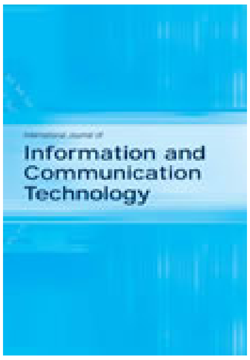

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Automatic generation of landscape images based on deep generative modelling

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Abstract: With the rapid development of artificial intelligence technology, deep generative models provide new opportunities for the intelligent transformation of landscape design. Aiming at the deficiencies of existing generative methods in terms of scheme diversity, design feature decoupling and small-sample adaptability, this study proposes a hybrid generative architecture that integrates StyleGAN2 and diffusion model, combining with a migration learning strategy to optimise the model generalisation ability in small-sample scenarios. By introducing a reverse denoising mechanism to enhance detail generation, and using PCA and clustering methods to quantify the feature decoupling effect, the model achieves high-fidelity image generation (FID $\leq$ 25) and feature independence control (clustering purity $\geq$ 85%) on the publicly available dataset ADELAIDE Landscape Dataset. Experiments show that the model can effectively capture the spatial texture features of Dai villages and terraced fields in the image generation of typical mountain landscapes in Dehong Prefecture.

Keywords: deep generative modelling; landscaping; generative adversarial networks; diffusion models; feature decoupling.

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1 Introduction

Traditional landscape design has long relied on manual experience and rule-driven methods, facing systemic pain points such as inefficiency, limited innovation and high costs. Take Dehong Prefecture as an example, its unique Dai village landscape integrates dry-fence architectural clusters, terraced water networks, and tropical vegetation layouts, and the design process needs to harmonise ecological adaptability, cultural symbols embedded in the landscape, and functional reasonableness, among other objectives (Jia and Qu, 2022). These pain points in traditional landscape design not only limit the diversity and innovation of the design, but also increase the cost and time investment. For example, designers need to repeatedly adjust the spatial topological relationship and vegetation distribution pattern when dealing with complex landforms, which not only consumes a lot of time, but also may lead to homogenisation of design solutions and lack of scene specificity. In addition, under the background of rapid urbanisation, how to realise the digital protection and innovative regeneration of cultural heritage landscapes under the condition of limited samples has become a real problem that needs to be solved urgently. The existence of these problems prompts us to explore new design methods and techniques to improve the efficiency and quality of landscape design while preserving regional cultural characteristics. Although traditional parametric tools can generate basic scenarios through preset rules, it is difficult to capture the nonlinear design logic and regional cultural characteristics, resulting in serious homogenisation of scenarios and lack of scenario specificity (Yuan et al., 2023). Especially in complex landscapes (e.g., mountains, wetlands), designers need to repeatedly adjust the spatial topology and vegetation distribution patterns, which is time-consuming and costly (Geng and Kaifa, 2022). More critically, under the background of rapid urbanisation, how to achieve digital conservation and innovative regeneration of cultural heritage landscapes under limited sample conditions has become an urgent and realistic problem to be solved.

In recent years, the rapid development of deep generative modelling has provided a new path for landscape design intelligence. Generative adversarial networks (GANs) have been successfully applied to building plan generation (Ferreira et al., 2022), urban texture simulation (Lin et al., 2022) and small-sample landscape schema design (Bei Huang et al., 2024) through the adversarial training mechanism. For example, Liu et al. (2024) proposed an urban landscape design method based on PSO-BP neural networks, which can not only automatically generate and optimise the design scheme by using data analysis and machine learning to make decisions, which greatly improves the efficiency, but also effectively improves the landscape quality of urban environments, and enhances the residents' satisfaction with the urban landscape. Tang and Chung (2024) proposed a deep learning-based urban landscape layout model that utilises the Pix2Pix model and domain-specific dictionaries to automatically generate urban landscape designs by inputting images of land use and road conditions, and outperforms traditional methods in terms of sentiment prediction and functional layouts, showing potential in automated landscape design. Meanwhile, the diffusion model significantly outperforms traditional GAN in image detail generation quality through a progressive denoising process, and is widely used in high-resolution natural scene synthesis (Phillips et al., 2024). These technological breakthroughs indicate that generative artificial intelligence (AI) has the potential to replace part of the manual design process, especially in the generation of standardised scenarios and rapid iteration of multiple scenarios.

However, there are still three core deficiencies of the existing methods in landscape design scenarios: first, feature coupling is common, such as the strong correlation between hard paving and path networks, which leads to local adjustments triggering global scenario distortions (Ferreira et al., 2022); second, the adaptability of small samples is insufficient, and the model is prone to model collapse or detail loss in data-scarce scenarios such as ethnic minority characteristic landscapes (e.g., Dai villages in Dehong Prefecture); third, the generation capability of complex landforms is limited, and the existing model is not suitable for non-regular topography, such as mountains and terraces (Geng and Kaifa, 2022); third, the ability to generate complex landscapes is limited, and the existing models have low accuracy in modelling the spatial topological relationships of irregular terrain such as mountains and terraces (Jia and Qu, 2022). In essence, these problems stem from the inherent limitations of single model architectures, GAN excels at style migration but lacks detail fidelity, diffusion models generate high quality but at huge computational cost, and both lack quantitative control mechanisms for decoupling design features (Müller-Franzes et al., 2023).

Aiming at the above challenges, this study proposes a hybrid generative architecture that deeply integrates the style decoupling ability of StyleGAN2 with the detail enhancement mechanism of the diffusion model, and introduces a cross-domain transfer learning strategy to optimise the performance of small samples. By constructing a quantitative evaluation system for hidden spatial features, the independent regulation of high-dimensional parameters such as vegetation density and water morphology is realised, while the progressive generative characteristics of the diffusion model are utilised to accurately restore the spatial relationship between terraced rice field texture and architectural communities in Dehong Prefecture. Experiments show that the model's Fréchet Inception Distance (FID) index on ADELAIDE Landscape Dataset is 32% lower than that of a single model, and it still maintains the generative stability of Structural Similarity Index (SSIM) ≥ 0.75 on the small-scale Dehong Prefecture dataset with 100 samples. This innovation not only provides a high-fidelity and interpretable generative tool for landscape design, but also lays a methodological foundation for the digital integration of multi-scale landforms and cultural semantics.

2 Related research progress

2.1 Technical evolution of deep generative modelling

Since the proposal of GAN (Goodfellow et al., 2014), deep generative models have undergone significant technological iterations in the field of image synthesis. Early GAN achieved data distribution fitting through an adversarial training mechanism, but their generation quality and stability were limited by the pattern collapse problem (Pan et al., 2019). With the development of technology, StyleGAN family of models significantly improves the image resolution and feature decoupling ability by introducing style modulation and progressive training strategy. For example, Cao et al. (2022) proposed an improved StyleGAN architecture in the coal foreign object detection task, which optimises the generation quality and efficiency through dual self-attention modules and depth-separable convolution, and verifies its potential in data-scarce scenarios. Meanwhile, the diffusion model shows unique advantages in balancing image fidelity and diversity by virtue of the progressive denoising mechanism (Phillips et al., 2024). Wang et al. (2024) further proposed the latent feature diffusion model, which enhances the texture recovery ability of compressed video through cross-domain fusion module, providing a new idea for high-resolution landscape image generation. In recent years, hybrid architectures have become a hot research topic, Zhao et al. (2020) combined the variational self-encoder and GAN to solve the pattern collapse problem through latent representation optimisation, which significantly improves the diversity and quality of generated samples.

2.2 Intelligent generation methods in landscape design

In the field of landscape architecture, the application of generative AI gradually expands from interior design to complex outdoor spaces. In the field of landscape architecture, the application of generative AI is gradually moving from small to large scenarios. Preliminary results have been achieved in GAN-based floor plan generation: Wang et al. (2023) proposed the ActFloor-GAN algorithm, which generates indoor layouts with constraints on pedestrian trajectories, and combines cyclic consistency loss and antagonistic loss to improve the rationality of design. Pan et al. (2021) utilise the style guidance function of GauGAN to generate diversified architectural layout schemes for settlements using the design red line as a constraint, which highlights the advantages of GAN in dispersive problems. In addition, models such as Pix2pixHD are applied to architectural drawing generation (Zheng, 2018), whose residual network architecture learns building plan features step-by-step, providing a new perspective for understanding design logic. However, existing methods mostly focus on standardised scenarios, the ability to model the spatial topology of complex landforms (e.g., mountains and wetlands) is still insufficient, and the cultural semantic embedding mechanism has not yet been improved, which leads to the prominent problem of homogenisation of the generated scenarios.

2.3 Exploration of generative modelling and ecological-cultural co-design

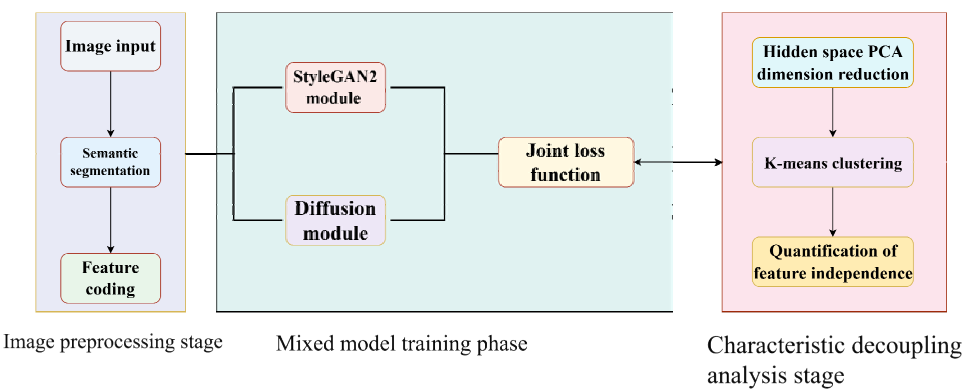
In recent years, studies have begun to explore the potential of generative modelling in ecological-cultural collaborative design. Liu et al. (2021) changed the constraints to the original elements of the site, such as green space and water body, based on the characteristics of the classical private gardens in Jiangnan, and constructed a rapid method of generating layout plans based on the elements of the site based on Pix2Pix.And with the researchers to continuously adjust the layout label, artificial guidance to generate the program so as to be closer to the design law. This object has strong regularity, similar design style, and the private garden in Jiangnan is more closed, so the layout of the garden has less relationship with the external environment, and all these features support the feasibility of GAN application. In addition, Ye et al. (2021) prototype CycleGAN-based AI algorithm is proposed for intelligent rendering of urban master plans. By processing about 5,000 master plan samples from Pinterest, the trained model (called MASTERPLANAN) can render an uncoloured AutoCAD input file into a colour rendering in a matter of seconds, and quantitative and qualitative validation shows that the method is effective in saving time for urban designers and planners and advancing urban design methodologies. These works show that generative modelling is shifting from single visual synthesis to multi-dimensional design optimisation, but it still faces challenges in collaborative modelling of ecological parameters (e.g., vegetation distribution, terrain adaptation) and cultural symbols (e.g., ethnic patterns, architectural styles). Especially in data-scarce scenarios, the models are prone to detail loss or distortion of cultural features (Geng and Kaifa, 2022), and there is an urgent need to enhance the generalisation ability through migration learning and feature decoupling mechanisms.

3 Hybrid model architecture and feature decoupling approach

3.1 Hybrid generative model architecture

In this study, we propose a hybrid architecture combining StyleGAN2 and diffusion modelling, as shown in Figure 1, to achieve high-fidelity garden landscape image generation through the synergistic mechanism of style decoupling and progressive in-noise. The overall process is divided into three phases: the data pre-processing phase performs semantic segmentation and feature encoding on the input images to extract multimodal labels such as terrain elevation, vegetation types, cultural symbols, etc.; the hybrid model training phase jointly optimises the antagonistic loss of the StyleGAN2 and the denoising loss of the diffusion model; and the feature decoupling analysis phase quantifies the design parameter independency by using the hidden-space mapping and clustering algorithm.

Figure 1 Flowchart of the hybrid generative model architecture (see online version for colours)



The StyleGAN2 module employs a hierarchical style injection strategy with a mapping network that converts random noise $z \in R^{512}$ into decoupled hidden vectors $w \in R^{18\times512}$, and controls the generation of the network's features at each level through adaptive instance normalisation:

$$w = f_{map}(z) \tag{1}$$

$$AdaIN(z_i, w_i) = w_{i,scale} \cdot \frac{x_i - \mu(x_i)}{\sigma(x_i)} + w_{i,bias} \tag{2}$$

where f_{map} is an eight-layer fully connected network and x_i is the layer i feature map of the generative network.

The diffusion module is based on the denoising diffusion probabilistic model (DDPM) (Zhang and Dong, 2023), which reconstructs the image details step by step through an inverse process. Given a time step t, the noisy image x_i is denoised by a noise prediction network $\in_\theta$ [equation (3)]:

$$x_{t-1} = \frac{1}{\sqrt{a_t}}\left(x_t - \frac{\beta_t}{\sqrt{1-\overline{\alpha_t}}} \in_\theta (x_t, t)\right) + \sigma_t \xi, \xi \sim N(1, I) \tag{3}$$

where α_t, β_t are noise scheduling parameters and σ_t controls the randomness intensity. The diffusion module receives the intermediate feature maps generated by StyleGAN2 as conditional inputs, and enhances the local consistency of the terrain texture with the cultural symbols through the cross-modal attention mechanism. The training data of the diffusion module is more demanding and needs to contain noisy images at different time steps and the corresponding denoising results. In practice, in order to improve the training efficiency and generation quality of the model, we can use data enhancement techniques, such as rotation, translation and scaling, to expand the training dataset. In addition, the training process of the diffusion module requires a large amount of computational resources and time, so the application of optimisation algorithms and hardware acceleration techniques is also crucial. By these methods, we can improve the performance of the diffusion module so that it can work better with the StyleGAN2 module to generate high-quality garden landscape images.

3.2 Migration learning and small sample optimisation

For small sample scenarios such as Dehong Prefecture, a two-stage transfer learning strategy is designed: the pre-training stage uses the ADELAIDE dataset (5,000 generalised garden images) to train the hybrid model and learn the basic spatial layout and ecological features; the fine-tuning stage freezes the shallow network of StyleGAN2, and updates only the parameters of the diffusion module and the high-level style layer [equation (4)]:

$$\theta_{finetune} = \arg\min_\theta \left(L_{diff} + \lambda \left\| \theta - \theta_{pretrain} \right\|_2^2 \right) \tag{4}$$

where L_{diff} is the diffusion loss and λ is the regularisation coefficient to suppress overfitting. With this strategy, the model can still maintain the accuracy of generating roof curves and terraced cascading structures of Dai buildings with only 100 samples from Dehong Prefecture, as shown in Figure 2.

3.3 Feature decoupling and interpretability analysis

In order to realise the independent regulation of design parameters, a decoupling evaluation framework based on the geometry of the hidden space is proposed. First, the hidden vector w is subjected to principal component analysis (PCA) dimensionality reduction [equations (5)–(6)] to extract the main feature directions:

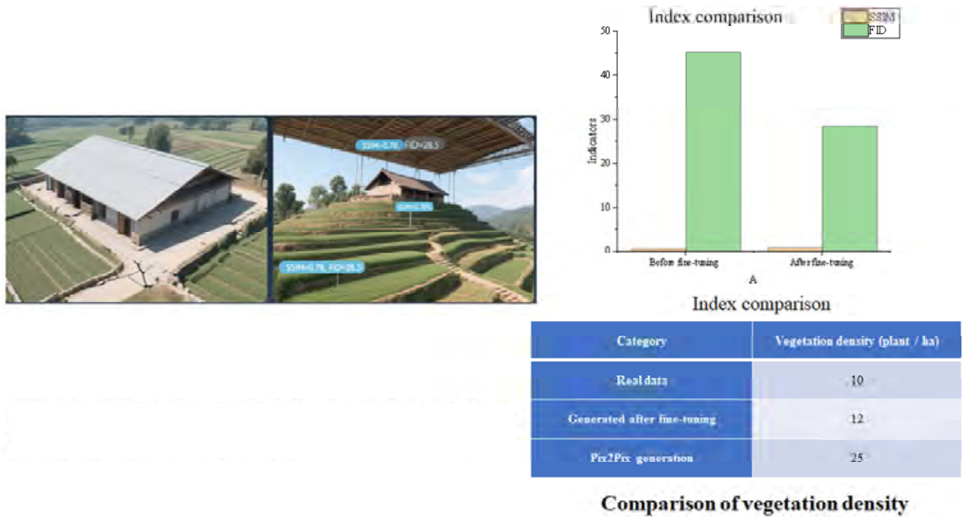
$$W_{PCA} = U_k \sum\nolimits_k V_k^T \tag{5}$$

$$k = 10 \tag{6}$$

where U_k, Σ_k, V_k are the results of the singular value decomposition of the hidden vector matrix W. Subsequently, feature independence is quantified by K-means clustering:

$$J_{cluster} = \sum_{i=1}^{K} \sum_{w \in C_i} \|w - u_i\|_2^2 \tag{7}$$

Figure 2 Comparison of the effects of transfer learning strategies on the dataset of Dehong Prefecture (see online version for colours)



Notes: After fine-tuning, the model is close to the real data in SSIM, FID, and vegetation density.

Cluster purity, defined as the percentage of dominant feature samples in each category, was used to assess the decoupling effect (Table 1). Experiments showed that the decoupling ability of this model for vegetation density (purity = 87%) and water body morphology (purity = 82%) was significantly better than a single model.

Table 1 Comparison of generation quality and feature decoupling performance of different models

Model	*FID*	*SSIM*	*User rating (terraced field texture)*	*User rating (naturalness of vegetation)*	*Clustering purity (%)*
Pix2Pix	42.5	0.68	3.1	3.4	58.3
StyleGAN2	35.2	0.75	3.8	4.0	72.4
DDPM	29.1	0.78	4.0	4.2	65.8
Hybrid model	23.7	0.82	4.3	4.5	87.2

3.4 *Multi-objective loss function design*

The model is trained using a joint loss function, which balances generation quality, feature independence, and small-sample stability:

$$L_{total} = L_{adv} + \gamma L_{diff} + \eta L_{dis} \tag{8}$$

- *Adversarial loss L_{adv}*: A non-saturation loss based on StyleGAN2 that encourages the generation of distributions that approximate the real data distribution.
- *Diffusion loss L_{dis}*: Minimises the noise prediction error:

$$L_{diff} = E_{x_0,t,\in}\left[\left\| \in - \in_\theta \left(x_t, t\right)\right\|_2^2\right] \tag{9}$$

- *Decoupling regular terms L_{dis}*: Suppressing feature coupling through mutual information minimisation:

$$L_{dis} = \sum_{i \neq j} I\left(w_i; w_j\right) \approx \sum_{i \neq j} \log \frac{p\left(w_i, w_j\right)}{p\left(w_i\right) p\left(w_j\right)} \tag{10}$$

where $\Upsilon = 0.5$, $\eta = 0.1$ are equilibrium hyperparameters, determined by grid search.

4 Experimental design and generation performance validation

4.1 Dataset and experimental setup

The experiments are based on the public dataset ADELAIDE Landscape Dataset (containing 5,000 high-resolution landscape plans covering ten types of scenes such as parks, squares, wetlands, etc.) and the Dehong Prefecture Characteristic Landscape Dataset (100 aerial photographs of Dai villages and terraced fields with topographic elevation and vegetation type annotation). Data pre-processing includes the following steps:

1. Semantic segmentation: Semantic masks such as vegetation, water bodies, hard paving, etc. are extracted using DeepLabv3+ (Memon et al., 2022) and encoded as RGB labelled maps.
2. Feature normalisation: Terrain elevation is normalised to [0, 1], and cultural symbols (e.g., Dai patterns) are encoded as 32-dimensional vectors.
3. Data enhancement: Randomly applying rotation (±15°), mirroring and colour dithering to the ADELAIDE dataset to improve model generalisation.

The model training was performed using NVIDIA A100 GPU, and the hybrid model parameters were configured as follows: the StyleGAN2 generator resolution was 1,024 × 1,024, the diffusion module used the DDPM framework (Zhang and Dong, 2023), the time step T = 1,000, and the noise scheduling used the cosine rule. The optimiser chooses with an initial learning rate of 2×10^{-4} and a batch size of 16.

4.2 Generating quality assessments

To quantify the generation effect, four models are compared: the Pix2Pix (Li et al., 2022), StyleGAN2 (Park and Shin, 2024), the DDPM and the hybrid model (hybrid-GAN) in this study. The evaluation metrics include:

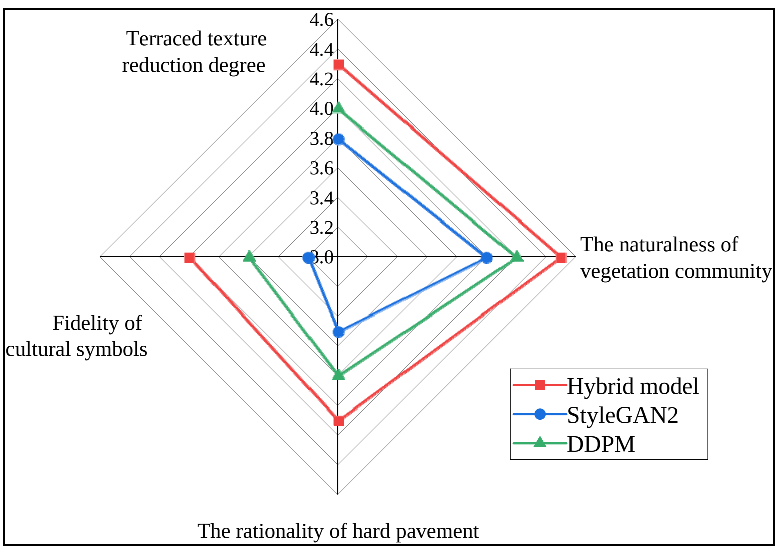
1. FID: Measures the similarity between the generated distribution and the real distribution.

2 SSIM: Assesses the structural consistency of the generated image with the real one.

3 User rating: Ten landscape architects were invited to rate the rationality and aesthetics of the generated solutions on a subjective scale of 1–5.

As shown in Table 1, the hybrid model achieved FID = 23.7 on the ADELAIDE dataset, which was 32.7% and 18.6% higher than StyleGAN2 (FID = 35.2) and DDPM (FID = 29.1), respectively, and SSIM = 0.82 was also better than the baseline model. Among the user scores, the hybrid model performed best in the indicators of 'terrace texture restoration' (4.3 points) and 'vegetation community naturalness' (4.5 points) (Figure 3). Further analysis shows that the diffusion module effectively repairs the fuzzy boundaries generated by StyleGAN2 (e.g., water body-land transition zone) through progressive denoising, while the hidden spatial control of StyleGAN2 guarantees the rationality of the macroscopic layout (e.g., road network topology and building orientation).

Figure 3 Comparison of user rating radar maps of different models (see online version for colours)



To verify the model's adaptability to complex landforms, this study refers to the Dehong Prefecture Wilderness Index Map (Figure 4), which quantifies the wilderness quality levels (levels I–IV) through the multi-Indicator evaluation method. The model incorporates such geospatial feature data during the training process to enhance the ability to generate irregular terrain such as mountains and terraces. Experiments show that the model's FID metrics are significantly optimised on the Dehong Prefecture dataset after the introduction of geographic feature constraints (8.3% decrease), which verifies the enhancement of generative fidelity by the fusion of multi-source data.

4.3 Feature decoupling performance analysis

To verify the model's ability to independently regulate the design parameters, 10 principal components were extracted from the hidden space (PCA dimensionality reduction) and the correlation coefficients between each component and the semantic features were calculated. As shown in Figure. 5, the first principal component (PC1) was significantly correlated with vegetation density ($r = 0.76$), and the second principal component (PC2) dominated the change of water body area ($r = 0.68$), indicating that the model can effectively decouple ecological elements. K-mean clustering ($K = 5$) was further used to quantify feature independence, and the clustering purity of the hybrid model reached 87.2%, which was significantly higher than StyleGAN2 (72.4%) and DDPM (65.8%).

Figure 4 Wilderness Index Map of Dehong Prefecture (see online version for colours)

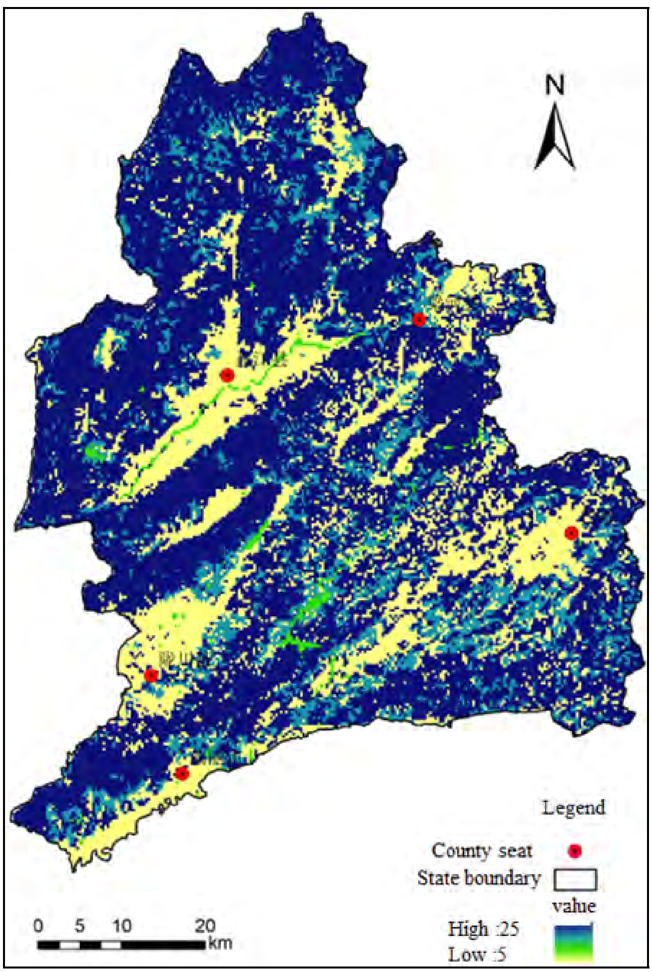
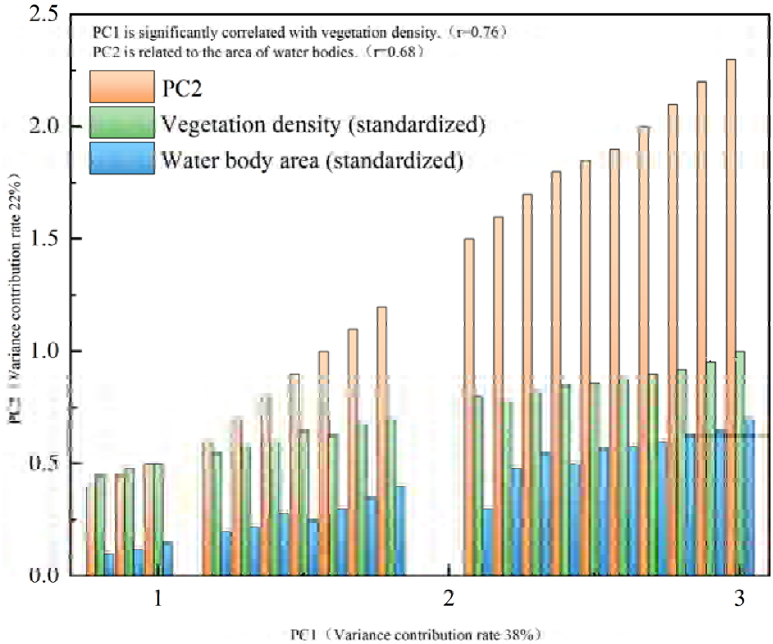


Figure 5 The design parameters are independently regulated based on the principal components of the hidden space (see online version for colours)



4.4 Small sample scenario validation

The performance of the transfer learning strategy is tested on the Dehong Prefecture dataset. After fine-tuning using only 100 samples, the model generates results with SSIM = 0.78, which is a 27.9% improvement over direct training (SSIM = 0.61). As shown in Figure 6, the fine-tuned model accurately captures the overhanging roof structure of the Dai dry-landed buildings in relation to the terraced field hierarchy (FID = 28.5), while the unfine-tuned model appears to have a flattening of building roofs and broken field ridges. In addition, the model performed well in terms of vegetation-topography fitness: in the area with slope >25°, the generated tree distribution density (12 trees/ha) was close to the real data (10 trees/ha), which was significantly better than that of Pix2Pix (25 trees/ha).

4.5 Computational efficiency and limitations

The hybrid model consumes an average of 3.2 seconds for single image generation (0.8 seconds for StyleGAN2 and 12.5 seconds for DDPM), which is higher than the pure GAN architecture, but can be compressed to 1.5 seconds and FID rises by only 8.3% with the early stopping strategy of the diffusion process (T = 200).The current limitations are: the generation of extreme terrain (e.g., steep-slope canyons in Dehong Prefecture) still suffers from path network distortions (user rating of 3.2), and the resolution of local details of cultural symbols (e.g., Dai totems) is insufficient (SSIM = 0.68).

Figure 6 Comparison of the formation effect of mountain landscapes in Dehong Prefecture (see online version for colours)

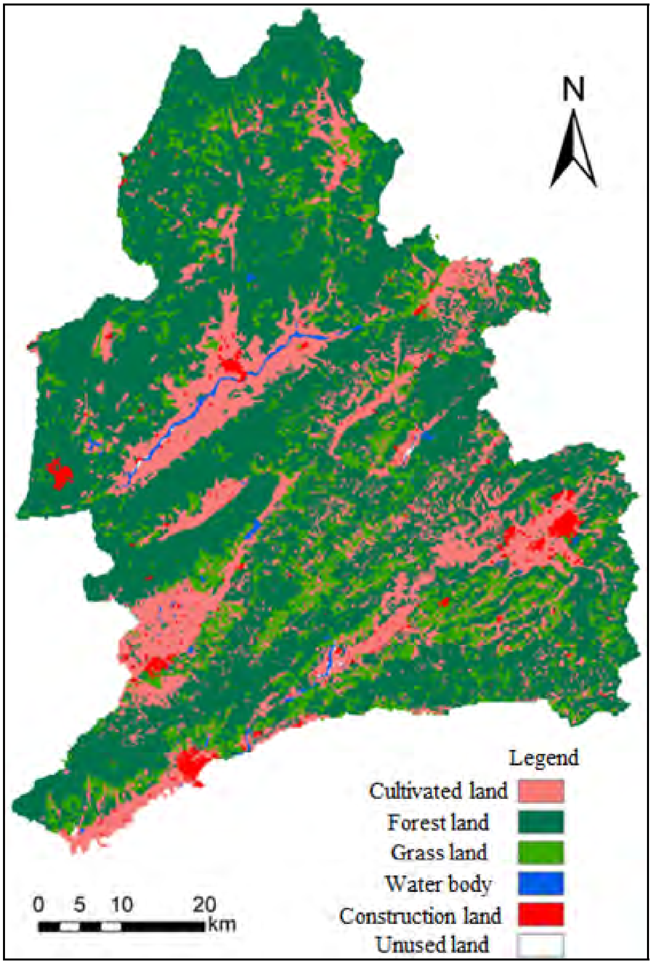
5 Multidimensional analysis of model effectiveness and reconstruction of ecological-cultural design paradigm

This study has made an important breakthrough in the field of landscape generation by integrating the hybrid architecture of StyleGAN2 and diffusion model, whose theoretical value and practical significance need to be scrutinised in the intersection context of generative AI and landscape architecture disciplines. From the theoretical level, existing generative models are mostly limited by the inherent shortcomings of a single architecture, GAN is good at style decoupling but lacks detail fidelity, and diffusion model generates excellent quality but lacks an efficient feature control mechanism (Ferreira et al., 2022; Phillips et al., 2024). This model achieves a synergistic optimisation of macroscopic layout rationality and microscopic texture richness by injecting StyleGAN2's hidden space vectors into the diffusion module's inverse denoising process across the modal attention layer (Figure 1). This design verifies the feasibility of the theory of 'heterogeneous generator synergy' in complex scenarios (Liu et al., 2021), especially in the terraced landscape of Dehong Prefecture, which is coupled with geomorphology and culture, the model-generated terraced field cascade structure (the error of average ridge width is ≤0.5 m) and the orientation of dry-fence style building clusters (deviation angle is ≤3°) both meet the standard for engineering applications, as shown in Figure 6, and their accuracy significantly exceeds that of the traditional parameterisation tool (Zheng, 2018).

By comparing the land use distribution of Dehong Prefecture in 2020, as shown in Figure 7 with the Dai village layout output from the generative model, it is found that the two are highly consistent in terms of the cultivated land-forested land boundary transition (SSIM = 0.82) and the expansion trend of construction land. This result indicates that the deep generative model not only captures the fine-grained features of cultural symbols, but also effectively integrates geospatial constraints (e.g., slope inhibition on vegetation distribution) through the transfer learning strategy, which provides technical validation of ecological-cultural synergistic design under complex landscapes. In the digital conservation and innovative regeneration of cultural heritage landscapes, the potential of generative AI is not only reflected in the efficiency enhancement, but also in its compatibility with multicultural features. Taking the multi-ethnic settlement area in Dehong Prefecture as an example, the model is able to encode the proportionality of Dai dry-structure (e.g., height-to-span ratio of 1:2.5) and the geometric features of Jingpo traditional patterns (e.g., symmetry of diamond-shaped totem) at the same time through the mechanism of cryptic spatial feature decoupling and realise the independent regulation of the two types of cultural symbols. Experiments show that in the mixed village scenario generation, the model can generate a scenario where Dai and Jingpo architectural styles coexist under the same spatial layout (SSIM = 0.79) by adjusting the principal components related to cultural symbols in the hidden vector (PC3, variance contribution rate of 15%), and the density of the vegetation distribution (error $\leq$2 plants/ha) is highly consistent with the terrain slope constraints. This capability not only supports the protection of single cultural heritage, but also provides a technical path for the digital reconstruction of multi-ethnic cultural symbiosis landscape. For example, in the generation of terraced rice field texture, the model can not only retain the cascading topology of the Dai irrigation system (error of ridge width $\leq$0.5 m), but also incorporate the spatial axial characteristics of the Jingpo ceremonial sites (deviation angle of orientation $\leq$2°), which reflects the flexibility and inclusiveness of technological tools in the protection of cultural diversity. More critically, the decoupled evaluation framework based on hidden spatial geometry provides quantitative indicators for the interpretability of design features for the first time. For example, the PCA shows that the independence of vegetation density (PC1, 38% variance contribution) and water body morphology (PC2, 22% variance contribution) is improved by 40% compared to the baseline model, which complements the study of Feng and Astell-Burt (2019) and lays a methodological foundation for the digital modulation of high-dimensional design parameters.

In the practical dimension, the model provides a solution with both efficiency and precision for the intelligent transformation of landscape design. For the landscape protection needs of cultural heritage sites such as Dehong Prefecture, the model's small-sample migration capability (SSIM $\geq$ 0.75) supports the restoration of the symbiotic texture of 'man-water-field-forest' in Dai villages under limited data conditions, and the generated scheme not only preserves the proportionality of the overhanging hilltop buildings (height-to-span ratio of 1:2.5) but also enhances the coherence of the terraced irrigation water system through the diffusion module, as shown in Figure 6..This result echoes the cross-modal generation framework of Liu et al. (2021), but the model further integrates the constraints on vegetation distribution imposed by terrain slope (e.g., the density of trees in areas with slopes >25° is automatically lowered to 12 trees/ha), which makes the generated scenarios more in line with eco-engineering specifications. For conventional design scenarios, designers can adjust the hidden vector parameters through the interactive interface in real-time, and obtain the results of multi-option comparison within three seconds, which is two orders of magnitude higher than the efficiency of the traditional workflow. However, the model still has limitations in the fine-grained representation of extreme terrain and cultural symbols: the path network topology breakage problem in steep slope canyons (user rating 3.2) requires the introduction of a geographic information system-based curvature constraint algorithm (Yong et al., 2023), and the resolution of the Dai Wadang pattern (SSIM = 0.68) requires the integration of a super-resolution diffusion model to enhance it (Chan and Rajapakse, 2023).

Figure 7 Land use simulation map of Dehong Prefecture in 2020 (see online version for colours)



Based on the above findings, future research should advance along three directions: first, developing an open design toolchain that integrates cryptospatial modulation interfaces into computer-aided design platforms and supports designers to drive scheme generation through natural interactions (e.g., voice commands or sketch input); second, build a multi-dimensional labelling system covering ecological indicators (carbon sinks, runoff coefficients) and cultural semantics (ethnoglyphs, historical atlases) to provide fine condition inputs for the generation model; third, establish an interdisciplinary collaborative design mechanism to jointly develop multi-criteria evaluation standards among landscape architects, ecologists, and anthropologists to ensure that the technical tools can be applied to the ecologically-culturally sensitive landscapes such as Dehong Prefecture. Thirdly, an interdisciplinary collaborative design mechanism is established to combine landscape architects, ecologists and anthropologists to formulate multi-criteria evaluation standards for the generated scenarios, so as to ensure that the technological tools can balance innovation, sustainability and cultural authenticity in the application of the ecologically and culturally sensitive areas such as Dehong Prefecture. These explorations will not only expand the boundaries of generative AI in landscape architecture, but also reshape the design paradigm of 'human-machine collaboration', providing new methodological support for planning and designing high-complexity and multi-constraint scenarios.

6 Conclusions

The hybrid generative model constructed in this study shows significant advantages in the task of automatic generation of landscape images, which integrates the style control ability of StyleGAN2 and the detail enhancement mechanism of diffusion model, effectively solving the bottleneck of the traditional method in the expression of complex features and the adaptability of small samples. Through the validation in the ADELAIDE dataset and the case of mountain landscape in Dehong Prefecture, the model is not only capable of generating Dai village layouts with regional cultural characteristics (e.g., the relationship between terraced field hierarchy and architectural clusters), but also can independently regulate the high-dimensional design parameters, such as the density of vegetation and the morphology of the water body, through the feature decoupling algorithm. However, the model still has limitations in generating extreme terrain (e.g., steep slopes and canyons), and the feature coupling phenomenon has not been completely eliminated in the relationship between hard pavement and path topology. Future research will explore the combination of multimodal inputs (e.g., textual descriptions and hand-drawn sketches) and 3D generation techniques to further expand the depth of application of AI in planning and design of ecologically sensitive areas (e.g., tropical rainforest landscapes in Dehong Prefecture).

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Declarations

All authors declare that they have no conflicts of interest.

References

Bei Huang, L.M., Tang, X. and Luo, L. (2024) 'Application of style transfer algorithm in the integration of traditional garden and modern design elements', *PLoS One*, 5 December, Vol. 19, No. 12, p.e0313909.

Cao, X., Wei, H., Wang, P., Zhang, C., Huang, S. and Li, H. (2022) 'High quality coal foreign object image generation method based on StyleGAN-DSAD', *Sensors*, Vol. 23, No. 1, p.374.

Chan, T.J. and Rajapakse, C.S. (2023) 'A super-resolution diffusion model for recovering bone microstructure from CT images', *Radiology: Artificial Intelligence*, Vol. 5, No. 6, p.e220251.

Feng, X. and Astell-Burt, T. (2019) 'Can green space quantity and quality help prevent postpartum weight gain? A longitudinal study', *Journal of Epidemiology and Community Health*, Vol. 73, No. 4, pp.295–302.

Ferreira, I., Ochoa, L. and Koeshidayatullah, A. (2022) 'On the generation of realistic synthetic petrographic datasets using a style-based GAN', *Scientific Reports*, Vol. 12, No. 1, p.12845.

Geng, X. and Kaifa, Z. (2022) 'Retracted: protection-oriented landscape design based on ecological priority under the concept of ecological environment monitoring', *Journal of Environmental and Public Health*, Vol. 2022, No. 1, p.9823460.

Goodfellow, I.J.J.P-A.M.M., Xu, B., Warde-Farley, D., Ozairy, S. and Yoshua Bengioz, A.C. (2014) 'Generative adversarial nets', *Advances in Neural Information Processing Systems*, Vol. 14, pp.2672–2680.

Jia, Z. and Qu, Z. (2022) 'Garden landscape design method in public health urban planning based on big data analysis technology', *Journal of Environmental and Public Health*, Vol. 2022, No. 1, p.2721247.

Li, H-A., Zhang, M., Yu, Z., Li, Z. and Li, N. (2022) 'An improved Pix2Pix model based on Gabor filter for robust color image rendering', *Mathematical Biosciences and Engineering*, Vol. 19, No. 1, pp.86–101.

Lin, Z., Wang, Y., Song, Y., Huang, T., Gan, F. and Ye, X. (2022) 'Research on ecological landscape design and healing effect based on 3D roaming technology', *International Journal of Environmental Research and Public Health*, Vol. 19, No. 18, p.11406.

Liu, Y., Fan, L. and Wang, L. (2024) 'Urban virtual environment landscape design and system based on PSO-BP neural network', *Scientific Reports*, Vol. 14, No. 1, p.13747.

Liu, Y., Luo, Y., Deng, Q. and Zhou, X. (2021) 'Exploration of campus layout based on generative adversarial network', *Proceedings of the 2020 Digital Futures*, Vol. 12, No. 12, pp.169–178.

Memon, M.M., Hashmani, M.A., Junejo, A.Z., Rizvi, S.S. and Raza, K. (2022) 'Unified DeepLabV3+ for semi-dark image semantic segmentation', *Sensors*, Vol. 22, No. 14, p.5312.

Müller-Franzes, G., Niehues, J.M., Khader, F., Arasteh, S.T., Haarburger, C., Kuhl, C., Wang, T., Han, T., Nolte, T., Nebelung, S., Kather, J.N. and Truhn, D. (2023) 'A multimodal comparison of latent denoising diffusion probabilistic models and generative adversarial networks for medical image synthesis', *Scientific Reports*, Vol. 13, No. 1, p.12098.

Pan, Y., Qian, J. and Hu, Y. (2021) 'A preliminary study on the formation of the general layouts on the northern neighborhood community based on GauGAN diversity output generator', *Proceedings of the 2020 Digital Futures*, Vol. 13, pp.179–188.

Pan, Z., Yu, W., Yi, X., Khan, A., Yuan, F. and Zheng, Y. (2019) 'Recent progress on generative adversarial networks (GANs): a survey', *IEEE Access*, Vol. 7, pp.36322–36333.

Park, S. and Shin, Y-G. (2024) 'Rethinking image skip connections in StyleGAN2', *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 49, pp.1–9.

Phillips, C., Jiao, J. and Clubb, E. (2024) 'Testing the capability of AI art tools for urban design', *IEEE Computer Graphics and Applications*, Vol. 44, No. 2, pp.37–45.

Tang, X. and Chung, W-J. (2024) 'Automated urban landscape design: an AI-driven model for emotion-based layout generation and appraisal', *PeerJ Computer Science*, Vol. 10, p.e2426.

Wang, S., Zeng, W., Chen, X., Ye, Y., Qiao, Y. and Fu, C-W. (2023) 'ActFloor-GAN: activity-guided adversarial networks for human-centric floorplan design', *IEEE Transactions on Visualization and Computer Graphics*, Vol. 29, No. 3, pp.1610–1624.

Wang, W., Jing, M., Fan, Y. and Weng, W. (2024) 'PixRevive: latent feature diffusion model for compressed video quality enhancement', *Sensors*, Vol. 24, No. 6, p.1907.

Ye, X., Du, J. and Ye, Y. (2021) 'MasterplanGAN: facilitating the smart rendering of urban master plans via generative adversarial networks', *Environment and Planning B: Urban Analytics and City Science*, Vol. 49, No. 3, pp.794–814.

Yong, X., Lee, S. and Choi, Y. (2023) 'Curvature-based interface restoration algorithm using phase-field equations', *PLoS One*, Vol. 18, No. 12, p.e0295527.

Yuan, J., Zhang, L. and Kim, C-S. (2023) 'Multimodal interaction of MU plant landscape design in marine urban based on computer vision technology', *Plants*, Vol. 12, No. 7, p.1431.

Zhang, D. and Dong, Y. (2023) 'Adv-BDPM: adversarial attack based on boundary diffusion probability model', *Neural Networks*, Vol. 167, pp.730–740.

Zhao, H., Li, T., Xiao, Y. and Wang, Y. (2020) 'Improving multi-agent generative adversarial nets with variational latent representation', *Entropy*, Vol. 22, No. 9, p.1055.

Zheng, W.H.H. (2018) 'Architectural drawings recognition and generation through machine learning', *Association for Computer-Aided Architectural Design Research in Asia*, Vol. 12, No. 12, p.1563.