 https://doi.org/10.3390/RS12183017.

Velasquez-Camacho, L., Etxegarai, M., De-Miguel, S., 2023. Implementing deep learning algorithms for urban tree detection and geolocation with high-resolution aerial, satellite and ground-level images. Comput. Environ. Urban Syst. Preprint 102025. https://doi.org/10.1016/j.compenvurbsys.2023.102025.

Wäldchen, J., Mäder, P., 2018. Machine learning for image based species identification. Methods Ecol. Evol. 9, 2216–2225. https://doi.org/10.1111/2041-210X.13075.

Wäldchen, J., Rzanny, M., Seeland, M., Mäder, P., 2018. Automated plant species identification—trends and future directions. PLoS Comput. Biol. 14, 1–19. https://doi.org/10.1371/journal.pcbi.1005993.

Wang, K., Wang, T., Liu, X., 2018. A review : individual tree species classification using integrated airborne LiDAR and optical imagery with a focus on the urban environment. Forests 10, 1–18. https://doi.org/10.3390/f10010001.

Wood, E., Harsant, A., Dallimer, M., de Chavez, A.C., McEachan, R.R.C., Hassall, C., 2018. Not all green space is created equal: Biodiversity predicts psychological restorative benefits from urban green space. Front. Psychol. 9, 1–13. https://doi.org/10.3389/fpsyg.2018.02320.

Xing, D., Yang, J., Jin, J., Luo, X., 2021. Potential of plant identification apps in urban forestry studies in China: comparison of recognition accuracy and user experience of five apps. J. for. Res. 32, 1889–1897. https://doi.org/10.1007/s11676-020-01234-3.

Yahiaoui, I., Mzoughi, O., Boujemaa, N., 2012. Leaf shape descriptor for tree species identification. Proc. - IEEE Int. Conf. Multimed. Expo. 254–259. https://doi.org/10.1109/ICME.2012.130.

Zhang, C., Zhou, Y., Qiu, F., 2015. Individual tree segmentation from LiDAR point clouds for urban forest inventory. Remote Sens. 7, 7892–7913. https://doi.org/10.3390/rs70607892.