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Prediction of Urban Trees Planting Base on Guided Cellular Automata to Enhance the Connection of Green Infrastructure

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Abstract: Urbanization and climate change pose significant challenges to urban ecosystems, underscoring the necessity for innovative strategies to enhance urban green infrastructure. Tree planting, a crucial aspect of green infrastructure, has been analyzed for optimized positioning using data metrics, priority scoring, and GIS. However, due to the dynamic nature of environmental information, the accuracy of current approaches is compromised. This study aims to present a novel approach integrating deep learning and cellular automata to prioritize urban tree planting locations to anticipate the optimal urban tree network. Initially, GIS data were collated and visualized to identify a suitable study site within London. CycleGAN models were trained using cellular automata outputs and forest mycorrhizal network samples. The comparison validated cellular automata's applicability, enabled observing spatial feature information in the outputs and guiding the parameter design of our 3D cellular automata system for predicting tree planting locations. The locations were optimized by simulating the network connectivity of urban trees after planting, following the spatial-behavioral pattern of the forest mycorrhizal network. The results highlight the role of robust tree networks in fostering ecological stability and cushioning climate change impacts in urban contexts. The proposed approach addresses existing methodological and practical limitations, providing innovative strategies for optimal tree planting and prioritization of urban green infrastructure, thereby informing sustainable urban planning and design. Our findings illustrate the symbiotic relationship between urban trees and future cities and offer insights into street tree density planning, optimizing the spatial distribution of trees within urban landscapes for sustainable urban development.

Keywords: carbon emissions; urban planting; ecological system; urban forestry; green infrastructure

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1. Introduction

Carbon dioxide plays an important role in ecosystems [1,2]. Since pre-industrial times, seasonal mean temperatures have been anomalous over most land areas and atmospheric CO_2 has been steadily increasing, leading to global warming and more frequent natural disasters [3–5]. The Intergovernmental Panel on Climate Change (IPCC) concluded in its Climate Change 2001 report that "humans have a clear impact on the global climate" [6]. The increasing concentrations of carbon dioxide (CO_2), ozone (O3), methane (CH4) and nitrous oxide (NO) in the atmosphere make it difficult for the heat radiated by the sun to radiate into the air, resulting in higher temperatures near the surface and causing the greenhouse effect [7,8]. The rise in carbon emissions is driven by the burning of fossil fuels, the manufacture of commodities, deforestation, the use of transport, food production, the use of electricity in buildings, etc. [9,10]. The world's main sources of carbon emissions are concentrated in three main regions—the USA, China and Europe—and the highest emissions are spread around cities [11,12]. Excessive urban carbon emission makes the temperature in the city center significantly higher than that in the surrounding areas, which increases the temperature difference between day and night and leads to the urban heat island effect, and also aggravates the frequency of natural disasters [13–15]. The growing demand for transportation in urban life causes the imbalance of the urban ecosystem and damages the urban environment [7,16]. Climate change has become one of the greatest challenges facing humanity in the 21st century [17,18].

Forests are the largest plant communities on land and play an important role in the absorption of CO_2 [19,20]. Trees in forests, from growth to death, absorb carbon dioxide through photosynthesis and respiration and fix it in the vegetation and soil, and the capacity of different parts of the forest tree to absorb carbon varies [21]. There are different types of forests on the planet, such as tropical rainforests, temperate rainforests, temperate deciduous broadleaf forests, and temperate coniferous forests. The biodiversity and carbon storage capacity of forests at different latitudes also differ [22,23]. The Amazon basin is particularly rich and is the largest ecosystem carbon sink on Earth that could help mitigate carbon emissions [24,25]. The richness of the forest hierarchy helps to build solid forest ecosystems [26,27]. However, with human deforestation and forest degradation, the Amazon's carbon sink capacity has gradually diminished and the growth rate of above-ground biomass in the forest has fallen by a third, releasing large amounts of carbon emissions into the air that cannot be trapped, a shift that has turned the once carbon-dioxide-absorbing forest into a source of global warming [25,28]. Governments around the world are currently seeking solutions to reduce carbon emissions, with net-zero carbon emissions becoming the focus of global climate change research [29,30]. In the Paris Agreement, net-zero carbon emissions is described as a system that "balances anthropogenic emissions by sources and removals by sinks". Many European countries have started to develop policies to achieve this goal [31].

Some scholars have proposed the concept of urban forestry to further strengthen the urban ecological cycle system by optimizing urban green infrastructure in pursuit of sustainable development [32–34]. Although European countries have a long history in the design and management of urban green space, there is still controversy on the specific content of the concept of urban forestry [35]. In the broad sense, natural resource management activities such as forestry plantations are supposed to take place in suburban clearings but, in reality, such activities can take place in any tree-growing area of the city [36]. A more comprehensive definition of urban forests is networks or systems of all trees in a city, including green infrastructure or individual trees [37–40]. In China, research has addressed several issues related to the benefits of urban forests in relation to air quality, forest cover, and spatial pattern [41–43]. Meanwhile, in Europe and the USA, studies have explored the diversity of tree composition in urban forests and the relationship between forests and people [44,45]. Part of the urban forest focuses on the potential of urban economic benefits, biodiversity conservation, and urban climate regulation [36,46–48], which provides ample evidence of the role of urban forests in the human living environment.

Previous researchers have demonstrated the importance of optimizing the location of urban trees by analyzing data indicators related to urban trees, setting priority standard classification scores or using prioritized geographic information systems [49,50]. Although adequate use was made of existing urban tree data, the data variables changed in real time and the lack of correlation between the data meant that the final data-oriented results could be biased. Other studies have analyzed and counted urban natural resources to improve tree survival by constructing comprehensive indicators and providing a tree planting priority index [51,52]. Alternatively, a design model approach has been used to try to change the relationship between the location of urban trees and the roadway to increase the comfort of the habitat [53,54]. However, the fact that improper planting of urban trees will reduce the ecological value of trees and cause environmental problems and potential risks has been ignored [55].

It is worth noting that previous approaches to urban planning have used computer models to predict future urban change and to help justify urban planning from a holistic perspective [56,57]. Computational results from model simulations confirm that cellular automata perform better in computational urban simulation models [58,59]. Cellular automata have the ability to simulate dynamic processes, and are suitable for considering neighborhood relationships and the urban spatial dimension, and are widely used in predicting the urban expansion process and land use planning [60–62]. This approach was previously used in early urban studies, where tree roads were generated using cellular automata, and plots of land to be developed were placed on both sides of the road [63,64]. Cellular automata are capable of simple rule making based on the local urban environment, reflecting the spatial organization of the city in a dynamic process [63]. However, most of these studies have used formulae and urban tree data to calculate comparisons that can only be obtained over a wide range of tree planting areas, or data over a real period of time to explore index relationships. There are also limitations in the dynamic iterations of cellular automata, which lead to uncertainty and uncontrollability of the iterations [65]. Cellular automata have been used to test a large range of cities, and the predictions were altered at the urban texture level, but failed to optimize urban green infrastructure to improve urban climatic issues from an urban ecological sustainability perspective. Few studies have attempted to model the precise location of tree planting in a block, particularly in terms of the connectivity between urban green infrastructure at the regional scale, ignoring the location of existing and new trees in the city.

This study addresses the following questions: (1) How can potential urban tree planting sites be identified to face the current situation of fragmented tree planting in urban forestry? (2) How can the connectivity between green infrastructures be strengthened? (3) How can deep learning and cellular automata, representing connectionist and behaviorist AI, respectively, be combined to innovate urban forms? This paper aims to address these questions with the goals of elucidating the significance of urban trees in urban ecosystems, bolstering the design and management of green infrastructure to mitigate the impact of urban climate change, and laying a foundation for future sustainable urban development.

2. Materials and Methods

2.1. Introduction and Definition of the Main Methodological Components

With the rapid development of deep learning technology in recent years, implicit learning [66–68] has been widely used to handle the dynamism of information input, wherein dynamic cognitive models replace predefined ones. Consequently, we harness the implicit learning and generative capabilities of deep learning as an enhancement, guiding the computational simulation of discrete models to reason complex, dynamic behavior in response to environmental dynamics. The combination of CycleGAN and cellular automata techniques is adopted to establish the methodological framework of this study.

Cellular automata are a type of computational discrete model introduced by S. Ulan and J. von Neumann in the late 1940s [69]. The advantage of the cellular automata model is that it is able to model complex discrete dynamical systems [70], for instance, integrating the spatial and temporal dimensions of a city. Early scholars first proposed the application of cellular spatial models to geographical modeling [71]. In the 1980s and 1990s, cellular automata began to be used to simulate urban sprawl as the computational power and concepts of cellular automata models were updated [72,73]. The spatial patterns formed by the iterative process of cellular automata and the development of theories have facilitated the design of simulation models for urban evolution, allowing the cellular automata method to be used to test the assumptions of urban theories and to simulate the urban form [62,72]. In previous studies, researchers have adapted different transition rules to fit the study plots based on the model, for example, cellular automata model testing based on a strict rule-based transformation where the cellular grid space was set to 250 m and urban spatial changes were simulated by changing the rule setting [74]. Other researchers transformed rules based on urban morphology to use the model for visualizing future urban growth [75]. However, in response to the development of urban cellular automata models, some scholars have suggested that this may lead to problems in practice when a high number of influences are included within the model and questioned whether extensive rule adjustments can actually constitute cellular automata models [69]. Such experiments with large urban scales usually have a large range of individual cell space settings in the cellular automata model, which can easily lead to a lack of precision. In addition, cellular automata models lack a standard method for defining transformation rules, which can be aided by incorporating a CycleGAN model.

This paper's exploration of neurally guided cellular automata involves the development of a validation method based upon the hierarchical identification of urban data in learning zones. It also investigates the potential of combining cellular automata with deep learning, extending the research methods of cellular automata models beyond traditional urban theory, with an aim to bridge the gaps in past methods. The CycleGAN model can execute powerful image generation by completing image-to-image translation using cycle-consistent adversarial networks [76]. Specifically, this technical approach can generate a potential representation of an image X by identifying a corresponding representation and presenting this potential as a style Y. Other researchers have similarly employed adversarial loss for training to complete image-to-image translations [77]. The generated output can provide an initial design guide for model experiments, aiding in generating the desired target urban morphology. This can assist in defining the transition rules in the cellular automata model to find an approach better suited to improving the accuracy of tree planting in the study area.

2.2. Study Framework

As the first country in Europe to plan for urban forestry, England has a long-term plan for urban trees and a vision of zero greenhouse gas emissions by 2050 [36]. London, as the capital of the UK, is a good candidate for this study as it is vital to improve its urban forestry. In order to improve the ecological value of urban trees in urban forestry, a program was designed to predict the best planting position of trees in future urban forestry by learning the connection relation of the underground tree network in primary forest and the basic rules of cellular automata, including the following stages (Figure 1). The first stage focused on collecting carbon emission data and spatial coverage of green space in different London boroughs, visualizing the data using GIS spatial data analysis, comparing the data, selecting areas with high carbon emission and low green space based on the visualization results, selecting learning areas, and analyzing the data related to street trees. In the second stage, CycleGAN was used to propose a hypothesis of future urban morphological changes and to try to realize an ecological construction orientation of the urban forest, surrounded by trees and buildings. The third stage used the rules and principles of cellular automata to translate the programming language into the parametric software Grasshopper to simulate and more accurately predict the generated results by adding field site constraints. The fourth stage compared the predicted iterations of the cellular automata to analyze the results of the iterations under different variable settings, to see the network connections between urban trees after planting new trees, and to test the feasibility of previous assumptions.

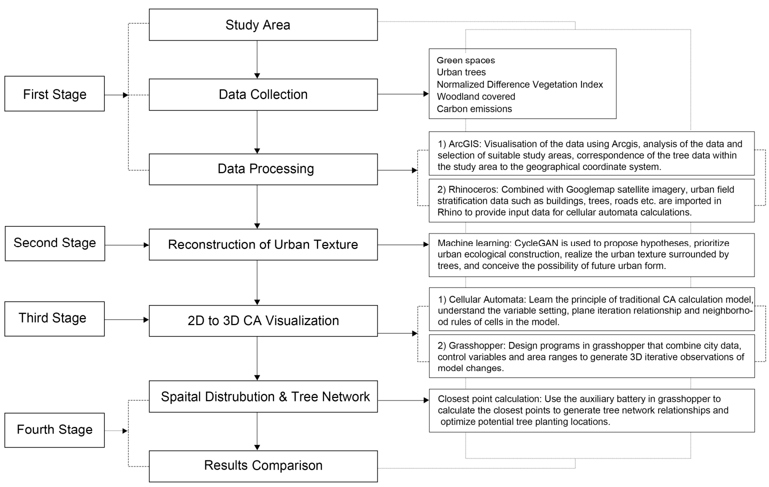

Figure 1. The workflow of data processing in our proposed framework.

2.3. Study Area

The study area excludes parcels with large urban ecological parks, focusing on parcels with a predominantly built-up distribution and a small and scattered distribution of green spaces and trees, which were then further selected according to the road hierarchy characteristics of the urban neighborhood. The study area is located in the northern part of the Camden district at a scale of 1:80 m (51°56′ N–51°55′ N, 0°12′ W–0°11′ W) and contains roads with predominantly service functions, and the urban distribution analysis includes water, green infrastructure, buildings, and roads (Figure 2). The distribution map shows that more traffic arteries are located in communities with little green infrastructure and scattered urban street trees, making it difficult to cope with the carbon emissions from daily traffic.

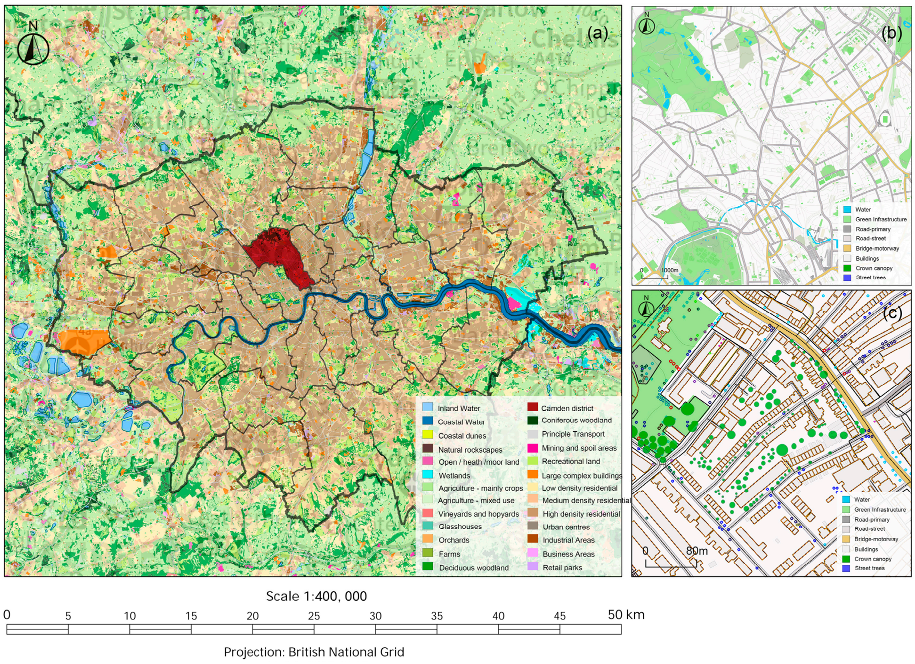

Figure 2. (**a**) Camden in Greater London; (**b**) 1 KM × 1 KM map of Camden; (**c**) study area.

2.4. Data Source and Processing

The GIS spatial data analysis method can help analyze the collected spatial data through the geographic information system. In this study, spatial data analysis can be used to more intuitively visualize the data and compare the differences between different regions. Spatial data analysis can be flexibly applied according to Excel tables to identify different categories, and the size of data in the classification can be matched according to geographical coordinates without being restricted by the regional area. The Office for National Statistics has collected and provided a table of annual average carbon dioxide emissions for London in 2019 and the woodland cover area for local authority areas in London in the same year (Figure 3). The information from the Excel spreadsheet was combined to match the UK regions' geographic coordinate system and then visualized using ArcGIS. The boroughs near downtown London tend to have the highest carbon emissions per square meter, according to the annual statistics on carbon emissions. Additionally, the distribution of green spaces in London, as well as the amount of tree cover in each London borough, were entered in the same coordinate system for comparison. The data visualization's findings indicate that, with a high concentration of real estate development, over half of all London boroughs currently have a proportion of tree cover of only 0–8%. The distribution of green space from the urban fringes of London towards the city center is characterized by an over-representation of large whole areas of green space to small pockets of fragmented green space. At the same time, through the comparison of the three groups of data, we find that there are administrative districts with a wide distribution of green space and low carbon emissions, but there are still some administrative districts with important roads, resulting in an imbalance between the green space and the average annual carbon emissions.

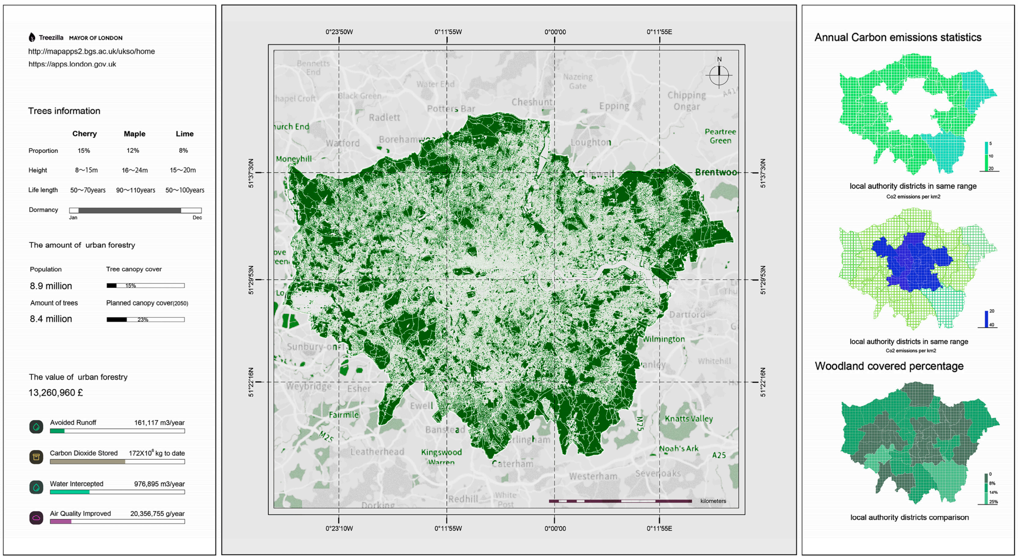

Figure 3. Comparison of London carbon emissions, woodland cover, and green spaces.

Camden has a higher average annual carbon footprint than the rest of London and less tree cover in the area. A small and medium-sized community with abundant data information and dense traffic network was selected from the 1 KM × 1 KM region in Camden district. Data analysis included water conservation (normalized difference moisture index, NDMI); plant health (normalized difference vegetation index, NDVI; sunlight (direct sun hours of the site); and existing tree canopy and tree species. To gain an in-depth understanding of the vegetation health status of the site from multiple perspectives, the street tree data in the learning area were imported into Rhino by tree species stratification and merged with building, road, and other data to restore the status quo of the site. The position of each tree was corresponded to the geographical coordinate system individually to prepare for the subsequent data calculation of cellular automata (Table 1).

Table 1. Street trees of study area, Camden.

Gla_id	Tree Species and Scientific Names	Longitude	Latitude
glaid_682290	Plane (Platanus hispanica)	−0.12786102449052	51.5675131207381
glaid_682291	Plane (Platanus hispanica)	−0.12788095908132	51.5675441929378
glaid_682292	Ash (Fraxinus excelsior)	−0.12772311698794	51.5675262975231
glaid_682293	Plane (Platanus hispanica)	−0.12762451064078	51.5675697763205
glaid_682294	Pear (Pyrus communis)	−0.12755616291557	51.5676037562588
glaid_682295	Plane (Platanus hispanica)	−0.12747623124352	51.5676387203248
glaid_682296	Plane (Platanus hispanica)	−0.12735170738228	51.5677124495487
glaid_682297	Plane (Platanus hispanica)	−0.12726708752885	51.5677561512526
glaid_682298	Plane (Platanus hispanica)	−0.12719287232343	51.5678064935142
glaid_682299	Cherry (Prunus genus)	−0.12715312606818	51.5678958735313
glaid_682300	Cherry (Prunus genus)	−0.12710738384612	51.5679380374256
glaid_682301	Cherry (Prunus genus)	−0.12706859431744	51.5679374183132
glaid_682394	Cherry (Prunus genus)	−0.12700819278152	51.5676059818775
glaid_682398	Whitebeam (Sorbus aria)	−0.12713078708266	51.5672386188778
glaid_682399	Whitebeam (Sorbus aria)	−0.12711551260981	51.5672240770995
glaid_682400	Whitebeam (Sorbus aria)	−0.12714728020639	51.5672235050338
glaid_682401	Whitebeam (Sorbus aria)	−0.12713378040792	51.5672079124889
glaid_682402	Ash (Fraxinus excelsior)	−0.12705398809426	51.5671341598225

Table 1. *Cont.*

Gla_id	Tree Species and Scientific Names	Longitude	Latitude
glaid_682618	Hawthorn (Crataegus)	−0.12798605750201	51.5679855102208
glaid_688705	Cherry (Prunus genus)	−0.12737171242051	51.5670113580804
glaid_697556	Lime (Tilia europaea)	−0.12774688769460	51.5673551009506
glaid_697557	Cherry (Prunus genus)	−0.12779069456203	51.5673635333951
glaid_697558	Cherry (Prunus genus)	−0.12777973154878	51.5674161441307
glaid_697559	Lime (Tilia europaea)	−0.12742623316460	51.5676018627646
glaid_697560	Cherry (Prunus genus)	−0.12748077097416	51.5674334053296
glaid_697561	Pear (Pyrus communis)	−0.12745816111797	51.5674253110274
glaid_697562	Pear (Pyrus communis)	−0.12744097518780	51.5674151450884
glaid_697563	Cherry (Prunus genus)	−0.12744327917633	51.5673590689984
glaid_697564	Pear (Pyrus communis)	−0.12737621039910	51.5673162737598
glaid_697565	Pear (Pyrus communis)	−0.12734530308466	51.5672959072194
glaid_697566	Cherry (Prunus genus)	−0.12751479831096	51.5673778354607
glaid_697567	Pear (Pyrus communis)	−0.12756027765596	51.5673455589041
glaid_697568	Pear (Pyrus communis)	−0.12758720845964	51.5673327697381

2.5. Methods

We investigated the possibility of using cellular automata (CA) to alter urban spaces by training CycleGAN with the outputs of CA and the samples from the forest mycorrhizal network. By comparing these two, we validated the applicability of CA and visually collected spatial feature information to guide the parameter setting of CA design. Subsequently, we utilized this information to set up a 3D cellular automata for predicting tree planting locations for the site.

2.5.1. CycleGAN Image-to-Image Translation

To enhance urban green ecology and combat urban climate change, CycleGAN reshapes existing urban surfaces through image style transformation, creating a diversity of future urban forms and providing guidance for urban design. The morphological design of urban neighborhoods greatly affects the outdoor environment. In this paper, satellite images containing learning areas of 1 KM $\times$ 1 KM and two different image samples were selected and tested separately to find ways to enhance the effective construction of urban forestry. This was used as a design guide to improve the management of urban forestry in the city. CycleGAN is commonly used to solve migration problems between images [78]. This method performs image transformation from reference image domain X to target image domain Y without relying on paired images. In this case, G and F are mapping functions between two image domains X and Y. The model includes two discriminators D_Y and D_x. D_Y promotes G to translate X into outputs that are identical to domain Y, and vice versa for D_x, F, and X. CycleGAN also uses the adversary loss [79] and cyclic consistency loss, which are two loss functions that are expressed respectively in the following formulas [76]:

$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{dat}}\ (y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}\ (x)}[\log(1 - D_Y(G(x))], \tag{1}$$

$$\mathcal{L}_{\text{cyc}}\ (G, F) = \mathbb{E}_{x \sim p_{\text{data}}\ (x)}[\| F(G(x)) - x \|_1] + \mathbb{E}_{y \sim p_{\text{dat}}\ (y)}[\| G(F(y)) - y \|_1]. \tag{2}$$

CycleGAN requires the collection of hundreds of sets in each example folder. Due to the limitations of collecting samples of the same type of data, this paper cuts the samples into 1000 sheets each and selects 300 (180 $\times$ 180 pixels) of the field features that need to be preserved as the training dataset for transformation training.

2.5.2. Calculation Principles of Cellular Automata

Cellular automata are made up of a grid of cells, the size of which can be changed according to the requirements of the setup. Each cell's life and death relationship are controlled by setting rules in the grid [80,81]. The basic principle in cellular automata is that if the life and death relationship of a cell changes, other cells in the vicinity of that cell will also be affected [82]. Some of the cells in the lattice are given an initial state (usually time t = 0), while others are given a state (advance t by 1). The cells in the grid are housed in separate compartments but are closely related to each other, with a neighborhood effect, just as the trees in a forest exist as a whole. There are two common types of communities in which cellular automata identify neighbors, named after the theorists who invented them, Moore neighbors and Von Neumann neighbors (Figure 4). The Moore neighborhood consists of eight orthogonally adjacent unit cells, and the von Neumann neighborhood consists of four diagonally adjacent unit cells. The two differ in their results for visualizing changes in cellular automata [83]. Some scholars have examined the urban matrix layout of satellite images of residential areas in Australia to determine the applicability of the rules of the cellular automata model, and have proposed that Moore neighbors allow diagonal or vertical access to cellular space, whereas Von Neumann neighbors allow only vertical access to the space [84]. In terms of the more regular grid layout of modern cities, Moore neighbors possess stronger accessibility characteristics to help achieve the spatial distribution of urban trees. Therefore, we chose Moore neighbors to conduct the urban form experiment for deep learning.

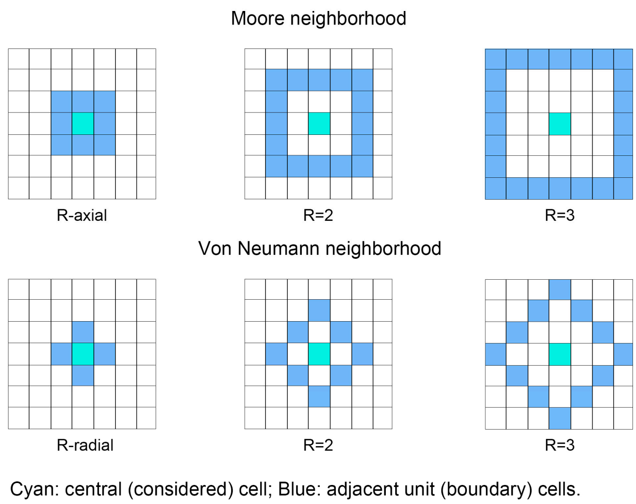

Figure 4. Rules of cellular automata.

2.5.3. Urban Reconstruction by CycleGAN

In this study, two sets of tests were conducted using CycleGAN. The first group (Figure 5) is an image transformation between satellite images of London city (sample A) and the forest mycorrhizal network intention map (sample B), in order to make the transformation results achieve the urban design orientation of green space as the main feature and the rest as secondary. In this training set, the images containing more green space features were selected. From the final training results obtained, although the green areas cover the largest area, the results cover the original building sites and roads, forming an urban surface with traffic networks cutting through the green areas and not realizing the urban green infrastructure construction with trees surrounding buildings.

The second group (Figure 6) uses the original sample A, but this time selecting feature points with 50 percent each of the images having a green space or building feature to ensure that the building footprint was not completely covered and lost in the final results. Sample B was chosen as the result of one iteration in the cellular automata. The samples used Moore neighbors, which modeled the canopy layer growth competition between trees in an urban forest, with common features between them and the problem of urban land competition. The results of the second image transformation test achieved a similar area of green space occupation to that of building occupation. Some of these areas formed a more coherent image of urban green space surrounding the building sites, but the main roads were completely covered in the results. The outcomes produced by the CycleGAN model demonstrate that the experimental results, derived from the Moore neighbor samples, can alter urban morphological features. Furthermore, they maintain several recognizable spatial features and deliver more reasonable spatial layouts compared to group 1 outputs.

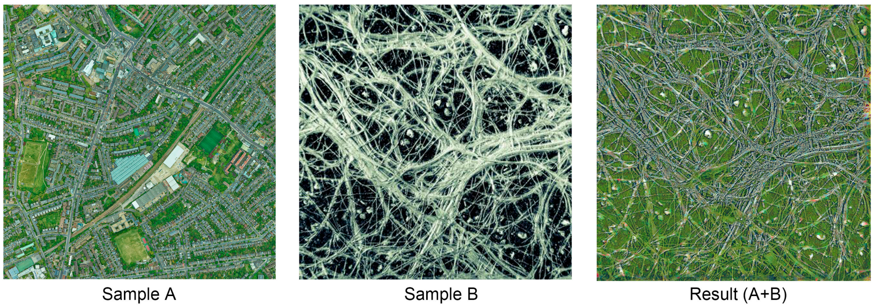

Figure 5. CycleGAN output group 1.

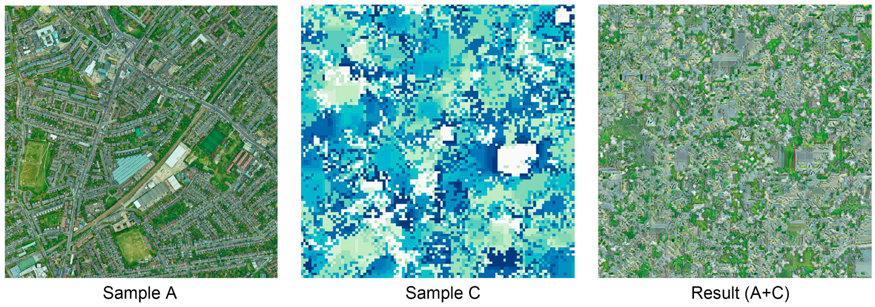

Figure 6. CycleGAN output group 2.

2.5.4. Grasshopper Transformation and Tree Networks

The cellular automata were implemented in the code as a two-dimensional spatial iteration, using previously prepared site data to set up the grid according to the size of the study area. In Grasshopper, the two-dimensional iterative change procedure is built according to the rules of cellular automata, setting up adjustable parameter entries and iteration rules, and the initial state of each grid cell is divided into two types: alive and dead. In the original code, the starting point for the calculation of cellular automata is randomly generated, whereas in Grasshopper the starting point can be set manually by combining the existing tree location data from the Rhino with the box selection to increase the controllability of the calculation. In this cellular automata model, we set the Moore neighborhood rules as follows: (1) a dead cell becomes alive when it is surrounded by exactly three living neighbors; (2) a cell becomes dead when it is surrounded by a single or four or more living neighbors; (3) a living cell continues to live until the next iteration when it is surrounded by two or three living neighbors. Cellular automata also have the ability to pause and restart, and the relationship between cell life and death changes continuously after multiple iterations. In Grasshopper, the grid is set up to look at the life and death status of cells centered on a single cell, with a set rule to find the neighboring cells in each row and column moving in the direction of the surrounding cells. The cellular automata will first look for cells in the grid around existing trees in the city and calculate whether the cellular cells are likely to be symbiotic. In the design program, the two-dimensional iterations are made three-dimensional to allow visual comparison of the planting changes between old and new trees. In addition, a new constraint was added to the conversion procedure to accurately calculate the location of new trees. Cells cannot be calculated in grids where buildings or main roads are distributed. This method enhances the urban ecology while preserving the existing buildings and traffic on the site.

After obtaining the iterative results of the cellular automata, it is still necessary to determine the validity of the urban tree planting locations. By combining the commonalities between tree dimensional networks in forests and cellular automata, urban tree networks are created using the program Closest point and Graft tree to analyze and optimize the reasonableness of the computational results. Scientists have experimentally demonstrated that trees in a forest interact with each other to form a large interconnected community. A team of researchers utilized DNA analysis to map a fungal network in a patch of Canadian forest [85] (Figure 7(a1,a2)). Model simulations revealed that more connections are lost when some trees are removed (Figure 7(b1,b2)). We categorized the different canopy sizes in the mycorrhizal network and viewed the tree connectivity relationships hierarchically (Figure 7(c1,c2,d1,d2)). These trees act as important hubs in the urban transport network, communicating with neighboring trees [85,86], supporting the energy transfer between the rest of the small trees, and enhancing the ecological stability of the urban green infrastructure area.

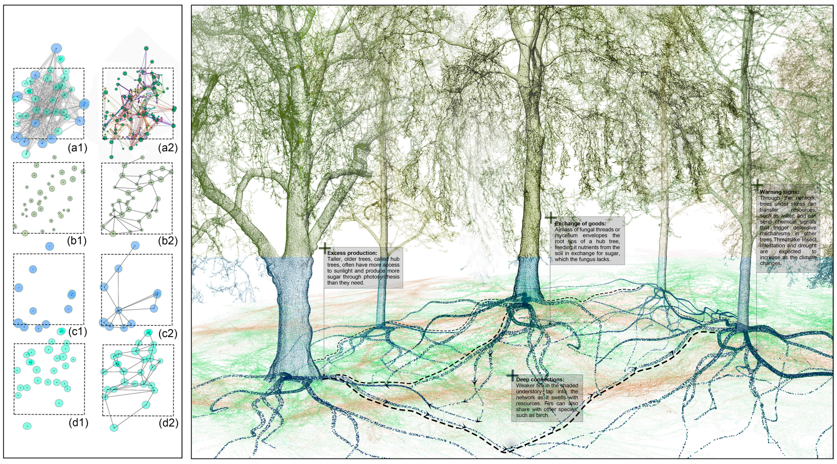

Figure 7. Tree networks and communication.

3. Experimental Results

3.1. Relationship between CycleGAN Results and Cellular Automata

According to its experimental output, CycleGAN can help to adjust the cellular automata model. From the first set of CycleGAN experimental outputs, it can be seen that restrictions should be set before the calculation of the urban cellular automata to exclude cellular grids that cannot be used for the calculation in order to keep the residential areas or major roads in the study area, so as to avoid the situation that the urban tree planting will cover all the cellular space in the cellular automata at the later stage of the calculation. The second set of CycleGAN outputs shows more intuitively that the grid size of the cellular automata model affects the distribution pattern of green space in the city when a larger city range is selected. With a larger spatial extent of a single cell, its green space distribution area may be prone to a scattered distribution, weakening the aggregation connection between green spaces. The current results suggest that this kind of urban surface remodeling orientation is more suitable for small and medium-sized urban ecological development, such as four-level roads in urban communities, and that such urban side roads are more preferable to urban traffic arteries for ecological development. The results of the test orientation were rationalized and applied to the cellular automata model. Therefore, the range of the setup grid was reduced in this model setup, and the individual cell space was set to 10 M $\times$ 10 M for calculation with reference to the canopy size of the most planted tree species in the study area. Furthermore, from examining the image generation pattern, the generation pattern of the Moore neighborhood extending from a single cell in all directions constitutes a more ideal tree planting condition, which can support part of the assumption that the tree surrounds the building. The experimental results show that the cellular automata model can be used for simulation when both CycleGAN output and urban satellite data maintain some common features.

3.2. Iteration of Cellular Automata

The results of the cellular automata iterations were transformed from 2D planes to 3D stereoscopic images using a design program to transfer the tree data within the learning area (Figure 8). The 3D iterative results provide a clearer view of the iterative life and death relationships between each generation of the cellular automata than the 2D flat images, making it easier to adjust the model parameters.

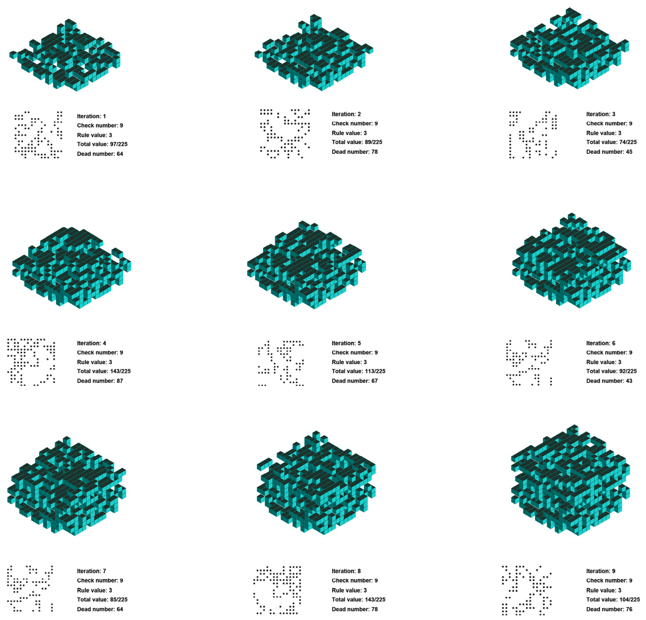

Figure 8. From 2D to 3D visualization.

Cellular automata can set different starting points for the test results obtained according to the tree classification. According to the statistics of the number of tree species in the learning area, this paper selected three most common street trees in London, namely cherry, maple, and whitebeam, for calculation. The final result of the first generation is the superposition of the three tree species in separate iterations, and the same is true for the third and sixth generations (Figure 9). The number of iterated trees increases gradually with the number of iterations compared to the 3D iterations without classification. The number of iterations is positively correlated without taking into account the life cycle of the tree and the precise location of the tree planting in the grid. Urban forestry construction is prioritized but access to feeder roads within urban communities needs to be reclassified.

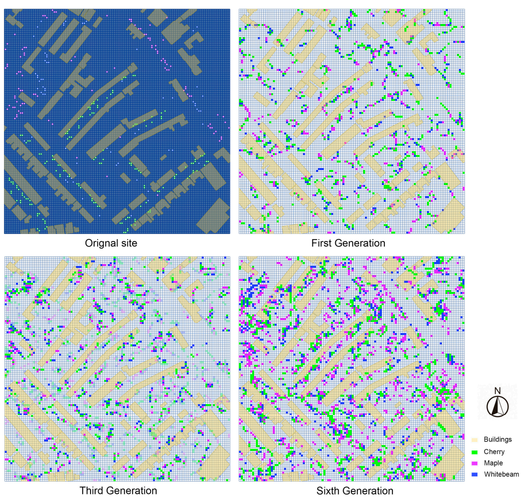

Figure 9. Calculation of tree species classification.

3.3. Trees Network Connection

Predicting tree network connections from the iterative results can further optimize urban tree locations and enhance urban green ecology. One of the tree location iterations is randomly selected from the results of the cellular automata iteration using the closest point assisted network calculation (Figure 10). According to the results, in the first single tree location connectivity network, some of the tree locations were scattered within the cellular automata grid at a distance from the densely populated areas of trees. In the end, the tree network was compiled over a long distance and there was an unreasonable tree network structure. In the second tree network test, the tree network connections were recalculated with the addition of scrub data from the urban green infrastructure. The results show that when the proportion of the iteration result data reaches a certain level, the tree network connection begins to rationalize and the density of the tree network becomes more concentrated. The distance from planting is judged based on the connectivity results, and the tree planting location is improved.

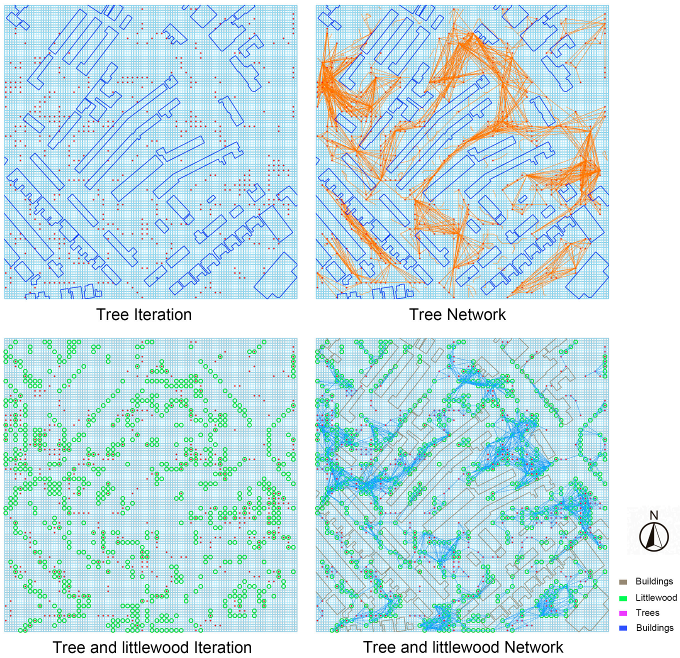

Figure 10. Network connection.

3.4. Results Comparison of Cellular Automata and CycleGAN

The cellular automata model calculates the weaving range of the network composition that can inform the construction of green infrastructure in cities, and the comparison with CycleGAN results also confirms the possibility of trees surrounding buildings. We compare the cellular automata output with the CycleGAN output at the same range, observing the changes in the reshaped urban morphology. We find that the model simulation results are oriented towards clustering and tightly connecting the otherwise fragmented distribution of green spaces in a piecemeal form compared to the traditional urban form, creating an ideal urban form that prioritizes urban green spaces more in accordance with the urban forest (Figure 11). Remarkably, we found that the network relationships simulated by the cellular automata constitute a morphological distribution of urban green space infrastructure with striking similarities to the CycleGAN output, an approach that alters the priority hierarchical order of the traditional urban planning distribution. In the original urban morphological distribution of the site, urban green spaces, buildings, and urban public spaces are divided by roads. With the rapid development of global urbanization, urban expansion and regeneration have led to an increase in urban areas and roads, and the development of urban road networks has had an impact on the urban form. The buildings in the study area of this experiment are residential, and with the original residential areas unchanged, we chose to prioritize the optimization of the green infrastructure in the site and calculate its connectivity, before reprogramming the auxiliary roads in the residential areas to ensure the connectivity between the community and the rest of the main roads.

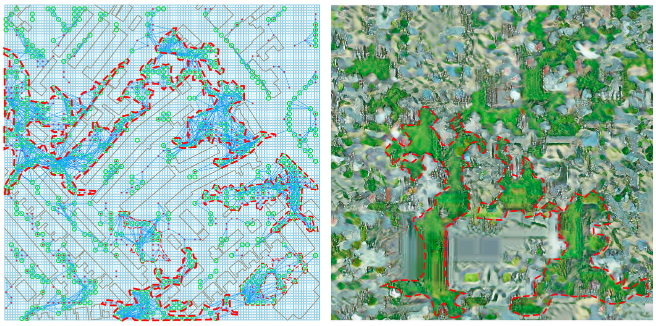

Figure 11. Comparison of green space composition.

4. Discussion

4.1. Urban Planning and Design Implication

Determining where to plant trees will be an important issue in the future sustainable development of cities. The findings of this paper highlight strategies to further optimize the spatial distribution of potential future urban tree planting locations based on existing trees on the site to help restore urban ecosystems. Other studies emphasizing the role of urban trees and ecosystems are also supported [87,88], complementing the approach to pinpointing specific locations for tree planting in space and improving biodiversity by creating green infrastructure patches, while providing a habitat for birds, insects, etc. Regulation of biodiversity is one of the influencing factors in the stability of urban ecosystems [88]. Furthermore, urban trees play an important role in urban ecosystems. Increased planting of trees can better conserve soil moisture and help reduce temperatures near the ground, thereby mitigating the effects of urban climate change, such as the urban heat island effect. Developing a strategy for well-planted trees can help protect the urban environment and enhance the eco-efficiency of urban ecosystems. It creates a healthy spatial environment for the daily activity space of city dwellers and reduces the interaction distance between people and the natural environment. It can also help alleviate people's daily work anxiety and other problems at a spiritual and psychological level, and connect humans with nature to provide more entertaining spatial environments that promote health and well-being.

This study proposes a new approach combining CycleGAN and cellular automata techniques to prioritize urban tree planting locations to predict the optimal urban tree network to help enhance connectivity between urban infrastructure developments. The results of the current work may be important for urban planners, designers, and researchers related to urban sustainability in urban planning and design, and advocate exploring the value of urban forest planning methods in future green space development. Firstly, the results of the cycle-consistent adversarial network training in CycleGAN show the diversity and possibilities of urban morphological change. Instead of setting standards for urban morphology or using inertial thinking in planning and design, we should constantly optimize design principles to suit the current urban situation. The trained CycleGAN model differs from traditional urban planning and design perspectives by creating urban forms where trees surround community buildings, changing the status quo where green spaces are fragmented by buildings. Green infrastructure zones are considered on a regional scale to reshape the distribution of urban residents, green spaces, and roads. Secondly, trees are an important part of the green infrastructure in the urban form. It is essential to enhance urban forestry by improving the location of potential tree planting in future urban planning and design management. Botanists emphasize that we need to plant trees in the right places [89]. Cellular automata calculation results elucidate the urban ecological construct relationships between different levels of data by distinguishing between urban tree species and urban forest hierarchies. The study provided a reference for improving the way street tree planting density is planned and managed in urban forestry by pinpointing the potential planting locations of different tree species. In addition, sustainable urban ecological construction is the current goal of urban planning and design. A well-connected network of urban trees will contribute to the stability of urban ecosystems in the face of increasing urban CO_2 emissions. Previous studies have shown that street trees in urban centers are scattered and fragmented, lacking a holistic approach to tree connectivity [90,91]. The small size of the tree planting may affect the root growth and the smoothness of the road surface, resulting in bending and deformation [92]. It also affects the life cycle of trees, reducing survival rates and ecological benefits [93]. In contrast to traditional forestry, tree networks do not focus on individual trees, but form a large, closely-knit community. The transfer of nutrient energy through underground rhizomes increases tree survival and builds a strong and stable ecosystem [85,86]. Study results on tree network connectivity encourage the construction of green infrastructure areas with a high density of tree networks, which will act as a link to maintain the ecological health of their surroundings.

4.2. Limitations and Further Research

This article has identified potential locations for tree planting to support the design and management of green infrastructure and enhance its connectivity, but there are still limitations to the ecological value of tree species planted in this study. For example, the determination of urban tree species requires an analysis of urban soil conditions, canopy size, and tree life cycle to maximize the ecological benefits of urban forestry in response to urban climate change, which is not considered in the current work. It was also found during field research and street tree data collection in the study area that the urban tree database was not up to date with information on newly planted trees, and the limited data available may lead to some uncertainty in the calculation results. In addition, it was found during the cellular automata simulation that this method may not be applicable to areas with a large building occupation area, and the large number of buildings occupying the grid space may lead to unsatisfactory results in the final iterative calculations. In future studies, it might be necessary to test the classification of different site occupation areas, for instance, blocks with mainly public facilities land or industrial land. At the same time, there is a need for further experimentation and validation to determine the feasibility of urban green infrastructure in terms of its eco-efficiency. It is worth noting that, in conjunction with the comprehensive analysis of the current urban situation, the connectivity of the urban tree dimensional network will pose a challenge to the distribution of minor roads and branch roads within urban communities in the future. The branch roads within urban communities should be further explored in order to guarantee community access and connectivity to surrounding roads while prioritizing green infrastructure, and to rethink the symbiotic relationship between urban trees and the future city. The environment in which trees grow in cities is different from that in forests. The environment in which urban trees grow is influenced by human activities, so continuous awareness-raising on urban forestry is required to increase the ecological resilience of cities.

5. Conclusions

This study, by employing a multitude of methodologies, scrutinizes selected learning zones and lays the groundwork for ideas aimed at the future of urban ecology. One significant outcome is the design orientation that fuses urban buildings with trees, effectively reimagining the current urban planning priorities from an urban design perspective. Our findings strongly emphasize the transformative potential of machine learning tools in reshaping the urban landscape. By employing CycleGAN and cellular automata models, we demonstrated a novel method to prioritize and optimize urban tree planting locations, hence paving the way towards more sustainable and eco-friendly urban environments.

This research challenges the existing paradigm where urban land use is primarily dominated by traffic and buildings, proposing instead a shift towards prioritizing urban ecology. Such a shift has the potential to transform future urban transport and road planning, offering more sustainable and eco-friendly alternatives. Building on field data from the study area, we utilized a design program to simulate and calculate potential tree planting locations for future urban forestry. These computations, combined with features of the forest ecology network, aided in determining the network connections between urban trees, thus enhancing urban green infrastructure.

The results suggest that the integration of these tools can reshape urban landscapes, fostering green infrastructure and prioritizing urban forests. This approach creates an urban form where green spaces surround and interact with buildings, challenging the traditional urban planning methods where green spaces are often fragmented by infrastructure. Furthermore, the dynamic iterations of the cellular automata principle offered a unique lens to simulate urban tree health and mortality. The specificity of the results to the site area of each tree bolsters the confidence and adaptability of the simulation outcomes. The insights gleaned from the three-dimensional network connections facilitated the further optimization of potential tree-planting locations. When juxtaposed with machine learning results, the network connections not only confirm the feasibility of the proposed design orientation, but also enrich our understanding of urban green infrastructure network connections.

This research demonstrated a novel approach to computationally guide urban planning in enhancing urban forestry, leading to a reduction in carbon emissions and mitigating the impacts of urban climate change. Notably, in this study, the application of CycleGAN to the rule-making process of cellular automata occurs at the level of qualitative reference based on visual observations of the CycleGAN outputs. Theoretically, the rules can be customized according to the visual feature representation of the training image data, i.e., the feature maps, extracted within the CycleGAN model. Such customized rules may enable the cellular automata to output more desired states of urban landscapes. This concept warrants further exploration in future research.

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