# A Review of Machine Learning Approaches to Terrain Generation

Literature Review

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## ABSTRACT

Terrain generation is a crucial aspect of virtual environment creation with widespread use in applications such as gaming, simulations, and movies. Authoring such synthetic terrains in real-time is difficult as realism, accuracy, scale, and user control need to be considered simultaneously in authoring a variety of land-forms. Although there are many effective tools for terrain generation such as procedural or simulation approaches, machine-learning models using diffusion-based terrain synthesizers have shown great success. The models prioritize real-time interactive user feedback while generating realistic and accurate terrain. This review lays the fundamental framework for terrain representation with Digital Elevation Models. It analyses the different approaches to terrain generation (procedural, simulation, and example-based), and discusses the different methods of terrain authoring (Parametric, feature-based and painting with brushes). This review will provide a comprehensive analysis of machine learning models used for synthetic terrain generation; and illustrate the potential application of the models with evaluation techniques, to show the quality and efficiency of the terrain generation.

## CCS CONCEPTS

• **Computing methodologies → Shape modelling; Machine learning;**; • **Applied computing**;

## KEYWORDS

Terrain generation, machine learning

## 1 INTRODUCTION

Terrain features are essential elements within three-dimensional landscapes, playing a crucial role in authentically depicting natural settings [15]. Naturally occurring terrain is difficult to replicate with the vast differences in the variety of land formations such as hills, cliffs, valleys, and grasslands. Real-world terrain has complex geological factors and has had millennia to deform and erode. For example, weathering, gradual erosive forces, and the movement of tectonic plates have all changed the formation of natural land formation. Generating synthetic terrain with a close resemblance to the natural deformation of land is critical in film, and game design. While the development of terrain generation has been extensively researched, it is still a largely unsolved problem to generate realistic and naturally portrayed terrains. [11].

It is important for an artist to have a method to generate reality-based terrain on demand and have the versatility to employ artistic vision in the placement of rivers or mountain ranges. Terrain authoring is the technique referred to when manipulating land formation and is a critical element in terrain generation. While terrain authoring and user control are crucial, they need to be met with a balance of realism and performance [9].

Recent developments in terrain generation using machine learning have shown significant improvement in the management and processing of geospatial datasets[24]. Diffusion models [23] and Conditional Generative Adversarial Networks [14] in particular have shown success in generating synthetic terrains from user feature sketches.

As the array of techniques for generating terrain expands, the necessity for thorough evaluation and analysis grows proportionately. Various criteria for effective evaluation have been established [11]. Evaluation of the generated terrains using quantitative or perceptual evaluation is necessary to show the variety of landforms, realism, scale, degree of authoring and efficiency of the model. Not all developments of the terrain synthesis models can adequately cover all the criteria, so it is useful for future development to consider the evaluation criteria which would best suit their model.

**Terrain Representation** This section describes the underlying models used to represent and synthesize terrain. The terrain elevation can be defined as a function $h : \mathbb{R}^2 \rightarrow \mathbb{R}$ and represents the altitude at any point in $\mathbb{R}^2$. This can be expanded to *h(x,y)* where $h$ represents the altitude and *(x,y)* represents the point. The definition limits the models' representations of the underlying geology without overhangs, arches, or caves [11]. Terrain is often represented using this model due to its simplicity. Representing elevation in the form of heightfields through 8-bit or 16-bit quantization reduces the computational complexity as well as the number of elevation points $h(\mathbf{p})$ as shown in (Figure 1, right).

**Discrete height fields** are stored in the form of a Digital Elevation Model (DEM) which is a digital representation of the topography or terrain of the Earth's surface, typically represented as a grid of elevation values[1]. This method of organizing elevation data is crucial for translating geographic information into a format that is computer-processable [17].

Gridded DEM (GDEM). This model represents the heightmap collection of altitudes as a 2D grid and stores the data in a simple matrix allowing for easy access of the stored values. The accuracy of the GDEM depends on the size of the grid and the number of elevation samples. [11]

Triangulated irregular networks (TIN) uses a dense network of non-overlapping irregular triangles to capture rough terrain. However, a sparse network is used to cover smooth terrain [20]. The model is useful as it can capture the topographic irregularity,

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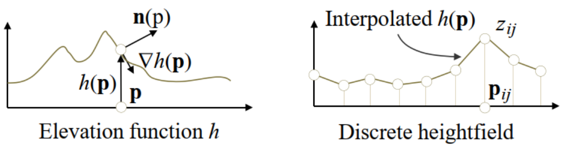



**Figure 1:** *Discrete heightfield data shows that elevation is reconstructed by interpolation* [11]

without a significant increase in the data size. However, due to the triangle edge grid representation, the land formation does not appear natural.

Layered representations use different materials such as sand, rocks, or water on top of bedrock to form a terrain representation [11]. The layered representations are widely used for erosion simulations with a predefined encoded collection of ordered functions to represent the thickness of each layer.

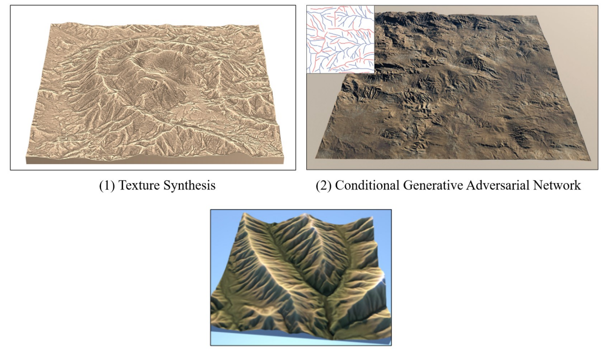
## 2 TERRAIN GENERATION

There are many terrain generation models, however, they are generally categorized into three models[11]:

**Procedural generation** is a technique used to generate large-scale synthetic terrain which does not use real-world data exemplars. It utilizes algorithms and parametric specifications to replicate the effects of the real-life geomorphological process. It sculpts the terrain through subdivision schemes [6], faulting [8], and noise. Hanaidi *et al.* [16] showed efficient and intuitive tools for controlling landforms using a multi-grid diffusion of constraints for procedurally generating realistic terrains. While this approach is phenomenological, it does not represent the structure of real-world terrain with a variety of land formations and conforms to the parametric approaches of terrain authoring.

**Simulation-based** approaches mimic Earth's geomorphological processes to create lifelike terrain, simulating natural occurrences like erosion and tectonic activity through multiple iterative steps [11]. Thermal erosion techniques simulate erosion as the downward movement of rocks and sediments on slopes, driven by gravitational forces and the thermal expansion of water [28]. Other simulation methods use the movement of tectonic plates to simulate the uplift of mountain ranges [3, 4, 26]. Hydraulic erosion techniques use the motion of water against bedrock surfaces to simulate fluid movements and sediment dispersion. Hydraulic erosion can be computed using Eulerian approaches [2] or Lagrangian approaches [19]. However, these models are computationally expensive and time-consuming and do not cater for effective user control as they prioritize the geologically accurate process.

**Example-based** approaches to synthetic terrain generation have demonstrated an effective balance of user control, highly realistic terrain and performance. The example-based approaches, unlike procedural and simulated use real-world terrain from discrete heightfields in the form of Digital Elevation Models as examplars. The U.S Geological Survey [12] provides real-world fidelity Digital Elevation Models. Example-based approaches construct a database



(1) Texture Synthesis

(2) Conditional Generative Adversarial Network

(3) Diffusion-based

**Figure 2:** *Differing Example-based models approaches to terrain generation: [10], [14], [23]*

of the DEMs after which the fragments are blended to create a seamless terrain. The following two example-based models have shown potential for terrain synthesis:

**Machine Learning** Guérin *et al.*[14] proposes a conditional generative adversarial network (CGAN) which utilizes two competing neural networks to synthesize terrain. Lochner *et al.* [23] shows the effectiveness of diffusion-based terrain authoring techniques. These approaches show high levels of user control and versatility as they can fill in the gaps of missing input data, however, they are limited by the quantity, range, and quality of the input data.

**Texture Synthesis** generates new textures by taking in input images (usually DEMs), reassembles continuous regions from the images, and aims to create visually coherent and realistic textures that resemble the characteristics of the input data. Gain *et al.*[10] utilizes a parallel pixel-based terrain synthesis method to improve efficiency and user control. They were able to achieve an average of 165ms when updating a $1024^2$ terrain with a brush interface for painting terrain characteristics.

## 3 TERRAIN AUTHORING

Terrain authoring is a high-level toolset in terrain generation which allows a user to intuitively manipulate the formation of land. Authoring methods should be analysed by the degree to which they provide the user with control over the landscape [11]. Authoring needs to allow a user to have varying levels of control over the terrain generation while representing the changes to the land formation without having to manually refine every detail. While control is important, it is essential to integrate a style of use comprehensible for a novice user without geomorphic knowledge. This means that a novice user should be able to represent, for example, a river and mountain ridge-line formation with a few simple stylizing tools. It is imperative to use a terrain authoring technique which provides intuitive user feedback in real-time for fine-tuning [10]. However, the authoring tool set is not responsible for the quality and realism of the render which relies on the terrain generation model.

**Parametric Approaches** is a course scale terrain authoring method for modelling terrains. Users can interact indirectly with the terrain by simulating the act of painting on a canvas. Parametic approaches are usually in the numeric form of parameter specification. Procedural [6] or simulation-based models use numeric parameters before the terrain generation to specify the characteristics of the land formation. The parametric approaches require significant fine-tuning to achieve the required result and as such, new methods of authoring which could provide higher levels of user control needed to be developed.

**Feature based sketching** allows users to conceptualize terrain features by drawing and outlining regions onto a terrain canvas. It focuses on creating specific terrain features such as rivers, cliffs, and valleys. Once the user maps out the vector sketch, the features can be generated on the landscape. The vector sketches serve as input parameters with encoded meaning within the stylisation for example-based methods to convey the user's intent[23, 33]. This methodology of terrain authoring allows for a greater level of user control and a more accurate depiction of the natural terrain.

**Panting with Brushes** is a set of high-level tools for modelling terrains. It is the next step in the evolution of terrain authoring where once the terrain is generated, it allows for a course scale manipulation of the landscape [11]. Guérin *et al.* [14] implemented an interactive authoring technique which takes place after the network training preprocessing step. This approach allows the user to first draw a course sketch of the terrain and incrementally modify detail by adding or removing curves or interactively editing the level-set. The authoring tool is fast and easy to use however, it provides less control than curve sketches. Figure 3 shows a professional artist's authoring session, incrementally adjusting the terrain by adding rivers (middle) and defining elevation points (right)

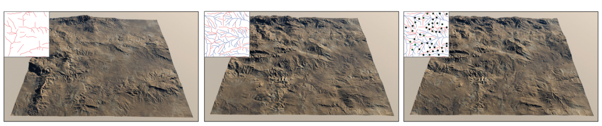


**Figure 3:** *An approach to terrain authoring using level-set modification. [14]*

**Silhouette Sketching** is a method of terrain authoring which is based on a first-person sketching interface [11]. Dos Passos and Igarashi [7] propose a silhouette sketching method which alters mountain ranges from a first-person perspective standing in a particular location. The user is given the perspective of an artist who would sketch the outlines of the real terrain. Their system operates by first situating sample viewpoints in a radial arrangement around the source heightfield, followed by automatic extraction of prominent silhouettes. This approach has its weaknesses, strong artefacts are prominent in the blending process and the variety of landforms is limited.

## 4 MACHINE LEARNING

Traditionally terrain generation has been implemented using simulation, procedural, or example-based techniques [11]. These methods have tried to address the complex issues around terrain authoring. Recently machine-learning approaches to terrain generation have shown the effectiveness of using discrete height fields to convey the user's intent onto the landscape.

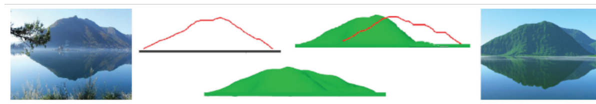


**Figure 4:** *Silhouette terrain authoring [7]*

### 4.1 Diffusion Models

Diffusion models draw inspiration from nonequilibrium thermodynamics [34] in which the structure in the data distribution is slowly and systematically destroyed through an iterative forward diffusion process. The reverse process is then applied to restructure and restore the data. The forward trajectory uses the Markov diffusion kernel to gradually covert the distributed data into a tractable distribution which corresponds to Gaussian diffusion with identity covariance. The reverse trajectory applies the forward trajectory in reverse[34]. The result of this process is the model's ability to take a sample image, apply Gaussian noise to systematically destroy it and reverse the process to maintain the structure of the initial image [21].

Diffusion models have shown great success in terrain generation while maintaining an interactive authoring session. Gain *et al.*[23] has utilized diffusion models for conditional image synthesis to develop a terrain authoring framework which balances user control, the fidelity of global terrain structure and perceptual realism. Inspired by the effectiveness of Denoising Diffusion Probabilistic Models [25] and the high sample diversity [5], the framework provides interactive authoring through style selection and feature sketching. The diffusion model methodology describes the architecture in two steps, the pre-processing and training stage. The preprocessing uses CNN-based classifiers to remove abnormalities from the sample data which is followed by signature extraction and model training. Signature extraction is an important process in modelling terrains as it allows for feature-based sketching. The model is trained to extract key features focusing on ridges, drainage networks, cliff lines and flat regions from digital elevation models [23]. A light Gaussian blur is applied before the feature extraction to account for abnormalities in imprecise user sketches after which each sketch is stored in an RGBA image with one feature per channel.

Once the signatures from the data preprocessing have been extracted, the architecture implements a sketch-to-terrain model which relies on a time-controlled U-net [5, 32], augmented with cross-attention and skip-connections. Figure 4 shows how Gaussian noise is applied to a vector sketch coupled with the U-net to generate synthetic terrain. Upscaling is further performed as a post-processing stage to allow the user to fine-tune the fidelity of the terrain.

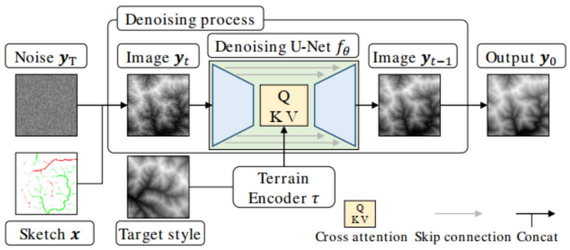



**Figure 5:** *Diffusion model approach to terrain syntheses. [23]*

## 4.2 Conditional Generative Adversarial Networks

Generative models analyze a set of training instances and understand the probability distribution that produced them. Generative Adversarial Networks (GANs) excel in generating additional instances from the inferred probability distribution and are effective for producing lifelike, high-resolution images [13]. The GAN architecture comprises of a generator and a discriminator. The generator aims to create realistic data samples from the training set, while the discriminator evaluates these samples, distinguishing between real and generated data. Through iterative training, the generator learns to produce increasingly convincing samples as the discriminator improves its ability to differentiate between real and fake data, thus improving each other.

Conditional Generative Adversarial Networks used by Mirza *et al.* [27] extends the GAN and uses an additional input layer to the generator and discriminator such as class labels or data from other modalities which allows considerable flexibility in how the hidden representation is composed.

Guérin *et al.* proposes an Interactive Example-Based Terrain Authoring with Conditional Generative Adversarial Networks [14]. The training is built on real-world exemplars and the style vector counterparts to extract features such as ridgelines and river networks. This model uses a set of CGAN terrain synthesizers, each dedicated to a specific task. Figure 5 shows the implementation of a sketch-to-terrain synthesizer $\mathcal{S}$, levelset-to-terrain synthesizer $\mathcal{L}$, eraser synthesizer, and erosion synthesizer $\mathcal{R}$ that learns the correlations between the terrains and the sparse data. The terrain authoring allows the user to sketch a rough outline of the terrain and a lightweight erosion simulation with a low computational cost is applied to the model to synthesize the terrain.

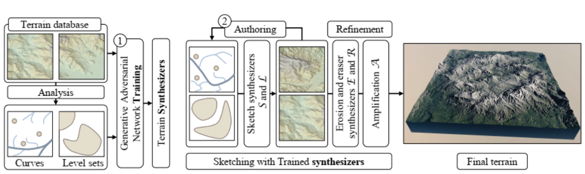



**Figure 6:** *Conditional Generative Adversarial Networks approach to terrain syntheses. [14]*

# 5 EVALUATION

The realism evaluation of synthesised terrains is a difficult topic to explore [11]. Evaluating the quality of synthesized terrains involves assessing their realism, efficiency, user control, and adherence to specific design constraints. Quantitative metrics for terrain realism provide an objective method of analysis. Qualitative metrics, on the other hand, emphasize the importance of the user's perception of the realism of the synthesized terrain. The user's criteria for realistic terrains is based on their evaluation of the perceived realism. However, quantitative and qualitative measurements may form opposing results to the realism of the terrain. A user may perceive a terrain as realistic but fundamentally the terrain violates the topological principles such as incorrect drainage patterns. Consequently, research into terrain realism and terrain generation methods typically evaluate realism using multiple approaches. Moreover, advancements in example-based models, such as Generative Adversarial Networks and diffusion models, have significantly influenced terrain synthesis methodologies, prompting the need for robust evaluation methodologies to ensure the reliability and effectiveness of generated terrains in various applications.

## 5.1 Quantitative evaluation

*Accuracy.* The simplest and most effective method for quantitative evaluation is accuracy which measures how accurately the synthesised terrain matches the real source terrain. Utilizing the mean squared error between the source terrain and the synthesized elevation maps at a pixel level provides a simple differentiation between the two[29]. The mean squared error however does account for the variation of features and how they interact with one another to compose the landscape. To address this issue, Li *et al.* [22] proposes using the Pearson correlation coefficient, a measure between -1 and 1 which shows the linear relationship between variables. A high coefficient indicates the simulated synthetic terrain includes similar topographic characteristics to those of the reference DEM. While the Pearson coefficient is a more effective measure of quantitative evaluation over the mean squared error, it does not consider the relationship between features in the source data.

Jasiewicz *et al.* [18] propose a method of quantitative evaluation according to the principle of pattern recognition rather than differential geometry. Pattern recognition classifies the geomorphological features using machine vision to identify the pattern differences between the local terrain and synthesized terrain.

*Performance.* An important quantitative metric when evaluating a model's ability to produce synthetic terrain is computational efficiency. The performance directly affects the response rate of a user's interaction with the system. The evaluation of performance can be categorised as both the generation of the terrain as well as the terrain authoring techniques.

Galin *et al.* [11] propose a technique to categorise time efficiency into four general classes: real-time (less than one-third of a second or 3 Hz ), interactive (less than 3 seconds per update), seconds (between 3 seconds and a minute per update), minutes (any update that takes longer than a minute). The difference between interactive and real-time performance influences the user experience and the type of interface that can be developed. Space efficiency examines the memory allocation of the model during the generation process

[11]. The memory overhead of example-based models during the generation process is high as they rely on a database of the terrain exemplars. The approach taken by Gain *et al.* [23] shows a real-time response rate during active sketches which allows for rapid user authoring.

## 5.2 Perceptual evaluation

Perceptual evaluation is a difficult metric to analyse as various factors such as lighting, perspective, rendering style, or texturing of the generated terrain influence the user's perception of realism. When conducting perceptual studies it is important to ensure the statistical significance and reliability of the measurements. A sufficiently large number of participants and a variety of samples are required to ensure statistical significance and the superiority of the approach. Gain *et al.* [23] performed a perceptual study to test the perceived realism obtained from their diffusion-based framework, the real terrains, and the cGAN model [14]. The study was performed with 41 participants in which each trial required that the user choose between two $5x5km^2$ landscapes. To ensure statistical significance and avoid selection bias, they categorised the selection of land formations by cliffs, hills, mountains, and flatland. The study showed participants were able to distinguish the difference between real and generated terrains for hills, cliffs, and mountain ranges, but not flat plains.

## 5.3 Hybrid Evaluation

Rajasekaran *et al.* propose a perceptual evaluation technique which estimates the human-perceived realism of a terrain. Their approach categorizes geomorphology-based landform features (geomorphomns) such as valleys, hollows, and ridges and shows how the absence or presence of the features affects perceptual realism. Additionally, they use a generative deep neural network to analyse the distribution of the features with their perceived realism to create a metric which estimates how realistically a human would perceive the synthetic terrain. However, their approach has limitations. Geomorphons are limited to small terrain areas and may not accurately reflect the distributions of large features like rivers and valleys, leading to variability in perceived realism. Their approach assumed a constant illumination, camera angle and texturing, while these elements were purposefully constant, the approach does not consider variations in those elements. Additionally, certain terrains may achieve a low PRTM score as they lack variety in the geomorphons and may be perceived as unrealistic while the synthetic terrain is consistent with the underlying natural terrain. As stated in the paper, further work is aimed to resolve these issues.

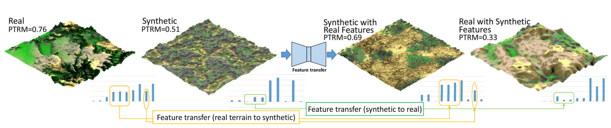



**Figure 7:** *Estimated PRTM of synthetic terrains [31]*

Argudo *et al.* [30] propose a method of evaluation for terrain synthesis that relies on techniques from orometry, focusing on the measurement of mountains and other relief features. They develop a sparse metric which is constructed based on peaks and saddles of mountain ranges. This metric is then employed with a synthesis method, which takes a coarse elevation map as input and builds a graph of peaks and saddles adhering to a specified orometric distribution. Based on a perceptual study, their result show that the terrain analysis and synthesis that incorporates orometric properties is more visually plausible than other terrain generation and methods [30] . However, limitations arise from the simplified assumptions regarding river paths and ridge formations, potentially leading to discrepancies between synthesized and real terrains, particularly in capturing local characteristics like ridge and valley profiles suggesting a need for deeper metrics to refine the synthesis process.

# 6 DISCUSSION

When considering a model's ability to generate terrain, it is important to analyze aspects of the evaluation to allow for a thorough comparison of the current models [11]. Variety describes the diversity of the landforms which is the result of complex geological factors; realism shows the geomorphological accuracy of the generated terrain through perceptual or quantitative analysis; scale entails the size and fidelity of the output; authoring is the technique to allow for effective user control over the terrain shape; and efficiency shows the computation complexity of the model to produce the terrain. These criteria form the basis of the discussion and evaluate how effective the model is at producing a synthetic terrain.

Procedural approaches to terrain generation [6, 8, 16] are limited by their ability to produce a low variety of landscapes as the terrain is generated based on parametric criteria. The variety of simulation-based approaches [3, 19, 26, 28] show their ability to reproduce geologically accurate terrains with different erosion simulations. They can model a variety of landforms and employ effective user control, however, the process of simulating erosion is computationally expensive with multiple iterative steps and is usually conformed to a smaller scale as a result of the performance requirements. Example-based methods have shown promise as they use data sampled from real-world exemplars in the form of digital elevation models to produce coherent terrain [11]. These models however are limited by the diversity and size of the input data.

Machine learning approaches are at the frontier of synthetic terrain generation and have shown improvements over previous models. Diffusion models [23] can replicate a variety of landforms through the denoising process of the input data to create semantic sketches. The preprocessing of the diffusion models requires high computational complexity, however, once the model is developed, it allows for real-time user authoring of the landscape. The framework implements an upscaling method to increase the fidelity of the produced synthetic terrain. However, after minor adjustments to the canvas flickering and inconsistent output could be seen although increasing the detail of the input sketch fixed the problem [23]. Conditional Generative Adversarial Networks using real-world exemplars have shown to be an effective machine-learning method for terrain generation. With the use of multiple terrain synthesizers, the cGAN model provides an intuitive control interface for users to create plausible terrain with a few brush strokes. The perceptual study performed by Gain *et al.* showed that their model outperformed the cGANs for plains and hills due to the well-defined erosion detail. The cGAN approach tended to produce small artefacts with close inspection [14].

## 7 CONCLUSIONS

While various methodologies exist for terrain representation, discrete height fields in the form of gridded digital elevation models remain the prominent underlying method for processing digital terrain. This is due to the simplicity and versatility of their application for example based methods of terrain generation.

Procedural modelling methodologies for terrain generation are phenomenological and aim at directly reproducing the effects of the phenomena. They construct the terrain from real-world observations without taking the real-world data as input. As such procedural methods do not conform to real-world attributes of terrain. Simulation of erosion techniques has shown promise in their application for synthetic terrain generation with the incorporation of real-world features, however, are computationally expensive as they prioritize the geologically accurate process.

Recent developments in machine learning algorithms, more specifically, diffusion models and Conditional Generative Adversarial Networks have shown success in their ability to produce custom realistic synthetic terrain while maintaining a high level of user authoring. The diffusion models use real-world exemplars paired with a real-time authoring technique to produce high-fidelity terrains. however perceptual user studies have shown users were able to differentiate between real terrains and the synthesized terrains showing that the terrains are not suitable for geological studies.

Advancements in synthetic terrain evaluation introduce a range of metrics for evaluating the perceptual realism of generated landscapes. The PRTM and orometric distribution evaluation techniques provide greater insight into the perceived realism of the terrain. However, the majority of studies into terrain generation lack statistically significant user perceptual studies. The avenues for evaluating the geomorphological accuracy of terrains remain restricted, warranting the need for additional research in this domain.

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