Journal of Urban Development and Smart Cities
2024, 1(1), 33-43

AI-ASSISTED GREEN SPACE LAYOUT OPTIMIZATION FOR SMART-CITY ENVIRONMENTAL DESIGN

Patsy Healey
Kongjian Yu
Xianheng Zheng

As ecological principles increasingly guide contemporary architectural and urban design, optimizing green-space layouts has become central to improving built-environment performance. This study applies the Pix2Pix model to interpret planning-area maps and develops a green-space layout support system implemented in a Unity3D engine with a Python-based workflow. The system enables visual simulation of alternative green-layout schemes and helps designers compare options to identify a preferred configuration. In a case validation, the AI-assisted optimization adopts a zoned daylighting strategy for public areas. Simulation results show reductions in district-building energy use, with cooling demand decreasing from 75.64 kWh/m² to 65.32 kWh/m² and heating demand dropping from 45.26 kWh/m² to 42.31 kWh/m². Residents also reported high satisfaction with the simulated retrofit outcomes. Overall, the proposed approach supports environmentally responsible and sustainable smart-city development by lowering environmental impacts and contributing to healthier, more livable urban spaces.

Index Terms — Pix2Pix algorithm, Unity3D, building spatial layout, urban green planning, sustainable development

INTRODUCTION

With the rapid pace of urbanization, cities are increasingly confronted with a wide range of challenges, including traffic congestion, environmental degradation, inefficient resource utilization, and declining living conditions. In response to these issues, the concept of the smart city has gradually emerged, aiming to enhance the efficiency of urban management and operations through the integration of advanced technologies, while creating more livable and resilient urban environments. Within this framework, green and sustainable development has become a core principle, and the realization of an ecologically balanced and sustainable green space configuration has become an urgent task in contemporary urban planning [1, 2, 3].

Urban green spaces—such as parks, community gardens, waterfront areas, and urban forests—play a vital role in improving environmental quality, promoting public health, and enhancing residents' overall well-being. Smart city initiatives emphasize the strategic planning and construction of such spaces to foster healthy and inclusive urban ecosystems. By integrating vegetation coverage, water-sensitive design, and ecological restoration, cities can establish more sustainable green infrastructures. Moreover, intelligent technologies enable the implementation of smart irrigation systems, adaptive lighting, and automated environmental monitoring, thereby improving the ecological performance of green spaces and strengthening their long-term sustainability. With ongoing technological advancements, artificial intelligence (AI) has emerged as a powerful tool that is increasingly being applied across diverse sectors. Its application in urban green space planning introduces innovative approaches to spatial optimization and decision-making, offering new possibilities for smart city development [4, 5, 6, 7].

Previous studies have highlighted the role of smart cities in addressing complex urban challenges and creating more comfortable and sustainable living environments. For instance, the concept of "cyber-physical" cities emphasizes the integration of sustainability with environmental, social, and governance dimensions in urban operations [8]. Other research has incorporated AI-based algorithms into green landscape design, developing visual systems that operate in both online and offline modes, thereby improving efficiency without disrupting ongoing workflows [9]. Some scholars have focused on designing roadways that accommodate both pedestrian activities and vehicular traffic while aligning with green economic principles, using GIS technologies and genetic algorithms to optimize public street spaces and bridge the gap between urban development and public health [10].

In the field of generative design, generative adversarial networks (GANs) have been shown to produce novel images that conform to domain-specific design rules. Experimental results indicate that GANs can extract implicit design principles and enhance data augmentation, thereby improving the generative capacity of design algorithms [11]. Other studies have emphasized the significance of green indices in urban planning, demonstrating that areas with low green coverage still possess potential for ecological improvement, and stressing the importance of reserving green space as a key strategy for achieving urban well-being [12]. Research on smart city development has further explored the role of information and communication technologies (ICT) in transportation systems and their impacts on citizens' quality of life [13].

Urban green space has also been recognized as a fundamental component of urban infrastructure. Scholars have proposed classification frameworks based on functional combinations of green spaces and investigated variations in public demand for different types of green areas, revealing strong preferences and growing diversification in green space typologies [14]. Additional studies have confirmed the positive effects of urban green spaces on residents' lifestyles, using statistical and spatial analyses to demonstrate how human activity patterns correlate with park distributions, thereby highlighting the need for policy support for accessible green spaces [16]. Furthermore, it has been argued that while urban expansion can alleviate population pressure, ecological sustainability must remain a top priority in smart city construction [17]. Comparative studies of European cities have shown that the effectiveness of green space planning and management is closely linked to governance structures, levels of public participation, and citizen engagement [18].

Against this background, this paper proposes an AI-assisted green space layout design framework for smart cities based on the Pix2Pix algorithm. The model is intended to support optimal spatial planning by automatically generating and refining green space configurations that promote sustainable urban development. Using the Unity3D engine and Python as the development platform, the generator and discriminator components of the Pix2Pix architecture are employed to interpret and analyze floor plans of target urban areas. After inputting relevant design parameters, the model produces simulation-based layout schemes, which are iteratively adjusted to obtain an optimal solution.

To validate the proposed approach, a residential neighborhood is selected as a case study. The model is applied to assist in the intelligent design of green space layouts while accounting for local climatic conditions. By examining changes in energy consumption and resident satisfaction before and after the implementation of the proposed layout, this study evaluates the effectiveness of AI-assisted green space planning and demonstrates its potential in advancing sustainable smart city development.

METHOD

Fundamental principles and advantages of the Pix2Pix algorithm

Core concepts of the Pix2Pix framework

In this research, the Pix2Pix algorithm is adopted as the primary method for generating green space layouts in urban environmental design. Based on its inherent characteristics, a systematic experimental framework is developed to support the layout generation process.

Pix2Pix [19] is a supervised learning model that belongs to the family of conditional generative adversarial networks (cGANs). A cGAN is an extension of the standard generative adversarial network (GAN), and understanding Pix2Pix first requires a basic understanding of GAN principles.

GAN is a deep learning framework inspired by game theory, in which two networks compete in a zero-sum game: a generator and a discriminator. The generator learns a mapping $G : z \to y$, transforming a random noise vector z into a synthetic output y, while the discriminator attempts to distinguish between real and generated samples. Through continuous adversarial training, the generator improves its ability to produce outputs that resemble real data.

Conditional GANs enhance this framework by introducing conditional information into the generation process. Instead of learning from random noise alone, cGANs learn a conditional mapping $G : \{x, z\} \to y$, where x represents a given input condition (such as an image or structural map), z is a random noise vector, and y is the corresponding output. This conditional mechanism enables the model to generate outputs that are consistent with specific constraints or semantic contexts.

Pix2Pix architecture and its advantages

Beyond generating images based on textual descriptions, cGANs are well suited for a wide range of image-to-image translation tasks, where an input image serves as the condition. Pix2Pix was specifically designed to address such problems.

The Pix2Pix architecture consists of two main components: a generator G and a discriminator D. Its objective function is derived from the cGAN framework. A paired dataset is first prepared, containing input images x and their corresponding target images y. The input image x acts as a conditional constraint and is fed into both the generator and the discriminator. The generator also receives a random noise vector z and produces a synthesized image $G(x,z)$. The discriminator then evaluates whether the pair $\{x, G(x,z)\}$ is real or fake by comparing it with the ground-truth pair $\{x,y\}$, outputting a scalar value between 0 and 1. A value closer to 1 indicates a higher likelihood of authenticity.

During training, the generator continuously updates its parameters to fool the discriminator, while the discriminator simultaneously improves its classification accuracy. This iterative process gradually enhances the realism and fidelity of the generated images.

The objective function of the cGAN framework can be written as

$$\mathscr{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[\log D(x,y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x,z)))]. \tag{1}$$

In this adversarial process, the generator attempts to minimize the loss, whereas the discriminator aims to maximize it.

Previous studies have shown that combining adversarial loss with traditional pixel-wise loss functions can significantly improve output stability and realism. Therefore, Pix2Pix introduces an additional L_1 loss term, which encourages the generated image to be structurally similar to the target image. The final optimization objective becomes

$$G^* = \arg\min_G \max_D \mathscr{L}_{cGAN}(G,D) + \lambda \mathscr{L}_{L1}(G), \tag{2}$$

where λ controls the relative importance of the L_1 constraint.

One of the most important strengths of Pix2Pix is its generality. Unlike many task-specific cGAN models, Pix2Pix does not rely on customized network structures for different applications. Instead, it can be adapted to a wide range of problems simply by modifying the training dataset, making it particularly suitable for interdisciplinary studies such as urban green space planning.

Construction of the green space layout design model

Simulation platform and programming environment

The simulation environment in this study is developed using the Unity3D engine [20], a cross-platform real-time rendering engine created by Unity Technologies. Unity3D has become a popular choice in recent years due to its versatility and strong visualization capabilities. Its main advantages in this research include:

- Integrated development environment: Unity3D follows an "all-in-one" design philosophy, integrating scene editing, scripting, rendering, and debugging into a single platform.
- Real-time visualization: Parameters can be modified dynamically during execution, allowing instant visual feedback on green space layout designs.
- Extensive resource support: Unity's Asset Store provides a large collection of free and paid resources, significantly reducing development time.

The programming language used is C#, a modern, object-oriented, and component-based language supported by the Mono framework. C# is widely used in Unity-based development due to its stability, ease of learning, and strong industry support.

Model implementation

The Pix2Pix-based green space layout generation model is implemented using Python [21] in the PyCharm development environment. The main steps of the modeling process are summarized as follows:

1. Two folders are created within the dataset directory: one for input layout maps and the other for corresponding labeled maps. The numbers and filenames of these images must match exactly. The script `combine_A_and_B.py` is then executed to merge paired images into a single training format.
2. Before training, key parameters are configured, including dataset paths, multi-GPU options, generator and discriminator architectures, batch size, and the number of data loading threads. Training-related parameters such as the number of epochs, learning rate, and loss function type are also specified.
3. The model is trained by running the `train.py` script. During training, the Visdom visualization tool is used to monitor the evolution of the loss curves and the quality of generated images.
4. After training, the generated layouts are evaluated against real data. If the results are unsatisfactory, training can be resumed by enabling the `continue_train` option. The `test.py` script is then used to generate final layout outputs for evaluation.

Loss functions and optimization strategy

The Pix2Pix loss function is derived from the conditional GAN framework:

$$\mathscr{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[\log D(x,y)] + \mathbb{E}_{x,z}[\log(1 - D(x,G(x,z)))]. \tag{3}$$

The generator seeks to minimize this loss, while the discriminator aims to maximize it. To further constrain the similarity between the generated and real images, Pix2Pix incorporates an L_1 loss term. The combined objective function is

$$G^* = \arg\min_G \max_D \mathscr{L}_{cGAN}(G,D) + \lambda \mathscr{L}_{L1}(G). \tag{4}$$

For optimization, the Adam algorithm is employed, with momentum parameters $\beta_1 = 0.5$ and $\beta_2 = 0.999$. This optimizer provides stable convergence and is well suited for adversarial training tasks.

RESULTS AND DISCUSSION

Selection of the research site

Basic information of the selected residential project

The case study selected for this research is a high-rise residential community located in Xi'an, China. Although the project has obtained a two-star green building design certification, it still exhibits notable deficiencies in several key indicators, including plot ratio, green space coverage, and building density. Moreover, the overall energy consumption of the residential buildings remains high, while the satisfaction level of residents is relatively low. At present, the evaluation system for high-standard green buildings in China is still under development, and the correlation between mandatory and scoring items in the "Four Sections and One

Environmental Protection" framework remains insufficiently precise. This often results in suboptimal spatial configurations of green buildings.

To address these shortcomings, this study applies an AI-assisted green spatial layout design model to optimize both the neighborhood environment and the spatial organization of buildings. The selected site is located on Guo Du Street in Chang'an District, Xi'an, bordered by the planned Gao Yang 4th Road to the west, Gao Yang 3rd Road to the east, Jian Ye 3rd Road to the south, and Jian Ye 2nd Road to the north. The total planned land area is 35,624.62 m^2, with a gross floor area of 136,542.26 m^2. Of this, 96,524.35 m^2 is dedicated to residential use above ground. Commercial buildings occupy 6,642.35 m^2, while public service facilities account for 2,364.52 m^2, with the remainder consisting of ancillary neighborhood amenities such as fitness and recreational spaces.

The project has a plot ratio of 3.4, a green space ratio of 29.65%, and a building density of 20.14%, accommodating a total of 962 households. In this study, both the community environment and the residential buildings are redesigned using the AI-assisted green layout framework. The sample includes five 13-story buildings, five 15-story buildings, two 17-story buildings, one 21-story building, one 26-story building, and one 30-story building. Detailed information is summarized in Table 1.

Table 1: Single building information

Floor number	Function	Monomer building area (m^2)	Building number	Altitude (m)	Structural form	Household number
A-1#	Business and office	6384.98	15F/-2F	92.36	Shear wall	——
A-2#	Supporting house	9737.86	26F/-2F	96.42	Shear wall	164
A-3#	Housing	5848.83	30F/-1F	99.86	Shear wall	172
A-4#	Housing	8326.45	21F/-1F	92.34	Shear wall	62
A-5#	Housing	4908.07	15F/-1F	48.92	Shear wall	50
A-6#	Housing	15748.9	17F/-1F	53.64	Shear wall	37
A-7#	Housing	7705.77	15F/-1F	48.92	Shear wall	39
A-8#	Housing	8646.55	15F/-1F	48.92	Shear wall	74
A-9#	Housing	13491.68	17F/-1F	53.64	Shear wall	39
A-10#	Housing	5108.82	15F/-1F	48.92	Shear wall	39
A-11#	Housing	15806.1	13F/-1F	42.36	Shear wall	21
A-12#	Housing	9346.39	13F/-1F	42.36	Shear wall	54
A-13#	Housing	8246.71	13F/-1F	42.36	Shear wall	73
A-14#	Housing	5247.85	13F/-1F	42.36	Shear wall	79
A-15#	Housing	7429.79	13F/-1F	42.36	Shear wall	79

Climatic conditions of the study area

Prior to the green layout optimization, a detailed climatic analysis of the site was conducted to ensure that the design could effectively respond to local environmental conditions. Xi'an is situated in the southern Guanzhong Plain and experiences a warm temperate semi-humid continental monsoon climate, classified as cold zone B.

Meteorological data extracted using Ecotect software were employed to generate annual wind rose diagrams for the study area. Figure 1 illustrates the prevailing wind directions and velocities for the entire year, as well as for winter and summer periods. The annual dominant wind direction is southwest, with a maximum recorded speed of 34.9 knots/h and a frequency of 11.11%. During winter, the dominant wind directions are east-northeast and west-southwest, each with a frequency of 11.87%. In summer, the prevailing wind direction shifts to the west, with wind speeds ranging from 0.2 m/s to 30 m/s.

Additional climatic parameters are listed in Table 2. The extreme maximum and minimum temperatures are 40.63°C and -15.23°C, respectively. The annual sunshine duration is approximately 1,426.32 h, with an average annual precipitation of 542.36 mm. Xi'an belongs to the general solar resource zone in China, with

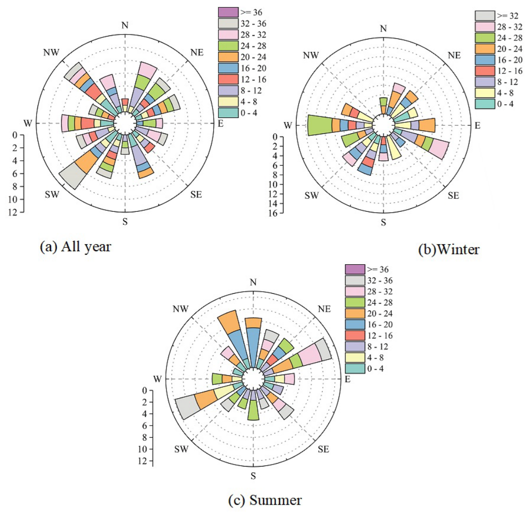

Figure 1: Wind velocity analysis

an annual total solar radiation of 4,752.62 MJ/m^2 and an average daily radiation of 13.02 MJ/m^2. The average daily sunshine duration ranges from 4.5 h in winter to 7.5 h in summer, providing favorable conditions for the utilization of renewable energy in green layout planning.

Table 2: Analysis of major natural environment conditions

Serial number	Species	Numerical value
1	Annual average temperature	14.23°C
2	Annual average rainfall	542.36 mm
3	Average temperature for the coldest month	-1.32°C
4	Average temperature of the hottest month	28.63°C
5	Minimum extreme temperature	-15.23°C
6	Maximum extreme temperature	40.63°C
7	Maximum annual precipitation	923.64 mm
8	Minimum annual precipitation	306.52 mm
9	Average annual relative humidity	68.92%
10	Mean sea level pressure value	1052.62 hPa

Simulation results of green layout optimization

The Pix2Pix-based green layout design model was employed to assist planners in optimizing the environmental configuration of the selected residential community. The resulting land-use distribution before and after the transformation is presented in Table 3.

The AI-assisted design incorporates a variety of passive and active energy-saving strategies. Passive strategies primarily focus on the spatial reorganization of green infrastructure, such as the installation of permeable pavements and the optimized placement of solar panels. These measures are aligned with the energy-saving requirements of public buildings in Shaanxi Province and meet the mandatory criteria for two-star green buildings.

Permeable pavements constitute the largest proportion of green infrastructure in the optimized layout. Over 96% of sidewalks, open spaces, and parking areas are converted to permeable surfaces. Due to structural

Table 3: Design results of the environment and layout of the building

Land type	Before transformation		After transformation	
	Occupied land (m^2)	Occupied proportion (%)	Occupied land (m^2)	Occupied proportion (%)
Building roof	3654.26	91.07%	3654.2	82.62%
Road surface	115.42	2.88%	106.35	2.40%
Urban green space	69.52	1.73%	91.26	2.06%
Walkways and parking lots	56.93	1.42%	52.34	1.18%
Water float	36.42	0.91%	95.64	2.16%
Green roof	64.26	1.60%	96.35	2.18%
Solar panel	0	0.00%	265.34	6.00%
Sunken green space	15.24	0.38%	56.54	1.28%
Biostranded facilities	0.65	0.02%	4.96	0.11%
Rainwater bucket	4	——	16	——

constraints and cost-benefit considerations, green roofs are implemented only on selected buildings, increasing their coverage from 0.91% to 2.16%. Flat green spaces are redesigned as sunken green areas and bioretention facilities to improve stormwater management and water purification. Consequently, the proportion of sunken green spaces increases from 0.38% to 1.28%, while bioretention facilities grow from 0.02% to 0.11%.

Rainwater harvesting systems, including 16 rain barrels, are integrated into the design to enhance water reuse. Furthermore, given the high solar potential of the site, 265.34 m^2 of photovoltaic panels are installed to reduce reliance on non-renewable energy sources.

Active strategies primarily target the optimization of HVAC and lighting systems. The coefficient of performance (COP) of the cooling system is improved by 17.42% compared to baseline energy-saving standards. High-efficiency LED lighting is adopted throughout the project, with zoning strategies applied to corridors, stairwells, and entrance halls to reduce lighting power density and minimize unnecessary energy consumption.

Evaluation of optimization performance

Comparative analysis of energy consumption

To quantify the effectiveness of the proposed layout, energy simulations were conducted using the DesignBuilder platform. Table 4 summarizes the energy consumption per unit area before and after optimization.

Table 4: Unit building area energy consumption value

Energy consumption project	Before (kWh/m^2)		After (kWh/m^2)		Energy efficiency (%)	
	General building	Residential building	General building	Residential building	General building	Residential building
Total energy consumption	150.84	131.41	129.18	111.16	14.36%	15.41%
Refrigeration energy consumption	75.64	68.52	65.32	58.94	13.64%	13.98%
Heat consumption	45.26	41.23	42.31	36.48	6.52%	11.52%
Lighting energy consumption	15.42	11.49	9.63	7.52	37.55%	34.55%
Equipment energy consumption	9.87	6.52	8.97	6.09	9.12%	6.60%
Energy consumption in hot water	4.65	3.65	2.95	2.13	36.56%	41.64%

Before optimization, the total energy consumption of the general buildings and residential buildings was 150.84 kWh/m^2 and 131.41 kWh/m^2, respectively, exceeding the benchmark values specified by local standards. After applying the optimized green layout, significant reductions were observed in cooling, heating, lighting, and domestic hot water consumption. For instance, cooling energy decreased from 75.64 kWh/m^2 to 65.32 kWh/m^2, while heating energy dropped from 45.26 kWh/m^2 to 42.31 kWh/m^2.

Overall, the energy-saving rate for residential buildings reached 15.41%, demonstrating the substantial impact of the AI-assisted design approach on sustainable community development.

Resident satisfaction analysis

In addition to energy efficiency, resident satisfaction is a critical indicator of smart city performance. Based on previous studies, five evaluation dimensions were established: natural environment (A1), built environment (A2), green activity areas (A3), spatial distribution of facilities (A4), and energy-saving measures (A5).

A Likert-scale questionnaire was used to assess satisfaction among young, middle-aged, and elderly residents. As illustrated in Figure 2, all dimensions scored above the neutral midpoint of 3. Specifically, satisfaction with the natural environment (4.18), built environment (4.16), green activity areas (3.86), and energy-saving measures (3.96) indicates a generally positive perception of the optimized layout.

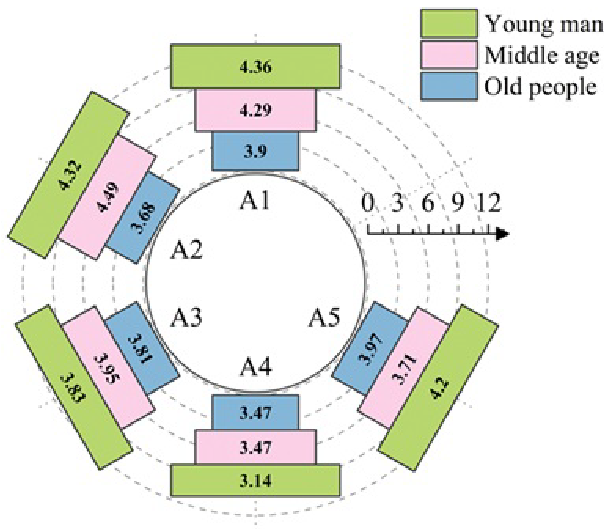

Figure 2: Analysis of environmental satisfaction in the community

The highest score for the natural environment reflects the improved vegetation coverage and spatial coherence achieved through the AI-assisted design. The relatively lower score for facility distribution (3.36) suggests that further refinement is needed in the placement and accessibility of service and rest facilities.

Overall, the results confirm that the proposed green layout framework not only improves energy performance but also enhances residents' perceived comfort and quality of life.

CONCLUSION

This study proposes an intelligent auxiliary design framework for green space layout in smart city environments by integrating the Pix2Pix algorithm with the Unity3D simulation platform. Through a real-world community case study, the feasibility and effectiveness of the proposed model were validated. The main conclusions can be summarized as follows.

1. To enhance stormwater management and improve water purification capacity, the original flat green areas within the community were redesigned as sunken green spaces and bioretention facilities. As a result, the proportions of sunken green spaces and bioretention facilities increased from 0.38% and 0.02% to 1.28% and 0.11%, respectively. In addition, a zoned lighting strategy was implemented in public areas, with reduced lighting power density in corridors, stairwells, and foyers. This demand-oriented allocation effectively minimized unnecessary energy consumption.

2. After implementing the optimized layout generated by the proposed green space design model, significant reductions in building energy consumption were observed. Specifically, the cooling and heating energy demands of the community buildings decreased from 75.64 kWh/m^2 and 45.26 kWh/m^2 to 65.32 kWh/m^2 and 42.31 kWh/m^2, respectively. Moreover, the overall energy-saving rate of residential buildings reached 15.41%, demonstrating the substantial energy efficiency gains enabled by the AI-assisted approach.

3. The post-renovation satisfaction levels of residents were generally high, with the natural environment receiving the highest score (4.18 points). This indicates that the green space layout generated with artificial intelligence support provides richer vegetation coverage and a more rational spatial organization, significantly improving the perceived quality of the living environment.

4. The proposed artificial intelligence-based framework offers a practical tool for assisting the design of rational building environments and spatial configurations. It supports sustainable development objectives in urban construction and provides valuable insights and methodological references for future green and eco-friendly building projects.

REFERENCES

[1] Picon A. Smart Cities: A Spatialised Intelligence. John Wiley & Sons; 2015 Nov 16.

[2] Davis K. The rise of the smart city. PowerGrid International. 2010. https://www.renewableenergyworld.com/power-grid/smart-grids/the-rise-of-the-smart-city/.

[3] Picon A. Urban infrastructure, imagination and politics: from the networked metropolis to the smart city. International Journal of Urban and Regional Research. 2018 Mar;42(2):263-75.

[4] Roscia M, Longo M, Lazaroiu GC. Smart City by multi-agent systems. In2013 International Conference on Renewable Energy Research and Applications (ICRERA) 2013 Oct 20 (pp. 371-376). IEEE.

[5] Corbett J, Mellouli S. Winning the SDG battle in cities: how an integrated information ecosystem can contribute to the achievement of the 2030 sustainable development goals. Information Systems Journal. 2017 Jul;27(4):427-61.

[6] Aronson MF, Lepczyk CA, Evans KL, Goddard MA, Lerman SB, MacIvor JS, Nilon CH, Vargo T. Biodiversity in the city: key challenges for urban green space management. Frontiers in Ecology and the Environment. 2017 May;15(4):189-96.

[7] Wang F. Does the construction of smart cities make cities green? Evidence from a quasi-natural experiment in China. Cities. 2023 Sep 1;140:104436.

[8] Molnár B, Pisoni G, Kherbouche M, Zghal Y. Blockchain-based business process management (BPM) for finance: the case of credit and claim requests. Smart Cities. 2023 May 3;6(3):1254-78.

[9] Zhou J. Visualization of green building landscape space environment design based on image processing and artificial intelligence algorithm. Soft Computing. 2023 Jul;27(14):10225-35.

[10] Liu Y, Qin S, Li J, Jin T. Artificial intelligence and street space optimization in green cities: new evidence from China. Sustainability. 2023 Nov 28;15(23):16367.

[11] Chen R, Zhao J, Yao X, Jiang S, He Y, Bao B, Luo X, Xu S, Wang C. Generative design of outdoor green spaces based on generative adversarial networks. Buildings. 2023 Apr 20;13(4):1083.

[12] Anguluri R, Narayanan P. Role of green space in urban planning: Outlook towards smart cities. Urban Forestry & Urban Greening. 2017 Jul 1;25:58-65.

[13] Dameri RP. Smart City and ICT. Shaping urban space for better quality of life. InInformation and Communication Technologies in Organizations and Society: Past, Present and Future Issues 2016 (pp. 85-98). Springer International Publishing.

[14] Shan J, Huang Z, Chen S, Li Y, Ji W.

[15] Green Space Planning and Landscape Sustainable Design in Smart Cities considering Public Green Space Demands of Different Formats. Complexity. 2021;2021(1):5086636.

[16] Liu Q, Hou L, Shaukat S, Tariq U, Riaz R, Rizvi SS. Perceptions of spatial patterns of visitors in urban green spaces for the sustainability of smart city. International Journal of Distributed Sensor Networks. 2021 Aug;17(8):15501477211034069.

[17] Northfield R. Greening the smart city. Engineering & Technology. 2016 Jun;11(5):38-41.

[18] Baycan-Levent T, Nijkamp P. Planning and management of urban green spaces in Europe: Comparative analysis. Journal of Urban Planning and Development. 2009 Mar;135(1):1-2.

[19] Tirel L, Ali AM, Hashim HA. Novel hybrid integrated Pix2Pix and WGAN model with Gradient Penalty for binary images denoising. Systems and Soft Computing. 2024 Dec 1;6:200122.

[20] Zhang B, Shi H, Wang X. An auxiliary development framework for lightweight RPG games based on Unity3D. Computer Animation and Virtual Worlds. 2024 Jan;35(1):e2206.

[21] Kovaˇc N, Ratkovi´c K, Farahani H, Watson P. A practical applications guide to machine learning regression models in psychology with Python. Methods in Psychology. 2024 Dec 1;11:100156.

Patsy Healey, Patsy Healey, Newcastle University, King's Gate, Newcastle upon Tyne, NE17RU, UK

Kongjian Yu, College of Architecture and Landscape Architecture, Peking University, Beijing 100871, China; 1986762@163.com

Xianheng Zheng, College of Architecture and Landscape Architecture, Peking University, Beijing 100871, China

Manuscript Published; 02 November 2024.