Research Article

Research on the Change in Public Art Landscape Pattern Based on Deep Learning

Lei Zhao and Congcong Tang

School of Architecture and Art Design, Hebei Academy of Fine Arts, Shijiazhuang 050700, China

Correspondence should be addressed to Lei Zhao; zhaolei2021@hbafa.edu.cn

Received 7 February 2022; Revised 16 March 2022; Accepted 21 March 2022; Published 11 May 2022

Academic Editor: Man Fai Leung

Copyright © 2022 Lei Zhao and Congcong Tang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

With the limited design level of urban external space and place environment, however, the city image design and public art design play an important role in urban development, which leads to the lack of rational understanding that vague urban style is the effective implementation. In this article, a deep learning model is proposed to study the changes in public art landscape pattern in urban space, and it is constantly found that the changes in urban spatial layout have an impact on urban development. Firstly, the landscape index was analyzed effectively, and the Markov model was used to predict land use change, which provided a theoretical basis for the analysis of urban landscape change. Then the GeoSOS-FLUS model based on deep learning is used to make up for the lack of diversity of land use types by using the suitability probability calculation module of ANN and the adaptive inertia and competition mechanism, and the competition between different land use types is introduced. The experimental results show that the GeoSOS-FLUS framework based on deep learning model has good prediction effect and application ability.

1. Introduction

With the prevalence of art planning forms that use public art to render urban vitality and promote urban culture in major cities, public art works gradually assume the important role of "city business cards." The research on the dynamic change in artistic landscape in public places shows that landscape structure, landscape function, and landscape spatial pattern are the core issues of landscape ecology. Landscape pattern refers to the arrangement of landscape patches with different sizes, shapes, and attributes in landscape space. Literature [1] elaborates that people's environmental needs for public streets far exceed simple material enjoyment but pay more attention to people's real feelings about landscape structure. Literature [2] describes the Humanistic design of public places around the characteristics of art design and city image. Literature [3] analyzes the three intervention ways of cities' art design in public territory, and then analyzes how to apply public art design in public territory from four aspects, namely scientific and technological innovation, experience service, interaction and cooperation, and citizen aesthetics, so as to build a good city image and promote the new round of construction and development of urban culture. In literature [4], the combination of public art landscape pattern design and regional culture is studied. Literature [5] focuses on the two characteristics of public space and public art in urban centers and studies the relationship among public art, people, and natural environment. The paper expounds how to combine the characteristics of the city to carry out artistic transformation [6]. Literature [7] describes the concept of public art design, literature [8] thinks around the concept of public art design, and literature [9] expounds that the change in landscape pattern is due to the process of landscape change. Understanding the driving mechanism of landscape pattern evolution is the premise and foundation of landscape pattern analysis combined with patch scale. Literature [10] describes the quantitative research method of landscape pattern. Literature [11] shows the changes in landscape pattern indicators to different landscape patterns, and the main data source of literature [12] is remote sensing images, which systematically studies the evolution of landscape pattern from three aspects: situation, relationship, and
mechanism. Literature [13] vividly expounds the characteristics of urban ecosystem landscape pattern and the development direction of landscape pattern optimization in literature [14], and literature [15] makes an in-depth study on public art design under the influence of history and culture. Literature [16] puts forward a method based on deep learning and uses landscape model to make two deforestation hotspots, which shows that the reliability of monthly forest harvesting mapping using Sentinel-1 data is high; the average IoU is superior to the traditional object-based method. Samples collected at a specific time in a place are trained, and sparse local samples from the new area are used for fine tuning to achieve the best performance. Therefore, when applied to a new research site, the workload of training data collection can be greatly reduced. Literature [17] is applied to urban landscape design and proposed the processing and application of urban landscape images to analyze landscape changes.

2. Publicity of Public Art

Public space is the material space carrier of people's public activities, communication and life, and the place of public life, which embodies the functional attributes of society. Because public space is changeable, that is to say, the ownership of space will change with time, urban space is the possibility of mutual transformation from private space to public space. Urban public space should be a region that concentrates all elements and functions in the city. This region can be a space shared by individuals and collectives, and they enjoy the services and convenience brought by this space. Urban public space is a traditional sense of public space, such as streets, riverside squares, parks, green spaces, etc. Today, it includes museums, shopping centers, transportation hubs, etc. The meaning of public space is becoming more broader. Words such as "popular," "common," "public pragmatic," and "shared" are used to describe "public." This shows from the side of a word that the characteristics of what we call public space lie in that it is different from the space form, which generally belongs to private field, nonpublic nature, and nonpublic welfare nature. Habermas thinks that publicity embodies fairness and democratization in all fields of society. His exposition is of great significance for explaining art about public areas. Herzberg thinks that "public" and "private" can be regarded as homosexual words related to "collective" and "individual," and the meaning of "public space" lies in the area that anyone can enter at any time. Publicity firstly means openness, no matter in principle or form, anyone can enter freely, and everyone has the right to express their opinions and be respected. Secondly, publicity means universal application, which specifically refers to the needs of all the contents in the public space that are applicable to all the subjects in the space. Finally, publicity also means public interests. Compared with emphasizing the interests of individuals, classes, and groups, publicity is the interests of all existing subjects, and the public sphere seeks public welfare rather than private interests. As a popular art, the essence of public art is to realize its social value through "publicity," regardless of its appearance or design concept. Publicity must be a common feature of shared space and public art, and the publicity of shared space promotes the communication and sharing between people. As the art of shared space, shared art is to better serve the public and meet people's psychological and spiritual needs, and it is an effective way to realize the publicity of shared space (Figure 1).


The organizational form of rural public buildings has changed from autonomous form to organized form in the early stage of the founding of the People's Republic of China. In the period of new rural construction, it presents a government-led organizational form. In terms of spatial characteristics, it has changed from the original closed and single to diversified and modern characteristics. The role of space is becoming more and more colorful. From the original traditional architectural forms such as stage, school, ancestral hall, and cooperative, the villagers' activity center with weaving and planning has gradually begun to form (Table 1).

2.2. Digital Reform of Public Art.

The fundamental purpose of digital public art is to serve the public and meet the needs of the public. Communication thinking is the basic demand of the public for digital public art, and interactive thinking is the main guiding ideology. It is a form of interactive thinking in creation that creates communicative thinking. Communication thinking is a two-way interactive behavior, a unique expression of digital public art, and also the purpose of digital public art creation (Figure 2).

3. Study on Landscape Pattern

3.1. Landscape Index Analysis Method. Landscape index analysis is an extensive method for the quantitative evaluation of landscape bureau at present. Referring to previous research methods and combining with the characteristics of the study area, this article selects the indicators that can best reflect the landscape index from two types, patch type level and landscape level, to quantitatively describe the landscape pattern change process, and further expounds the relationship between the future trend and process of landscape in timescale in connection with ecological process. Four landscape classification vector maps in 2012, 2014, 2016, and 2018 were transformed into 10x10 grid images with a granularity of 30 m by using ArcGIS 4.1 vector-to-grid theory, and then imported into Fragstats 4.2 software to calculate each landscape index.

This article analyzes the dynamic changes in landscape pattern from two levels: patch type level and landscape level. At the level of patch type, patch area (CA), landscape percentage (PLAND), patch number (NP), patch density (PD), landscape shape index (LSI), maximum patch area index (LPI), average patch area (AREA-MN), aggregation degree (AI), and cohesion index (COHESION) were selected. At the landscape level, patch number (NP), patch density (PD), landscape shape index (LSI), edge density (ED), perimeter area fractal dimension (PAFRAC),
Table 1: Changes in organizational forms and other characteristics of rural public buildings.

<table>
<thead>
<tr>
<th>Time</th>
<th>Organizational form</th>
<th>Spatial characteristics</th>
<th>Function of public space shelf</th>
<th>The nature of public space</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before the founding of the</td>
<td>Self-organizing form</td>
<td>Closed, single</td>
<td>Get outside information, living and entertainment</td>
<td>Have a strong breath of life</td>
</tr>
<tr>
<td>People’s Republic of China</td>
<td></td>
<td></td>
<td>places</td>
<td></td>
</tr>
<tr>
<td>Economic planning period</td>
<td>Organized form</td>
<td>Open and unitary</td>
<td>The main place of political propaganda</td>
<td>Strong political color</td>
</tr>
<tr>
<td>After the reform</td>
<td>Take “family” as the</td>
<td>Public space is diversified and</td>
<td>Social place</td>
<td>Diversification of public space forms</td>
</tr>
<tr>
<td>New rural construction</td>
<td>Passive organization</td>
<td>modernized</td>
<td>Become the center of government activities</td>
<td></td>
</tr>
<tr>
<td>period</td>
<td></td>
<td></td>
<td></td>
<td>There are no traditional customs in the countryside</td>
</tr>
</tbody>
</table>
maximum patch area index (LPI), aggregation degree (AI), cohesion index (COHESION), contagion degree (CON-
TAG), separation degree (DIVISION), Shannon diversity
index (SHDI), and Shannon evenness index (SHEI) were
selected. The ecological meaning of each index is listed in
the Table 2:

(1) Plaque area CA

\[
CA = \sum_{i=1}^{n} a_{ij} \times \frac{1}{10000},
\]

where \(a_{ij}\) indicates the area of type \(i\) patch and \(n\) is the total number of type plaques.

(2) PLAND

\[
PLAND = \frac{\sum_{i=1}^{n} a_{ij}}{A} \times 100, \tag{2}
\]

where \(a_{ij}\) represents the covered area of patch \(j\) of type \(i\) and \(A\) is the overall landscape area, with a value of 0–100.

(3) Plaque number NP

\[
NP = N_i, \tag{3}
\]

where \(N_i\) is the number of patches of type \(i\) or the total number in all landscapes.

(4) Plaque density PD

\[
PD = \frac{n_i}{A} \times 10000, \tag{4}
\]

where \(n_i\) is the total area of Class I landscape elements or the total area within all landscapes.

(5) Landscape shape index LSI

\[
LSI = \frac{0.25E}{\sqrt{A}}, \tag{5}
\]

where \(E\) is the total boundary length of patch type or landscape, LSI \(\geq 1\), and there is no upper limit.

(6) Maximum patch area index LPI

\[
LPI = \frac{\text{MAX}^{n}_{i=1}(a_{ij})}{A} \times 100. \tag{6}
\]

Max is the maximum number of patches or landscape pixels that may be adjacent, and the value is 0–100.

(7) Average patch area AREA-MN

\[
\text{ARENA} – MN = \frac{\text{LPI}}{A} \tag{7}
\]

(8) Degree of polymerization AI

\[
AI = 1 - \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}}{\sum_{j=1}^{n} \sum_{i=1}^{n} d_{ij} \times (\text{MAX} \times a_{ij})} \times 100, \tag{8}
\]

g\(i\) represents the number of adjacent pixels of type \(i\) or landscape patches, and \(p_i\) contains the landscape percentage of type \(i\) patches or landscapes, with a value of 0–100.

(9) Cohesion index COHESION

\[
\text{COHESION} = \frac{1 - \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij}}{\sum_{j=1}^{n} \sum_{i=1}^{m} d_{ij} \times (\text{MAX} \times a_{ij})} \times \frac{1}{A} \tag{9}
\]

\(n\) is the total number of types of plaques and \(m\) is the number of all types. For example, \(d_{ij}\) is the perimeter of plaque \(ij\), and the value is 0–10.

(10) Edge density ED

\[
E D = \frac{\sum_{j=1}^{n} e_{ij} \times (10000)}{A} \tag{10}
\]

where \(e_{ij}\) is the total edge length of patches in the landscape.

(11) Perimeter area fractal dimension PAFRAC

\[
\text{PAFRAC} = \frac{2(n \sum_{j=1}^{n} \text{Ina}_{ij})}{n \sum_{i=1}^{n} \left(\text{L}_{a_{ij}} \times \text{Ind}_{ij}\right) - \left(\sum_{j=1}^{n} a_{ij}\right) \times \left(\sum_{j=1}^{n} d_{ij}\right)} \tag{11}
\]

(12) Spreading degree CONTAG

\[
\text{CONTAG} = 1 + \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} \left(\text{pi} \times (\text{gi} / \sum_{k=1}^{m} \text{gi}) \times (\text{ln} \times (\text{gi} / \sum_{k=1}^{m} \text{gi}))\right)}{2 \times \text{ln}(m)} \tag{12}
\]

(13) Separation degree DIVISION

\[
\text{DIVISION} = 1 - \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (a_{ij} / A)^2}{2} \tag{13}
\]

(14) Diversity Index SHDI

\[
\text{SHDI} = \sum_{i=1}^{m} (\text{pi}, \text{lnpi}). \tag{14}
\]

(15) Evenness index SHEI
$\text{Shei} = -\frac{\sum_{i=1}^{m} (pi, \ln(p_i))}{\ln(m)}$, \hspace{1cm} (15)

$pi$ is the percentage of landscapes that contain type $i$ patches or landscapes, $\ln(p_i)$ is the logarithm of the landscape percentage.

### 3.2. Analysis Method of Spatial Development Pattern

#### 3.2.1. Markov Prediction Model

Markov model was put forward by Soviet mathematician Markov, which is often used to predict land use transformation, and it is also called discrete-time stochastic process model Markov chain. This model emphasizes the stochastic process with discrete states and is a probabilistic prediction method based on stochastic processes. Therefore, the model has time homogeneity, that is, during the transition from time $T_{n-1}$ to time $T_n$, it is found that the state of the system at time $T_{n-1}$ is only related to the state of the system at time $T_n$ in a certain period of time. The process of land use type conversion has typical Markov model characteristics. In a specific area, land use types can be converted to each other, however, the transformation between land use types is predicted and expressed by mathematical functions, which is the most distressing. Markov model can obtain the conversion probability matrix of land use according to the state of land use at the beginning and end of the period, so as to predict the future land use. Its calculation process is as follows:

$$C_{T_n} = C_{T_{n-1}} \times P,$$

$$P = P_{ab},$$

$$= \begin{bmatrix} p_{a1} & \cdots & p_{an} \\ \vdots & \ddots & \vdots \\ p_{na} & \cdots & p_{nn} \end{bmatrix}.$$ \hspace{1cm} (16)

In the formula, $P$ denotes the probability of conversion between various types of land in the region, $P_{ab}$ denotes the probability of conversion of land use type $a$ to $b$, $n$ denotes land use type $n$ in formula (17) and the total number of land use types in formula (17), so the matrix should satisfy the following two conditions:

$$0 \leq P_{ab} \leq 1,$$

$$\sum_{b=1}^{n} P_{ab} = 1 \hspace{1cm} (a, b = 1, 2, 3, \ldots, n).$$ \hspace{1cm} (17)

Therefore, when $n = 0$, that is, at the initial time, the matrix of land use type state is as follows:
The land use status after \( n \) times of land use type conversion can be expressed as follows:

\[
C^{(n)} = C^{(0)} \times P^{(n)},
\]

where \( P((n)) \) is the probability matrix of the land use type at the initial moment after \( n \) transformations, so:

\[
C^{(n)} = C^{(n-1)} \times P = C^{(n-2)} \times P^2 = \ldots = C^{(0)} \times P^n,
\]

Get: \( P^{(n)} = P^n \).

Therefore, according to the land use state and probability matrix at the initial time, the land use state at any time in the future can be calculated. The conversion between land use types depends on the land use status. By studying the state transition of land use types at the initial and final moments in a certain time, the probability matrix describes the change value of each point in the process of land use transition probability. According to the land use state at the initial moment, the land use, evolution law, and development trend at any time in the future can be predicted.

3.2.2. GeoSOS-FLUS Model. The change in urban spatial development pattern is manifested in the change in land use and has large spatial autocorrelation. Traditional analysis models of urban spatial development pattern include CA and its improved model. This kind of model is widely used in the delineation of urban growth boundary and the spatiotemporal dynamic simulation of urban land use. However, because the cellular automata model only pays attention to the conversion between urban construction land and non-construction land, ignoring the diversity of land use types, it cannot meet the reality of analyzing the conversion between various types of land. The GeoSOS-FLUS model contains module 1: ANN-based suitability probability calculation module (ANN-based suitability probability estimation); and module 2: self-adaptive inertia and competition mechanism CA based on autonomous adaptive inertial mechanism. CA model makes up for the lack of diversity of land use types, and the model introduces the competition between different land types, reflects the relationship between various land use types, and proposes the nonconstruction area as the ecological constraints of FLUS model, more realistic simulation ability. Cellular automation model is the most commonly used network dynamics model. Network dynamics models include cellular automata, Boolean networks, neural networks, and L-systems. Cellular automata are dynamic models with discrete time and space.

Module 1: The suitability probability calculation based on neural network is used to analyze the suitability probability of mutual conversion among various land use types. The probability is related to the current situation of urban land use and the driving factors affecting urban spatial expansion. Generally, natural influence factors and human influence factors are included, and root mean square error (RMSE) is provided in the calculation results to test the accuracy of the simulated plot. The sum of suitability probabilities for all land use types of a grid in the simulated plot is 1, and the formula is as follows:

\[
sp(p, i, t) = \sum_j w_{ij} \exp^{-s(i,j)(p,t)} \sum_j sp(p, i, t) = 1.
\]

where \( sp(p, i, t) \) is the calculated suitability probability, \( i \) is the land use type, \( p \) represents the grid, \( j \) is the set hidden layer, \( w_{ij} \) is the weight, and \( net(p, t) \) is the received signal.

Module 2: The suitability probability data obtained by the above modules are imported into module 2 for analysis, and the land use data of previous years are input. The parameters such as the ability, rules, iteration times, and limiting conversion conditions between land use types are set, and the future land use results are obtained by simulation. FLUS model adopts selection method to realize the competitive relationship between different land. In the simulation process, the total probability of convertible land use type on grid \( p \) is calculated, and then the land use type \( i \) is given to grid \( p \), and the formula is as follows:

\[
TP_{p,i} = sp(p, i, t) \times Inertia_i^p \times \left( 1 - s_{c_{t-1}i} \times \frac{\sum_{N \times N} \text{con}(c_{t-1} = i)}{N \times (N-1)} \right) \times W_i,
\]

where \( TP_{p,i} \) is an index of the total probability of land use type \( i \) on grid \( p \) at \( t \) time node, \( s_{c_{t-1}i} \) is an index of the cost of land use type conversion, \( \sum_{N \times N} \text{con}(c_{t-1} = i) \) is the quantitative index of land use type \( i \) in the calculation results, and \( W_i \) represents the domain weight of various land use types.

4. Experimental Part

4.1. Model Testing. In this article, GeoSOS-FLU model is used to study and analyze the future land use from the perspective of deep learning, and the model needs to be tested before using this model.

4.1.1. Model Comparison. We compare Markov prediction model with GeoSOS-FLU model, evaluate and analyze the future land use, and compare their accuracy (Figure 3).

By comparing the two prediction models, GeoSOS-FLU model is more suitable for the calculation of land use transformation than Markov model, and the accuracy is above 60%, which shows that this model is more suitable for future land use analysis.

4.1.2. Performance Comparison. In this experiment, the neural network-based suitability calculation method of GeoSOS-FLU model proposed in this article is compared
Table 3: Comparative experiment of deep learning model.

<table>
<thead>
<tr>
<th>Type</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>0.7990</td>
<td>0.8401</td>
<td>0.8728</td>
<td>0.8561</td>
<td>0.7557</td>
</tr>
<tr>
<td>SVM</td>
<td>0.8324</td>
<td>0.8464</td>
<td>0.9229</td>
<td>0.8830</td>
<td>0.7793</td>
</tr>
<tr>
<td>FM</td>
<td>0.8431</td>
<td>0.8552</td>
<td>0.9281</td>
<td>0.8902</td>
<td>0.7933</td>
</tr>
<tr>
<td>DNN</td>
<td>0.8440</td>
<td>0.8554</td>
<td>0.9294</td>
<td>0.8908</td>
<td>0.7939</td>
</tr>
<tr>
<td>DeepFM</td>
<td>0.8485</td>
<td>0.8603</td>
<td>0.9297</td>
<td>0.8937</td>
<td>0.8008</td>
</tr>
<tr>
<td>PNN</td>
<td>0.8576</td>
<td>0.8646</td>
<td>0.9392</td>
<td>0.9004</td>
<td>0.8098</td>
</tr>
<tr>
<td>GeoSOS-FLU</td>
<td>0.8768</td>
<td>0.8780</td>
<td>0.9599</td>
<td>0.9171</td>
<td>0.8279</td>
</tr>
</tbody>
</table>

Figure 3: Model comparision of Markov and GeoSoS.

Figure 4: Performance comparison of different models.
The final experimental results are shown in Figure 4:

It can be seen from the experimental results that the deep learning GeoSOS-FLU model has achieved better evaluation results than KNN, MF, NCF, and DMF methods. GeoSOS-FLU model has the smallest difference between RMSE and MAE and has obvious advantages in model execution results. In the MAPE evaluation, the MAPE of GeoSOS-FLU model has the minimum value, and the evaluation of the model has a good performance.
GeoSOS-FLU model is the best learning method for future land use analysis and research. GeoSOS-FLU model has stronger prediction ability, flexibility, and accuracy.

4.1.3. Contrast Experiment. In this article, LR, SVM, FM, DNN, DeepFM, and PNN deep learning models are compared with GeoSOS-FLU deep learning models. The results are shown in Table 3:

According to the data in the table, a chart is drawn as shown in Figure 5.

From the experimental results in Figure 5, it can be seen that the accuracy and AUC of GeoSOS-FLU model are improved by 2.3% compared with the best traditional method, and the three indexes of precision, recall, and F1 are also significantly improved. By comparing the models proposed in this article, good evaluation results have been achieved.

4.2. Application Effect of Landscape Pattern Change Model. Using the model of landscape pattern change in this article, the landscape pattern change of a certain area is analyzed and studied based on the landscape index of that region.

4.2.1. Survey Results of Five Landscape Indexes. Six different land types were selected, according to the patch area, patch number, landscape shape index, dispersion index, and aggregation of five landscape indexes on the future changes in landscape pattern of the impact of specific analysis (Table 4 and Figure 6).

Based on GeoSOS-FLU model, some land types, landscape indexes of different regions, and analysis factors matching with specific regions are selected, and a perfect index system is constructed to expand the practicality of the study.

4.2.2. Index Survey Results in Different Years. In different periods, four different types of land were selected, according to the patch area, patch number, landscape shape index, dispersion index, and aggregation degree of these five landscape indexes to analyze the landscape pattern change range (Table 5 and Figure 7).

5. Conclusion

With the rapid development of economy, the natural environment in which we live has gradually lost its original balance system, and how the landscape pattern will change dynamically in the future has become a problem that we need to predict now. Mastering the future utilization rate of land has also become an answer that people are eager to get. The landscape pattern change model under deep learning proposed in this article can analyze the future change trend in landscape pattern more accurately. The research results show that:
(1) By comparing GeoSOS-FLU model with Markov prediction model, the accuracy of GeoSOS-FLU model is over 60% in five comparisons and it is higher than Markov prediction model.

(2) In the model comparison stage, GeoSOS-FLU deep learning method is compared with several traditional methods (KNN, MF, NCF, and DMF), and the RMSE, MAE, and MAPE of GeoSOS-FLU method are higher than the other four traditional methods.

(3) Compared with the best traditional method, the accuracy and AUC of GeoSOS-FLU model are improved by 2.3%, and the accuracy, recall, and F1 of GeoSOS-FLU model are also improved significantly.

(4) Through the analysis of five landscape indexes of six different land types, such as patch area, patch number, landscape shape index, dispersion index, and aggregation degree, it is concluded that the dynamic analysis of landscape pattern mainly depends on two levels, namely patch type level and landscape level.

(5) In order to analyze the changing trend in landscape pattern, the cultivated land area increases year by year, the grassland and water area decrease year by year, and the woodland area tends to be balanced [18–25].

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

References


