Quest Journals
Journal of Architecture and Civil Engineering
Volume 9 ~ Issue 7 (2024) pp: 01-07
ISSN(Online) : 2321-8193
www.questjournals.org

Research Paper

Application of Machine Learning in Landscape Analysis and Design

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Abstract
Integrating machine learning (ML) into urban landscape design can revolutionise design processes and outcomes. This research categorises and analyses ML studies on landscape design stages and elements to determine how ML might be used to solve urban landscape design problems. The study describes urban landscape design's conceptualisation, planning, implementation, and assessment stages. It then examines how ML approaches have been used across various stages, highlighting their merits and drawbacks.This review shows landscape architects how ML can improve decision-making, design efficiency, and sustainability by examining case studies and research on predictive modelling of landscape changes, green space distribution optimisation, and automated design generation. The categorisation also indicates research gaps and upcoming ideas, such as deep learning for complex geographical data analysis or reinforcement learning for dynamic design modifications. The research also explores the practical implications of ML in urban landscape design, including the possibility for ML technologies to be integrated into design workflows and their adoption issues. We identify key study areas that require multidisciplinary approaches that combine ML with ecological and sociocultural perspectives. This research covers how ML techniques might transform urban landscape design, providing useful information for practitioners and researchers interested in exploring and applying these advanced methodologies. The findings show that ML may streamline design, encourage innovation, and increase urban landscape resilience and functionality.
Keywords: *Machine Learning, Urban Landscape Design, ML Applications, Landscape Architecture*

***R**eceived 14 July, 2024; **R**evised 28 July, 2024; **A**ccepted 30 July, 2024 © The author(s) 2024.*
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I. Introduction

The emergence of large urban datasets from diverse sources such as environmental sensors, satellite imagery, the internet, and ubiquitous computing presents new opportunities for addressing research questions and solving practical problems across various disciplines, from business to design. In this context, machine learning (ML) has been increasingly applied to analyze 'big' urban data. However, most of these studies originate from scientific fields focused on outcomes such as air pollution analysis or intelligent transportation systems, with limited connection to the design of the built environment.

In urban landscape design, there are several potential applications of ML. While ML-generated landscape design solutions are theoretically possible, they remain an underexplored area of research. Most existing studies on the application of ML to urban landscapes are found outside the landscape architecture and design fields, lacking direct relevance to design practices. Therefore, review researchs that categorize and clarify these applications, and bridge the gap to design, are essential for guiding future research at this intersection. Such reviews can serve as valuable resources for landscape architects and urban landscape researchers, helping them understand the potential applications of ML methods in their respective contexts.

This research aims to address this gap by providing a comprehensive review of the application of ML methods in urban landscape design. One way to categorize these applications is by their relevance to different stages of the urban landscape design process—evaluation, design, or post-occupancy. Another categorization involves examining ML studies based on central themes pertinent to urban landscape projects, such as resilience, ecosystem services, and green infrastructure. This research uses both categorization approaches to explore how urban landscape design can benefit from ML-enabled studies.

To achieve this, the research reviews scholarly literature on the application of ML in urban landscape design. The main citation databases used for this review include Scopus, Web of Science, and Google Scholar. Table 1 lists the primary search terms employed in these databases.

Table 1: Keywords searched in the databases

ML in Design Fields	ML and Urban Landscape Systems	ML and Urban Landscape
Machine learning and landscape architecture	Machine Learning and Urban water	Machine learning and green infrastructure
Machine Learning and Urban design	Machine Learning and Urban vegetation	Machine learning and urban resilience
Machine learning and spatial design	Machine Learning and Urban buildings	Machine Learning and ecosystem services
Machine learning and environmental design	Machine Learning and Urban infrastructure	

Given the limited literature directly linking ML to urban landscape design, the inclusion criteria focused on studies addressing the modeling or design of urban phenomena, systems, functions, or characteristics relevant to the urban landscape design process. Research that do not directly study the physical context of cities were included if they potentially relate to physical aspects of the built environment or play a crucial role in understanding the urban landscape.

II. Machine Learning, Landscape Design Process and Topics

2.1 General Characteristics of the Reviewed Studies

The final search query, combining results from Web of Science, Scopus, and Google Scholar, yielded 1,275 entries. The analysis revealed a steep increase in publications over recent years. After applying the inclusion criteria, 456 researchs remained in the relevant literature pool. From this subset, 71 researchs were selected for review. The primary inclusion criteria for this subset were relevance to general topics within the larger dataset and direct applicability to design and planning.

A word cloud visualization of the abstracts from all entries and the reviewed set (Figure 1) indicates a shift in focus towards researchs more closely related to design and planning.

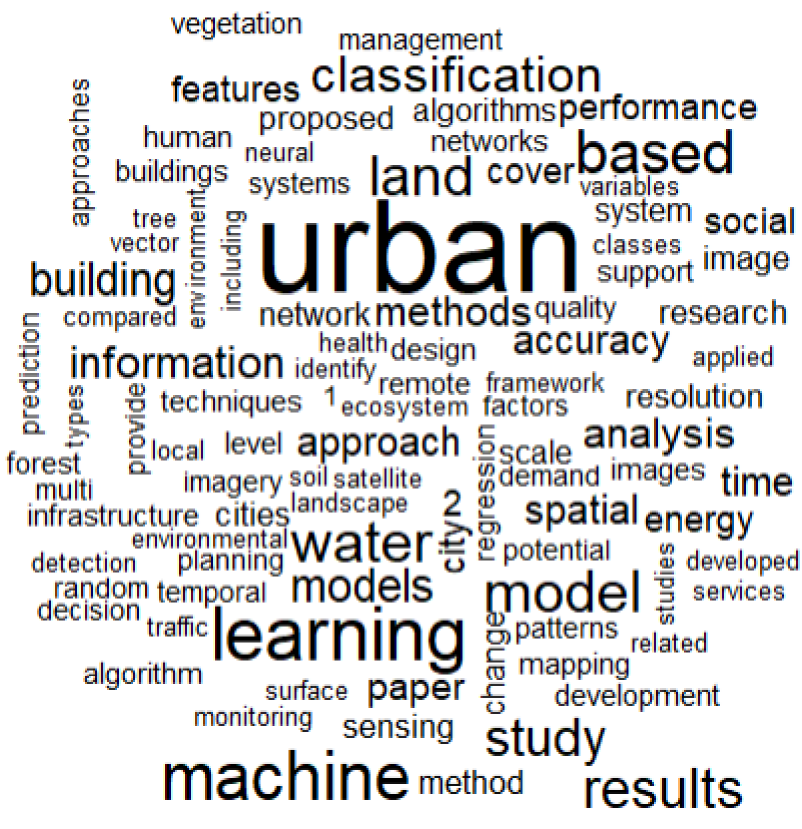

Figure 1: Word cloud visualization of all the data (above) and the reviewed set (below)

Among the 71 reviewed studies, 34 were published in 2019 and 15 in 2018, reflecting the broader trend of an increasing number of machine learning studies. The earliest research reviewed dates back to 2005. To further analyze the main areas covered by the reviewed studies, a Latent Dirichlet Allocation (LDA) algorithm was applied to the abstracts using the topicmodels package in R. The topic modeling analysis revealed three main categories of topics (Figure 2):

1. **Urban Design and Building Parameters:** This category focuses on evaluating urban landscape performance, with a particular emphasis on energy performance.
2. **Green Infrastructure and Urban Landscape Quality:** Studies in this group address green infrastructure, the quality of urban landscapes, and the human components within urban landscapes.
3. **Land Use Land Cover (LULC) Classification:** This group predominantly deals with LULC classification of satellite imagery to understand various characteristics of the urban landscape, including ecosystem services.

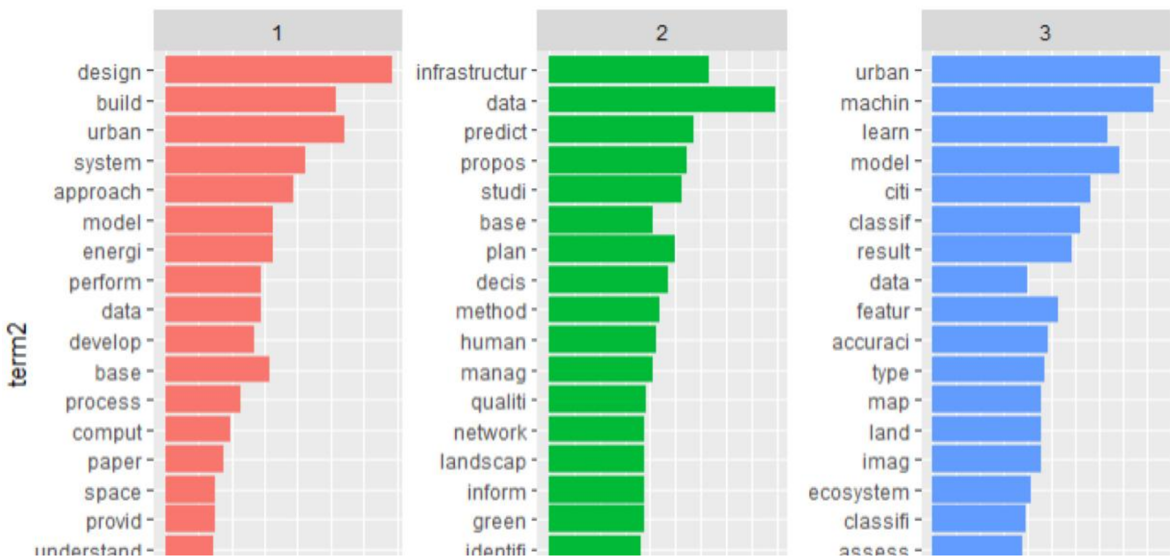

Figure 2: Clusters resulted from topic modelling of the reviewed researchs

2.2 Relevant Machine Learning Methods

Machine learning focuses on enabling computers to improve their performance through experience (Horvitz & Mulligan, 2015). Machine learning methods are generally classified into three main categories:

1. **Supervised Learning:** This category is the most widely used and involves methods where the model is trained on labeled data. Classification is a key task in supervised learning.
2. **Unsupervised Learning:** This involves methods where the model is trained on unlabeled data to identify patterns or groupings.
3. **Reinforcement Learning:** This category involves training models to make sequences of decisions by rewarding desirable outcomes.

In the review, the query results from Web of Science (WOS) (n=654) were analyzed using the bibliometrix R package. The analysis revealed the following insights:

- **Most Frequent Machine Learning Methods:**
  - **Random Forest**
  - **Support Vector Machine/Regression**
  - **Deep Learning**
  - **Artificial Neural Networks**
  - **Convolutional Neural Networks**
- **Most Frequent Data Types:**
  - **Social Media**
  - **Land Use Land Cover (LULC)**
  - **Landsat Imagery**
  - **LiDAR Data**

The keyword co-occurrence network from the WOS results highlighted:

- **Classification** as a dominant keyword, closely associated with Support Vector Machines and Random Forests.
- **Prediction** as another prominent keyword, more closely related to Regression and Neural Networks.

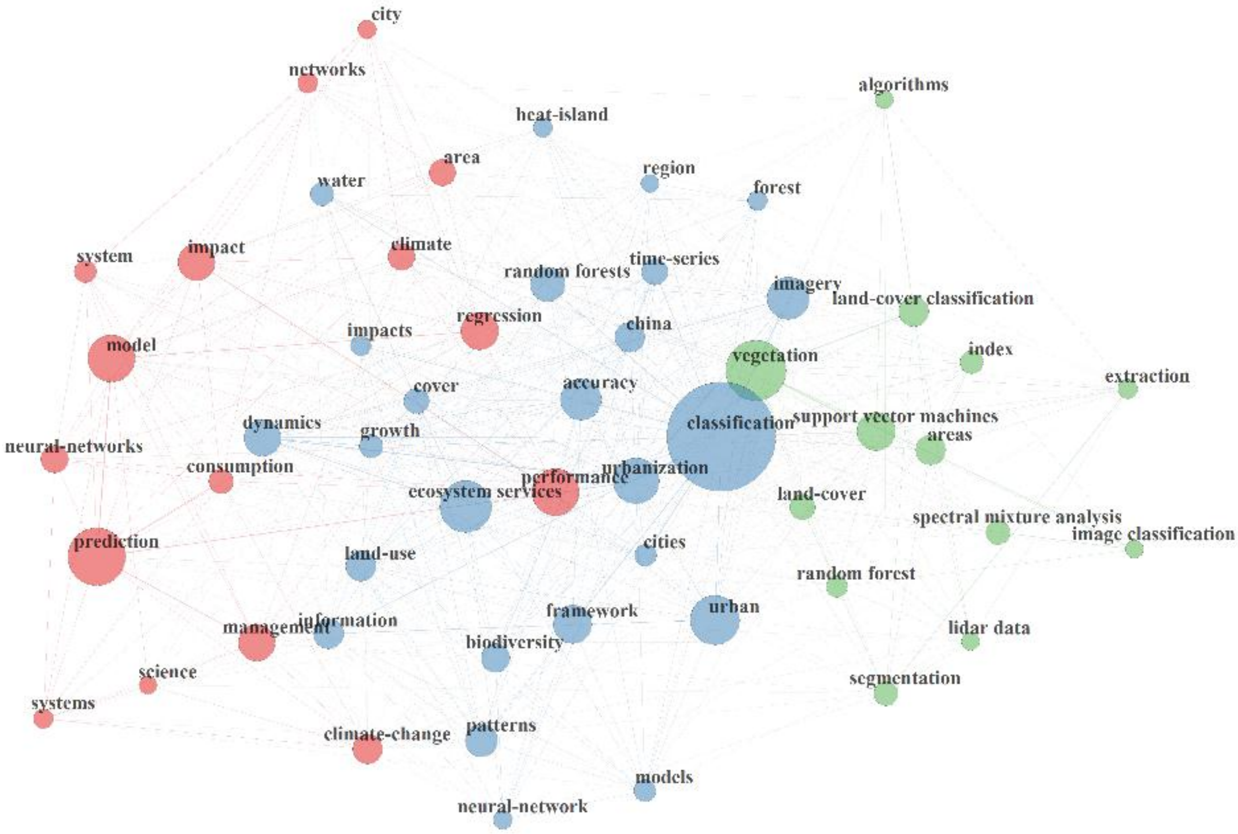

Figure 3: Keyword co-occurrence network illustrating the relationships between classification, prediction, and the associated methods.

2.3 Potentials in Urban Landscape Design Process

The urban landscape design process can be divided into evaluation, design, construction, and post-occupancy phases (Felson et al., 2013). This research focuses on evaluation, design, and post-occupancy, excluding construction. Table 2 provides a general categorization of machine learning-enabled research relevant to each step:

Table 2: General Categorization of Machine Learning-Enabled Research Studies

Urban Landscape Design Process Step	Types of Relevant Machine Learning-Enabled Research Studies
Evaluation	- Urban pattern classification - Urban quality evaluation - Urban landscape characteristics inventory - Citizens’ perception of the urban landscape
Design	- Effect of built environment characteristics/features on design goals - Drawing and generative systems
Post-occupancy	- Urban monitoring and citizen science - Citizens’ perception of the urban landscape

2.3.1 The Evaluation Step

Machine learning (ML) enhances the understanding of urban landscape patterns and processes on a large scale. For instance, ML has been employed to classify urban buildings (Hussain & Chen, 2014), land use (Chang et al., 2015), settlements (Wieland & Pittore, 2016), and roof types (Mohajeri et al., 2018) using satellite imagery and other data sources. ML aids urban designers and planners in identifying issues and opportunities for design interventions. Urban quality evaluation studies use ML to assess building façades (Liu et al., 2017) and visual quality of streets (Yu Ye et al., 2019). Urban landscape characteristics inventory includes large-scale inventories like color palettes (Kato & Matsukawa, 2019) and greenery exposure (Ye et al., 2019). ML methods also help link citizens' perceptions to the built environment (Rossetti et al., 2019) and explore how urban form impacts perceptions of safety and pleasantness (Candeia et al., 2017).

2.3.2 The Design Step

Although there are limited ML-enabled tools for urban landscape design, existing studies provide a foundation for integrating ML into design/analysis tools. These studies explore how design parameters impact goals at various scales. ML techniques have been used to study urban landscape elements’ impact on temperature, visual quality, perception, and walkability (Duncan et al., 2019; Rossetti et al., 2019). Other studies focus on energy performance related to urban design/building parameters (Oh & Kim, 2019). Some research investigates the relationship between urban amenities and citizen behavior (Noyman et al., 2019). Emerging studies are integrating ML into computer-aided design tools for real-time design evaluation (Chang et al., 2019; Koenig & Schmitt, 2016) and facilitating urban landscape design drawings (Zheng & Vega, 2019).

2.3.3 The Post-occupancy Step

Monitoring is central to the post-occupancy phase, with citizen science playing a significant role. Online platforms enable crowdsourced reporting and documentation of urban landscape characteristics. Studies like Hsu et al. (2019) demonstrate crowdsourced mapping and ML for predicting odor, while Harris et al. (2017) propose ML-based ranking systems for infrastructure health. Research on citizens' perceptions and urban quality evaluations from the evaluation phase is also useful for post-occupancy assessment.

2.4 Potentials for Urban Landscape Design Topics

Machine learning applications related to key urban landscape topics such as resilience, green infrastructure, and urban ecosystem services are explored in this section. Table 3 categorizes ML-enabled studies relevant to each topic:

Table 3: General Categorization of Machine Learning-Enabled Research Studies by Urban Landscape Design Topic

Urban Landscape Design Topic	Types of Relevant Machine Learning-Enabled Research Studies
Resilience	- Built environment characteristics and extreme environmental events
Green Infrastructure	- Green infrastructure adoption predictive modeling - Green infrastructure placement optimization - Green infrastructure classification
Urban Ecosystem Services	- Urban ecosystem unit classification

2.5 Resilience

Resilience is a critical topic in urban landscape design. ML helps evaluate urban landscape vulnerability to extreme events like earthquakes (Gei et al., 2016), landslides (Chen et al., 2019), and floods (Saravi et al., 2019). Other studies use ML to assess damage from these events (Yang & Cervone, 2019).

2.6 Green Infrastructure

ML methods have been applied to differentiate types of green infrastructure through satellite imagery (Kranjčić et al., 2019) and predict adoption based on socioeconomic and physical attributes (Amodeo & Francis, 2019; Labib, 2019). ML also aids in predicting land use changes with existing green infrastructure policies (Shade & Kremer, 2019) and analyzing sentiments about green infrastructure through social media (Rai et al., 2018). Additionally, ML helps optimize green infrastructure placement and design patterns promoting human well-being (Rai et al., 2019; Raei et al., 2019).

2.7 Urban Ecosystem Services

Several studies focus on ML for classifying ecosystem service units from satellite imagery (Sannigrahi et al., 2019) and assessing cultural ecosystem services from social media photos (Richards & Tuncer, 2018). Machine learning methods, such as decision trees and neural networks, can explain overall ecosystem services supply based on environmental and socio-economic factors (Mouchet et al., 2014).

III. Conclusion and Outlook

A recent survey by ASLA (2019) indicates that over 25% of landscape architecture firms plan to incorporate AI/ML into their computational workflows. This trend, coupled with the increasing focus on the potential of ML in landscape architecture (Cantrell &Mekies, 2018; Schlickman, 2019), underscores the significance of studies like this one. This review is part of an ongoing systematic exploration of machine learning applications in urban landscape design. Although the 71 studies reviewed here do not encompass all relevant research, they provide a strong foundation for examining ML methods' potential in urban landscape design.The primary question addressed by this review is: How can machine learning be applied to urban landscape design problems? This research offers initial answers by categorizing ML studies relevant to various steps of the urban landscape design process and specific design topics. This categorization enables landscape architects to locate pertinent studies according to their design phase or topic of interest. Although the literature on integrating ML with computer-aided design (CAD) tools is expanding, it remains limited. This area represents a critical opportunity for future research aimed at enhancing the integration of ML into urban landscape design workflows.

While the main audience for this review is landscape architects and designers, it also aims to stimulate cross-disciplinary dialogue between urban technologists and designers. This dialogue is essential for addressing timely design and research questions and leveraging computational advancements to answer them. Furthermore, this study highlights the civic implications of using ML in the urban landscape design process, suggesting it as an important avenue for future exploration.

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