

Article

Geo-Aesthetics: An Application-Oriented Generative Framework for Translating Remote Sensing Landscape Morphologies into Parametric Design Patterns

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Abstract

This paper presents Geo-Esthetics, an application-oriented workflow that uses remote sensing imagery as source morphology for generative design. The study addresses a design problem: how can large-scale terrestrial textures be extracted, abstracted, and organized as pattern references for parametric and visual design? Nine representative geomorphological settings were selected. For each case, Sentinel-2 imagery was cropped into a 2 km × 2 km geographic window, enhanced using spectral-index selection and Contrast Limited Adaptive Histogram Equalization (CLAHE), and used as an image prompt in Midjourney v6.0. A consistent prompt structure and parameter setting were applied. Four variants were generated for each case and screened according to topological fidelity, level of abstraction, and design applicability. Box-counting dimension and lacunarity were calculated to compare morphological complexity between source images and generated patterns. The cases show that hydrological, tectonic, desert, agricultural, and reef morphologies can be translated into design-oriented pattern prototypes for paving, façades, interfaces, acoustic elements, and biomimetic surfaces. The contribution of this work lies mainly in design methodology: it provides a documented workflow for connecting Earth observation data, generative AI, and design ideation, while retaining clear boundaries around model reproducibility, prompt sensitivity, case representativeness, and perceptual evaluation.

Keywords: remote sensing; generative AI; geo-esthetics; design patterns; geomorphology; parametric design



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1. Introduction

1.1. The Anthropocene, Biophilia, and Earth's Morphological Treasury

In the context of the Anthropocene, artificial environments and natural systems are increasingly intertwined. For design disciplines, this raises a practical question: how can natural forms be reintroduced into standardized urban and visual environments without merely copying familiar organic motifs [1]? The biophilia hypothesis and attention restoration theory suggest that humans may respond positively to certain natural visual structures [2–6], but this study does not attempt to test psychological effects directly.

Instead, these theories are used as a design motivation for exploring more systematic sources of nature-derived pattern generation [7–10].

However, traditional design methodologies—such as architectural façade texture generation, landscape paving matrices, and planar visual compositions—often rely on designers’ subjective experience or closed image libraries [11–14]. Recent earth-observation and geomorphological studies continue to emphasize monitoring, hazard assessment, and process interpretation, while recent AIGC studies in landscape architecture focus mainly on scene visualization, concept rendering, and design communication. Comparatively little attention has been paid to using remote sensing landform textures as direct morphological inputs for reusable design patterns. This gap defines the practical focus of the present study: not to improve AI models, but to explore how existing generative AI can support design ideation by translating large-scale geo-textures into abstract design elements.

1.2. Cognitive Heuristics of High-Altitude Perspectives: The Overview Effect

Human spatial perception has traditionally been accustomed to an eye-level perspective constrained by gravity, which limits the holistic cognition of large-scale spatial topologies and dynamic patterns. With the advancement of Earth observation satellite constellations, humanity has gained a macro-level aerial perspective to overlook the entire surface of the planet. This high-altitude gaze directly triggers the “Overview Effect” described in aerospace psychology [15,16], often facilitating a fundamental shift in the observer’s spatial cognitive framework.

From a design perspective, this change in viewpoint shifts attention from objects to patterns. Mountain ridges, river networks, deltas, dunes, and reef structures can be read as lines, fields, gradients, and networks [11,17,18]. Such observations do not by themselves establish esthetic value, but they provide a useful visual basis for pattern abstraction in design.

1.3. Paradigm Shift at the Intersection of Generative AI and Earth Sciences

In recent years, advancements in Generative Artificial Intelligence (AI) within computer vision and multimodal alignment have altered the paradigm of image synthesis [19,20]. Since the popularization of Latent Diffusion Models (LDM) [21] and related image-to-image systems, AI can generate visuals under both image and textual constraints [22,23]. In this paper, generative AI is treated as an applied design tool rather than as the object of algorithmic innovation [24–26].

The specific research gap is therefore threefold. First, remote sensing imagery is rarely discussed as a systematic source of design morphology rather than as a scientific observation product alone. Second, the translation from geo-texture to design pattern is usually manual, slow, and highly dependent on individual designers. Third, existing AI-assisted design studies rarely foreground terrestrial texture itself as the main input constraint. To address these issues, this study proposes a Geo-Esthetics workflow with three modest objectives: (1) to acquire and enhance representative geomorphological textures from remote sensing imagery; (2) to use a fixed image-prompt and text-prompt procedure to generate design-oriented abstractions; and (3) to discuss their potential design associations while recognizing the limits of qualitative interpretation, proprietary model reproducibility, and the absence of perceptual user validation.

2. Research Framework and Methodology

2.1. Overall Research Architecture of the Geo-Esthetics System

This study constructs an application-oriented processing and design translation workflow named “Geo-Esthetics”. The workflow is intended for design research rather than AI

model development. Its purpose is to connect remote sensing-based landform observation, image enhancement, generative abstraction, and downstream design interpretation in a transparent sequence (Figure 1).

Generating Artistic Earth Observation Images

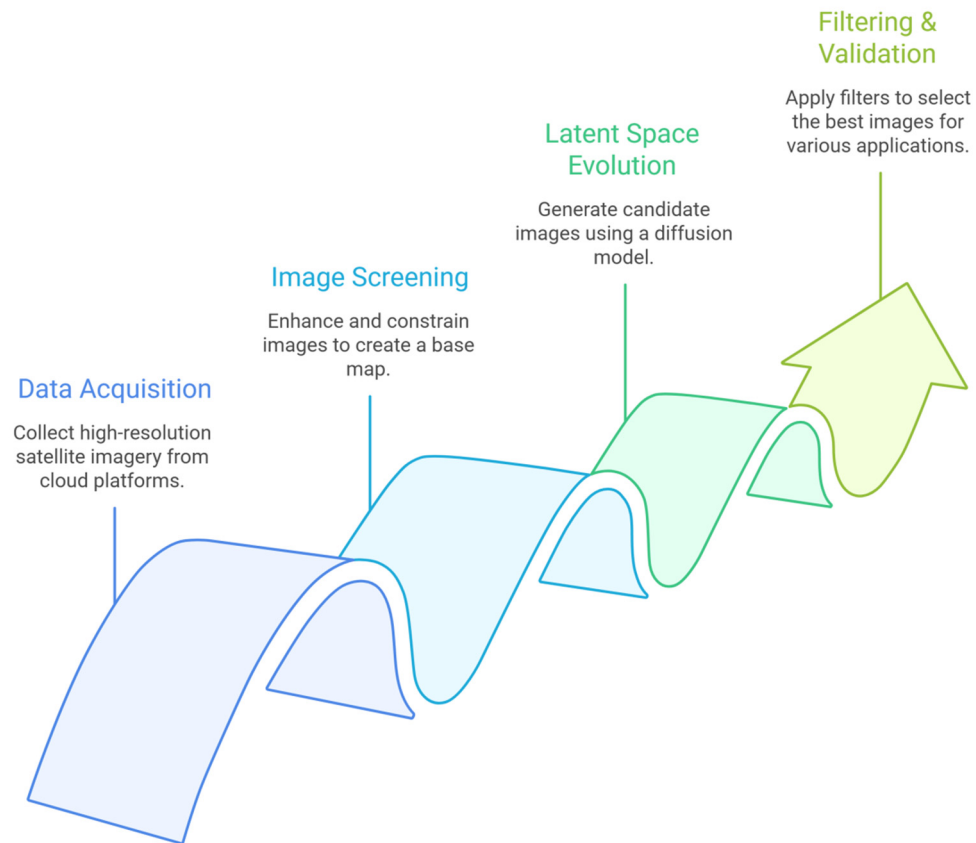


Figure 1. Architecture diagram of the Geo-Esthetics automated processing and esthetic evolution system.

2.2. Data Acquisition and Structural Enhancement

To help the downstream generative model capture visible landform structures, the data and preprocessing stage was defined as follows. The study used Sentinel-2 multispectral imagery as the primary Earth observation source. Sentinel-2 provides bands at 10 m, 20 m, and 60 m spatial resolutions. Each case was standardized as a 2 km × 2 km geographic window, and image resizing was performed only for visual normalization and generative-model input.

Case selection followed a typological rather than statistical sampling logic. The nine cases were selected to cover three broad categories of morphology that are meaningful for design translation: hydrological branching and flow systems, tectonic or erosion-related rigid/contour systems, and surface, biogenic, or anthropogenic micro-texture systems. The cases are therefore representative demonstrations of the framework's feasibility, not a statistically exhaustive global sample.

Atmospheric Denoising and Spectral Indexation: Using the QA60 band to eliminate cloud interference, and calculating spectral indices via Short-Wave Infrared (SWIR) and Near-Infrared (NIR) bands. For example, the Normalized Difference Water Index (NDWI) maximizes land–water contrast, accurately extracting water network skeletons.

CLAHE Enhancement Algorithm: Applying Contrast Limited Adaptive Histogram Equalization to the single-band grayscale images. This algorithm independently equal-

izes image tiles, effectively amplifying local micro-folds and gradient features without introducing significant global noise [27].

2.3. Prompt-Driven and Latent Space Translation Principles

The preprocessed morphological skeleton maps were used as image conditions in Midjourney v6.0. Because Midjourney is a proprietary generative system, exact replication may vary across model updates and system settings. To improve transparency, this paper reports the data source type, crop extent, preprocessing logic, prompt syntax, and parameter settings so that the workflow can be repeated, compared, or adapted in future design studies.

Image Weighting Control: Using image prompts (via the `--iw` parameter), the enhanced map provides a spatial structure reference during generation. This helps the output retain the main axes and network relationships of the source landform [28,29].

Textual Semantic Translation: Direct extraction often produces rigid linework. Structured text prompts were therefore used to guide the model toward minimalist lines, parametric grids, or flat graphic compositions [30].

2.4. Latent Space Multi-Sampling and Human-in-the-Loop Screening Mechanism

Generative models can produce different outputs from the same input. To improve consistency across cases, this study used the same parameter framework and the same human-in-the-loop screening criteria for all cases.

2.4.1. Determination of Core Hyperparameters:

All geomorphological cases were processed under a uniform parameter framework:

Base Model `--v6.0`: Midjourney v6.0 was used as the image-to-image generative engine for all cases.

Image Weight Constraint `--iw1.5`: This parameter was kept constant across all cases to balance input-image morphology and textual abstraction. Empirically, this value helped retain the main terrain skeleton while allowing the model to remove literal material appearance and produce more design-oriented patterns.

Stylization Parameter (`--stylize 150`): This parameter controls the degree of stylistic variation. The value of 150 was used consistently to allow for a moderate level of graphic abstraction while retaining the main structure of the source image.

2.4.2. Horizontal Array Screening Mechanism:

For each operation under identical parameters, the system generated a horizontal 1×4 array containing four variations (V1/V2/V3/V4) [31,32].

Because the same physical skeleton can produce several abstract variants, the researchers used the following criteria for selection:

- (a) **Topological Fidelity:** Checking whether the primary and secondary skeletons of the landform remain intact and excluding variants with broken or inconsistent networks.
- (b) **Graphic Abstraction:** Assessing whether realistic material traces, such as sand grains or vegetation, have been reduced while avoiding simple pixel tracing.
- (c) **Design Applicability:** Evaluating line rhythm, density, and overall complexity to judge whether the pattern can be further developed into parametric or vector-based design materials.

2.5. Auxiliary Morphological Description and Scene Association

Fractal geometry metrics were used to describe and compare the morphological complexity of the source images and generated patterns [33,34]:

$$D_b = \lim_{\epsilon \rightarrow 0} \frac{\log N(\epsilon)}{\log(1/\epsilon)} \quad (1)$$

By calculating the box-counting dimension (D_b) and lacunarity (Λ) of the original enhanced map and the generated pattern, the study compares whether major aspects of morphological complexity are retained after abstraction [35]. These metrics are used together with visual screening and scene association. Based on the ecological psychology theory of “Affordance” [36], physical implications, such as flow and permeability, are then linked with possible downstream design scenarios [37].

3. Deep Empirical Study of Global Geomorphological Art Patterns

To demonstrate the feasibility of the workflow, we selected nine representative geomorphological cases (Figure 2). Each case was processed as a 2 km × 2 km geographic window from Sentinel-2 imagery. The Sentinel-2 bands used in preprocessing have native spatial resolutions of 10 m, 20 m, and 60 m; generated outputs were resized only for visual comparison and layout presentation. This section shows how terrestrial landscapes can be abstracted by image-to-image generation and used to support design ideation.

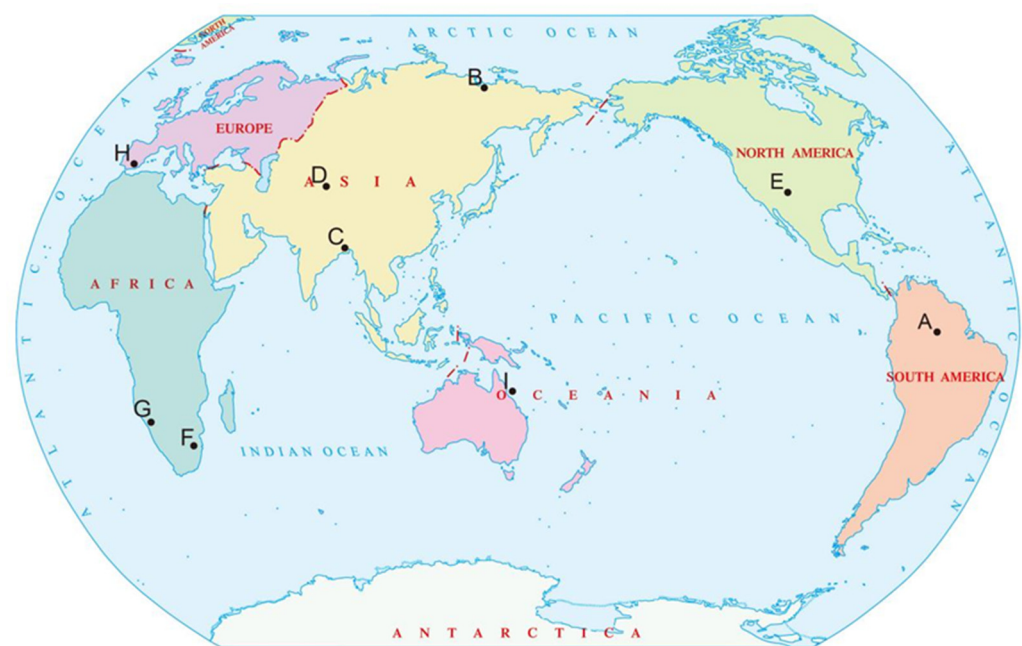


Figure 2. Global distribution map of the nine selected geomorphological case studies.

Hydrological Systems (A: Amazon Delta, B: Lena River Polar Delta, C: Ganges-Brahmaputra Estuary), Tectonic Systems (D: Tianshan Mountain Orogenic Belt, E: Colorado Grand Canyon, F: South African Drakensberg Escarpment), and Surface/Biogenic Systems (G: Namib Desert Sand Dunes, H: Spanish Anthropogenic Olive Groves, I: Great Barrier Reef).

3.1. Flow Abstraction Group of Hydrological Textures (Hydro-Morphology)

Showcase of original remote sensing imagery (Figure 3), AI generative arrays, and selected design applications for Case A, B, and C (V1/V2/V3/V4).

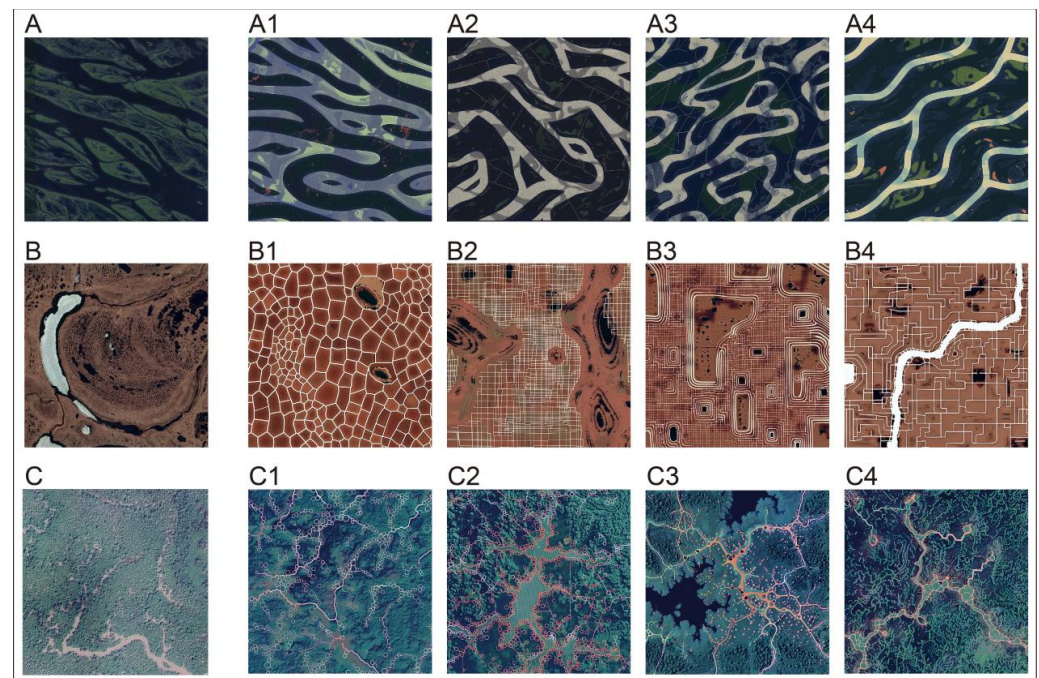


Figure 3. Hydro-morphology translation group. (A) Original remote sensing imagery of the Equatorial Amazon River Delta and its AI-generated pattern variants (A1–A4); (B) Original imagery of the Lena River Polar Delta and its generated variants (B1–B4); (C) Original imagery of the Ganges-Brahmaputra Estuary and its generated variants (C1–C4).

3.1.1. Case A: Equatorial Amazon River Delta (0.1534° N, 49.3321° W)

Geographical Scene: This equatorial region presents a complex braided channel network, faithfully recording the dynamic searching and interlacing of water flow under massive sedimentary resistance. **Structured Prompt:** Abstract braided river channels, parametric fluid geometry, elegant flat graphic design, continuous topological network, minimalist 2D vector art, monochrome high contrast, terrazzo paving pattern esthetic --no 3d realism, photorealism, muddy water, shading --iw 1.5 --stylize 150 --v 6.0. **Screening Mechanism:** During the human-in-the-loop curatorial process, we excluded noisy renderings that retained sediment textures and variants with broken tributaries. The selected variant effectively removed visual noise, retaining the fluid dynamic cascade structure of interleaving channels with smooth line transitions. **Application Association:** Bearing a strong “flow and channeling” physical implication, this topological pattern is mapped to indoor terrazzo wayfinding paving design for large transit hubs (e.g., airport terminals). The design merges functional circulation with natural esthetics.

3.1.2. Case B: Lena River Polar Delta (73.0112° N, 126.5415° E)

Geographical Scene: In the polar permafrost, the physical stress of thermal expansion and contraction over long periods has carved out a regular ice-wedge polygonal network. **Structured Prompt:** Irregular polygonal ice-wedge network, parametric cellular automata, non-Euclidean geometric grid, abstract architectural facade pattern, flat 2D graphic design, variable line thickness, monochromatic terracotta tone --no realism, ice, photography, shadows, 3d render --iw 1.5 --stylize 150 --v 6.0. **Screening Mechanism:** We systematically rejected mechanically perfect regular hexagonal variants. The selected image highlighted non-Euclidean geometric features, showcasing uneven cell boundary thickness and organic micro-textures. **Application Association:** The network’s intrinsic “permeability and respiration” features inspired the geometric generation for Sponge City permeable rainwater plaza paving and provided prototypes for adaptive breathing facades.

3.1.3. Case C: Ganges-Brahmaputra Estuary (21.9056° N, 89.1523° E)

Geographical Scene: Subject to tidal actions and coastal mangrove ecosystems, this region has formed a typical dendritic tidal drainage system with strong centripetal convergence. **Structured Prompt:** Complex dendritic tidal drainage system, generative data art visualization, fractal recursion, abstract non-linear topological network, flat 2D vector illustration, UI data visualization esthetic, high tension fluid geometry --no 3d landscape, realism, photography, mud --iw 1.5 --stylize 150 --v 6.0. **Screening Mechanism:** We filtered out overly dense central convergences. Patterns with highly legible infinite recursion and self-similarity were prioritized. **Application Association:** These highly self-similar fractal network designs offer topological inspiration for UI/UX big data visual digital panels and micro-fluidic chip channel layouts.

3.2. Rigid Order Rebuilding Group of Tectonic Geomorphologies (Tectonic Systems)

Showcasing Case D, E, and F demonstrating the translation of macro geological stress into planar compositions and geometric blocks (V1/V2/V3/V4) (Figure 4).

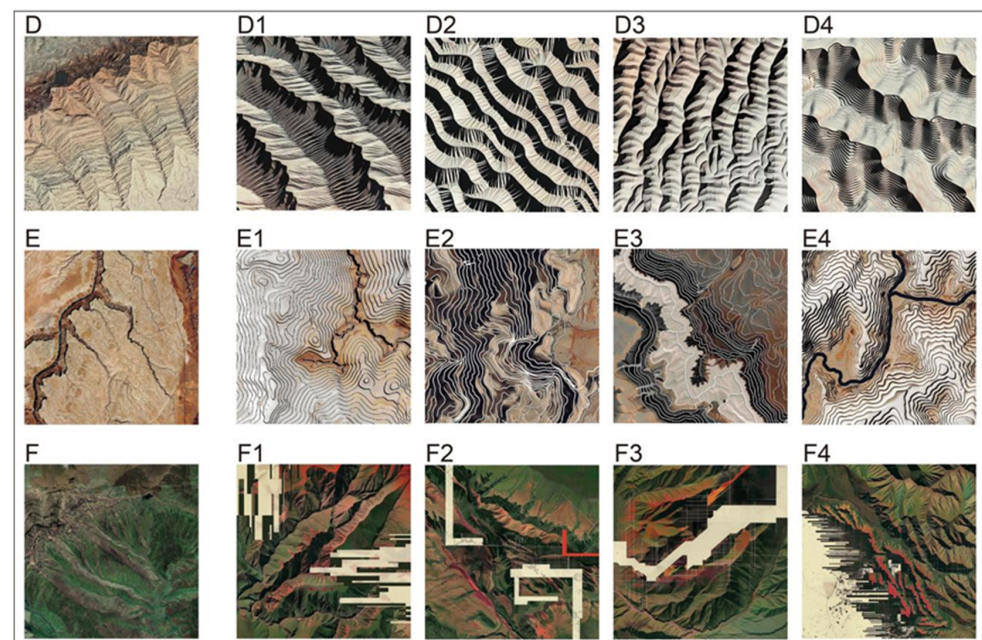


Figure 4. Tectonic geomorphology translation group. (D) Original remote sensing imagery of the Tianshan Mountain Orogenic Belt and its AI-generated pattern variants (D1–D4); (E) Original imagery of the Colorado Grand Canyon and its generated variants (E1–E4); (F) Original imagery of the South African Drakensberg Escarpment and its generated variants (F1–F4).

3.2.1. Case D: Tianshan Mountain Orogenic Belt (42.0456° N, 80.0821° E)

Geographical Scene: The remote collision effect of tectonic plates caused intense ductile deformation, forming high-frequency compression folds and thrust fault zones. **Structured Prompt:** High-frequency compression folds, parametric acoustic panel texture, abstract corrugated wave pattern, dynamic tension, Op-Art style, flat graphic design, frequency gradients, black and white --no landscape photography, realism, 3d shadows, mountains --iw 1.5 --stylize 150 --v 6.0. **Screening Mechanism:** Basic contour tracings were filtered out. We selected patterns translating ridge compressive stress into frequency-gradient ripples with visual depth (Op-Art). **Application Association:** Containing high-frequency textures implying “compression and rebound,” it extends its application to parametric acoustic diffusing panels inside theaters, or as a stress distribution reference for advanced 3D-printed textile design.

3.2.2. Case E: Colorado Grand Canyon (36.1023° N, 112.1156° W)

Geographical Scene: Millions of years of vertical downcutting by the river exposed the stratigraphic sedimentary structures of various historical periods. Structured Prompt: Highly rhythmic contour lines and rock slabs, abstract topographical relief pattern, layered parametric geometry, crypto art collection style, pure grayscale levels, flat 2D illustration, minimalist graphic design --no 3d realism, sun shadows, canyon photography, gradients --iw 1.5 --stylize 150 --v 6.0. Screening Mechanism: We discarded 3D realistic cliff renderings. The algorithm distilled the high-contrast horizontal features into a mixed art of rhythmic contours building a concept of geological time. Application Association: This artistic result can be directly translated into generative digital crypto art collections (NFTs) or serve as geological-time concept custom wallpaper for commercial interiors.

3.2.3. Case F: South African Drakensberg Escarpment (29.3145° S, 29.5123° E)

Geographical Scene: The hard basalt plateau formed a fragmented, step-like dropping escarpment morphology under long-term marginal weathering. Structured Prompt: Interpenetration of 2D rectangular blocks, jagged dropping edges, abstract Constructivism style, fragmented rigid geometric layout, avant-garde typography grid, flat graphic poster design, muted earth colors --no realistic terrain, 3d render, shadows, photography --iw 1.5 --stylize 150 --v 6.0. Screening Mechanism: Discarding realistic canyon shadow rendering, the AI dimensionally reduced the rugged incisions into 2D rectangular block interpenetrations while retaining the jaggedness of the dropping edges. Application Association: Implications of “block interlocking, order, and destruction” provide a geometric framework for a Deconstructivist typography layout and the master planning puzzle logic of terraced housing.

3.3. Micro-Texture Emergence Group of Desert, Biogenic, and Anthropogenic Systems

Including Case G (Namib dunes), Case H (Spanish olive groves), and Case I (Great Barrier Reef) (Figure 5).

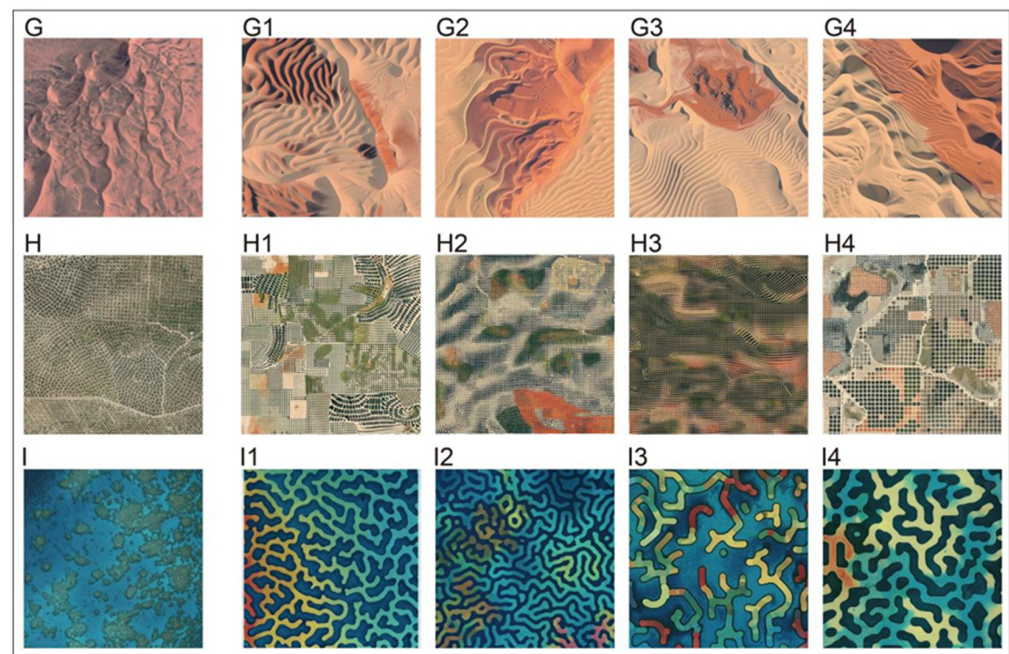


Figure 5. Surface, biogenic, and anthropogenic texture translation group. (G) Original remote sensing imagery of the Namib Desert Sand Dunes and its AI-generated pattern variants (G1–G4); (H) Original imagery of the Spanish Anthropogenic Olive Groves and its generated variants (H1–H4); (I) Original imagery of the Great Barrier Reef and its generated variants (I1–I4).

3.3.1. Case G: Namib Desert Sand Dunes (24.5123° S, 15.3456° E)

Geographical Scene: The combined action of the Atlantic cold current and complex multidirectional wind systems sculpted star and linear dune complexes in the Namib Desert. **Structured Prompt:** Abstract aerodynamic flowlines, sweeping organic curves, fluid minimalism, asymmetric sine wave rhythm, parametric wind kinetic sculpture pattern, elegant flat graphic design, warm desert color palette --no 3d realism, sand texture, photography, shadows --iw 1.5 --stylize 150 --v 6.0. **Screening Mechanism:** We excluded realistic sand grain textures. We selected minimalist streamlines where spacing variations accurately mapped the asymmetric aerodynamic rhythm of the windward and leeward slopes. **Application Association:** Breaking the stiffness of manual CAD offset commands, it provides a fluid dynamics atlas for standing seam metal interlocking flowlines on stadium roofs or wind-directing blade arrangements for kinetic sculptures.

3.3.2. Case H: Anthropogenic Olive Grove Mosaics, Spain (37.8542° N, 3.5412° W)

Geographical Scene: As a profound manifestation of the Anthropocene, the vast olive groves of Andalusia imprint a rhythmic, high-contrast linear texture across undulating topography. **Structured Prompt:** Organic-geometric agricultural mosaic, topological rhythm, contour-following dot matrices, flat 2D graphic design, minimalist landscape architecture plan, high contrast, warm colors --no 3d realism, realistic trees, photography, shadows --iw 1.5 --stylize 150 --v 6.0. **Screening Mechanism:** The AI deconstructed the mechanical agricultural arrays, pursuing an organic-geometric composition mapping the interplay between human intervention and natural resistance. **Application Association:** This “Topological-Geometric Rhythm” provides morphological guidance for contour-based urban plaza layouts, pavilion columns, or dynamic acoustic ceiling installations.

3.3.3. Case I: Great Barrier Reef (18.3215° S, 146.8123° E)

Geographical Scene: Coral polyp communities co-evolved to form porous self-organizing ecological morphologies to maximize light absorption and nutrient capture. **Structured Prompt:** Abstract porous Turing pattern, continuous labyrinthine channels, biomimetic vector texture, organic interconnected network, flat 2D graphic design, biological cell metabolism abstraction, solid monochromatic colors --no underwater photography, realistic coral, 3d render, shading --iw 1.5 --stylize 150 --v 6.0. **Screening Mechanism:** We rejected overly dense renderings that hinder visual permeability. The selected Turing Pattern evolution possessed principal axis continuity and microscopic porous permeability. **Application Association:** The ecological hints of “porosity and permeability” inspired the cross-sectional morphological design of porous artificial reefs and surface micro-structure grooves in bio-receptive concrete.

3.4. Global Geomorphological Art Pattern Summary Comparison

To present the relationship between geographical morphology and generative design abstraction, this study compiled a matrix summary of the remote sensing native images of the nine typical geomorphologies and the parametric art patterns translated cross-modally by AI.

This matrix compares how hydrological flow (Figure 6), tectonic stress, biological organization, and anthropogenic spatial order can be reinterpreted as two-dimensional design assets. It provides an overview of the nine cases and helps compare their source morphology, generated pattern structure, and potential design use.

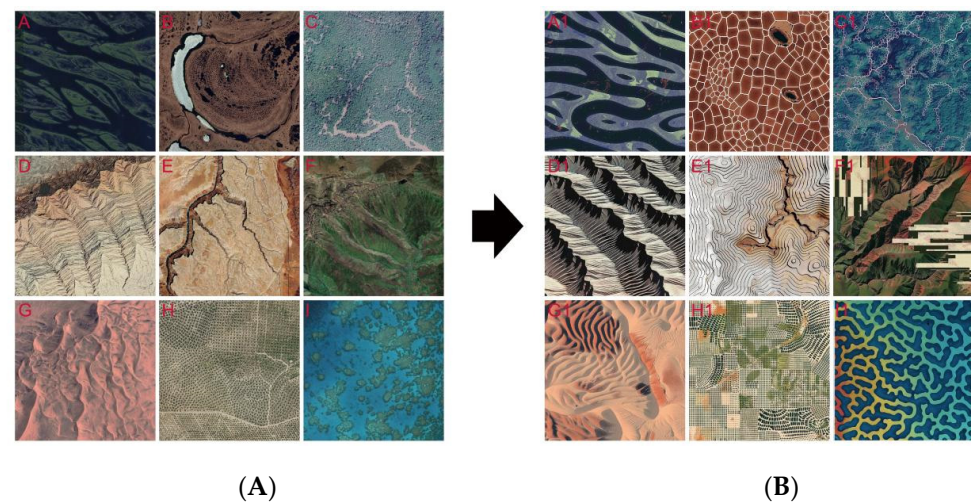


Figure 6. Global nine typical geomorphologies “Geo-Esthetics” translation matrix summary (nine-grid). (A) Original Remote Sensing Imagery, (B) AI-Generated Art Patterns.

4. Discussion: Expansion of Multidisciplinary Dimensions

4.1. Expanding the Cognition of Non-Euclidean Geometry and Breaking Intuition

The main design implication of the Geo-Esthetics workflow is that it helps designers move beyond regular Euclidean motifs and manually drawn organic patterns. By using remote sensing imagery as a morphological constraint, the generated outputs can retain asymmetry, branching, porosity, and density gradients that are difficult to invent from scratch. However, these outputs should be regarded as design prototypes. Their functional performance, user preference, and manufacturability require further testing in specific design contexts.

4.2. Design Applicability and Boundaries of Translation

The generative textures acquired by the Geo-Esthetics framework may support several design fields, but each application should be interpreted as an ideation pathway rather than as direct proof of performance:

Fine Art and Digital Media Art: The combination of terrestrial narratives and algorithmic abstraction can provide visual materials for data-driven installations [38].

Graphic and Packaging Design: Patterns derived from landform structures can support visual identity systems and product packaging textures.

Architectural Design and Structural Optimization: In parametric design contexts [39], porous reef-like structures may provide references for façade patterning, shell components, or 3D-printed surface systems. Their engineering performance would require separate testing.

Landscape Architecture: At the macro scale, the branching logic of deltas can provide references for trail networks, water-flow organization, or wetland park layouts [40–42].

5. Limitations and Future Work

5.1. Model Reproducibility and Prompt Sensitivity

The prompts in the current workflow rely on the experience of the researchers, and differences in wording can influence outputs. A central limitation is that the generative process uses Midjourney v6.0, a proprietary model whose weights, training data, and seed-level behavior are not open for audit. Therefore, the study cannot claim full computational reproducibility. The method is presented as a documented applied design workflow based on disclosed source data type, crop scale, preprocessing steps, prompt structure, and

parameter settings. Future work should compare this workflow with open-source diffusion models and include systematic prompt-sensitivity analysis.

5.2. Subjectivity, Bias, and Lack of Perceptual Validation

The screening of generated outputs remains partly subjective because design evaluation involves esthetic judgment, project intention, and contextual suitability. The latent space of generative AI is also shaped by human visual culture and training data, which may introduce stylistic bias. This study does not claim that AI outputs are superior to human design. Future work should include designer panels, user questionnaires, or perceptual experiments to evaluate whether geo-derived patterns are preferred, more legible, or more useful in design practice.

5.3. Scale, Resolution, and Case Representativeness

Natural physical textures exhibit strong scale dependence. The 2 km × 2 km Sentinel-2 windows used here are appropriate for demonstrating macro-scale texture translation, but they cannot capture all micro-topographic details. The nine cases were selected to cover major morphological types rather than to represent the full statistical diversity of global landforms. Future studies could integrate Sentinel-2 with higher-resolution commercial imagery, UAV data, LiDAR, or Structure-from-Motion photogrammetry [43] to build a multi-scale texture atlas.

5.4. From Static Feature Extraction to Time-Series Dynamic Generation (4D Morphogenesis)

The research currently extracts remote sensing image states only at static moments. Geographical textures are often accompanied by seasonal and long-term evolutionary characteristics. Future research could introduce long time-series remote sensing data cubes and video-generation diffusion models to explore dynamic pattern evolution, such as delta migration, glacier retreat, dune movement, or vegetation phenology [44–47].

5.5. Toward Broader Geo-Esthetic Pattern Libraries

A longer-term direction is to build a curated library of Geo-Esthetic pattern cases that links source location, landform process, preprocessing method, prompt structure, generated variants, and possible design applications [48–50]. Such a library would allow designers and researchers to compare results across regions, environmental conditions, and model types. It should also record data provenance, cultural interpretation, ecological sensitivity, and the limits of esthetic generalization [51–53].

6. Conclusions

This study demonstrates that existing image-to-image generative AI tools can be organized into a practical workflow for translating geomorphological textures from remote sensing imagery into design-oriented pattern prototypes. The contribution is an applied design framework that connects Earth observation, visual enhancement, prompt-guided abstraction, and human-in-the-loop design screening.

Across nine representative cases, hydrological, tectonic, desert, agricultural, and reef morphologies were converted into pattern families with potential applications in paving, façades, interfaces, acoustic surfaces, and biomimetic design. The results indicate that the Earth's surface can provide a useful source of morphological inspiration when processed through a transparent and consistently applied design workflow.

At the same time, the study has clear limitations. Midjourney-based generation is not fully auditable, prompt wording can influence outputs, the nine cases are demonstrative rather than statistically representative, and the proposed design associations have not yet been validated through user studies, perceptual experiments, or engineering performance

tests. For these reasons, the findings should be interpreted as exploratory but practically useful for design ideation.

By repositioning remote sensing imagery from an analytical data source to a design morphology resource, Geo-Esthetics offers a possible pathway for designers to work with natural landform logic at large spatial scales. Future research should expand the dataset, compare multiple generative models, test prompt sensitivity, and evaluate design outcomes through both expert and user-based assessments.

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Data Availability Statement: The Sentinel-2 source imagery used in this study is available from public Earth observation platforms. The case coordinates, prompt texts, and parameter settings are reported in the manuscript to support procedural reproducibility. Generated outputs and preprocessing records can be made available by the authors upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

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