Application of Machine Learning for Urban Landscape Design: A Primer for Landscape Architects

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Abstract: How can machine learning (ML) be applied to urban landscape design problems? This paper provides primary answers to this question by categorizing the ML studies relevant to different steps of urban landscape design process as well as different urban landscape design topics. Given the landscape design stage and topic, this categorization helps landscape architects to utilize the existing ML studies and help to frame new relevant ML research questions.

Keywords: Machine learning, urban landscape design, review

1 Introduction

The increasing emergence of large urban datasets from different sources such as environmental sensors, satellite imagery, internet, and ubiquitous computing provides new ground to answer research questions and solve practical problems in different disciplines from business to design. In this context, many disciplines have applied machine learning (ML) for analysis of 'big' urban data. Most of these studies are not coming from design disciplines and have a focused scientific outcome such as air pollution analysis or intelligent transportation systems without a strong connection to the design of the built environment.

There are several ways that ML can be applied in urban landscape design. While ML generated landscape design solutions are possible, they rarely have been studied and remain a future field of research. Most of the relevant studies on the application of ML for understanding urban landscapes exist outside of landscape architecture and design fields and thus lack the connection to design. Within this context, review papers that clearly describe and classify these applications and make the connection to design are crucial for any future research at this intersection. They can serve as guidelines for landscape architects and urban landscape researchers to understand the potentials of machine learning methods in their relevant contexts. However, such reviews are rare. This research aims to address this gap by providing a review of the application of machine learning methods in urban landscape design.

One possible categorization of the applications of ML in urban landscape design is by the relevance of existing studies to different steps of the urban landscape design process. What types of ML-enabled studies are useful in the evaluation, design or post-occupancy phases of urban landscape design? Another possible categorization application of ML in urban landscape design is by studies based on the central themes that are relevant to many urban landscape projects. Dominant in many discussions on urban landscape architecture are topics of resilience, ecosystem services, and green infrastructure. This paper uses both categorizations to map the pathways that urban landscape design can benefit from ML-enabled urban landscape studies.

To do so, this paper reviews scholarly literature that is relevant to the application of machine learning in urban landscape design. The main citation databases that have been used in this

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review are Scopus, Web of Science and Google Scholar to obtain scholarly studies. Table 1 shows the main terms that have been searched in three main sections.

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	

Since there is a very limited body of literature that directly links machine learning to urban landscape design, the main inclusion criteria was to keep the studies that address modelling or design of an urban phenomenon, system, function or characteristic that is relevant to the urban landscape design process. The 'borderline' papers in which the physical context of the cities is not studied have been kept if they generally have the potential to be related to physical aspects of the built environment or they have a crucial role in understanding the urban landscape.

2 Machine Learning, Landscape Design Process and Topics

2.1 General Characteristics of the Reviewed Studies

The final search query was the combination of the search results from Web of Science, Scopus and Google scholar with 1275 entries. The timelines of the studies show a steep increasing trend in just the last few years. Conforming with the inclusion criteria described above, 456 papers were remaining in the relevant literature pool. The final reviewed papers were selected from this set and included 71 papers. The main inclusion criteria for this subset were to be reflective of general topics in the larger dataset and also to be more directly applicable in design and planning. A word cloud visualization of the abstracts of all the entries and the reviewed set shows that the focus has shifted to the papers that were connected more to design and planning (Figure 1).

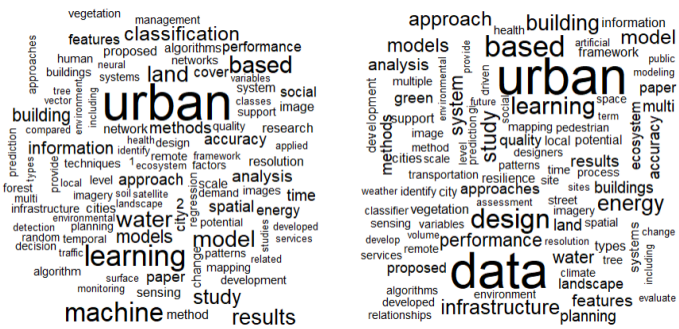

Fig. 1: Word cloud visualization of all the data (left) and the reviewed set (right)

Among the 71 reviewed studies, 34 were published in 2019 and 15 in 2018, reflecting the same trend in the larger search results which indicates the on-going explosion of machine learning studies. The oldest paper reviewed dates back to 2005. In order to further understand the main areas of the studies reviewed, a Latent Dirichlet Allocation algorithm (LDA) was run on the articles' abstracts through the use of *topicmodels* package in the R programming language. The topic modelling analysis revealed three main topic categories (Figure 2). The first category is focused more on urban design and building parameters for evaluating urban landscape performance, particularly energy performance. The second group of the studies focuses on topics such as green infrastructure, urban landscape quality and human component of the urban landscape. The third group of studies is mostly focused on Land Use Land Cover (LULC) classification of satellite imagery for understanding different characteristics of the urban landscape including ecosystem services.

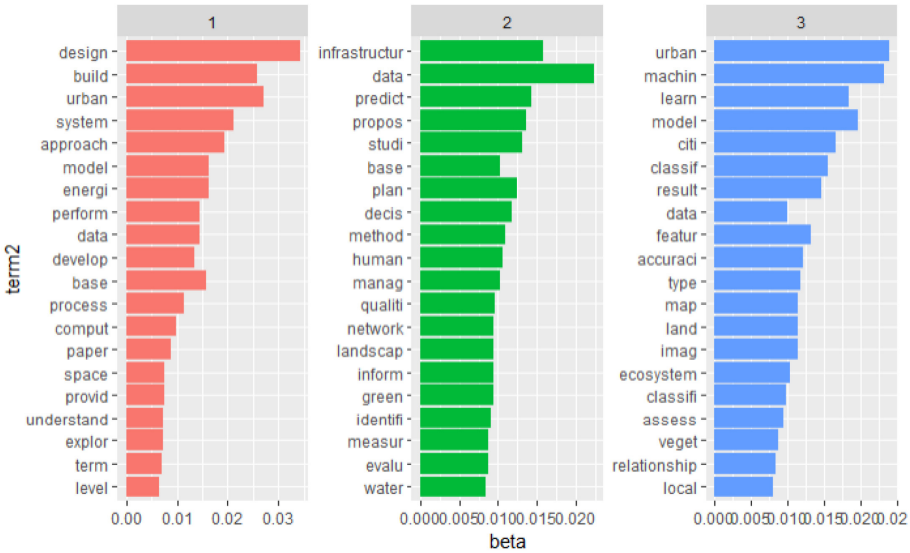

Fig. 2: Clusters resulted from topic modelling of the reviewed papers

2.2 Relevant Machine Learning Methods

"Machine learning addresses the question of how to build computers that improve automatically through experience" (HORVITZ & MULLIGAN 2015). The machine learning methods can be classified into three main categories of 1) supervised, 2) unsupervised and 3) reinforcement learning. Supervised learning methods are the most widely used machine-learning methods and classification is the main task associated with these methods.

The query results from Web of Science (WOS) (n=654) were further analysed with bibliometrix R package (due to its compatibility with the package). The resulting summary of the most frequent author keywords shows the most frequent machine learning methods used in these studies were random forest, support vector machine/regression, deep learning, artificial neural networks, and convolutional neural networks while the most frequent data types were social media, Land Use Land Cover, Landsat, and LiDAR. The keyword co-occurrence net-

work of WOS results shows recurrent keywords that appeared together (Figure 3). Classification is the dominant keyword that is closely related to Support Vector Machines and Random Forests. Prediction is another dominant keyword and is more closely related to Regression and Neural Networks in these studies.

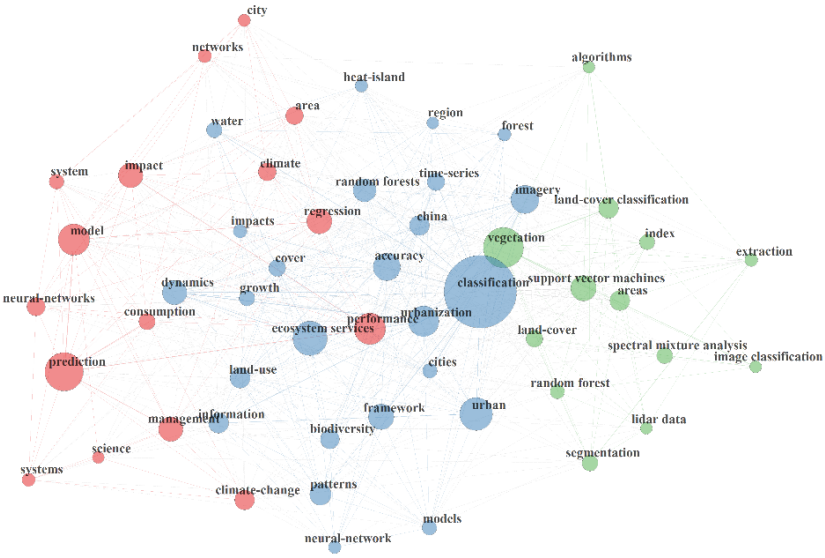

Fig. 3: The keyword co-occurrence network of WOS results

2.3 Potentials in Urban Landscape Design Process

The urban landscape design process can roughly be summarized in *evaluation*, *design*, *construction* and *post-occupancy* tasks (FELSON et al. 2013). This paper doesn't focus on construction but shows the potentials of the reviewed studies for each step of evaluation, design and post-occupancy. Table 2 shows a general categorization of the types of reviewed studies that are relevant to each step.

Table 2: General categorization of the types of reviewed studies that are relevant to each step of the urban landscape design process

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 a design goal • Drawing and generative systems
Post-occupancy	• Urban monitoring and citizen science • Citizens' perception of the urban landscape

The evaluation step. This step can benefit ML to understand the patterns and processes of the urban landscape on an unprecedented scale. There are numerous studies on using ML to classify urban buildings (HUSSAIN & CHEN 2014), land use (C. CHANG et al. 2015), settlements (WIELAND & PITTORE 2016), landscape patterns (ZHANG & BOWES, 2019), roof types (MOHAJERI et al. 2018) from satellite imagery alone or combined with other data sources. Understanding the existing types of the built environment and automating the classification at the city scale help urban landscape designers and planners to identify existing issues and future opportunities for design interventions. Examples of urban quality evaluation studies include the use of ML for evaluating the quality of building façades across the city to identify areas for regeneration (LIU et al. 2017) or evaluating the visual quality of streets (YU YE et al. 2019, L. ZHANG et al. 2019). Urban landscape characteristics inventory studies give us large scale inventory of urban characteristics such as colour palette (KATO & MATSUKAWA 2019), and exposure to greenery (Y. YE et al. 2019). Understanding the citizens' perception of the urban landscape is also crucial for both evaluating the performance of existing conditions but also for post-occupancy monitoring of a new design or development. For example, ROSSETTI et al. (2019) connected subjective data sources of citizens' perception to the characteristics of the built environment with the help of ML methods. CANDEIA et al. (2017) have used ML to explore how urban form can affect people's perception of safety or pleasantness of urban spaces.

The design step. While there are not many machine learning-enabled tools for designing urban landscapes, several papers reviewed in this study can be considered as a foundation for future integrated design/analysis tools in which machine learning helps the urban landscape designers to understand how the design parameters affect design objectives in different scales. The reviewed papers in this category have used machine learning techniques to explore the relationship of configuration and presence of urban landscape elements on urban temperature, visual quality, human perception and walkability (DUNCAN et al. 2019, ROSSETTI et al. 2019, YIN & WANG 2016, YU YE et al. 2019). Urban landscape features explored include urban landscap10e elements themselves (e. g. sidewalk, road, traffic sign), configuration of the elements, or characteristics indicators (e. g. visual enclosure, vegetation configuration, landscape elements diversity). Other studies have focused on built environment characteristics such as urban design and building parameters to evaluate energy performance at the urban scale (S. CHANG et al. 2019, OH & KIM 2019). For example, OH & KIM (2019) used machine learning to study the urban design/building parameters (such as ratio of perimeter to area, orientation of building, etc.) to evaluate energy performances of an urban setting. More in the context of urban planning than design, the relationship between the location of urban amenities and citizens' behavioural patterns has been explored in the urban context with ML techniques (NOYMAN et al. 2019).

In addition to these studies, there are limited but growing numbers of studies that explore the integration of machine learning to computer-aided design tools. These studies try to fill the gap between design and analysis and provide real-time evaluation of design decisions (S. CHANG et al. 2019, KOENIG & SCHMITT 2016). Within this context, there are also examples of using machine learning to facilitate urban landscape design drawings (e. g. landscape site plans) (ZHENG & VEGA 2019).

The Post-Occupancy step. Central to the post-occupancy phase of urban landscape design is monitoring. Citizen science has been increasingly used as an effective urban landscape monitoring approach. The advancement of online platforms has created crowd-sourced systems

that enable urban communities to report and document urban landscape characteristics. Several recent studies connected the crowd-sourced urban sensing data with machine-learning enabled predictive or descriptive models to return feedback to the citizens. HSU et al. (2019) provide an example of this through crowd-sourced mapping and machine learning-enabled predicting of odour in Pittsburgh. HARRIS et al. (2017) have proposed a learning-enabled ranking system of infrastructure health based on crowdsourced citizen reports. Many studies described in the evaluation phase such as citizens' perception of urban space or urban quality evaluation are also useful for post-occupancy evaluation of new urban landscape designs.

2.4 Potentials for Urban Landscape Design Topics

Search results with the use of machine learning for understanding different *urban systems* that urban landscape designers interact with were embedded in the studies explored in the previous section. The search results that directly looked for this connection (such as machine learning for urban infrastructure) were mostly deep in other fields such as engineering. Further attempts are needed to connect some of these studies to the design of the urban landscape. Another possible categorization of application of machine learning in urban landscape design is categorizing the studies based on the central themes that are relevant to many urban landscape projects. Dominant in many discussions on urban landscape architecture are topics of resilience, ecosystem services, and green infrastructure. Table 3 shows a general categorization of the types of reviewed studies that are relevant to each urban landscape design topic. The scope of this paper does not allow for an in-depth discussion of the use of machine learning in these topics and it is limited to the relevant examples that have been reviewed in this study.

Table 3: General categorization of the types of reviewed studies that are relevant to each 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 modelling • Green Infrastructure placement optimization • Green infrastructure classification
Urban Ecosystem Services	• Urban ecosystem unit classification

Resilience. Resilience has been a key topic in urban landscape design in recent years. Understanding the vulnerability of urban landscape to different extreme environmental events is the first step for resilient urban landscape design. Several studies used machine learning to evaluate the urban landscape characteristics to identify areas that are vulnerable to an earthquake (GEI et al. 2016), landslide (CHEN et al. 2019) or flood damage (SARAVI et al. 2019). Another group of studies uses machine learning to assess built environment damage after an extreme environmental event such as flood (YANG & CERVONE 2019).

Green infrastructure. Machine learning methods have been used to differentiate types of existing green infrastructure in the cities through land use classification of satellite imagery

(KRANJČIĆ et al. 2019). Green infrastructure adoption is another context that researchers used machine learning for predicting adoption based on socioeconomic (such as population density or wealth) and physical attributes (such as site size) of an urban context (AMODEO & FRANCIS 2019, LABIB 2019). Another study used machine learning to predict the land use change given existing green infrastructure policies (SHADE & KREMER 2019). People's sentiments about urban green infrastructure were captured through the classification of social media posts (RAI et al., 2018). More related to green infrastructure design, RAI et al. (2019) used "a supervised machine-learning model to identify specific patterns in urban green spaces that promote human wellbeing". RAEI et al. (2019) used machine learning as a part of their integrated methodology for optimizing green infrastructure placement.

Urban ecosystem services. There are several studies on this topic. The papers reviewed include studies on using machine learning for ecosystem service unit classification from satellite imagery (SANNIGRAHI et al. 2019) or assessment of cultural ecosystem services from social media photographs (RICHARDS & TUNCER 2018). MOUCHET et al. (2014) mention that machine learning methods such as decision trees and artificial neural network can be used for understanding how the overall ecosystem services (ES) supply can be explained by a set of environmental and/or socio-economic factors as well as identifying the most influential demand for ES on the overall ES supply.

3 Conclusion and Outlook

A recent survey by ASLA (2019) shows that more than 25 % of the landscape architecture firms intended to adopt AI/ML to their future computational workflow. The on-going explosion of ML studies in different fields and increasing attention to the potentials of ML for landscape architecture (CANTRELL & MEKIES 2018, SCHLICKMAN 2019) reinforce the importance of studies such as this review. This review is part of an on-going systematic review on the application of machine learning in urban landscape design. While the studies reviewed for this paper (n=71) did not include all the relevant studies, it provided a solid base for exploring the potentials of ML methods for urban landscape design. The main question that this review explores is: How can machine learning be applied to urban landscape design problems? This paper provided primary answers to this question by categorizing the ML studies relevant to different steps of the urban landscape design process as well as urban landscape design topics. This categorization helps landscape architects to refer to the relevant studies given the stage of design they are in or the topic they work on. The literature on the integration of ML methods to CAD tools is growing but limited. This remains a very crucial area of future research for creating a more effective integration of ML potentials to urban landscape design workflows.

While the main audience of this review is landscape architects and designers, this research hopes to start a cross-disciplinary dialogue between urban technologists and designers in order to ask the timeliest design/research questions and utilize the potentials of computational advancements to answer them. Beyond the urban experts, this study emphasizes the importance of civic implications of using ML in the urban landscape design process as an important future direction.

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