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AI-Driven Urban Biodiversity Mapping: Integrating Geospatial Intelligence, Ecology and Citizen Science

Xiangzhong Luo

Assistant Professor, National University of Singapore (NUS), Singapore

Abstract

Urban areas contain heterogeneous ecological environments, including public parks, wetlands, gardens, vacant land, street trees, transport corridors, waterways, green roofs, institutional campuses, and small informal green spaces. These habitats can support diverse plant and animal communities, but their ecological value is often insufficiently represented in conventional land-use inventories. Field surveys remain essential for reliable biodiversity assessment, yet they can be expensive, spatially restricted, and difficult to repeat frequently across an entire city. Artificial intelligence and geospatial technologies provide opportunities to extend ecological monitoring by integrating satellite imagery, aerial data, environmental sensors, species observations, acoustic recordings, photographs, and citizen-science contributions.This paper examines an integrated framework for AI-driven urban biodiversity mapping.

The study combines a conceptual literature review with an illustrative simulation assessing how complementary data layers may expand validated species-record coverage. In the simulation, a normalized validated species-record index increases from 45 for professional field surveys alone to 94 after citizen observations, satellite data, acoustic and image sensors, and AI-assisted validation are incorporated. These values are methodological illustrations and do not represent field-survey findings. The analysis demonstrates that AI can support land-cover classification, species identification, habitat-suitability modelling, ecological-corridor assessment, and identification of under-surveyed locations.

The paper also identifies substantial challenges involving uneven observation effort, geographic bias, species misidentification, limited detection of inconspicuous organisms, remote-sensing resolution, algorithmic uncertainty, privacy, and the potential exclusion of communities with limited digital access. Citizen observations should therefore be treated as valuable but nonuniform ecological evidence requiring validation and bias correction. Responsible urban biodiversity mapping should combine automated analysis with professional field verification, transparent uncertainty estimates, reproducible data standards, and meaningful community participation. Such integration can support more spatially equitable conservation planning and improve understanding of biodiversity within rapidly changing urban environments.

Keywords: artificial intelligence; urban biodiversity; geospatial intelligence; citizen science; remote sensing; species-distribution modelling; ecological planning; green infrastructure

1. Introduction

Urbanization transforms ecological systems by replacing or fragmenting natural and semi-natural habitats, altering water movement, modifying temperature, introducing artificial light, and increasing exposure to pollution and disturbance. Despite these pressures, cities are not biologically empty. Urban landscapes can contain native vegetation, migratory species, pollinators, aquatic organisms, soil biodiversity, and species that adapt to built environments. The distribution of this biodiversity is spatially uneven and often poorly documented.

Conventional urban biodiversity assessments rely on professional field surveys, vegetation inventories, habitat classifications, and administrative land-use records. These methods provide reliable observations but require specialist expertise and considerable time. Surveys may concentrate on designated parks or protected areas while small gardens, roadside vegetation, informal green spaces, drainage corridors, and private land remain underexamined.

Geospatial intelligence extends ecological observation across larger areas. Satellite imagery can identify vegetation cover, surface water, canopy structure, impervious surfaces, land-surface temperature, and changes in habitat configuration. Drones and aerial imagery can provide finer spatial detail, while geographic information systems allow ecological observations to be connected with land use, infrastructure, population, and environmental conditions.

Citizen science adds a participatory layer. Residents can report birds, plants, insects, mammals, fungi, and other organisms through photographs, audio recordings, or structured surveys. These observations may expand spatial and temporal coverage while increasing public engagement with local ecology. They also contain biases because participants differ in expertise, mobility, technology access, preferred species, and choice of survey locations.

Artificial intelligence can help organize these heterogeneous sources. Computer vision may suggest species identities from photographs, acoustic models can classify animal calls, and spatial algorithms can estimate habitat suitability. The principal research question is how these capabilities can be integrated without treating algorithmic predictions or unverified public observations as equivalent to confirmed ecological evidence.

2. Review of Literature

2.1 Geospatial Technologies in Urban Ecology

Remote sensing has become an important component of biodiversity and habitat monitoring. Satellite-derived vegetation indices, land-cover classifications, canopy measurements, and surface-temperature estimates can reveal environmental patterns across entire metropolitan regions. Geospatial analysis can also measure habitat size, isolation, edge effects, connectivity, and proximity to ecological pressures.

Turner and colleagues explained how remote sensing can contribute to biodiversity science by connecting spatially continuous environmental observations with field-based ecological measurements. Pettorelli and colleagues emphasized that satellite information can support conservation monitoring, although its ecological meaning depends on sensor properties, spatial resolution, temporal frequency, and ground validation.

Urban environments create particular classification difficulties. A single satellite pixel may contain trees, buildings, grass, pavement, and shadow. Small wetlands, narrow green corridors, individual street trees, or green roofs may not be visible at coarse resolution. Imagery should therefore be selected according to the scale of the ecological question.

Species-distribution models connect observed species locations with environmental variables. Machine learning can represent nonlinear relationships among vegetation, climate, topography, water, disturbance, and urban structure. However, predicted habitat suitability is not equivalent to confirmed species presence. Field validation remains necessary.

2.2 Artificial Intelligence for Species Recognition

Computer-vision systems can classify organisms from photographs when training data contain sufficiently representative examples. Convolutional neural networks have been used for plants, birds, insects, and other taxonomic groups. Automated identification can provide rapid feedback to citizen participants and help experts prioritize observations for review.

Species-recognition performance varies across taxa. Common and visually distinctive organisms are generally easier to identify than rare, cryptic, juvenile, damaged, or morphologically similar species. Photographic quality, lighting, viewing angle, seasonal appearance, and incomplete body visibility can affect predictions.

Acoustic monitoring offers another data source. Bird, bat, frog, insect, and other animal sounds can be recorded through fixed sensors or mobile devices. Machine-learning systems may classify calls across long recordings that would be impractical to review manually. Background noise, overlapping vocalizations, equipment differences, and geographic variation in calls remain important limitations.

AI validation should therefore be probabilistic. A model can assign a confidence score, compare candidate species, and identify observations that require expert examination. It should not convert every uncertain prediction into a confirmed occurrence record.

2.3 Citizen Science and Ecological Participation

Citizen science can extend monitoring beyond the spatial and financial capacity of professional survey teams. Boakes and colleagues found that volunteer contributions are often unevenly distributed, with a relatively small number of participants supplying a large proportion of records. Observation patterns may reflect accessibility and personal interest rather than ecological abundance.

Chandler and colleagues discussed citizen science as a significant source of biodiversity information while emphasizing the need for protocols, quality control, metadata, and appropriate analytical treatment. Public participation can also strengthen environmental awareness and local stewardship.

3. Objectives of the Study

3.1 Ecological Mapping Objectives

The study aims to examine how professional surveys, citizen observations, remote sensing, acoustic sensors, image records, and artificial intelligence can be combined to improve urban biodiversity mapping. A related objective is to distinguish confirmed occurrence, probable presence, habitat suitability, and absence of evidence. These categories should not be combined into a single undifferentiated biodiversity layer.

3.2 Planning and Conservation Objectives

The second objective is to evaluate how integrated maps can support identification of biodiversity hotspots, habitat gaps, ecological corridors, restoration opportunities, and underserved neighborhoods.

The analysis also considers whether urban mapping can connect ecological value with land-use planning, green-infrastructure investment, heat adaptation, stormwater management, and public access to nature.

3.3 Participation and Governance Objectives

The third objective is to assess how citizen science can contribute to ecological knowledge while maintaining data quality, informed participation, privacy, and community recognition.

The paper seeks to define AI as a validation and prioritization tool operating alongside ecological expertise rather than as an automatic authority over species identification or conservation decisions.

4. Research Methodology

4.1 Research Design

The study adopted a conceptual and simulation-based design. It synthesized literature from urban ecology, remote sensing, geographic information science, machine learning, conservation planning, and citizen science. No live species surveys, identifiable participant information, or actual municipal datasets were used.

Relevant literature was identified through multidisciplinary academic databases and peer-reviewed environmental journals. Search concepts included “AI biodiversity mapping,” “urban ecology remote sensing,” “citizen science species data,” “machine-learning species identification,” and “geospatial habitat modelling.”

4.2 Integrated Mapping Framework

The framework organizes mapping evidence into five layers.

Table 1: Data Components of Integrated Urban Biodiversity Mapping

Mapping layer	Representative information	Primary contribution
Professional surveys	Verified species, abundance and habitat condition	Provides high-confidence ecological evidence
Citizen observations	Photographs, audio and georeferenced reports	Expands temporal and spatial coverage
Satellite and aerial data	Vegetation, water, canopy and land-cover patterns	Provides continuous environmental context
Acoustic and image sensors	Repeated recordings and automated cameras	Detects species beyond scheduled field visits

Mapping layer	Representative information	Primary contribution
AI-assisted validation	Classification, anomaly detection and bias correction	Prioritizes records and supports quality control

4.3 Illustrative Simulation

A normalized validated species-record index was used to illustrate the contribution of complementary data. Field surveys were assigned an index of 45. The index increased to 66 after citizen observations, 77 after satellite data, 88 after acoustic and image sensors, and 94 after AI-assisted validation.

These figures are hypothetical. They do not represent actual species richness, survey completeness, detection probability, or municipal biodiversity performance. The simulation demonstrates an analytical principle rather than an empirical ecological result.

5. Analysis

5.1 Spatial Integration and Ecological Interpretation

Professional observations provide the primary reference for interpreting other sources. Field ecologists can verify species, assess habitat condition, record abundance, and identify ecological relationships that imagery alone cannot capture.

Citizen observations extend coverage but require correction for uneven sampling. Frequently visited parks may contain many records because they are accessible, while industrial land or low-income neighborhoods may appear species-poor because fewer observations are submitted. Mapping observation effort alongside species records helps prevent this bias from being misinterpreted as ecological absence.

5.2 Simulated Mapping Results

Table 2: Illustrative Change in Validated Biodiversity Coverage

Integrated configuration	Record index	Incremental gain	Cumulative gain
Professional field surveys	45	—	—
Addition of citizen observations	66	21	21
Addition of satellite data	77	11	32
Addition of acoustic and image sensors	88	11	43
Addition of AI-assisted validation	94	6	49

The largest simulated increase follows the integration of citizen observations. This reflects their potential to broaden geographic and seasonal coverage. Satellite data add environmental continuity, while sensor networks contribute observations during periods when human surveyors are absent.

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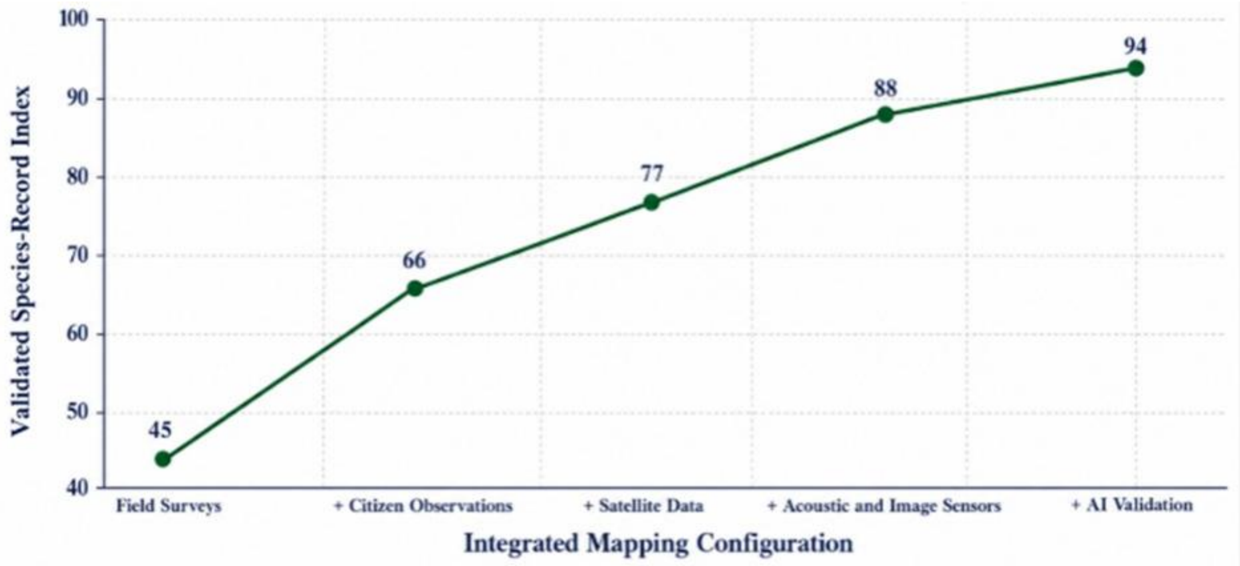
AI-assisted validation provides a smaller final increase because it primarily improves the reliability and organization of information already collected. The pattern does not imply that automated validation can replace taxonomic expertise.

Graph 1: Illustrative Gain in Validated Urban Biodiversity Records



Supporting data: Field surveys = 45; citizen observations = 66; satellite data = 77; acoustic and image sensors = 88; AI-assisted validation = 94.
Source: Author-developed illustrative simulation; values are not field-survey results.
Interpretation: Within the simulation, validated coverage increases as complementary data sources are incorporated. The declining incremental gain reflects partial overlap among data layers.
Key Finding: Integrated mapping may provide broader coverage than any single method, but trustworthy results require validation, explicit uncertainty, and correction for uneven observation effort.

5.3 Applications in Urban Planning

Integrated biodiversity maps can identify locations where development may fragment habitats or disrupt movement corridors. They can also reveal opportunities to connect parks through street trees, riparian vegetation, railway margins, green roofs, and restored vacant land.

Mapping should support spatial equity. Neighborhoods with limited green infrastructure may also be underrepresented in biodiversity databases. Survey investment should not flow exclusively toward locations already rich in observations.

Ecological priority should be evaluated alongside community needs, land ownership, safety, maintenance, water availability, climate resilience, and long-term governance. A technically suitable restoration site may fail if local residents are excluded from planning.

6. Challenges

6.1 Observation Bias and Species Misidentification

Citizen-science records are influenced by participant location, expertise, interest, and access. Charismatic or easily photographed organisms may be overrepresented, while nocturnal, microscopic, subterranean, or visually similar species remain underdetected.

AI classification inherits the composition of its training data. Rare species may be assigned to common classes, and models developed in one region may perform poorly elsewhere. Confidence thresholds and expert-review pathways are therefore necessary.

Repeated observations of the same individual can also create misleading patterns. Spatial, temporal, and photographic metadata should be examined before records are aggregated.

6.2 Remote-Sensing and Model Limitations

Remote sensing measures environmental characteristics rather than biodiversity directly. Similar vegetation indices may represent ecologically different plant communities. Tree canopy does not reveal whether vegetation is native, invasive, structurally diverse, or biologically functional.

Model predictions are sensitive to resolution, sampling design, variable selection, and spatial autocorrelation. Randomly dividing nearby observations between training and testing data can exaggerate apparent performance.

Independent geographic validation is essential. Models should be evaluated in locations not used during training and across different seasons where possible.

6.3 Privacy, Participation and Data Ownership

Georeferenced biodiversity records may reveal participant movement, private property, sensitive species locations, or culturally significant ecological knowledge. Exact coordinates should be restricted when disclosure could increase disturbance, collection, or habitat damage.

Citizen participants should understand how their observations will be used, attributed, shared, and retained. Community knowledge should not be extracted without recognition or reciprocal benefit.

Digital participation must not become the only route into urban ecological planning. Offline surveys, community workshops, schools, local organizations, and professional outreach remain important for inclusive participation.

7. Discussion

7.1 Combining Evidence Without Collapsing Its Meaning

The study shows that different data sources answer different ecological questions. Field surveys provide verified observations, remote sensing describes environmental conditions, sensors extend temporal coverage, and citizen science broadens participation and geographic reach.

These sources should be connected without being treated as interchangeable. A modelled probability of presence should not appear on a map as a confirmed occurrence. Maps should distinguish verified, probable, predicted, and unobserved categories.

Uncertainty should be visible to planners and the public. Confidence intervals, observation density, validation status, and model limitations are more informative than a single biodiversity score.

7.2 Human–AI Collaboration in Urban Ecology

AI can process imagery and recordings at a scale that exceeds manual capacity. Ecologists contribute taxonomic knowledge, survey design, causal reasoning, and understanding of habitat processes.

Citizen scientists contribute local familiarity and repeated observation. Their role should extend beyond supplying raw data. Communities can help identify monitoring questions, select sites, interpret change, and evaluate proposed interventions.

The strongest model is therefore collaborative: AI organizes and prioritizes information, experts validate ecological meaning, and communities contribute observations and local priorities.

7.3 From Mapping to Responsible Conservation

A detailed map does not automatically improve biodiversity. Its value depends on whether it informs zoning, restoration, infrastructure design, maintenance, pollution control, and investment.

Planning agencies should document how biodiversity evidence influences decisions. Monitoring should continue after intervention so that ecological outcomes can be assessed rather than assumed.

Maps should also avoid stigmatizing neighborhoods as ecologically deficient when low recorded diversity reflects limited survey effort. Additional investigation should precede conclusions about ecological absence.

8. Conclusion

AI-driven urban biodiversity mapping can integrate professional ecological surveys, satellite and aerial remote sensing, environmental sensors, citizen observations, and automated species classification to develop a broader understanding of urban ecological patterns. Each data source provides different forms of information while also introducing specific limitations related to accuracy, spatial coverage, temporal consistency, or identification quality. Integrating these complementary sources can strengthen ecological assessment by connecting field-based observations with continuous environmental measurements and geospatial information, thereby supporting more comprehensive interpretation of biodiversity across complex urban landscapes.

The illustrative simulation demonstrates how combining multiple information layers may expand a validated species-record index across an urban study area. However, these simulated values are presented only to explain the potential analytical framework and should not be interpreted as empirical findings or evidence of guaranteed performance improvement. Actual biodiversity mapping outcomes depend on data quality, sampling intensity, geographic coverage, species detectability, classification accuracy, and validation procedures. Therefore, real-world applications require independent datasets and systematic evaluation before conclusions about effectiveness can be established.

Responsible biodiversity mapping requires transparent validation procedures, systematic correction for spatial and sampling biases, protection of sensitive species locations, and a clear distinction between directly observed records and predicted distributions. Automated identification systems should operate with predefined uncertainty thresholds and should flag ambiguous cases for expert review. Data governance is equally important because public biodiversity platforms may contain sensitive information about endangered species or vulnerable habitats. Combining artificial intelligence with ecological expertise can improve efficiency while maintaining scientific credibility, transparency, and responsible interpretation of biodiversity information.

When geospatial intelligence, ecological expertise, and citizen participation are carefully integrated, AI-driven biodiversity mapping can provide valuable support for urban environmental planning and conservation. Reliable spatial information can help identify habitat connectivity, prioritize ecological restoration, evaluate green-space distribution, and guide equitable green-infrastructure development. Citizen participation can further expand observation networks while strengthening public awareness and engagement with urban nature. However, sustained benefits depend on continuous data validation, community involvement, expert oversight, and adaptive management. Such an integrated approach can connect technological innovation with practical ecological decision-making.

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