Construction And Application Of A Natural Landscape Generation System Based On L-system And Complex Network Theory

Xiaoyu Cai[1*] and Bin Hu[2]

[1] School of Design, Hefei University, Hefei, Anhui 230601, China
[2] Anhui Geological Museum, Hefei, Anhui 230031, China
[*] Corresponding author. E-mail: 18133692667@163.com

Received: Apr. 25, 2026; Accepted: Jul. 08, 2026

Accurate quantification of natural landscapes is of great significance to the study of ecological benefits. At present, most systems are still dominated by human intervention. This paper addresses the limitation of existing landscape design systems that prioritize visual aesthetics over ecological functionality and lack accurate ecosystem simulation. It proposes a natural landscape generation model combining L-system theory, complex network analysis, and Generative Adversarial Networks (GAN). The system encodes L-system rules as input to a GAN generator, enabling the creation of realistic and ecologically meaningful landscape structures. By analyzing landscape characteristics, topology, and growth functions, the model ensures effective visualization of complex landscape components. Experimental results demonstrate that the proposed L-system-GAN model achieves significantly higher resolvability and operates 5.4 times faster than traditional GAN approaches. Additionally, it meets commercial standards in generation quality, computational efficiency, and user experience, with strong potential for deployment in embedded systems. Therefore, subsequent optimization directions can focus on extreme scenario robustness and energy consumption control. The proposed framework utilizes publicly available terrain and landscape-related datasets, with key training parameters including controlled learning rate, batch size, and iteration settings for GAN optimization. Performance is evaluated using fractal dimension (FD), resolvability (SVR), and generation time metrics, ensuring consistent and verifiable assessment of model effectiveness.

Keywords: L-system; complex networks; natural landscapes; generation system; ecological modeling, topology analysis, generative design

http://dx.doi.org/10.6180/jase.202611_34.047

1. Introduction

Natural landscapes include terrain, textures, and vegetation that are interdependent and collectively form diverse scenery. With advances in computer hardware, there is increasing demand for more realistic, complex, aesthetic, and large-scale digital terrain landscape generation and visualization systems[1].

Traditional digital natural terrain landscape generation methods can be roughly divided into process-based, simulation-based, and example-based. These methods often have problems such as obscure parameters, poor controllability, and inability to balance generation quality and computational complexity [2].

Digital natural terrain landscapes not only include terrain models, but also terrain surface material distribution, vegetation distribution, etc., and these elements are highly correlated. However, existing generation methods often only focus on one of these modules, and few researchers study these modules completely.

With advances in deep learning, neural networks now leverage large-scale data for generation tasks, outperforming traditional methods. GANs have become widely used for image translation and generation due to their strong feature learning and reconstruction capabilities.

Deep learning methods for terrain generation still face limitations in scalability and detail quality. Neural networks often perform well only on small images and struggle with large terrain maps. For example, Pix2Pix generates height maps up to 256 × 256 pixels [3], which lack fine terrain details and require traditional methods for refinement. Additionally, most deep learning-based approaches cannot support editable terrain styles or allow only global style control, limiting their ability to customize local terrain features and reducing practical application scope.

This paper proposes a natural landscape generation system using L-system and complex network theory, enhanced by GANs to improve realism. It analyzes landscape rules, topology, and growth functions to construct integrated visual landscapes, supporting studies on fragmentation, biodiversity loss, and ecological modeling applications, and systems research.

2. Materials and methods

2.1. Related work

2.1.1. Terrain model generation method

Terrain model refers to the digital representation of surface elevation used to describe geometric and structural variations of natural landscapes, typically expressed as height fields or 3D surface meshes. Landscape system denotes the integrated composition of terrain, vegetation, and environmental components that collectively define a complete ecological scene. Ecological functionality describes the behavior and interaction of landscape elements influenced by environmental factors, including vegetation growth patterns, spatial distribution, and ecosystem-level responses within the generated environment. Procedural generation enables fast, realistic modeling but has limited controllability using fractals, noise, and semantic structures [4].

Hydraulic erosion models generate geologically realistic river channels, while thermal erosion forms sedimentary structures under steep slopes. Case-based synthesis uses sketches and examples for terrain generation [5], and dictionary-based methods enable sparse terrain reconstruction [6]. Deep learning has advanced data generation and feature extraction by learning input-output mappings to create new features. Kikuchi et al. used pix2pix for sketch-to-heightmap terrain generation [7], while Pereković et al. improved ProGAN for high-resolution, smoothly stitched terrain blocks.

2.1.2. Ground surface material distribution generation method

Surface materials define terrain appearance using procedural mapping with elevation, slope, and environmental factors; advanced methods improve realism over simple altitude-based approaches [8]. Amani-Beni et al. used CGAN for terrain and texture generation but lacked distribution constraints [9].

Terrain characteristics influence material distribution through elevation, slope, and moisture variations. These factors affect soil properties and resource availability, which govern vegetation growth and spatial patterns within landscape generation systems.

2.1.3. Vegetation distribution generation method

Vegetation appearance and distribution are shaped by climate, soil, altitude, species adaptability, and interactions. Vegetation distribution is further guided by ecological principles such as niche competition and succession dynamics. These mechanisms influence species coexistence, resource utilization, and community development, thereby enhancing the ecological realism of generated landscape patterns. Vegetation distribution is influenced by both biotic interactions, such as competition and spacing, and abiotic factors, including rainfall, temperature, and soil conditions. Their combined effect governs realistic ecological pattern formation.

Procedural vegetation generation uses noise-based and hybrid methods, combining simulation and editing, but faces scalability, complexity, and real-time limits. GAN-based approaches are discussed in [10–12].

3. Result and discussion

3.1. Natural landscape modeling and generation technology

Landscape generation integrates characteristics, growth functions, L-systems, and topology to model rules and create realistic systems.

3.1.1. 3D morphological modeling of landscape

Figure 1 represents the landscape axis as a quartic Bezier curve with five control points. The expression for constructing the quartic Bezier curve of the axis is shown in Eq. (1) [13]:

$$p(t) = \sum_{i=0}^{4} P_i B_{i,4}(t) \tag{1}$$

The quartic Bezier curve uses five control points, with their selection illustrated in Fig. 1.

In NURBS, weight ω_i represents analytical curves and shape control; i data points need i + 2 control points, with

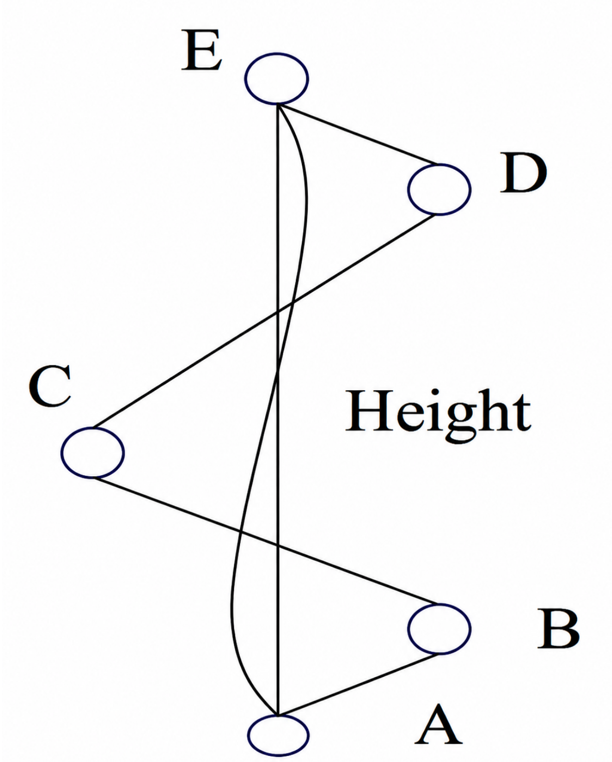

Fig. 1. Landscape axis

cubic curves defined by nodes and control vectors. The basis function is shown in Eq. (2) [14]:

$$\begin{cases} N_{i,0} = \begin{cases} 1, u \in [u_i, u_{i+1}]] \\ 0, \text{Others} \end{cases} \\ N(u)\dfrac{u - u_i}{u_{i+k+1_{i,k}-1}}(u)\dfrac{u_{i+k} - u}{u_{i+k} - u_{i+1_{i+1,k-1}}}(u)_{i,k}\{ \\ \text{Rule } \dfrac{0}{0} = 0 \end{cases} \quad (2)$$

From Eq. (2), B-spline basis functions are recursively defined using $N_{i,k+1}$ and $N_{i,k-1}$.

3.1.2. Natural landscape rendering

Lambert material models point light illumination with uniform reflection to simulate shadow effects in 3D models. Lambert shading improves ecological realism and efficiency by modeling diffuse reflection in terrain and vegetation. This model is based on the Lambert lighting model [15], and its lighting model is given as follows:

$$\text{diffuse} = Kd \times Id \times \cos(theta) \quad (3)$$

Eq. (3) defines diffuse reflection using surface property, light intensity, and incident angle. Warm light is obtained by calculating seasonal radians, as shown in Eq. (4):

$$\text{HotLight} = \sin(\text{seasonRad}) \quad (4)$$

When a positive number is used as the parameter, the ambient light can be made to appear as if there were full sunlight.

The cold light intensity setting is shown in Eq. (5):

$$\text{ColdLight} = -\sin(\text{seasonRad}) \times 0.5 \quad (5)$$

Negative paparameters create cool ambient light while maintaining low intensity to prevent excessive lighting interference. Simulated lighting includes seasonal and diurnal variations, modeling solar position and ambient light to enhance realism and ensure consistent environmental rendering across time conditions.

3.2. Digitally generative design method

GANs and L-systems can synergize for structured data generation and optimization in specific scenarios. The proposed framework integrates L-systems, GANs, and complex network theory for controllable and realistic landscape generation. Encoded L-system rule vectors are used as GAN inputs, where the generator produces landscape structures, and the discriminator evaluates authenticity against real samples. Training is optimized using the Adam optimizer and loss functions to improve realism, diversity, and structural consistency. Complex network analysis models landscape elements as nodes and interactions as edges, preserving connectivity and guiding topology-aware design. Decoded outputs reconstruct L-system rules enabling recursive coherent landscape generation with ecological spatial realism.

Algorithm 1 presents the L-system GAN using encoded rules and noise for adversarial rule generation.

The L-system-GAN framework preserves structural consistency by using L-system rules as constraints during generation. GAN improves realism; L-system decoding maintains rule-based coherence between encoded symbols and outputs. It uses a generator-discriminator architecture with vector rules optimized via learning rate, batch size, and iterations. Python-based GPU system enables efficient encoding, adversarial training, and large-scale coherent landscape generation. The L-system rules are encoded as vectors and input into the GAN generator to generate a new rule set, and then the final structure is generated through L-system parsing. Intermediate visualization outputs are included at each generation stage, showing rule encoding, GAN transformation, and decoding progression. These stepwise results improve interpretability and provide a clearer understanding of model behavior. The L -systemGAN combines rule encoding and GAN learning

Algorithm 1: L-system GAN-Based Landscape Generation

Input:
Encoded L-system rules R, dataset D, noise vector z
Output:
Generated landscape structure L
Step 1: Rule Encoding
Convert L-system rules R into vector form R_v
Step 2: GAN Input Preparation
Feed R_v, and noise z into generator
Step 3: GAN Training
Generator produces R_g, the discriminator evaluates realism
Optimize using Adam and adversarial loss:

$$L_{\text{GAN}} = L_G + L_D$$

Step 4: Rule Generation
Generate new rule vector:

$$R_g = G(z, R_v)$$

Step 5: L-system Decoding
Decode R_g and apply L-system grammar
Step 6: Landscape Output
Generate final landscape structure L

for realistic landscape generation. The specific process is shown in Fig. 2.

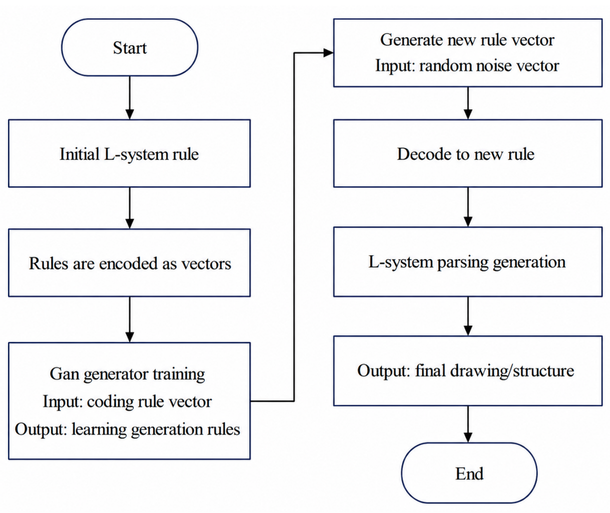

Fig. 2. L-system-GAN landscape graphics generation process

(1) L-system rules are encoded into vectors and trained in a GAN model using rule-graph datasets. (2) Noise generates new rule vectors. (3) Outputs are decoded and processed by an L-system parser to recursively create final graphical structures.

The dataset uses a rule-environment-graph triplet where L-system rules define structure, environmental factors describe conditions, and graphs represent spatial connectivity. This representation ensures consistent mapping between inputs and generated landscape outputs. It improves model generalization across diverse ecological and geographic conditions by capturing multi-level dependencies. Landscape installation components include form, structure, materials, and multimedia; design follows conceptual, geometric, and solid modeling stages as shown in Fig. 3.

Fig. 3 shows that digital generative landscape design follows traditional steps using computational data for generation, evaluation, and implementation. Fig. 4 integrates L-system tools, networks, and simulation systems for data-driven responsive landscape design. The integrated tool platform combines environmental data acquisition, virtual modeling, and physical control systems for landscape generation.

The paper classifies landscape devices, analyzes cases, and proposes a generative strategy. Environmental strategy

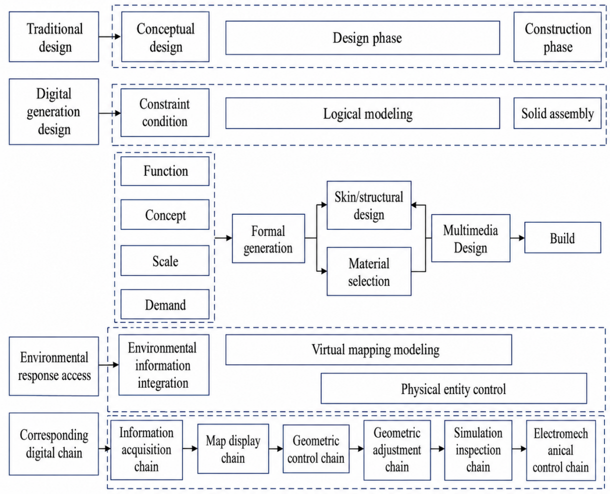

Fig. 3. The process of generating design nodes by integrating environmental response into digitalization

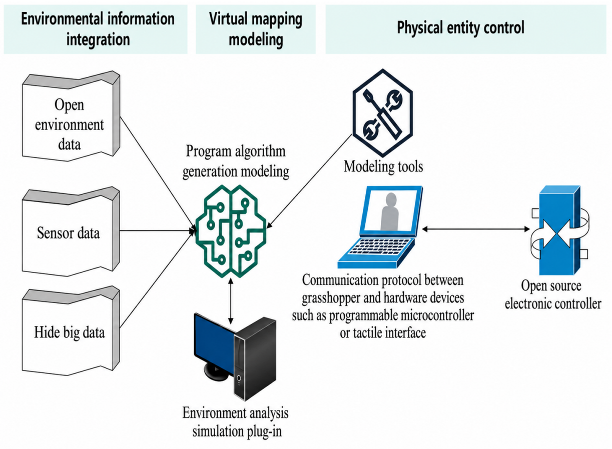

Fig. 4. Digital tool platform for L-system and complex network-based landscape response generation

adapts across forests, mountains, urban, and arid zones, ensuring consistent ecological and spatial performance.

3.3. System testing

3.3.1. Test methods

The dataset includes L-system rules, parameters, and graph features forming a rule-environment-graph triplet; baselines GAN, Diffusion, Neural L-system; evaluation uses A/B testing, FD (1.2-1.8), Pearson's r, runtime, GPU memory, and RL speed.

3.3.2. Test Results

Table 1 shows that L-system-GAN is 5.4 times faster than traditional GAN due to efficient symbolic rule parsing. As rainfall increased, tributaries rose to 30, matching real basin scenarios in Table 2. Table 3 shows that L-system-GAN outperforms traditional rainfall models. The vegetation diversity results in Table 4 show dynamic matching between functional groups and environmental carrying capacity. Biodiversity assessment was enhanced using Margalef, Menhinick, Berger-Parker, and Fisher's Alpha indices alongside Shannon and Simpson metrics as shown in Table 5.

Model requires 3.2 GB GPU memory, uses A100-class training, supports NPU and ARM edge devices with reduced speed for deployment.

Table 1. Comparison of Generation Quality Across Different Landscape Generation Methods

Models	Method Category	Fractal dimension (FD)	Generation time (ms)	Resolvability (SVR)
L-system GAN model	Hybrid (Procedural + Deep Learning)	1.67 ±0.09	15.2	97.30%
Traditional GAN	Deep Learning-Based	1.28 ±0.14	82.5	-
The nervous L-system	Procedural-Based	1.53 ±0.11	28.7	88.10%

Note: The closer the FD is to the natural range (1.2-1.8), the better, and the SVR reflects the rule rationality.

Table 2. Experimental data of the influence of rainfall change on tributary number

Rainfall (mm)	Number of tributaries generated	Horton tributary number ratio	Channel curvature (KL divergence)	Network node degree standard deviation
50	8 ± 1	3.1 ± 0.2	0.18 ± 0.03	0.52 ± 0.07
100	15 ± 2	3.3 ± 0.2	0.15 ± 0.02	1.12 ± 0.11
150	23 ± 3	3.2 ± 0.1	0.13 ± 0.02	1.54 ± 0.09
200	30 ± 4	3.4 ± 0.3	0.12 ± 0.01	1.83 ± 0.14

Experiments across mountains, rivers, forests, semi-arid regions, and wetlands evaluate framework generalizability under varied conditions, shown in Fig. 5.

3.3.3. Analysis and discussion

Table 1 shows that L-system-GAN achieves natural fractal dimension, higher rule validity, and 5.4× faster generation speed. Table 2 shows rainfall-tributary correlation ($r = 0.89, p < 0.01$) with hydrological changes. Table 3 highlights improved Horton ratio error and KL divergence. Table 4 shows ecological accuracy, Shannon difference (2.3%), and the K-S test (92%). Table 5 shows that bio-

Table 3. Comparative test of model performance for simulating rainfall change

Index	L-system -GAN model (200 mm rain)	Conventional GAN (200 mm rainfall)	Improvement range
Horton tributary number ratio error	3.4 ± 0.3 vs. 3.2	1.8 ± 0.5 vs. 3.2	0.813
River channel curvature KL divergence	0.12 ± 0.01	0.31 ± 0.05	0.613

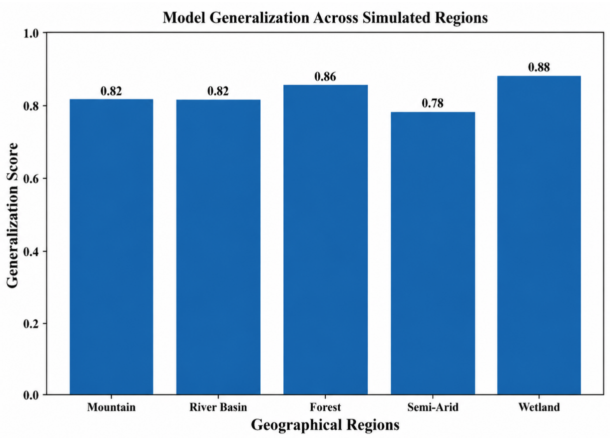

Fig. 5. Model Generalization Across Diverse Geographical Regions

diversity varies by region, with forests and wetlands higher than semi-arid areas. Environmental parameters like rainfall, temperature, and vegetation dynamically guide rules to ensure realistic landscape formation.

4. Conclusion

This paper combines a landscape generative model with landscape characteristics, analyzes landscape generation rules, studies landscape topology, and combines growth function and L-system to reasonably combine various parts to complete the visualization construction of the landscape system. In addition, this paper classifies landscape devices according to environmental factors and response purposes, analyzes the design components of typical cases and the mapping method of digital design, forms design strategies, and proposes the design mechanism of digital generative design. Combined with the experimental analysis, it can be seen that the parsability rate of the L-system-GAN model is significantly higher than that of the baseline model, indicating that the generated L-system rules have higher grammatical legitimacy. In terms of generation speed, the generation speed of L-system-GAN is 5.4 times faster than that of traditional GAN. This is due to the high efficiency of symbolic rule parsing. Furthermore, it has achieved systematic breakthroughs in both technical performance and user experience. The L-system-GAN model has reached commercial application standards in three key dimensions: generation quality, resource efficiency, and user experience, and has the potential to expand to embedded devices. Therefore, the subsequent optimization direction can focus on extreme scenario robustness and energy consumption control.

For plant modeling, this paper uses geometric simulation with the lowest computational complexity, which can model general natural landscapes. If highprecision restoration modeling is needed, methods such as SFM need to be used for modeling. For machines with powerful computing power, 3D point cloud data can be used combined with machine learning methods for modeling, which can generate models closer to the native, and is also a future research direction. Limitations include reduced robustness under extreme environmental conditions, scalability constraints for large terrains, and energy consumption challenges. Future work will focus on efficiency optimization, adaptive modeling, and sustainable deployment improvements.

5. Acknowledgements

The authors would like to express their sincere gratitude to Hefei University and Anhui Geological Museum for their support in this research.

Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

This research was funded by the Anhui Province Social Science Innovation and Development Research Project, "Research on the Activation and Utilization of Ancient Village Landscapes in Anhui Under Digitalization" (Project No. 2023CX123), and the Key Research Project of Anhui Provincial Universities, "Research on the Construction of a Digital Atlas Model and Inheritance Protection Strategies for Huizhou Ancient Village Landscapes Based on Spatial Genes" (Project No. 2023AH052159).

Authors' contributions

Xiaoyu Cai: Conceptualization, Methodology, Writing – original draft, Supervision.

Table 4. Experimental data of vegetation community diversity assessment

Assessment index	L-system-GAN model simulation values	True observations	Significance of difference (p-value)
Shannon Diversity Index	2.45 ± 0.21	2.51 ± 0.18	0.09
Simpson dominance index	0.83 ± 0.05	0.79 ± 0.04	0.12
Pielou's evenness index	0.68 ± 0.03	0.71 ± 0.02	0.07
K-S test pass rate for the spatial distribution of tree species	92%	95%	0.08

Table 5. Comparative biodiversity across simulated geographic regions

Region	Shannon	Simpson	Margalef	Menhinick	Berger-Parker	Fishers Alpha
Mountain	2.45	0.83	4.386	2.008	0.045	4.595
River Basin	2.52	0.81	4.689	2.066	0.042	4.893
Forest	2.61	0.85	5.389	2.286	0.036	5.588
Semi-Arid	2.31	0.78	3.617	1.716	0.056	3.829
Wetland	2.68	0.87	5.876	2.413	0.032	6.071

Bin Hu: Data curation, Investigation, Writing – review & editing.
All authors read and approved the final manuscript.

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