Adaptive Color Transfer From Images to Terrain Visualizations

Mingguang Wu, Yanjie Sun, and Shangjing Jiang

Abstract—Terrain mapping is not only dedicated to communicating how high or steep a landscape is but can also help to indicate how we feel about a place. However, crafting effective and expressive elevation colors is challenging for both nonexperts and experts. In this article, we present a two-step image-to-terrain color transfer method that can transfer color from arbitrary images to diverse terrain models. First, we present a new image color organization method that organizes discrete, irregular image colors into a continuous, regular color grid that facilitates a series of color operations, such as local and global searching, categorical color selection and sequential color interpolation. Second, we quantify a series of cartographic concerns about elevation color crafting, such as the “lower, higher” principle, color conventions, and aerial perspectives. We also define color similarity between images and terrain visualizations with aesthetic quality. We then mathematically formulate image-to-terrain color transfer as a dual-objective optimization problem and offer a heuristic searching method to solve the problem. Finally, we compare elevation colors from our method with a standard color scheme and a representative color scale generation tool based on four test terrains. The evaluations show that the elevation colors from the proposed method are most effective and that our results are visually favorable. We also showcase that our method can transfer emotion from images to terrain visualizations.

Index Terms—Elevation colors, color transfer, terrain visualization.

I. INTRODUCTION

In this paper, we present an automatic method to transfer color from arbitrary images to terrain visualizations, which can facilitate the creation of expressive terrain maps for both nonexperts and experts. With centuries of experience and innovation, cartographers have developed a series of methods to present terrain, such as profiles, form lines, contours, hillshades, and hachures [1], [2], [3], [4]. Among them, the color scale, also called elevation colors, is critical to make effective and vivid terrain visualizations. By matching colors with elevations, elevation zones can be identified; leveraging the color stereoscopic effect, the three-dimensional appearance can be enhanced (often with contours and hillshades) [5]. Elevation colors also play an important role in making terrain maps visually favorable.

Both naturalism and symbolism should be considered when crafting expressive elevation colors. Natural images, such as aerial photography, imitate the natural color of terrain, carrying an impression of reality, but the natural color of terrain may vary with weather conditions, seasons and/or observation times (e.g., sunrise or sunset). Generally, a constant natural color does not appear in a patch, much less in an elevation zone. Moreover, natural color may not always be effective for differentiation. For example, different elevation zones may fall into the same color, introducing confusion when using color differences to distinguish elevation. On the other hand, cartographers often select representative colors to symbolize elevation zones, such as green for lowlands and white for highlands. As terrain is geographically variable across space, which color is representative? It may depend on location and observers.

The diversity of both terrains and observers should be considered to make expressive terrain maps. Contemporarily, terrain maps no longer exist only in atlases or on wall maps, and they are also favored by nonexperts to narrate an experience using a landscape, e.g., making a story map of a wonderful road trip. In this case, not only elevation and terrain features (such as landform and slope) but also aesthetic and emotional aspects of the landscape should be addressed. Casey [6] stated that “such mapping concerns the way one experiences certain parts of the known world: the issue is no longer how to get there or just where there is in world-space, but how it feels to be there, with/in that very place or region”. Mapping experience is not a new concept. In practice, an observer’s point of view (e.g., looking up from low altitude or down from high altitude or at ground level) and distance from the landscape impact its visual impression. Accordingly, a series of principles, such as “the higher, the lighter”, “the richer in color, the nearer”, and aerial perspective, are suggested [3]. However, individuality, such as preference and emotional response to a landscape, is not considered when crafting elevation colors.

In this study, we focus on transferring color from images to terrain maps to make effective and expressive terrain visualizations. Color transfer refers to transferring the visual impact of the color of one image to another [7]. Because designing expressive colors from scratch is difficult, a common approach is to find an inspiration, such as a master’s painting or an impressive photograph. Considerable work has been done on transferring color from image to image in the field of computer graphics, such as neural network-based color methods [8], [9] (which will...
be further discussed in Section II-B). It also draws the attention of many cartographers. Wu, et al. [10] presented an adaptive method to transfer color from an image to a map; however, it is topologic map oriented. Computational image-to-terrain color transfer is not yet available.

To fill this gap, we present an adaptive method that can transfer color from arbitrary images to terrain visualizations. We implement our method; it is available as an open-source package distributed under the MIT License at https://doi.org/10.5281/zenodo.4727805 for reproduction and extension. The main contributions of our approach are as follows:

- For the first time, we refine the criteria for color transfer from images to terrain visualizations. We formulate the problem of color transfer as a dual-objective optimization problem by coupling a series of considerations for making elevation colors, such as “the higher, the lighter”, aerial perspective, and visual similarity between images and terrain visualizations.
- We present a hierarchical color grid to efficiently organize image colors, which can support the generation of categorical and sequential color maps through local adjustment and global exploration color operations.
- We conduct an evaluation with two comparative methods. The evaluation shows that the elevation colors from the proposed method are most effective and that our results are the most visually favorable. We also showcase that our method can transfer emotion from images to terrain visualizations.

In the following, we summarize related work on crafting elevation colors, color transfer and color scale generation in Section II. In Section III, we introduce an overview of the proposed method and then present the details of how to formulize and solve the problem. We evaluate our method in the fourth section. We discuss the advantages and limitations of the proposed method in the fifth section. Finally, we conclude the paper with a summary of the key contributions and outline future studies in Section VI.

II. RELATED WORK

Considerable work has been carried out on crafting elevation colors. Here, we summarize major principles on crafting elevation colors, and then we review available computational color transfer methods.

A. Principles of Elevation Colors

Continuity of Elevation: The natural continuity of elevation requires a corresponding continuity in elevation colors to be applied. Two opposite principles exist: “the higher, the darker” and “the higher, the lighter” [3]. “The higher, the lighter” can be interpreted as the natural result of diffuse lighting overhead (the sun). The closer an object is to the light source (the higher the altitude), the lighter it becomes [3]. Themes for low-layer zones (e.g., building and transportation) are often conventionally symbolized with saturated color, as they will become less readable if dark colors are applied as background or even worse when elevation colors are combined with shaded relief. In contrast, the “the higher, the darker” scheme keeps the lowland lighter, but mountainous regions will become darker overall and therefore lack a three-dimensional appearance [11]. In practice, these two principles may be combined for specific mapping contexts.

Color Conventions: Elevation colors can be assigned naturally according to the real landscape. However, the reality for an elevation zone may vary across space and over time. Instead, colors can be set up in a symbolic way, such as green for lowlands, yellow for mid-elevations, and white for highlands. Color conventions can be interpreted as a resonance between a color and a semantic meaning [12], such as greenish colors for fertile plains and white for snow [3], [11]. Semantically aware and associated colors can better facilitate visual communication [13], [14]. Color conventions are now widely accepted, especially in standardized topological maps.

However, conventional colors, as a one-size-fits-all strategy, may introduce misleading results [15]. For instance, a green lowland color in a dry desert and a red color in highlands rich in forests may confuse map readers [3]. Patterson and Jenny [11] designed environment-aware elevation colors, in which environmental factors, such as polar, humid, and arid conditions, are distinguished, anticipating computational methods that can weight and combine naturalism and symbolism.

Aerial Perspective: Due to dust and droplets in the atmosphere, light can be scattered, resulting in atmospheric haze over the landscape, which is called the aerial perspective [3]. Correspondingly, visual contrast may decrease with increasing distance. For elevation colors that consider the aerial perspective, closer elevation zones should be colorized with higher brightness and color contrast [16].

Many approaches are now available to make aerial perspectives with reliefs, such as luminance adjustments [17], [18], elevation masks [19], and neural networks [20].

Esthetics: Visual pleasure is constructive to an object’s value as a creation but not in a rational and functional way in terms of practical use (e.g., identification tasks). Imhof [3] observed that “the greatest clarity, the greatest power of expression, balance and simplicity are concurrent with beauty”. Ideally, similar to other types of visual works, terrain maps should be esthetically colorized for reading and be visually pleasing.

Elevation colors therefore should be compatible. There are well-accepted principles for crafting compatible color schemes, such as rule-based (e.g., Mansell’s four rules on color harmony [21]), distance-based [22], template-based (e.g., Matsuda’s eight templates on a color wheel [23]), and learning-based models [24]. Color esthetics are also dominated by preference, which may vary by individual, age, gender, and/or nation and over time.

Emotion: While colors can encode semantic meaning [25], [26], colors can also carry affective connotations [27], [28]. Map colors can be operationalized to evoke specific emotions when reading the map [29]. More specifically, while emotionally consistent colors amplify the impact of map themes, emotional inconsistencies can confuse map readers (Anderson [30]). For
B. Color Transfer

Color transfer refers to the process of imposing the color characteristics of one image onto another [31]. Existing image-to-image color transfer methods can be grouped into three categories: statistical-based [31], [32], [33], content-based [34], [35], and neural network-based [7], [8], [36] methods.

In the first group, an image’s color appearance is characterized as a series of statistical color factors, such as the mean and deviation [31] and histogram [32], [33]. Then, color transfer is conducted to statistically match those factors between images. These global statistical factors may be too general for a given image, such that local characteristics (such as contrast and topology) cannot be preserved well. Since image content is not explicitly modeled, mismatching on semantics may be largely introduced.

In the second group, image content is detected and then matched. Greenfield and House [37] segment an image into regions according to the color similarity among pixels. A representative color with the proportion of each segment can then be detected. By establishing representative color matching between the reference and target images, chromatic content can be preserved. Generally, Greenfield and House [37] is limited in nonphotorealistic images. Wu, et al. [35] segmented images into regions using scene analysis (such as sky, buildings, and vertical layout) according to the clarity of the image content. Matching those regions, color transfer with visual coherence can be achieved. Additional constants, such as saliency, can be further incorporated to enable more sophisticated color matching [38]. While content is addressed well in this group, discussion on the style of the reference (e.g., tone and esthetic quality) is lacking.

Both style and content are considered in neural network-based methods. Convolutional neural networks (CNNs) are introduced to extract image characteristics and conduct style transfer (including color) between images [7]. In this method, a deep neural network with multiple hidden layers is trained to represent the hierarchical information of an image, from low-level pixel values to high-level objects and their arrangement, called content. In addition to content, texture information can also be obtained by using a Gram matrix, which indicates the feature correlation of multiple layers, called style. The content of the target image and style of the reference image can then be weighed and synthesized to make a restyled image.

While learning an adaptive loss function to balance diverse styles and image content is challenging for CNNs, Isola, et al. [8] use a generative adversarial network (GAN) to recolor an image. A GAN introduces a classifier to guide loss learning (such as an output image that cannot be blurry) to adapt to data. A series of tools are now available to conduct image-to-image style transfer, such as pix2pix for paired training data [8] and CycleGAN for unpaired training data [36].

There are few existing studies on color or style transfer in terrain mapping. Bratkova, et al. [39] proposed an algorithm for automatically generating panoramic maps, in which two artist-cartographer color styles (e.g., base colors and brush-stroke colors) are analyzed and algorithmically applied to a terrain. Jenny and Jenny [40] proposed an example-based texture synthesis method to transfer the appearance of a hand-painted panorama to a digital panorama map. Recently, Jenny, et al. [20] trained a deep neural network using manual relief shading images as samples. The result can transfer trained Swiss style to digital elevation models with high quality. However, elevation colors have not yet been considered. For cartographic color transfer, Wu, et al. [10] reported an algorithm that can extract color palates from paintings and photos and then assign them to discrete cartographic features, such as roads, rivers and parcels. It can also compose a sequential color scheme, but incorporating the terrain model and the concerns are not discussed.

C. Color Scale Generation

Considerable efforts have been made on color scale generation, such as rule-based and data-driven methods. Rule-based methods use color design rules, such as discrimination, uniformity, and smoothness [41], to create a color scale. Wu et al. [42] treated color scale generation as a constrained search problem in a continuous color space; they also proposed a heuristic algorithm to craft color scales.

Data-driven-based methods focus on learning the color scale from existing visualizations. Yuan et al. [43] proposed a deep learning-based method to automatically extract color scales from visualizations.

Many color scale generation tools are now available, such as ColorBrewer [44], which provides a set of predefined color maps for qualitative and quantitative data; Charting Continuous Colormaps (CCC-Tool) [45], which can help to interactively design continuous color scales; ColorCrafter [46], which can automatically create color scales from a single seed color; and ColorLoom[47], which specifies reference images rather than colors and can extract dominant colors as a palette from the reference image, then interactively adjust the color and interpolate to achieve continuous color scales. However, for color transfer, visual similarity and the correspondence between the color scale and terrain have not yet been considered.

To date, there is no method that can transfer color from arbitrary images to terrain maps with consideration of the principles. Systematically operationalizing the above concerns remains challenging.

III. Method

A. Overview

We aim to generate elevation colors from arbitrary images for diverse terrain models. Artists and photographers may have already captured expressive visual experiences on diverse landscapes. We believe that paintings and photos of landscapes can
provide inspiration to craft high-quality elevation colors. In this study, we extract expressive colors from any image type and then apply them to terrains. Elevation colors can be applied in hillshades, and they can be used to color illuminated contours and as triangular irregular networks (TINs). In this study, three types of terrain representations are considered: hillshades, TINs and illuminated contours (see Fig. 1 for the differentiation of those three types of models).

We also aim to computationally automate color transfer for both nonexperts and experts. Nonexperts may not have enough knowledge or skill to address the concerns; it is also time- and effort-consuming for experts to weigh and compromise the above concerns. We provide an automatic color transfer method for both: nonexperts can pick up the resulting colors directly without any prior knowledge on terrain mapping, and experts can customize the process to generate a series of candidates.

Fig. 1 shows our two-step method. First, for a given image, we extract salient colors. We then organize the extracted colors into a hierarchical color grid for further color operations. Second, we search the color grid according to cartographic and aesthetic concerns and output satisfying colors in graded or continuous mode. As mentioned in Section IV-A, affective response is also a major concern when mapping landscape experience. As emotion is sensitive to diverse factors, such as content and texture, we do not quantify emotional facts in our model. However, we explicitly quantify the visual similarity between the reference image and the resulting terrain maps. We aim to achieve higher color similarity, hoping to transfer emotion from the reference image and the resulting terrain maps. We aim to achieve higher color similarity, hoping to transfer emotion from the reference image and the resulting terrain maps. Our image color organization consists of three consequent steps: 1) salient color extraction, 2) structurization and 3) dominant color identification.

Salient Color Extraction: We consider two types of elevation colors: a graded color scheme, which consists of distinct colors with noticeable color intervals, and a continuous color scheme with smooth color transitions. The second can be considered a derivation of the first using color interpolation. We therefore extract salient colors and then interpolate them if needed. To transfer color to maps, Wu, et al. [10] separate images into blobs, edges, patches and backgrounds according to the changing intensity and visual saliency. While the features in a map are discrete and abruptly change, the terrain is continuous. Furthermore, a landscape painting or photo may not embody clear figure-ground separation (e.g., the areal perspective effort). We therefore do not separate figures from the ground but extract color patches with relatively high saliency. A series of methods are available to measure an image’s saliency. Among them, the Zhu, et al. [48] method is adaptive to diverse image content. We therefore use it to extract visually continuous color blocks, as shown in Fig. 2(b).

While trivial colors are reduced by selecting only salient colors, the remaining colors remain visually indiscriminating with noticeable color distances. We select $M$ visually distinguishable colors from the extracted salient colors using $k$-means; the color proportion of color $i (0 < i < M)$ is accumulated through all colors in the $i$-th cluster.

Structurization: As shown in Fig. 2(b), similar to an image’s color gamut, salient colors distributed across a three-dimensional space are extracted, which is challenging for both brute-force and heuristic searching. We use the self-organizing map (SOM) algorithm [49] to organize them into a two-dimensional space (hereafter called the color grid). The SOM algorithm is a two-layer unsupervised neural network algorithm. Applying competitive learning, it can produce a nonlinear mapping from the $D$-dimensional space to an $F$-dimensional ($D$ is often lower than $F$) grid of weight nodes. Compared with the general dimensional-reduction method, the SOM algorithm can preserve the topological structure of the input samples.
We train the SOM network by iteratively adjusting the node weight according to its distance to the extracted colors in CIELab color space; we use the winner-takes-all strategy to update the weights: a node’s weight was assigned to the color value of the closest input color. Then, a \( w \times w \) color grid can be obtained, in which all color node weights at each cell come from the above distinguishable colors. In this manner, discrete distinguishable colors in three-dimensional CIELab are organized into a continuous two-dimensional grid. Benefiting from the SOM algorithm, topology (such as adjacency) among distinguishable colors is persevered well in the color grid.

**Dominant Color Identification:** In addition to topology, color category and tone also need to be compromised among the concerns. For example, visual perception may be guided by color category; affective response is much more likely to be associated with color tones. We further segment the color grid into regions. The central point in each region is determined as a dominant color. Here, we choose the hierarchical clustering algorithm to segment a color grid with dominant color identification. To avoid the parameter sensitivity caused by directly specifying the count of clusters, we use a just noticeable color distance (JNCD) threshold to conduct bottom-up hierarchical clustering. If the count of clustered regions is much greater than the count of the needed color category, then we further cluster those regions by using two times the JNCD threshold. Clustering can be continued with an increased clustering threshold until we obtain the proper number of dominant colors. As shown in Fig. 2(d), after clustering twice, we obtain three dominant colors in a two-layer color grid.

Our image color organization is able to facilitate both brute-force and heuristic color searching. Local color adjustment can be executed within a region. For example, in Fig. 3, if \( c_1 \) is assigned to represent lowland, according to color conventions (e.g., green for lowland, blue for the sea), \( c_1 \) generally matches the elevation zone in terms of green hue, but it is too dark according to the “the lower, the lighter” principle. Then, a similar but lighter color, \( c_2 \), can be found around \( c_1 \). If \( c_1 \) is assigned to represent the sea, it breaks the color conventions. Local adjustment cannot possibly meet the need because all surrounding colors are greenish. In this case, global exploration is needed, which shifts to a distant color region for searching. Jumping to another candidate color, such as \( c_4 \), color conventions can be weighted again. In this manner, our color grid can facilitate both local and global searching.

Our image color organization is also able to facilitate making two primitive types of elevation colors: categorical and sequential. The categorical scheme embodies hue differences, which help to distinguish different elevation zones; the categorical scheme can be picked up from different grid regions. For example, a three-color scheme can be found by sampling three distant regions (see Fig. 3(b)). Encoding smooth changes on evaluations, a sequential color scheme can be generated by interpolating two colors from two different grid regions. For example, as shown in Fig. 3(b), a green-gray sequential scheme can be sampled by using \( c_1 \) and \( c_3 \), and a green gray-blue scheme can also be made by using continuous interpolation among \( c_1, c_3 \) and \( c_4 \).

In general, existing color palate extraction methods are primarily dedicated to color selection by hand, and our color grid is designed to facilitate color computation. In the following section, we further introduce how to make expressive elevation colors with the compromise of the aforementioned concerns with the color grid.

### C. Relief Color Compromise

Similarly, making the results resemble the references is a widely used evaluation criterion among current color transfer methods (e.g., histogram and semantic matching and loss in CNNs). Gatys, et al. [7] noted that the criteria of similarity are “neither mathematically precise nor universally agreed upon”. For elevation colors, Imhof [3] noted: “Objective considerations alone have not always been the deciding factors. Tradition, partiality and whim, preconceived opinions, esthetic sensitivity or barbarity of taste often play leading roles in the selection of colors.” We therefore refine the evaluation criteria as follows. We group all concerns mentioned in Section II-B into two categories: first, cartographic concerns, including continuity, aerial perspective and color conventions; and second, visual similarity with esthetic quality. We do not explicitly encode affective concern, but we hope to provoke a similar affective response between the terrain visualization and the reference image. We discuss these two criteria in detail.

1) **Operationalization of Cartographic Concerns. Continuity:** Both luminance and saturation are effective depth cues for the human visual system [50], [51]. Here, we use the goodness of fit of both luminance and saturation to measure the continuous variation in elevation color \( C \), denoted as \( f_g(C) \), as follows:

\[
\begin{align*}
    f_g(C) &= R^2(L(C,L)) \ast R^2(L(C,ch_{ab}^*) \ast f_L(t)) \\
    f_L(t) &= \begin{cases} 
    1 & \text{if } a_{k,C,L} \ast t > 0 \quad k = 1, 2, 3 \text{ and } t = 1, -1 \\
    0 & \text{otherwise}
    \end{cases}
\end{align*}
\]

where \( C = (c_1, c_2, \ldots, c_k) \), \( c_i \) is the color for elevation zone \( i \), \( n \) is the color amount in \( C \), \( R^2(y) \) is the goodness of fit in the \( k \)-degree polynomial fit \( \sum_{m=0}^{k} a_m x^m, x = [1, 2, \ldots n]^T \),
f_i(t) is the correction function of luminance change, and t is the correction factor. Considering device independence and perceptual uniformity, all color computations here are performed in the CIELab space; C_i L is the luminance component of C_i and

\[ C_i \Delta E_{ab}^* = \sqrt{\Delta L^2 + \Delta a^2 + \Delta b^2} \]

is the color chromaticity of C_i. k can be 1, 2, or 3, representing monotonic, dichromatic and polychromatic, respectively. When t = 1, f_i(t) reflects "the higher, the darker" principle, and conversely, -1 reflects "the higher, the lighter" principle.

Aerial Perspective: The aerial perspective suggests a decrease in color contrast with increasing distance. Here, we understand it as the monotonicity of the color difference, denoted as \( f_{ap}(C) \), which is as follows:

\[
f_{ap}(C) = \begin{cases} 
\frac{\sum_{i=1}^{n} \max(0, \Delta E_{ab}^{*}(c_{i}))}{\sum |\Delta E_{ab}^{*}(c_{i})|} & \text{if } C \text{ follow aerial perspective} \\
1 & \text{otherwise}
\end{cases}
\]

\[
\Delta E_{ab}^{*}(c_{i}) = \Delta E_{ab}^{*}(c_{i+1}, c_{i}) - \Delta E_{ab}^{*}(c_{i}, c_{i-1})
\]

(2)

where \( \Delta E_{ab}^{*} \) is the Euclidean distance between two colors in CIELab.

Color Conventions: We quantify the color convention as the degree of shifting from a ‘standard’ color for an elevation zone i as follows:

\[
f_c(c_i) = \begin{cases} 
\min(1.0, \gamma/\Delta E_{ab}^{*}(c_{i}, c'_{i})) & \text{if } c_{i'} \text{ follow a color convention} \\
0 & \text{otherwise}
\end{cases}
\]

(3)

where \( c_{i'} \) is the conventional color of elevation zone i, and \( \gamma \) is the color distance threshold respecting the color convention. The total scores of respecting color conventions for all elevation colors C can be denoted as:

\[
f_c(C) = \frac{1}{m} \sum_i f_c(c_i)
\]

(4)

As above, we operationalize three cartographic concerns, \( F_r(C) \), by multiple \( f_g, f_s \) and \( f_c(C) \). As all three components are normalized, \( F_r(C) \) ranges from 0 to 1.

2) Definition of Similarity With Esthetic Quality: We quantify the overall color similarity between an image and elevation as their color alignment to the identified dominant colors. Histograms are widely used to quantify color similarity between images. Since a terrain map’s color proportion may be dramatically different from that of the reference image, overfitting of histogram matching is inevitable. Since key elevation colors all come from a reference, we quantify color similarity as the alignment of elevation colors to an image’s dominant colors with consideration of their proportions. An image’s color distribution is measured as N dominant colors. For each dominant color, its proportion is accumulated over all the colors sharing the same region in the color grid. On the other hand, we anchor all elevation colors to dominant colors; the proportion of a dominant color is accumulated through all discrete colors in the graded color scheme and along the interpolation in the continuous color scheme. Since elevation colors may not be the dominant colors, we weigh their proportion according to their inverse distance to the dominant color. In this manner, all elevation colors are aligned to the dominant color with weighted proportion. The overall color similarity between the image and elevation colors can be measured as the degree of their alignment as follows:

\[
f_s(C) = \sum_{i=1}^{n} \min\left(1.0, \frac{\Delta E_{ab}^{*}(c_{i}, c_{i,j})}{|\Delta E_{ab}^{*}(c_{i})|}\right)
\]

\[
P_{j}^{map} = \sum_{j} P_{j}^{map} \cdot \frac{\alpha}{1.0 + \Delta E_{ab}^{*}(c_{i,j}, c_{i,j}^{\text{image}})}
\]

(5)

where \( P_{j}^{image} \) is the proportion of the i-th dominant color in the reference image; \( P_{j}^{map} \) is the weighted proportion of the j-th dominant color in the elevation colors; j is the j-th color whose dominant color is i; \( P_{j}^{map} \) is its proportion; and \( \alpha \) is a color distance threshold.

Color similarity plays a dual role in our model. First, color can influence human perception through both emotional responses and associative connotations [52], [53], and we hope to use similar colors to provoke similar emotions. Second, we assume that the input reference is favorable to the users, and similar colors will therefore accommodate the user’s color preference.

In addition to color preference, color harmony is a major aspect of esthetic quality. We do not restrict that the reference should be perfect, but we hope to derive elevation colors with harmony. We therefore explicitly score color harmony. Several attempts have been made to generalize rules for color harmony, such as the principles of color similarity [54], [55] and color contrast [56]. Here, we use Kita and Miyata [57] to assess the harmony of elevation colors, denoted as \( \text{Harmony}(C) \). This method employs a regression model to rate color harmony by utilizing high-dimensional color features from a large dataset. These features include color proximity and contrast features and are not limited by the number of colors. The overall similarity with esthetic quality, \( F_a(C) \), is quantified as follows:

\[
F_a(C) = f_s(C) \cdot \text{Harmony}(C)
\]

(6)

We normalize the score on color harmony. Since color similarity is also normalized, the overall similarity with esthetic quality also ranges from 0 to 1.

Since only elevation and area are needed, our model supports diverse terrain models, such as a digital elevation model (DEM), TIN, and contours: elevation can be derived from a grid, triangle, or contour; area can be calculated according to the amount of the grid or triangle or the coverage of the contour that falls into the elevation zone.

3) Problem Solving: Based on the above scoring of subjective concerns and esthetic quality, we formulize the color transfer problem as a dual-objective optimization problem, maximizing both \( F_r(C) \) and \( F_a(C) \). In addition to the above two objectives, constraints could be added optionally. For example, if graded elevation colors are desired, then a color discrimination constraint should be added to ensure that all colors are mutually distinguishable.

Color transfer from images to terrain maps is now formulized as a MAX-MAX problem. All objectives and constraints are clearly defined, and both \( F_r(C) \) and \( F_a(C) \) are normalized. All color variables are limited in a color grid, which can be solved
using existing dual-objective optimization methods, such as an artificial bee colony (ABC) [58] or evolutionary algorithm [59], with a series of color operations, such as local and global searching supported by a color grid. Note that dual-objective optimization often has a set of solutions in which one is not superior to another. These nondominated solution sets are mathematically called the Pareto frontier. Following the Wu, et al. [10] sampling strategy, we treat the midpoint of the Pareto frontier as the balanced solution in terms of the score on cartographic concerns and similarity with esthetic quality. The Pareto frontier can also be sampled to yield a series of satisfying solutions that may be favorable by experts. For example, to make seasonal terrain maps for a national park that exhibits an attractive valley for public tourists, a fantastic landscape painting from an artist is available by the designer as an inspiration. In this case, cartographic concerns would be partly compromised. An optimum similarity with esthetic quality may be desired to engage audiences.

IV. IMPLEMENTATION AND EVALUATION

A. Implementation With Examples

We purposefully sampled four typical terrains to test our method, including a ridge, a canyon, a crater, and a mountain (see Fig. 4). All four terrains are gathered in DEM data format. Our method does not require color input at all. We color them using a standard color scheme from the 1962 International Map of the World for further comparison, and we extract the colors from Patterson and Jenny (2011). These four terrains can be colored with either graded or continuous elevation colors; to test both types of elevation colors, the ridge and the canyon are colored with continuous colors, and the crater and the mountain are assigned graded colors.

To our knowledge, there is no counterpart method that can adaptively transfer color from images to terrain visualizations. Instead, we compare our method with the color scale generation method. From the discussion in Section II-C, Samsel’s ColorLoom tool [47] can extract dominant colors from images and create a continuous color scale; it has been applied to environmental data visualization. Therefore, we select Samsel’s ColorLoom tool for comparison.

Ten reference images are sampled via an image searching engine by using “landscape” as the key word. Five natural landscape photos and five paintings are collected, which are shown in Fig. 5. Other types of images can also be candidates (see Section V for further discussion).

We implement our method in the C++ programming language; the source code and the test data can be found at https://doi.org/10.5281/zenodo.6509472. The involved parameters are assigned as follows across sample terrains and reference images: in Formula (1), $t = 1$ means the colors follow the “the higher, the darker” principle; in Formula (3), $\gamma = 10$ (an average color distance threshold for color conventions); and in Formula (5), $\alpha = 10$ (an average color distance threshold for dominant colors). Considering the specific elevation range and location, the mountain and canyon are colored with multihued colors, and the degree of polynomial for quantifying continuity ($k$) is set to 3. The crater and ridge are assigned dichromatic colors, and $k = 2$. The results of the color transfer from reference a and reference b to the four terrains are shown in Fig. 6.

We use the canyon terrain and reference painting c to test our method’s performance on supporting continuity. By setting $t$ to 1 and $-1$, respectively, “the higher, the lighter” (see Fig. 7(c)) and “the higher, the darker” (see Fig. 7(d)) can be obtained. The ColorLoom tool does not explicitly support this principle Fig. 7(b).

We use the ridge terrain and reference photo d to show the performance on supporting color conventions. The ridge is in the subtropical seasonal climate zone in China, where grassland and forest grow. Therefore, we assign the lowland a green color. The ColorLoom tool does not explicitly support color convention Fig. 8(b). Our results are shown in Fig. 8(c). For comparison, we also provide the result without color convention assignment Fig. 8(d). Benefiting from our dual-objective optimization, both results are similar to the reference. While Fig. 8(d) looks dusty, Fig. 8(c) appears greenish, which is more coherent with the real landscape.

We also employ the mountain terrain and reference e to investigate our method’s ability to make aerial perspective efforts. An aerial perspective effort can be made on color or hillshade.
Fig. 6. Results of our color transfer method and ColorLoom with the four terrains; (a) using reference a; (b) using reference b.

Fig. 7. Performance on continuity (a) reference image c, (b) result of ColorLoom, (c) result of our method by applying “the higher, the lighter” principle, \( t = 1 \) and (d) result of our method by applying “the higher, the darker” principle, \( t = -1 \).

We make two gray hillshades on the mountain terrain, with and without an aerial perspective (see Fig. 9(e) and (f)). We overlap our result with the aerial perspective in Fig. 9(e) and (f) for comparison (see Fig. 9(c) and (d)). This shows that elevation colors with areal perspective effort from our method can help to enhance the “the farther, the less contrast” principle. Fig. 9(b) shows the result from ColorLoom, which does not explicitly support aerial perspectives.
Finally, we use the crater terrain and reference painting f to investigate the performance on diverse terrain models. We derive the TIN and contours from the DEM data and then identify elevation zones and calculate the corresponding area from them. The results of the shaded TIN and illuminated contour are shown in Fig. 10(a) and (b). For hillshade from the DEM, multidirectional hillshade is common, but feature-enhanced hillshade (such as aspect and curvature) is also widely used in practice. We overlap our result with a multidirectional hillshade (see Fig. 10(e)) and a curvature-enhanced hillshade (see Fig. 10(f)). They share a visual appearance similar to that of the reference.

**B. Evaluation**

We compared the output color scheme from our method with the standard scheme and the ColorLoom method. We design three tasks to examine their performance in terms of efficiency. We used one questionnaire for esthetic quality and one questionnaire for affective response. We describe the materials, the participants, the procedure, and the results as follows.

1) **Materials:** We select four reference images for each test terrain. As shown in Fig. 6, we use photo and painting b as two common references. We further use photos d and g for Terrain A, painting c and photo h for Terrain B, paintings f and i for Terrain C, and painting e and photo j for Terrain D. In total, we make four styled terrains for each test terrain. The first three are shown in Figs. 5, 6, 7, and 8. The fourth for each test terrain can be found in Fig. 11. To avoid color distortion between displaying devices, all materials are displayed on a desktop computer with a screen resolution of 1920 × 1080 pixels in a distraction-free room.

2) **Procedure:** We design three tasks to evaluate the cartographic quality: identify, locate, and compare (see Fig. 12). For the *identify* task, we asked participants to identify the elevation
zone of three test points; nine elevation zones are given in the legend. For the location task, we asked participants to point out which side of the highlighted region (i.e., east, south, west, or north) is the lowland. For the comparison task, participants were asked to compare the elevations of three points. All testing points and regions are systematically sampled according to partitioning of the whole terrain to ensure that they have different elevations. We use the same testing point and regions for both comparisons. Participants were asked to choose the correct answer from three options for each task. All answers are assessed in a binary manner: correct or incorrect. Then, the accuracy of the rate of correct answers can be calculated.

We designed a questionnaire to evaluate esthetic quality:

**Question 1:** At which level do you agree that the color relief is visually pleasing?

Seven-point scales are used to record participant feedback, from 1 (totally disagree) to 7 (strongly agree).

We also designed a questionnaire to investigate affective response. Here, we use the hourglass emotion model, which distinguishes four dimensions of emotion: introspection, temper, attitude and sensitivity [60]. Before scoring, we explained these four dimensions to all participants with the four emotion pairs derived from [60]: sadness-joy for introspection; anger-calmness for temper; disgust-pleasantness for attitude; and anger-eagerness for sensitivity. For each dimension, five levels of response were designed in this evaluation.

We then asked the following:

**Question 2:** At which level is your affective response to the given material?

Four dimensions are scored separately. To determine whether the emotion embedded in the reference image is transferred, we also invite participants to score their response on the reference, but we do not inform them which color relief is transferred from which reference.

Furthermore, we believe that in addition to color, many other factors will impact an observer’s affective response, so we also asked them the following question after they scored the materials:

**Question 3:** Which of the following factors impact your affective response when scoring the terrains and references?

Participants were asked to choose at least one and up to three of six factors, including content, form, texture, color, background, and others.

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**Table I**

| Task | Factor     | Estimate | SE | p-value  | Cohen’s d |
|------|------------|----------|----|----------|-----------|
| Identify | Method type | -0.040 | 0.011 | 0.000* | 1.774 |
|       | Terrain    | 0.000    | 0.008 | 1.000  | 1.932 |
| Locate | Method type | -0.060 | 0.022 | 0.006* | 1.792 |
|       | Terrain    | 0.020    | 0.016 | 0.209  | 1.957 |
| Compare | Method type | -0.035 | 0.015 | 0.021* | 1.754 |
|       | Terrain    | 0.009    | 0.011 | 0.398  | 1.921 |

*SE = standard error.

*Difference is significant (p < 0.05).*

**Table II**

| Task | Factor     | Estimate | SE  | p-value  | Cohen’s d |
|------|------------|----------|-----|----------|-----------|
| Identify | Method type | 2.008    | 0.628 | 0.001* | 3.524 |
|       | Terrain    | -4.244   | 0.459 | 0.000* | 3.445 |
| Locate | Method type | 1.390    | 0.337 | 0.000* | 2.598 |
|       | Terrain    | -0.877   | 0.305 | 0.004* | 2.444 |
| Compare | Method type | 1.314    | 0.447 | 0.003* | 2.685 |
|       | Terrain    | -1.216   | 0.363 | 0.001* | 2.566 |

*SE = standard error.

*Difference is significant (p < 0.05).*

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We recruited volunteer students of geography or cartography majors at the authors’ college to conduct the evaluation. First, we excluded those with familiarity with the four terrains, such as those who had traveled to or read terrain maps in the pertinent areas. Then, participants were given a color vision deficiency (CVD) test with 12 Ishihara plates. We excluded those whose accuracy was lower than 94%. In total, 135 participants (73 male and 62 females, ages from 21 to 27) were enrolled. Then, seventy-five of these participants read four terrain maps: terrain maps in a standard color scheme, in colors from ColorLoom tools and from our method (randomly selected for each participant). We recorded the accuracy and the response time for the three tasks on each terrain visualization.

To avoid excessive answer time causing fatigue, the remaining 60 participants were asked to complete the three questionnaires. We invited them to score the esthetic quality first and then the affective response. To avoid being impacted by the last review, we show a blank page to them before reading any piece of material. After the experiment, each participant received a reward of 10 CNY. All participants gave informed consent, and the protocol was reviewed and approved by the university’s institutional review board.

3) Results: First, we used a linear mixed effects model to analyze the independent effects of method type and terrain type on the results. The results of the mixed linear model for accuracy are shown in Table I. The results show that method type has a significant impact (p value < 0.05) and large effect size (Cohen’s d > 0.8) on accuracy, while the impact of terrain type is not significant. The results of the mixed linear model for time taken are shown in Table II, which shows that both method type and
terrain type independently have a significant impact on time taken.

Then, we used Bonferroni-corrected multiple comparisons to analyze the differences in method types across four terrains. The results of multiple accuracy comparisons are shown in Table III. It shows that there is a slight difference in accuracy between our terrains and the standard terrains, suggesting that our terrains can work as well as the standard. Note that most cases (9 out of 12) are higher than the standard, suggesting that our results are occasionally better than the standard. Our results generally achieved higher accuracy than ColorLoom: 4 (out of 12) passed the significance test ($p$-value < 0.05) and had a medium effect size (Cohen’s $d$ > 0.5).

The statistical results of the time taken are shown in Table IV. Similar to the accuracy performance, Table IV suggests that our stylized terrains and the standard terrains are at the same effectiveness level. Our method performed better in 2 cases (out of 12). In addition, participants work more efficiently with our results than with ColorLoom’s results: 7 tests (out of 12) are statistically significant ($p$-value < 0.05) and have a large negative effect size (Cohen’s $d$ < −0.7).

Generally, the above preliminary results show that our stylized terrains are not inferior to standard terrains. Benefiting from the high quality of the references, our terrains are more effective than standard terrains.

### Table III

**Bonferroni-Corrected Multiple Comparisons for Accuracy on the Tasks**

| Terrain | Method | Differences | $M$ | $SE$ | p-value | Cohen’s $d$ |
|---------|--------|-------------|-----|------|---------|-------------|
| Identify | A | Our | 0.040 | 0.045 | 1.000 | 0.288 |
| | | Std | 0.066 | 0.045 | 0.446 | 0.449 |
| | B | Our | -0.013 | 0.042 | 1.000 | -0.283 |
| | | Std | 0.106 | 0.041 | 0.044* | 0.578 |
| | C | Our | 0.093 | 0.042 | 0.071 | 0.605 |
| | | Std | 0.026 | 0.042 | 1.000 | 0.283 |
| | D | Our | 0.026 | 0.042 | 1.000 | 0.283 |
| | | Std | 0.120 | 0.047 | 0.036* | 0.672 |

**Locate**

| Terrain | Method | Differences | $M$ | $SE$ | p-value | Cohen’s $d$ |
|---------|--------|-------------|-----|------|---------|-------------|
| A | Our | 0.120 | 0.112 | 0.857 | 0.310 |
| | Std | 0.080 | 0.112 | 1.000 | 0.215 |
| B | Our | 0.040 | 0.078 | 1.000 | 0.166 |
| | Std | 0.080 | 0.078 | 0.921 | 0.292 |
| C | Our | 0.040 | 0.056 | 1.000 | 0.283 |
| | Std | 0.080 | 0.056 | 0.467 | 0.409 |
| D | Our | 0.160 | 0.094 | 0.277 | 0.605 |
| | Std | 0.240 | 0.094 | 0.038* | 0.779 |

| Compare | A | Our | 0.040 | 0.069 | 1.000 | 0.283 |
| | Std | 0.200 | 0.074 | 0.026* | 0.693 |
| B | Our | 0.000 | 0.057 | 1.000 | 0.000 |
| | Std | 0.000 | 0.057 | 1.000 | 0.000 |
| C | Our | -0.040 | 0.046 | 1.000 | -0.283 |
| | Std | 0.000 | 0.046 | 1.000 | 0.000 |
| D | Our | 0.080 | 0.064 | 0.645 | 0.409 |
| | Std | 0.040 | 0.056 | 1.000 | 0.409 |

$M = \text{mean, } SE = \text{standard error}$.

Std = standard terrain, CL = ColorLoom, Our = our method

*Difference is significant ($p$ < 0.05).

### Table IV

**Bonferroni-Corrected Multiple Comparisons for the Time Taken in Seconds to Complete the Tasks**

| Terrain | Method | Differences | $M$ | $SE$ | p-value | Cohen’s $d$ |
|---------|--------|-------------|-----|------|---------|-------------|
| Identify | A | Our | -3.524 | 3.275 | 0.857 | -0.329 |
| | Std | -8.860 | 3.275 | 0.026* | -0.774 |
| B | Our | 0.032 | 2.222 | 1.000 | 0.005 |
| | Std | -5.772 | 2.222 | 0.034* | -0.746 |
| C | Our | -0.140 | 1.868 | 1.000 | -0.019 |
| | Std | -0.964 | 1.868 | 1.000 | -0.171 |
| D | Our | -0.112 | 1.765 | 1.000 | -0.017 |
| | Std | -0.472 | 1.765 | 1.000 | -0.094 |

**Locate**

| Terrain | Method | Differences | $M$ | $SE$ | p-value | Cohen’s $d$ |
|---------|--------|-------------|-----|------|---------|-------------|
| A | Our | 3.000 | 1.464 | 0.132 | -0.506 |
| | Std | -0.994 | 1.464 | 1.000 | -0.207 |
| B | Our | -1.008 | 0.857 | 0.730 | -0.328 |
| | Std | -2.744 | 0.857 | 0.006* | -0.915 |
| C | Our | 0.032 | 0.816 | 1.000 | -0.051 |
| | Std | -2.520 | 0.816 | 0.009* | -0.875 |
| D | Our | -4.828 | 1.957 | 0.048* | -0.709 |
| | Std | -4.916 | 1.957 | 0.043* | -0.895 |

| Compare | A | Our | 0.476 | 3.056 | 1.000 | 0.037 |
| | Std | -1.764 | 3.056 | 1.000 | -0.153 |
| B | Our | -2.760 | 1.059 | 0.034* | -0.649 |
| | Std | -2.956 | 1.059 | 0.020* | -1.054 |
| C | Our | -0.108 | 1.323 | 1.000 | -0.022 |
| | Std | -2.796 | 1.323 | 0.114 | -0.941 |
| D | Our | -0.396 | 1.255 | 1.000 | -0.079 |
| | Std | -3.236 | 1.289 | 0.043* | -0.712 |

$M = \text{mean, } SE = \text{standard error}$.

Std = standard terrain, CL = ColorLoom, Our = our method

*Difference is significant ($p$ < 0.05).

Fig. 13. Correlation difference of affective response between our method and ColorLoom with standard terrains.

The results of the evaluation of esthetic quality are shown in Table V. The results suggest that our results are more esthetically favorable: 15 tests (out of 16) are statistically significant ($p$ value < 0.05) compared with standard terrains, and 8 tests (out of 16) are statistically significant ($p$ value < 0.05) compared with ColorLoom results.

We used correlation analysis to validate the overall effectiveness of our method in affective response. Fig. 13 illustrates the correlation difference between our method and ColorLoom with standard terrains.
TABLE V
BONFERRONI-CORRECTED MULTIPLE COMPARISONS FOR THE SCORES ON ESTHETICS

| Terrain | Reference | Method | Differences | M       | SE      | p-value | Cohen's d |
|---------|-----------|--------|-------------|---------|---------|---------|------------|
| A       | a         | Our    | -2.050      | 0.252   | 0.000*  | -1.509  |
|         |           | Std    | -1.433      | 0.252   | 0.000*  | -1.047  |
|         | b         | Our    | -0.950      | 0.251   | 0.001*  | -0.693  |
|         |           | Std    | -0.150      | 0.251   | 1.000   | -0.110  |
|         | d         | Our    | -0.250      | 0.254   | 0.976   | -0.187  |
|         |           | Std    | 0.067       | 0.254   | 1.000   | 0.048   |
|         | g         | Our    | -1.133      | 0.255   | 0.000*  | -0.803  |
|         |           | Std    | -0.450      | 0.255   | 0.239   | -0.322  |

B

| Terrain | Reference | Method | Differences | M       | SE      | p-value | Cohen's d |
|---------|-----------|--------|-------------|---------|---------|---------|------------|
|         | a         | Our    | -2.083      | 0.270   | 0.000*  | -1.537  |
|         |           | Std    | -1.433      | 0.270   | 0.000*  | -0.981  |
|         | b         | Our    | -0.750      | 0.253   | 0.010*  | -0.560  |
|         |           | Std    | -0.033      | 0.253   | 1.000   | -0.025  |
|         | c         | Our    | -1.083      | 0.274   | 0.000*  | -0.771  |
|         |           | Std    | -1.083      | 0.274   | 0.000*  | -0.726  |
|         | h         | Our    | -1.100      | 0.256   | 0.000*  | -0.820  |
|         |           | Std    | -0.117      | 0.256   | 1.000   | -0.087  |

C

| Terrain | Reference | Method | Differences | M       | SE      | p-value | Cohen's d |
|---------|-----------|--------|-------------|---------|---------|---------|------------|
|         | a         | Our    | -2.083      | 0.248   | 0.000*  | -1.744  |
|         |           | Std    | -0.917      | 0.248   | 0.000*  | -0.676  |
|         | b         | Our    | -0.883      | 0.225   | 0.000*  | -0.741  |
|         |           | Std    | -0.333      | 0.225   | 0.420   | -0.287  |
|         | f         | Our    | -1.400      | 0.237   | 0.000*  | -1.121  |
|         |           | Std    | -0.500      | 0.237   | 0.108   | -0.396  |
|         | i         | Our    | -1.250      | 0.231   | 0.000*  | -1.004  |
|         |           | Std    | -0.250      | 0.231   | 0.840   | -0.206  |

D

| Terrain | Reference | Method | Differences | M       | SE      | p-value | Cohen's d |
|---------|-----------|--------|-------------|---------|---------|---------|------------|
|         | a         | Our    | -0.883      | 0.237   | 0.001*  | -0.702  |
|         |           | Std    | -1.000      | 0.237   | 0.000*  | -0.762  |
|         | b         | Our    | -0.600      | 0.221   | 0.022*  | -0.471  |
|         |           | Std    | -0.950      | 0.221   | 0.000*  | -0.801  |
|         | c         | Our    | -1.067      | 0.236   | 0.000*  | -0.897  |
|         |           | Std    | -0.950      | 0.236   | 0.000*  | -0.728  |
|         | j         | Our    | -1.100      | 0.238   | 0.000*  | -0.883  |
|         |           | Std    | -0.817      | 0.238   | 0.002*  | -0.616  |

M = mean, SE = standard error.
Std = standard terrain, CL = ColorLoom, Our = our method
*Difference is significant (p < 0.05).

standard terrains. The difference shows that our method has a lower emotional correlation with standard terrains. Note that the differences in the correlation coefficients of 35 cases (out of 64) are negative, and all were significant. Fig. 14 shows the correlation difference between our method and ColorLoom with reference images. This demonstrates that our method has a better emotional correlation with reference images. Note that almost all cases showed a positive difference in the correlation coefficient, and 30 cases (out of 64) were significantly different.

The affective response varies across terrains and references. Therefore, we compare affective responses at the individual level of references. The affective response of the reference (using references a, h, f and b) is shown in Fig. 15. Nine emotions (out of 16) are negative and significantly different (p value < 0.05) when comparing the emotion correlation of our stylized terrains and ColorLoom results with standard terrains, suggesting that emotions carried by the terrain maps are transferred after colorizing and that our method shifted even more. Ten emotions (out of 16) are positive and significantly different (p value < 0.05) when comparing the emotion correlation of our stylized terrains and ColorLoom results with reference images, suggesting that our method also transfers emotions well.

When referring to references g, c, i and e (see Fig. 16), 4 emotions (out of 16) are significantly different for our method when compared with the correlation with standard terrains, and 6 emotions (out of 16) are more significantly correlated for our method when compared with the correlation with the reference image. This indicates that emotions are partially transferred.

We further investigate what factors impact a terrain map reader’s emotion. We pool all feedback from Question 3 into Fig. 17. It shows that color plays a critical role, but content, texture, form, background, and others (e.g., viewpoint) are also important. Importantly, those facts impact affective response.
Fig. 16. Comparison of percentage accumulation with affective response to the standard terrains, the ColorLoom results, our terrain visualizations and the reference images, (a), (b), (c) and (d) using references g, c, i and e, respectively.

Fig. 17. Statistical results of emotional factors for both styled terrains and reference images.

at different levels for styled terrains and reference images. For instance, many participants mentioned the background and surroundings of the reference image, but very few participants mentioned that fact on styled terrains. Note that since all data are at high resolution, topological details (e.g., aspect and slope) (generally called texture here to avoid using too much expertise for the general participants) are presented; the majority of participants agree that texture significantly impacts their affective response on styled terrains, but texture influences their affective response on references much less. When transferring color from the reference to terrain, if content, form, texture and background are all matched well, then emotion can be transferred faithfully. However, it is too restricted in practice, and it will also dramatically narrow the scope of color inspiration. We therefore claim that our method can conditionally transfer emotions from reference images to terrain maps.

V. DISCUSSION

Although our method shows advantages in adaptive image-to-terrain color transfer with high esthetic quality, it also has several limitations for further consideration:

First, semantic matching. As mentioned in Section II-B, there are a series of methods that transfer color by keeping the semantic content. In this study, we do not model semantic matching to relax the constraint that the reference should include elements about terrain. We selected all references using “landscape” as the key word. However, other types of images, such as portraits and still life paintings, can also be used as references. As shown in Fig. 18, we apply van Gogh’s two paintings on the crater terrain, and the styled terrains all look expressive. In this paper, semantic-color consonants are considered color conventions; semantic matching will be addressed in the future.

The second is adaptability. As discussed in the Introduction, naturalism and symbolism should be balanced when crafting expressive elevation colors. They should be compromised according to the specific terrain. In our model, we quantify color convention as color shifting from a given representative color, which is initialized using a standard scheme. However, the representative color for elevation zones may vary across space (e.g., climate zones). Furthermore, we apply multihued colors on the mountain and canyon, dichromatic colors to the crater and ridge, and proper hue ranges also vary across space. To adapt to diverse terrains, these parameters should be extended in the future.

Third, reference suggestion. We show that our method can transfer arbitrary images to diverse terrains. However, this does not mean that all images are suitable for good color inspiration. As shown in Tables I and II, the cartographic quality also varies on different terrains. Then, a question is naturally raised: how can a proper reference be chosen for a given terrain? Many other map-use contexts should also be considered, such as the audience and activities (e.g., wayfinding). These considerations will be addressed in the future.

VI. CONCLUSION

In this paper, we argue that terrain mapping not only communicates how high or steep a landscape is but also includes
how we feel about a place. Both cartographic concerns and
esthetic quality should be accounted for, as should emotion.
Involving much expertise in cartography, topography, and color
science, crafting expressive and affective elevation colors for
terrain mapping is challenging for both nonexperts and experts.
In this paper, we present an image-to-terrain color transfer
method that can transfer color from arbitrary images to di-
verse terrain models. Our contributions can be highlighted as:
First, we present a new image color organization method. We
use the SOM algorithm and hierarchical clustering technique to
organize discrete, irregular image colors into a continuous, reg-
ular color grid. It is able to facilitate a series of color operations,
such as local color adjustment and global color exploration,
categorical color selection and sequential color interpolation.
It adapts to diverse images.
Second, we mathematically treat image-to-terrain color trans-
fer as a dual-objective optimization problem. We operationalized
a series of cartographic concerns of terrain mapping, such as
“the lower, the higher” principle, color conventions, and aerial
perspective. We also define color similarity between the image
and terrain map with esthetic quality. The evaluations show
that the elevation colors from the proposed method can work
as well as the standard terrains, and our stylized terrains are
more visually favorable. We also showcase that our method can
conditionaly transfer emotion.
Our method can potentially facilitate making effective, beau-
tiful, and affective terrain maps. A series of future works still
needs to be addressed, such as semantic matching and reference
suggestions; extensions are also anticipated to be adaptive to
diverse terrains.

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