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A REVIEW OF GENERATIVE ARTIFICIAL INTELLIGENCE-ASSISTED SCENARIO DEVELOPMENT APPROACHES IN LANDSCAPE ARCHITECTURE

Peyzaj Mimarlığında Üretken Yapay Zeka Destekli Senaryo Geliştirme Yaklaşımlarına Bir Bakış

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Abstract

In this article, we offer a comprehensive review of the evolution, progress and current state of Artificial Intelligence supported scenario generation research in Landscape Architecture. This technological development is enables a deep paradigm transformation centred on the shift from designing static "objects" to fostering dynamic "processes" and "systems" capable of self-adaption and evolve over time. The authors cover key generative methods such as Parametric Generatives Generative Design, focusing on rule-based optimization, Generative Adversarial Networks which leverage training via competition between networks and Text-to-Image models that generate instant conceptual visualisations. These are not merely tools to make artefacts of the design but sophisticated instruments for informed site analysis and performance-based optimization—the results of which involving hundreds if not thousands of design alternatives within minutes, are captured and tabulated efficiently. In addition, the study helps to understand crucial concerns regarding creativity, algorithmic bias and transparency. It emphasizes that Artificial Intelligence systems have the potential to exacerbate human biases present in training data and that these models can be so opaque as to create significant trust issues. In order to tackle these challenges, the paper calls for Explainable Artificial Intelligence techniques that provide interpretability, as well as User Interface/User Experience design tactics to minimize cognitive biases such as Confirmation Bias and Automation Bias. The dialogue progresses to discuss more sophisticated notions of Reinforcement Learning and World Models, in which Artificial Intelligence plays an active role in the design of dynamic, adaptive and regenerative landscape systems.

Keywords: G.A.R.D.E.N. framework, generative artificial intelligence, landscape architecture, scenario generation

Özet

Bu makalede, Peyzaj Mimarlığı alanında Yapay Zeka destekli senaryo üretimi araştırmalarının evrimi, ilerlemesi ve mevcut durumu hakkında kapsamlı bir inceleme sunulmaktadır. Bu teknolojik gelişme aslında, statik "nesneler" tasarlamaktan, zaman

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içinde kendi kendine adapte olabilen ve gelişebilen dinamik "süreçler" ve "sistemler" geliştirmeye doğru kayan derin bir paradigma dönüşümünü mümkün kılmaktadır. Çalışmada, kural tabanlı optimizasyon olan Parametrik Üretken Tasarım, ağlar arasındaki rekabetçi eğitimden yararlanan Üretken Çekişmeli Ağlar ve anlık kavramsal görselleştirme üreten Metinden-Görüntüye modeller gibi temel üretken yöntemler ele alınmıştır. Bunlar, tasarımın çıktılarını ortaya koymak için bir araç olmanın yanı sıra, bilgilendirilmiş saha çalışması analizleri ve performansa dayalı optimizasyon için kullanılan araçlardır. Bu değerlendirmeler dakikalar içinde yüzlerce hatta binlerce tasarım alternatifi haline getirilmektedir. Bunun yanı sıra, çalışmada yaratıcılık, algoritmik önyargı ve şeffaflık ile ilgili kritik endişelerin anlaşılmasına eleştirel bir bakış açısıyla yaklaşılmıştır. Yapay zeka sistemlerinin, eğitim verilerinde mevcut olan insan önyargılarına dayalı sonuçlar üretme potansiyeline sahip olduğu ve bu nedenle bu modellerin, önemli güven sorunları yaratabilecekleri de vurgulanmaktadır. Böylesi olumsuz durumlara müdahale etmek için araştırmada, yorumlanabilirlik sağlayan Açıklanabilir Yapay Zeka tekniklerinin yanı sıra Onay Önyargısı ve Otomasyon Önyargısı gibi bilişsel önyargıları en aza indirmek için Kullanıcı Arayüzü/Kullanıcı Deneyimi tasarım sistemleri de ele alınmıştır. Araştırma, yapay zekanın statik çıktı üretmenin yanı sıra dinamik, uyarlanabilir ve rejeneratif peyzaj sistemlerinin tasarımında etken bir rol oynamayı içerdiği Pekiştirmeli Öğrenme ve Dünya Modelleri gibi daha sofistike kavramları tartışmaya açmıştır.

Anahtar Kelimeler: G.A.R.D.E.N. tekniği, üretken yapay zeka, peyzaj mimarlığı, senaryo üretimi

1. INTRODUCTION

Traditionally landscape design was based on subjective judgments of individuals backed by experience (expertise) and manual representation [AG 2024 Source]. This conventional method is time-consuming and resource-intensive, especially in the ideation stage, for generating novel and creative design alternatives (Kahvecioğlu et al., 2025). While it is valuable to ground the process in the subjective view of the designer, this approach inevitably restricts the range of alternatives that can be explored—especially when dealing with complex environmental and social systems (e.g., those related to climate change, rapid urbanization, or declining biodiversity). The development of artificial intelligence (AI) technology is fundamentally shaking the traditional paradigm and pioneering a revolutionary era in both landscape architectural practice and research (Fernberg, 2024; Arup, 2024).

It is not a simple technological progression that has taken place. The new emphasis is on moving from the creation of static, finished "objects," such as parks and public squares, to the provision of dynamic "processes" and "systems"—modes of urbanism that can adjust to changing circumstances over time. AI holds out the promise of being the driving force behind this evolution, by offering tools that make it possible to interpret data in a multivariate world, visually explore and generate images and text or carry out design optimization and performance simulation. As a result, designers are empowered with more sophisticated tools and abilities (Arup 2024).

In the realm of artificial intelligence, the term "scenario generation" has significantly evolved, transitioning from merely producing small models to including diverse design alternatives. Today, this would extend to the development of new, targeted insights using ever more real-time data (Arup, 2024). Generative AI models allow designers to explore a broader range of ideas than previously possible within a few minutes (Spremulli & Wright, 2023; Arup, 2024).

Current literature indicates that the integration of artificial intelligence in landscape architecture is evolving into a non-linear, interactive co-design process between the designer and the machine. Schroth and Maier (2025) place this process within a framework of creative collaboration, emphasizing that AI is not merely an output generator but a "co-designer" that triggers human creativity during the conceptual stage of design. This shift represents a methodological move from parametric approaches toward much more flexible and learning systems. Manzoni, de Paz and Nistal (2025) define the discipline's transition from parametric modelling to Generative AI as a strategic turning point within the historical evolution of computational tools. In the technical dimension of the process, the potential of Large Language Models (LLMs) to transform design briefs into spatial scenarios is noteworthy. Saabith, Vinothraj and Fareez (2024) demonstrate that translating client expectations and complex design texts into tangible landscape scenarios through AI increases the speed and accuracy of data processing in the initial stages of design. However, this speed must be balanced with ecological necessities. Frazier and Song (2025) advocate that generative methods should be combined with principles of "Computational Ecology" rather than solely aesthetic concerns, proposing a new methodology that places AI's ecological performance metrics at the heart of the design. Consequently, these frameworks aim to move landscape architecture away from being a static planning discipline toward a dynamic, data-driven and performance-based system management.

Today, the production of spatial morphology is developing from traditional methods toward deep learning-based approaches. A comparative study by Shao et al. (2025) examines the performance of Diffusion models versus GAN models in creating urban park layout plans, highlighting the effectiveness of GANs in preserving spatial hierarchy and structural integrity. These models possess the capacity to develop context-sensitive new morphologies by analysing existing urban fabric. Hakim and Tsai (2025) have revealed how critical a foundation the automated classification of vegetation and topography data—integrated directly into site analysis through deep learning techniques—forms for GAN-based design scenarios. The balance between the aesthetic and technical dimensions of spatial production is being redefined by next-generation neural networks. Zhang (2024) offers an approach that utilizes Neural Style Transfer methods to preserve the designer's artistic intuition in landscape visualizations while benefiting from AI's technical precision. This is proposed as a solution to the risk of AI outputs being soulless and generic. On the other hand, to ensure design processes remain uninterrupted in data-scarce regions, Goyal and Mahmoud (2024) address the importance of Synthetic Data Generation, proving that GAN models can produce high-accuracy spatial scenarios even in areas with limited GIS infrastructure.

The use of text-to-image (T2I) models in landscape architecture is transitioning from pure creativity to a controlled and professional production stage. Kim, Yang and Min (2024) succeeded in transforming sketches into real-time design iterations using Conditional Latent Diffusion Models, thereby building a direct bridge

between the designer's hand drawing and the visualization power of AI. Such advanced control mechanisms bring the design process closer to professional standards by reducing its speculative nature. Yun and Kim (2025) move beyond general prompt engineering to argue for the necessity of fine-tuning Stable Diffusion models for specific planting palette styles, emphasizing the critical role of various developed techniques in ensuring local vegetation accuracy. However, debates regarding the accuracy of AI-generated scenes continue. Frazier and Song (2025) examine the conflict between visual plausibility and ecological accuracy, stating that the aesthetic success of generated images does not always align with scientific reality, which can be misleading in professional applications. Conversely, the democratization of this visualization capacity is also on the agenda. Wang and Lin (2023) present a new methodology that integrates AI with Augmented Reality (AR) to enable public participation in urban design processes and visualize scenarios in real-time.

AI applications are focusing on dynamic decision-making mechanisms capable of responding to environmental changes rather than static design outputs. Song et al. (2024) demonstrate, in a model developed for adaptive stormwater management in urban landscapes using Reinforcement Learning (RL), that the system can autonomously determine strategies based on changing climate conditions. This approach represents a paradigm shift where design is evaluated not just in its initial state, but by its performance throughout its life cycle. Similarly, Santos and Carvalho (2025) incorporate the concept of "agentic landscapes" into ecosystem restoration monitoring processes, emphasizing that AI systems are transforming from passive observers in restoration areas into active participants making intervention decisions. Simulation capacity for the future has reached a new dimension through World Models. Lu, Gaur and Lacasse (2024) examined the ability of AI to abstractly "grasp" complex urban environments and predict future environmental risks by simulating decadal heat island scenarios with World Models developed for urban climate resilience. This situation fundamentally changes the temporality of the design process, allowing systems to self-optimize. On the other hand, Devi (2025) focuses on the practical application areas of these agentic systems, addressing how RL-based autonomous management systems will revolutionize landscape maintenance and operation processes alongside societal acceptance and implementation challenges.

This new definition leads us to start thinking about both landscapes and cities as also "a collaborative and constantly renewing playground that can reshape its condition in real-time, according to the evolving lack of demand from environmental context or user's need" (Arup, 2024). Beneath this, the scenarios produced are more than mere images of spatial disposition. They are crystallized and dynamic expressions of what a landscape may act on, perform within or adapt as over time. As a result, the category "design," which has its origin in the primitive idea of a "final drawing" transcends into different shapes. This is a holistic system consisting of series of systems and rules defined through data inputs and feedback loops that drives the performance and progression of the landscape.

This research investigates the development of artificial intelligence in landscape architecture, tracing a transformation from homogenized design tool to intelligent collaborator and form generator that expresses enriched creative processes. This change enables the creation of adaptive and resilient landscapes that are part of sound responses to complex ecological and social systems.

2. METHODOLOGY

A systematic process based on an extensive literature review and conceptual analysis of the current state, historical evolution and future potential of AI-assisted scenario generation in landscape architecture was applied in this research. Such a methodology was devised in order to comprehensively investigate a number of AI techniques, their adoption into design phases and the ethical issues that arise from them utilizing academic papers, professional reports and technical documents. This analytic structure evolved in three stages.

In the first stage, the basic methodological strategies in AI-supported scenario generation were systematically categorized and critically assessed. This review paper provides an overview of the existing technical background already published, as well as a detailed overview of parametric generative design (GD), deep learning in terms of generative adversarial networks (GANs) and text-to-image-T2I models. Advanced strategies, such as ControlNet-based structural control in T2I models were emphasised regarding compatibility of creativity with geometric accuracy. This classification has been carefully structured to facilitate comparison of each method's fundamental principles, input/output types, degree of control and main advantages/disadvantages. The orientation of the second phase was to explore AI's impact on modulating the landscape architecture design process as a cyclical and integrated approach. This evaluation includes the analysis of sites using data, which begins by quantifying site features and discovering hidden relationships. In this respect, the potential of ML methods to work with very large and disparate datasets was stressed, as well as the importance of "Human-in-the-Loop" (HITL) collaboration. The subsequent performance-based life cycle evaluation and optimization of a series of generated design alternatives were based on quantitative measures such as stormwater runoff volume, carbon sequestration, recreational use (in social), economic during environmental, social and economic factors—under the G.A.R.D.E.N. framework.

The last phase focused on ethics within the AI integration process and explored the future potential of the field. This included a discussion about the risks associated with algorithmic biases – specifically selection and stereotyping biases being embedded in the datasets used to train these AI models, as well as technical strategies to help address those issues. There was significant analysis on the need for transparency and trust, especially regarding Explainable AI (XAI), including techniques like SHAP/LIME, which aim to eliminate the "black-box" nature of AI systems. In addition, cognitive biases that designers may have (e.g., Confirmation, Automation and Quick Response Bias) and user interface (UI/UX) design tactics used to account for biases encountered when interacting with AI tools (including trust levels and the presentation of alternative scenarios) are also addressed. The conceptual analysis concluded with a presentation of high-level ideas such as Reinforcement Learning (RL) and World Models to show how AI tools can evolve from static plans to the dynamic construction of agentic environment systems.

3. METHODOLOGICAL APPROACHES IN SCENARIO GENERATION

3.1. Parametric Design (GD)

AI-assisted scenario creation is rooted in the conceptual basis of parametric and generative design (GD). GD is a rule-based quantitative process that enables the generation of a large number of 'finished' designs according to

the rules, descriptions and constraints set by the designer, for example land-use, environmental capacity and cost (Thamma, 2024; Netser et al., 2025) (Fig. 1). This approach transforms the designer from a craftsman with an emphasis on producing one answer to a curator working alongside technology as a co-author (Spremulli & Wright, 2023).

Figure 1: *Some parametric and generative design examples (Bhattacharjee, 2024)*

As illustrated in Figure 1 of this study, the production process of the visuals is based on the integration of traditional computer-aided design (CAD) tools with generative artificial intelligence (GAI) algorithms. Rather than relying on a single closed system, these visuals were created using Stable Diffusion-based open-source models alongside the ControlNet extension, which ensures structural fidelity to the input data. The process begins with the landscape architect creating schematic diagrams or sketches—including basic spatial organization, massing schemes, or topographic lines—within professional drafting software, such as AutoCAD or Rhino/Grasshopper.

The "Generative Design" process is activated at the stage where these raw geometric data are transferred to the AI interface as a "conditional input." At this stage, the system is not merely performing a standard "render" or visualization. Instead of this, the ecological and aesthetic parameters defined by the designer through text prompts are reinterpreted within the precise geometric boundaries of the schematic drawing via ControlNet. Consequently, the AI generates numerous alternative scenarios across layers such as planting texture, material quality and atmospheric conditions, all while adhering to the structural skeleton predetermined by the designer. By providing a dialectical synthesis between creative exploration and geometric control, this workflow enables the production of results that are technically verifiable and faithful to the designer's intent, rather than speculative or randomized imagery.

Parametric modelling techniques, such as visual programming environments like Grasshopper and Dynamo (Chen et al., 2023; Paananen et al., 2023), allow landscape architects to interlace complex and multi-dimensional information including local ecology, climate change impacts and society's requirements into the design processes (Spremulli & Wright, 2023). These facilitate the optimization of environmental aspects like air quality and living comfort, social factors like behaviour perception, as well as economic elements like return on investment (Han et al., 2023). Due to the quantitative, predictable and rule-based nature of generative design it is highly suited for performance-driven objectives (Netser et al., 2025).

3.2. Generative Adversarial Networks (GANs)

The generative adversarial networks (GAN) are an advanced form of artificial intelligence model which operate on the principle of a dynamic game between two neural network structures practicing to become increasingly proficient at their task. The process starts with the Generator network, which produces data — such as a synthetic image of a projected new park plan — based on a random noise. On the other hand, the Discriminator network takes its input and determines if it comes from a real data collection or was generated by the Generator (Chen et al., 2024) (Fig. 2 and Fig. 3). This adversarial setting encourages a perpetual feedback loop in which the Generator gradually improves its output to a level of realism and novelty level that effectively confuses the Discriminator.

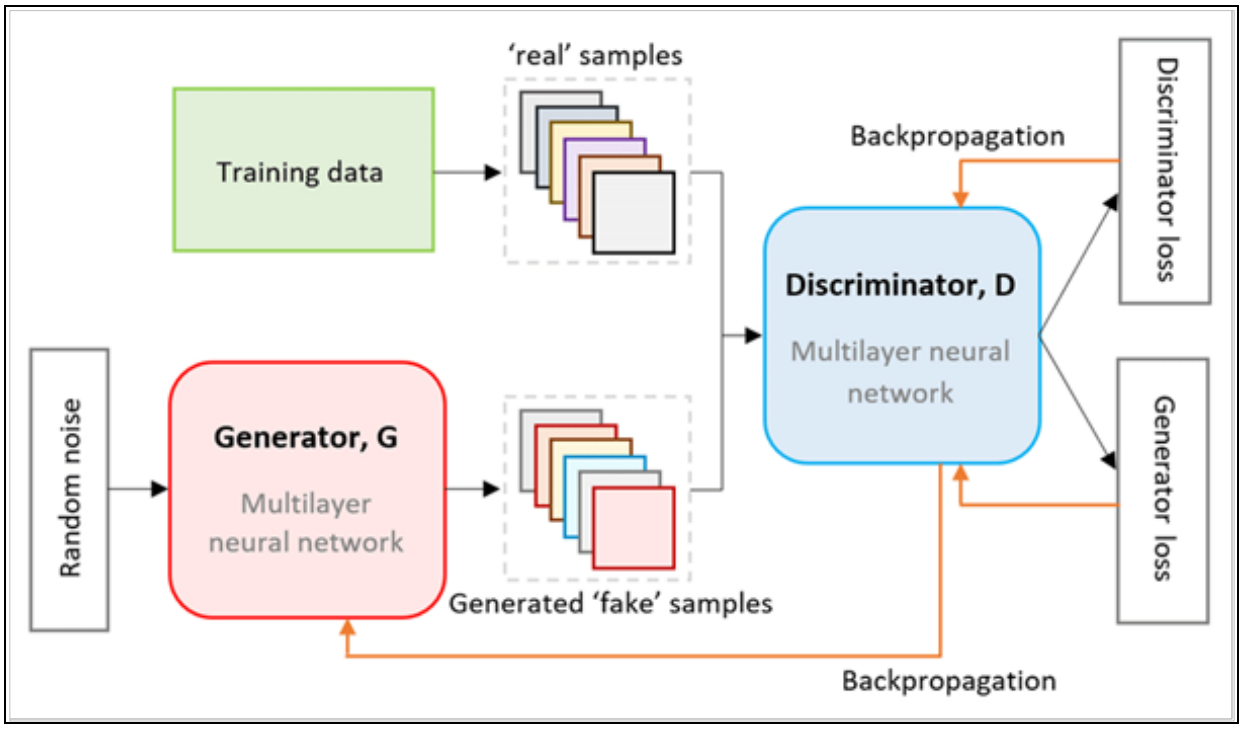

***Figure 2**: Example of GAN Architecture (Little et al., 2021)*

Figure 3: *Example of GAN Architecture (Pix2Pix and CycleGAN) (Wang et al., 2025)*

In the field of landscape architecture, GANs have become a promising tool to generate spatial layout schemas, specifically through 'site-layout-plan' paradigms. These models can produce novel and coherent designs that deviate from the common styles conceived by human designers, borrowing implicit rules extracted from existing parks. In addition, GANs have successfully been applied to tasks like synthesizing hand-drawn sketches (Chen et al., 2024) and schematic diagrams (Chen et al., 2023) and even morphing satellite images into a realistic coloured plans (rendering). This can improve the aesthetic quality while increasing learnability by augmenting limited datasets via data augmentation.

Nevertheless, the incorporation of GANs into landscape design is faced with several difficulties. The heterogeneous nature of landscape elements combined with the fine details and lack of complete databases makes it difficult to fully achieve high performance outputs (Chen et al. 2024). In addition to convergence issues, technical problems such as "mode collapse" could limit diversity and constrain the model to generate a narrow range of designs in practice (Chen et al., 2023).

3.3. Text-to-Image (T2I) Models

So there is a moment early in the design process where T2I models offer effectively boundless creativity (Fig. 4). One can generate rich and detailed artwork in just a matter of seconds using the text-based User Interfaces (UIs) provided by platforms like Midjourney, DALL-E and Stable Diffusion. With their exceptional catalytic influence, these tools are among the most helpful resources in the inspiring and ideation stages, saving time and costs for designers while helping them tackle their creative blockages (Benliay & Kılıç, 2024; Kahvecioğlu et al., 2025).

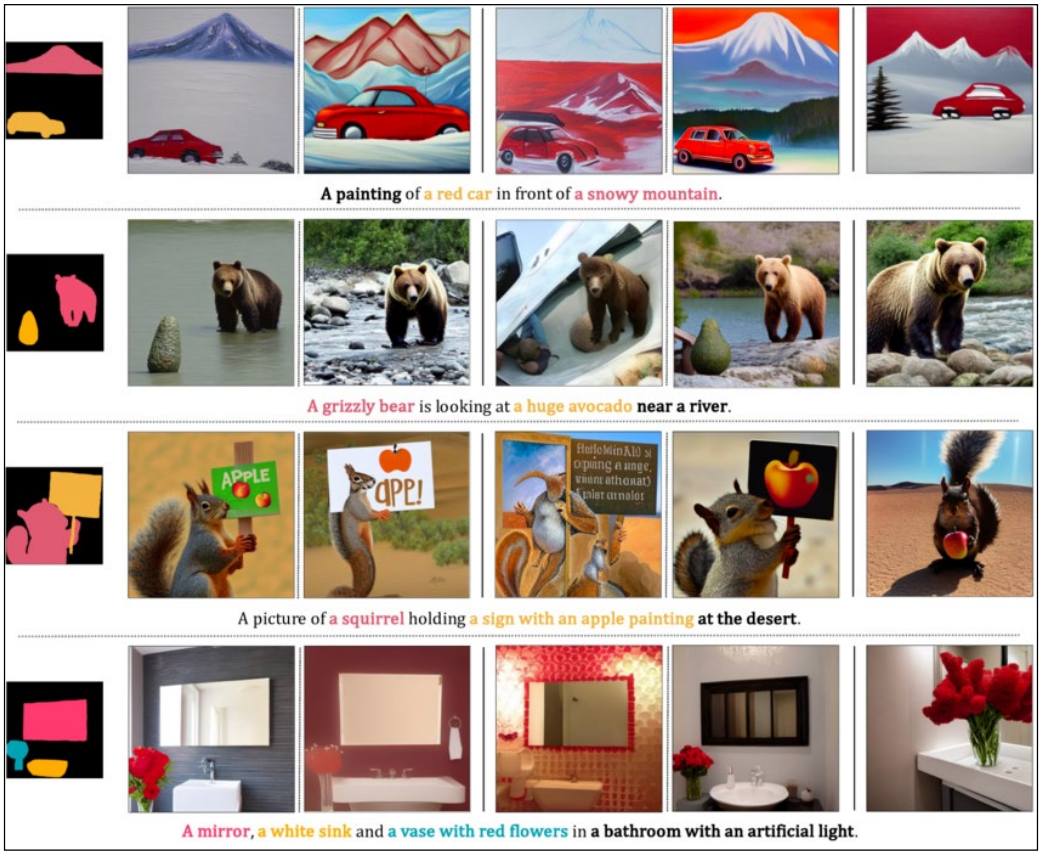

Figure 4: *Text-to-Image (T2I) models examples (Kim et al., 2023)*

As academic studies in Turkey have revealed, these models can interpret abstract and technical professional terms, such as "sustainable landscape" and the "therapeutic garden" with a reasonable level of accuracy. However, these studies also expose significant limitations regarding the representation of detailed landscape designs such as plant species accuracy and the proportionality of spatial elements. Although the visuals produced are often inspiring, they frequently exhibit elements of "hallucination" relative to professional reality. As a result, these outputs must to be improved and validated by human experts to guide final design operations (Kahvecioğlu et al., 2025).

3.4. Advanced Control with ControlNet

ControlNet lies at the intersection of the limitless exploration provided by the T2I model and the consistent human control requested by professional design. It is a neural network model that injects an additional layer of control into large pre-trained diffusion models like Stable Diffusion. This is because this architecture can be augmented with auxiliary visual information, e.g. edge maps (Canny) depth maps, human skeleton poses, floor plans or even simple sketches—in addition to textual input prompts (Zhang et al., 2023) (Fig. 5). In this way it provides for exquisite control over the nature, structure and location of the resulting picture.

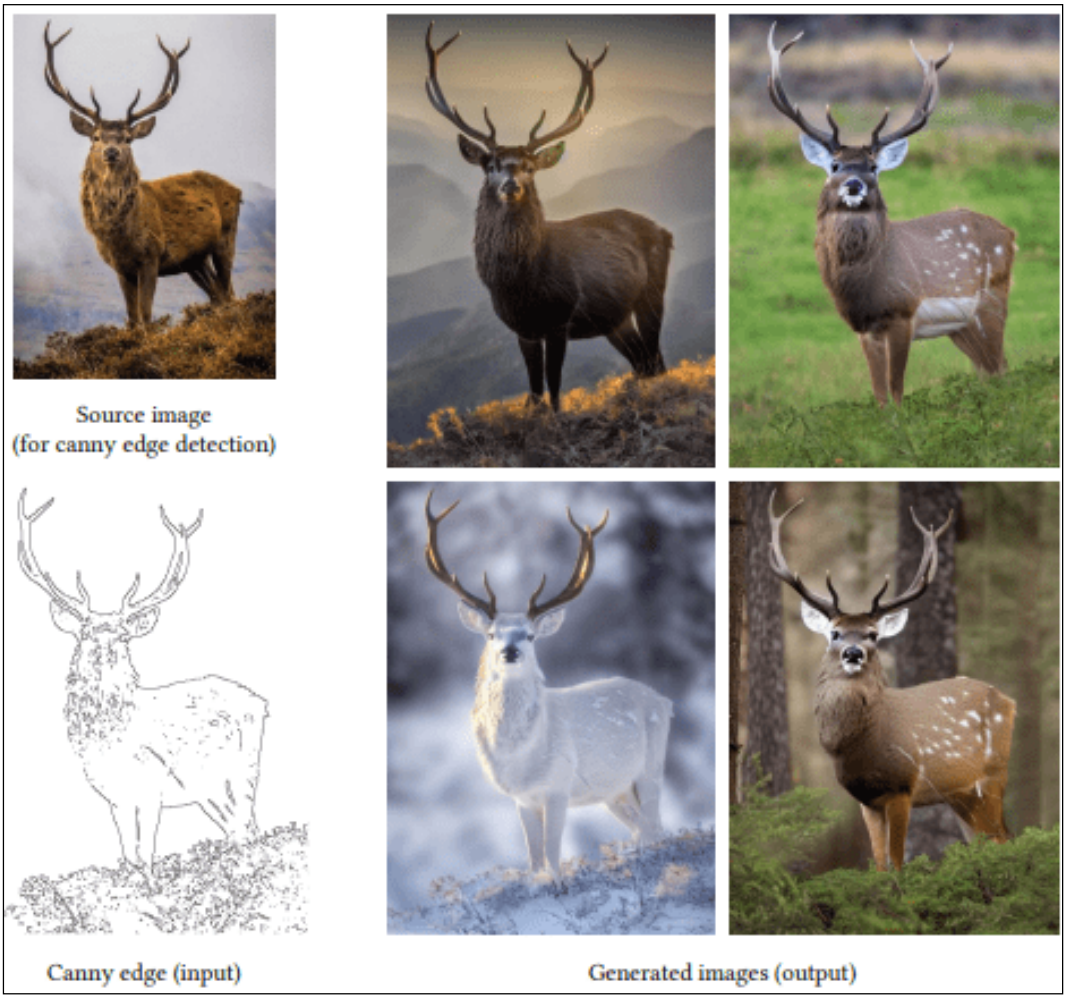

Figure 5: *ControlNet images (Rath, 2023)*

In the context of landscape and building design, ControlNet is used for generating stylistically rich and geometrically accurate visuals. This can be realized using depth maps obtained from 3D models (Paananen et al., 2023), line maps generated from CAD drawings (Chen et al., 2023) or human sketches. The technology carries the potential to disrupt the speculative and uncontrolled nature of text-to-image (T2I) generation by coupling it with structured and purposeful feedback methodologies that are synonymous with generative design (GD). In this way, ControlNet becomes a useful instrument for practitioners within the area. This is part of the dialectical merging between creativity and control that has been evolving. A comparison of different artificial intelligence scenario generation methodology is shown in Table 1.

Table 1: *Comparison of AI Scenario Generation Methodologies*

Methodology	Core Principle	Input Type	Output Type	Level of Control	Main Advantages	Main Limitations	Typical Application Area in Landscape Architecture
Parametric Design (GD)	Rule-based optimization	Parameters, objectives, constraints	Geometric models, performance data	Very High	Performance optimization, quantitative analysis, efficiency	Limited creativity, complex setup	Performance-focused design, sustainable system optimization, complex geometry generation
GANs	Adversarial learning	Random noise, schematic images	Realistic images, plan layouts	Low-Medium	Innovative and original designs, style transfer, data augmentation	Difficult training process, risk of mode collapse, poor detail control	Automatic plan layout generation, rendering from sketch, stylistic exploration
Text-to-Image (T2I)	Diffusion models	Text prompts	Conceptual visuals, mood boards	Very Low	Rapid idea generation, overcoming creative block, accessibility	Lack of control, professional accuracy issues, "hallucination"	Concept development, brainstorming, visual style exploration
ControlNet	Conditional diffusion	Text prompt + Control image (line, depth, etc.)	Structurally controlled, stylized visuals	High	Combining creative flexibility with geometric control	Technically more complex, requires additional input	Controlled visualization from sketch or 3D model, design iteration

4. AI-ASSISTED DESIGN PROCESS

Embedding artificial intelligence in landscape architecture is redefining design from a linear sequence of stages into a dynamical, interconnected process centred around iterative feedback and adjustment. Starting with quantitative data analysis, the process continues through design possibility generation to performance optimization. However, while this iterative view does offer substantial potential for improvement, it also carries the risk of underestimating values with limited quantitative expression.

4.1. Data-Driven Site Analysis

The conventional process consists of analysing of the site based usually on observations, maps and existing documents. Although with the introduction of AI, this process becomes a much deeper and more holistic pursuit. ML algorithms can ingest huge and diverse data sets such as satellite imagery, GIS data and demographic information, as well as weather models and traffic flow forecasts. Such algorithms could potentially unlock hidden patterns, correlations and anomalies that a human analyst might overlook (Arup, 2024). For example, ML models can achieve 98% end-to-end accuracy for land cover classification using satellite imagery, discover the places where urban heat island effects are the most severe or mimic quantitatively how physical features may influence human perceptions of safety in cities.

Case studies demonstrate this improved analytical capability when open environmental data (e.g., temperature data from NASA or NDVI vegetation index from Sentinel-2 satellite images) is pre-processed using pipelines in programming languages like Python and then provided to Large Language Models (LLMs) like ChatGPT for

analysis. This approach represents a "Human-in-the-Loop (HITL) method for collaboration between humans and AI in which the expert creates relevant and precise data, the AI processes this information to extrapolate interpretations from it and then the expert checks and refines the final outcome (Er & Bozkurt, 2025).

Nonetheless, a significant limitation persists. Although Artificial Intelligence systems excel with spatial data, they lack the ability to understand a place's "soul" or what makes it unique socially, culturally and communally (Arup, 2024). It's therefore clear that while there is a strong basis for the use of data-driven analysis, AI tools may be overly relied upon to drive site analysis leading to projects which lack contextual relevance and emotional texture.

4.2. Scenario Generation and Evaluation

The results, consisting of both the quantitative and qualitative information that have been collected during the analysis phase, are crucial to support the generation of scenarios. Here comes the use of generative approaches such as Generative Design (GD), Generative Adversarial Networks (GAN), Text-to-Image (T2I). In this step the designer expresses particular goals of the project — for example, "maximize biodiversity" — alongside constraints such as "the budget may not be more than X" and fundamental conditions revealed by the analysis, such as "south-facing slopes." On these inputs the AI can derive hundreds or thousands of potential designs in seconds or minutes (Spremulli & Wright, 2023; Thamma, 2024) (Fig. 6 and Fig. 7).

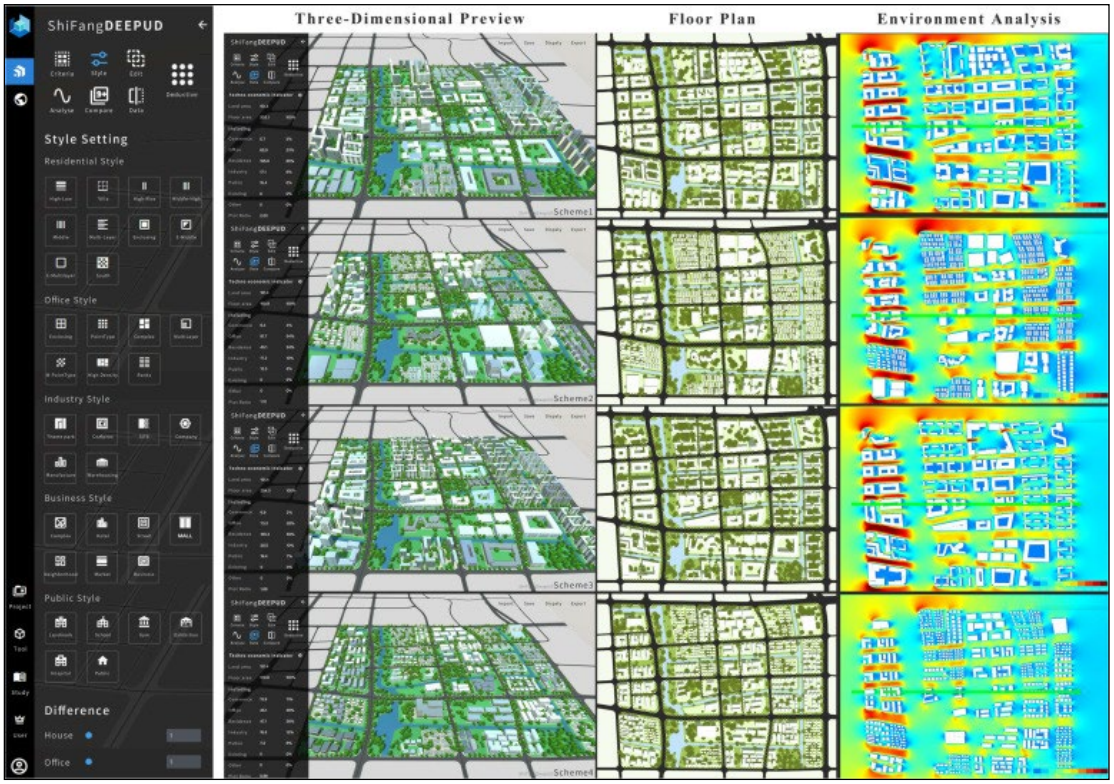

Figure 6: *AI for landscape planning and environmental analysis (Ref: Chen et al., 2025)*

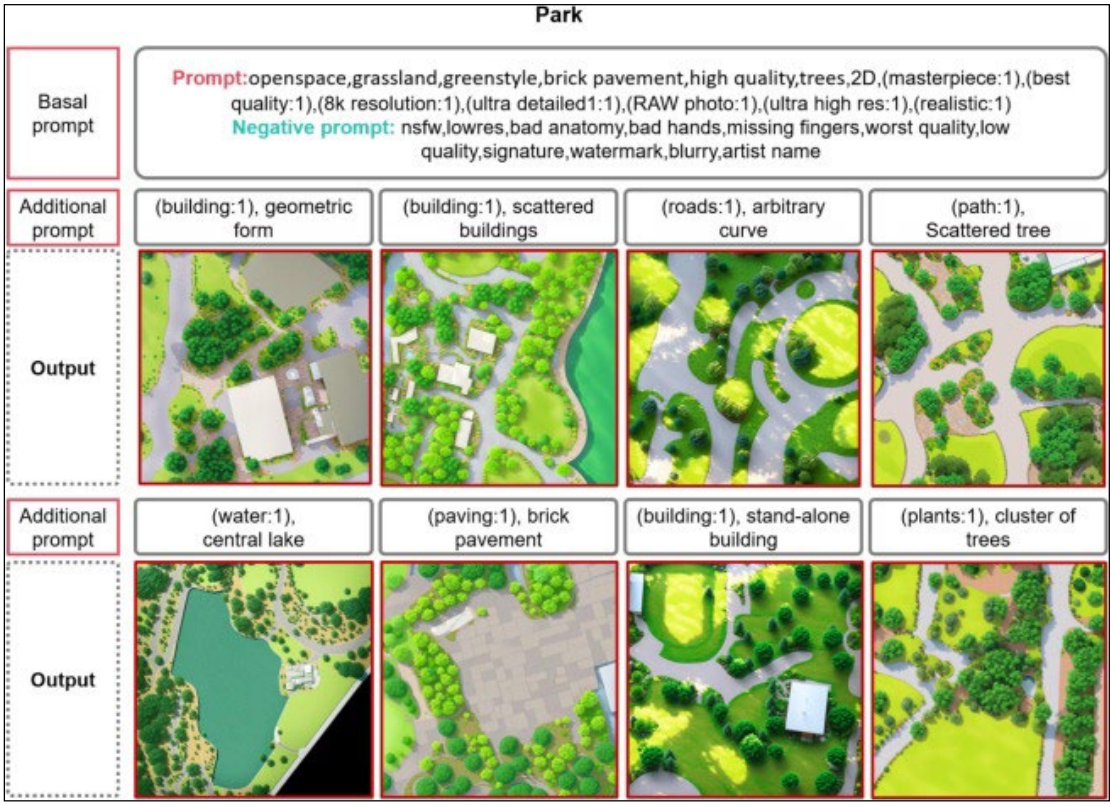

Figure 7: *AI for landscape design and planning (Ref: Chen et al., 2025)*

The G.A.R.D.E.N. framework can abstract a model based on both "Generate" and "Analyze" processes described above. In the "Generate" step, creative and cutting-edge designs, in addition to basic massing models are created by means of AI tools. Then the "Analyze" task is to screen out of the technical, economic and practical feasibility of these new ideas (Qiu et al., 2025). This workflow fundamentally changes the role of the designer. Instead of being just an artisan who builds a unique solution from scratch, the designer now acts as a curator and strategist that "evaluates," "ranks" and choose among the best candidates (Spremulli & Wright, 2023).

The G.A.R.D.E.N. framework (Generate, Analyze, Rank, Design, Evaluate, Narrative) serves as a strategic workflow that brings methodological discipline to AI integration in landscape architecture, elevating the designer to the position of a "decision-making curator". This approach aims to transform the design process from a traditional linear model into a data-driven, cyclical performance optimization system. Conceptualized by Qiu, Chen and Ma (2025), this structure incorporates computational logic into professional practice at every stage, from initial design to stakeholder presentation.

The first steps of the process, "Generate" and "Analyze," represent the "divergent thinking" phase of design. During this stage, AI tools can produce thousands of potential design scenarios within seconds based on defined constraints and objectives. As emphasized by Thamma (2024), this production process is not merely the use of a tool but a "co-designer" interaction that pushes the creative boundaries of the designer.

Immediately following this, in the analysis phase, machine learning algorithms process massive datasets, such as satellite imagery and climate models, to ground the design's starting point in concrete, quantitative data.

In the "Rank" and "Design & Develop" stages, where generated scenarios are refined, the designer's role evolves from an "artist drawing from scratch" to a "curator evaluating possibilities". Popescu and Schut (2023) argue that in this phase, the designer must select and rank the most promising options among thousands of alternatives, optimizing them according to the unique context of the project. These selected scenarios are then stripped of the uncontrolled nature of Text-to-Image (T2I) models and brought to geometric precision at professional standards using advanced control mechanisms, such as ControlNet, developed by Zhang, Rao and Agrawala (2023).

The final links in the methodology, "Evaluate" and "Narrative & Represent," aim to prove the performance of the designed landscape as a "system". These evaluations, conducted under the guidance of the Landscape Architecture Foundation (2018), are performed through simulation tools using quantitative metrics such as reduced stormwater runoff or urban heat island effects. In the final stage, complex performance data is transformed into visual narratives through the "Narrative" step, making them understandable for stakeholders. This transparent representation process is a fundamental element that increases the technical validity and social acceptance of the design, as also stated in Arup (2024) reports.

The scenarios are optimized toward performance in the last step of this workflow. This stage focuses on measurably optimizing designs. AI connects to a variety of simulation tools – e.g., energy analysis software or multi-objective optimization algorithms – for the prediction of performance based on environmental, social and economic variances in each design alternative (Qiu et al., 2025).

The indicators used in this assessment can be extracted from standardized schemes, such as the Landscape Performance Series (LPS), created by the Landscape Architecture Foundation (LAF) (Landscape Architecture Foundation, 2018). Example metrics may include:

- Environmental performance: The greater part of green infrastructure penetration has generated a significant decrease in stormwater runoff volume (estimated in several cubic meters per year). There is also value in the magnitude of carbon stored per year, which is counted in Tons! This strategy has also helped reduce the phenomenon of Urban Heat Islands with temperature decrease in Celsius. Finally, the habitat creation area GMHs represent was large enough to be measured in square meters (Han et al., 2023; Landscape Architecture Foundation, 2018).
- Social Impact: Upgrades to public life have generated higher levels of leisure use – measured by number of people per day. Ambient noise levels have also been observed to drop in decibels. Perceptions of safety and comfort have also risen in the community, as described by survey scores (Landscape Architecture Foundation, 2018; Han et al., 2023; Arup, 2024).
- Economic Effectiveness: The financial impacts of these interventions are reported and saving costs in construction or maintenance phase are presented in percentage. The value of homes has likewise

surged, appearing similarly in percentage form. Further, this investment has provided jobs in terms of persons employed (Han et al., 2023).

AI can help computer-aided design (CAD) systems pinpoint designs with optimum configurations for certain metrics or automatically optimize a given design to satisfy such requirements. This quantitative and iterative optimization approach has potential to lead the landscape towards 'system' of superior performance and sustain ability. The dangers that were characterized in the workflow still re-appear here, however. An exclusive focus on optimising quantifiable parameters entails a potential systematic disregard of qualities that cannot be easily measured, but, at the same time, are essential to what constitutes a 'place': these include cultural embeddedness or identity, aesthetic appeal and spontaneous social interaction (Arup 2024; Netser et al. 2025). In addition, the "Represent" step of the G.A.R.D.E.N. framework emphasizes AI's potential to translate complex performance data into visualizations that are dynamic and interactive, allowing stakeholders to easily perceive them - for example animated graphs showing a project's water savings or heat maps comparing energy performance across alternative design scenarios (Qiu et al., 2025).

In this new world order, creativity is no longer thought of as that one bright spark firing in the brain of a lone genius. Instead, it is reframed as a "distributed" phenomenon contingent upon dynamic relations within a socio-material network of human (designer–user stakeholder) and non-human (AI algorithm, datasets, physical environment) actants. The creative process involves moving back and forth between two core processes of thinking: divergent and convergent thinking (Popescu & Schut, 2024). Evidence shows that AI can be a great assistance to humans, particularly when it comes to idea generation and alternative creation, processes of divergent thinking (Paananen et al., 2023). Stages that imply convergent thinking, namely selection, judging and deciding which of several ideas will make the cut for development as a service are however still largely driven by human critical judgment and value judgments (Paananen et al., 2023; Popescu & Schut, 2024).

4.3. Algorithmic Biases

One of the most significant shortcomings of AI systems is that they are susceptible to inheriting or propagating societal, cultural and historical biases included in the training data sets. If an AI model is trained on samples that only come from certain geographies, aesthetic sensibilities or socio-economic demographics, the landscapes it suggests will consistently embed these biases. There is a risk that local identities may become systematically marginalized, the requirements of minority communities ignored and non-standard aesthetics overlooked (Arup, 2024). For example, a T2I model that has been taught on the images that are seen as very attractive or pleasant within a cultural context will produce photo-realistic visual similarities to the basic aesthetic of the region when shown an example of "a beautiful park," while overlooking alternative traditions in cultural landscapes. This finding highlights concepts such as "selection bias" and "stereotyping bias" in the context of design (Popescu & Schut, 2024). Multiple technical solutions can help alleviate these algorithmic injustices, some of which include curated datasets that are diverse and representative and span a wide spectrum of cultures, ecologies and design approaches (dataset curation), augmenting existing datasets artificially (data augmentation) and more strongly representing

underrepresented factions by re-sampling them, or training models using adversarial networks so they avoid generating biased outputs (adversarial training) (Jindal et al., 2024).

The "black-box" nature of many of these advanced AI models, especially deep neural networks, is a chief factor driving scepticism of these systems, which can be ill-equipped to explain how they reach certain decisions. Where the reason for a design solution remains unclear, landscape architects may be afraid of implementing advice produced by an AI. Explainability challenge the challenge of model explainability has recently given rise to the new field of Explainable Artificial Intelligence (XAI). Explainable AI refers to a set of approaches and principles that make the decision's taken by AI models transparent, interpretable and understandable by humans. Shapley Additive Explanations (SAE) and Local Interpretable Model-agnostic Explanations (LIME) are used to shed light on the importance assigned to certain input features (clarifying variables such as sun exposures or soil type) to make visible potential bias and improve stakeholder trust in the system (Perera et al. 2025).

Yet the need for transparency is not only a machine issue, it is also hugely important on the human side too. Designers can have cognitive bias when using AI tools. The most common type of these are:

- Confirmation Bias: This is the designer's bias toward selecting, interpreting and favouring AI outputs that are deemed to confirm their own existing views or beliefs (Popescu & Schut, 2024).
- Automation Bias: This bias refers to an over-reliance on the information produced by AI systems such that we believe to be true and perfect anything it gives us, particularly when it provides this output quickly and convincingly (Dobre, 2025).
- Prompt Bias: When interacting with the question and answer AI the designer might force the AI to trigger a pre-determined output by providing an essentially limited or leading command, which potentially will reduce chances of discovering more creative answers for given task (Popescu & Schut 2024).

In fact, to mitigate human biases and encourage a critical assessment of AI, certain techniques can be incorporated into the UI/UX design of AI tools. For example, an AI interface could show the confidence value for its proposed solutions, actively propose situations that contradict or diverge from the user's initial perspective, ask users to explain their own reasoning before they accept any suggestion, offer regular feedback mechanisms (Dobre 2025). These human-centred design principles change the status of AI from a superior being to an equal supporting partner that facilitates critical conversation. This three-pronged strategy of using technical measures to minimize biases in algorithms, using explainable AI (XAI) for transparency and addressing human-level biases though UI/UX design also establishes a solid foundation for integrating AI into design ethically and responsibly. Table 2 summarizes the cognitive biases found in AI design tools and their corresponding mitigation strategies.

Table 2: Cognitive Biases Observed in AI Design Tools and UI/UX-Based Mitigation Strategies

Cognitive Bias	Definition	Risk in the Design Process	UI/UX Mitigation Strategy
Confirmation Bias	The tendency to search for and prefer information that confirms existing beliefs or hypotheses	The designer uses AI merely to confirm their initial ideas, overlooking innovative or better alternatives	The interface proactively presents alternative scenarios containing data contrary or opposite to the user's idea. Adding probing features such as "What are 3 pieces of evidence that could refute this idea?"(Dobre, 2025)
Automation Bias	The tendency to over-rely on information from automated systems and accept it without question	Acceptance of potentially flawed, biased, or suboptimal designs generated by AI without critical evaluation	Displaying confidence or uncertainty scores alongside AI outputs. Adding steps that require the user to write their justification before confirming a decision (Dobre, 2025)
Prompt Bias	Limitation of the output's diversity and quality due to the initial command (prompt) given to the AI being narrow or leading	Narrowing the scope of creative exploration; the full potential of AI not being utilized	Providing tutorials and templates for users on writing more effective commands (prompt engineering). A "co-pilot" feature that suggests ways to expand or diversify the prompt (Dobre, 2025)
Framing Effect	The way information is presented affects a person's decisions independently of its content	AI presents a solution in a positive frame, such as "most popular" or "most efficient," causing the designer to overlook other important criteria.	Designing balanced and unbiased comparison dashboards among different metrics (e.g., cost, ecological impact, social benefit) (Dobre, 2025)

5. DYNAMIC SCENARIOS FOR DYNAMIC LANDSCAPES

Current generative AI applications mainly produce a fixed setting or set of plans for a specific time frame. Yet, landscapes are natural living and complex evolving systems. To shift this, two novel event hour ideas could transform AI from a process of making static plans that are executed to coexisting in and learning from the landscape and helping to actively maintain it. These two ideas are Reinforcement Learning and World Models.

RL is a considerable progress in generation of scenario. RL is a type of machine learning in which an "agent" discovers the best "policy" or behavioural strategy, for maximizing a particular "reward" signal by interacting with an "environment" using trial and error (Sutton & Barto, 2018). This approach leads to the creation of decision-making system, which is able to react on various changes instead of predefined static solutions.

One especially ambitious and transformational vision for AI's role in landscape architecture stems from World Models, as outlined by Ha and Schmidhuber (2018). A World Model enables an RL agent to build a compact, high-level, non-spatial and temporally extended model of the dynamics of its underlying environment. This is an

analogue of the human ability to perceive and create models of our surroundings and then to use those models both for prediction and for planning (Ha & Schmidhuber, 2018). This skeleton, essentially consisting of three elements:

- Vision (VAE): The Variational Autoencoder (VAE) is used to compress high-dimensional sensory input, such as an instantaneous camera image or satellite photo of a landscape, into a low-dimensional latent vector (z). This procedure successfully summarizes important aspects of the landscape at a time point and provides for an interpretable view on visual data (Ha & Schmidhuber, 2018).
- Memory (MDN-RNN): This module predicts the probability distribution of the next latent vector conditioned on past latent vectors and actions taken, using a Recurrent Neural Network. This produces the system understanding of temporal dynamics, like any natural concept (for instance, for seasons, plant development or hydrology) and also allows one to form some kind of "memory" in the model (Ha & Schmidhuber, 2018).
- Controller (C): The controller is a simple and direct neural network that search for the policy through trial-and-error exclusively within its internal world model - a simulator. This form of learning is called "hallucination" or "dreaming" (Ha & Schmidhuber, 2018).

This is a crucial metaphor for landscape architecture, which suggests AI can be more than just an analysis of an existing site or the design of a static plan. It builds an internal "world model" that represents rather than replicates the dynamics of that terrain. In this virtual domain, AI could reveal the most robust, agile and regenerative designs and management techniques by simulating millions of times over the course of decades the ecological and social implications of different interventions — e.g. diverse plant mixtures, water harvesting strategies or transportation networks. This alters the time frame of design completely. The aspiration changed from developing a plan for a particular future state to designing a self-organizing system that is flexible with respect to an infinite variety of potential futures. This vision represents the highest level of agentic and dynamic futurity for landscape architecture.

6. CONCLUSION

This research serves as a proof that artificial-intelligence has shifted from being a tool to help landscape-architects towards an agentic participant, actively reconstructing the discipline's processes, methodologies and epistemology. More advanced approaches, such as Parametric Design (GD), Generative Adversarial Networks (GANs), Text-to-Image (T2I) models and ControlNet, have expanded the range of generated scenarios on one hand while increasing control over this generation on the other. These advanced technology tools allowing solution orientated workflows from data driven site analysis to the generation of alternative proposals and performance based optimisation. So the designer becomes more of a curator and a strategist. This novel approach can be used to statistically enhance the environmental, social and economic values of landscapes.

However, such invention entails challenges. We also analyse the relation between conventional and creative aspects, some remarks regarding algorithmic prejudices due to training on unrepresentative data that can lead to unfair or similar design patterns. The lack of transparency in the models raises questions about trust with designers and technology. In addition, they should refrain from any interaction with AI systems that is affected

by cognitive biases. Current literature suggests that overcoming these challenges requires more than just technical solutions, it also necessitates strong ethical foundations. Explainable AI (XAI) and human-centred design approaches to UI/UX are essential practices for the responsible application of these technologies.

The rise of artificial intelligence is not the enemy to landscape architects, but rather a powerful friend — a tool will enable great leaps forward in solving complex challenges of the 21st century such as climate change, urbanization and environmental crises. This collaboration aims to offer affordable and efficient designs that are also visually appealing at the same time. It is intended to assist in the development of systems and environments that are fair, strong and sustainable for people while living within the constraints of, but not damaging to nature. This vision will only become a reality through recognition of the role of technology by a critical and conscientious public, with humanism as design's guiding principle.

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