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Geo-InkGAN: An Adaptive Generative Framework for Topographically Faithful Ink-Wash Style Transfer in Terrain Mapping

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Abstract

The compelling visualization of Digital Elevation Models (DEMs) constitutes a vital intersection between Geographic Information Science (GIS) and the digital humanities. Nevertheless, traditional Generative Adversarial Networks (GANs) frequently demonstrate a “geography-blind” characteristic, resulting in structural “topographic drift” by dissociating geomorphic complexity from cartographic constraints. To overcome this limitation, we propose Geo-InkGAN, a geo-heuristic framework that integrates geographic principles with generative processes to achieve high-fidelity ink-wash style synthesis. A key component of our approach is an adaptive optimization strategy grounded in the Slope Standard Deviation (SSD). By establishing a quantitative relationship between geomorphological entropy and the cycle-consistency loss weight (λ_{cyc}), we effectively address the Pareto trade-off between geomorphic accuracy and esthetic representation. Our results indicate that alluvial plains benefit from low-intensity constraints to facilitate fluid ink diffusion, whereas rugged terrains require high-intensity constraints to maintain the integrity of the topological framework. Additionally, the HCEG-SE mechanism (Hillshade-Contour Edge-Guided Stroke Enhancement) narrows the semantic divide between terrain skeletons and artistic textures by combining multi-directional non-photorealistic rendering with precise edge extraction techniques. Evaluated across five geomorphologically diverse regions—from karst towers to loess plateaus—Geo-InkGAN demonstrably surpasses existing benchmarks in Geomorphological Structure Correlation (GSC). This geomorphology-aware approach advances the scientific rigor of AI-driven cartography and offers a refined methodology for the cultural representation of digital twin landscapes.

Keywords: Digital Elevation Model (DEM); Geo-InkGAN; adaptive parameters; Slope Standard Deviation (SSD); Chinese ink-wash painting; geography-informed deep learning; geomorphological textures



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1. Introduction

Maps serve not merely as repositories of projected geometric data but as integrations of geographic understanding and esthetic exploration [1]. Within the history of cartography, traditional Chinese ink-wash landscape paintings have cultivated a sophisticated visual language conveying geomorphological meaning, characterized by concepts such as “polycentric perspective” and “poetic spatiality” [2–4]. The deliberate application of rhythmic artistic textures to features including ridges, valleys, and slope transitions encapsulate

an advanced semantic abstraction of the underlying geographic structure. In contrast, contemporary digital cartography predominantly employs Lambertian-based single-source illumination models for rendering Digital Elevation Models (DEMs) [5]. Although these conventional approaches provide essential morphometric information, they are frequently constrained by “shadow blind spots” resulting from self-occlusion in complex terrain configurations [6]. Furthermore, they fail to capture the artistic nuances of “ink-wash tonality” or the subtle geomorphic clarity—essentially a form of non-photorealistic rendering—that is intrinsic to traditional landscape representation.

As the field of Geographic Artificial Intelligence (Geo-AI) [7,8] progresses from general visual representation toward a deeper semantic understanding of geographic phenomena, image-to-image translation methodologies—particularly those based on Generative Adversarial Networks (GANs)—have emerged as essential tools for cross-domain mapping and visual reconstruction of heterogeneous geographic datasets [3,9–11]. Although models such as CycleGAN and Pix2Pix exhibit remarkable efficacy in natural image style transfer, their intrinsic stochastic nature often compromises the preservation of geographic regularities when applied to DEMs, which are subject to strict physical constraints [12]. This limitation primarily arises because generic generative algorithms, lacking geomorphological prior knowledge, exhibit pronounced “geography-blindness.” Consequently, they tend to neglect the fractal characteristics inherent in DEMs—ranging from large-scale formations to fine-scale textures—resulting in generated artistic features that diverge from the true physical orientation of the terrain. Such discrepancies manifest as “terrain drift” or “topological fracture” [13,14], significantly diminishing the scientific reliability of these generated maps as cartographic tools [15]. Hence, the development of geography-informed constraint mechanisms capable of accurately translating ink-wash esthetic elements into topographic gradient information constitutes a critical technical challenge at the nexus of cartography and deep learning.

To address these scientific challenges, this study presents Geo-InkGAN, a geography-informed deep learning framework designed to facilitate automated and topographically precise mapping in the traditional Chinese ink-wash style. The principal contribution lies in the development of the Hillshade-Contour Edge-Guided Stroke Enhancement (HCEG-SE) mechanism, which synergistically combines multi-directional hillshade rendering [14,16,17] with Sobel operator-based edge detection techniques [18,19]. This mechanism transforms geomorphological skeletal data into structural guidance signals interpretable by the model, thereby enabling a scientifically grounded reconstruction of the intrinsic logic underlying traditional texture strokes. Moreover, to mitigate “topographic drift” across diverse landscapes, the study proposes a geomorphology-aware adaptive weighting strategy informed by Slope Standard Deviation (SSD) [20]. By establishing a linear mapping function between geomorphological complexity and the cycle-consistency weight (λ_{cyc}), the method attains a Pareto optimal balance between topographic accuracy and esthetic quality across diverse landscapes, ranging from expansive plains to rugged mountainous regions (Figure 1, Black Forest region, Germany; SSD = 10.60; λ_{cyc} = 18). Beyond these technical advancements, the research formalizes a cross-domain semantic mapping between heterogeneous geomorphic units and ink-wash esthetics, establishing a novel methodological basis for the evocative representation of digital twin landscapes. To evaluate the efficacy of Geo-InkGAN, comparative experiments were conducted across five representative geomorphic regions—the North China Plain (Daxing), rolling hills (Anyue), the Loess Plateau (Yan’an), stony mountains (Beijing), and Karst peak forests (Yangshuo). The results demonstrate that Geo-InkGAN substantially outperforms baseline models in terms of Geomorphological Structure Correlation (GSC) [21] and Kernel Inception Distance (KID) [22], thereby confirming its superior capability in preserving geographic topological consistency.

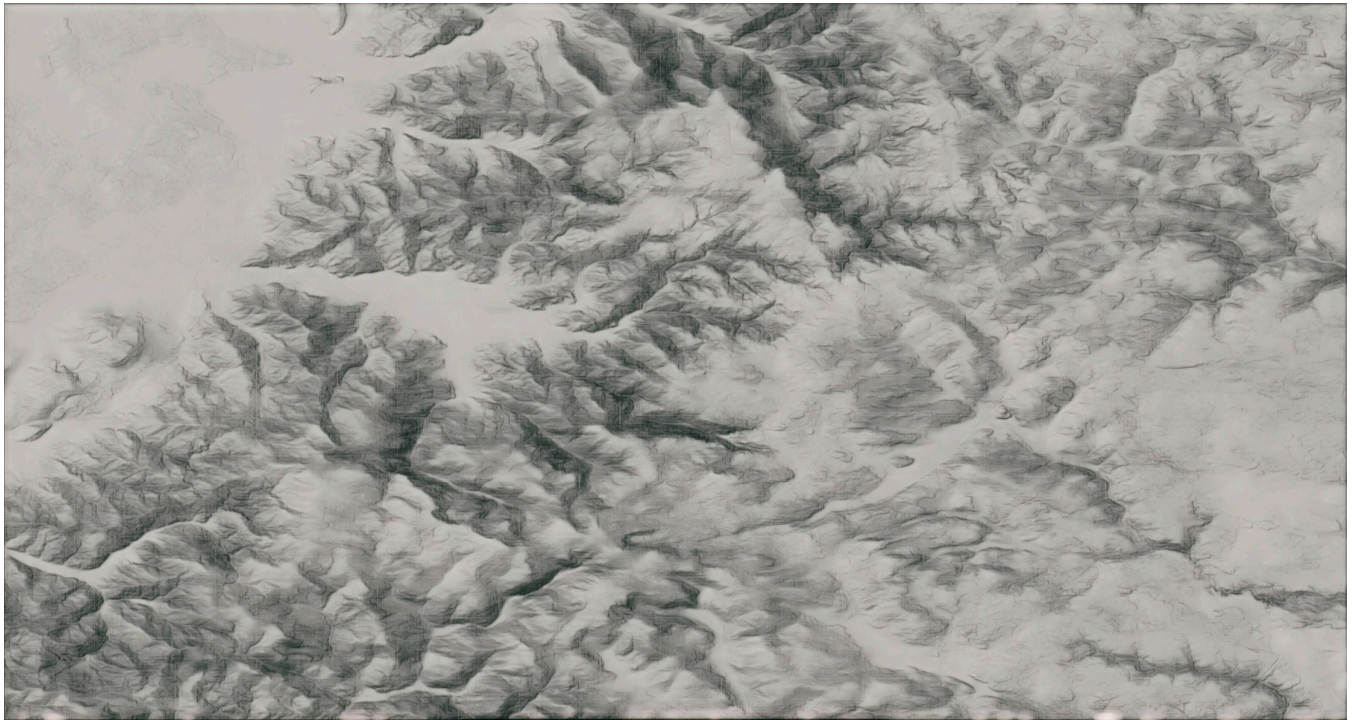


Figure 1. High-fidelity ink-wash mapping of the Black Forest (DE) generated by Geo-InkGAN.

2. Related Studies

2.1. Terrain Visualization and Geomorphological Fidelity Strategies

Terrain visualization continues to serve as a foundational pillar of cartographic research. Early advancements were primarily anchored in physical illumination models, most notably the manual relief shading principles articulated by Imhof [23], which established the theoretical cornerstone for modern analytical algorithms. With the advent of digital cartography, Yoëli [24] formalized the transition toward algorithmic automation, thereby facilitating the development of advanced morphometric techniques—including multi-directional shading [25], Sky View Factor (SVF) [26], and multifaceted curvature analysis. Beyond mere metric fidelity, the preservation of prominent geomorphological features—specifically ridgelines and valley systems—constitutes a fundamental requirement for cartographic rigor. Traditional feature extraction addresses this requirement through deterministic morphometric operators such as D8 flow algorithms or the Topographic Position Index (TPI). Although artistic cartography [27,28] has emerged to enhance the esthetic depth of terrain representation, extant frameworks frequently encounter challenges in harmonizing the dynamic expressiveness of brushstroke-like effects with the structural integrity of the underlying landscape [11]. This underscores the necessity for a more flexible approach to maintaining geomorphological fidelity.

2.2. Neural Style Transfer and Digital Ink-Wash Simulation

In the field of computer vision, the field of image style transfer has undergone a significant transformation, evolving from the alignment of heuristic statistical features to the synthesis of deep neural representations. Gatys et al. [29] pioneered the disentanglement of spatial content from stylistic texture through the application of Convolutional Neural Networks (CNNs). This was followed by the development of the Pix2Pix framework [30], which enabled supervised image-to-image (I2I) translation, and the introduction of CycleGAN [30,31], leveraging cycle-consistency loss, which obviated the need for paired training datasets and established a robust paradigm for unsupervised style synthesis. Within the GIS

community, GAN architectures have been widely applied to tasks including spatiotemporal remote sensing fusion, automated cartography, and satellite imagery enhancement [32]. For instance, Kang et al. [33] demonstrated the stylistic conversion of web map tiles into various artistic styles. Building upon these foundations, researchers have investigated more intricate cartographic synthesis processes, such as the cross-domain translation between satellite imagery and stylized vector maps [34], and the digital reconstruction of historical map esthetics from contemporary geospatial layers [35]. Additionally, GANs have been utilized to automate map generalization and semantic feature extraction, ensuring that cartographic elements maintain structural consistency across multiple scales [36]. However, these predominantly planimetric approaches focus chiefly on transferring two-dimensional planimetric textures, often neglecting the rigid three-dimensional topological constraints inherent in topographic data. This limitation is particularly evident in the digital simulation of ink-wash landscape painting [37], where traditional fluid simulations [38] and recent GAN-based synthesis often result in “geographically unanchored” representations. Critically, the current literature lacks a mechanism to dynamically balance artistic fluidity with geomorphological rigidity across diverse terrain complexities—a gap that leads to “topographic drift” in rugged regions. Therefore, transitioning from purely visual emulation to geography-informed synthesis is crucial for Virtual Geographic Environments (VGEs) and digital twin landscapes [39], which aim to integrate scientific accuracy with traditional esthetic principles in a seamless manner.

3. Methods

3.1. Geo-InkGAN Framework

The architectural framework of Geo-InkGAN is based on a CycleGAN backbone, featuring a symmetrical dual-stream configuration of generator-discriminator pairs (G/D_B and F/D_A). This structure facilitates robust bidirectional semantic mapping between the topographic source domain (A) and the ink-wash stylistic domain (B), enabling cross-domain synthesis through cyclic consistency (Figure 2).

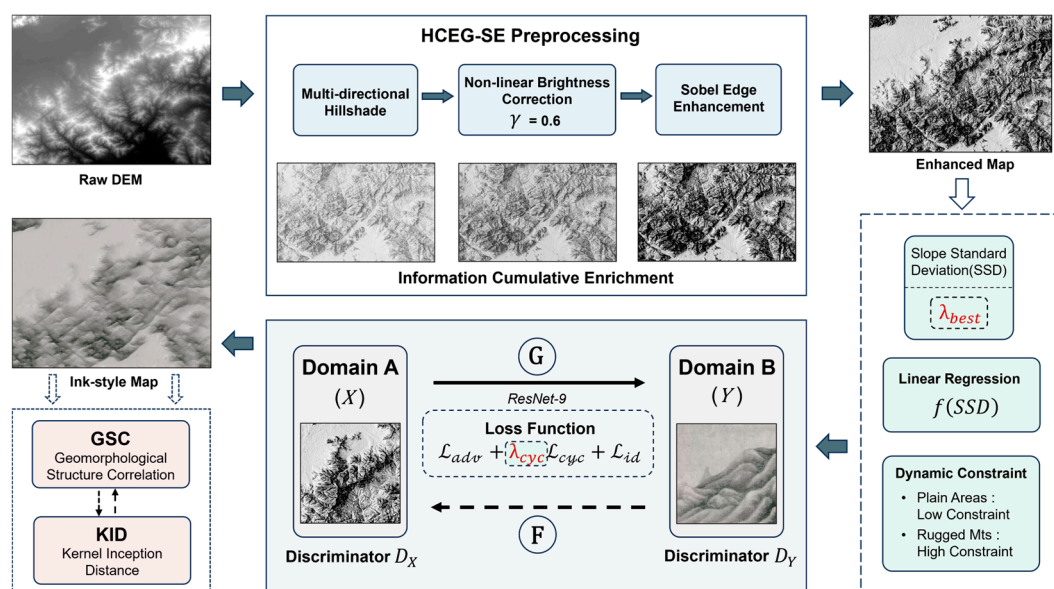


Figure 2. Overall technical framework of the Geo-InkGAN.

3.1.1. Generator and Discriminator

The generator utilizes a ResNet-9 architecture, consisting of an encoder for high-dimensional feature embedding, a bottleneck comprising nine residual blocks, and a

symmetric decoder for reconstruction. To ensure geomorphic integrity and prevent metric distortion, skip connections are integrated to preserve low-level spatial features throughout the semantic transformation. Subsequently, the decoder reconstructs the feature maps to the target resolution of 512×512 via paired transposed convolutions, with the final output layer employing a Tanh activation function. This symmetrical encoder–decoder design is crucial for maintaining precise spatial alignment, serving as a key safeguard against metric distortion and ensuring that the synthesized geomorphic structures retain their scale-specific integrity [40].

The discriminator is constructed based on the PatchGAN architecture, which utilizes a fully convolutional network to evaluate local textural characteristics. With a receptive field size at 70×70 pixels, it effectively captures the fine-grained scale and rhythmic patterns characteristic of stylized ink-wash brushwork. In contrast to global discriminators that evaluate entire image distributions, PatchGAN conducts patch-level discrimination to precisely match artistic micro-textures. This methodology enables the discriminator to guide the generator toward achieving stylistic fidelity at the level of individual brushstrokes, thereby circumventing dependence on global image statistics and fostering a more refined NPR [40].

3.1.2. Loss Function

The comprehensive objective function of Geo-InkGAN comprises three distinct loss components: the adversarial loss, the cycle-consistency constraint which guarantees topographic fidelity, and the identity mapping constraint. Each of these components possesses a well-defined geomorphological interpretation, collectively balancing the trade-off between esthetic abstraction and geomorphic rigor.

The adversarial loss is designed to guide the generator G to map images from the geomorphic domain $\mathbb{X}$ to the ink-wash stylistic domain $\mathbb{Y}$, ensuring that the synthesized representations are visually indistinguishable from authentic landscape paintings. Simultaneously, the discriminator D_Y is trained to distinguish between genuine ink-wash artworks and generated outputs. To enhance training stability and mitigate gradient vanishing, this study employs the Least Squares GAN (LSGAN) formulation for the adversarial objective [41]:

$$\mathcal{L}_{adv}(G, D_Y, X, Y) = \mathbb{E}_{y \sim \mathbb{Y}} \left[(D_Y(y) - 1)^2 \right] + \mathbb{E}_{x \sim \mathbb{X}} \left[D_Y(G(x))^2 \right]. \quad (1)$$

This component primarily governs the esthetic performance of the model. By minimizing $\mathcal{L}_{adv}$, the framework captures high-dimensional stylistic features—such as ink diffusion and rhythmic brushwork—ensuring that the synthesized outputs statistically align with the artistic characteristics of the target domain.

The cycle-consistency loss embodies the unique mechanism of CycleGAN. From the perspective of geospatial fidelity, $\mathcal{L}_{cyc}$ functions as a topological persistence constraint, ensuring that the underlying geomorphic structures are preserved throughout the bidirectional transformation. Its mathematical definition is expressed as follows:

$$\mathcal{L}_{cyc}(G, F) = \mathbb{E}_{x \sim \mathbb{X}} [\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim \mathbb{Y}} [\|G(F(y)) - y\|_1]. \quad (2)$$

In unsupervised learning contexts where paired training datasets are unavailable, a generator guided exclusively by adversarial loss is susceptible to topographic drift. Consequently, the generated images may visually mimic an ink-wash style yet display substantial discrepancies from the original DEM in terms of geomorphic features, such as ridgeline orientation, valley morphology, and relative relief relationships. The incorporation of cycle-consistency loss mitigates this problem by imposing an end-to-end “generation-

reconstruction” constraint, which compels the generator to maintain the spatial structural information of the source terrain at the pixel level throughout the style transfer process. Consequently, $\mathcal{L}_{cyc}$ is the primary determinant of geomorphological accuracy. It captures the topographic skeleton through pixel-level L1-norm reconstruction fidelity, enforcing a rigorous structural correspondence between the source elevation data and the synthesized ink-style representation.

The identity mapping loss is used to maintain the stability of the generator when it receives inputs from its own target domain. It is defined as follows:

$$\mathcal{L}_{idt}(G, F) = \mathbb{E}_{y \sim \mathbb{Y}}[\|G(y) - y\|_1] + \mathbb{E}_{x \sim \mathbb{X}}[\|F(x) - x\|_1]. \quad (3)$$

This loss term imposes a constraint on the generator to prevent unnecessary chromatic or luminance shifts when processing inputs from its native domain. This mechanism is crucial for preserving the characteristic ink-wash tonality inherent to the stylistic domain [42], with its weight specifically calibrated as $\lambda_{idt} = 0.5 \times \lambda_{cyc}$.

In summary, the objective function of Geo-InkGAN balances esthetic abstraction and geomorphic rigor. These loss components capture features across distinct dimensions. The adversarial loss captures stylistic artistic features through the alignment of statistical distributions while the cycle-consistency loss captures the geomorphological skeleton through deterministic pixel-level alignment. This formulation establishes the mathematical foundation for capturing both geographic features and esthetic expressions within the style transfer framework (Figure 3).

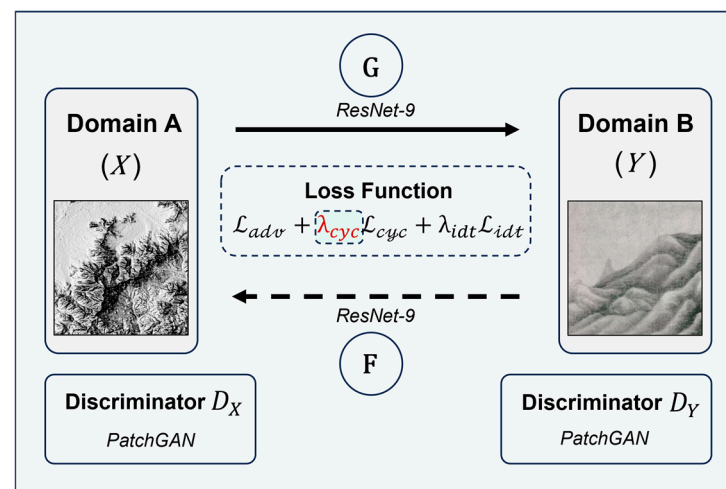


Figure 3. Internal neural architecture and objective functions of Geo-InkGAN.

3.2. HCEG-SE

The Hillshade-Contour Edge-Guided Stroke Enhancement (HCEG-SE) preprocessing mechanism constitutes the fundamental basis of the proposed framework. It addresses the limitations of single-source hillshading by integrating multi-directional illumination with geomorphological edge information. The HCEG-SE mechanism consists of three stages: Multi-directional Hillshading Synthesis, Non-linear Gamma Luminance Correction, and Sobel-based Geomorphological Skeleton Extraction.

3.2.1. Multi-Directional Terrain Shading Synthesis

Conventional analytical hillshading in GIS typically utilizes a single-azimuth light source, often configured with an azimuth of 315° and an altitude of 45° , formulated as:

$$H = \cos(Z_s) \cos(Z_n) + \sin(Z_s) \sin(Z_n) \cos(A_s - A_n), \quad (4)$$

where H denotes the hillshade value at pixel P ($H \in [0, 1]$), Z_s represents the solar zenith angle, Z_n is the zenith angle of the surface normal, A_s signifies the solar azimuth, and A_n refers to the surface slope aspect.

Single-source illumination models are affected by self-occlusion, resulting in attenuated geomorphic features and reduced in textural stratification.

To remediate this limitation, this research adopts a multi-directional weighted synthesis strategy. By configuring $N = 6$ uniformly distributed azimuths—with a 60° interval ($A_s \in \{0^\circ, 60^\circ, 120^\circ, 180^\circ, 240^\circ, 300^\circ\}$) and a fixed solar altitude of 45° —individual hillshade values are calculated for each direction. These discrete outputs are subsequently aggregated through an equal-weight averaging process to generate a comprehensive multi-directional hillshade representation [16]:

$$H_{\text{multi}} = \frac{1}{N} \sum_{k=1}^N H_k. \quad (5)$$

Multi-directional synthesis reduces directional bias and produces a luminance-neutral base map, offering a more dependable basis for subsequent edge-guided fusion processes [17,43].

3.2.2. Nonlinear Gamma Brightness Correction

Raw hillshade images usually exhibit positive brightness skew, causing insufficient grayscale differentiation in low-luminance areas such as backslopes and valleys. This limitation conflicts with the multi-level tonal transitions required by traditional “five ink tonalities” (charcoal, dense, heavy, light, and clear). Therefore, Gamma correction is applied:

$$H_{\text{gamma}} = (H_{\text{multi}})^\gamma. \quad (6)$$

With γ set to 0.6 [43,44], this transformation nonlinearly enhances contrast in low-luminance regions, and improves alignment between terrain information and artistic representation.

3.2.3. Sobel Edge-Guided Landform Skeleton Extraction and Fusion

The core principle of traditional Chinese landscape painting is the depiction of mountain contours and geomorphic formations through the use of linear strokes, a technique referred to as “bone-method brushwork.”

The Sobel operator is applied to H_{gamma} to extract geomorphological edges [18,19]. The normalized edge map $\hat{E}$ ($\hat{E} \in [0, 1]$) is fused with H_{multi} to generate the enhanced topographic representation:

$$I_{\text{HCEG}}(i, j) = \alpha \cdot H_{\text{gamma}} + (1 - \alpha) \cdot \hat{E}(i, j). \quad (7)$$

Within this formulation, the fusion weight α modulates the relative proportions of the hillshade base map and the geomorphic skeletal delineations. For the purposes of this experiment, α was assigned a value of 0.7, deliberately selected to replicate the conventional artistic ratio of “seven parts ink rendering to three parts linear sketching,” thereby providing the generator with salient textural anchors.

Through these procedures, the raw SRTM DEM is converted into an HCEG-SE enhanced representation integrating illumination information and geomorphic structures, which serves as the standardized input of Geo-InkGAN.

3.3. Landform Adaptive Weight

3.3.1. Slope Standard Deviation

To quantitatively characterize terrain complexity and determine the corresponding constraint requirements of the generative model, this study utilizes the Slope Standard Deviation (SSD) as the primary metric for evaluating surface roughness and spatial heterogeneity [20,45,46]. A slope raster is derived from the 30 m DEM, and SSD is calculated using each image patch as the statistical unit:

$$S_i = \arctan \left(\sqrt{\left(\frac{\partial z}{\partial x} \right)^2 + \left(\frac{\partial z}{\partial y} \right)^2} \right), \quad (8)$$

$$SSD = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - \bar{S})^2}, \quad (9)$$

where S_i denotes the slope value of pixel i , n is the total number of pixels within the patch, and $\bar{S}$ represents the mean slope value for that unit. Higher SSD values correspond more rugged terrain with denser geomorphic structures.

3.3.2. Weight Mapping Logic

During the optimization process, the cycle-consistency loss weight (λ_{cyc}) controls the structural constraint between generated images and topographic inputs. A fixed λ_{cyc} cannot effectively adapt to the spatial heterogeneity of geographic landscapes.

For high-SSD regions with complex geomorphic structures, stronger constraints are required to prevent structural distortion. Therefore, a higher λ_{cyc} constraint ranging from 15.0 to 20.0 is applied to preserve terrain fidelity.

Conversely, because low-SSD regions such as plains and gentle hills contain simpler geographic structures, a lower λ_{cyc} ranging from 10.0 to 12.0 is adopted to enhance stylistic flexibility and preserve ink diffusion characteristics.

3.3.3. Construction of Adaptive Function

To establish a balance between geomorphic fidelity and esthetic appeal across diverse landscape units [47], this study constructs a heuristic search matrix based on the SSD and derives linear mapping function. Based on terrain morphology, the proposed mechanism dynamically adjusts λ_{cyc} according to SSD values, enabling Geo-InkGAN to balance structural preservation and artistic flexibility. This adaptive strategy improves the compatibility between geographic constraints and ink-wash style generation.

3.4. Quantitative Evaluation Metrics

3.4.1. Geomorphological Structure Correlation

To quantitatively evaluate the geomorphological fidelity of Geo-InkGAN, this study defines the Geomorphological Structure Correlation (GSC) as the primary structural metric. The design of GSC is inspired by the methodology in [21], which utilizes spatial correlation to quantify the consistency between different topographic parameters. In this research, GSC is adapted to measure the cross-domain consistency between the “topographic skeleton layer” and the “artistic feature layer.” Mathematically, GSC is calculated using the pixel-level Pearson Correlation Coefficient:

$$GSC = \frac{\sum_{i=1}^n (R_i - \bar{R})(F_i - \bar{F})}{\sqrt{\sum_{i=1}^n (R_i - \bar{R})^2 \sum_{i=1}^n (F_i - \bar{F})^2}}, \quad (10)$$

where n represents the total number of pixels, R_i and F_i correspond to the grayscale values of the i -th pixel in the input reference map and the generated map, respectively, and $\bar{R}$ and $\bar{F}$ denote their mean values. Operationally, the input reference map is the topographic gradient map processed via the HCEG-SE mechanism, while the output is the grayscale-converted ink-wash image generated by Geo-InkGAN. Since darker pixels in both the representations correspond to mountain ridges or high-relief structures, GSC is evaluated within the $[0,1]$ range. A GSC value closer to 1 indicates higher geomorphological fidelity, signifying that ink-wash brushwork is precisely anchored onto the authentic topographic skeleton.

3.4.2. Kernel Inception Distance

In addition to structural evaluation, this study employs the Kernel Inception Distance (KID) to quantify artistic style similarity. KID utilizes an unbiased estimator to calculate the Squared Maximum Mean Discrepancy between feature distributions of authentic ink-wash paintings and generated results within the Inception feature space. Compared to the Fréchet Inception Distance (FID), KID is more suitable for evaluating the relatively small validation samples used in this study. A lower KID score indicates that generated images are closer to the artistic distribution of Gong Xian's style in terms of brushwork, ink layering, and compositional logic.

4. Experiments

4.1. Study Areas and Data Sources

4.1.1. Study Area Selection and Geomorphic Characteristics

To evaluate the generalization capacity and structural robustness of the model, we selected five geomorphic provinces in China as our empirical study sites (Figure 4). These regions represent quintessential geological prototypes that define the esthetic principles of traditional Chinese landscape painting. Specifically, topographically homogeneous regions like the Daxing plain yield near-blank HCEG-SE outputs, reflecting flat terrain's lack of distinct ridge-valley skeletons and serving as a baseline for model testing under minimal structural guidance.

The Complexity Level assigned to each study area is derived from its Slope Standard Deviation (SSD), categorized from Low to Extreme (Table 1). These levels serve as internal benchmarks to reflect the specific topographic character of each selected region during the adaptive weighting experiments.

Table 1. Geomorphic characteristics and data statistics of the study area.

Study Area	Geomorphic Type	SSD (°)	Complexity Level
Daxing, Beijing	Alluvial Plain	2.3	Low
Anyue, Sichuan	Red-bed Hills	4.5	Gentle
Yan'an, Shaanxi	Eroded Plateau	8.0	Moderate
Yanshan, Beijing	Tectonic Mountains	10.0	Rugged
Yangshuo, Guangxi	Karst Peak Forest	12.5	Extreme

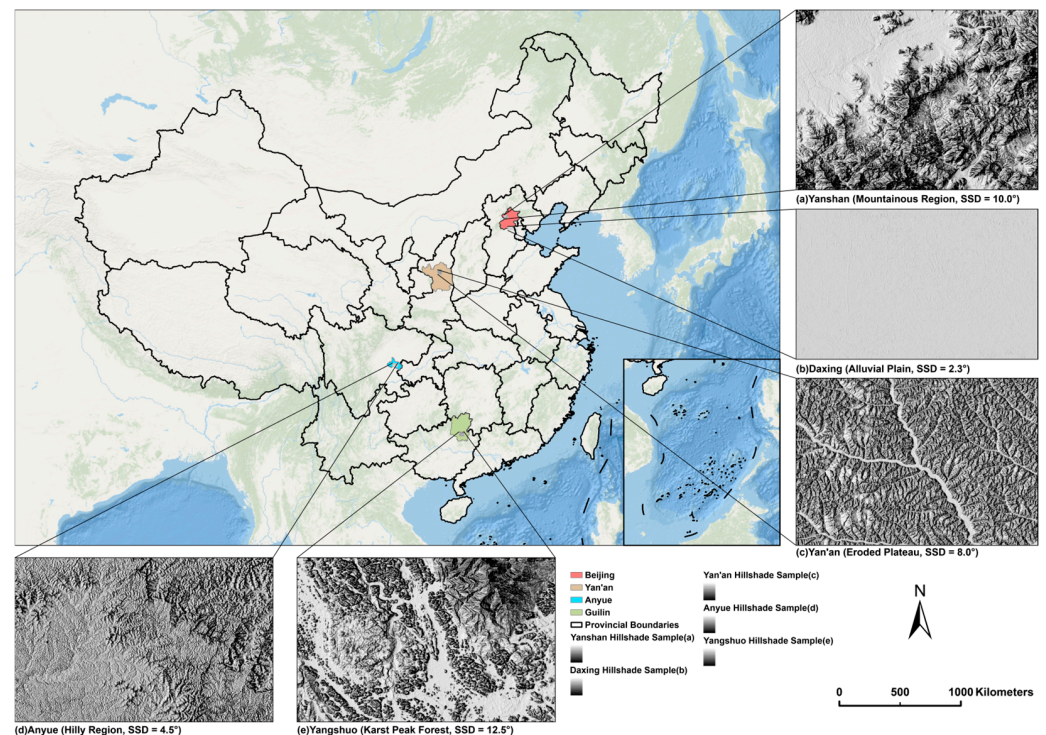


Figure 4. Locations and topographic characteristics of the five study areas.

4.1.2. Data Sources

The topographic foundation of this study is based on the NASA Shuttle Radar Topography Mission (SRTM) V3 global dataset. With a spatial resolution of approximately 30 m (1 arc-second), this dataset offers the necessary detail to capture intricate micro-topographic textures, such as ridgelines and valley systems, which are essential for maintaining geographic integrity.

Complementarily, the corresponding artistic style is derived from the *Landscape Album* by Gong Xian (1618–1689), whose mastery of ink density and textural depth aligns with the structural complexity of natural topography.

The raw topographic imagery was obtained through the Google Earth Engine (GEE) platform. Each study area covers an extent of approximately 45 by 35 km, a spatial threshold strategically defined to encompass integrated geographic units and maintain the structural continuity of the landscape throughout the generative process.

4.1.3. Dataset Construction

This research established an unpaired training dataset consisting of a topographic imagery domain (Domain A) and an ink-wash stylistic domain (Domain B). The composition of this training dataset and the preparation of the independent test dataset are detailed as follows:

For Domain A, samples were collected from five representative regions using a sliding window with a small stride to extract patches at a resolution of 512×512 pixels. From these, 500 patches exhibiting distinct features were randomly selected to enhance the model's sensitivity to local geomorphic transitions.

Domain B was similarly partitioned into patches of 512×512 pixels. Following a refined selection process, 540 authentic black-and-white landscape painting patches were identified as stylistic references. The selection criteria strictly excluded samples containing color, complex vegetation dot patterns, or aged paper textures to ensure the model could exclusively capture the grayscale gradient characteristics of the “five ink tonalities” [11] and the structural logic of rock textures.

The test set comprises the complete original DEM scenes of the five regions. All reported quantitative metrics, including GSC and KID, were computed based on the full-scale inference results of these entire scenes. Specifically, GSC was calculated as a global pixel-wise correlation, while KID was aggregated by re-tiling the generated full-scale map into non-overlapping patches to assess the distribution discrepancy relative to the style corpus.

4.2. Experimental Configuration

To ensure computational efficiency and numerical stability during the transformation of large-scale, high-resolution raster data, the framework was deployed on a high-performance cloud computing platform. The computational infrastructure featured an NVIDIA GeForce RTX 5090 GPU (32 GB GDDR7), an Intel Xeon Platinum 8470Q (25-core) processor, and 90 GB of RAM. The software environment was orchestrated on Ubuntu 22.04 using PyTorch 2.8.0 and CUDA 12.8 for hardware acceleration. Key hyperparameters were configured as follows: The initial learning rate was set to 0.0002 using the Adam optimizer with $\beta_1 = 0.5$ and $\beta_2 = 0.999$. To harmonize computational throughput with the preservation of intricate geomorphic details, all input imagery was scaled and randomly cropped to 512×512 pixels with a batch size of 4. The total training duration was established at 200 epochs. The initial learning rate was held constant for the first 100 epochs to facilitate the exhaustive exploration of the mapping space between topographic structures and artistic strokes, followed by a linear decay strategy for the remaining 100 epochs.

4.3. Data Augmentation Strategy

To mitigate the risk of overfitting stemming from the constrained sample size (500 images in Domain A), this research employs stochastic horizontal flipping with a probability of 0.5 as a data augmentation strategy. Notably, vertical flipping was explicitly excluded from the training process in deference to the intrinsic geographic attributes and coordinate system logic of DEM data. This precautionary measure prevents the generation of geomorphologically illogical “inverted terrain” samples, which could otherwise mislead the generator’s semantic comprehension of topographic structures.

5. Results and Discussion

5.1. Geomorphological Preservation Through HCEG-SE

The experimental evidence results validate the effectiveness of the proposed HCEG-SE mechanism in enhancing geomorphological preservation during artistic style transfer. To rigorously isolate the performance improvements attributable to HCEG-SE, a controlled ablation strategy was adopted. Throughout this ablation study, all training hyperparameters and loss weights were maintained consistently with the baseline framework, ensuring that the observed improvements in geomorphological fidelity were primarily derived from the proposed structural enhancement rather than additional optimization adjustments.

Specifically, visual analyses distinctly highlight a pronounced loss of geomorphological information within shadowed blind spots. As illustrated in Figure 5, conventional single-source rendering techniques fail to address the self-occlusion present on backslopes, leading the baseline CycleGAN model to lack adequate structural guidance in these areas. Consequently, this results in the generation of disorganized stochastic noise rather than authentic geographic textures. In contrast, the Geo-InkGAN model effectively reconstructs the underlying geographic framework obscured by shadows through the implementation of the HCEG-SE mechanism. This approach preserves the legibility of terrain undulations and transitions throughout the style transfer process. Such a configuration ensures that the

synthesized brushwork is accurately and robustly anchored to the physical characteristics of the geomorphic landform.

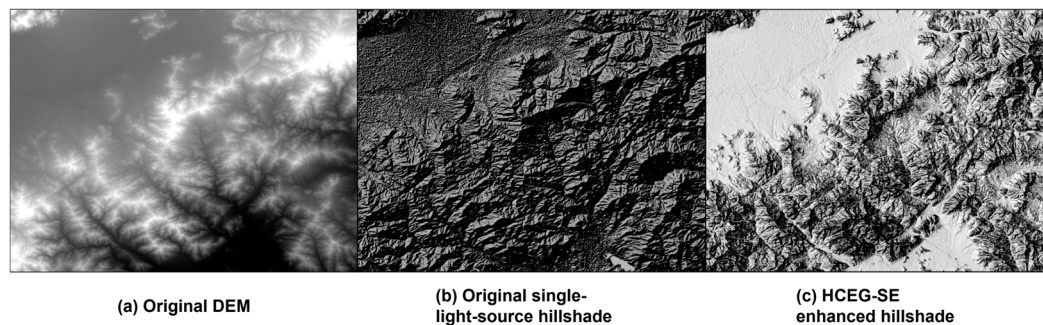


Figure 5. Comparison between single-source hillshading and the HCEG-SE mechanism.

Secondly, quantitative evaluations corroborate the functional improvements introduced by the feature enhancement module across diverse geomorphic settings. As presented in Table 2, Geo-InkGAN exhibits a substantial increase in Geomorphological Structure Correlation (GSC) indices across all five examined regions. In areas characterized by pronounced relief, the fidelity enhancements enabled by HCEG-SE are especially notable and consistent; for instance, the Yangshuo sample area experienced an increase of 0.3197, corresponding to a 111.24% improvement relative to the baseline CycleGAN model. These findings indicate that, within Karst landscapes marked by significant spatial heterogeneity, the incorporation of explicit skeleton guidance constitutes a critical factor for accurately anchoring topographic structures within the generative modeling framework. Meanwhile, for regions with more regular topography such as Anyue, the baseline model already captures substantial structural information, as evidenced by a higher initial GSC of 0.3040. In such cases, the HCEG-SE mechanism provides a stable refinement with a relative improvement of 9.24%, demonstrating that this mechanism effectively resolves structural ambiguities in complex terrains while further consolidating skeletal accuracy in simpler landscapes.

Table 2. Quantitative comparison of GSC index before and after HCEG-SE enhancement.

Study Area	Baseline GSC (Without HCEG-SE)	Enhanced GSC (With HCEG-SE)	Absolute Increment (Δ GSC)	Improvement (%)
Yangshuo, Guangxi	0.2874	0.6071	0.3197	111.24%
Yanshan, Beijing	0.4071	0.6631	0.2560	62.88%
Yan'an, Shaanxi	0.2347	0.4101	0.1754	74.73%
Anyue, Sichuan	0.3040	0.3321	0.0281	9.24%
Daxing, Beijing	0.0022	0.1310	0.1288	5854.55%

Thirdly, the model exhibits an enhanced ability to detect subtle topographic features within low-relief landscapes. In areas such as Daxing, which are characterized by extremely low-SSD values, the baseline model is unable to effectively distinguish structural details, yielding a GSC value close to zero (0.0022). This near-zero baseline is a statistical reflection of the extremely low signal-to-noise ratio (SNR) in plain landscapes, where the lack of distinctive topographic ‘signals’ leads to a near-total decoupling between the terrain and the artistic textures in the absence of specialized guidance. Despite this low absolute value, Daxing serves as a critical ‘plain end-member’ in our experimental spectrum to test the detection limits of the framework. However, with the incorporation of the HCEG-SE mechanism, the model is able to reconstruct geomorphic textures from background noise by redistributing grayscale levels through Gamma correction, thereby

increasing the GSC to 0.1310. This finding demonstrates that the HCEG-SE not only improves the representation of complex terrain but also significantly enhances the detection of micro-topographic information.

Beyond improving visual representation, HCEG-SE functions as a geographic prior encoding mechanism that introduces explicit terrain constraints before style transfer. By integrating multi-directional shading synthesis and Sobel edge enhancement, the proposed preprocessing strategy enables the prior alignment of geographic and artistic semantics during data preparation. Furthermore, Gamma correction effectively reconciles the disparity between physical elevation gradients and the artistic constraints imposed by the “five ink tonalities.” This integration provides the generative model with an interpretable geomorphic framework and reduces the geography-agnostic limitations commonly observed in general image translation models, thereby facilitating high-fidelity artistic synthesis [48].

5.2. Adaptive Constraint Optimization Based on Landform Complexity

The principal findings of this study are based on 25 gradient search experiments focusing on the parameter λ_{cyc} , conducted across five distinct geomorphic regions. Through a quantitative examination of the evolutionary patterns of the GSC and KID metrics in relation to varying constraint intensities, the experiments reveal a co-evolutionary relationship between geomorphological complexity and model parameter optimization. The results demonstrate that the GSC index exhibits a predominantly positive correlation with rising λ_{cyc} values across all landscape units (Figure 6), confirming the critical role of cycle-consistency loss in maintaining terrain topological structures. Notably, this enhancement in fidelity exhibits “diminishing marginal returns” rather than a linear increase. Concurrently, the KID index displays a U-shaped progression, where local minima precisely identify the optimal balance between artistic expression and structural preservation. Beyond these thresholds, excessive constraints introduce textural rigidity and reduce stylistic consistency.

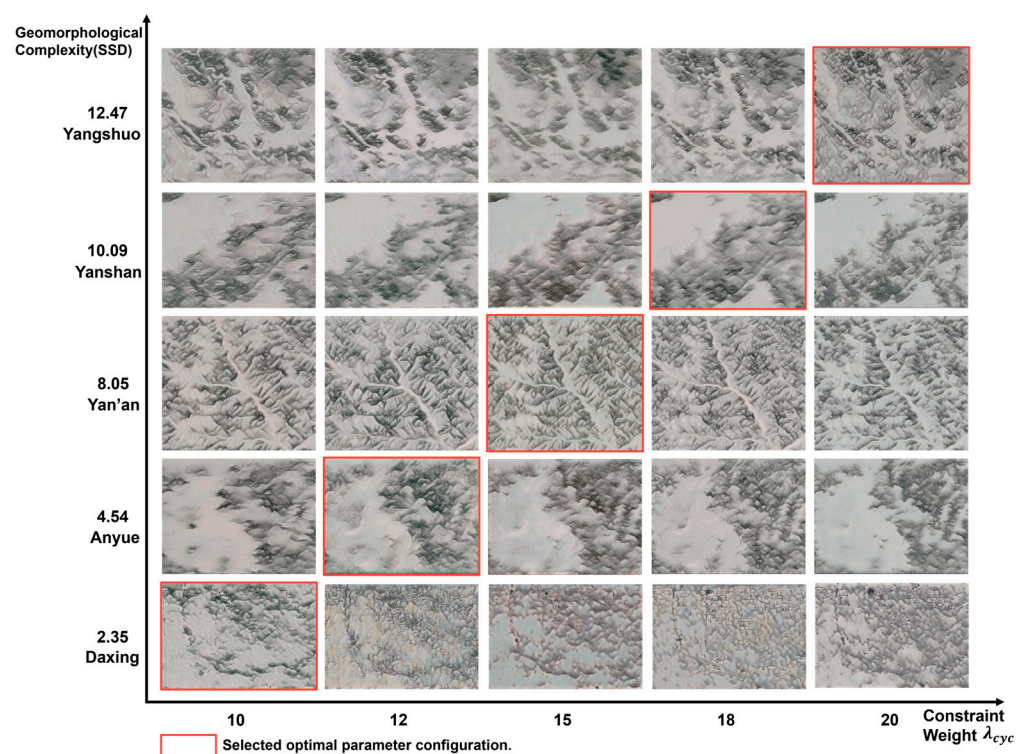


Figure 6. Matrix of mapping results across different landforms and λ_{cyc} weights.

By conducting a comparative analysis of 25 observational datasets (Table 3), this study reveals a critical parametric equilibrium: the inflection point of marginal returns in GSC exhibits strong consistency with the low-value intervals of the stylistic perception metric (KID) along the parametric continuum (Figure 7). This result demonstrates a consistent parametric adjustment across landscapes exhibiting varying degrees of complexity. In the alluvial plains of Daxing (SSD = 2.35, Figure 7a), where topographic signals are inherently minimal, a moderated constraint of $\lambda_{cyc} = 10$ achieves the lowest KID value (336.5889) while preserving subtle geomorphic characteristics. Excessive weighting in such environments may cause the generative model to interpret weak topographic noise as meaningful geographic signal, resulting in textural incoherence. Conversely, as terrain complexity increases in Anyue (SSD = 4.54, Figure 7b) and Yan'an (SSD = 8.05, Figure 7c), the optimal parameter values shift to 12 and 15, respectively, where marked improvements in GSC effectively mitigate topographic drift. For the most rugged terrains characterized by rigid geomorphic frameworks, such as Yanshan (SSD = 10.09, Figure 7d) and Yangshuo (SSD = 12.47, Figure 7e), the model produces brushstrokes that align with geomorphic logic only when the weighting parameter is elevated to 18 or 20, thereby achieving simultaneous optimization of both GSC and KID metrics.

Table 3. Performance matrix of Geo-InkGAN across entire study area and full weight gradient.

λ_{cyc}	Metric	Daxing	Anyue	Yan'an	Yanshan	Yangshuo
	SSD	2.35	4.54	8.05	10.09	12.47
10	GSC	0.1310	0.3321	0.4101	0.6631	0.6071
	KID ($\times 10^{-3}$)	336.5889	261.7343	177.4545	258.4700	235.8687
12	GSC	0.1576	0.4519	0.4985	0.6741	0.6305
	KID ($\times 10^{-3}$)	398.1960	231.4549	238.0011	310.0231	283.1223
15	GSC	0.1728	0.4759	0.5729	0.7094	0.6413
	KID ($\times 10^{-3}$)	458.3178	258.5382	223.9251	298.8062	330.1456
18	GSC	0.1706	0.4967	0.5670	0.7232	0.6691
	KID ($\times 10^{-3}$)	409.0104	273.1495	264.7571	252.7986	284.2939
20	GSC	0.1829	0.4638	0.5070	0.7600	0.7349
	KID ($\times 10^{-3}$)	433.2669	243.3834	257.3733	264.2512	250.3483

Note: SSD = Slope Standard Deviation; GSC = Geomorphological Structure Correlation; KID = Kernel Inception Distance. Bold values indicate the optimal performance for each geomorphological unit.

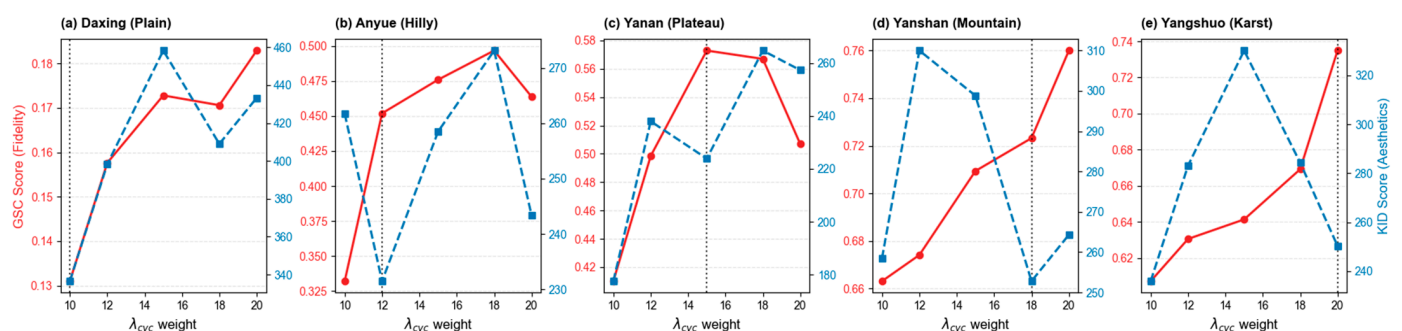


Figure 7. Evolutionary trends of GSC and esthetic scores across constraint weights.

By synthesizing the five optimal parameter configurations (Figure 8), this study identifies a geomorphology-informed scaling law through linear regression analysis. The findings reveal a robust linear relationship between the SSD and the optimal cycle-consistency weight λ_{cyc} , exhibiting a high level of statistical significance ($R^2 = 0.996$, $p < 0.001$; Table 4). This relationship represents more than a site-specific fit; it reveals a consis-

tent parametric trajectory where the demand for structural consistency scales linearly with topographic complexity. The resulting formula serves as a transferable heuristic for automated cartography:

$$\lambda_{best} = 1.004 \cdot SSD + 7.473. \quad (11)$$

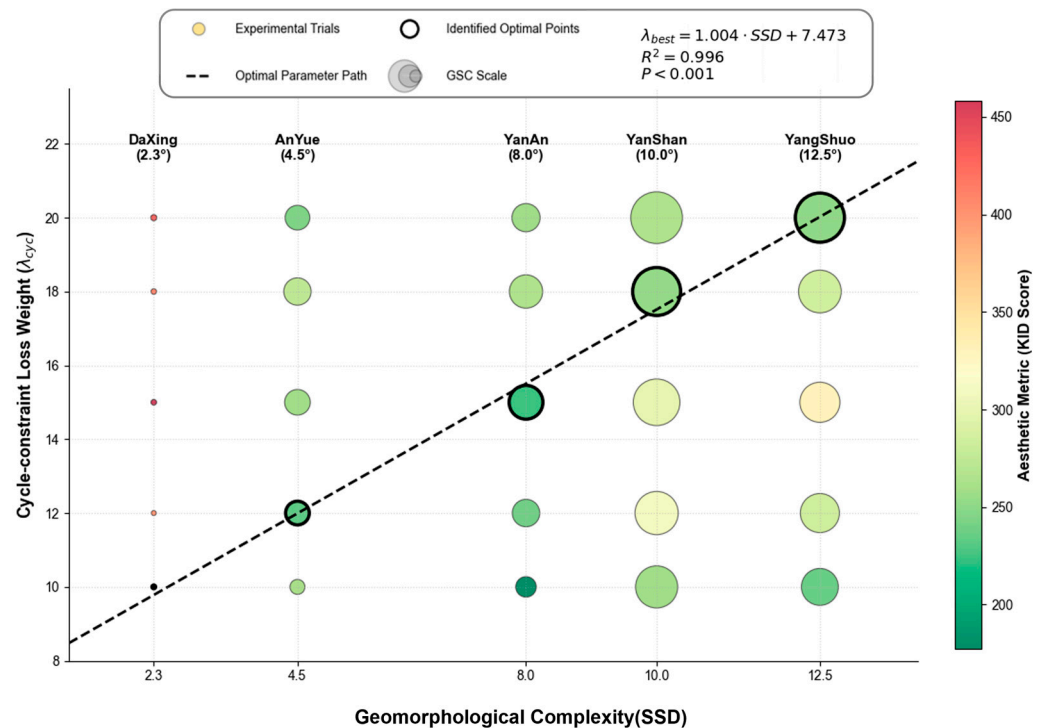


Figure 8. Quantitative mapping between geomorphological complexity and generative constraints: linear regression between SSD and optimal λ_{cyc} within the global performance landscape.

Table 4. Regression statistics of Slope Standard Deviation (SSD) and optimal weight λ_{cyc} .

Regression Function	R^2	p
$\lambda_{best} = 1.004 \cdot SSD + 7.473$	0.996	<0.001

The theoretical significance of this equation is embodied in its distinct parameters: a slope of approximately $k \approx 1$ indicates an isometric compensation mechanism between geomorphological forces and the intensity of constraints imposed by the generative model. This finding implies that a linear augmentation in topographic relief necessitates a commensurate enhancement in pixel-level structural preservation to maintain geomorphic coherence. While regional heterogeneity may cause minor empirical fluctuations, the intercept near $b \approx 7.5$ defines a fundamental structural baseline for automated artistic cartography, ensuring that even in regions characterized by minimal relief, a minimum level of constraint is preserved to sustain the integrity of essential geographic logic.

This relationship can also be interpreted as a signal-to-noise ratio adaptation mechanism for heterogeneous geospatial datasets. In low-relief landscapes, excessive cycle-consistency constraints may force the model to amplify minor elevation variations or DEM-related artifacts, whereas insufficient constraints in complex terrains may cause structural degradation. Therefore, adaptive regulation of λ_{cyc} enables the model to balance geographic fidelity and artistic flexibility.

To assess the generalizability of the geomorphology-informed scaling law, this study further evaluates three independent European regions: Cévennes (France, $SSD = 7.98$),

Sierra de Gredos (Spain, SSD = 9.07), and the Black Forest (Germany, SSD = 10.60). By conducting the same discrete gradient search strategy described in Table 5, we observed that the optima consistently converged toward the predicted range. In the Cévennes region, the peak performance identified at $\lambda_{cyc} = 15$ aligns almost perfectly with the formula's theoretical prediction of $\lambda_{cyc} \approx 15.5$. As topographic entropy increases in the Sierra de Gredos region, the optimal configuration shifts to $\lambda_{cyc} = 18$, confirming the predicted upward trajectory required to maintain structural stability in more rugged terrains. Most notably, the Black Forest case demonstrates the scaling law's critical role in risk mitigation: while a standard mid-range weight of $\lambda_{cyc} = 15$ leads to a severe structural collapse (GSC dropping to 0.6562), the adaptive formula successfully guides the model toward higher intensities ($\lambda_{cyc} = 18$), effectively bypassing this performance instability. Collectively, these cross-continental validations suggest that the scaling law provides a robust predictive heuristic for parameter optimization across diverse geomorphic environments. Beyond parameter adjustment, this geomorphology-informed regulation mechanism establishes a quantitative connection between physical landscape complexity and generative model constraints, providing a foundation for high-fidelity artistic synthesis in geo-aware cartography [48].

Table 5. Performance matrix across external validation regions and full weight gradient.

λ_{cyc}	Metric	Cévennes	Sierra de Gredos	the Black Forest
	SSD	7.98	9.07	10.60
10	GSC	0.6870	0.7792	0.7847
	KID ($\times 10^{-3}$)	272.3494	233.3915	242.8343
12	GSC	0.7815	0.7997	0.7795
	KID ($\times 10^{-3}$)	355.1905	224.4432	224.8938
15	GSC	0.8159	0.7961	0.6562
	KID ($\times 10^{-3}$)	297.3645	270.6940	310.7626
18	GSC	0.7944	0.8197	0.8311
	KID ($\times 10^{-3}$)	307.3730	224.9577	244.5703
20	GSC	0.7935	0.8162	0.8455
	KID ($\times 10^{-3}$)	293.5705	277.0429	275.9922

Note: SSD = Slope Standard Deviation; GSC = Geomorphological Structure Correlation; KID = Kernel Inception Distance. Bold values indicate the optimal performance for each geomorphological unit.

5.3. Comparative Analysis of Models

To comprehensively evaluate the efficacy of the proposed framework, this study conducted comparative experiments with representative image-to-image translation and style transfer methods. The evaluation incorporated classical methods grounded in second-order statistical matching (Gatys-NST), contemporary frameworks utilizing contrastive learning techniques (DCLGAN), the cycle-consistency baseline model (CycleGAN), as well as global attention-based Transformer architectures (StyTR2).

The visual analyses presented in Figure 9 highlight the limitations of universal generative models when applied to geomorphological frameworks. The Gatys-NST algorithm relying primarily on texture statistics through Gram matrix matching fails to preserve geographic structures, resulting in fragmented ridgelines and valley networks. Although the StyTR2 model produces enhanced artistic textures, its performance is hindered by diffusion effects associated with the Transformer's global attention mechanism. This phenomenon induces notable digital artifacts at localized geomorphic boundaries, leading to considerable stochastic alterations in the representation of topographic semantics.

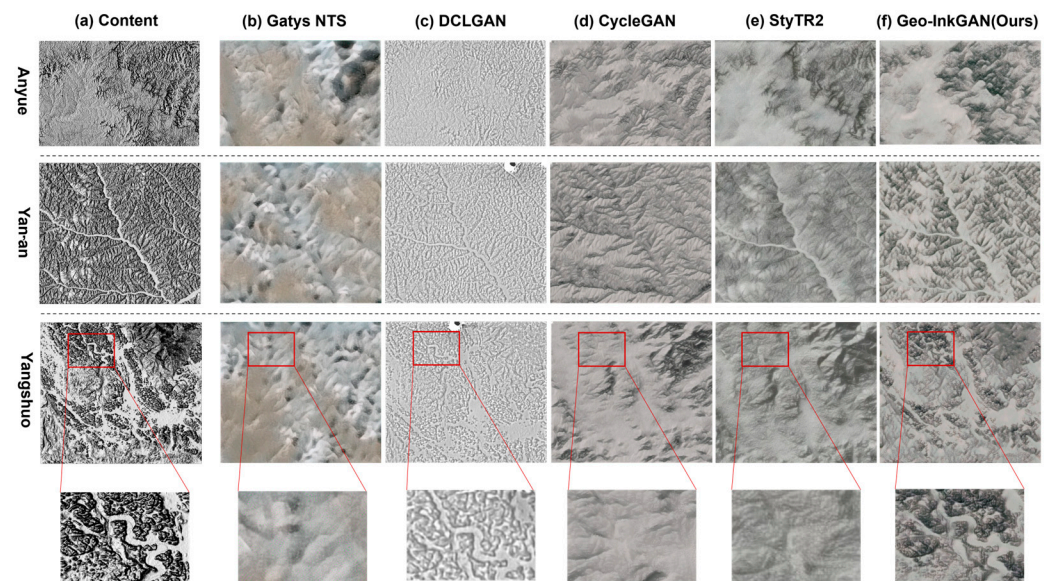


Figure 9. Visual comparison between Geo-InkGAN, the Gatys-NTS, the DCLGAN, the baseline CycleGAN, and the StyTR2 algorithms.

Contemporary state-of-the-art models also demonstrate notable adaptation challenges in this context. Specifically, the DCLGAN model exhibits adaptation difficulties when applied to limited-sample topographic datasets, producing relatively uniform textures and insufficient terrain representation. Conversely, although the baseline CycleGAN preserves major relief patterns but shows structural degradation at the micro-topographic scale, where generated brushstrokes lack consistent geographic orientation.

In contrast, Geo-InkGAN achieves a superior balance between geographic accuracy and esthetic appeal. Through the explicit geomorphic constraints provided by the HCEG-SE mechanism, the generated brushstrokes maintain stronger correspondence with physical terrain structures, demonstrating the advantage of incorporating geographic priors into artistic cartographic synthesis.

5.4. Human Evaluation of Geographic Fidelity and Artistic Expression

To provide a complementary validation of the discrepancy between automated evaluation metrics—such as GSC and KID—and human visual perception, this study conducted a double-blind perceptual assessment.

5.4.1. Experimental Design and Subjects' Background

The experiment collected 35 valid responses from participants with diverse professional backgrounds. Specifically, 60.00% of the participants were experts and researchers specializing in Geography, GIS, and Remote Sensing (designated as the expert group). The remaining 40.00% were from fields including Art and Design, Artificial Intelligence, and the general public (referred to as the general group). The majority of participants (77.14%) were aged between 18 and 30, a demographic known for frequent engagement with digital maps and advanced esthetic discernment. Utilizing a double-blind methodology, the outputs generated by Geo-InkGAN and baseline models were randomly presented to participants, who evaluated the results using a 5-point Likert scale.

5.4.2. Statistical Evaluation Results

A statistical examination of the 35 double-blind evaluation responses reveals that Geo-InkGAN achieved higher perceptual scores than the baseline models across all assessed dimensions (Table 6, Figure 10). Regarding geomorphological fidelity, Geo-InkGAN

achieved the highest mean score of 4.34, indicating that its generated brushstrokes effectively convey the underlying logic of topographic relief. Additionally, Geo-InkGAN achieved improvements of 10.8% and 45.3% in artistic consistency and visual naturalness, respectively, compared with baseline approaches. Importantly, Geo-InkGAN exhibited a 0% incidence of negative evaluations (scores below 2), whereas competing models experienced negative evaluation rates of up to 25.7%. Moreover, the overall cartographic utility score of 4.7 further demonstrates its effectiveness in balancing geographic fidelity and artistic expression.

Table 6. Statistical comparison of perceptual evaluation scores for different models (Means).

Metrics	Gatys NTS	DCLGAN	CycleGAN	StyTR2	Geo-InkGAN
Geomorphological Fidelity	2.83	3.17	3.77	3.80	4.34
Artistic Consistency	2.83	2.91	3.71	3.86	4.11
Visual Naturalness	3.69	3.23	3.09	3.54	4.49

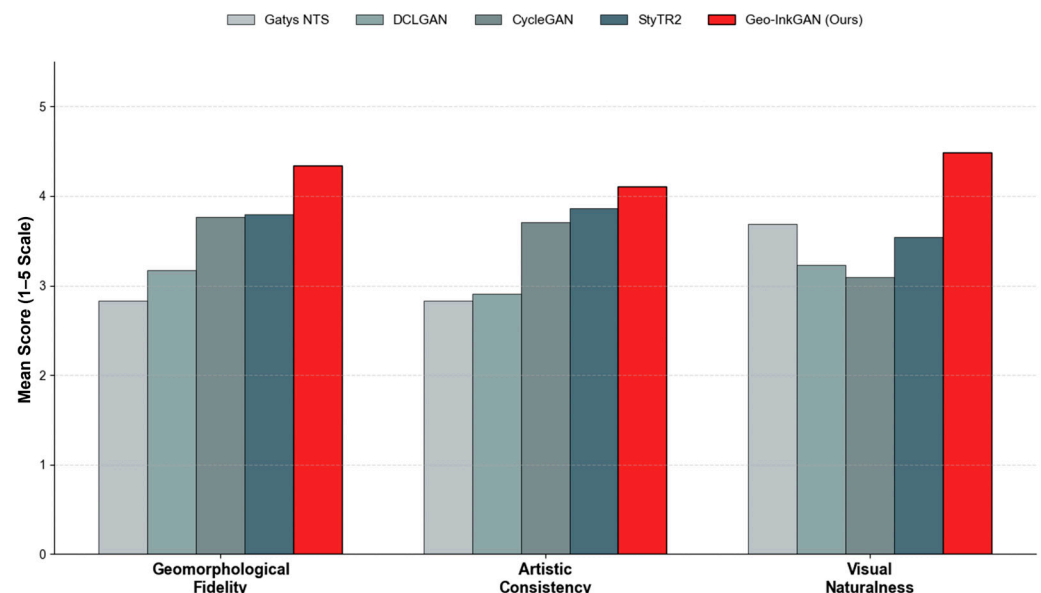


Figure 10. Quantitative results of the user perception evaluation.

5.4.3. Multidimensional Statistical Evaluation

The assessment scale utilized in this research demonstrates strong internal consistency, as evidenced by an overall Cronbach's alpha coefficient of 0.844, which surpasses the conventional benchmark of 0.8 indicative of high reliability. Regarding the specific evaluative dimensions, the reliability coefficients were 0.789 for geomorphic skeleton fidelity, 0.676 for artistic style consistency, and 0.682 for textural naturalness. These results imply that participants from varied backgrounds consistently interpreted the survey items, thereby affirming the reliability and robustness of the experimental data.

A stratified analysis considering participants' backgrounds reveals a notable cognitive alignment between the geographic expert group ($n = 21$) and the general group ($n = 14$). Notably, the expert group attributed a higher mean score to geomorphic skeleton fidelity ($M = 4.38$) relative to the general group ($M = 4.28$). To rigorously evaluate the statistical significance of this difference, a non-parametric Mann–Whitney U test was conducted. The findings, presented in Table 7 ($U = 143.5$, $p = 0.907$), reveal that professional background did not produce a statistically significant difference in evaluations, thereby supporting the acceptance of the null hypothesis.

Table 7. Group differences in geomorphological fidelity scores verified by Mann–Whitney U test.

Group	N	Mean	SD	U	p-Value	Decision
Geo. Majors	21	4.38	0.74	143.5	0.907	Retain Null
Non-Geo. Majors	14	4.28	1.07			

From the standpoint of cognitive psychology, this phenomenon holds significant implications for geoscience: specialists with geographic expertise demonstrate heightened sensitivity to subtle micro-topographic characteristics, including ridgeline orientation and ravine structure. Their elevated evaluations offer strong evidence that the skeletal signals derived through the HCEG-SE mechanism effectively encapsulate the intrinsic physical properties of geomorphological forms, rather than generating random artistic patterns. Moreover, the lack of notable differences among participants from diverse backgrounds indicates that the geographic semantics produced by Geo-InkGAN exhibit remarkable clarity and broad applicability. By successfully overcoming disciplinary knowledge barriers, this framework enables a profound integration of scientific precision and esthetic experience within the domain of human visual perception.

5.5. Interaction Between Geomorphological Structures and Ink-Wash Stylization

Our analysis suggests that although Geo-InkGAN does not explicitly utilize semantic terrain labels, it achieves an implicit identification and differentiation of geomorphic structures through the synergistic effect of the HCEG-SE mechanism and the SSD-based adaptive mechanism. Specifically, the HCEG-SE mechanism transforms geometric DEM features into explicit “geomorphological skeletons” via multi-directional hillshading and edge enhancement. In rugged regions with high-SSD values, the dense skeletal textures compel the generator to prioritize geomorphological rigidity by assigning a higher λ_{cyc} . This results in sharp, rhythmic, and intermittent strokes that mimic the “bony” esthetic of traditional brushwork. Conversely, in simpler terrains with low-SSD values, the sparse skeletal constraints and relaxed weights allow for greater ink diffusion and blending, effectively simulating “fleshy” or washed textures. This demonstrates that the framework identifies landform characteristics not through discrete semantic classification, but through the continuous spectrum of topographic complexity. Such an implicit recognition mechanism ensures that the synthesized results are not only artistically evocative but also geographically anchored, achieving a “topographically faithful” style transfer that adapts to local geomorphic nuances.

6. Conclusions

This research rigorously validates the Geo-InkGAN framework, introducing a geographic knowledge-driven deep learning paradigm for the automated synthesis of representative global landscapes. This methodology enables an end-to-end, cross-domain transformation from physical DEM data to high-fidelity artistic cartographic representations. Initially, the HCEG-SE preprocessing technique developed herein effectively addresses persistent issues of self-occlusion and topographic drift in generative cartography by employing multi-directional shading synthesis and edge enhancement, thereby preserving the topological integrity of the geomorphic structure at the data source. Furthermore, this study formalizes a geomorphology-informed scaling law between geomorphological complexity and the intensity of generative constraints. The derived law, $\lambda_{best} = 1.004 \cdot SSD + 7.473$ (with $R^2 = 0.996$), elucidates a compensatory relationship between geographic environmental pressures and model regularization strength. This advancement signifies a pivotal shift in AI-driven cartography, moving from opaque parameter tuning toward interpretable Geo-AI.

From a disciplinary perspective, this framework addresses the emerging trend in international cartography that endeavors to synthesize evocative artistic expression with rigorous scientific semantic precision. It serves as a theoretical model for advancing general artificial intelligence endowed with geographic common sense. From a global societal perspective, Geo-InkGAN introduces innovative technical methodologies that align with UNESCO's initiatives for the digital preservation of cultural heritage, the development of global digital twin landscapes, and the facilitation of cross-cultural geographic communication [44,49,50]. By converting raw geospatial data into artistic symbols imbued with rich cultural significance, the framework bridges the gap between scientific information and public comprehension, thereby promoting the widespread dissemination of geospatial knowledge and fostering the exploration of digital humanistic values within a globalized context.

Despite these achievements, certain limitations persist that warrant attention in subsequent research. Although Geo-InkGAN demonstrates robust performance across a majority of landforms, its perceptual sensitivity exhibits a modest decline in extremely flat alluvial plains, a limitation attributed to the scarcity of topographic features. Future investigations will aim to examine the scale dependency of the adaptive mapping function across multi-resolution datasets, such as ALOS PALSAR and LiDAR, and to expand the framework to accommodate a broader range of artistic styles beyond monochromatic schemes. These advancements are anticipated to further improve the robustness of geographically informed cartographic representations across diverse and complex global terrains.

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Abbreviations

The following abbreviations are used in this manuscript:

DEMs	Digital Elevation Models
GIS	Geographic Information Science
Geo-AI	Geographic Artificial Intelligence
GANs	Generative Adversarial Networks
CycleGAN	Cycle-Consistent Generative Adversarial Network
HCEG-SE	Hillshade-Contour Edge-Guided Stroke Enhancement

SSD	Slope Standard Deviation
GSC	Geomorphological Structure Correlation
KID	Kernel Inception Distance
SVF	Sky View Factor
NPR	Non-Photorealistic Rendering
DE	Germany (ISO 3166-1 alpha-2 country code)
CNNs	Convolutional Neural Networks
I2I	Image-to-Image
TPI	Topographic Position Index
CG	Computer Graphics
VGES	Virtual Geographic Environments
SRTM	Shuttle Radar Topography Mission

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