ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

HUMAN-MACHINE COLLABORATION IN LANDSCAPE ARCHITECTURE: MULTI-STAGE INTEGRATION OF AI INTO LANDSCAPE SITE ANALYSIS WORKFLOW

M.Sc. THESIS

Buse Ezgi ER

Department of Landscape Architecture

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

PEYZAJ MİMARLIĞINDA İNSAN-MAKİNE İŞBİRLİĞİ: YAPAY ZEKANIN ÇEVRE ANALİZİ SÜRECİNE ÇOK KATMANLI ENTEGRASYONU

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Buse Ezgi Er, a M.Sc student of ITU Graduate School student ID 502211613, successfully defended the thesis/dissertation entitled "HUMAN-MACHINE COLLABORATION IN LANDSCAPE ARCHITECTURE: MULTI-STAGE INTEGRATION OF AI INTO LANDSCAPE SITE ANALYSIS WORKFLOW", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 31 December 2025
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To my beloved family,

FOREWORD

As an architect, my motivation to pursue a master's degree in Landscape Architecture led me on this challenging yet rewarding journey; which allowed me to experience the privilege of interdisciplinary work, versatility, and the valuable lessons learned from every single experience. This study has been very rewarding in terms of both my academic development and professional perspective. As I always intended, it also offered me the opportunity to delve deeply into the field.

I would like to express my gratitude to my esteemed advisor and Vice Head of Department, Assoc. Prof. Dr. Melih BOZKURT, who guided me and providing me with new perspectives throughout the thesis process; to my beloved father İbrahim, mother Sevil, and sister Nehir, who always encouraged me and stood by me no matter the circumstances; to our esteemed Head of Department, Prof. Dr. Hayriye EŞBAH TUNÇAY, from whom I learned so much and gained invaluable knowledge throughout my education; to the DLA team, for such an unforgettable experience during the publication and presentation process of my article; and to all my valuable professors and classmates who played a major role in helping me embracing ITU from day one.

I sincerely hope that this study will be beneficial to the community and serve as a guide for future research.

February 2026

Buse Ezgi Er
(Architect)

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ABBREVIATIONS

AI	: Artificial Intelligence
API	: Application Programming Interface
ANN	: Artificial Neural Network
ANT	: Actor-Network Theory
CMD	: Command Prompt
CNN	: Convolutional Neural Network
DNN	: Deep Neural Network
ESA	: European Space Agency
GAN	: Generative Adversarial Network
GBA	: Global Building Atlas
GEE	: Google Earth Engine
GenAI	: Generative Artificial Intelligence
GIS	: Geographic Information System
IDLE	: Integrated Development and Learning Environment
IoT	: Internet of Things
IoU	: Intersection over Union
HITL	: Human-in-the-Loop
HMC	: Human-machine Communication
HPC	: High Performance Computing
HRL	: High Resolution Layer
LiDAR	: Light Detection and Ranging
LLM	: Large Language Model
ML	: Machine Learning
NASA	: National Aeronautics and Space Administration
NDVI	: Normalized Difference Vegetation Index
NIR	: Near Infrared
NN	: Neural Network
N8N	: Nodemation
OSM	: Open Street Map
UI	: User Interface

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HUMAN-MACHINE COLLABORATION IN LANDSCAPE ARCHITECTURE: MULTI-STAGE INTEGRATION OF AI INTO LANDSCAPE SITE ANALYSIS WORKFLOW

SUMMARY

The 21st century's multifaceted problems such as rapidly increasing population, climate crisis, and uncontrolled urbanization have necessitated the acceleration of the production of functional solutions in landscape architecture, going beyond mere aesthetics. This situation underscores the need to work with more precise data sets in the planning process and the importance of interdisciplinary approaches. Within today's dynamic urbanization practices, landscape architecture plays a critical role in maintaining ecosystem services and increasing urban resilience. However, the speed required to produce solutions to these complex problems often strains the manual capacity of traditional design and analysis methods, forcing designers to choose between the need for up-to-date data and limited time. At this point, data-driven design approaches are no longer just technical support, but a fundamental paradigm shift for producing rational and ecologically consistent solutions. Especially in the last decade, remote sensing in obtaining geographic data, artificial intelligence (AI) tools in architectural visualization and modeling, cloud-based systems in automation, and satellite data in disaster prevention strategies have been used more frequently. The integration of these techniques with AI has led to revolutionary transformations in site analysis processes, which are the most critical stage of the design process. The time lost with traditional methods is compensated for by machine learning (ML), facilitating the decision-making process. This contributes to increased productivity and improved built environment quality in today's frequently encountered emergency and disaster scenarios. However, a review of existing academic literature and professional practice reveals a significant technical barrier to the use of these technologies. Maximizing the effectiveness of AI tools requires expertise and programming knowledge.

This thesis aims to overcome these technical barriers by proposing a new workflow that allows designers without professional coding training to benefit from the power of artificial intelligence in a transparent and auditable way. The fundamental philosophy of the research is to position artificial intelligence not as an automation mechanism replacing humans, but as a 'collaborator' that supports human creative intelligence and intuitive capacity. At the same time, the thesis examines both the advantages and limitations of using AI-assisted tools in the context of landscape architecture, while also addressing ethical issues. This alternative Human-in-the-Loop (HITL) approach is practical and repeatable, especially for landscape architects, and encourages the effective use of programming and AI tools in education and professional practice. The HITL model is based on the continuous optimization of AI-generated data through user feedback.

The AI-assisted coding (vibe-coding) concept, discussed within the theoretical framework of this study, is a method that enables the generation of functional code blocks via AI according to the user's needs. Thanks to this method, integration between complex tools such as Python libraries and ArcGIS can be achieved without requiring technical software expertise from the user. The use of natural language processing capabilities in this way reduces the cognitive burden created by technical details in the analysis process, allowing for a focus on interpreting spatial data and making strategic decisions.

The fundamental element defining the original value of this study and its departure from existing approaches in the literature is its conceptualization of AI not merely as a producer of end products in landscape architecture practice, but as a proposal for an environment that radically transforms the designer's relationship with spatial data. While most existing research defines processes requiring advanced data analysis and coding as a field of technical expertise, this study creates a space for technical democratization in professional practice by offering a methodology that overcomes complex software barriers. Unlike autonomous systems where the process cannot be controlled, in the proposed model, the landscape architect's intuition and knowledge are preserved as a controlling filter at every step of the analysis process. Furthermore, testing the proposed model on three sites with diverse geographical and urban characteristics proves that the method has universal validity, independent of scale and location, and thus distinguishes it from studies based on individual samples.

The research has a multi-layered structure consisting of literature review, tool comparison, and application phases. This study, conducted in 2024-2025, clarified the breaking points at the intersection of AI and landscape architecture and related technical terms; tested the visual generation capabilities of commonly used generative AI (GenAI) tools such as Midjourney, ArchiVinci, and ChatGPT; and compared the production performance and data analysis consistency of various tools (Python, ArcGIS, and web-based GIS platforms). Multi-layered analyses were performed using vibe-coding, and the results were automatically visualized (e.g. plant health, building function, land use analyses). To test the validity of the proposed workflow, three significant urban open spaces with different characteristics, climates, and urban textures were selected as examples from around the world.

The research steps were carried out for Izmir Kültürpark, New York Central Park, and Singapore Gardens by the Bay. These sites were chosen as the focus of the research due to their biodiversity and multi-purpose uses, as well as their data density and the different ecological-urban problems they represent. In all three sites, it was observed that AI-assisted analyses reduced data processing times, which could take weeks with traditional methods, to minutes and minimized the margin of error. The aim is to enable landscape architects to focus on interpreting the obtained spatial data in a practical way, rather than getting lost in complex details.

Data obtained during the implementation process revealed that incorporating AI into the landscape architecture workflow dramatically increased production efficiency. However, the discussion also highlighted the potential for misleading results when combined with data that has not been critically examined by the landscape architect. Algorithmic biases, data privacy, and the ethical implications of AI-generated results were among the critical questions addressed in the research. It was emphasized that the obtained outputs should always be validated against the local context and ecological realities. This situation demonstrates that technology is not replacing the landscape architect, but rather taking their data processing capabilities to the next level, enabling them to conduct more in-depth analyses.

It is predicted that landscape architecture practice will become more democratic and data-driven by overcoming technical barriers and adopting approaches such as ‘vibe-coding’. The HITL-based workflow proposed in this research not only offers an academic model but also serves as a practical roadmap that can be used in professional practice and educational curricula. Future projections emphasize that integrating AI into the decision-making mechanisms of local governments and using real-time ecological analyses in planning processes will make it possible to create more socially inclusive cities that are more resilient to physical change. This study demonstrates, within a scientific framework, that technology can be used not merely as a technical necessity, but as a strategic lever to create a more livable and sustainable built environment.

PEYZAJ MİMARLIĞINDA İNSAN-MAKİNE İŞBİRLİĞİ: YAPAY ZEKANIN ÇEVRE ANALİZİ SÜRECİNE ÇOK KATMANLI ENTEGRASYONU

ÖZET

21. yy'da hızla artan nüfus, iklim krizi ve kontrolsüz kentleşme gibi çok katmanlı sorunlar, peyzaj mimarlığında estetikten öte, işlevsel çözümlerin üretiminin hızlandırılmasını zorunlu kılmıştır. Bu durum, planlama sürecinde daha hassas veri setleriyle çalışılmasını ve disiplinlerarası yaklaşımların öneminin altını çizmektedir. Günümüzün dinamik kentleşme pratikleri içerisinde peyzaj mimarlığı, ekosistem servislerinin sürdürülmesi ve kentsel dirençliliğin artırılması noktasında kritik bir rol oynamaktadır. Ancak bu karmaşık sorunlara karşı üretilecek çözümlerin hızı, geleneksel tasarım ve analiz yöntemlerinin manuel kapasitesini sıklıkla zorlamakta; tasarımcıları güncel veri ihtiyacı ile kısıtlı zaman arasında bir tercihe zorlamaktadır. Bu noktada, veri temelli tasarım yaklaşımları artık sadece teknik bir destek değil, rasyonel ve ekolojik açıdan tutarlı çözümler üretmek için temel bir paradigma değişimi olarak karşımıza çıkmaktadır. Özellikle son on yıldır; coğrafi verilerin elde edilmesinde uzaktan algılama, mimari görsel üretimi ve modellemede yapay zeka (YZ) araçları, otomasyonda bulut tabanlı sistemler, afet önleme stratejilerinde ise uydu verilerinden daha sık faydalanılmaktadır. Bu tekniklerinin YZ ile entegrasyonu, tasarım sürecinin en kritik aşaması olan alan analizi süreçlerinde devrim niteliğinde dönüşümlere yol açmıştır. Geleneksel yöntemler ile kaybedilen zaman, makine öğrenimi ile telafi edilerek karar süreci kolaylaştırılmaktadır. Bu durum günümüzde sık karşılaşılan acil durumlarda ve afet senaryolarında, üretimde verimliliği sağlayarak yapılı çevre kalitesinin artmasına destek olmaktadır. Ancak mevcut akademik literatür ve mesleki pratik incelendiğinde, bu teknolojilerin kullanımında ciddi bir teknik bariyer sorunu gözlemlenmektedir. YZ araçlarından maksimum verim sağlanabilmesi için bu teknolojiyi kullanabilecek yetkinlikte olunması ve program bilgisine sahip olunması gerekmektedir.

Söz konusu tez çalışması, bu teknik engelleri ortadan kaldırmayı hedefleyerek, profesyonel kodlama eğitimi almamış tasarımcıların da yapay zekanın gücünden şeffaf ve denetlenebilir bir şekilde faydalanabileceği yeni bir iş akışı önermektedir. Araştırmanın temel felsefesi, yapay zekayı insanın yerine geçen bir otomasyon mekanizması olarak değil, insanın yaratıcı zekasını ve sezgisel kapasitesini destekleyen bir 'işbirlikçi' olarak konumlandırmaktır. Aynı zamanda tez, YZ destekli araçların peyzaj mimarlığı bağlamında hem kullanım avantajlarını hem de kısıtlarını incelerken, etik sorunları da ele almaktadır. Bu alternatif İnsan-Döngüde (HITL) yaklaşımı, özellikle peyzaj mimarları için pratik ve tekrarlanabilir olup, programlama ve YZ araçlarının eğitim ve mesleki uygulamada etkin kullanımını da teşvik etmektedir. HITL modeli, YZ'nın ürettiği verilerin kullanıcı tarafından sürekli olarak geri beslemelerle optimize edilmesini temel alır.

Çalışmanın kuramsal çerçevesinde ele alınan YZ destekli kodlama (vibe-coding) kavramı ise, kullanıcının ihtiyacına göre YZ aracılığıyla işlevsel kod blokları üretmesini sağlayan bir yöntemdir. Bu yöntem sayesinde, Python kütüphaneleri ve ArcGIS gibi karmaşık araçlar arasındaki entegrasyon, kullanıcıdan teknik bir yazılım uzmanlığı talep etmeksizin gerçekleştirilebilmektedir. Doğal dil işleme yeteneklerinin bu vesileyle kullanımı, analiz sürecinde teknik ayrıntıların yarattığı bilişsel yükü azaltarak mekansal veriyi yorumlamaya ve stratejik kararlara odaklanılmasına olanak tanımaktadır.

Çalışmanın özgün değerini ve literatürdeki mevcut yaklaşımlardan ayrışan yönlerini tanımlayan temel unsur, YZ'yı peyzaj mimarlığı pratiğinde sadece bir sonuç ürünü üreticisi değil, tasarımcının mekansal verilerle kurduğu ilişkiyi kökten dönüştüren bir ortam önerisi olarak kurgulamasıdır. Mevcut araştırmaların çoğu, ileri düzey veri analizi ve kodlama gerektiren süreçleri teknik uzmanlık alanı olarak tanımlarken; bu çalışmada, karmaşık yazılım bariyerlerini aşan bir metodoloji sunularak mesleki pratikte teknik bir demokratikleşme alanı yaratılmaktadır. Sürecin kontrol edilemediği otonom sistemlerin aksine, önerilen modelde peyzaj mimarının sezgisi ve bilgi birikimi, analiz sürecinin her adımında denetleyici bir filtre olarak korunmaktadır. Ayrıca, önerilen modelin çeşitli coğrafi ve kentsel karakterlere sahip üç alan üzerinden test edilmesi; yöntemin ölçekten ve konumdan bağımsız, evrensel bir geçerliliğe sahip olduğunu kanıtlamakta ve bu niteliğiyle tekil örneklemler üzerine kurulu çalışmalardan ayrışmaktadır.

Araştırma; literatür taraması, araç kıyaslaması ve uygulama aşamalarından oluşan çok katmanlı bir yapıya sahiptir. 2024-2025'te sürdürülen bu çalışma kapsamında, YZ ve peyzaj mimarlığı kesişimindeki kırılma noktaları ve ilgili teknik terimler açıklanmış; sektörde yaygın olarak kullanılan üretken YZ (GenAI) araçlarından Midjourney, ArchiVinci ve ChatGPT'nin görsel üretim kapasiteleri test edilmiş; çeşitli araçların (Python, ArcGIS ve web tabanlı GIS platformları) üretim performansları ve veri analizi tutarlılıkları kıyaslanmıştır. Vibe-coding ile çok katmanlı analizler yapılmış ve sonuçlar otomatik olarak görselleştirilmiştir (örn. bitki sağlığı, bina fonksiyonu, arazi kullanım analizleri). Önerilen iş akışının geçerliliğini test etmek amacıyla, dünya ölçeğinde farklı karakterlere, iklimlere ve kentsel dokulara sahip üç önemli kentsel açık alan örneklem olarak seçilmiştir.

Araştırma basamakları, İzmir Kültürpark, New York Central Park ve Singapur Gardens by the Bay projeleri özelinde gerçekleştirilmiştir. Bu alanlar, biyoçeşitlilik ve çok amaçlı kullanımlarının yanı sıra, veri yoğunlukları ve temsil ettikleri farklı ekolojik-kentsel problemler nedeniyle araştırmanın merkezine alınmıştır. Her üç uygulama alanında da, YZ destekli analizlerin geleneksel yöntemlerle haftalar sürebilecek veri işleme süreçlerini dakikalara indirdiği ve hata payını minimize ettiği gözlemlenmiştir. Amaç, peyzaj mimarlarının kompleks ayrıntılarda kaybolmak yerine, elde edilen mekansal verileri pratik bir şekilde yorumlamaya odaklanmalarını sağlamaktır.

Uygulama sürecinde elde edilen veriler, YZ'nın peyzaj mimarlığı iş akışına dahil edilmesinin üretim verimliliğinde dramatik bir artış sağladığını ortaya koymuştur. Ancak bu hız artışının, peyzaj mimarının eleştirel süzgecinden geçmeyen verilerle birleşmesi durumunda yanıltıcı sonuçlar doğurabileceği de tartışma bölümünde önemli bir yer tutmaktadır. Algoritmik yanlılıklar, veri gizliliği ve YZ'nın ürettiği sonuçların etik boyutu, araştırmanın kritik sorgulamaları arasındadır. Elde edilen çıktıların her zaman yerel bağlam ve ekolojik gerçekliklerle doğrulanması gerektiği vurgulanmıştır.

Bu durum, teknolojinin peyzaj mimarının yerine geçmediğini, aksine elindeki veri işleme kapasitesini bir üst seviyeye taşıyarak ona daha derinlemesine analiz yapma imkanı verdiğini göstermektedir.

Teknik bariyerlerinin aşılması ve 'vibe-coding' gibi yaklaşımların benimsenmesiyle birlikte, peyzaj mimarlığı pratiğinin daha demokratik ve veri odaklı bir yapıya kavuşacağı öngörülmektedir. Araştırmanın önerdiği HITL tabanlı iş akışı, sadece akademik bir model sunmakla kalmayıp, mesleki uygulamada ve eğitim müfredatlarında kullanılabilecek pratik bir yol haritası niteliğindedir. Gelecek projeksiyonlarında, YZ'nın yerel yönetimlerin karar destek mekanizmalarına entegre edilmesi ve planlama süreçlerinde gerçek zamanlı ekolojik analizlerin kullanılmasıyla, sosyal açıdan daha kapsayıcı ve fiziksel değişimlere daha dirençli kentlerin üretilmesinin mümkün olduğu vurgulanmaktadır. Bu çalışma, teknolojinin teknik bir zorunluluktan ziyade, daha yaşanabilir ve sürdürülebilir bir yapılı çevre üretmek için stratejik bir kaldıraç olarak kullanılabileceğini bilimsel bir çerçeveyle ortaya koymaktadır.

1. INTRODUCTION

In the 21st century, the discipline of landscape architecture -like other environmental design disciplines, is constantly grappling with issues like the climate crisis, wars, natural disasters, biodiversity loss, rapid population growth, and rapid urbanization (Das et al, 2024). These serious problems challenge the capacity and practicality of traditional and analog design processes (Nickayin, 2022). In this era of urgent planning strategies to create a more livable environment, especially in the face of natural disasters and man-made catastrophes, the integration of automation is much needed to shorten the environmental analysis process (Sabri & Witte, 2023). In this context, while the digital revolution has led to the emergence of approaches such as computational design and data-driven design, we are on the verge of a new paradigm shift known as the ‘artificial intelligence revolution’ (Goralski & Tan, 2019).

The applications encompassed by artificial intelligence (AI) range from big data analytics to the identification of cityscapes and even designing alternatives (Gao et al, 2025). The utilization and training of these technological applications are being implemented within academia as well (Li et al, 2025). The community is advised to make use of such applications for their own purposes, particularly throguh free subscriptions offered by such companies (e.g. Google Gemini Pro). However, applications encompassing AI face transparency and ethical issues; this raises important points for not only relying on this technology but also aiming to incorporate design elements (Jobin et al, 2019). While AI still lacks human-specific aspects such as creativity and originality, it is clearly taking over various duties (Lukovich, 2023); particularly nowadays in creative industries such as graphic design and advertisement (Hertzmann, 2018). Nevertheless, it simultaneously creates new profession fields and increases competition while replacing the entry-level jobs (Altchek & Perkel, 2025).

1.1 Purpose & Framework of Thesis

The primary aim of this research is to offer a new theoretical and methodological paradigm that can change the nature of AI applications from being a passive instrument or what is termed a ‘threat’ to landscape architecture -to a more transparent, collaborative, and synergistic one involving human and machine partnership (Batty, 2018; Shneiderman, 2020; Davenport & Miller, 2022). The research investigates how AI can be conceived not only as a productivity instrument that consumes less time and energy but also how it can function as a ‘non-human actor’ which can enrich the cognitive faculties of the landscape architect to offer more ecologically valid solutions (Latour, 2005; Garibay et al, 2023).

1.2 Originality of Thesis

Current AI research in landscape architecture generally focuses on two main axes: analytical studies that analyze large-scale ecological and urban patterns using Geographic Information Systems (GIS) (Choi, 2023), remote sensing, and machine learning (ML) (Saygıner & Nurlu, 2025); and the studies that focus on generating architectural plans and visual design alternatives based on hundreds of training samples using Generative Adversarial Networks (GAN) or diffusion models (Chaillou, 2019; Feng et al, 2025). Although these studies provide various creative perspectives, they still address open-ended research questions that need to be worked on in terms of applicability (Li et al, 2024).

The novelty of this research work is embodied within its combination of these two axes. The study proposes a workflow that directs concrete inputs from open-access databases (e.g. NASA, GEE, OSM), into a processing cycle using prompts and scripts, to attain outputs of generative AI and validate them through the GIS database. Another idea advocated within this research work is that training on AI and coding should find its place within the educational system such that users can make optimal use of these technologies within their profession (Burrell, 2016; Fahmy et al,2024). In this process, humans must maintain their place as decision-makers who evaluate AI's outputs with their professional expertise. Therefore, they must acquire the ability to accurately evaluate responsible AI-supported systems (Li et al, 2024).

The second and more profound originality of the thesis is its attempt to ground this technical integration within a robust theoretical framework such as Actor-Network Theory (ANT) conceptualized by French philosopher, anthropologist, and sociologist Bruno Latour (Latour, 2005; Nehrlich, 2006), and Human-in-the Loop (HITL) approach (So, 2020; Wu et al, 2022). By defining AI not merely as a ‘tool’ but as an active ‘actor’, it opens up a theoretical discussion of the profession's future role (Akay, 2025). For this reason, it is particularly underlined that with the support of human-machine collaboration, more qualified results can be achieved (So, 2020).

In this study, the preference for the concept of human-machine ‘collaboration’ over the traditional term, human-machine ‘communication’ (HMC) (Carlisle, 1976; Guzman, 2018) is a conscious methodological choice. While the concept of ‘communication’ primarily focuses on the exchange of information between parties and the clarity of the message (prompts, scripts, and dialogue structure), ‘collaboration’ represents a collective and ‘symbiotic’ action exhibited towards a common design goal. Therefore, collaboration is the process of creating a hybrid intelligence that surpasses the capacity of a single actor, by combining the computational power of the ‘machine’ with the contextual intuition of the landscape architect.

1.3 The Need of Innovative Approaches in Landscape Architecture Practice

The common landscape design process relies heavily on the landscape architect's intuition and discretion (Brown & Corry, 2011). However, when working with endless invisible data layers like climate change scenarios, complex hydrological models, or the movement patterns of millions of people, human intuition alone is insufficient (Steinitz, 2012; Yexuan et al, 2020). Knowing the physical and social dynamics of the site and finding appropriate solutions is essential to create a sustainable living environment. Thus, the constant necessity of new approaches both in geodesign and landscape design is undeniable (Brown & Corry, 2011).

Today's AI-powered software are able to produce more up-to-date and reliable results (Xing et al, 2025). However, the real need is to go beyond the capabilities of existing software. The innovation needed is for landscape architects to actively participate in the AI training process, integrating domain-specific data and disciplinary knowledge into the AI model (Lukovich, 2023).

1.4 Human-Machine Collaboration

The development of AI in creative fields often triggers a fear of replacement. However, this study argues for a human-machine ‘collaboration’ rather than a perception of ‘threat’ (Cantrell et al, 2022; Davenport & Miller, 2022). As the recent publication clearly demonstrates (Er & Bozkurt, 2025), AI is unreliable when left unaided. The fact that the results obtained from widely-used language models (e.g. GPT, Claude, Gemini) fed only with basic prompts and web-based data that needs verification, proves the critical importance of human expertise (Fernberg et al, 2021).

This study embraces the mentioned ANT and HITL approaches as the guiding principle. This interaction creates twofold value, with the user training AI by providing continuous feedback, and AI providing the user with analyses in seconds -that would otherwise take much longer to obtain. The aim of the thesis is to define the critical steps of the collaboration, to propose a medium and to transform it into a continuous workflow.

2. LITERATURE REVIEW

2.1 Milestones in AI

Nilsson's (2009) book titled "The Quest for Artificial Intelligence" has been eye-opening in establishing a timeline. It is an extensive source that offers a critical evaluation of the ideas and achievements in AI (Figure 2.1). Although research on modelling artificial neural systems (ANN) has been on the agenda since the beginning of the 20th century (McCulloch & Pitts, 1943); Turing's (1950) article "Computing Machinery and Intelligence" is considered the source that questions and tests the thinking capacity of machines, and forms the foundation of today's related scientific studies (Şenyapar et al, 2025). During the Darthmouth Conference (1956), mathematics professor John McCarthy and his colleagues coined the term 'AI' and credited it as a research field (Chow, 2021). In his book published by MIT Press, Negroponte (1970) emphasized that computers could be the collaborators of designers. He defined the architect and the machine not as the 'master and slave', but as 'partners' who unlock each other's potential. Alexander et al. (1977) laid the foundation for today's algorithmic design language by addressing the concept of 'patterns' in cities. The Lighthill Report (1973) harshly criticized AI for exceeding the capacity of existing computers, leading to the period called the 'AI Winter' in the early 1980s. This report argued that AI had no future and could not go beyond solving simple mathematical problems (Lighthill, 1973). During this period, the budget allocated to AI research was reduced by approximately $16 million between 1987 and 1989. Nevertheless, research continued during and after the recession period (Nilsson, 2009). Mitchell (1987), played a major role in understanding CAD software with his book explaining the working principles of computer-aided software for architects. In 1997, IBM's Deep Blue, a chess-playing computer that defeated the 1985 World Chess Champion Garry Kasparov, caused a major stir in the media by proving that a computer could surpass even human intuition through 'deep thinking' (Campbell et al, 2002). In the beginning of the 21st century, AI innovations has accelerated rapidly, and began to seep into our lives (Nilsson, 2009). The launch of Google Earth & Maps in 2005 democratized geographic data and satellite imagery. It marked a milestone in accessing remote sensing data for designers (Butler, 2006). Deng et al. (2009) designed ImageNet, a large-scale and hierarchical image database, to advance computer vision research. This massive library of millions of labeled images has become a fundamental training set used to visually teach AI concepts such as ‘tree’, ‘road’, and ‘square’. Krizhevsky et al. (2012) made it possible to automate large datasets with AlexNet by reducing the error rate of ImageNet. This brought image recognition technologies closer to human-level capabilities. Introduced by Goodfellow et al. (2014), General Adversarial Networks (GAN) were the first major step enabling AI not only to classify data but also to create something new from it. This was the year AI began generating realistic faces, landscapes, or textures from scratch. Studies on automated plan generation and style transfer in landscape architecture gained momentum after this period. Vaswani et al. (2017), in their article "Attention Is All You Need," introduced the ‘transformer’ architecture, which laid the foundation for all modern language models today. AI has begun to understand the context and logical relationship between words in a text. AI finally reached a level of maturity where designers could directly intervene (vibe coding, prompt engineering) with the public release of ChatGPT at the end of 2022 (OpenAI, 2022).

Upon carefully investigating the peer-reviewed journals, papers and academic dissertations on multidisciplinary databases (e.g. Scopus, ScienceDirect, Web of Science, MDPI, Google Scholar, JSTOR, Springer Nature) with related keywords (e.g. AI, landscape design, landscape architecture, machine learning, deep learning, NDVI, Google Earth Engine, GIS, remote sensing), it is evident that the research on the intersection of AI and landscape architecture has developed rapidly and diversified across environmental and sociological disciplines especially over the last decade (2010-2025). Notably, AI's contributions to the field are largely limited to surveys, literature reviews, data analysis, visualization, and decision-support systems (Fernberg & Chamberlain, 2023). However, with the proliferation of fields such as deep learning (DL) (Zhou & Dong, 2024), parametric design and biomimicry (Menges & Ahlquist, 2011; Verbrugghe et al, 2023), AI applications have slowly but surely begun to play a significant role in solving current landscape-related complexities. In particular, ML-based field analyses, ecological performance assessment techniques, and scenario-based AI-supported optimization models have brought a new dimension to the literature (Vartholomaios, 2019; Tehrani et al, 2023; Zhou et al, 2025).

However, another important point frequently emphasized in international publications is that AI should not be used solely as a technological tool, but rather as an integral part of the process. It is noted that technology-driven advancements in projects that fail to consider ethical, social, and ecological dimensions can be problematic for long term sustainability (Yigitcanlar et al, 2020). Furthermore, new theoretical and applied studies in the design fields, data privacy and creative diversity are appearing in the literature; showing AI's adaptation to the discipline is becoming accepted over time (Cugurullo, 2020).

Literature reviews reveal significant gaps or 'data deserts' in the field, refering to limitation of related sources, despite the increasing number of articles and researches on the use of AI in landscape architecture (Rekittke & Hayles, 2025). The absence of these specific sources causes ML-driven models to remain universal, which results in culturally relevant information being left out. Therefore, to make AI-driven models functional within practical applications, there is a need to incorporate context-sensitive and heterogenous information.

Moreover, most existing studies are restricted to large databases from metropolitan areas in North America, Asia and Europe, failing to provide sufficient information on design problems in rural areas or developing countries (Kuffer et al, 2020; Tamiminia et al, 2020). This situation affects both transferability, sustainability and bias negatively (Ntoutsi et al, 2020). This gap in the literature should be addressed in the future studies through site-specific sampling, open-access data repositories, and regional multidisciplinary collaboration (Boeing, 2019).

Figure 2.1 : Milestones in AI.

2.2 Pioneering Applications in the Field

Due to the needs arising after the COVID-19 pandemic, global-scale studies have been prioritized since 2020. The practicality of ML has been utilized in health, planning, geographic systems, business automation, and production processes. In this context, the processing of large-scale data (e.g., locating and detecting of all buildings, green spaces, and trees in the world; creation of disaster and climate change simulations to take precautions for the future) has become more practical by training AI tools, and many studies benefiting humanity and the environment have emerged. This section discusses ‘cutting-edge’ works that combine coding, ML, and human capabilities.

In December 2025, with the GlobalBuildingAtlas (GBA) project, led by Prof. Xiao Xiang Zhu, Chair of Data Science in Earth Observation at the Technical University of Munich, the modeling of 2.75 billion buildings worldwide was opened to online access. Based on data obtained from 2019 PlanetScope satellite images, 97% of the world’s buildings were 3D modeled at Level of Detail 1 (LoDL1) (TUM, 2025). The databases used in the modeling vary according to geographic region and level of detail. OSM and Google Open Buildings were used to create building polygons (GBA Polygons), and Light Detection and Ranging (LiDAR) was used for distance measurements. Based on this data, the world map was divided into equally sized grids, creating 142.722 training samples. The system was trained using DL with 160.000 iterations. The most up-to-date data available and the highest resolution (3 m) building models were created with ML integration (Zhu et al, 2025a). This dataset, made openly accessible via GitHub, aims to be an effective tool in addressing climate adaptation, rapid urbanization, urban poverty, infrastructure problems, and natural disaster risk (Zhu et al, 2025b; Zhu-Xlab, 2025).

Similarly, in the Google Open Buildings study, all buildings in the African continent were identified using satellite imagery and U-Net pixel segmentation. Due to the scarcity of data specifically for the developing African continent, this study aims to support applications such as disaster risk analysis, population and building density mapping, and vaccination planning. The model was trained with 100.000 satellite images and 1.75 million manually-added building samples, and 516 million building footprints were generated on Google Maps (Sirko et al, 2021). The generated dataset has been published on the website (Google Research, n.d.).

The Destination Earth (DestinE) project is a flagship initiative of the European Commission that aims to create a ‘digital twin’ of the Earth using high-resolution digital data. With the support of European High Performance Computing (HPC) technology and AI, it will simulate human-nature interaction through its precise observation and simulation capabilities. Development process of the model, which began in June 2024, is expected to be completed in 2030. The aim is to achieve socio-economic and environmental sustainability goals by making it accessible not only to experts in the scientific field, but to general public (Destination Earth, 2025).

Nodemation (n8n), an open-source automation platform, is supported by AI agents to create visual workflows. It automates data flow between different applications and services without the need for complex automation and coding. By processing Internet of Things (IoT) data in real time, it can offer innovative automation applications in smart cities, such as traffic congestion detection, air quality measurement, automated street lighting, and disaster notification to authorities (n8n, 2025).

2.3 Ethics & Bias Concerns

The increasing prevalence of ML in various professions has frequently led to more discussions about ethics and bias. In particular, doubts have arisen regarding the bias and validity of the results they produce due to their integration into decision-making processes (Dehghani et al, 2024). Like any groundbreaking technological development, AI is not yet fully accepted, and its objectivity is still debatable (Suresh & Guttag, 2021). Unless trained with transparent and complete data, it may cause several problems: It generates synthetic results that lead to discrimination between communities, restricts these results on locations with higher rates of AI use; thus negatively impacts the reliability of AI (Ferrara, 2023). Therefore, global principles such as justice, transparency, and respect for human autonomy should be addressed at the level of governance mechanisms (Curto & Comim, 2023). Lin (2024) evaluated the problems of using AI in scientific research by summarizing the specific ethical goals in Large Language Models (LLM) under 5 main categories:

- **Understanding model training, fine-tuning, and output:** Understanding the production stages of AI, enabling proper source verification to eliminate biased content, and comprehending the working principles of AI models.

- **Respecting privacy, confidentiality, and copyright:** Paying attention to sensitive content, personal data protection and regulations during training.
- **Avoiding plagiarism and policy violations:** Citing relevant work, seeking regular feedback from peers and paying attention to copyright instead of directly using AI outputs in scientific studies.
- **Applying AI beneficially as compared with alternatives:** Comparing alternative outputs while acknowledging AI's algorithmic limitations, without relying solely on assumptions.
- **Using AI transparently and reproducibly:** Presenting the research process transparently, listing the used AI tools accurately, and providing all necessary documentation.

In light of these goals and proposed strategies, a crucial conclusion is reached: the training process of LLMs should encompass both the benefits and ethical risks of AI. The misuse of AI can be minimized through the implementation of necessary policies by regulatory bodies. This allows for the protection of ethical standards while encouraging innovation (Lin, 2024). Additionally, steps should be taken to promote social equality by considering norms such as religion, race/ ethnicity, color and gender to ensure individual justice. AI tools should be developed in a way that does not negatively impact human rights and freedom. Racism and discrimination, or incorporate stereotypes concerning vulnerable social groups must not be tolerated (Curto & Comim, 2023). Eliminating bias and increasing reliability is possible through the inclusiveness and diversity in experimental groups (Dehghani et al, 2024).

2.4 The AI hierarchy

The role of hierarchy within the realm of AI encompasses not only the technological development, but also clarifies the complexities involved within related terminology (Fernberg et al, 2021). The most primary level within this hierarchy consists of data pipelines, which is succeeded by advanced versions such as ML, DL, and finally complete autonomy concerning decision-making and scenario development (Figure 2.2). This encompasses a broad spectrum that runs from raw data collection like sensors to analytical and creative processes concerning decision-making, which ultimately results in innovative design scenario development via GANs (Chaillou, 2019).

This hierarchical method helps to take into account variables such as management of data, algorithm-driven decision support, ethics, and social responsibility (Fernberg & Chamberlain, 2023). The mentioned interdisciplinary grounds are required to be understood in landscape architecture for innovative design proposals (Rodrigues et al, 2023).

The technical terms used in this thesis are categorized as follows. In the following sections, the glossary of frequently used AI terms will be explained.

1. **Umbrella terms:** Artificial intelligence (AI), Machine learning (ML), Deep learning (DL),
2. **Computational architectures:** Neural networks (NNs), Generative adversarial networks (GANs), Diffusion models,
3. **Operational mechanics:** Dataset & training, Latent space,
4. **Theoretical approaches:** Actor-network theory (ANT), Human-in-the-loop (HITL) approach.

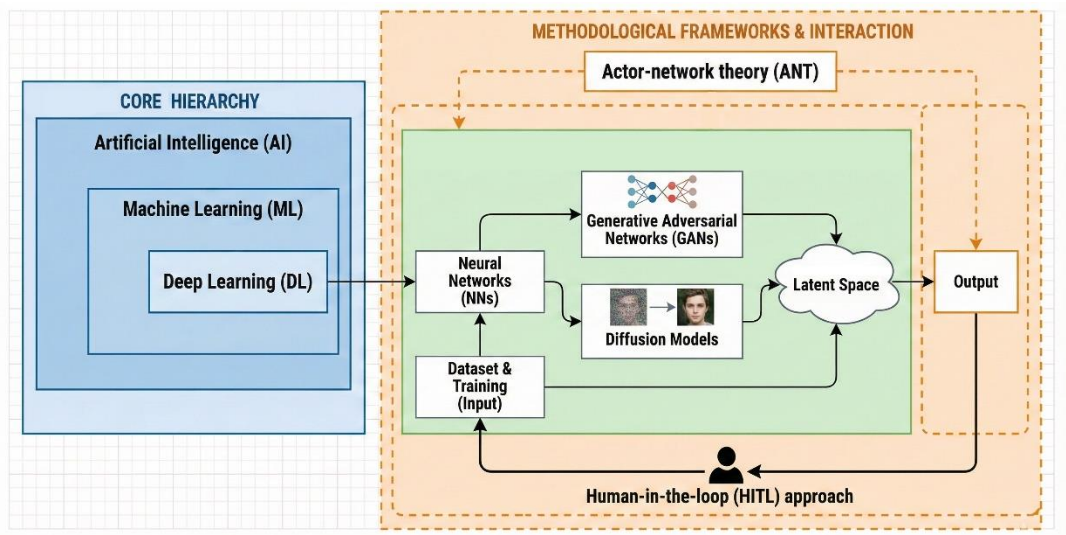

Figure 2.2 : AI hierarchy chart. Generated and edited via Nano Banana Pro.

2.4.1 Artificial intelligence (AI)

AI forms the outermost layer in the hierarchy. It encompasses all systems that use human intelligence to perform functions such as learning, problem-solving, and recognizing recurring patterns. Over time, the advancement of computers has enabled them to process large databases, giving rise to the sub-fields of ML and DL. This allows for improvements in solving more complex problems and performing multi-step tasks (Russel & Norvig, 1995).

2.4.2 Machine learning (ML)

ML is currently the most widespread method within landscape architecture for analyzing and predicting the outcomes. ML is already being applied comprehensively to vegetation analysis, generation of terrains, modeling topographic patterns, and simulating urban modifications after being trained on a huge and complex database (Shao et al, 2025). The representation of data and the precision of its inherent structure directly affect the ML process. ML is mainly divided into 3 subfields: Supervised (uses labeled data), Unsupervised (finds patterns without labeled data) and Reinforcement Learning (uses decision making algorithms and repeated actions) (Capicua, 2024).

More recently, there have been applications of diffusion models to mathematically generate distributions to represent more dynamic and time-variant sets of data (Lin et al, 2023). The analysis of ecological variables such as Normalized Difference Vegetation Index (NDVI), data mining, and generating alternative design scenarios using ML represent some examples that have shown rapid growth (Tamiminia et al, 2020).

2.4.3 Deep learning (DL)

DL provides an extra layer of prediction and correlation within data analysis by utilizing neural networks (Reichstein et al, 2019). Neural networks have indeed introduced new approaches to analyze environmental streams of data and to represent landscape attributes on a multi-layered to multi-scale level (Ma et al, 2019). On the other hand, ANN have problems like having an overfitting or so-called ‘overlearning’ function where it can memorize noises rather than extracting patterns (Maxwell et al, 2021).

Generative adversarial networks (GAN) offer unique opportunities for shaping, simulation, and scenario design. GANs synthesize optimal landscape variants that can be aesthetically pleasing and ecologically optimal and also involve data augmentation and database expansion (Liu et al, 2024). The disadvantage with GAN is that they require massive amounts of high-quality and precise database information and also a considerable amount of computing resources. This can also prove to be a very time-consuming activity. Models such as these can also learn biases present within training sets, raising ethical issues (Mehrabi et al, 2021).

A next-generation application with proper training can impact landscape architecture, because it can offer a tool which can combine human knowledge regarding remote sensing and design process (Shahtahmassebi et al, 2020), can be traceable via performance measurement, and can present both scientific and practical solutions.

2.4.4 Neural networks (NNs)

Artificial neural networks (ANN) and deep neural networks (DNN) are multi-layered AI technologies modeled after the ‘human brain’. Weights and non-linear processes are applied to input information within each ‘neuron’, which transmits information to other layers (Castelvecchi, 2016). The use of NN is advantageous within landscape and urban studies concerning the assessment of complex information, enabling the extraction of high-level features through successive hidden layers. In the context of landscape and urban studies, it is capable of processing more than one parameter simultaneously, such as climatic factors, topographic variables and human movements.

In recent years, specialized neural network types specifically for analyzing visual data such as convolutional neural networks (CNNs) have significantly increased success rates in remote sensing, NDVI analysis, and extracting spatial patterns. However, there is a big difference on how humans and DNNs recognize objects (Nguyen et al, 2015). While NNs identify patterns based on pixel-level statistical features, they often lack the contextual and semantic understanding inherent to human expertise. This cognitive divergence underscores the necessity of the Human-Machine Synergy proposed in this study, where the analytical speed of NNs is balanced by the expert's contextual judgment to ensure the production of meaningful architectural solutions.

2.4.5 Generative adversarial networks (GANs)

First proposed by Goodfellow et al. (2014) as ‘generative adversarial nets’, GAN is a significantly innovative framework used in architectural design for generating original images, displaying alternative scenarios, and boosting data augmentation. GANs consist of two neural networks: a ‘generator’ that synthesizes synthetic data samples from random noise, and a ‘discriminator’ that functions as an evaluator to distinguish between authentic and generated samples (Goodfellow et al, 2014). This iterative competition drives the model to produce landscape scenarios that are not mere copies of existing data, but high-fidelity representations of spatial patterns.

Recent advancements such as StyleGAN, CycleGAN and BigGAN have further refined this process, allowing for the generation of complex ecological and aesthetic scenarios that align with existing site’s characteristics. Still, it should be noted that the contextual relevance and sustainability of generated images via GAN depend on human expert interventions, reinforcing the necessity of a human-machine collaboration to ensure that generated scenarios meet real-world requirements. (Tokgöz & Altın, 2025).

2.4.6 Diffusion models

Diffusion models are among the newest and most potent tools within the realm of generative AI (Lin et al, 2023). Essentially, they are a learning technique that gradually build data samples by adding information from the noise. Unlike the competitive nature of GANs, diffusion models operate through a dual-phase process: a forward phase that introduces Gaussian noise to data until it becomes unrecognizable, and a reverse denoising phase where the model learns to recover structural information from the noise to synthesize new samples (Croitoru et al, 2022). In landscape architecture, diffusion models can be used both to simulate natural phenomena and to generate model spatial patterns. For example, how soil moisture, vegetation, or urban green spaces can transform over time can be realistically simulated with these models (Leinonen et al, 2023; Ling et al, 2024).

Tools such as Midjourney, ChatGPT, Google Imagen and Stable Diffusion (Fahmy et al, 2024; He et al, 2025), offer new possibilities for both text-to-image generation and landscape transformation scenarios. Diffusion models represent the contemporary frontier of GenAI, offering a more stable and high-fidelity alternative to GANs (Dhariwal & Nichol, 2021). However, fine-tuning the model for novel cases requires very high computer graphics and computational knowledge, making them less accessible to individual users (Yang et al, 2023). Additionally, diffusion models struggle with creating realistically applicable designs (Gattupalli, 2022; Ploennigs & Berger, 2023). Therefore, as hypothesized in this study, the true potential of diffusion models in landscape architecture is realized only when they are integrated into a collaborative workflow that utilizes human-led prompts and data-based validation to ensure ecological and technical viability.

2.4.7 Dataset & training

Forming datasets and the training process are very crucial to the success and generalization ability of ML (Dubuc et al, 2020). Specific to the use of AI in landscape architecture, it is crucial to first establish a multilayered and heterogeneous dataset: satellite imagery (e.g. NDVI, elevation maps), topographic data and climatic measurements collected manually. The data included in the training process enables the model to recognize realistic, multidimensional patterns and generate more authentic scenarios. This ‘big data’ can include geospatial (GIS), environmental (climate, water, soil, pollution levels), plant & biodiversity (species distribution, growth patterns), and architectural data (CAD drawings, blueprints, urban transformation) (Wäldchen & Mäder, 2017).

In recent years, the literature has particularly emphasized the risk of a data desert -the problem of results being universal, superficial, and disconnected from the local context due to the scarcity of authentic datasets. As such, local data collection and open-access AI data repositories have become a priority area of research in current AI applications. The meticulous preparation and processing of databases is crucial for both model accuracy and the applicability of new design alternatives (Sambasivan et al, 2021).

2.4.8 Latent space

The latent space is a mathematical construct within both ML and DL, whereby significant patterns and relationships are hidden within this space. The complexities involved within landscape design - such as environmental relationships, plant dispersions, water flows, and microclimate - are not directly interpretable using raw data (Reichstein et al, 2019). The idea of ‘latent space’ helps to incorporate analyzed relationships and possible patterns concerning unseen information. Using latent space, these complexities are uncovered by AI, whereby they assess similarities and differences statistically.

The latent space is indeed part of the black box, but is a ‘representation of data’ within a model, not the model per se. The modern algorithm approaches such as GAN and autoencoders make very good use of latent space, whereby they ascertain novel design options, such as new ecological conditions, using micropatterns within structure (Uzun et al, 2020).

2.4.9 Actor-network theory (ANT)

ANT provides a methodological tool that studies how different actors such as developers, users, tools, algorithms, and software interact within a network during the design of landscapes and environments with the use of AI. Conventional frameworks tend to describe technology as an independent entity, but with the use of the ANT, there is a system whereby human beings and AI are equally active entities (Sayes, 2014).

In this context, it focuses on how this algorithmic model needs to interface with contextual, cultural, and societal factors, specifically within design examples related to site-specific design. The theory attempts to describe how sustainability and acceptability can be achieved by facilitating a transition from social reality to the technical aspects of design.

Concepts in ANT which can prove to be relevant to research on design within the realm of AI include translation (which involves negotiation and role allocation within a network), inscription (which entails encoding human intentions into technological devices), and exploring human and non-human agency on an equal footing.

2.4.10 Human-in-the-loop (HITL) approach

In contrast, HITL incorporates both the analysis and diversity of data that make up one of the strengths present within AI models and human experience and intuitive decision-making processes. HITL incorporates human oversight and/or correction of results generated by AI, such as human supervisors and/or human oracles, while AI take care of more routine and scalable work (Shneiderman, 2020). The human control framework in HITL considers human discernment to be more paramount with AI being supplementary (Holzinger, 2016).

In landscape architecture, cyclical processes where AI goes beyond pure automation and receive continuous feedback from the architect are highly valued. In most projects, an expert steps in, following the initial suggestions of AI systems, guiding the final decisions with their preferences, interpretations, and cultural background (Bernal et al, 2015). This overcomes AI's black box limitations and enables both ethical and creative diversity. The term ‘black box’ here refers to systems whose internal decision-making processes or mechanisms are not visible or understandable to users, who can only observe inputs and outputs (Castelvecchi, 2016; Adadi & Berrada, 2018). The HITL model greatly improves success rates in most applications, particularly in complex design, ecological planning, and sustainable scenario development.

3. METHODOLOGY

3.1 Aims & Objectives

The open-access generative AI tools work by pattern recognition and probabilistic synthesis. With the help of these tools, users who do not have professional training in landscape architecture -as well as in creative fields such as advertising, marketing, product design, graphic design, gaming, animation & illustration, urban design, interior design, web design, photography & video editing- are now in a position to produce visuals for both independent and professional purposes. Since these tools only use the accessible data and cannot carry out the whole process by identifying the needs and producing context-sensitive design solutions, which constitute the most important criteria, the outcomes are inadequate in terms of the functionality and applicability. This lack of technical grounding may lead to ecologically unsustainable outcomes and jeopardize the integrity of sustainable landscape planning.

This study aims to investigate how AI integration in the discipline of landscape architecture can extend beyond visualization to include data-driven analysis and design processes. While current studies demonstrate the potential of GenAI tools in creativity and ideation processes, the synthesis of these tools with the technical and scientific requirements of landscape architecture (e.g. geographical data and ecological accuracy) is still a developing field. Examining relevant studies in the literature, it was seen that similar GenAI-based studies were held. For instance, in their study, Paananen et al. (2023) tested the ideation and creativity of popular text-to-image generators such as Midjourney, DALL-E, and Stable Diffusion and determined the potentials and limitations of these tools through surveys and group interviews. Similarly, Yildirim (2023) compared the visual and functional capacity of Leonardo AI, Midjourney, and DALL-E in the field of landscape architecture via 6 different prompts, and indicated the strengths and weaknesses of the tools. Kim & Lee (2024) compared the ability of Midjourney, Synthesys X, and Playground AI to distinguish landscape elements by leveraging ChatGPT's prompt engineering; while Thampanichwat et al. (2025)

compared the 'mindful' design capabilities of Midjourney, DALL-E, and Stable Diffusion.

The presented research is grounded on the crucial point: AI and related learning models can be a powerful complement to traditional HITL methods in the sustainability, ecological performance, and creative diversity domains of landscape architecture. AI and DL models, especially those developed on a data-grounded manner, are expected to yield more holistic and adaptable results in site-specific analysis and problem detection.

Furthermore, the relevance and importance of human knowledge within decision-making processes that involve ethics, authenticity, and social responsibility should never be negated, and this should impact how applications are developed using AI in an open, human-centered, and transparent manner. Ultimately, while AI is a key tool, a collaborative model where final decisions are made in collaboration with a human expert is assumed to be the most effective path forward in academic and professional settings. In the light of these, two main research questions arise:

- How can a multi-stage HITL workflow be structured to transform raw open-access spatial data into context-sensitive site analyses?
- As landscape architects, can we consciously shape the learning process of AI and contribute to its efficiency to reduce our workload?

3.2 Building the Workflow

In this context, the research is structured around a three-phase workflow centered on the ANT and HITL approach between the architecture's cognitive processes and the machine's processing power. The aim here is to transform AI into a scientifically verifiable analysis and concept development partner without losing the architect's critical perspective. The steps were followed for the workflow:

- In the first phase (Section 3.4), the ability of AI to create feasible concepts was tested. This was to test AI's capacity to distinguish elements and respond to feedback. On this occasion, the visual design capabilities of popular generative AI (GenAI) tools (Midjourney, ArchiVinci, ChatGPT) were measured via prompt engineering. To ensure fairness in comparison, the same prompts and locations were used for each tool.

- In the second phase (Section 3.5), it was decided to continue with ChatGPT due to its ability to communicate interactively and evaluate user feedback. In this phase, AI-training process was divided into 3 stages: Site analysis with prompt engineering (Section 3.5.1), site analysis with external tool assisting (Section 3.5.2), and site analysis with datasets (Section 3.5.3). Three urban green spaces from Turkey, USA and Singapore were selected for training, and ChatGPT was trained to perform geographical analyses of these areas using open sources. The integration of the architect's knowledge and critical perspective into the ChatGPT training process was aimed at obtaining scientifically verifiable analysis outputs. Another study on 3-staged model training by He et al. (2025) addresses the collaboration between humans and GenAI in urban design.
- In the final phase (Results Section), the resulting visual outputs were collected into a dataset and shared with ChatGPT. Finally, the site analysis and output qualities were compared (Table 4.1). The validity of the outputs was evaluated via GIS, OSM, Copernicus and Felt databases.

The following sections (Sections 3.3-3.6) clarify all the phases and evaluate the study from an ethical standpoint.

3.3 Establishing the Medium

The integration of AI into landscape architecture has become more widespread over the last decade (Fernberg & Chamberlain, 2023). While established architectural software has increasingly incorporated AI-driven plugins, standalone GenAI tools have gained prominence due to their democratized accessibility. Unlike commercial architectural software with AI plugins, these tools are free-of-charge to a certain degree (offering foundational capabilities with certain usage or resolution constraints), requiring minimal specialized computational expertise from the designer.

Currently, text-to-image platforms such as OpenAI’s ChatGPT, Google Gemini, and Stable Diffusion, alongside discipline-specific tools like ArchiVinci, are extensively utilized in conceptual design to augment creativity and produce rapid visual prototypes. Additionally, platforms like Midjourney, Aino World, and Adobe Firefly primarily rely on subscription-based models to provide high-fidelity, editable outputs (Figure 3.1). For this research, accessibility, prompt responsiveness, trainability, editability, and high output resolution were prioritized. Therefore Midjourney, Archivinci, and ChatGPT's design skills were tested prior to training for site analysis. This selection represents a diverse spectrum of AI capabilities, ranging from high-end aesthetic synthesis to structural architectural logic and multimodal reasoning, essential for a comprehensive site analysis workflow.

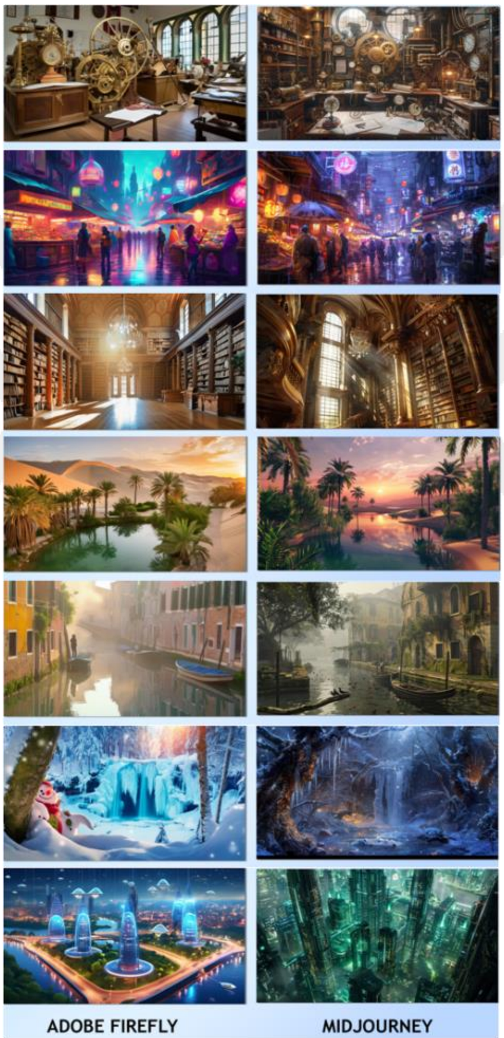

Figure 3.1 : Comparison of text-to-image AI generated visuals from the same prompts, Adobe Firefly (left) and Midjourney (right). Derived from tomsguide.com (Morrison, 2024).

3.3.1 Midjourney

Midjourney has released 10 distinct model variants since its first launch in 2022 and has managed to reach a level of producing incredibly realistic visuals within a short time. In 2024, Midjourney (v6) introduced advanced 'In-painting' and 'Vary Region' features. Released in April 3, 2025, v7 focused on user-specific personalization algorithms, allowing the model to learn and mimic a designer's unique aesthetic style (Midjourney, 2025).

The first step was to test Midjourney's design capabilities. To achieve the best result, the prompt had to be detailed. ChatGPT was used for improving the prompts throughout the process. It was given the task of 'thinking like a professional landscape architect', and asked to write a precise prompt for Midjourney to produce a practically applicable design. First, it gave step-by-step instructions for prompt creation and asked for specific information such as location, climate, design goals, functions, main elements, furnitures, materials and aesthetic preferences (Figure 3.2).

"...Create a landscape design for a coastal park in a Mediterranean climate. The park is located on a gently sloping terrain by the seaside. The design should be sustainable, seamlessly integrated with nature, relaxing, and attractive to the public.

Include the following elements:
- Wide lawn areas
- Colorful flower beds
- Water features such as a small pond or fountain
- Wooden walkways and bridges
- Seating areas with benches and picnic tables
- Shaded areas with trees and pergolas
- Natural stone pathways and steps

The design style should be natural and rustic, featuring organic shapes, local vegetation, wooden and stone materials, and a natural color palette.

Additionally, incorporate the following functional areas:
- A children's playground made from natural materials
- A small café or tea house with a wooden structure
- Walking and cycling paths
- An outdoor event space with a grass amphitheater"

Figure 3.2 : Example prompt generated by ChatGPT-4o.

The following steps were done by first giving Midjourney an image of Üsküdar Square as a reference (Figure 3.3), then adding the prompt *"Create a landscape design for Üsküdar Square in Istanbul. The real site should not be changed. Keep the existing features of the square & its surroundings. Do not change the context or the real Istanbul view. The design should prioritize pedestrians, providing safe and pleasant walking spaces while enhancing the aesthetic and functional aspects of the square. The area should integrate with the historical and cultural context of Üsküdar. The* *design style should be modern with traditional touches, featuring clean lines, natural materials like stone and wood, and a color palette that complements the historical buildings in the area. Ensure the design is inclusive and accessible for all ages and abilities".*

3.3.2 ArchiVinci

First released in 2024, ArchiVinci is a credit-based AI-rendering platform that we frequently encounter online. It generates 3D interior and exterior models, draws masterplans and enhances existing renders based on prompts and various architectural styles. It aims to minimize the rendering time for the users who want fast and high-quality models. It allows the user to choose what type of rendering (Interior, Exterior, Masterplan, etc.) and the type of structure (Building Complex, Residential, Commercial, etc.) they request. On the specialized front, ArchiVinci transitioned from a simple rendering skin to a more structurally aware tool in 2025, incorporating better BIM-to-Image alignment and material-specific depth mapping, which enhanced its reliability for technical site simulations (ArchiVinci, 2025). To test it, the same reference image and prompt were used.

3.3.3 ChatGPT

Released in 2021 and named after the famous painter Salvador Dali and Pixar movie "WALL-E", DALL-E was the visualization product of OpenAI's ChatGPT (Dunn, 2021). It is also one of the pioneers of text-to-image softwares. While the first version was mostly used for trending social media posts and generating cartoonish images, DALL-E 2 (released in 2022), and DALL-E 3 (released in 2023), trained to be more context-aware by filling in the blanks in a prompt, filtering out the biased & harmful content and following the latest trends (Singh, 2022).

However, the real turning point for the methodological framework of this study was the direct integration of DALL-E 3 into ChatGPT in 2023. This integration brought with it several critical advantages. With this update, ChatGPT acts as an interface to understand the designer's intent, rather than directly visualizing. The designer can refine complex landscape scenarios by discussing them with ChatGPT, and the AI translates this dialogue into a visual command. The visualization power of DALL-E, combined with ChatGPT's logical reasoning capabilities, allows for the inclusion of not only the aesthetic aspects but also the functional requirements (spatial hierarchy, material texture, etc.) in the modeling process.

3.4 Testing Midjourney, ArchiVinci and ChatGPT's Visual Generations

Midjourney is unable to re-design an existing place or a building without altering its geographical features and environment. In other words, it only creates various imaginary places that contain some of the features we requested in the prompt, but these images usually contain irrational elements. To clarify the issue, it was given a reference site image (Fig. 3.3) and asked to re-design the site (Fig. 3.4).

Figure 3.3 : Reference photo of Üsküdar Square (IHA, 2020).

Figure 3.4 : Designs generated by Midjourney v6.0.

Although its visualization capabilities are higher compared to other image tools, Midjourney (v6-v7) lacks the reasoning ability and its interface is non-trainable. Furthermore, the fact that it is a paid tool made it impractical to continue working with it for the study. It was deemed suitable only for enhancing creativity and concept designing. Considering the resulting images (Figure 3.4), the following findings were obtained regarding Midjourney's design process:

- Midjourney cannot yield the best results based solely on the information in the prompt unless a reference image is provided. It can produce images that contain the requested features, but it cannot place the actual sites in these images.
- When a reference image (Figure 3.3) is provided and the location of the image is indicated in the prompt, it can distinguish elements such as houses, mosques, bridges, trees and plants in the reference image. However, instead of keeping the original elements as they are in the resulting image, it creates different building and plant images. So once again, a nonexistent place appears. When the resulting image is requested to be recreated, it creates completely independent images each time, unable to edit or add to the previous image.
- The final visuals cannot be improved in parallel with the quality of the reference image and the prompt.

It is observable that Midjourney is still unable to analyze the geographical data of an existing place and re-design this area in a feasible way. Nevertheless, it excels at generating limitless conceptual ideas (Paananen et al, 2024). This, in fact, could be an opportunity that allows us to expand our imagination while designing.

For the next step, choosing the landscaping mode, the same reference image was uploaded (Figure 3.3) to the ArchiVinci website and typed in the same prompt, having to summarize it -since ArchiVinci interestingly suggests to keep it short for best results. When the prompt was kept long, it resulted in being irrelevant to the reference (Figure 3.5, bottom right). On the first 3 trials (Figure 3.5), ArchiVinci did not change the actual landform, as specifically stated in the prompt. Instead, it turned existing buildings into trees or added a complex of imaginary elements to the square. This feature is quite different from the working principle of Midjourney. Archivinci keeps the boundaries that should not be altered, and adds a new design on top of them. If

Midjourney's realistic high-quality visualisation was combined with ArchiVinci's discriminatory feature, a very prominent AI tool could be developed.

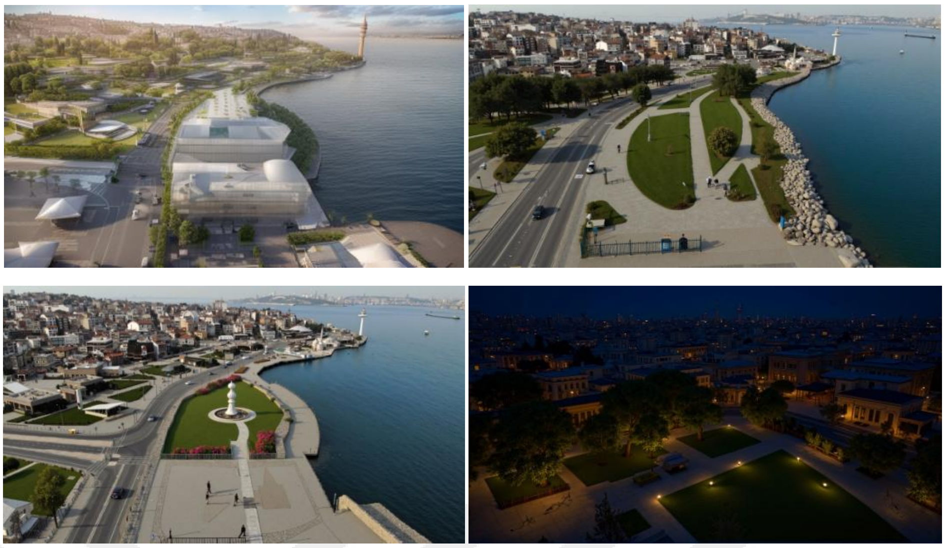

Figure 3.5 : Designs generated by ArchiVinci (2024 vs. 2025).

Lastly, ChatGPT was the third tool to put into test. As seen in the result images (Figure 3.6), it did not use the reference image (Fig. 3.3). In the earlier version, it created an imaginary animated-style visual of Istanbul based only on some details in the visual and the prompt (Figure 3.6, left). However, in the latest version, it made the landscape look more realistic, and visually closer to the features of the existing site (Figure 3.6, right).

Figure 3.6 : Designs generated by ChatGPT (2024 vs. 2025).

Figure 3.7 : Designs for Kültürpark, generated by ChatGPT (2024 vs. 2025).

After testing the aforementioned AI tools, it was decided that Midjourney and ArchiVinci were not suitable for further training, beyond generating high-fidelity aesthetic visuals based on references and prompts. Therefore, ChatGPT was chosen for the training phase, due to its multimodal reasoning capabilities and its receptiveness to iterative user feedback. ChatGPT allows for 'conversational fine-tuning', where technical parameters and site-specific constraints can be refined through a continuous dialogue, making it the most suitable partner for developing a synergistic intelligence. In other words, the main reason ChatGPT was chosen for this study is not only because it produces a visual output, but also because it can synthesize the technical knowledge, analysis data, and design criteria to guide its visualization engines in a more conscious way (Table 3.1).

Table 3.1 : Comparative table of AI tools (2024-2025). Red = low, yellow = medium, green = high.

AI Tool	Version	Strengths/ Weaknesses	Training Approach	Data Integration	Outcomes	Outcome Quality	Image Quality	Applicability	Reliability	Accessibility	Average
Midjourney	v6 (2024)	Editable, high-resolution image production / Inability to grasp context and scale	Prompt engineering	Prompts, reference images	Generated images	High: Very good conceptual design	High: Realistic image quality	Low: Irrational elements, lack of scale	Low: Weak processing of site-specific data, random generation	Low: Closed interface, untrainable, paid access	Medium
Midjourney	v7 (2025)	Editable, high-resolution image production / Inability to grasp context and scale	Prompt engineering	Prompts, reference images	Generated images	High: Very good conceptual design	High: Realistic image quality	Medium: Better at establishing relationship between spatial elements	Low: Weak processing of site-specific data, random generation	Low: Closed interface, untrainable, paid access	Medium
ArchiVinci	2.0 (2024)	Editable conceptual production / Inability to grasp context and scale	Prompt engineering	Prompts, reference images	Generated images	Low: Poor conceptual design	Medium: Good image quality	Low: Irrational elements, lack of scale	Low: Weak processing of site-specific data, random generation	Medium: Closed interface, untrainable, limited access	Low
ArchiVinci	2.1 (2025)	Editable, high-resolution conceptual production / Inability to grasp context and scale	Prompt engineering	Prompts, reference images	Generated images	Medium: Good conceptual design	Medium: Good image quality	Medium: Better at establishing relationship between spatial elements	Low: Weak processing of site-specific data, random generation	Medium: Closed interface, untrainable, limited access	Medium
ChatGPT	GPT-4o, DALL-E 3 (2024)	Editable, logical, context-related concept and text production / Inability to produce viable designs	Prompt engineering, Python coding	Prompts, reference images, external open source data	Site analysis diagrams, recognizing context, establishing cause-and-effect relationships	High: Very good conceptual design and site analysis data	Medium: Good image quality	High: Accurate environmental analyses (post-training)	High: Access to reliable sources, very good evaluation ability	High: Open interface, trainable, limited access	High
ChatGPT	GPT-5, GPT Image (2025)	Editable, logical, context-related concept and text production / Inability to produce viable designs	Prompt engineering, Python coding	Prompts, reference images, external open source data	Site analysis diagrams, recognizing context, establishing cause-and-effect relationships	High: Very good conceptual design and site analysis data	Medium: Good image quality	High: Accurate environmental analyses (post-training)	High: Access to reliable sources, very good evaluation ability	High: Open interface, trainable, limited access	High

3.5 Steps for AI-Powered Analysis Process

To provide a scientifically grounded and context-sensitive site analysis, a multi-layered analytical framework was established, integrating diverse data sources and computational tools. The ecological dimension of the site was quantified through NDVI analysis, utilizing multi-spectral satellite imagery processed via Google Earth Engine (GEE). This approach allowed for the precise measurement of vegetative health and biomass density, providing a quantifiable biological baseline that generic AI tools typically lack. To ensure the design remains anchored within its urban fabric, OpenStreetMap (OSM) was utilized to extract vector data for landuse and building function analyses. These steps were critical for decoding the socio-spatial syntax of the area and ensuring that proposed interventions respect the functional connectivity of the city.

The technical execution of these analyses relied on custom scripts and GIS to ensure computational rigor and to eliminate the subjectivity often associated with manual site surveys. By automating the data extraction process, the study offers a repeatable medium. Furthermore, Copernicus and Felt were employed as a dynamic, cloud-based GIS interface to facilitate the visualization and collaborative validation of these complex datasets. This ensures evidence-based workflow where AI-generated scenarios are continuously cross referenced against real-world environmental and infrastructural constraints (Table 3.2).

Considering its deep-rooted history, wide variety of plant species and high number of daily visitors (KTB, 2024), Izmir Kültürpark was chosen as the initial study area and the location was not changed until all the analysis results were successfully obtained. After Kültürpark’s site analyses were gathered, Central Park, New York and Gardens by the Bay, Singapore projects were added and the test procedure was repeated. The training was planned and categorized under 3 main steps: with prompt-engineering, with external tools & scripting, and with datasets (Figure 3.8).

Table 3.2 : Selection criterias for the medium.

Category	Medium	Data Type	Accessibility	Cost	Status	Rationale for Selection / Elimination
Generative AI	Midjourney	Visual Generation (Pixels)	Subscription	Paid	ELIMINATED	Lacks geospatial coordinates and spectral data, focuses on aesthetics rather than site assessment.
Architectural AI	ArchiVinci	Conceptual Render	Credit-based	Paid	ELIMINATED	Presentation-oriented, unable to measure ecological processes or calculate health indices.
Analytical GIS & Remote Sensing	ArcGIS Pro	Numerical Vector / Raster	License	Free (Academic)	SELECTED	Provides full user control over attribute classification, offers the highest spatial precision for site assessment.
Algorithmic Data Processing	ChatGPT + API + Libraries + Python	Geospatial Big Data	Open Access	Free	SELECTED	Minimizes human bias, processes thousands of pixels instantly with high computational efficiency.
Cloud-based GIS Hybrids	Copernicus, GEE, OSM, NASA, Felt	Interactive Web	Open Access	Free	SELECTED	Offers rapid visualization and European Space Agency (ESA)-standard data validation.

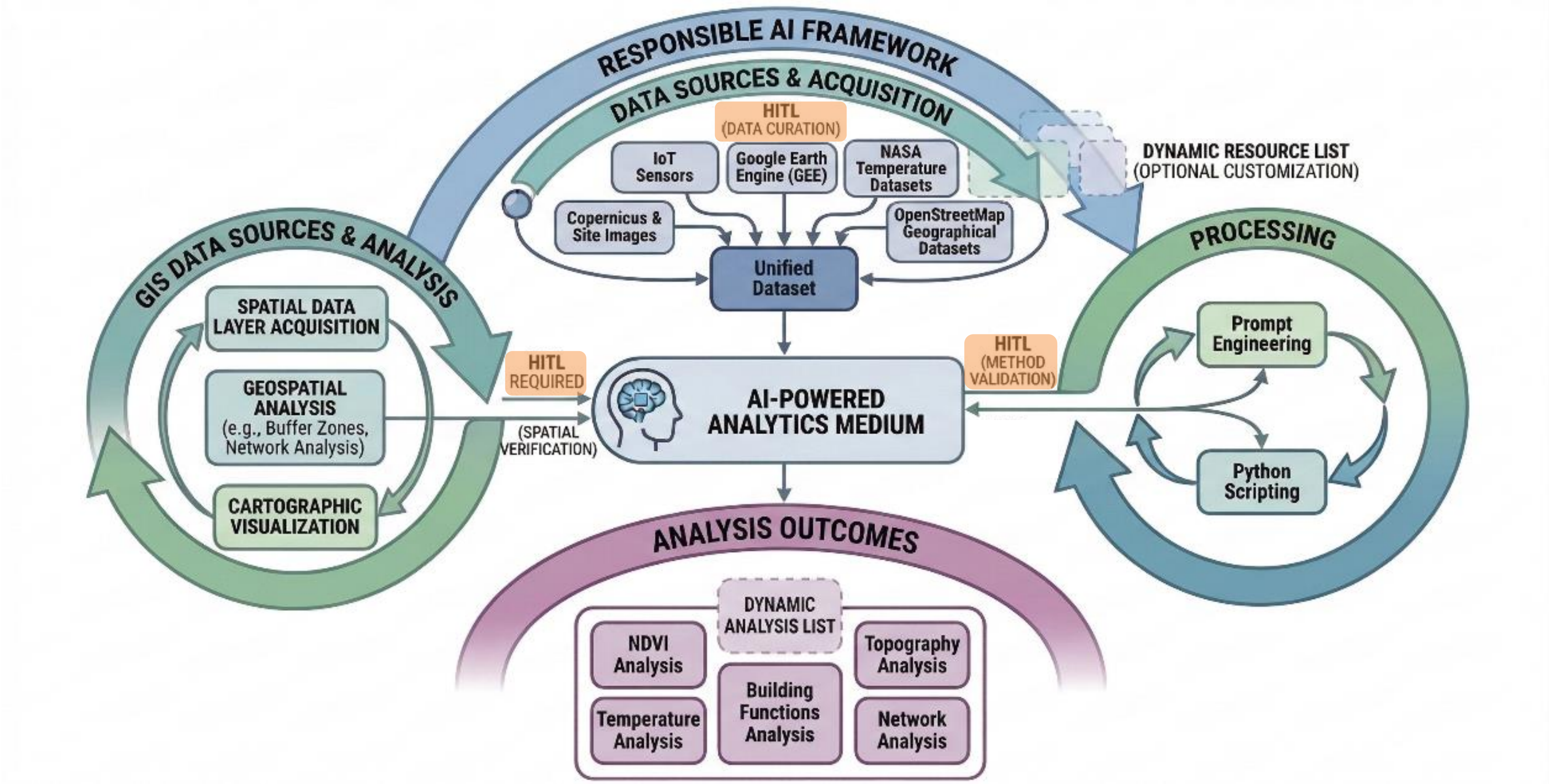

Figure 3.8 : Workflow diagram. Generated and edited via Nano Banana Pro (2025).

3.5.1 Site analysis with prompt engineering

On the first trial, ChatGPT was given a landscape architect's job description and the task of thinking like one via the prompt: *Landscape architecture is an interdisciplinary profession that plans and designs natural and man-made environments in an aesthetic, ecological, and functional whole. Landscape architects develop integrated solutions for both natural and built environments, taking into account topography, water resources, vegetation, infrastructure, and human use. The fundamental aim of this discipline is to provide people with aesthetically pleasing and functional living spaces while ensuring ecological sustainability* (Van Den Brink et al, 2022). Starting with the coordinates of Kültürpark (38.4259, 27.1428), it was asked if it could gather the latest information of the location, which it had no direct access to. Therefore, it was also provided with site images (Figure 3.9) and geographical data manually extracted from Copernicus Browser (Figure 3.10) to perform site analyses. Based on these analyses, it was asked to detect the problems and analyse the site. The analysis output mentioned in the Results section, was unsatisfactory in terms of provability and applicability (Fig. 4.1). Therefore, prompt-engineering was found to be insufficient for the ongoing steps.

Figure 3.9 : Site images. Derived from SPO (2022), OpenStreetMap (2024) and KTB (2024).

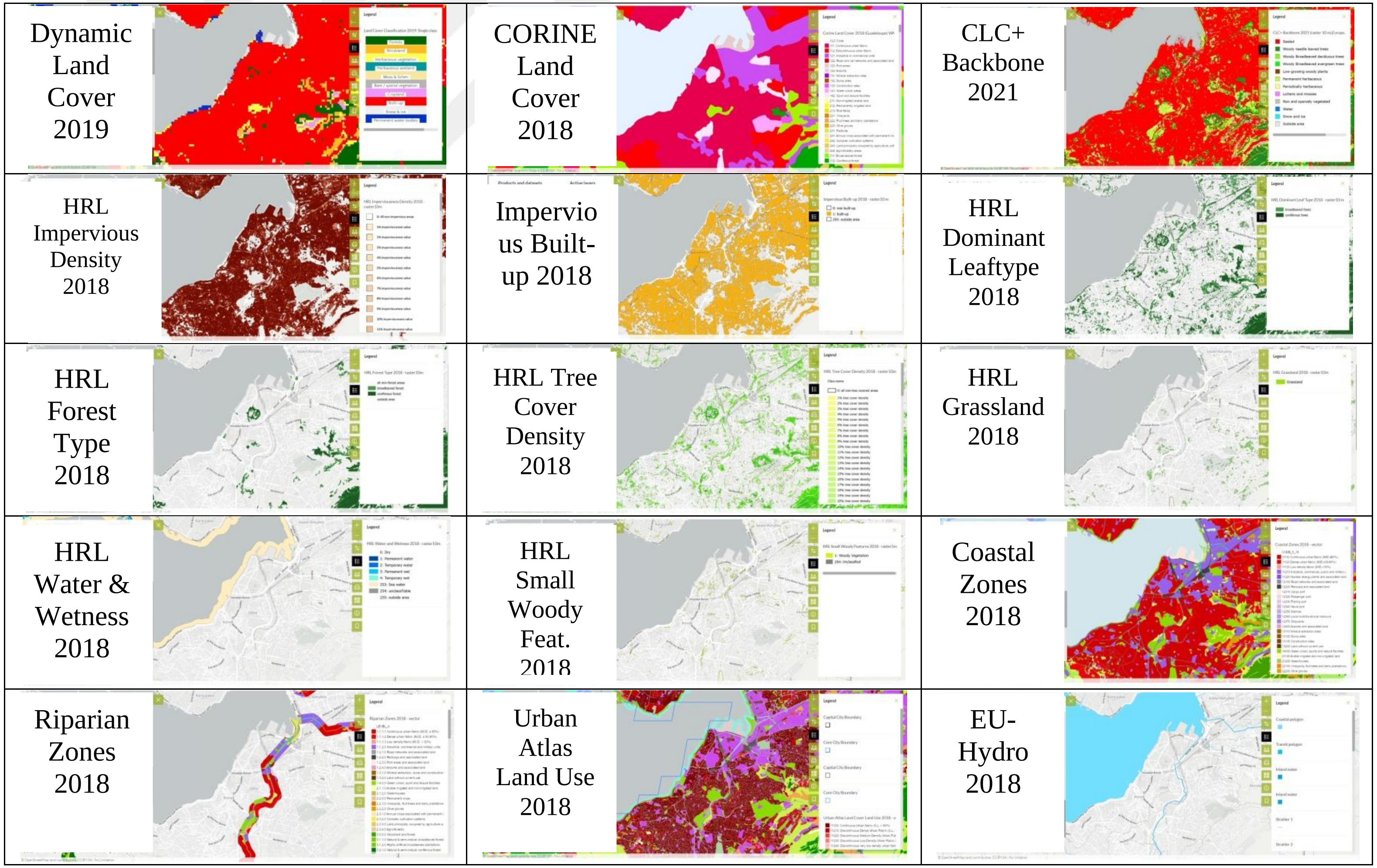

Figure 3.10 : The site’s manually-collected geographical data. Derived from Copernicus Browser (Er & Bozkurt, 2025).

3.5.2 Site analysis with external tool assisting

To improve the quality of analysis and make these outputs usable, ChatGPT was asked which open sources it should access for best results. In response, it stated that it must access data from Google Earth Engine (GEE), the National Aeronautics and Space Administration (NASA), and OpenStreetMap (OSM); adding that it could not access this data automatically, but could retrieve it itself if a user executed a code. At this critical stage, ‘vibe coding’ -a programming method by communicating with AI- was preferred. Today, vibe coding encourages programming in all disciplines without requiring expertise, shortens the coding process by 80-90% compared to traditional methods, and minimizes technical errors in the production phase (Sarkar & Drosos, 2025). In this study, the user is not a programmer proficient in Python, but rather a landscape architect using Python as an analytical tool. ChatGPT guides the user through every step of the code generation process.

Free memberships for academic research were created and authentication was performed on platforms to access open sources. Data flow from NASA (temperature data), OSM (spatial data), and GEE (Sentinel-2 satellite imagery) was established via the Application Programming Interface (API). The APIs were then integrated into the Python code. Before running the code, the following libraries were installed via Windows Command Prompt (CMD): *matplotlib* for graphic and data visualization, *numpy* for numerical calculations, *geemap* for mapping, *earthengine-api* for the GEE API, *folium* for web-based interactive mapping, *folium.plugins* for distance measurements and legends, *json* for reading GEE files, *pandas* for reading tabular data, *osmnx* for reading OSM data, and *selenium* for automatic data retrieval from platforms such as Copernicus Browser (e.g. *pip install matplotlib numpy pandas folium geemap earthengine-api osmnx selenium…*). Since all the codes take up many pages, a small excerpt from a single code is included in this study as an example (Figure 3.11).

A .json file was downloaded to the target folder to define the boundaries of our analyses and tell the satellite systems what to do. The coordinates of the study area (Kültürpark, Central Park, Gardens by the Bay) were also integrated into the code. For each area, the most up-to-date & cloudless Sentinel-2 satellite image from GEE, and current land use data from OSM were automatically retrieved. Screenshots from OSM were downloaded for comparison of land use analyses obtained by the code, .tiff files from Copernicus were downloaded for comparison of NDVI analyses, and .png graphs from NASA were downloaded for comparison of temperature data. The visuals were stored both as interactive maps in HTML format and high-resolution maps in PNG format.

All outputs were compared with GIS analyses, using regional .shp files. At the same time, web-based interactive maps processed with OSM data were downloaded from Felt. To compare the overlap ratio of all maps, coloring-legend properties, study area sizes, and resolution values were incorporated into the analysis code. The academic reliability, accessibility, and up-to-date status of these open sources are of great importance for the consistency of the study. AI-supported Python scripting (OSM, GEE, NASA API), ArcGIS Pro, Copernicus, and Felt were used to obtain images, which were then compared according to analysis types (Appendix M). The spatial overlap of the resulting graphs was calculated using the Intersection over Union (IoU) method, by overlaying pixels.

```python
import osmnx as ox
import geopandas as gpd
import pandas as pd
from shapely.geometry import box, Point
import folium
from folium import plugins
import os
import webbrowser
import time
from datetime import datetime
from selenium import webdriver
from webdriver_manager.chrome import ChromeDriverManager
from selenium.webdriver.chrome.service import Service

# ==========================================================================
# 1. CONFIGURATION (MODULAR PARAMETERS)
# ==========================================================================

OUTPUT_DIRECTORY =

# --- Spatial Parameters ---
TARGET_LAT = 38.4259  # Izmir Kulturpark Center Latitude
TARGET_LON = 27.1428  # Izmir Kulturpark Center Longitude
AREA_RADIUS_METERS = 1000  # 1000m radius -> exactly 2x2km bounding box

current_date = datetime.now().strftime('%Y-%m-%d')

# --- Color Palettes (Professional GIS Standards) ---
COLOR_PALETTES = {
    'Roads': {
        'Vehicular': '#404040',   # Dark Gray
        'Pedestrian': '#4CAF50',  # Green
        'Bicycle': '#FF9800',     # Orange
        'Railway': '#E91E63',     # Pink/Magenta
        'Other': '#B0BEC5'        # Light Gray
```

Figure 3.11 : Part of a Python code for OSM-grounded spatial analysis. Derived from ChatGPT.

3.5.3 Site analysis with datasets

A dataset was created using all the outputs obtained in sections 3.5.1 and 3.5.2 and fed into ChatGPT. It was then asked to generate graphs that evaluate the written and visual data using this dataset. The outcomes are added to the 'Results' section (Section 4).

4. RESULTS

Outcomes of Training ChatGPT with Prompts, Tool Assisting and Dataset

With the help of prompt engineering (Section 3.5.1), ChatGPT was quite capable of analyzing given images and generating solutions in text format. However, the visuals it generated were completely independent of the study area. When it was asked to visualize the analyses, it created various random graphs based on assumptions (Figure 4.1), while stating its need of reliable data and documents. The results prove that there is still much ground to cover in terms of AI’s visualisation and design skills, once more highlighting the unique aspect that distinguishes humans from AI. Human assistance still plays a big part in optimization of AI tools.

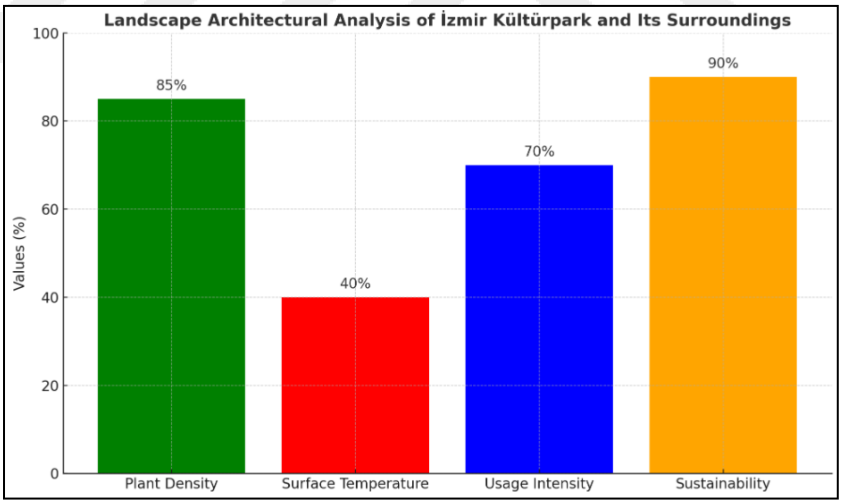

Figure 4.1 : Prompt engineering-based generated graph example. Derived from ChatGPT (Er & Bozkurt, 2025).

On the other hand, Python’s data retrieval from open sources was successful (Section 3.5.2). The implementation of Python-based workflows via the GEE, OSM and NASA API has proven to be a robust methodology for large-scale environmental assessment. Beyond mere data retrieval, this computational approach introduces parametric flexibility, allowing for the instantaneous adjustment of spatial boundaries, spectral indices, and temporal windows across diverse geographic contexts -ranging from the Mediterranean climate of Izmir to the temperate urban forest of New York and the tropical ecosystem of Singapore. By utilizing cloud-based processing, the workflow bypasses the hardware limitations of traditional GIS software, enabling high-resolution spatial analysis (10m Sentinel-2) in seconds. Furthermore, the script's ability to standardize visualization parameters ensures scientific reproducibility, allowing for direct comparative studies between disparate global sites that would otherwise be labor-intensive or cost-prohibitive under manual workflows. Thanks to this feature, many geographic analyses that would normally take a long time or require payment to obtain can be performed in seconds. The following images show the comparison of Kültürpark's analysis diagrams obtained via Python, ArcGIS, Copernicus Browser and Felt (Figures 4.2-4.5):

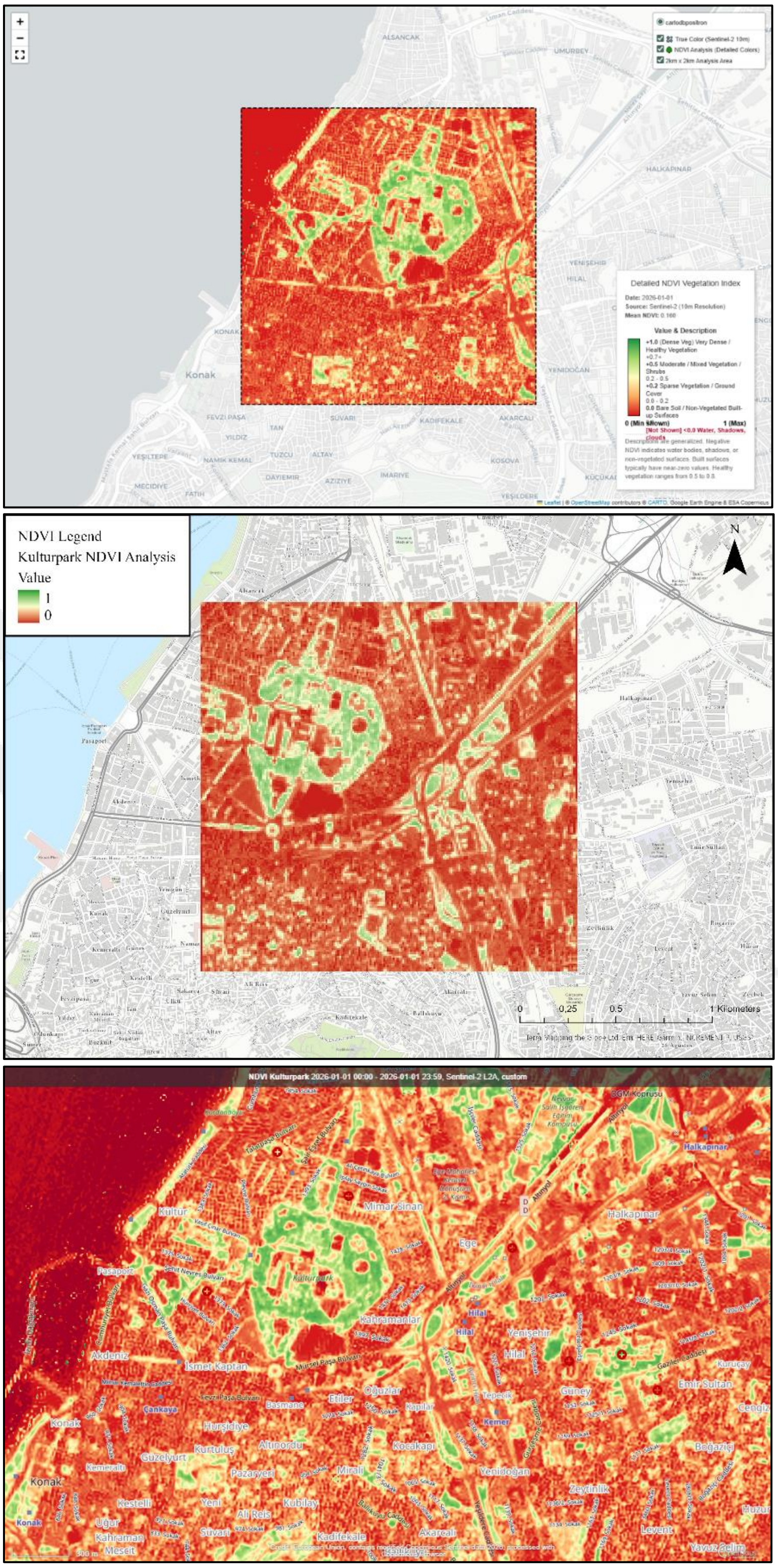

Figure 4.2 : NDVI analyses of Kültürpark. (From top to bottom) Generated via Python IDLE (GEE dataset), ArcGIS and Copernicus Browser.

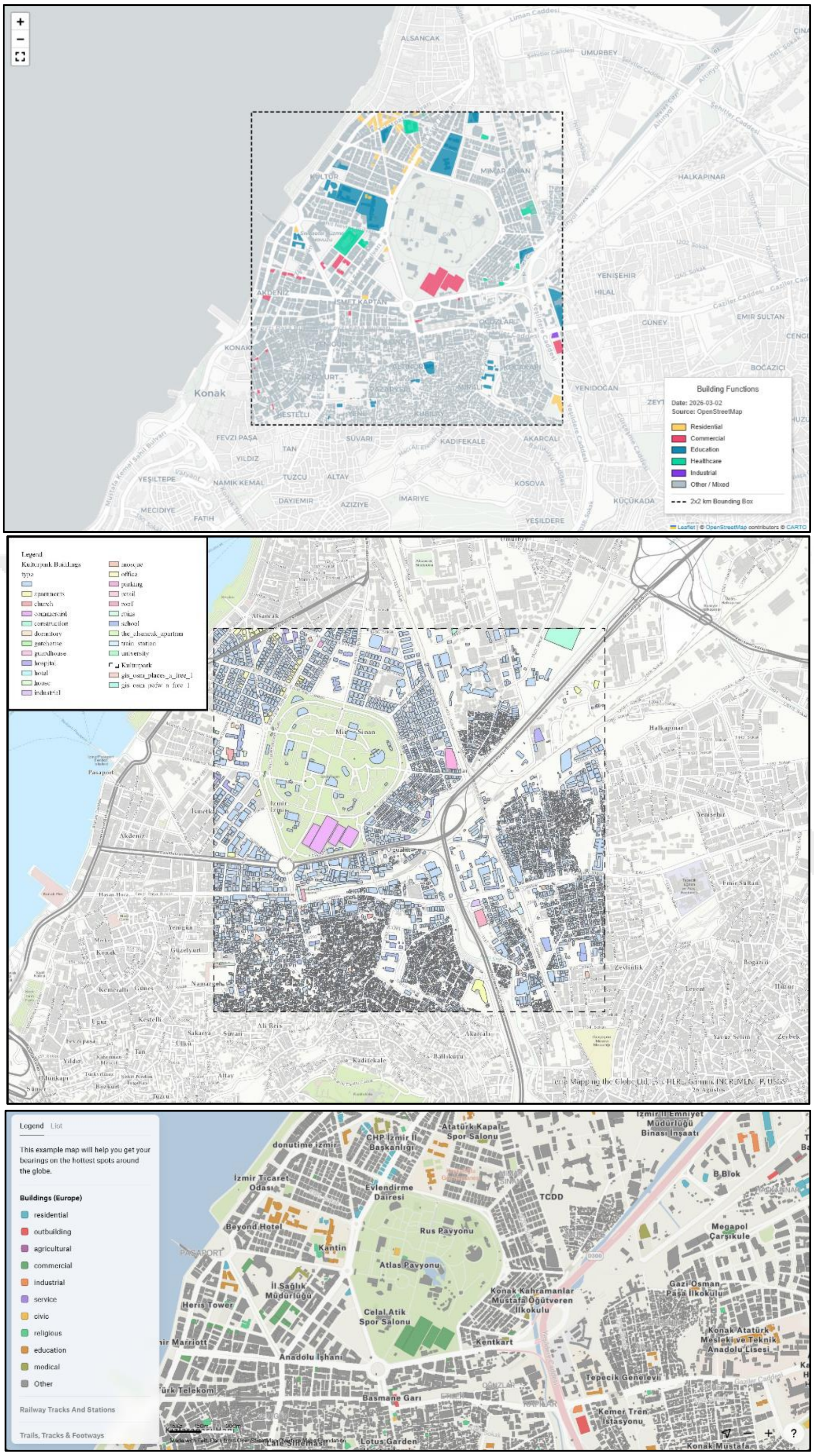

Figure 4.3 : Building function analyses of Kültürpark. (From top to bottom) Generated via Python IDLE (OSM dataset), ArcGIS and Copernicus Browser.

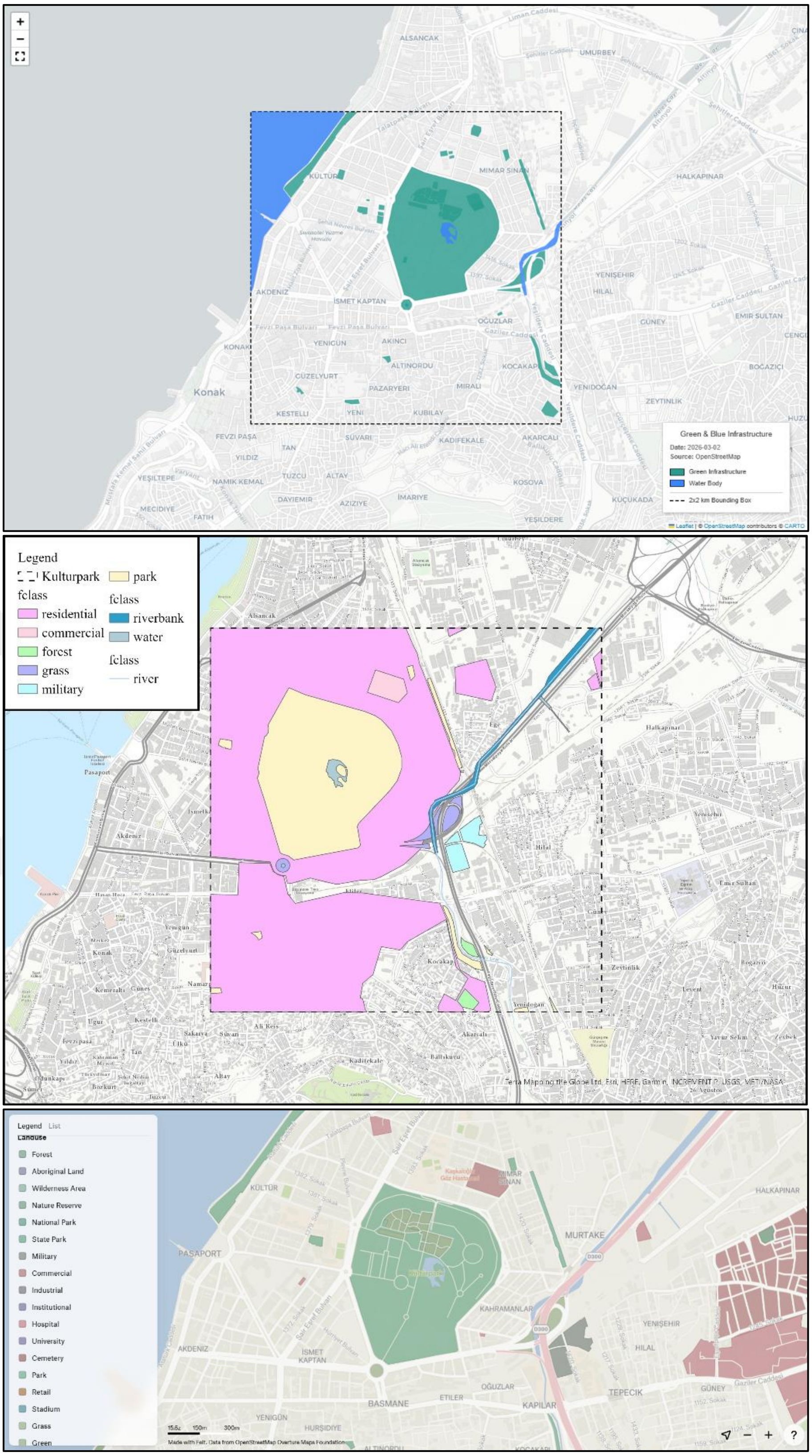

Figure 4.4 : Landuse analyses of Kültürpark. (From top to bottom) Generated via Python IDLE (OSM dataset), ArcGIS and Copernicus Browser.

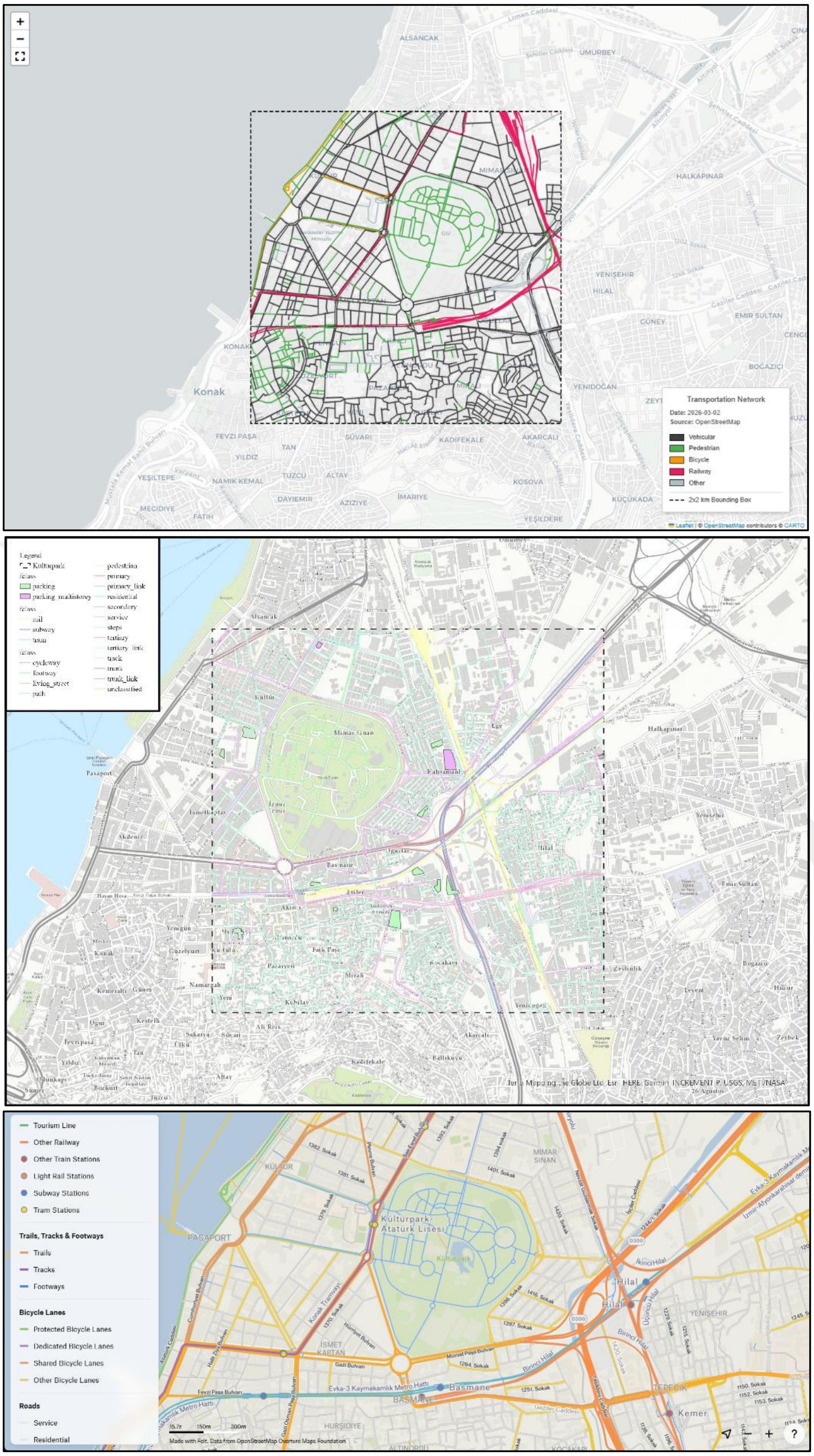

Figure 4.5 : Transportation analyses of Kültürpark. (From top to bottom) Generated via Python IDLE (OSM dataset), ArcGIS and Copernicus Browser.

For comparison, the analysis process was repeated for Central Park and Gardens by the Bay (all images and comparison tables are added into Appendix A-M). Additionally, terrain analysis of Grand Canyon, Arizona and elevation analysis of Mount Everest were carried out as well, proving that the analysis parameters could be modified according to needs (Fig. 4.6).

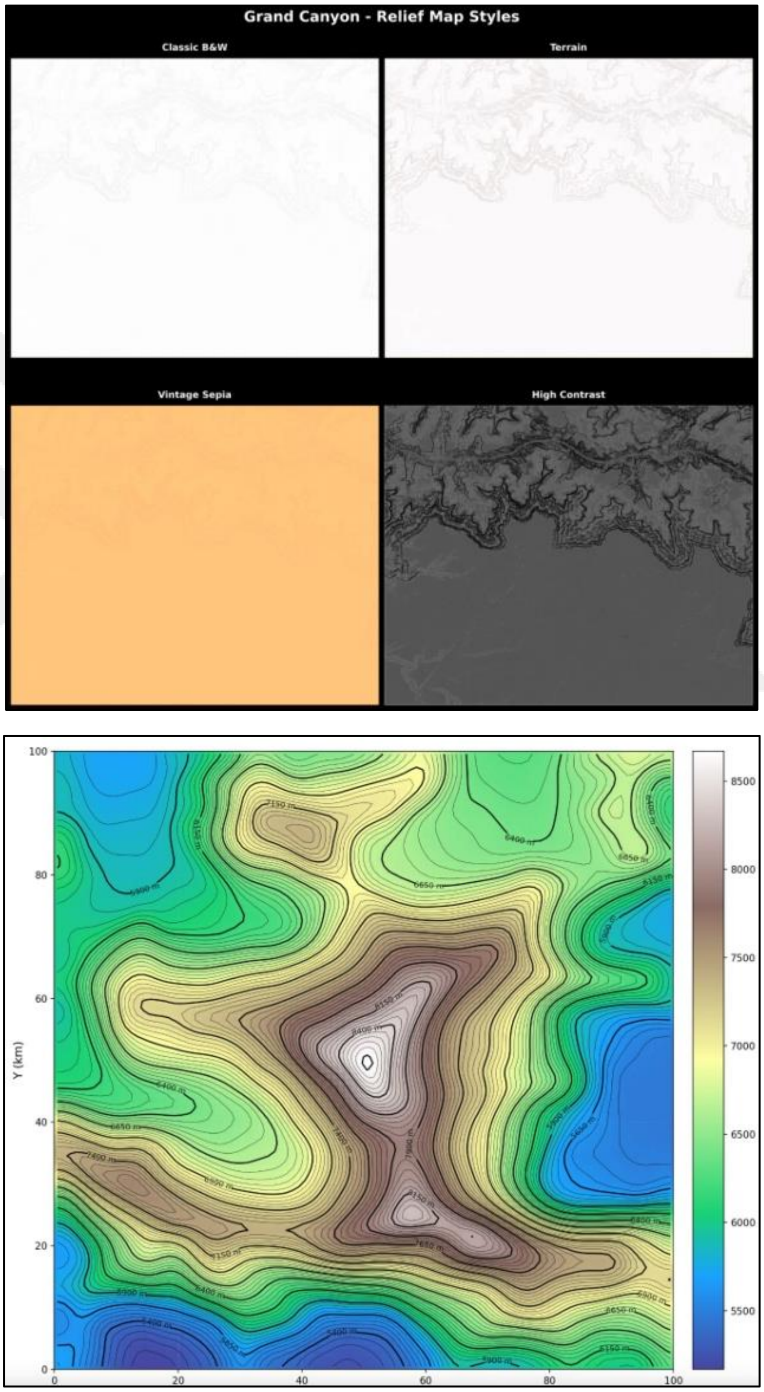

Figure 4.6 : Terrain analysis of Grand Canyon (left) and elevation analysis of Mount Everest (right). Generated via IDLE.

For the third stage (Section 3.5.3), with all the images provided and collected so far, ChatGPT has accurately assessed the site based entirely on these images, and eliminated the need for the double-checking that is required in any AI tool. In short, it finally successfully evaluated written and visual sources. However, when asked to graph its inferences, it once again failed to establish the correlation and produced graphs lacking scientific validity (Figure 4.7).

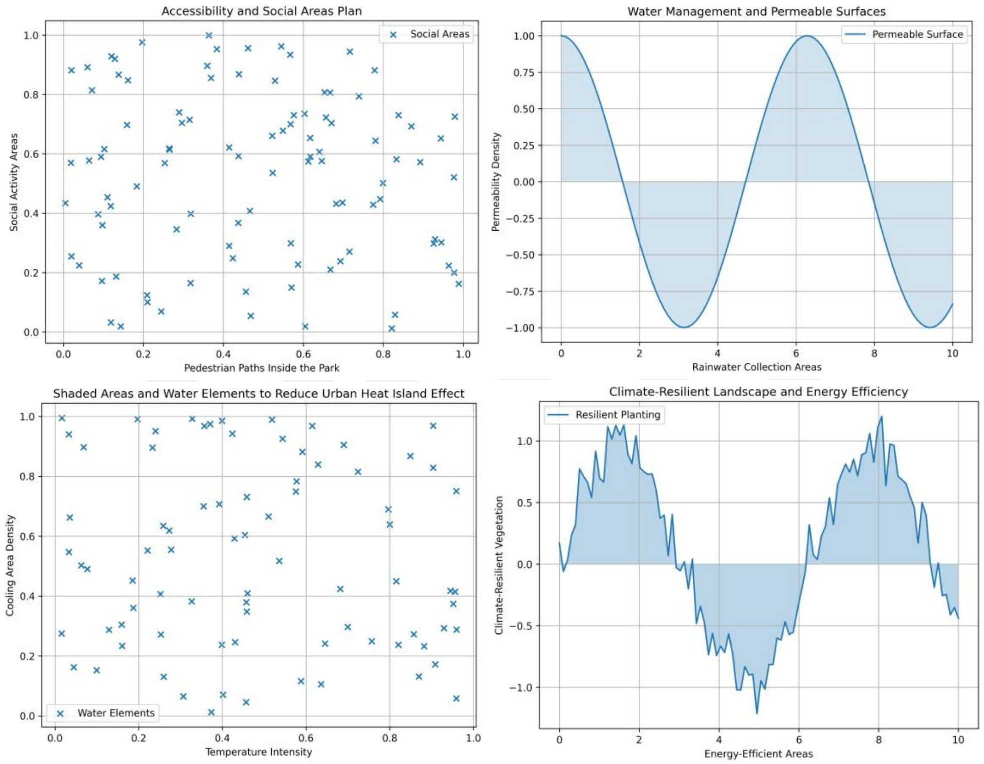

Figure 4.7 : Dataset-based generated graphs for Kültürpark. Derived from ChatGPT.

5. DISCUSSION

The findings of this research integrate the evolution and current limitations of AI in landscape architecture with the broad theoretical framework in the literature. The basis of the research is rooted in the timeline outlined by Nilsson (2009), extending from neural system modeling by McCulloch & Pitts (1943) to Turing's (1950) early work questioning machine intelligence, and subsequently to the widespread applications of AI today. The conducted experiments confirmed Negroponte's (1970) vision of computers as ‘partners’ of the designer. At the same time, according to the Lighthill Report (1973), which argues that the potential of AI is directly proportional to the capacity of computers, we see that contextual disconnect is still a point of resistance in modern visual production tools, while access to increasingly advanced machines is becoming easier. The findings reveal that AI is no longer just a technical tool, but a hybrid layer permeating every stage of design, this prevalence weakens the likelihood of another ‘AI Winter.’

In the initial trials, AI was successful in analyzing information gathered from open sources, but it was insufficient in adapting this information to a spatial context by establishing cause-effect relationships. Specifically, rather than considering land use and user needs, the outputs were more conceptual. These outputs were hypothetical and lacked a scientific basis. Therefore in subsequent stages, a collaborative human-machine model (Holzinger, 2016; Shneiderman, 2020) was developed, and necessary interventions were made with vibe coding (Sarkar & Drosos, 2025) to enable the AI to access and consistently interpret technical data. Thanks to the reliable information it acquired, it was able to perform analyses based on scientific sources, not assumptions. While manual GIS processes can take hours for data downloading, cleaning, and indexing, the developed Python script reduces this process to minutes. This increase in speed reduces the designer's technical workload, allowing them to focus on their ‘decision-maker’ role in the HITL approach (Holzinger, 2016). This approach also addresses the need for heterogeneous and domain-specific datasets highlighted by Tamiminia et al. (2020) and Kuffer et al. (2020), and incorporates remote sensing techniques advocated by Shahtahmassebi et al. (2020) into the design process. The modular structure of the code allows analyses to be rerun within seconds for different time periods or different geographical coordinates (e.g. from Izmir to Singapore). This defines a new standard for ‘dynamic site analysis’ in landscape architecture.

One of the most striking findings of the study is the high correlation between environmental analyses performed using Python and the outputs of industry-standard tools such as ArcGIS, Copernicus, and Felt. The findings also demonstrate the high level of visual quality achieved, while highlighting the feasibility and structural logic constraints mentioned by Gattupalli (2022) and Ploennigs & Berger (2023). This necessitated the provision of larger databases and clearer outputs. Thanks to the ‘reasoning’ and ‘searching’ features added to the interface, it was observed that it could read both visual and textual data together; developing more consistent spatial interpretations from graphs, maps, and statistical outputs. In particular, it was seen that it could more accurately establish fundamental landscape relationships such as green space- heat island, natural material use- sustainability, and building density-microclimate interaction. Similarly, it understands the coding requests better and guides the user more clearly. In addition, visuals have reached a more professional level in terms of clarity and readability.

Despite all these developments, the common finding is that AI falls short in areas requiring human intuition; such as aesthetic decisions, user experience, local cultural values, and implementation details. Therefore, the outputs should not be considered the final product, but rather an inspiring layer guiding the landscape architect. As Yigitcanlar et al. (2020) also support, these technology-driven advancements should not exclude ethical, social, and ecological dimensions. The risks of ‘data bias’ (Mehrabi et al, 2021; Ntoutsi et al, 2020), necessitate a critical perspective from the landscape architect at every stage. This situation demonstrates that while AI has become a powerful decision-support tool in the analysis and interpretation phase, it also clearly shows that it is a tool that strengthens the process when used with correct data, right methods, and expert supervision (Sayes, 2014; Holzinger, 2016).

6. CONCLUSION AND OUTLOOK

This research has comprehensively demonstrated how the integration of AI in the discipline of landscape architecture can transcend being a mere visualization tool or an aesthetic representation mechanism, evolving into a data-driven and site-specific analytical partner. Grounded in ANT and HITL approaches, the study constructs a unique theoretical foundation in the literature by positioning AI as an active ‘non-human actor’ in the design process rather than a passive software.

One of the most robust aspects of the thesis is its proposition of a hybrid workflow that automates data collection and GIS analyses -which traditionally cause significant time and effort loss in design studio practices -through the ‘vibe coding’ method. The integration of open-source databases such as GEE, OSM, and Copernicus with Python-based algorithms has enabled the generation of critical environmental analyses, including urban morphology, landuse, and NDVI, with high precision in a matter of seconds. Cross-examinations conducted on sites with vastly different climatic, topographic, and cultural contexts, such as Izmir’s Kültürpark, New York’s Central Park, and Singapore's Gardens by the Bay, substantiate the parametric flexibility and universal applicability of the proposed computational model.

Furthermore, the study empirically proves that popular generative AI tools (Midjourney, ArchiVinci, ChatGPT), when used in isolation, produce ‘data deserts’ that are disconnected from spatial context, devoid of topographic reality, and neglectful of ecosystem services. This delineates the limitations of AI's ‘black box’ algorithms and unequivocally highlights the vital importance of the landscape architect's role as the ‘decision-maker’ and ‘director’ in the process. A ‘human-machine collaboration’ that merges the computational capacity of ML with the landscape architect's intuitive and technical expertise in areas such as biophilia, sustainable drainage systems, and ecological restoration not only enhances creative diversity but also guarantees a transparent, accountable, and ethically standardized analysis process.

Ultimately, this thesis serves as a methodological milestone for the integration of AI technologies into landscape architecture practice and its academic curriculum. For landscape architects tasked with developing nature-based solutions in the face of complex climate crises, biodiversity loss, and rapid urbanization scenarios, this study offers an innovative and actionable vision that synthesizes the speed of algorithms with the ecological reality of the site. However, there were some limitation and there is still scope for further research.

6.1 Limitations & Scope for Future Research

The LLMs and text-to-image AI tools have not yet reached a sufficient level in visualization-based inferences. It is predicted that these models hold great potential in the near future; however, it is necessary to correctly identify and implement the points that need attention during this process. The source code needs to be modified by experts to access the data and analyze it from a landscape architect's perspective. For example, NDVI, temperature anomalies, land and building uses, topographic data, demographic information, socio-cultural structure -in short, all data covered by the architectural analysis process- should be integrated as well. Utilizing open-source geospatial data necessitates a rigorous validation process to mitigate risks associated with regional inconsistencies and data gaps. While platforms like Sentinel-2 offer global coverage, their spatial resolution (10m) may lack the granularity required for detailed site-scale interventions compared to regional datasets like NAIP. Furthermore, OSM introduces potential biases in urban morphology, where certain districts are more detailed than others. To ensure the reliability, this research employs a multi-source verification strategy, cross-referencing global satellite imagery with local data to ensure technical precision. In addition, fundamental design principles and architectural methods should also be meticulously incorporated during the visualization process. The integration of coding and AI tools into vocational training is also essential for adapting to technological advancements. To maintain a competitive edge, members of the discipline must keep pace with technological developments. This is possible through mastery of the AI production process and coding languages.

Although AI-assisted algorithms significantly increased the speed of the process, the code generation process did not follow a linear success graph; various situations requiring technical intervention from the designer were encountered. Issues such as authorization problems, the need to update downloaded libraries, code snippets that disregarded the geographical context, resolution problems, and the code not producing the desired results caused the code to take time to become operational. The margin of error was determined by cross-validation with threshold filters and atmospheric correction algorithms added to the code. This shows that the coding process is not automated production, but a continuous feedback process between the designer and the machine.

The codes and datasets are stored for use as reference in future studies. By using high-capacity computers, it is possible to expand and improve the research by diversifying the variables of the proposed medium, increasing the sample size, the size of the study area, the scope of analysis, and the duration of study. In future studies, collecting demographic and socio-cultural data in addition to geographical analyses will enable a more holistic approach. Scaling the methodology from a site-specific level to a regional landscape territory would test the limits of the human-machine collaboration, potentially transforming the AI from a design assistant into a comprehensive decision-support system.

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APPENDICES

APPENDIX A: Kulturpark maps generated via ArcGIS Pro.
APPENDIX B: Central Park maps generated via ArcGIS Pro.
APPENDIX C: Gardens by the Bay maps generated via ArcGIS Pro.
APPENDIX D: Kulturpark maps generated via GEE & OSM API on Python.
APPENDIX E: Central Park maps generated via GEE & OSM API on Python.
APPENDIX F: Gardens by the Bay maps generated via GEE & OSM API on Python.
APPENDIX G: Kulturpark NDVI map generated via Copernicus Browser.
APPENDIX H: Central Park NDVI map generated via Copernicus Browser.
APPENDIX I: Gardens by the Bay NDVI map generated via Copernicus Browser.
APPENDIX J: Kulturpark maps generated via Felt.
APPENDIX K: Central Park maps generated via Felt.
APPENDIX L: Gardens by the Bay maps generated via Felt.
APPENDIX M: Comparative tables of analysis outputs.

APPENDIX A

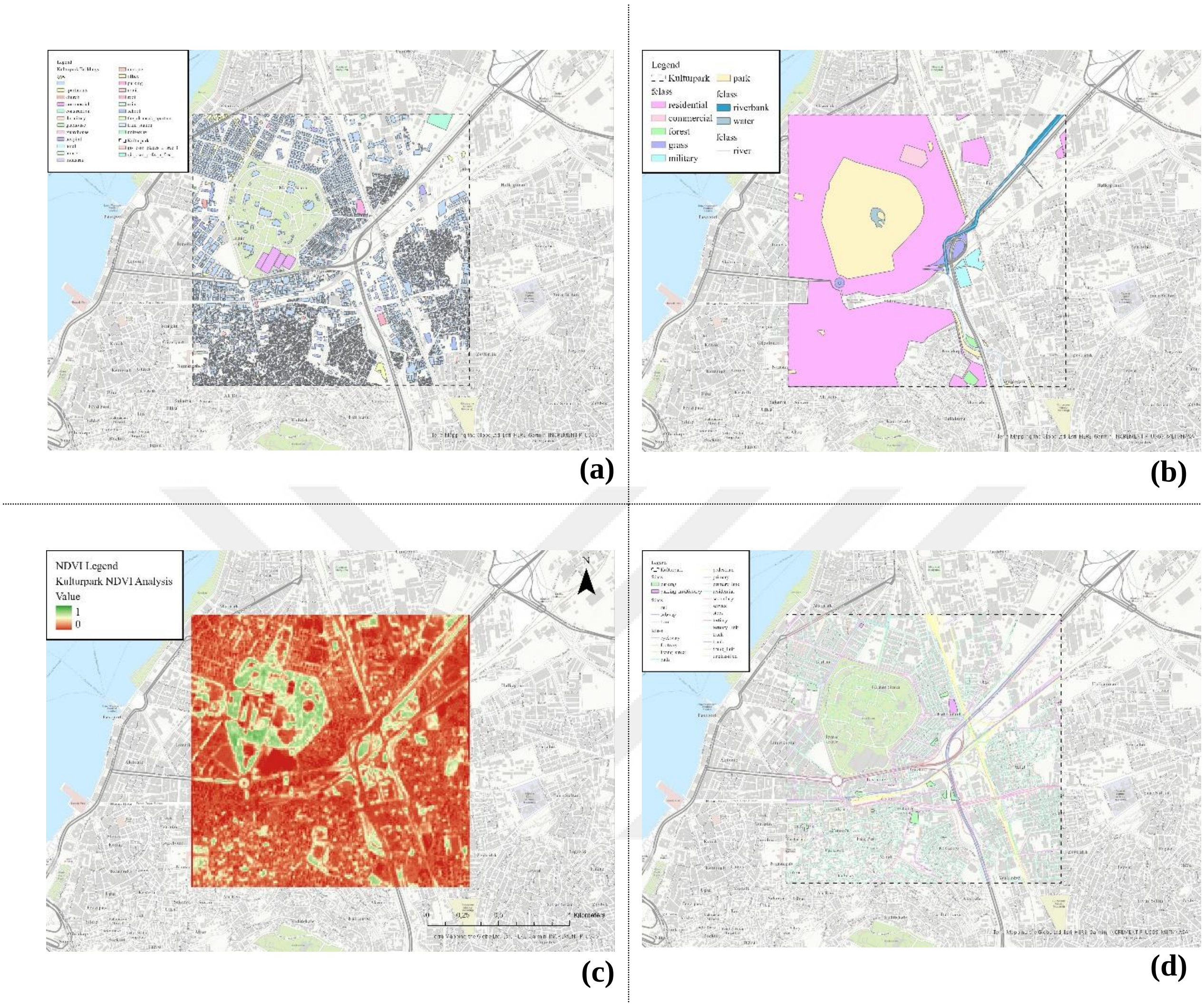


Figure A.1 : Kulturpark maps generated via ArcGIS Pro: (a)Building Functions. (b)Landuse. (c)NDVI. (d)Roads.

APPENDIX B

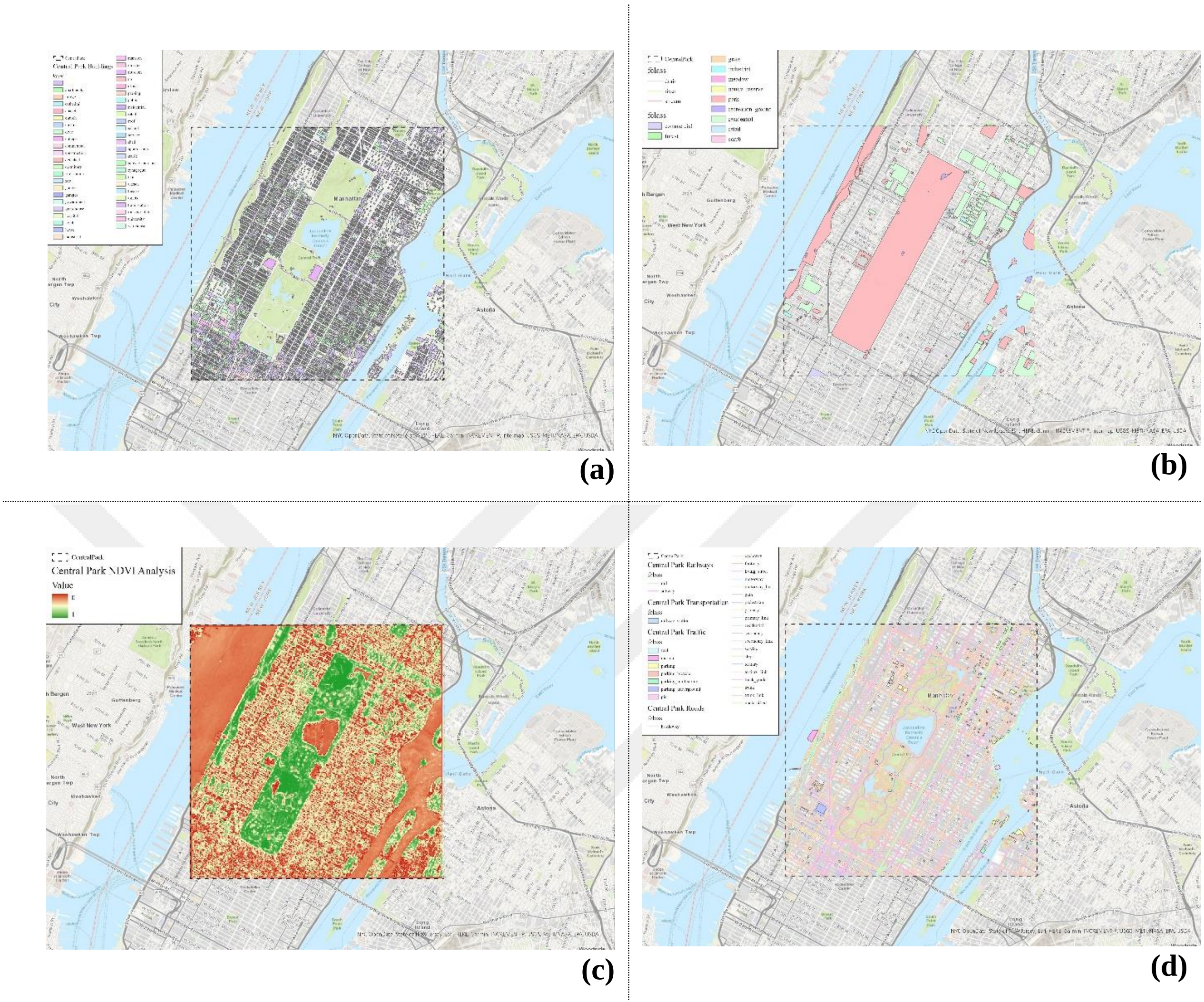


Figure B.1 : Central Park maps generated via ArcGIS Pro: (a)Building Functions. (b)Landuse. (c)NDVI. (d)Roads.

APPENDIX C

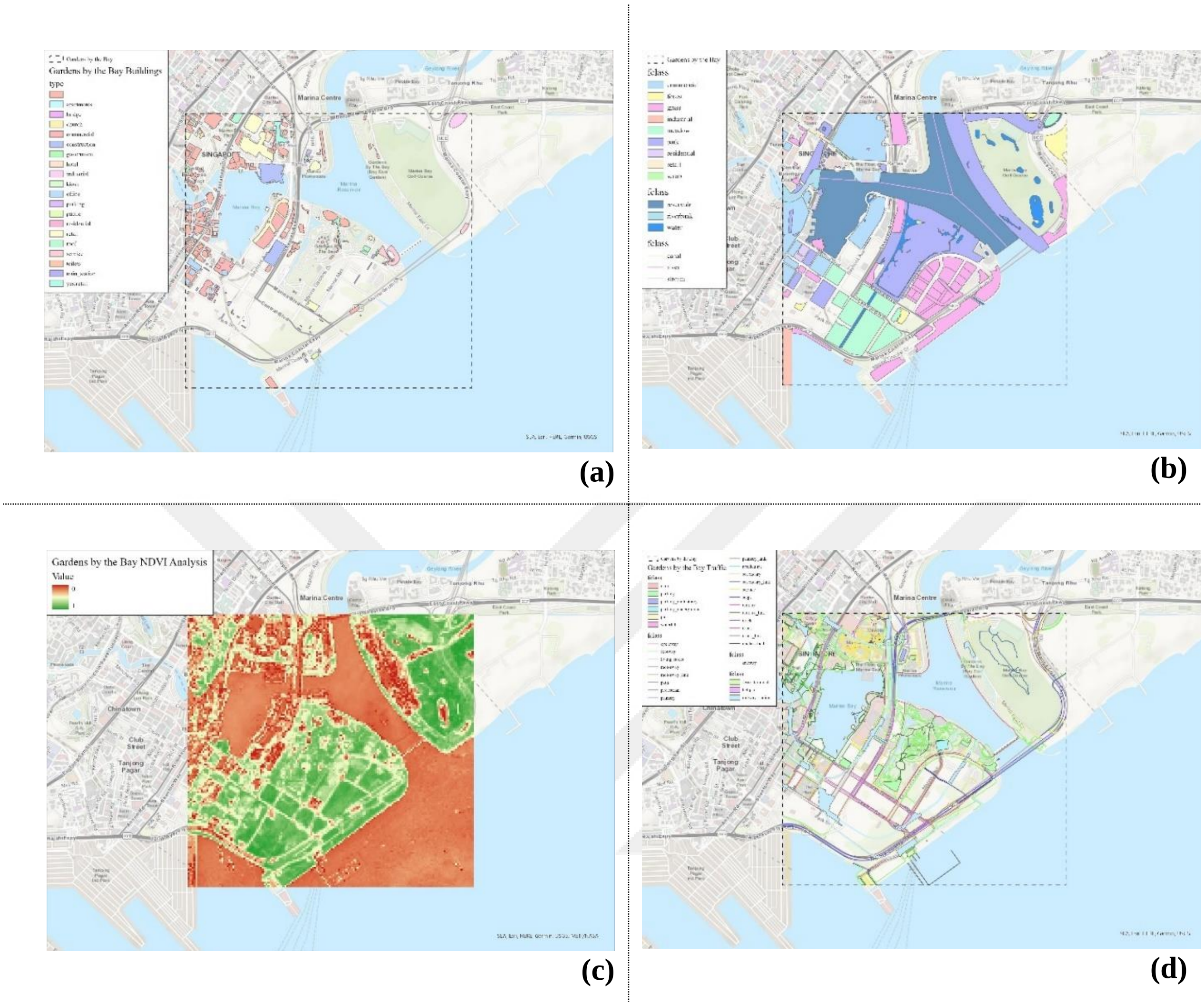


Figure C.1 : Gardens by the Bay maps generated via ArcGIS Pro: (a)Building Functions. (b)Landuse. (c)NDVI. (d)Roads.

APPENDIX D

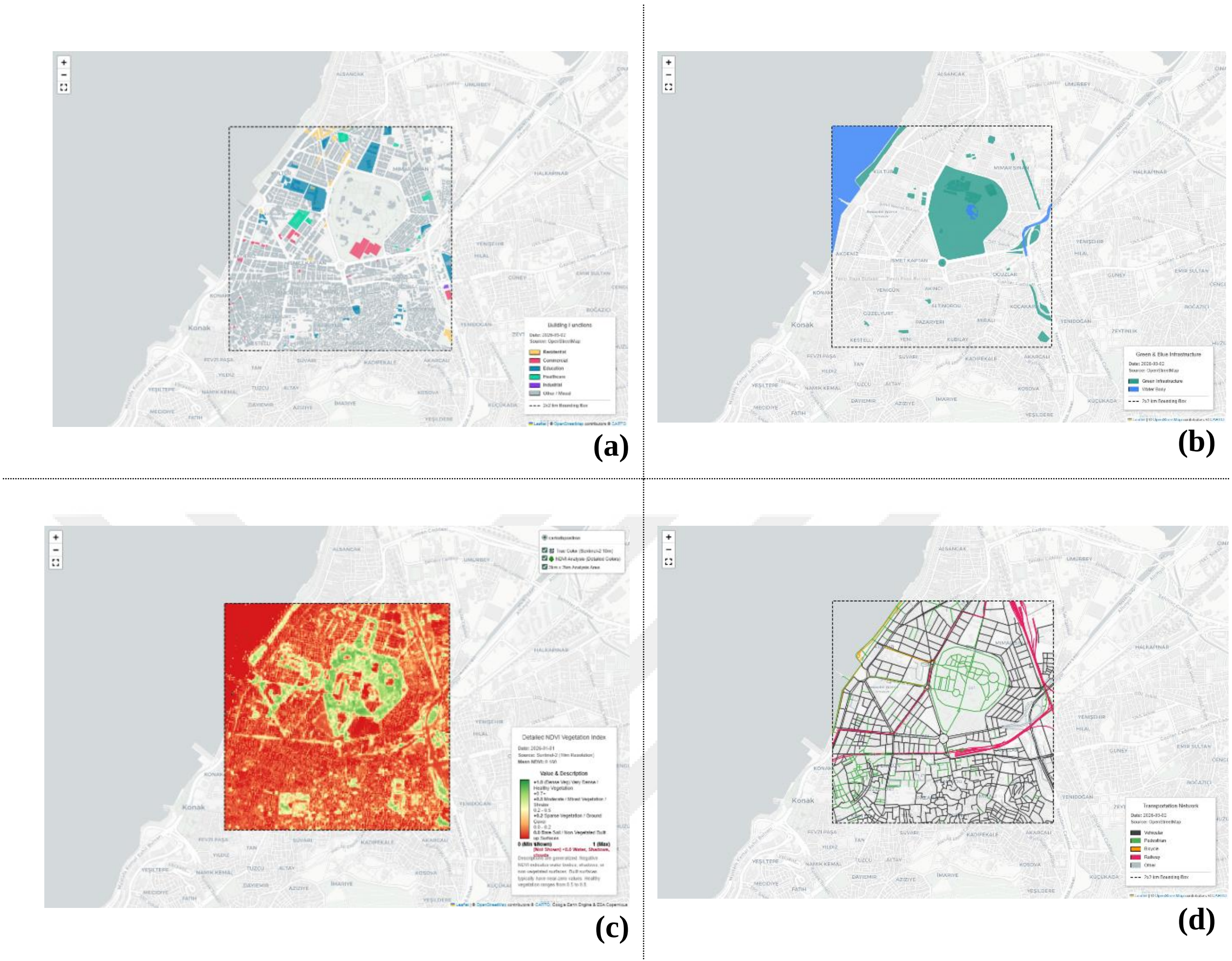


Figure D.1 : Kulturpark maps generated via GEE & OSM API on Python: (a)Building Functions. (b)Landuse. (c)NDVI. (d)Roads.

APPENDIX E

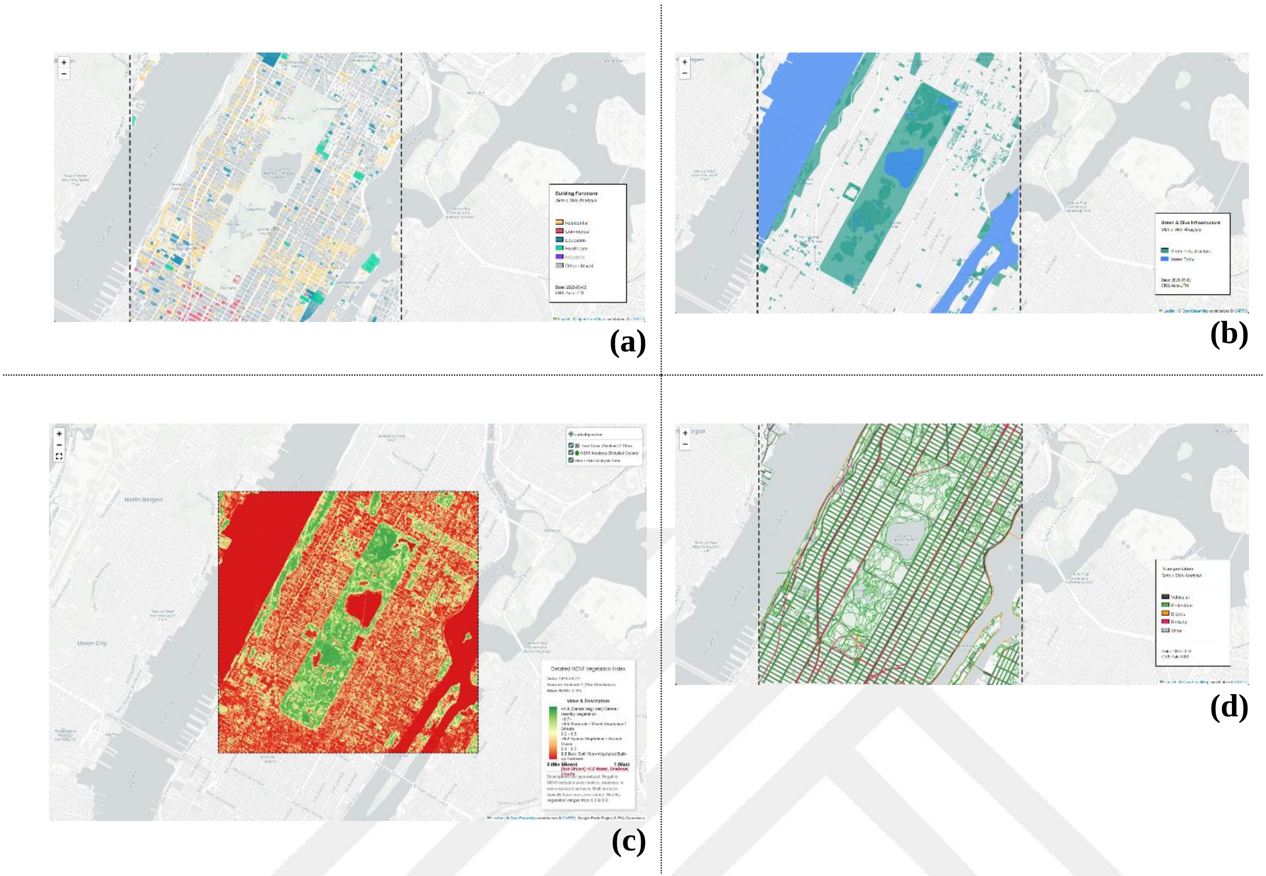


Figure E.1 : Central Park maps generated via GEE & OSM API on Python: (a)Building Functions. (b)Landuse. (c)NDVI. (d)Roads.

APPENDIX F

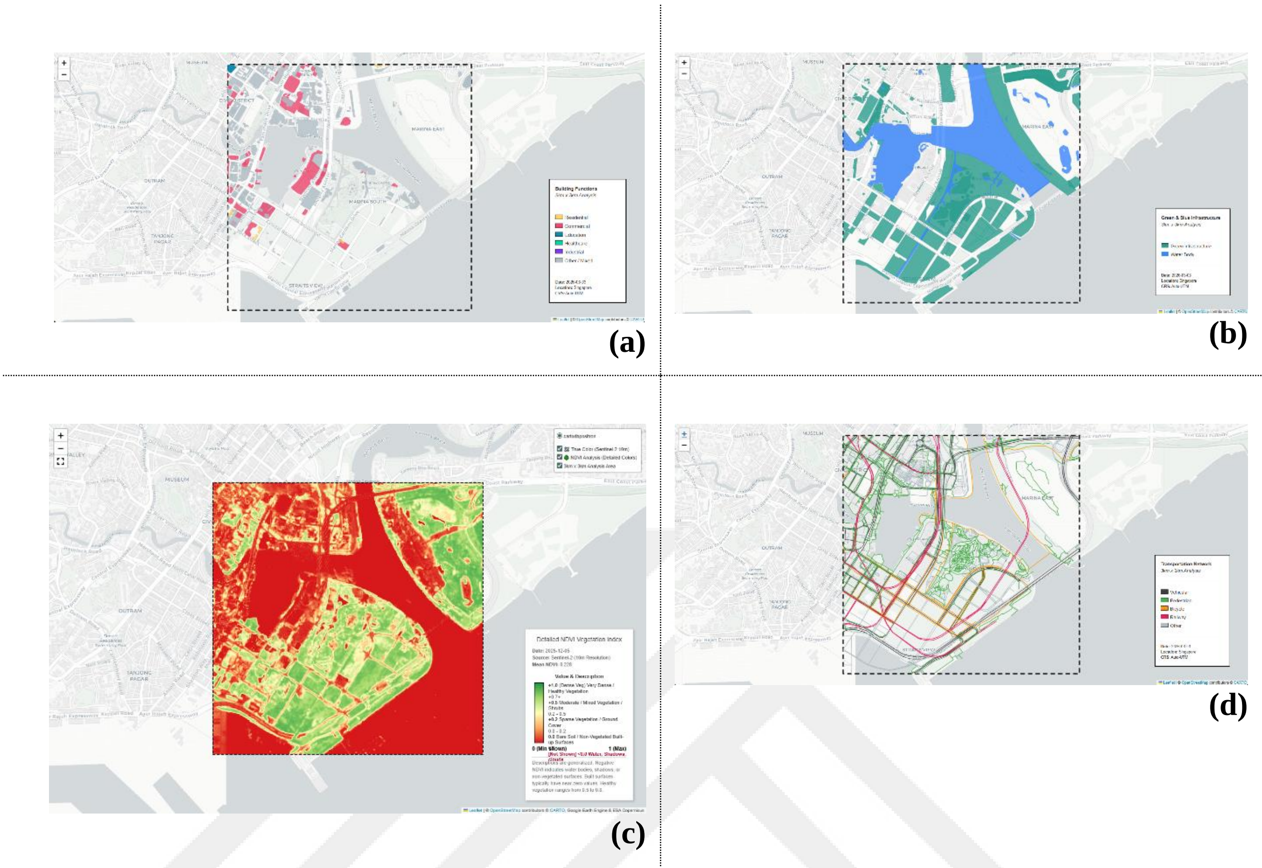
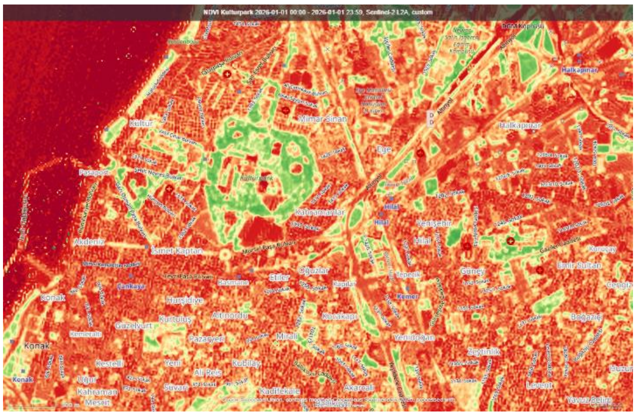


Figure F.1 : Gardens by the Bay maps generated via GEE & OSM API on Python: (a)Building Functions. (b)Landuse. (c)NDVI. (d)Roads.

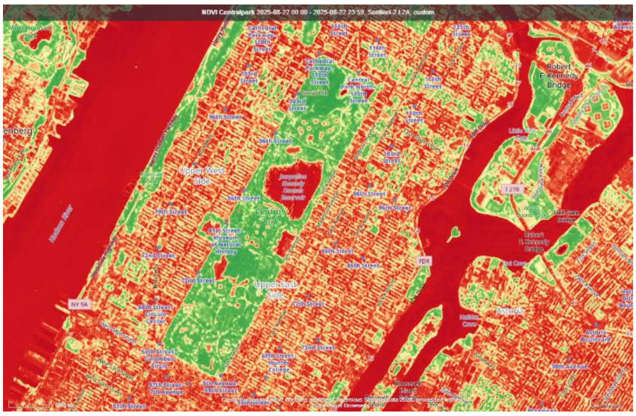
APPENDIX G



(a)

Figure G.1 : Kulturpark NDVI map generated via Copernicus Browser: (a)NDVI.

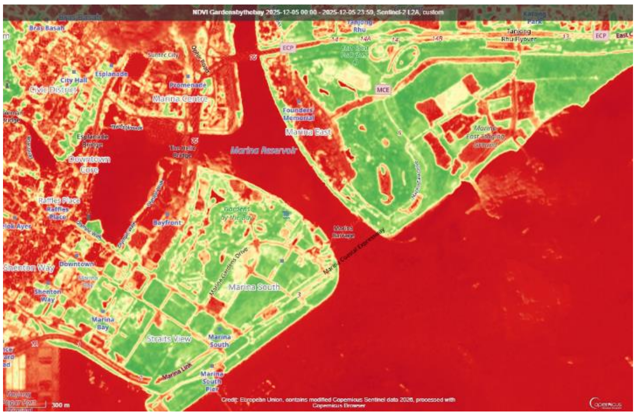
APPENDIX H



(a)

Figure H.1 : Central Park NDVI map generated via Copernicus Browser: (a)NDVI.

APPENDIX I



(a)

Figure I.1 : Gardens by the Bay NDVI map generated via Copernicus Browser: (a)NDVI.

APPENDIX J

Figure J.1 : Kulturpark maps generated via Felt: (a)Building Functions. (b)Landuse. (c)Railways. (d)Pedestrian & Bicycle Ways. (e)Roads. (f)Transportation.

APPENDIX K

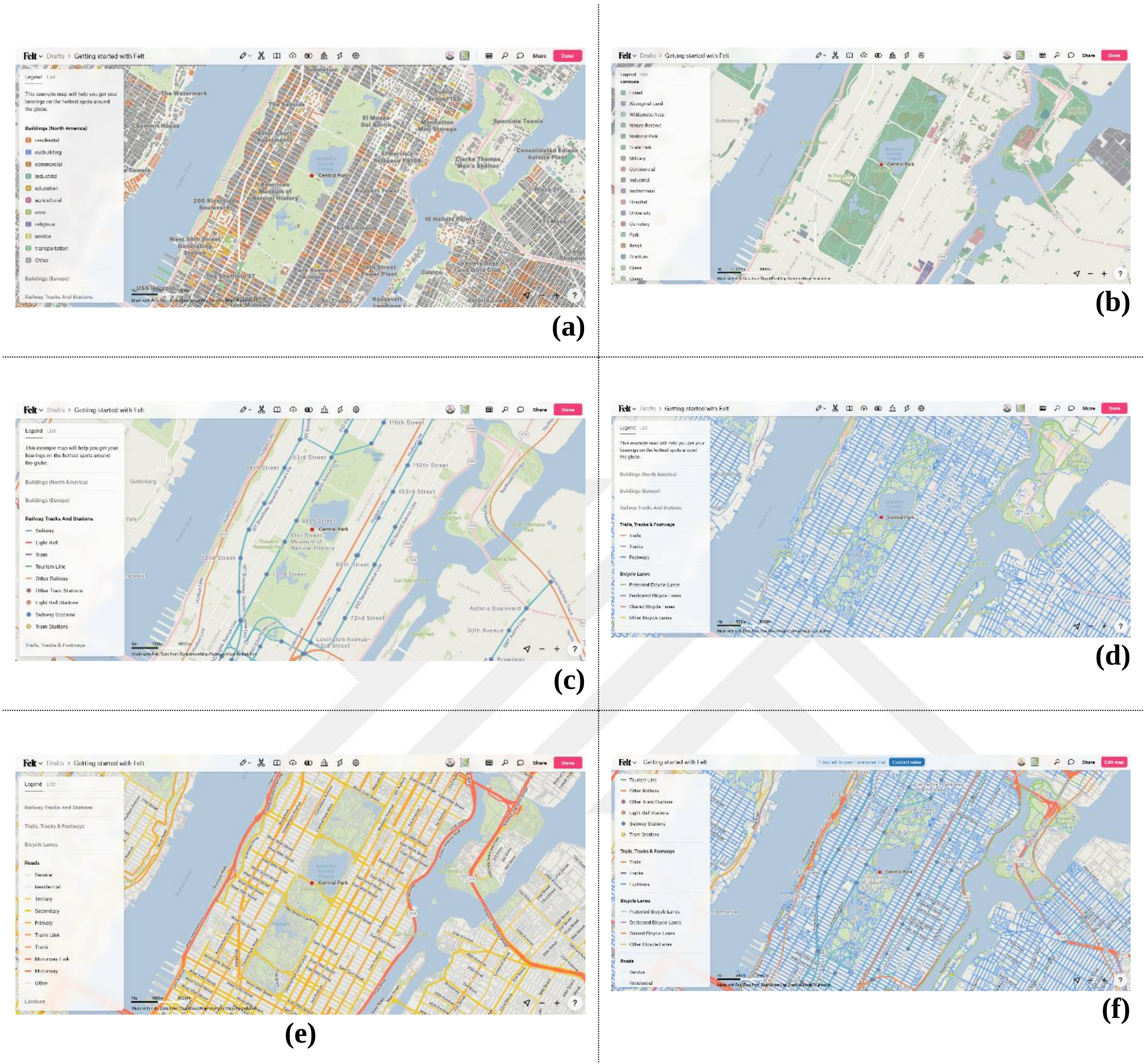


Figure K.1 : Central Park maps generated via Felt: (a)Building Functions. (b)Landuse. (c)Railways. (d)Pedestrian & Bicycle Ways. (e)Roads. (f)Transportation.

APPENDIX L

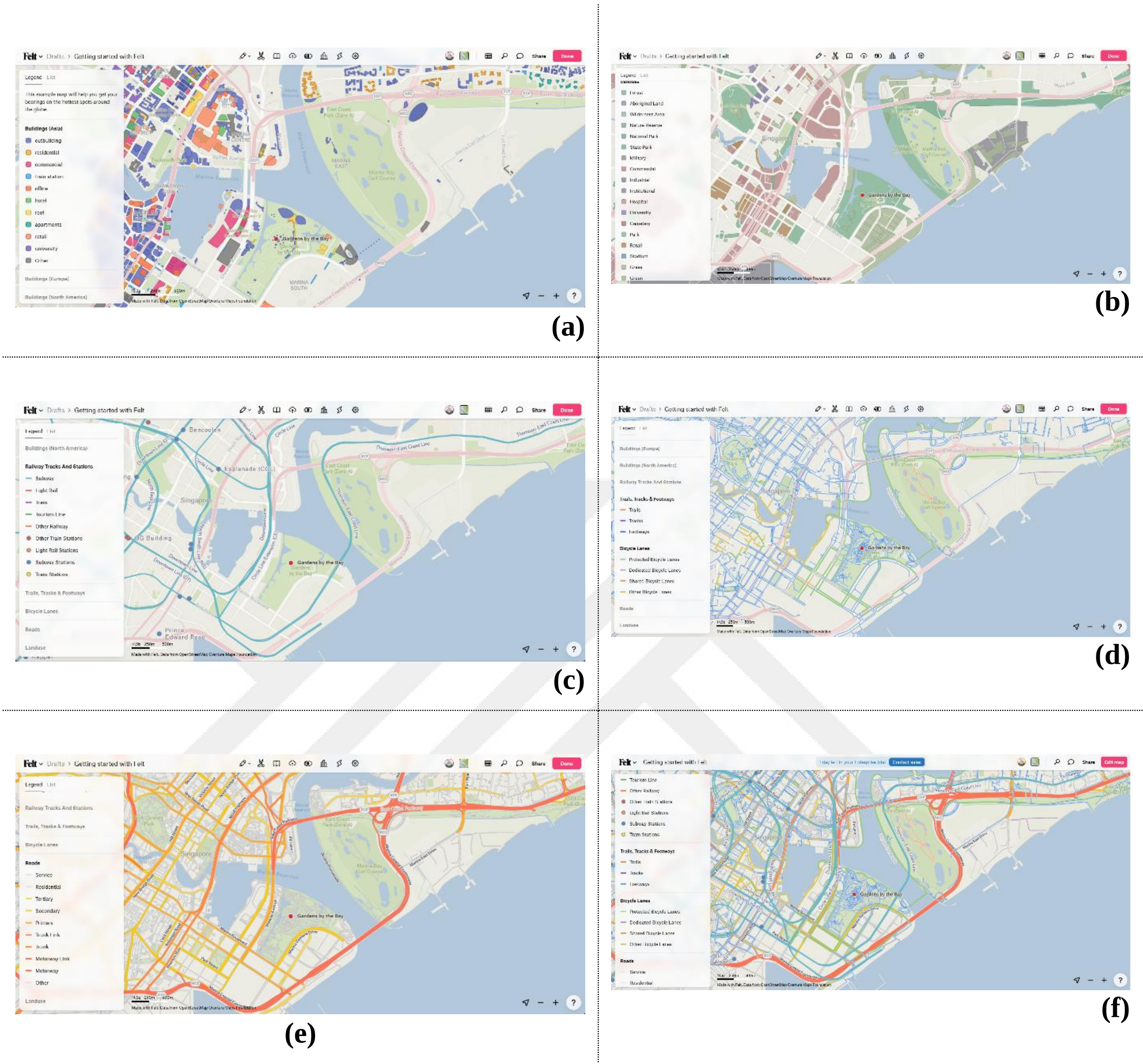


Figure L.1 : Gardens by the Bay maps generated via Felt: (a)Building Functions. (b)Landuse. (c)Railways. (d)Pedestrian & Bicycle Ways. (e)Roads. (f)Transportation.

APPENDIX M

Table M.1 : Comparative table of NDVI analysis outputs generated via ArcGIS Pro, coding and Copernicus Browser.

NDVI ANALYSES											
Medium	Data Source	Resolution	Processing Level	Calculation Method	Spatial Overlap Ratio	Error Margin	Strengths	Weaknesses	Kulturpark	Central Park	Gardens by the Bay
ArcGIS Pro	Sentinel-2	10m	Level-2A (Surface)	(NIR - Red) / (NIR + Red) formula applied via Raster Calculator. Used as the ground truth for spatial alignment.	100% (Baseline)	0% (Ground truth)	High local precision, full user control over masking.	Resource-intensive workflow requiring significant manual intervention.	Fig A.1(c)	Fig B.1(c)	Fig C.1(c)
Code-generated	GEE API + Sentinel-2 + Python	10m	Level-2A (Surface)	Calculated by Intersection / Union (IoU) of pixels against the GIS mask.	95.2%	±3% (Threshold bias)	High computational efficiency, ensures objective consistency across diverse datasets, raw-data processing.	Produces discrete output boundaries instead of continuous natural gradients.	Fig D.1(c)	Fig E.1(c)	Fig F.1(c)
Copernicus Browser	Sentinel-2	10m	Level-2A (Surface)	Calculated via pattern matching and mean value comparison.	93.8%	±4% (Global visualisation)	Verified by the European Space Agency (ESA) processing standards.	Visual quality is simplified for faster web loading.	Fig G.1(a)	Fig H.1(a)	Fig I.1(a)

Table M.2 : Comparative table of spatial & functional analysis outputs generated via ArcGIS Pro, coding and Felt.

SPATIAL & FUNCTIONAL ANALYSES											
Medium	Data Source	Representation	Processing Level	Calculation Method	Spatial Overlap Ratio	Error Margin	Strengths	Weaknesses	Kulturpark	Central Park	Gardens by the Bay
ArcGIS Pro	OSM local data	Layer-based GIS	Refined Vector	Manual symbology & spatial join of points to building footprints.	100% (Baseline)	0% (Ground truth)	High local precision, full user control over attribute classification.	Resource-intensive workflow requiring significant manual intervention.	Fig A.1(a,b,d)	Fig B.1(a,b,d)	Fig C.1(a,b,d)
Code-generated	OSM API + Libraries + Python	Data-driven plot	Algorithmic Filtering	Automated tag filtering (e.g. building=*) via GeoPandas.	95.2%	±3% (Threshold bias)	High computational efficiency, ensures objective consistency across diverse datasets, raw-data processing.	Requires technical meticulousness in script logic, sensitive to library dependencies and parameter errors.	Fig D.1(a,b,d)	Fig E.1(a,b,d)	Fig F.1(a,b,d)
Felt	Overture Maps + OSM	Interactive web	Cloud Rendering	Automatic attribute mapping via Overture's unified schema.	98.5%	±2% (Rendering)	Seamless polygon integration and modern, accessible UI.	Limited advanced spatial analysis tools.	Fig J.1(a,b,c,d,e,f)	Fig K.1(a,b,c,d,e,f)	Fig L.1(a,b,c,d,e,f)

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