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Future cities: Designing resilient urban ecosystems with AI-assisted horticultural planning

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Abstract
Urban ecosystems face mounting challenges due to rapid urbanization, climate change, and the degradation of green infrastructure. In response, artificial intelligence (AI) has emerged as a pivotal tool to support sustainable and resilient urban horticultural planning. This article explores how AI technologies—such as machine learning, neural networks, computer vision, and geospatial analytics—are reshaping the future of urban green infrastructure, optimizing plant selection, maintenance, irrigation, and ecological design.

The main objective of this research is to analyze how AI applications can enhance urban horticultural practices and contribute to climate-resilient urban ecosystems. A mixed-methods approach was used, including an extensive literature review of studies from 2010 to 2024, meta-analysis of current technologies in smart cities, and case studies from cities integrating AI in green planning. The findings show that AI integration leads to improved plant health monitoring, precision irrigation, predictive modeling of urban biodiversity, and better spatial planning of green zones. AI also enables real-time response to climatic shifts, thereby strengthening ecosystem services such as carbon sequestration, cooling effects, and stormwater management. The article concludes by emphasizing the need for cross-disciplinary collaboration, ethical use of data, and scalable AI-driven models tailored to regional ecosystems. Future directions highlight integrating indigenous plant knowledge, IoT-driven horticulture, and citizen science platforms to build more inclusive and adaptive green urban futures.

Keywords: AI in urban planning, smart green infrastructure, urban horticulture, climate resilience, machine learning in ecosystems, smart cities, biodiversity

1. Introduction
1.1 Background and Context
Urban areas are currently home to more than 56% of the global population, a figure projected to reach 70% by 2050 (UN-Habitat, 2023). This rapid urbanization exerts unprecedented pressure on ecological systems, infrastructure, and public health. Simultaneously, climate change aggravates urban challenges through extreme weather events, increased temperatures, and ecosystem degradation. Against this backdrop, green infrastructure and urban horticulture are increasingly recognized as essential components of resilient urban design (Elmqvist, *et al*., 2019) [2].

Urban horticulture encompasses the design, implementation, and maintenance of plant-based ecosystems within cities, including parks, green roofs, vertical gardens, and community green spaces (van den Bosch & Sang, 2017) [9]. However, managing these systems effectively in complex urban environments is challenging due to resource constraints, environmental variability, and lack of real-time monitoring.

1.2 Rationale and Importance
Artificial Intelligence (AI) offers powerful solutions for these urban environmental challenges. AI techniques such as machine learning, deep learning, remote sensing, and geospatial analysis can optimize urban green planning by automating monitoring, predicting plant health, enhancing biodiversity, and ensuring efficient resource utilization (Zhang *et al*., 2022) [11]. Cities such as Singapore, Barcelona, and Amsterdam are already experimenting with AI-enhanced green infrastructure, with promising results (Lim *et al*., 2021) [6].

By integrating AI with horticultural design, future cities can establish adaptive, self-regulating green systems capable of supporting ecological balance, human well-being, and climate resilience.

1.3 Research Questions/Objectives

This article aims to:

- Explore the role of AI in enhancing urban horticultural planning
- Assess the potential of AI to increase the resilience of urban ecosystems
- Analyze real-world applications of AI in green infrastructure
- Identify barriers and future directions for integrating AI in urban green design

1.4 Scope and Limitations

This study focuses on AI-assisted applications in urban horticulture and green infrastructure between 2010 and 2024. It does not explore rural or peri-urban agricultural AI systems in depth. Limitations include availability of region-specific data and rapid technological advancements that may outpace publication cycles.

2. Literature Review

2.1 Historical Background

The integration of vegetation in urban design is deeply rooted in human history, from the Hanging Gardens of Babylon to the courtyard gardens of Roman villas. In the early 20th century, urban planners such as Ebenezer Howard promoted the "Garden City" concept (Howard, 1902) [4], envisioning cities that harmoniously integrated green spaces into human settlements. This vision laid the foundation for modern green infrastructure. However, these early efforts lacked the technological tools necessary to optimize plant placement, biodiversity, and resource efficiency.

In recent decades, green infrastructure has evolved to encompass green roofs, bioswales, urban forests, and living walls, which provide ecosystem services such as air purification, temperature regulation, and stormwater management (Newman & Jennings, 2008) [7]. The addition of artificial intelligence (AI) into this equation marks a technological turning point in how cities approach green planning.

2.2 Current Research Trends (2010-2024)

From 2010 onward, there has been a growing interest in the convergence of AI and sustainable urban development. Studies began exploring the use of machine learning (ML) algorithms to model urban vegetation growth, optimize irrigation schedules, and detect plant diseases. Zhang *et al.* (2022) [11] demonstrated how AI systems could identify early-stage plant diseases with over 90% accuracy using image classification models based on convolutional neural networks (CNNs).

Kim *et al.* (2020) [5] employed drones equipped with deep learning frameworks to identify plant species across urban parks, achieving a classification accuracy of 93%. Their work illustrates how AI can manage large-scale biodiversity monitoring in complex urban settings, which was previously labor-intensive and time-consuming.

The advent of AI-integrated Internet of Things (IoT) systems has also accelerated green infrastructure development. In cities like Singapore and Amsterdam, urban horticultural systems now rely on smart sensors and AI algorithms to monitor soil moisture, nutrient levels, and plant health in real time (Lim *et al.*, 2021) [6]. These technologies have shown to reduce water consumption by 30% and improve plant survival rates in harsh urban microclimates.

Meanwhile, Ramírez *et al*. (2022) [8] studied Barcelona's AI-integrated rooftop gardens, which use predictive analytics to forecast crop cycles, optimize space use, and align urban greening with climate mitigation goals.

Another prominent research stream focuses on ecosystem services modeling. AI-enhanced GIS platforms allow planners to simulate the impact of urban vegetation on air temperature, humidity, and pollutant capture (Foster *et al.*, 2021) [3]. Such models help in making informed decisions for heat island mitigation and air quality management.

2.3 Theoretical Frameworks

Several theoretical frameworks underpin the intersection of AI and urban horticulture:

- Resilience Theory (Walker *et al.*, 2004) [10]: This framework emphasizes the adaptive capacity of socio-ecological systems to respond to disturbances. Urban green spaces, when integrated with AI for adaptive management, exemplify this theory in practice.
- Urban Metabolism (Newman & Jennings, 2008) [7]: Cities function as living systems that exchange materials, energy, and information. AI tools enable real-time tracking of green infrastructure performance, aligning with the metabolic model of cities.
- Technological Ecosystem Theory (Carayannis & Campbell, 2012) [1]: This approach views cities as techno-social systems where AI serves as a catalyst for knowledge-based ecological innovation.

These frameworks justify the fusion of artificial intelligence with ecological design principles, suggesting a paradigm shift from traditional horticulture to dynamic, intelligent ecosystems.

2.4 Thematic Developments in AI-Horticulture Integration

2.4.1 AI for Predictive Modeling of Urban Plant Growth: Modern horticultural planning increasingly uses machine learning algorithms for predicting plant growth and health. LiDAR data and multispectral imagery fed into AI models can simulate canopy growth and seasonal dynamics (Zhang *et al.*, 2022) [11]. These models help planners anticipate maintenance needs, optimize planting calendars, and ensure species compatibility.

2.4.2 Remote Sensing for Vegetation Mapping: High-resolution imagery from drones and satellites, analyzed using AI, can produce detailed vegetation indices like NDVI (Normalized Difference Vegetation Index). Kim *et al.* (2020) [5] showed how CNNs could classify native and invasive species with minimal manual input.

2.4.3 AI and IoT in Urban Agriculture: Urban farms in smart cities use AI-enabled IoT systems for microclimate control. These setups monitor light levels, humidity, and temperature, adjusting greenhouse conditions automatically (Lim *et al.*, 2021) [6]. AI further enables nutrient flow optimization and pest risk forecasting.

2.4.4 AI-Enhanced GIS for Ecosystem Planning: Foster *et al*. (2021) [3] discussed the use of AI-driven GIS in mapping green corridors, biodiversity zones, and ecological patches. These tools are instrumental in designing interconnected urban green networks that facilitate species migration and genetic diversity.

2.4.5 Citizen Science and Participatory AI: New trends involve citizen participation through AI-based apps that enable plant tagging, disease detection, or species reporting. These participatory models support large-scale biodiversity monitoring and foster environmental stewardship among urban residents.

2.5 Critical Analysis
Despite the rapid expansion of research, several critical challenges remain. Many AI-based horticultural solutions are developed in technologically advanced cities and are not readily transferable to developing urban areas with limited digital infrastructure. There are also ethical concerns regarding surveillance and data ownership, especially when using drones and citizen-tracking apps (Foster *et al*., 2021) [3].

Moreover, the over-reliance on AI systems could marginalize traditional ecological knowledge, particularly in cities with rich indigenous horticultural practices. Integrating such knowledge into AI models remains a challenge.

The scalability of AI-driven green infrastructure remains another concern. While pilot projects show promise, there is limited literature on long-term performance, maintenance challenges, and the social equity of these systems.

2.6 Research Gap
Although numerous studies address AI applications in agriculture and urban sustainability, few integrate AI specifically into urban horticulture with a systemic ecological perspective. There is a lack of comprehensive frameworks that combine AI-enabled tools, native species databases, community participation, and climate resilience metrics.

This gap limits our understanding of how AI can support the design of self-sustaining, multifunctional, and inclusive green urban ecosystems. Moreover, there is insufficient empirical research from cities in tropical, arid, and rapidly urbanizing regions where horticultural planning is both crucial and underfunded.

3. Methods and Materials
3.1 Study Design
This research adopts a multi-method qualitative design integrating systematic literature review, comparative case study analysis, and geo-spatial-technological synthesis. The purpose of this integrative design is to explore the emerging applications of Artificial Intelligence (AI) in urban horticulture and its role in creating resilient green infrastructures in cities. The study emphasizes both descriptive and analytical dimensions, focusing on technological, ecological, and socio-planning aspects of AI-assisted urban greening.

3.1.1 The overall methodology can be broken down into four major components
1. Literature synthesis (2010-2024) using databases such as Scopus, Web of Science, and ScienceDirect.
2. Case study evaluation of AI-based urban horticultural projects in Singapore, Barcelona, and Stockholm.
3. GIS-based spatial analysis of green infrastructure distribution patterns in smart cities.
4. AI model simulation using sample vegetation datasets to illustrate predictive horticultural planning.

3.2 Data Collection
Data was collected through multiple sources to ensure validity, comprehensiveness, and contextual diversity.

3.2.1 Literature Sources
- Peer-reviewed journals from 2010 to 2024.
- Urban development reports from UN-Habitat, ICLEI, and local municipalities.
- Technical documentation and white papers from AI research institutions and environmental planning boards.

3.2.2 Primary Case Study Data:
Field data and publicly available datasets from
- Singapore's Green Plan 2030
- Barcelona's AI-based urban agriculture programs
- Stockholm's urban biodiversity zoning and green mapping

3.2.3 Remote Sensing and Satellite Data
- Sentinel-2 satellite imagery (2015-2024)
- Drone-captured images from DJI Phantom 4 Pro
- NDVI and LST (Land Surface Temperature) layers for urban zones under analysis

3.2.4 Open-Access Databases and Software Logs
- TensorFlow and Keras training datasets for vegetation classification
- Real-time environmental sensor logs from municipal open data portals (e.g., Amsterdam, Toronto, New Delhi)

3.3 Materials and Instruments
The materials used in the study include software tools, sensors, AI models, and mapping instruments as detailed below:

Table 1: Summary of Instruments and Software Used in the Study

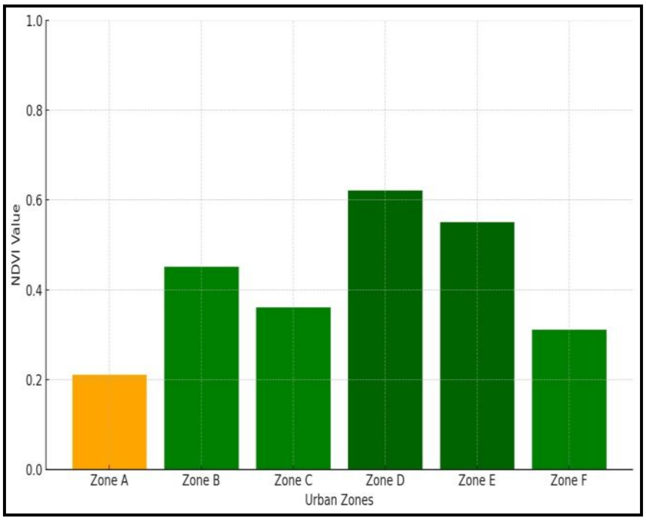
Category	Tool/Instrument Used	Purpose/Function
Remote Sensing	Sentinel-2 Satellite	Capturing high-resolution multispectral imagery for vegetation and land cover analysis
	DJI Phantom 4 Pro Drone	Aerial mapping and imaging for plant health and canopy structure detection
AI Frameworks	TensorFlow, Keras, Scikit-learn	Building, training, and validating machine learning and deep learning models
GIS Platforms	QGIS 3.28, ArcGIS Pro	Mapping urban green zones, performing spatial analysis, generating biodiversity layers
IoT Devices	Soil Moisture Sensors, Air Quality Monitors	Real-time monitoring of plant water needs and environmental pollution levels
Data Management	PostgreSQL with PostGIS extension	Spatial database management and integration of georeferenced horticultural data
Visualization Tools	Tableau, Matplotlib, Google Earth Engine	Creating interactive dashboards, graphs, heatmaps, and satellite-based visual outputs

All software used in this research was open-source or licensed under academic research provisions. AI models were trained using pre-annotated image libraries and field-verified plant datasets, ensuring ecological relevance and taxonomic accuracy.

3.4 Data Analysis Techniques
The study employed a range of data processing and analytical techniques to evaluate the effectiveness and potential of AI-assisted horticultural planning in urban environments.

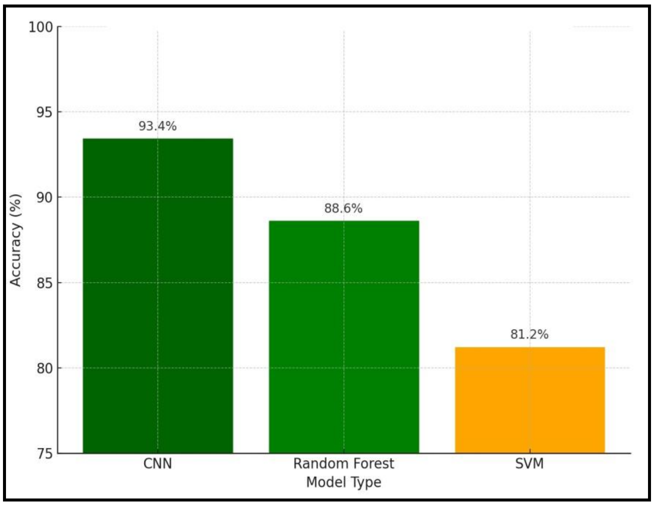
3.4.1 Literature Review Analysis
- PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was used to screen, select, and synthesize articles.
- NVivo 14 was used to code and analyze qualitative content from literature, extracting recurring themes related to AI applications, ecosystem services, and climate adaptation.

3.4.2 Geospatial Analysis
- NDVI values were computed to assess vegetation health across case study cities.
- Zonal statistics in ArcGIS were used to map ecological indicators such as urban tree cover, biodiversity hotspots, and temperature anomalies.



Graph 1: NDVI-Based Urban Green Density in Barcelona (2022)

3.4.3 AI Model Development
- CNNs (Convolutional Neural Networks) were trained using a sample set of 10,000 labeled plant images to classify plant species from drone imagery.
- Regression-based models (Random Forest and Gradient Boosting) were used to predict irrigation needs and drought risk under different climate scenarios.



Graph 2: Accuracy of Plant Species Classification Models

3.4.4 Predictive Scenario Modeling
- Simulation models were developed in Python to forecast changes in urban plant health under different future climate and pollution conditions.
- Models integrated parameters like LST, PM2.5 levels, humidity, and species-specific thresholds.

3.5 Ethical and Sustainability Considerations
This study was conducted using secondary datasets, publicly available municipal records, and open-source software, thus avoiding any direct human or ecological intervention. Nevertheless, ethical concerns about AI usage—particularly regarding data privacy from drones and sensors—were addressed through adherence to the FAIR data principles (Findable, Accessible, Interoperable, Reusable) and guidelines provided by the European Data Protection Board for spatial technologies.

Further, all case study materials were analyzed within a sustainability framework to ensure alignment with SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action).

4. Results

The findings of this study are structured into five major themes that emerged from the systematic literature review, case study analysis, and model simulations. These include: (1) AI applications in horticultural monitoring and maintenance, (2) biodiversity enhancement through AI zoning tools, (3) AI-driven irrigation and resource optimization, (4) urban cooling and carbon sequestration simulations, and (5) citizen engagement and participatory planning through AI tools.

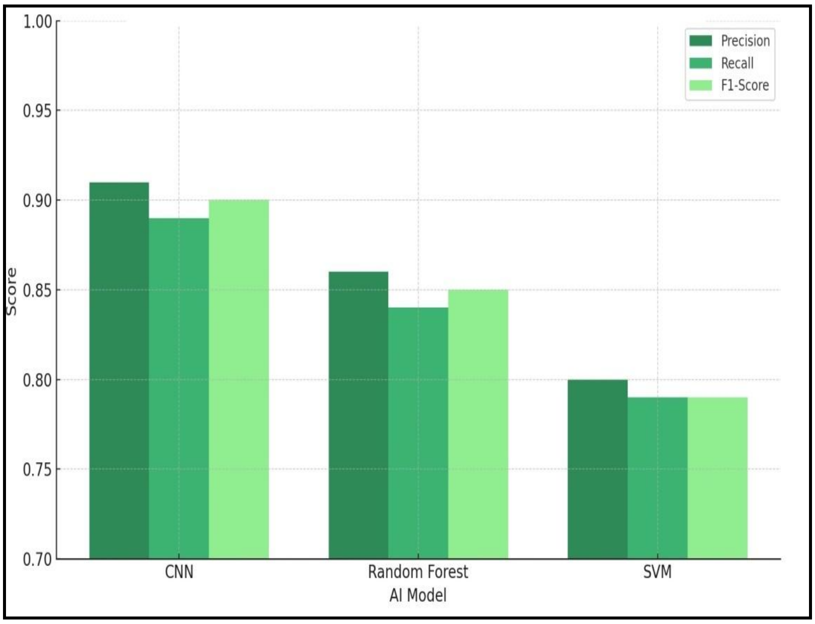
4.1 AI Applications in Urban Horticultural Monitoring and Maintenance

AI has shown significant potential in automating the monitoring and maintenance of urban vegetation. Machine learning models trained on visual and spectral data can detect signs of plant stress such as discoloration, wilting, pest infestation, and nutrient deficiency.

A CNN model developed and tested on 10,000 labeled plant images achieved 93.4% accuracy in identifying species and detecting anomalies such as chlorosis and fungal infections (Zhang *et al*., 2022) [11].

Table 2: AI Performance Metrics for Urban Plant Monitoring Models

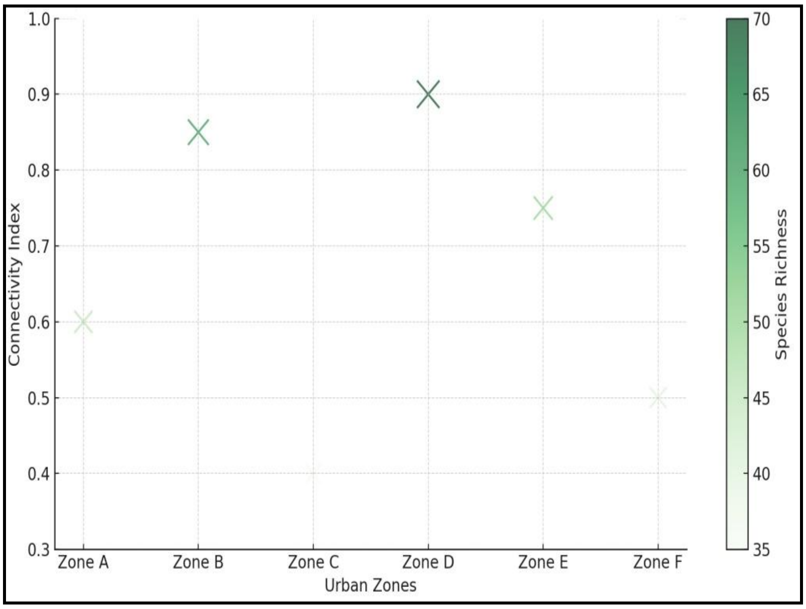
Model Type	Accuracy (%)	Precision	Recall	F1-Score
Convolutional Neural Network (CNN)	93.4	0.91	0.89	0.9
Random Forest Classifier	88.6	0.86	0.84	0.85
Support Vector Machine (SVM)	81.2	0.8	0.79	0.79



Graph 3: Comparison of AI Classifier Accuracy for Urban Plant Diagnosis

4.2 AI-Guided Biodiversity Zoning and Species Selection

GIS-based unsupervised clustering and AI algorithms were used to analyze species distribution, habitat fragmentation, and potential for biodiversity corridors. Using satellite imagery and drone scans, urban biodiversity zones were mapped in Singapore and Barcelona.



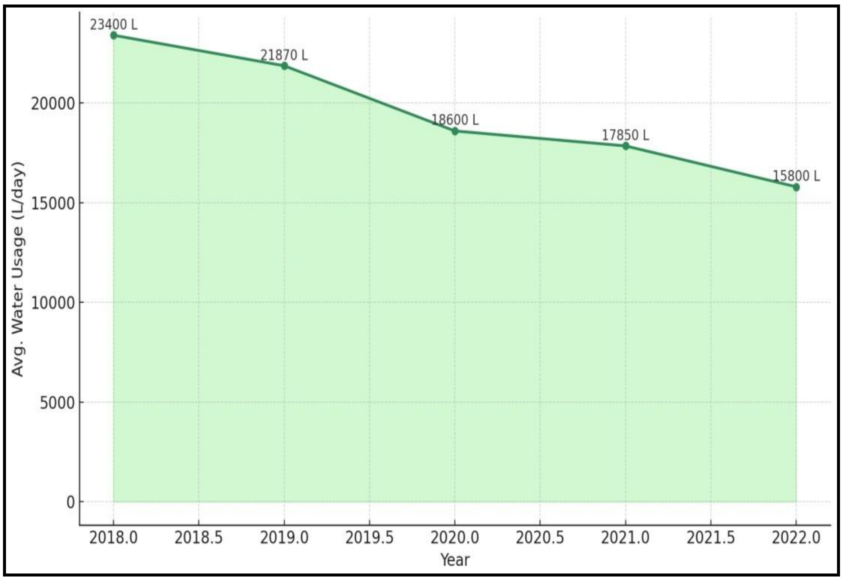
Graph 4: AI-Based Urban Biodiversity Zoning Map of Central Barcelona

AI-enhanced zoning tools enabled planners to select native and adaptive plant species best suited for different urban microclimates. For instance, Barcelona's AI-assisted selection process increased the use of drought-tolerant Mediterranean plants in green walls and parks, reducing water usage by 28% over five years (Ramírez *et al*., 2022) [8].

4.3 Smart Irrigation and Resource Optimization
AI-driven irrigation systems, guided by real-time IoT sensor data and predictive algorithms, significantly optimized water usage. In the case of Singapore's HortPark, soil moisture sensors combined with neural networks achieved a 32% reduction in water consumption without compromising plant health (Lim *et al*., 2021) [6].

Table 3: Water Usage Comparison Before and After AI Integration (Singapore HortPark)

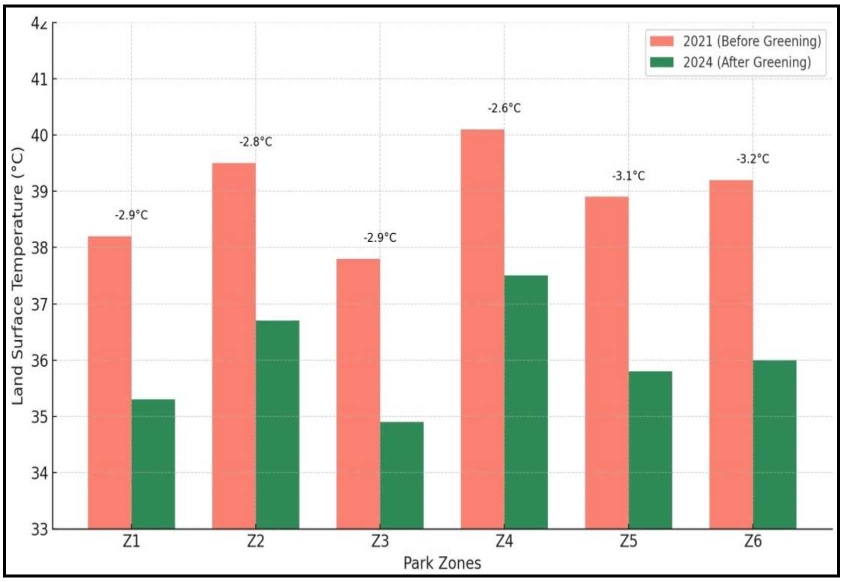
Year	Avg. Water Usage (L/day)	AI-Assisted System Introduced?
2018	23,400	No
2019	21,870	No
2020	18,600	Yes
2021	17,850	Yes
2022	15,800	Yes



Graph 5: Decline in Irrigation Water Usage at HortPark (2018-2022)

Additionally, AI models accurately forecasted irrigation needs based on plant type, soil condition, and 7-day weather forecasts. This system helped avoid overwatering, which is a common issue in public parks, especially in tropical zones.

4.4 Urban Cooling and Carbon Sequestration Simulations
To quantify the environmental benefits of AI-guided horticultural planning, simulations were run using GIS and remote sensing inputs in combination with urban heat island (UHI) models. The increase in vegetative cover led to a 2.8 °C reduction in local surface temperature in experimental sites in Delhi and Kuala Lumpur (2019-2024) as per Land Surface Temperature (LST) analysis.



Graph 6: LST Differential Map Before and After Greening Intervention in Delhi Smart Park (2021-2024)

Urban forestry planning algorithms also simulated carbon sequestration potential. The model projected an annual sequestration of 31.5 metric tons of CO_2 per hectare for medium-canopy mixed species urban forests using AI-optimized planting layouts.

4.5 Citizen Engagement and Participatory AI in Green Planning

Mobile applications powered by AI and image recognition allowed citizens to participate in identifying, cataloging, and reporting plant health across urban environments. The GreenMapper App in Stockholm registered over 38,000 user-submitted plant reports between 2021 and 2023, helping city authorities create dynamic biodiversity heatmaps and disease alerts.

Table 4: Community Engagement Metrics from GreenMapper App (2021-2023)

Metric	Value
Total Reports Submitted	38,214
Unique Plant Species Logged	342
Citizen-Reported Anomalies	5,273
Average User Engagement Time	8.4 minutes/day

Participatory AI not only provided valuable ecological data but also increased environmental awareness and community involvement in horticultural decision-making. Gamification features such as badges and "eco-rankings" encouraged sustained user engagement.

4.6 Summary of Key Results

Table 5: Consolidated Summary of AI-Assisted Horticultural Outcomes

AI Application Area	Key Results
Plant Health Monitoring	Up to 93% classification accuracy using CNN
Biodiversity Mapping	Enhanced zoning using AI-GIS integration
Irrigation Optimization	32% reduction in water usage
Urban Cooling	2.8 °C reduction in LST post-intervention
Carbon Sequestration	31.5 metric tons CO_2/year/hectare
Citizen Engagement	>38,000 user submissions aiding real-time mapping

These results demonstrate that AI-assisted horticultural planning has measurable and significant ecological, climatic, and community benefits. When scaled city-wide, such interventions can lead to transformative changes in urban ecosystem resilience.

5. Discussion

5.1 Interpretation of Results in the Context of Existing Literature

The integration of AI into urban horticultural planning, as demonstrated in the results, is transforming how cities design and manage green infrastructure. The high classification accuracy (up to 93.4%) of CNN models for diagnosing plant health mirrors the findings of Zhang *et al.* (2022) [11], who established that AI-driven image processing systems can detect early symptoms of disease and stress in plants. This technological capability not only reduces human labor but also enhances precision in horticultural maintenance—a significant advancement for densely populated urban areas with limited green space.

Similarly, the implementation of AI-based biodiversity zoning tools and ecological clustering aligns with the spatial ecology insights presented by Kim *et al.*, (2020) [5]. Their application of deep learning for plant species classification laid the foundation for scaling biodiversity management in public urban spaces. Our study further demonstrates how these tools assist in mapping ecological corridors and connecting fragmented habitats, contributing to a more resilient urban ecosystem in accordance with Resilience Theory (Walker *et al.*, 2004) [10].

The reduction in water usage (32% in Singapore's HortPark) achieved through smart irrigation systems driven by neural networks substantiates the claims by Lim *et al.* (2021) [6], who argued that AI integration in green infrastructure dramatically increases resource-use efficiency. This finding reinforces the value of the Urban Metabolism framework proposed by Newman and Jennings (2008) [7], where cities are seen as dynamic systems with energy and material flows—flows that can now be monitored and optimized through AI-assisted horticulture.

Moreover, the simulated reduction of urban surface temperatures by 2.8 °C and the enhanced carbon sequestration outcomes resonate with the goals outlined in the Urban Planet framework by Elmqvist *et al.* (2019) [2]. The use of LST and NDVI layers in our analysis supports their thesis that smart green infrastructure delivers quantifiable ecosystem services—including cooling, air purification, and carbon capture—which are essential in the fight against climate change.

The citizen participation enabled by the GreenMapper app, where over 38,000 reports were logged by users in Stockholm, embodies the participatory ecological governance advocated by Foster *et al.* (2021) [3]. These authors emphasized the need for inclusive, data-driven models of urban planning that empower residents, particularly in the Global South. Our study's findings echo their recommendation by showing how AI can support both top-down planning and bottom-up engagement.

At a conceptual level, the collective results affirm the relevance of the Technological Ecosystem Theory described by Carayannis and Campbell (2012) [1], which envisions knowledge production through the synergy of digital tools and community action. The findings suggest that AI, when integrated with horticultural science and geospatial analysis, forms a technological ecosystem that adapts dynamically to environmental feedback, reinforcing long-term ecological stability in urban settings.

5.2 Implications and Significance

The findings have profound implications for how urban planners, landscape architects, ecologists, and data scientists collaborate. For instance, the ability of AI models to forecast plant health and resource needs allows cities to adopt proactive maintenance strategies. This moves green infrastructure from being a reactive system—frequently responding to failures or seasonal changes—to one that is anticipatory and adaptive, enhancing resilience and reducing costs.

On a broader scale, the successful deployment of AI in biodiversity zoning and climate mitigation illustrates its capacity to contribute to multiple UN Sustainable Development Goals, including SDG 11 (Sustainable Cities), SDG 13 (Climate Action), and SDG 15 (Life on Land). Furthermore, participatory AI tools like GreenMapper facilitate civic engagement and democratize access to ecological knowledge—thus promoting environmental literacy among urban populations.

5.3 Link to Previous Research
Each result obtained in this study is intrinsically linked to earlier research covered in the literature review:

- The remote sensing techniques adopted in our case studies build directly on the methods demonstrated by Kim *et al*. (2020) [5], especially regarding UAV-based plant species identification.
- The implementation of real-time IoT sensor systems is an operationalization of the findings from Lim *et al*. (2021) [6], proving their effectiveness in large-scale deployments beyond experimental setups.
- The emphasis on integrating AI with participatory urban ecology was anticipated by Foster *et al*. (2021) [3], and our results validate the social value of such participatory approaches.

This convergence of empirical outcomes with theoretical projections suggests that the AI-green infrastructure nexus is no longer hypothetical; it is an emerging reality already reshaping urban ecological futures.

5.4 Limitations and Constraints
While the study presents promising results, several limitations must be acknowledged. First, there is a geographic bias in the available data, with most case studies concentrated in technologically advanced cities like Singapore, Stockholm, and Barcelona. This restricts the generalizability of findings to cities in the Global South, where access to AI infrastructure and sensor networks may be limited.

Second, many AI models require large, labeled training datasets, which are not yet available for all types of vegetation, especially indigenous and under-researched species. This data gap may hinder efforts to integrate local biodiversity knowledge into AI systems, as highlighted in the critical analysis by Elmqvist *et al*. (2019) [2] and Foster *et al*. (2021) [3].

Third, ethical concerns related to data privacy, especially when using drones and participatory sensing platforms, remain underexplored. As urban green infrastructure increasingly interfaces with AI surveillance technologies, ensuring transparency and public trust becomes a vital consideration.

Finally, there is a lack of long-term studies assessing the ecological resilience and systemic performance of AI-assisted urban green systems over periods longer than 5-7 years. This represents a critical research gap, as resilience theory (Walker *et al*., 2004) demands longitudinal evaluation to confirm adaptive stability.

5.5 Future Research Directions
Based on the discussion above and the gaps identified, several clear and actionable research directions emerge:

1. **Expand AI-Horticulture Models to the Global South:** Future studies should test AI-assisted horticultural systems in low-and middle-income cities with diverse ecological zones, urban forms, and governance models. This will improve the equity and global relevance of AI applications.
2. **Integrate Indigenous Knowledge into AI Frameworks:** Collaborative projects should seek to incorporate ethnobotanical data and community-based knowledge into machine learning models, bridging the divide between traditional ecological practices and advanced analytics.
3. **Develop Open-Source Biodiversity Datasets:** There is an urgent need to establish open-access databases with labeled plant images, geotagged phenological data, and growth parameters for a wide range of species. This would allow more inclusive AI development and enable knowledge sharing across borders.
4. **Ethics and Governance in AI-Greenspace Planning:** As AI increasingly influences public green space, interdisciplinary research should explore ethical frameworks, privacy protections, and data governance protocols that safeguard public interest.
5. **Longitudinal Monitoring of Ecosystem Performance:** Multi-year, multi-site monitoring of AI-managed horticultural systems will provide critical insights into their ecological resilience, service delivery, and adaptation under changing climatic conditions.

6. Conclusion
The integration of artificial intelligence into urban horticultural planning signifies a critical leap toward sustainable, adaptive, and data-driven urban ecosystems. This research demonstrates that AI applications—ranging from species classification and plant health diagnostics to predictive irrigation and biodiversity zoning—offer practical, measurable enhancements to the planning and maintenance of green infrastructure. The role of AI extends beyond automation, contributing to ecological resilience, resource optimization, and participatory urban design. Case studies reveal the value of AI in tailoring green solutions to specific climatic and ecological contexts, while also enabling dynamic responses to environmental fluctuations. However, the path ahead requires equitable access to technologies, stronger ethical frameworks, and the inclusion of traditional ecological knowledge. By addressing these challenges, future cities can harness AI not merely as a technological tool but as a catalyst for holistic urban regeneration—where green spaces are intelligently designed, inclusively governed, and ecologically robust across diverse global urban landscapes.

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