

APPLICATION OF MOBILE GIS AND THE FLORA INCOGNITA APP FOR DOCUMENTING VEGETATION ALONG THE GREEN ECOLOGICAL TRAIL IN THE BARLINEK LANDSCAPE PARK

Marcin PAWLIK ¹,

¹ Research Center of Post-Mining, Technische Hochschule Georg Agricola, Bochum, Germany

Abstract

This article examines the use of mobile Geographic Information Systems (GIS), particularly the Flora Incognita application, for documenting vegetation along the green ecological trail in the Barlinek Landscape Park. The study evaluates the usability of the application, the accuracy of plant identification, and its potential to generate high-quality georeferenced data. The results indicate that Flora Incognita is an efficient and cost-effective tool for rapid floristic surveys, achieving high identification accuracy which, when complemented by expert verification, can significantly enhance monitoring efforts. The analysis demonstrates how citizen-generated data can be utilized to develop dynamic spatial databases, supporting park management in tasks such as mapping invasive species and tracking phenological changes. The article concludes that, although mobile GIS applications cannot replace traditional scientific methods, they represent a complementary approach that promotes public engagement and contributes to a more comprehensive understanding of local and macroecological patterns.

Keywords: mobile GIS, Barlinek Landscape Park, floristic documentation, biodiversity, citizen science

1. INTRODUCTION

In the face of progressing environmental changes, precise and up-to-date monitoring of flora has become a key element in nature conservation strategies [1-3]. Traditional inventory methods carried out by expert botanists are irreplaceable in terms of accuracy; however, their time-consuming nature, high costs, and limited scalability present significant challenges [4]. An alternative source of data is citizen observations, which enable information to be collected on a much larger scale. This issue becomes particularly evident when analyzing datasets that are often incomplete or prone to errors [5].

¹ Corresponding author: Marcin P. Pawlik, Technische Hochschule Georg Agricola, Research Center of Post-Mining, Herner Straße 45, 44787 Bochum, Germany, e-mail: Marcin.Pawlik@thga.de, telephone: +49 234 968-3805

According to Isaac et al. [5], four main sources of difficulty can be identified:

- Uneven recording intensity over time – measured by the number of visits per year, where a visit is defined as a unique combination of location and date in the dataset.
- Uneven spatial coverage – resulting from the fact that not all areas are monitored equally.
- Uneven sampling effort during visits – leading to differences in data quality and completeness.
- Uneven detectability – reflecting the variable likelihood of recording a studied object depending on environmental conditions or observation methods.

As a result, there is a growing need for new tools that enable monitoring to be conducted in a more dynamic and efficient manner, complementing conventional approaches. As emphasized by Pocock et al. [6], citizen science provides an opportunity to globally strengthen biodiversity monitoring systems. Likewise, Sutherland et al. [7] highlight that the future of biological data recording will increasingly depend on integrating traditional methods with innovative forms of public engagement and new technologies.

A response to these limitations is the rapid development of citizen science, which over the past decade has revolutionized methods of biodiversity data collection [8]. Thanks to the involvement of volunteers supported by modern digital platforms, it has become possible to acquire enormous volumes of data on an unprecedented scale [6]. A key role in this process is played by mobile GIS, which utilizes ubiquitous smartphones [9-10]. These devices, equipped with GPS modules, cameras, and constant internet access, have become powerful tools for real-time field data collection, opening new horizons for ecological research [10,11].

Mobile applications for plant identification based on image recognition and artificial intelligence have developed rapidly in recent years, forming an important component of modern biodiversity monitoring systems. Among the most widely used tools are applications such as Flora Incognita, Pl@ntNet, iNaturalist, LeafSnap, PlantSnap and Google Lens, which differ in terms of methodology, data sources, and level of user involvement.

Pl@ntNet represents a collaborative, open-access platform that relies on a large, continuously expanding database of plant images contributed by users. Its functionality is based on image recognition combined with geolocation data and community validation, which allows for ongoing improvement of identification performance. Studies indicate that its accuracy is relatively high under favorable conditions, particularly for well-documented species, although it remains sensitive to image quality and dataset completeness [12].

iNaturalist employs a hybrid approach combining artificial intelligence with expert-supported crowdsourcing. Observations are initially identified using machine learning algorithms and subsequently verified by a global community of users, enabling the classification of record. This dual system significantly increases the reliability of collected information and makes the platform particularly valuable for scientific applications [13-16].

Applications such as LeafSnap and PlantSnap are primarily based on automated image recognition without extensive community verification. LeafSnap, originally developed for tree species identification, has demonstrated relatively high accuracy in controlled conditions, while PlantSnap offers a broad global database and user-friendly interface. However, studies indicate that their performance may vary considerably depending on species characteristics and environmental conditions [17].

General-purpose image recognition tools, such as Google Lens, have also shown high effectiveness in plant identification tasks, in some cases achieving accuracy comparable to dedicated applications. However, their performance is less consistent due to the absence of specialization in botanical datasets. [18-22].

Flora Incognita based on advanced neural networks that are continuously refined using data provided by a growing user community [23]. Scientific studies confirm its high accuracy, reaching up to 90% correct identifications at the species level, with a database covering more than 15,000 species worldwide [24,25]. Although data collected in this way are opportunistic and may show certain imperfections, their vast quantity and appropriate analytical processing enable the reconstruction of reliable biogeographical patterns and the effective monitoring of species, including invasive ones [23]. Overall, current research suggests that mobile plant identification applications should be regarded as supportive tools that enhance data collection and accessibility, rather than as fully reliable substitutes for expert-based floristic surveys.

Despite these promising results, the use of mobile applications in scientific research requires a critical perspective. First, identification accuracy is strongly dependent on image quality, environmental conditions, and the phenological stage of the plant. Second, algorithm performance may decrease significantly in the case of rare species, taxa poorly represented in training datasets, or morphologically similar groups. Third, user behavior introduces systematic bias, as observers tend to record visually distinctive or easily accessible species, leading to underrepresentation of less conspicuous taxa. Finally, the probability values provided by such applications represent model confidence rather than statistically validated accuracy, which may lead to overinterpretation of results if not properly contextualized.

In addition to methodological limitations, practical aspects of field usability remain insufficiently explored in the literature. These include the time efficiency of data collection, the impact of continuous application use on device battery life, and the overall feasibility of using such tools during extended field surveys. In this study, field data were collected during a single survey lasting approximately 4.5 hours, during which 334 observations were recorded using the Flora Incognita application. The time required for species identification varied depending on site conditions; nevertheless, the average identification time was approximately 20 seconds per observation. From the perspective of researchers and practitioners, these factors are crucial in determining whether mobile applications can be effectively integrated into routine environmental monitoring workflows.

Therefore, the primary aim of this study was to evaluate the practical applicability of the Flora Incognita application as a mobile GIS tool for rapid floristic inventory under real field conditions in the Barlinek Landscape Park. The study focused on three main aspects:

- (1) the reliability of automated plant identification expressed through algorithmic confidence values,
- (2) the usefulness of automatically generated georeferenced data for GIS-based spatial analyses, and
- (3) the operational efficiency of mobile-assisted field surveys.

The study also aimed to identify the main limitations of AI-supported plant recognition systems and assess their potential role as complementary tools within integrated biodiversity monitoring frameworks.

2. STUDY AREA

The study was conducted in the Barlinek Landscape Park, located in north-western Poland. The area is characterized by high habitat diversity, including forests, wetlands, and numerous lakes, which makes it suitable for testing plant identification applications under varied environmental conditions. The park

covers approximately 11,694 ha and is dominated by forest ecosystems, particularly beech forests typical of the Pomeranian region [26, 27].

Field research was carried out along the Green Hiking Trail “Around Lake Barlinek (Ecological)”, a circular route of approximately 10 km in length. The trail passes through diverse habitats, including forest stands, lake shores, and wetland areas, providing a representative range of plant species and environmental conditions for the evaluation of mobile identification tools. The high diversity of vegetation types and species composition in the study area creates a suitable testing environment for assessing the accuracy and usability of plant identification applications in real-world conditions.

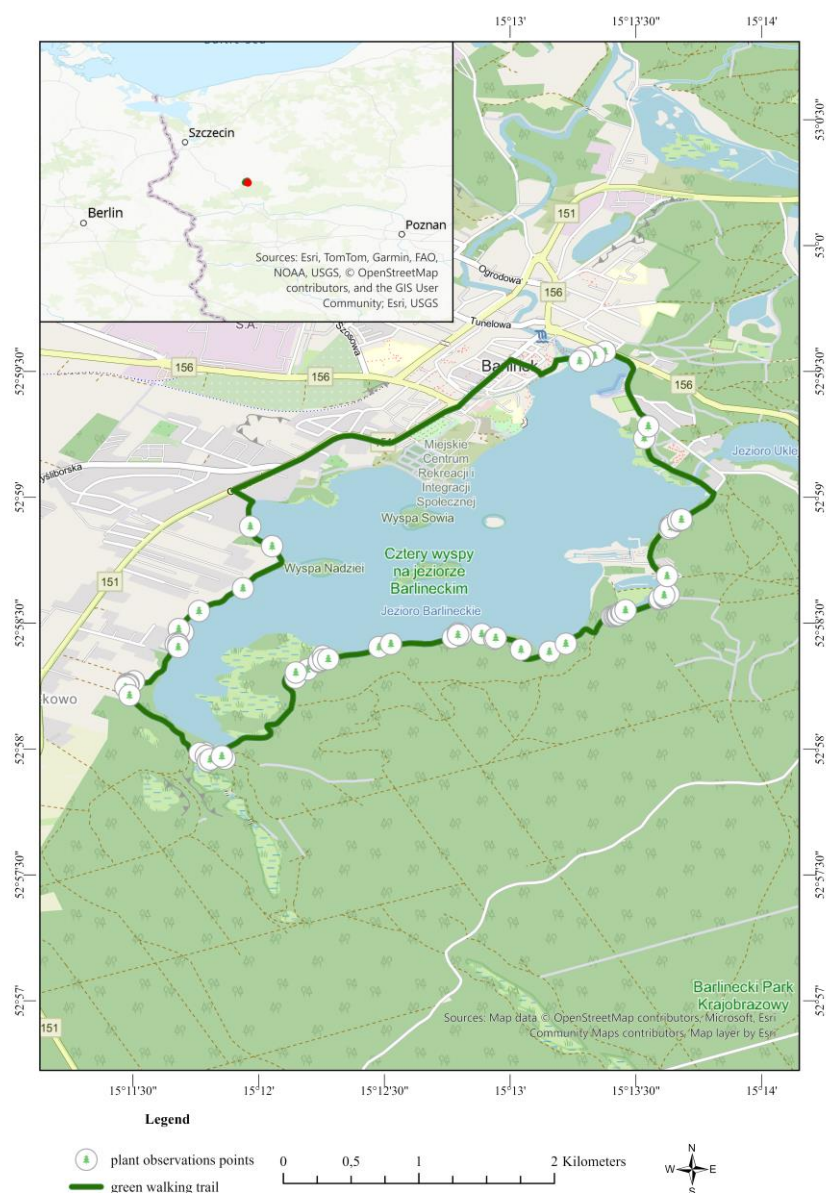


Fig. 1. Map of Barlinek Landscape Park with the green ecological trail marked. Source of walking trail: [28]. Source of basemaps: [29]

3. METHODOLOGY

The Flora Incognita application, available free of charge for devices running iOS, Android, and Harmony OS, is currently one of the most advanced tools for automatic plant identification in Central Europe [23]. The application has been developed by an interdisciplinary team of researchers from the Technische Universität Ilmenau and the Max Planck Institute for Biogeochemistry in Jena, combining botanical expertise with artificial intelligence algorithms.

The deep learning models implemented in Flora Incognita were trained using large-scale datasets containing plant images collected under diverse environmental and phenological conditions. The training datasets include photographs of multiple plant organs, such as flowers, leaves, fruits, stems, and bark, captured from different viewing angles and illumination conditions. The datasets are continuously expanded through expert-verified observations and user-contributed records, enabling iterative improvement of model performance and taxonomic coverage [24, 31]. The plant identification process within the app is multi-stage and interactive. Users are prompted to take photographs of selected diagnostic organs -typically flowers, leaves, fruits, or bark. The images are then analyzed using deep learning models that extract characteristic morphological features and compare them to reference patterns in the database. An important element of this process is the integration of contextual information such as geolocation and timestamp of the observation. The inclusion of these parameters allows the system to narrow down the number of potential species by considering biogeographical and phenological factors, such as typical flowering periods [32].

Previous studies have shown that the application achieves very high accuracy, often exceeding 90% correct identifications [23,30]. Moreover, when additional expert verification is applied, this value can increase to 98.8% [30], making the app comparable in precision to traditional botanical identification methods. However, some typical limitations are noted in the literature, including:

- Difficulties in recognizing rare species and those underrepresented in training datasets,
- High morphological similarity between closely related species,
- The influence of environmental factors (e.g., lighting, image quality, phenological stage) on classification accuracy [10,32].

Due to these limitations, authors highlight the need for external validation of results — preferably through comparison with traditional floristic inventories or expert consultation. This is particularly important when working with protected, rare, or invasive species, where misidentification could lead to erroneous ecological conclusions.

In this study, the Flora Incognita application was used to carry out a floristic inventory along the Green Ecological Trail in the Barlinek Landscape Park. As the trail forms a loop, observations were conducted in a single direction to ensure documentation consistency and facilitate subsequent spatial analysis.

Field Documentation Protocol

- Observation recording – Each encountered plant occurrence was documented in the Flora Incognita app and supported by photographic evidence.

- Data collection – For each species, a series of photos was taken showing various organs (leaves, flowers, fruits, bark), in accordance with the app’s recommendations, which increases the likelihood of correct identification [32].
- Identification and geolocation – The geographic coordinates of observation points were recorded using the integrated GNSS receiver of the mobile device within the Flora Incognita application. Under field conditions, the positional accuracy of the recorded locations was estimated at approximately 3–10 m, depending on satellite visibility and forest canopy density.
- Data recording – All observations were saved in the user’s profile within the app, allowing for later export to GIS-compatible formats. Additional field notes included phenological stage, plant condition, and habitat characteristics.
- Data analysis and visualization – The collected data were processed to assess identification accuracy and spatial distribution of recorded species.

4. RESULTS

The floristic inventory conducted using the Flora Incognita application yielded a comprehensive dataset of plant observations. During a single survey along the 10-kilometre Green Ecological Trail, 334 individual observations were recorded, corresponding to 106 plant taxa (Appendix A and Figure 2).

To improve readability, the full species list together with identification results is provided in Appendix A, where taxa are arranged alphabetically by scientific name. The effectiveness of the application was evaluated using the confidence score generated by the Flora Incognita classification model for each observation. This value represents the probability assigned by the convolutional neural network to the predicted taxon based on extracted morphological features and contextual metadata, including geolocation and observation date. The confidence score therefore reflects internal model certainty rather than independently verified taxonomic accuracy.

The mean confidence value was calculated as the arithmetic mean of all recorded observations. Because no expert validation or confusion-matrix-based assessment was performed, the reported values should be interpreted as indicators of algorithmic certainty rather than measures of true classification accuracy. This value represents the probability (expressed as a percentage) assigned by the algorithm to the suggested taxon. The average accuracy was calculated as the arithmetic mean of all recorded observations. The mean identification accuracy obtained in the study was 87%, indicating generally high confidence levels in automated recognition under field conditions. The highest scores were recorded for species with distinctive morphological traits, such as *Arctium tomentosum* (99.76%), *Cirsium oleraceum* (99.71%), *Impatiens parviflora* (99.69%), and *Lysimachia nummularia* (99.54%). In contrast, lower confidence values were observed for taxa such as *Cichorium intybus* (29.30%), *Pinus rigida* (33.61%), *Malus pumila* (41.43%), *Cephalozia bicuspidata* (41.30%), *Polytrichum commune* (43.64%), and *Populus deltoides* (47.79%). These discrepancies likely result from morphological similarity between taxa, phenological stage (e.g. absence of flowers), or limited representation in the training dataset.

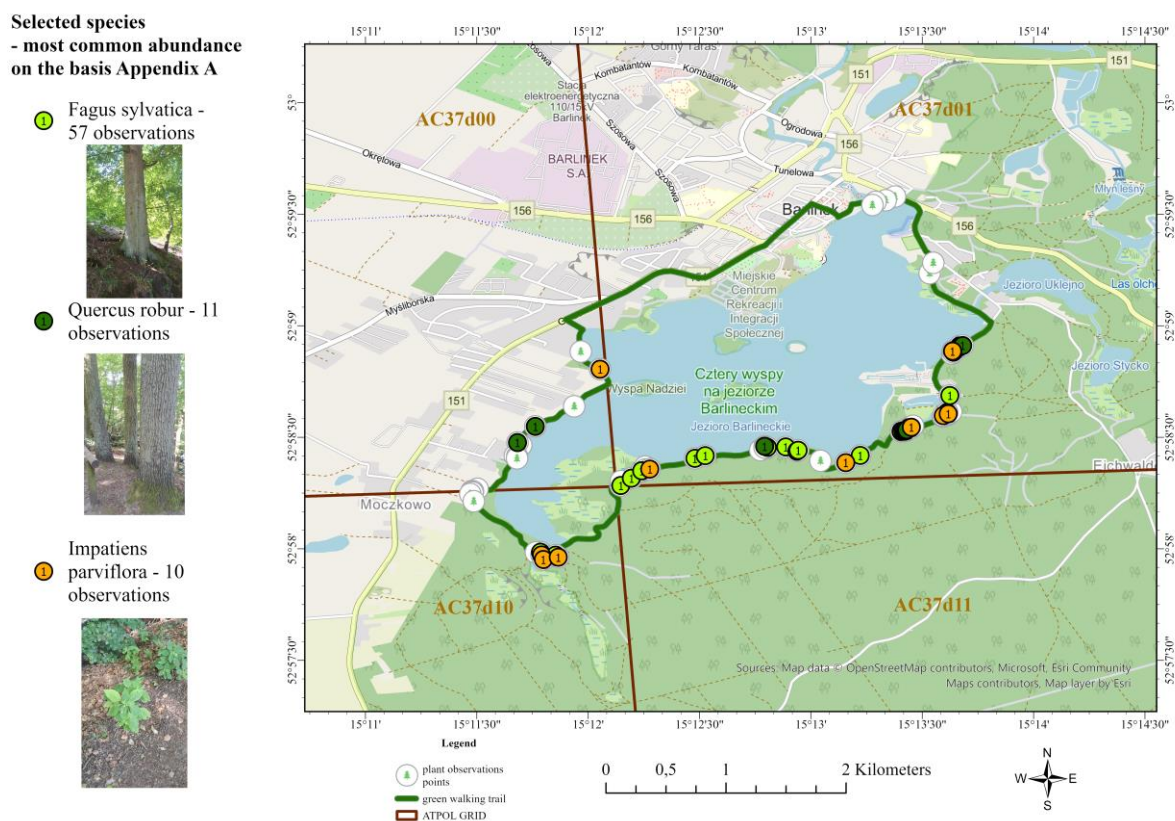


Fig. 2. Map of the green walking trail with observation points. Source of walking trail: [28]. Source of basemaps: [29]

It should be emphasized that the reported accuracy values reflect algorithmic confidence rather than verified taxonomic correctness. Due to the lack of independent expert validation or statistical testing (e.g. confusion matrix, precision/recall), the results should be interpreted as indicative rather than definitive measures of identification performance. The most frequently recorded species included *Fagus sylvatica* (57 observations), *Quercus robur* (11), *Impatiens parviflora* (10), and *Sambucus nigra* (9). Higher observation frequency increases the reliability of mean accuracy estimates, whereas taxa recorded only once should be treated with caution due to potential statistical bias. The main advantages of the application included high processing speed, with each identification taking only a few seconds, and the ability to automatically assign geographic coordinates to observations. This significantly enhances data collection efficiency compared to traditional floristic methods.

The most common sources of identification uncertainty were associated with:

- taxonomically complex groups (e.g. *Agrostis*, *Rubus*),
- incomplete or uneven training datasets, and
- nomenclatural inconsistencies.

Despite these limitations, the collected georeferenced data enabled spatial analysis of species distribution along the trail and identification of habitat-related patterns. The results demonstrate that the Flora Incognita application can serve as a useful tool for rapid biodiversity assessment, although it should be complemented by expert verification in scientific studies.

5. DISCUSSION

The results of this study indicate that the Flora Incognita application achieves generally high identification confidence under field conditions, with a predominance of values exceeding 90%. This finding is consistent with previous studies demonstrating that deep learning-based plant identification systems perform particularly well for common species with distinct morphological features [23, 30].

However, the variability observed in confidence scores highlights well-documented limitations of automated plant recognition. Lower performance for taxa such as *Cichorium intybus* or *Populus deltoides* reflects challenges related to morphological similarity, phenological variability, and insufficient representation in training datasets. Similar issues have been reported for other applications, including PlantNet and LeafSnap, where classification accuracy decreases significantly for taxonomically complex groups and under suboptimal imaging conditions [12, 17].

Importantly, the present study evaluates algorithmic confidence rather than true taxonomic accuracy. This distinction is critical, as previous research has shown that confidence scores may overestimate actual correctness when not validated against expert-identified reference data [14]. In this context, platforms such as iNaturalist offer an alternative approach by combining automated recognition with community-based verification, which enhances the reliability of verified observations. Despite these limitations, the integration of georeferenced data represents a major advantage of mobile identification tools. The spatial patterns observed in this study - including the differentiation between forest, wetland, and anthropogenic habitats - correspond well with known ecological gradients in temperate landscapes. Similar findings have been reported in studies using citizen science data, where large-scale datasets enable effective detection of biodiversity patterns and environmental change [14]. The ability to detect invasive species, such as *Impatiens parviflora*, further highlights the practical value of such tools. Early identification and spatial monitoring of invasive taxa are crucial for effective management, particularly in ecologically sensitive areas such as spring ecosystems [33]. Previous studies have emphasized the role of mobile applications in supporting rapid biodiversity assessments and early warning systems [30].

Nevertheless, the results confirm that mobile applications cannot replace traditional floristic surveys conducted by experts. While automated tools enable rapid and large-scale data collection, their performance remains dependent on image quality, species characteristics, and database completeness. Traditional methods, based on detailed morphological analysis and expert knowledge, continue to provide the highest level of taxonomic accuracy. A complementary approach appears to be the most effective strategy. Mobile applications can be used for large-scale preliminary screening, identification of biodiversity hotspots, and detection of spatial anomalies, whereas targeted expert surveys can provide validation and detailed ecological interpretation. This integration of artificial intelligence and expert-based methodologies reflects a broader trend in biodiversity monitoring, where citizen science and machine learning jointly contribute to data acquisition and analysis.

From a practical perspective, the use of the Flora Incognita application may support park management by enabling continuous and spatially explicit monitoring of plant diversity. The generation of georeferenced floristic databases facilitates the identification of areas requiring conservation measures and supports evidence-based decision-making. Furthermore, such tools play an important educational role, increasing public engagement and awareness of biodiversity conservation. Overall,

while mobile plant identification applications have clear limitations, their integration into ecological research and environmental management represents a significant advancement in the efficiency, scale, and accessibility of biodiversity monitoring.

6. CONCLUSIONS

This study evaluated the applicability of the Flora Incognita application as a mobile GIS tool for floristic inventory under field conditions. The results demonstrate that the application enables rapid and efficient collection of georeferenced plant observations, making it a useful tool for large-scale, preliminary biodiversity assessments. This finding is consistent with previous studies highlighting the effectiveness of AI-based plant identification systems in supporting ecological data acquisition [23, 30].

The majority of observations were associated with high confidence scores, indicating a generally strong performance of the underlying recognition algorithms. However, it must be emphasized that these values reflect algorithmic confidence rather than verified taxonomic accuracy. Lower confidence levels were observed for taxonomically complex or underrepresented taxa, which confirms limitations reported in the literature for automated plant identification tools [12]. Consequently, expert validation remains essential, particularly in studies requiring high taxonomic precision. The integration of georeferenced observations proved to be a significant advantage, enabling the identification of spatial patterns in vegetation distribution and the detection of habitat-related gradients. Such functionality supports the growing role of mobile technologies in spatially explicit biodiversity monitoring and environmental assessment, as demonstrated in studies based on large-scale citizen science datasets [14]. The findings also confirm that mobile applications should not be regarded as a substitute for traditional floristic surveys conducted by experts. Instead, they function most effectively as complementary tools, combining rapid data collection and scalability with the accuracy and reliability of expert-based methods. This integrated approach reflects a broader shift toward the use of digital tools and citizen science in environmental research, where large, user-generated datasets increasingly contribute to biodiversity monitoring and conservation planning [14].

Future research should focus on the long-term application of mobile identification tools, particularly through repeated surveys of the same locations, which would enable the analysis of temporal changes in species composition and phenology. Additionally, comparative studies involving different applications, such as PlantNet and iNaturalist, as well as the assessment of user-related biases, would further improve the reliability and applicability of citizen science-based monitoring frameworks.

REFERENCES

1. Balmford, A et al. 2003. Measuring the changing state of nature. *Trends in Ecology & Evolution* **18**, 326–330.
2. Balmford, A et al. 2005. The 2010 challenge: data availability, information needs and ex-traterrestrial insights. *Philosophical Transactions of the Royal Society of London Series B Biological Sciences* **360**, 221–228.
3. Schmeller, DS et al. 2009. Advantages of Volunteer-Based Biodiversity Monitoring in Europe. *Conservation Biology* **23**, 2, 307-316.
4. Dickinson, JL et al. 2010. Citizen science as an ecological research tool: Challenges and benefits. *Annual Review of Ecology, Evolution, and Systematics* **41**, 149–172.
5. Isaac, NJB et al. 2014. Statistics for citizen science: extracting signals of change from noisy ecological data. *Methods in Ecology and Evolution* **5**, 10, 1052–1060.

6. Pockock, MJO et al. 2018. A vision for global biodiversity monitoring with citizen science. *Advances in Ecological Research* **59**, 169–223.
7. Sutherland, WJ et al. 2015. An agenda for the future of biological recording for ecological monitoring and citizen science, *Biological Journal of the Linnean Society* **115**, 3,779–784.
8. Chandler, M et al. 2017. Contribution of citizen science towards international biodiversity monitoring. *Biological Conservation* **213**, 280–294.
9. Pawlik, M et al. 2023. The use of Mobile GIS in scientific research – Post-Mining Case Studies. *IOP Conference Series Earth and Environment Science* **1189 012023**, 1-19.
10. Pawlik, MP et al. 2025. Mobile GIS in Mapping Vegetation on Mine Heaps: A modern Approach to Reclamation of Post-mining Areas. *Civil and Environmental Engineering Reports* **35(3)**, 181-197.
11. Teacher, AGF et al. 2013. Smartphones in ecology and evolution: a guide for the app-rehensive. *Ecology and Evolution* **3(16)**, 5268–5278.
12. Bonnet, P, Goëau, H, Hang, ST, Lasseck, M, Milan Šulc, M, Malécot, V, Jauzein, P, Melet, J-C, You, C and Joly, A 2018. Plant identification: Experts vs. machines in the era of deep learning. In: Joly, A, Vrochidis, S, Karatzas, K, Karppinen, A, Bonnet, P (ed) *Multimedia Tools and Applications for Environmental & Biodiversity Informatics*. Cham: Springer, 131-149.
13. Seltzer, C 2019. Making biodiversity data social, shareable, and scalable: Reflections on iNaturalist and citizen science. *Biodiversity Information Science and Standards* **3 e46670**, 1-2.
14. Van Horn, G et al. 2018 *The iNaturalist species classification and detection dataset*. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Salt Lake City, USA, 8769-8778.
15. Nugent, J 2020 iNaturalist: Citizen science for the digital age. *The Science Teacher* **87(8)**, 58-63.
16. Mason, BM 2025 iNaturalist accelerates biodiversity research. *BioScience* **75, 11**, 953–965.
17. Carranza-Rojas, J et al. 2017 Going deeper in the automated identification of herbarium specimens. *BMC Evolutionary Biology* **17, 181**, 1-14.
18. Devi, A and Rav, G 2018. Reviews on Augmented Reality: Google Lens. *International Journal of Computer Trends and Technology* **58, 1**, 94–97.
19. du Plessis, LK 2015. *Through the Google Lens: Development of lecturing practice in Photography*. Master of Technology in Photography. Durban: Durban University of Technology.
20. Ahmad Syawalidi, F and Apandi, Y 2019. Augmented Reality (Studi Kasus: GoogleLens). *Informan's – Jurnal Ilmu-ilmu Informatika dan Manajemen* **2(1)**.
21. Shapovalov, VB, Shapovalov, YB, Bilyk, ZI, Megalinska, AP and Muzyka, IO 2019. The Google Lens analyzing quality: an analysis of the possibility to use in the educational process. *Educational Dimension* **1 (53)**, 219-234.
22. Bilyk, ZI, Shapovalov, YB, Shapovalov, VB, Megalinska, AP, Zhadan, SO, Andruszkiewicz, F, Dołhańczuk-Śródka, A and Antonenko, PD 2022. Comparing Google Lens Recognition Accuracy with Other Plant Recognition Apps. In: Semerikov, S, Osadchyi, V and Kuzminska, O (ed) *AET 2020 Proceedings of the 1st Symposium on Advances in Educational Technology Volume 2*, SciTePress, 20–33.
23. Mäder, P et al. 2021. The Flora Incognita app – Interactive plant species identification. *Methods in Ecology and Evolution* **12 (7)**, 1335–1342.
24. Wäldchen, J and Mäder, P 2018. Machine learning for image-based species identification. *Methods in Ecology and Evolution* **9 (11)**, 2216–2225.
25. TU Ilmenau (2023). TU Ilmenau: Neue KI für Flora Incognita. [TU Ilmenau: New AI for Flora Incognita.] <https://www.tu-ilmenau.de/aktuelles/tu-ilmenau-neue-ki-fuer-flora-incognita> (available on 07.10.2025)

26. Uchwała Sejmiku Województwa Zachodniopomorskiego. (2020). Uchwała nr XV/182/20 z dnia 27 maja 2020 r. w sprawie utworzenia Barlineckiego Parku Krajobrazowego. [Resolution No. XV/182/20 of 27 May 2020 on the establishment of the Barlinek Landscape Park] https://e-dziennik.szczecin.uw.gov.pl/WDU_Z/2020/4695/akt.pdf (accessed on 20.05.2026)
27. Mapa Barlineckiego Parku Krajobrazowego [Map of the Barlinek Landscape Park] https://www.zpkwz.pl/images/pdf/mapa_BPK_22.pdf (accessed on 20.05.2026)
28. Mapa turystyczna [Tourist Map] https://mapserver.bdl.lasy.gov.pl/ArcGIS/services/WMS_BDL_Mapa_turystyczna/MapServer/WMServer (accessed on 20.05.2026)
29. Openstreetmap <https://www.openstreetmap.org> (accessed on 20.05.2026)
30. Rzanny, M et al. 2024. More than rapid identification – Free plant identification apps can also be highly accurate. *People and Nature* **6(5)**, 1031–1043.
31. Araujo, VM et al. 2020. Two-view fine-grained classification of plant species. *Pattern Recognition Letters* **135**, 180–187.
32. Pärtel, J et al. 2021. Plant image identification application demonstrates high accuracy in Northern Europe. *AoB Plants* **13(4)**, **plab050**, 1-10.
33. Tokarska-Guzik, B, Dajdok, Z, Zajac, M, Zajac, A, Urbisz, A, Danielewicz, W and Hołdyński, C 2012. *Rośliny obcego pochodzenia w Polsce: ze szczególnym uwzględnieniem gatunków inwazyjnych*. Katowice: Generalna Dyrekcja Ochrony Środowiska [Plants of foreign origin in Poland: with particular emphasis on invasive species. Katowice: General Directorate for Environmental Protection].

Appendix A: List of recorded taxa and identification confidence scores

Scientific name	Mean confidence (%)	Number of observations
<i>Acer platanoides</i>	99,30	1
<i>Acer pseudoplatanus</i>	94,04	4
<i>Aegopodium podagraria</i>	98,51	1
<i>Agrimonia eupatoria</i>	60,74	1
<i>Agrostis capillaris</i>	79,01	1
<i>Agrostis stolonifera</i> agg.	40,74	1
<i>Alnus glutinosa</i>	89,04	5
<i>Arctium tomentosum</i>	99,76	1
<i>Artemisia vulgaris</i> agg.	93,02	6
<i>Athyrium filix-femina</i>	85,02	1
<i>Betula pendula</i>	89,76	2
<i>Bidens frondosa</i>	98,63	1
<i>Brachypodium sylvaticum</i>	98,30	1

<i>Calamagrostis arundinacea</i>	56,93	4
<i>Calamagrostis epigejos</i>	88,82	5
<i>Campanula rotundifolia</i> agg.	96,55	2
<i>Carduus crispus</i>	98,45	1
<i>Carex digitata</i>	75,76	1
<i>Carex pilosa</i>	66,70	1
<i>Carpinus betulus</i>	75,07	1
<i>Cephalozia bicuspidata</i>	41,30	1
<i>Chelidonium majus</i>	58,80	1
<i>Chenopodium album</i> agg.	97,84	1
<i>Cichorium intybus</i>	29,30	1
<i>Circaea lutetiana</i>	99,42	3
<i>Cirsium arvense</i>	81,68	5
<i>Cirsium oleraceum</i>	99,71	1
<i>Convallaria majalis</i>	94,10	4
<i>Corylus avellana</i>	96,51	7
<i>Crataegus monogyna</i>	84,96	4
<i>Dactylis glomerata</i> agg.	69,74	4
<i>Daucus carota</i>	82,86	2
<i>Deschampsia cespitosa</i> agg.	60,39	4
<i>Dryopteris filix-mas</i> agg.	95,84	4
<i>Equisetum arvense</i>	51,23	1
<i>Equisetum hyemale</i>	99,44	2
<i>Erigeron annuus</i>	87,98	3
<i>Erigeron canadensis</i>	99,33	2
<i>Euonymus europaeus</i>	83,58	6
<i>Eupatorium cannabinum</i>	99,04	6
<i>Fagus sylvatica</i>	85,56	57
<i>Fraxinus excelsior</i>	88,80	1
<i>Galeopsis pubescens</i>	96,04	3
<i>Galium odoratum</i>	98,19	4

<i>Galium sylvaticum</i> agg.	99,37	4
<i>Geranium robertianum</i> agg.	94,86	1
<i>Geum urbanum</i>	75,56	3
<i>Glechoma hederacea</i> agg.	98,92	1
<i>Heracleum sphondylium</i>	94,07	1
<i>Hieracium</i>	92,74	6
<i>Humulus lupulus</i>	87,80	3
<i>Hypericum perforatum</i>	94,26	1
<i>Impatiens parviflora</i>	99,69	10
<i>Juncus tenuis</i>	93,56	1
<i>Lactuca muralis</i>	92,20	2
<i>Lapsana communis</i>	99,51	2
<i>Lemna minor</i>	75,27	1
<i>Leucobryum glaucum</i>	83,82	1
<i>Luzula pilosa</i>	96,22	3
<i>Lysimachia nummularia</i>	99,54	1
<i>Lysimachia vulgaris</i>	98,92	1
<i>Lythrum salicaria</i>	88,28	1
<i>Malus pumila</i>	41,43	1
<i>Melica nutans</i>	69,71	1
<i>Milium effusum</i>	98,98	1
<i>Phragmites australis</i>	95,98	3
<i>Picris hieracioides</i>	94,31	3
<i>Pimpinella saxifraga</i> agg.	97,56	1
<i>Pinus rigida</i>	33,61	1
<i>Pinus sylvestris</i>	77,25	4
<i>Plantago major</i> agg.	99,51	1
<i>Poa nemoralis</i> agg.	97,62	1
<i>Polygonum aviculare</i> agg.	86,76	1
<i>Polytrichum commune</i>	43,64	2
<i>Populus deltoides</i>	47,79	1

<i>Populus tremula</i>	71,63	4
<i>Potentilla reptans</i>	88,33	2
<i>Prunus cerasifera</i>	87,23	1
<i>Pteridium aquilinum</i>	87,68	2
<i>Pyrus communis</i> agg.	91,73	1
<i>Quercus petraea</i>	55,06	6
<i>Quercus robur</i>	66,74	11
<i>Robinia pseudoacacia</i>	74,91	6
<i>Rosa canina</i>	85,42	1
<i>Rubus armeniacus</i>	58,96	1
<i>Rubus caesius</i>	96,06	3
<i>Rubus idaeus</i>	94,58	8
<i>Salix alba</i>	86,84	4
<i>Salix caprea</i>	98,73	1
<i>Sambucus nigra</i>	80,45	9
<i>Silene latifolia</i>	98,61	1
<i>Solidago canadensis</i>	73,64	3
<i>Solidago virgaurea</i>	99,40	2
<i>Sorbus aucuparia</i>	94,80	8
<i>Syntrichia ruralis</i>	95,17	1
<i>Taraxacum</i>	67,99	2
<i>Thuja plicata</i>	97,53	1
<i>Tilia cordata</i>	97,22	3
<i>Torilis japonica</i> agg.	62,21	1
<i>Trifolium repens</i>	66,79	1
<i>Tripleurospermum maritimum</i> agg.	97,74	1
<i>Ulmus glabra</i>	81,74	3
<i>Urtica dioica</i>	81,08	6
<i>Vaccinium myrtillus</i>	96,93	2
<i>Verbascum lychnitis</i>	96,17	2