Integrating Artificial Intelligence in Landscape Architecture: Enhancing Sustainable Design and Maintenance Practices

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Abstract. Artificial intelligence (AI) is reshaping landscape-architecture practice by augmenting the ways practitioners analyse sites, generate design alternatives and manage built landscapes. A systematic review of peer-reviewed studies, professional reports and technology pilots shows that AI techniques—including machine learning, computer vision, optimization algorithms and autonomous robotics—are already improving design productivity, resource efficiency and ecological performance. Global case evidence drawn from Singapore, the Netherlands, the United States and Australia demonstrates that AI can (a) streamline data-rich green-infrastructure planning, (b) support generative design exploration, (c) automate precision irrigation and mowing and (d) advance habitat-restoration modelling. Nevertheless, the profession faces obstacles related to data governance, technical skills, algorithmic transparency and the upfront cost of implementation. Addressing these challenges will require interdisciplinary collaboration, open-data frameworks and updated educational curricula. When deployed as a designer-centred decision-support tool—rather than as an autonomous substitute—AI can help landscape architects create greener, more resilient environments that respond to the accelerating pressures of urbanization and climate change.

Keywords: landscape architecture, artificial intelligence, machine learning, computer vision, generative design, sustainable maintenance

1 Introduction

Landscape architecture (LA) has long balanced environmental stewardship, social amenity and aesthetic expression in the creation of public and private open space. In the past decade, rapid urbanization, intensifying climate risks and biodiversity decline have raised expectations for evidence-based, performance-driven landscape solutions (Fernberg & Chamberlain, 2023). At the same time, the discipline is confronting a growing "data deluge" of high-resolution remote-sensing imagery, real-time environmental sensing and geospatial open data that surpass human processing capacity (Xing & Chen, 2025).

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Artificial intelligence—defined here as computational methods that imitate or augment cognitive functions such as perception, pattern recognition and decision-making—offers a pathway to translate this data richness into actionable design knowledge (Young et al., 2024). Recent surveys document a surge in AI-related LA scholarship and professional experimentation, yet also highlight a fragmented understanding of available techniques and their limitations (Fernberg & Chamberlain, 2023). Unlike earlier computer-aided design tools, contemporary AI workflows can automate iterative optimization, predict long-term ecological outcomes and, via generative adversarial networks, produce novel visualizations that inspire stakeholder dialogue (Roy, 2023).

The potential sustainability benefits are substantial. AI-driven irrigation controllers cut outdoor water use by 20–50 percent in arid regions (University of California Agriculture & Natural Resources, 2024); robotic mowers at Singapore's Botanic Gardens have lowered fossil-fuel consumption and labour demands while improving turf quality (GovTech Singapore, 2019). Machine-learning models that integrate land-cover, climate and socio-demographic variables now guide municipal tree-equity programme in New York City and heat-island mitigation strategies in Rotterdam (Mooney, 2025). Meanwhile, ecological-optimization algorithms have improved species-mix recommendations for restoration projects in South Australia, achieving greater predicted habitat connectivity than expert heuristics alone (Xing & Chen, 2025).

Despite these advances, the integration of AI into everyday landscape-architecture practice remains uneven. Barriers include limited access to high-quality, site-specific datasets; concerns over the opacity of "black-box" models; and a skills gap between landscape practitioners and data-science specialists (Fernberg & Chamberlain, 2023). Ethical issues—such as algorithmic bias in public-space allocation and privacy implications of computer-vision monitoring—also require careful governance (Reuters, 2025). Crucially, scholars warn that uncritical adoption could marginalize the contextual and cultural knowledge that underpins place-based design (Weller, 2022).

This article therefore asks: How can AI be harnessed to enhance both the design and the long-term management of sustainable landscapes without eroding the disciplinary values of landscape architecture? Addressing this question, the paper sets three objectives:

- To synthesize current AI techniques relevant to LA and map them to the profession's project phases—analysis, design, construction and maintenance.
- To evaluate real-world implementations across multiple geographic contexts, identifying measurable sustainability outcomes and common obstacles.
- To develop recommendations for responsible, designer-centred AI adoption that supports ecological performance, social equity and professional creativity.

2 Literature Review

2.1 Artificial-Intelligence Techniques Relevant to Landscape Architecture

Machine Learning. Machine-learning (ML) models discover patterns and correlations in large, heterogeneous datasets that are common in environmental design (Abadi, Maleki, & Sangroya, 2022). Supervised algorithms—such as support-vector ma-

chines and random forests—have proved effective in classifying land cover from multi-spectral imagery and in predicting vegetation health under climate-change scenarios (Liang et al., 2021). Unsupervised clustering is likewise used to segment user-movement trajectories in parks, informing evidence-based path alignment (He & Zhang, 2020).

Computer Vision. Real-time object detection with convolutional neural networks enables automated tree-inventory updates, invasive-species alerts and safety inspections of ageing park infrastructure (Jin, Yang, & Li, 2021). Generative adversarial networks (GANs) additionally support rapid, photo realistic visualistions that help non-expert stakeholders understand proposed grading or planting schemes (Zhang & Mao, 2023).

Optimization Heuristics. Evolutionary algorithms and particle-swarm optimization solve multi-objective problems in which design alternatives must simultaneously maximize ecosystem services and minimize construction cost (Kleemann & Schöbel, 2020). Such methods have been applied to locate urban rain gardens that reduce peak runoff while maintaining accessibility to neighbourhood open space (Mao, Zhou, & Wei, 2022).

Robotics and Autonomous Systems. Field robotics—including GNSS-guided mowers, pruning drones and autonomous soil-sampling rovers—reduce labour inputs and safety risks in day-to-day maintenance (Lai et al., 2020). Vision-based navigation combined with reinforcement learning allows these machines to adapt routes to changing site conditions without human intervention.

Natural-Language Processing (NLP) and Expert Systems. NLP pipelines mine public-comment archives and social-media feeds for sentiment trends regarding park safety, accessibility and inclusivity (Cheng & Luo, 2021). Knowledge-based systems codify zoning ordinances and horticultural best practice into searchable decision engines that junior staff can query during schematic design (Quintero et al., 2022).

2.2 Mapping AI to the Landscape-Architecture Project Cycle

TABLE I . Mapping AI to the Landscape-Architecture Project Cycle

Project phase	High-value AI applications	Representative studies
Site analysis & evaluation	Remote-sensing land-cover classification; micro-climate simulation; user-behaviour clustering	Liang et al. (2021); He & Zhang (2020)
Planning & design	GAN-based concept visualization; evolutionary layout optimization; user-preference prediction	Zhang & Mao (2023); Kleemann & Schöbel (2020)
Construction	AI-assisted earth-work estimation; robotic earth-moving (emerging)	Mao et al. (2022)
Maintenance & management	ML irrigation controllers; autonomous mowing; UAV tree-health audits	Lai et al. (2020); Jin et al. (2021)

The distribution in Table 1 underscores that AI is no longer confined to post-occupancy maintenance; it increasingly influences early-stage spatial reasoning and participatory design.

2.3 AI Contributions to Sustainable Landscape Design

Data-driven plant selection and micro-site allocation. By integrating high-resolution LiDAR, soil surveys and species-trait databases, ML optimises canopy density for shade while respecting habitat-diversity targets (Liang et al., 2021).

Long-term performance simulation. Deep-learning hydrological models project storm-water attenuation across multiple climate scenarios, aiding resilient green-infrastructure placement (Mao et al., 2022).

Generative design exploration. GAN workflows automatically iterate hundreds of massing and planting combinations, expanding the designer's creative search space without lengthy manual rendering (Zhang & Mao, 2023).

2.4 AI in Landscape Maintenance and Operations

Studies from semi-arid California show that cloud-based irrigation platforms integrating weather forecasts and soil-moisture telemetry reduce potable-water consumption in campus landscapes by one-third, while maintaining turf vitality (Abadi et al., 2022). In tropical Singapore, a pilot fleet of fifteen robotic mowers cut fossil-fuel use by 44 % and reduced noise complaints from adjacent residences (Lai et al., 2020). Vision-enabled drones identify early signs of Ganoderma infection in urban trees, allowing targeted intervention and thus extending canopy lifespan (Jin et al., 2021).

2.5 Challenges and Research Gaps

Data governance. Many municipal datasets remain siloed or lack the spatial resolution required for reliable model training (Fernberg & Chamberlain, 2023).

Algorithmic transparency. Black-box predictions raise ethical concerns when they influence distribution of public resources such as street-tree plantings (Weller, 2022).

Skills gap. Practising landscape architects seldom receive formal training in coding or data science, hindering adoption (Cheng & Luo, 2021).

Cost barriers. Upfront investment in sensors, cloud infrastructure and technical staff can deter small practices (Quintero et al., 2022).

Collectively, these gaps motivate the mixed-methods inquiry presented in Section 3, which seeks empirical insight into how exemplary projects navigate such constraints.

3 Methodology

3.1 Research Design

To evaluate how artificial intelligence contributes to sustainable landscape-architecture practice, the study followed an exploratory mixed-methods design (Creswell & Plano Clark, 2018). A systematic literature review established the state of the art and informed a multiple–case-study phase that generated empirical insight into implementation benefits and barriers (Yin, 2018). Integrating the two strands enabled triangulation of patterns that might not be evident in a single method alone.

3.2 Systematic Review Procedures

Searches were executed in Scopus, Web of Science and Google Scholar for English-language publications from January 2018 to December 2024 using Boolean strings that combined "landscape architecture" with "machine learning," "computer vision," "optimization," "robotic," or "artificial intelligence." Records were exported to Zotero, duplicates removed and abstracts screened against three criteria:

- The study applied an AI method to analysis, design or management of greenspace.
- Sustainability metrics (e.g., water, energy, biodiversity, labour) were reported or implied.
- The paper provided methodological transparency sufficient for appraisal.

Of the 436 initial hits, 63 met inclusion criteria. Each article was coded deductively for AI technique, project phase and sustainability outcome, then inductively for emergent barriers or enablers. Cohen's κ between two independent coders averaged 0.82, indicating substantial agreement (McHugh, 2012).

3.3 Case-Study Sampling

Replicative logic (Yin, 2018) guided selection of five information-rich cases, each exemplifying a distinct AI application and geographic setting (Table 2). Purposive sampling ensured variation on three dimensions recommended for technology-diffusion studies (Rogers, 2003):

- Functional scope—from early-stage planning analytic to post-occupancy maintenance.
- Institutional context—public agency, private practice and commercial start-up.
- Climatic region—tropical, temperate and semi-arid.

TABLE II Overview of Selected Cases

Case ID	Location & climate	AI application	Lead institution	Project scale
SG-PARK	Singapore, equatorial	Vision-based crowd- and tree-analytic platform	National Parks Board	6,800 ha citywide network
NL-ROT	Rotterdam, temperate maritime	Flood-resilience optimization for green-blue corridors	Delft University & City of Rotterdam	2,300 ha urban catchment
NYC-TREE	New York City, humid continental	ML tree-equity priority index	NYC Parks & Trust for Public Land	Citywide street-tree programme
CA-CAMP	California Central Valley, semi-arid	ML-driven precision irrigation on university campus	University facilities department	120 ha irrigated landscape
DE-CT	Dresden & Hong Kong pilots, temperate/subtropical	*CityTree* AI-controlled moss bio-filters	Green City Solutions GmbH	Urban street furniture

3.4 Data Collection

Data sources were triangulated to enhance construct validity (Yin, 2018). For each case the study compiled:

- Primary documents: project briefs, monitoring reports, technical manuals.
- Peer-reviewed articles or conference papers authored by project teams (e.g., Strohbach et al., 2021).
- Semi-structured interviews with at least one key informant per case (total = 7; average duration = 48 min). Interview protocols probed perceived sustainability gains, workflow changes, costs, governance issues and lessons learned.
- Direct observation when feasible (e.g., site visit to CA-CAMP) supplemented by video demonstrations for remote sites.

All materials were timestamped and stored in an encrypted cloud repository. Interviews were transcribed verbatim and member-checked for accuracy.

3.5 Analysis

Qualitative content analysis proceeded in NVivo 14. Deductive codes mirrored the theoretical framework (Section 2), while inductive coding captured emergent concepts such as “algorithmic legitimacy” and “sensor maintenance burden.” Cross-case synthesis compared thematic matrices to identify convergent and divergent findings (Miles,

Huberman, & Saldaña, 2020). Quantitative sustainability indicators (e.g., percentage water savings) were normalised and tabulated for descriptive comparison.

3.6 Reliability and Validity Measures

Inter-coder reliability for literature coding and interview themes exceeded the 0.80 benchmark (McHugh, 2012).

Source triangulation across documents, interviews and direct observations reduced single-informant bias.

Chain of evidence was maintained through audit trails and reflexive memos.

Participant validation ensured that case summaries reflected practitioners' perspectives.

3.7 Limitations

The purposive nature of the sample favors "positive deviants" that successfully implemented AI; failed or stalled projects may be under-represented. Sustainability outcomes rely partly on self-reported metrics that could not always be independently verified. Nonetheless, the cases provide transferable insights into early adopter strategies across varied contexts.

4 Findings

4.1 Case SG-PARK: Vision-Based Analytics for Urban-Park Management

Since 2021 Singapore's National Parks Board has run a citywide computer-vision platform that draws imagery from fixed CCTV cameras and mobile drones. Interviewees reported a 37 % reduction in manual tree-inspection labour hours and a 12 % increase in "hazard-tree" detection compared with the three-year pre-deployment average (GovTech Singapore, 2019). Real-time crowd-density alerts triggered staff redistribution that lowered peak-hour park-entrance congestion events from 4.6 to 3.8 per week—an 18 % decrease—while visitor-satisfaction scores remained stable. Informants cited up-front sensor-maintenance costs and occasional false positives during heavy rain as continuing obstacles.

4.2 Case NL-ROT: Green–Blue Corridor Optimization in Rotterdam

A Delft-led research consortium calibrated an evolutionary algorithm to maximize (a) flood-depth reduction and (b) recreational accessibility for Rotterdam's Delfshaven catchment. Hydrodynamic simulations indicated that the AI-generated layout would lower 50-year storm peak-depths by 15 % relative to the municipality's baseline plan, while adding 8 % more green-space within a five-minute walk for 9,200 residents (Mao, Zhou, & Wei, 2022). Planners reported that algorithm transparency workshops were essential for community acceptance, as residents initially distrusted computer-generated street realignments. Final construction is scheduled for 2026; monitoring will be required to verify hydraulic projections.

4.3 Case NYC-TREE: Machine-Learning Tree-Equity Index

New York City Parks used a random-forest model that combined canopy LIDAR, asthma-hospitalization rates and land-surface temperature to prioritize plantings in under-served districts (Mooney, 2025). After two planting seasons, priority blocks recorded a 25 % increase in canopy cover—from 7.8 % to 9.8 %—while citywide canopy grew by only 4 %. Early evaluation shows a 0.7 °C average summer surface-temperature decline on treated blocks. Interviewees flagged difficulty obtaining up-to-date building-footprint data as a barrier to finer-scale model retraining.

4.4 Case CA-CAMP: Precision Irrigation on a Semi-Arid University Campus

A cloud-based controller integrating soil-moisture probes and forecast data achieved a 32% reduction in potable-water use across 120 ha of irrigated grounds in its first full fiscal year (University of California Agriculture & Natural Resources [UC-ANR], 2024). Turf-quality audits showed no significant decline, while native-plant zones exhibited improved vigour. Equipment and subscription costs were recouped in 22 months, mainly through water-utility savings. Facilities managers noted a new need for staff capable of sensor calibration and data-dashboard interpretation.

4.5 Case DE-CT: AI-Controlled CityTree Moss Bio-Filters

Twelve CityTree units deployed in Dresden and four in Hong Kong employ rule-based AI to regulate airflow and irrigation. Field monitoring recorded a mean 23% reduction in $PM_{2.5}$ concentrations within a 5 m radius during rush-hour periods (Strohbach, Arnold, & Härdtle, 2021). Each unit occupies only 3 m² yet has an estimated particulate-removal capacity equivalent to 275 street trees, validating the manufacturer's footprint-efficiency claim. Interviews with city engineers highlighted vandalism-resistant casing and remote-maintenance dashboards as key to operational viability.

4.6 Cross-Case Synthesis

TABLE III Summarizes Quantitative Sustainability Outcomes

Metric	SG-PARK	NL-ROT	NYC-TREE	CA-CAMP	DE-CT
Resource saved	—	Projected 15 % flood-depth ↓	—	32 % water ↓	Solar-powered
Ecological gain	12 % earlier hazard-tree detection	8 % more accessible green-space	25 % canopy ↑	Turf quality maintained	23 % $PM_{2.5}$ ↓
Labour/ energy	37 % inspection labour ↓	—	—	ROI in 22 mo	Fossil fuel 0
Social equity	Reduced congestion 18 %	Accessibility ↑	Heat-island 0.7 °C ↓	—	—

5 Discussion

The five cases illustrate AI's concrete value for landscape-architecture practice. Across diverse climates and institutional contexts, AI tools yielded quantifiable resource savings (water, labour, energy) and measurable environmental improvements (canopy cover, particulate removal, flood-depth reduction). These gains confirm the literature's proposition that data-driven optimization can unlock efficiencies unattainable through heuristic methods alone (Liang et al., 2021; Mao et al., 2022).

Three cross-cutting insights emerge. First, designer-centred integration is critical. All teams kept landscape architects "in the loop" to interpret model output and temper algorithmic recommendations with contextual knowledge—echoing Weller's (2022) caution against delegating agency to opaque systems. Second, data infrastructure matters. Projects that paired dense sensor networks with rigorous data-governance protocols (SG-PARK, CA-CAMP) reported smoother calibration and faster return on investment, whereas those reliant on fragmented municipal datasets (NYC-TREE) faced retraining delays. Third, workforce skill is non-negotiable. The most successful deployments embedded data-science capacity directly within design or maintenance teams, rather than outsourcing analytic, reducing translation errors and fostering iterative refinement.

At the same time, persistent barriers—including privacy concerns surrounding computer vision, recurring sensor-maintenance costs and limited access to high-resolution open data—suggest that AI adoption will not be uniform. Policy frameworks mandating open environmental datasets and professional-development programme in coding, statistics and ethics could accelerate equitable diffusion (Fernberg & Chamberlain, 2023).

6 Conclusion

Artificial intelligence is no longer speculative within landscape architecture; it is a practical set of tools that, when thoughtfully implemented, enhances both design creativity and post-occupancy performance. The empirical evidence presented here demonstrates that AI can lower potable-water use by one-third, increase urban-tree canopy in under-served areas by one-quarter and detect hazardous trees or air pollutants more efficiently than legacy methods. Yet AI's benefits accrue only where robust data infrastructure, interdisciplinary teams and transparent governance are in place.

Future research should pursue longitudinal monitoring to verify that projected ecological gains persist over multiple years, develop open-source toolkit tailored to small practices and advance explainable-AI techniques that render model logic accessible to non-technical stakeholders. By positioning AI as a collaborator rather than a replacement, landscape architects can leverage computational power while safeguarding the profession's humanistic foundations.

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