

Exploring Factors Contributing to the Perception of Fractal Environments

by

Emily K. Owen

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Dissertation Committee:

Dr. Margaret Sereno, Chair

Dr. Paul Dassonville, Core Member

Dr. Benjamin Hutchinson, Core Member

Dr. Richard Taylor, Institutional Representative

University of Oregon

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DISSERTATION ABSTRACT

Emily K. Owen

Doctor of Philosophy in Psychology

Title: Exploring Factors Contributing to the Perception of Fractal Environments

From the branching of dendrites to the structure of watersheds, the natural world is written in the language of fractals. The fractal fluency theory postulates that the positive psychological effects associated with these self-repeating patterns are due to fluent visual processing. The human visual system evolved constantly processing fractal stimuli, and the subsequent perceptual fluency is the mechanism behind the pleasurable aesthetic response associated with fractal patterns. While prior research has extensively examined the influence of factors such as fractal dimension and the exactness of recursion, many aesthetic variables that are reflected in the variability of nature such as 1) layering, 2) seed effects, 3) value and contrast have not been examined at all. In three empirical studies the current dissertation demonstrates robust findings on several factors influencing fractal visual perception. The research presented further validates the fractal fluency theory and establishes novel variables that have the potential to maximize the benefits of biophilic design and architecture.

This dissertation includes previously published and unpublished co-authored material.

CURRICULUM VITAE

NAME OF AUTHOR: Emily K. Owen

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene

Colorado State University, Fort Collins

DEGREES AWARDED:

Doctor of Philosophy, Psychology, 2025, University of Oregon

Master of Science, Psychology, 2019, University of Oregon

Bachelor of Science, Psychology (Mind and Brain), 2016, Colorado State University

AREAS OF SPECIAL INTEREST:

Aesthetics and fractal perception, biophilia, visual perception

PROFESSIONAL EXPERIENCE:

Graduate Teaching Fellow, Department of Psychology, University of Oregon, 2018-2025

GRANTS, AWARDS, AND HONORS:

Graduate School First Year Fellowship, University of Oregon, 2018

COURSES WRITTEN:

Metacognition (2023)

Graduate School Prep (2019-2025)

Research Development (2019-2025)

Current Issues in Psychology (2019-2025)

PUBLICATIONS:

Owen, E., Rowland, C., Philliber, S., Sereno, M.E., Taylor, R.P. (2024). Using fractal iconography to emulate nature's aesthetics. *Nonlinear Dynamics, Psychology, and Life Sciences*, 28(1):111-120. <https://doi.org/10.1080/01973762.2024.2362464>

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Table of Contents

CHAPTER I: Introduction	12
Overview of the Dissertation	19
References	24
CHAPTER II: Composite Fractals	31
2. Methods	35
2.1 Literature Review	35
2.2 Behavioral Experiment	35
2.2.1 Participants	35
2.2.2 Stimuli	36
2.2.3 Measures	37
2.2.4 Design	37
2.2.5 Procedure	39
3. Results	40
3.1 Literature Review	40
3.2 Behavioral Experiment	40
3.2.1 Alternative Forced Choice Task	40
3.2.2 Slider Task	42
3.2.3 Mixed Slider Task	45
3.2.4 Qualitative Survey	46
4. Discussion	47
5. Conclusion	49
6. Implications and future directions	49
7. References	51
CHAPTER III: Magic Seeds	66

2. Method	70
2.1 Participants	70
2.2 Stimuli	71
2.3 Measures	71
2.4 Design	72
2.5 Procedure	72
3. Results	73
1.1 Preference for Fractal Stimuli Across Dimension	73
1.1.1 Subgroup Preferences Across Dimension	74
1.2 Seed Effects	75
1.3 Qualitative Responses	76
4. Discussion	77
5. Conclusion	79
6. Implications and Future Directions	79
7. References	81
<i>Chapter IV: Value and Contrast.....</i>	94
2. Method	98
2.1 Participants	98
2.2 Stimuli	98
2.3 Design	99
2.4 Procedure	100
3. Results	100
3.1 Fractal Dimension and Visual Appeal	100
3.2 Value and Visual Appeal	101
3.3 Contrast and Visual Appeal	103
4. Discussion	105

5. Conclusion	107
6. Implications and Future Directions	108
7. References	109
CHAPTER V: General Discussion.....	122
Composite Fractals and the Impact of Layering on Fractal Perception	124
The Influence of Seed on Fractal Aesthetics	125
The Role of Value and Contrast on the Perception of Fractals	126
Broader Implications	127
Limitations & Future Directions	128
General Conclusion	129
References	130

LIST OF FIGURES

Figure	Page
1.1 Examples of composite fractal environments	17
1.2 A fractal H-tree.....	18
1.3 Examples of distinct seeds	18
1.4 Examples of cluster and contour stimuli.....	22
2.1 Fractal stimuli	61
2.2 Histogram of natural objects by fractal dimension	61
2.3 Example stimuli for the first 4 blocks.....	62
2.4 Qualitative perception survey example.....	63
2.5 Comparison of two alternative forced choice (2AFC).....	63
2.6 Slider task results	64
2.7 Mixed slider task.....	65
3.1 Experiment Interface.....	89
3.2. Mean normalized rating by fractal dimension (D).....	90
3.3. Mean response time by fractal dimension (D).....	90
3.4. Mean normalized rating per fractal dimension for subgroups	91
3.5. The top five rated seeds	91
3.6. The bottom five rated seeds	92
3.7 Average normalized rating differences between seed groups	92
3.8 Seeds rated significantly differently between subgroups.....	93
4.1 Contour and cluster fractal examples.....	116
4.2 Stimuli examples.....	117
4.3 Contour fractal trial example	117
4.4 Mean rating by fractal dimension (D).....	118

4.5 Visual appeal by fractal dimension by sex	118
4.6 Mean visual appeal rating by value	119
4.7 Mean rating by overall value	119
4.8 Foreground Background Rating Heatmaps.....	120
4.9 Mean rating by fractal dimension (D).....	120
4.10 The mean rating by level of contrast.....	121
4.11 The mean rating by level of contrast by direction.....	121

LIST OF TABLES

2.1 Table of natural objects	55
2.2 Definitions for Block 3 slider task stimulus groupings	58
2.3 AFC paired t-tests for D values.....	59
2.4 AFC paired t-tests between groups	60
2.5 Qualitative survey results.....	60
3.1 Paired t-tests for normalized ratings by fractal dimension (D).....	86
3.2 Paired t-tests for response time (s) by fractal dimension (D)	86
3.3 Top and bottom rated seeds for normalized versus raw rating data.....	87
3.4 Paired t-tests for each seed group	87
3.5 Reasoning for the top and bottom five rated seeds	88
3.6 Comparison of qualitative justification for ratings by category	88
4.1 Paired t-tests for ratings by fractal dimension (D) for contour fractals	114
4.2 Independent samples t-tests comparing contrast between fractal types.....	114
4.3 Paired t-tests for ratings by contrast levels collapsed across fractal type	115
4.4 Paired t-tests for ratings by contrast levels and direction for contour fractals.....	115

CHAPTER I

INTRODUCTION

Ever since Mandelbrot first coined the term “fractal”, these recursive patterns have fascinated everyone familiar with the form (Mandelbrot, 1978). Fractals are self-repeating patterns, such that the fine structure of the object mirrors the broad structure (Mandelbrot 1982, Mandelbrot 1998). Natural objects across a variety of scales, from subatomic particles to galaxies demonstrate fractal structure (Banerjee, Bhattacharya, Chakrabarti, & Banerjee 2001; Canavesi, & Tapia, 2021). Perhaps most salient for the human visual system, the vast majority of natural objects visible to the naked human eye are fractal. Trees, mountain ridges, river networks, rock surfaces, mud cracks, coastlines, and clouds, all embody the self-repeating nature of fractals (Morse, Lawton, Dodson, & Williamson 1985; Keller, Crownover, & Chen 1987, Mark, & Aronson 1984; De Bartolo, Veltri, & Primavera 2006; Brown, & Scholz 1985; Velde 1999; Mandelbrot, 1967; Batista-Tomás, Díaz, Batista-Leyva, & Altshuler 2016).

Some have theorized that fractal geometry is abundant in nature because the self-similar structure is highly efficient (Mandelbrot, 1982; Weibel, 1991). This argument is further supported by the fractal nature of our own internal infrastructure, such as vasculature and the lung’s bronchioles (Liew et al., 2008; Weibel 1991). Even the structure of our neurons is fractal (Smith et al., 2021). The prevalence of fractal structures in the natural world is directly connected to our aesthetic perception of fractals. As described in Taylor & Spehar (2016), Fractal Fluency theory postulates that the human visual system evolved within the context of a fractal environment, therefore we easily and fluently process fractal information; this fluent processing leads to a pleasurable aesthetic response. Smith, Goodmon, and Hester (2018) found photographs of nature were rated more visually appealing than urban scenes or those incorporating humanmade content. Human beings display a distinct attraction to fractal

scenes, such as landscapes. Hägerhäll, Purcell, and Taylor (2004) found that more natural appearing silhouettes elicited higher preference ratings.

Preference between fractal patterns of differing complexity also mirrors the prevalence of levels of complexity within our fractal environments. The complexity of two-dimensional fractal images is measured as D value, or fractal dimension. D value ranges between $D = 1.00$ - 2.00 with values closer to $D = 1.00$ indicating lower complexity. Many studies have shown that humans prefer fractals of low to mid-level complexity, $D = 1.1$ - 1.5 D (Sprott, 1993; Spehar et al., 2003; Taylor, 2006; Taylor et al., 2011; Spehar and Taylor, 2013). In fact, Robles, Liaw, Taylor, Baldwin and Sereno (2020) found that children as young as three have been shown to mirror adult fractal preferences.

Exposure to nature has been linked to numerous psychological benefits. For example, Ulrich, Simons, Losito, Fiorito, Miles, and Zelson (1991) compared stress reduction between videos of nature versus videos of urban settings and found significantly greater stress reduction in the nature video condition, although both conditions commanded involuntary attention. Similarly, Bratman, Daily, Levy, and Gross (2015) found that walking in nature as opposed to an urban setting, was linked to a decrease in negative affect, specifically anxiety and rumination, as well as increased preservation of positive affect. Additionally, they found that walking in nature was associated with cognitive benefits such as increased working memory performance (Bratman, Daily, Levy, & Gross, 2015). Grassini, Segurini, and Koivisto (2022) found that exposure to videos of natural stimuli increased alpha wave activity, which are associated with wakeful relaxation and internalized attention, indicating that natural iconography in an indoor setting is sufficient to induce the beneficial effects of nature. Kaplan (1995) posits that exposure to natural stimuli is one avenue to promote attention restoration. Hägerhäll, Laike, Küller, Marcheschi, Boydston and Taylor (2015) found that EEG responses to statistical fractals (patterns that repeat approximately at different

scales, but not exactly) were linked to increased alpha waves, indicating that static natural images may be sufficient to induce the positive effects of nature. In a more general sense, Howell, Dopko, Passmore, and Buro (2011) found a significant association between measures of nature-connectedness and well-being. A meta-analysis on the relationship between natural environments and physiological stress responses by Gackwad, Moslehian, and Roös (2023) found that when compared to exposure to urban environments, exposure to natural environments had a small to medium effect on reducing physiological stress.

Visual complexity is a fundamental variable in the perception of beauty. Forsythe, Nadal, Sheehy, Cela-Conde, and Sawey (2011), found that natural images were rated more beautiful than other types of images, and were also more fractal. Fractal dimension accounted for 30% of variation in the perception of beauty in natural scenes and 19% of variance in the perception of beauty for abstract art (Forsythe, Nadal, Sheehy, Cela-Conde, & Sawey, 2011). Fractal analysis has also been applied to giants in modern art such as Jackson Pollock. Taylor, Micolich, and Jonas (1999), found that not only are Pollock's paintings fractal, but the fractal dimension of his artwork increased throughout his career, leveling out at $D = 1.7$. Taylor, Spehar, Van Donkelaar, and Hagerhall (2011) found that Pollock's fractals evoked the same positive perceptual and psychological responses associated with natural and computer-generated fractals. Fractal analysis has also proved to be a useful, although not foolproof, method to authenticate Pollocks paintings, as described in Taylor et al. (2007).

There is a long history detailing the relationship between nature and aesthetics. More contemporary literature has linked fractal geometry to the psychology of aesthetics. Aesthetics at its core is the principle that a stimulus is an appreciation without a desire to possess. Brown, Gao, Tisdelle, Eickhoff, and Liotti (2011) and Yue, Vessel and Biederman (2007) link aesthetic engagement to increased activity in the reward pathways. While aesthetic engagement could on its surface seem like a trivial goal, Tommaso, Sardaro, and

Livrea (2008) found that aesthetic pleasure is linked to profound physical effects like pain reduction. Redies, Hasenstein, and Denzler (2007) examined the mathematical properties of Western graphic art compared to photographs of random humanmade objects and found that Western graphic art displayed the same scale-invariant fractal properties as natural scenes. These findings were consistent regardless of the medium, origin, subject, or period of the artwork (Redies, Hasenstein, & Denzler, 2007).

The aesthetic value of fractals has a profound potential to bring the beneficial effects of nature indoors. It is well established that art and design incorporating the fractal properties of nature increase visual interest and preference, as outlined in Taylor (2021). The National Human Activity Pattern Survey (NHAPS) conducted by Klepeis et al., (2001), found that Americans spend 92.4% of their time indoors (86.9% within enclosed buildings and 5.5% in enclosed vehicles). With the looming threat of climate change, the need for simulated natural spaces indoors is only growing. The ever-increasing rate of population growth, urbanization, and subsequent dwindling of untouched natural spaces, means that the time the average human spends in the natural environment is rapidly declining.

Robles, Gonzales-Hess, Taylor, and Sereno (2023) examined the influence of 2D Euclidean context on fractal perception. The study found that Euclidean context alters ratings of interest and excitement of fractal patterns, but vitally not ratings of visual appeal, engagement, complexity, or relaxation (Robles, Gonzales-Hess, Taylor, & Sereno, 2023). Abboushi, Elzeyadi, Taylor, and Sereno (2019) examined the perception of fractal patterns within a Euclidean indoor space and showed that cluster fractal light patterns of mid to high level complexity ($D = 1.5-1.7$) elicited high levels of visual interest. Incorporating fractal structure to solar panels was shown to increase visual appeal in Roe et al., (2020).

Throughout fractal research and literature, the argument persists that the human affinity for these self-repeating patterns lies in its abundance throughout nature (Taylor &

Spehar, 2016). It would therefore stand to reason that human subjects would prefer fractal patterns that are reflective of nature in other facets. There are several qualities that influence the structure and subsequent perception of fractal images, such as the level of randomness introduced, fractal types, the seed being repeated, and the context surrounding the fractal. The current research aims to examine the qualitative and quantitative factors that influence the perception of computer simulated approximations of nature, referred to in this dissertation as fractal iconography.

One qualitative aspect of fractal patterns that can vary is where the pattern lies on the spectrum between exact and statistical fractality. While both statistical and exact fractals repeat structure across scales, exact fractals repeat the pattern exactly. With statistical fractals, the structure is similar across scales, but does not repeat exactly. In other words, statistical fractals introduce an element of randomness. While some natural fractals are more exact (e.g., snowflakes and ferns) most natural objects are statistical fractals. This is evident in the structure of trees, where the branching structure of the trunk resembles those of the larger and smaller boughs. This statistical branching fractal structure is also evident in river networks and vasculature. Research by Bies, Blanc-Goldhammer, Boydston, Taylor, and Sereno (2016a) showed that preference for exact fractals peaked at higher levels of complexity compared to statistical fractals, likely because the order inherent in statistical fractals makes them easier to process.

Another element vital for understanding fractal patterns is the type of fractal being examined. When fractals are artificially generated, the typical method is to create a three-dimensional fractal terrain, then slice either vertically or horizontally (see Bies et al., 2016b for generation methods). A vertical slice will create a “contour” fractal. A horizontal slice will create a “cluster” fractal. Branching fractals are created by setting a level of exactness and overlay, then allowing the pattern to fork or branch.

The context in which we observe the fractal patterns is also a vital factor in the perception of fractal iconography. In nature, we are rarely viewing a single pattern at any given time. Instead, we are viewing layers of fractal stimuli superimposed over each other. For example, a natural scene may consist of a mountain range with complexity ranging between $D = 1.10$ - 1.29 , as found in Keller, Crownover, and Chen (1987) and Mark and Aronson (1984). The vegetation which might be in the foreground has a complexity between $D = 1.10$ - 1.69 depending on the species (Morse, D. R., Lawton, J. H., Dodson, M. M., & Williamson, M. H., 1985). The clouds may range in complexity from $D = 1.10$ - 1.39 (Batista-Tomás, Díaz, Batista-Leyva, & Altshuler, 2016; Bies, Boydston, Taylor, & Sereno, 2015). It is the combination of all these layers overlapping each other that creates a striking natural landscape, not any one element. This tendency for fractal objects to overlap in nature has not been explored in the literature. The literature has also not considered how much any one object fills the visual space. In the framework of this dissertation overlapping fractal patterns will be referred to as composite fractals (see *Fig. 1.1* for examples from nature).



Fig. 1.1: Three examples of composite fractal environments with mountains, clouds, glaciers, rivers, and vegetation. These are original photos taken by the author in the Alaskan bush.

Perhaps the most abstract factor that influences the structure of fractal patterns is the seed. The seed is the element in the pattern that repeats. In an exact fractal pattern, such as an

H-tree, the element is the pattern repeated across scales. For example, in the H-tree the seed is the “H” itself (see *Fig. 1.2*). In a statistical fractal pattern, due to the randomness inherent to statistical fractals, the element that repeats is distorted across scales.

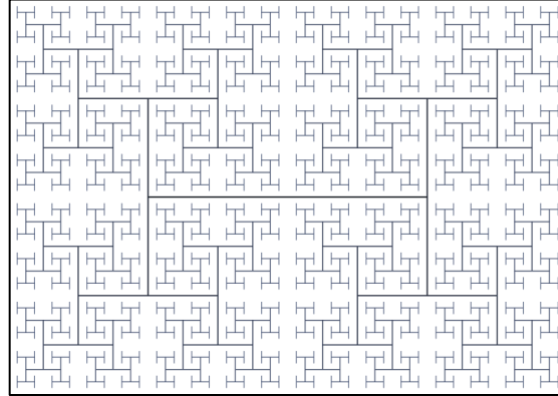


Fig. 1.2: A fractal H-tree. The H repeats across scale. In this example the H is the seed of the fractal.

The seed is the element of a fractal pattern that makes it distinct from other patterns of the same type and complexity. Just like how each tree, even within the same genus and species, has a distinct pattern, a statistical fractal pattern can have the same level of complexity but a distinct structure (see *Fig. 1.3*).

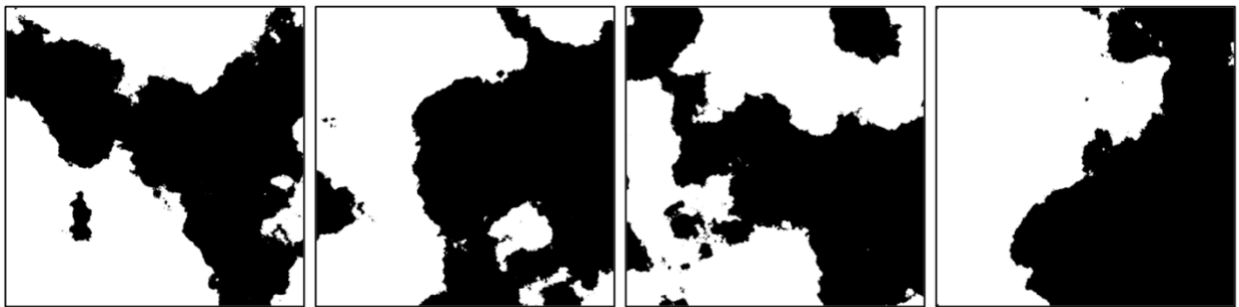


Fig. 1.3: Examples of distinct seeds of cluster fractals of complexity $D = 1.3$, highlighting that images of the same complexity can have drastically different structure.

There has been little research conducted to examine the impact of seed on visual perception. Research on strange attractors (another type of computer-generated fractal pattern) found that some randomly generated patterns were more aesthetically appealing than others, with high levels of chaos appearing to have a negative effect on aesthetic appeal

(Sprott, 1993). One question worth investigating is if some seeds have more aesthetic appeal than others. If some seeds are inherently more aesthetically appealing, is this because they happen to adhere to the principles of composition, or perhaps because they evoke some level of pareidolia?

The last facet of the perception of fractal environments that has not been examined in the literature is the level of contrast between the foreground and background of fractal patterns. Natural environments are rarely monochromatic, but instead are rich in color, however current research on fractal perception has not yet captured the impact of color. This is partially because color is an extremely complex and difficult variable to quantify. Color is not a single variable, but a set of variables, for example color can be quantified as the intersection of hue, saturation, and brightness. The first step to understanding how color influences the perception of fractal environments is to study each of these elements in isolation.

Overview of the Dissertation

The goals of the current dissertation are to 1) examine the impact of layers on the perception of fractal iconography, 2) evaluate the efficacy of fractal fluency theory with a systemic review of the literature on the measured fractal dimension of natural objects 3) evaluate the impact of seed on the perception of fractals, 4) determine how the level of contrast between the foreground and background of fractal images influences visual perception. In three empirical studies I will examine how the unique factors of fractal layering, seed, and contrast influence human visual perception of fractal iconography. These studies delve into the question of which qualities of fractal patterns influence visual perception. I will show that there are distinct preference curves depending on the type of fractal (cluster, contour, or composite), that some seeds seem to have more inherent visual

appeal than others, and that low contrast increases the tolerance for complexity in fractal images. Together, these studies will elucidate which factors are vital for effectively simulating nature and should be considered to maximize the positive psychological and physiological benefits associated with fractal art and design.

Chapter two will examine how layers of fractal stimuli influence the perception of fractals, increasing external efficacy of fractal design. Positive psychological and physiological impact of fractal patterns have consistently been linked to their relationship to nature (Howell, Dopko, Passmore, and Buro, 2011; Hägerhäll et al., 2015; by Gaekwad, Moslehian, and Roös, 2023). While a particular object within a natural scene may be a single fractal pattern, the scene itself is composed of overlapping fractal patterns (e.g., clouds, mountain ridge, foliage, shrubbery). However, no research has examined the perception of layered fractals. This study takes the first step to illuminate the perception of composite fractal iconography. The study accomplishes this by examining visual appeal of contour fractals superimposed over cluster fractals. Additionally, the study directly compares the visual appeal ratings of composite fractals to that of single fractals. Chapter two also includes an extensive literature review of the complexity of natural objects visible to the naked human eye. The aim of this is to examine the efficacy of fractal fluency theory and evaluate if the predominate fractal dimension of nature is in the low to mid level of complexity as hypothesized. The research questions examined include: Is the mean fractal dimension of natural objects within the low to mid-level complexity as hypothesized? How does perception of fractals change when we incorporate more than one layer? Are there differences in visual appeal between composite and single layered fractal iconography?

Chapter three dives further into the relationship between fractality and design by asking if some randomly generated fractal seeds are inherently more visually appealing than others. In nature, an object might have the same level of complexity and layers, but still has

its own unique shape. For example, two trees of the same species are similar but not identical, the qualia can be defined here as the seed. This study aims to answer two questions: Do we prefer some random seeds over others? If so, why do we prefer them? We hypothesize that some seeds are inherently more visually appealing than others. Qualitative analysis examined if higher aesthetic appeal was linked to aesthetic principles of composition or other perceptual qualities. For example, it's possible that seeds prompting more pareidolia, the perceptual phenomenon of seeing order in chaos, will elicit higher visual appeal. While fractals are prevalent in nature, out of context the patterns appear abstract, for examples Pollock's drip paintings. Previous literature has examined the visual appeal of abstract art. While abstract images can appear random, composition plays a vital part in the visual perception of abstract art. Bai, Guo, and Jia, (2019, October) found that abstract paintings positioned in the orientation intended by the artist tend to elicit greater appeal. Redi and Pova (2013, November) validated the long-held concept in art theory of simplicity, quantified as a lack of visual clutter, finding a significant negative correlation between visual clutter and aesthetic appeal. Bies et al., (2016c) specifically examined pareidolia in fractal patterns finding that images at fractal $D = 1.3$ elicited the highest number of precepts at the fastest response rate.

Chapter four takes the first step in evaluating the influence of color on fractal images by systematically varying the value of the foreground and background of fractal images and examining how brightness and subsequently contrast influences perception (see *Fig. 1.4*). Research into fractal imagery so far has focused mainly on black fractal patterns on a white background, or grayscale fractals which resemble something more akin to mist. However, nature is not monochromatic and the contrast between fractal objects and the background

differs depending on the biome, season, and time of day. Previous research by Penndorf (1956) on the coloring of natural scenes has shown that yellow-green wavelengths are dominant for natural objects. Additionally, Valdez and Mehrabian (1994), found that green, blue-green, and yellow-green are the most arousing colors. Lichtenfeld, Elliot, Maier, and

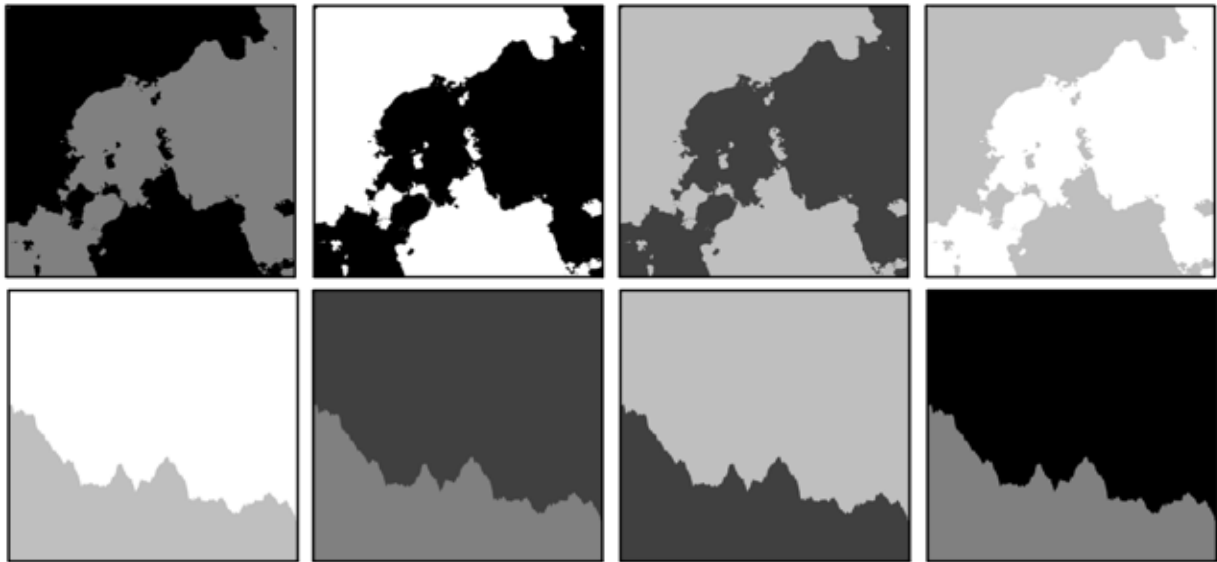


Fig. 1.4: Examples of cluster (top row) and contour (bottom row) stimuli with the background and foreground value systematically manipulated.

Pekrun (2012) showed that green has been linked to enhanced creative performance. Akers, Barton, Cossey, Gainsford, Griffin, and Micklewright (2012) linked exposure to green to a decrease in perceived exertion and mood disturbance during exercise. This suggests that coloring aligning with natural distributions could evoke similar benefits to fractals aligning with natural distributions. While color is a rich vein of research to examine, the first step in understanding this relationship is to study the most basic elements of color. Therefore, chapter four takes the first step into understanding this relationship by examining the variables of brightness and contrast in fractal perception. This study increases the realism of fractal iconography, as it takes the first step of incorporating color into fractal design, which has the

potential to greatly increase the efficacy of fractal imagery, helping it to reflect the properties of nature even further.

Chapter five integrates the findings from the three studies composing this dissertation to the larger body of work on the perception of fractal patterns. This research will incorporate the influence of layered composite fractals, seed effects, and variation in brightness and contrast and provide a general discussion tying these elements into Fractal Fluency theory and aesthetic principles.

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CHAPTER II

THE PERCEPTION OF COMPOSITE FRACTAL ENVIRONMENTS

From Owen, E.K., Taylor, R.P., & Sereno, M.E. (Submitted). Using Composite Fractal Patterns to Investigate the Aesthetic Perception of Nature's Scenery. *Journal of Environmental Psychology*.

1. Introduction

Patterns that repeat at different size scales are prevalent in natural scenery. Labelled by Mandelbrot (1977) as fractals, they have been referred to as “nature’s fingerprints” (Taylor et al., 1999). Fractal patterns can be divided into two categories, exact and statistical fractals. For exact fractals, the large-scale structure of the fractal is replicated precisely in the fine structure. For statistical fractals, which are the most common in nature, an element of randomness is introduced. The structures at different size scales then resemble but do not match each other. This can be seen in a tree, for example, where the finer branches simply look similar to the coarse branches. For both fractal categories, the repeating patterns generate visual complexity, which is quantified by their fractal dimension (D). Fractal dimension ranges between 1 and 2 for the two-dimensional images observed in natural scenes, with values closer to 1 indicating lower levels of complexity, and values closer to 2 indicating higher levels (see *Fig. 2.1a* for an example). In addition to their complexity, the visual appearance of fractals also depends on the character of the repeating ‘seed’ pattern. For example, two trees of the same species may share a fractal dimension (D) but are still discriminable. Consequently, fractals of the same D but different seeds are visually distinct (see *Fig. 2.1b* for examples, where random variations generate five different seed conditions).

Whereas human response to exact fractals has been investigated (Bies, Blanc-Goldhammer, Boydston, Taylor, & Sereno, 2016a), most studies have focused on two types of statistical fractals due to their resemblance to fractal objects in nature (Bies et al., 2016b). “Contour fractals” feature

repeating patterns embedded within lines and therefore resemble natural shapes such as the contours of mountain silhouettes. “Cluster fractals” form distributions of ‘blobs’ of multiple sizes and therefore resemble shapes such as clusters of clouds across the sky. Both contour (Westheimer, 1991) and cluster (Spehar et al., 2015) fractals elicit a remarkable capacity for discrimination between varying levels of complexity in human subjects. In both fractal types, visual appeal peaks for low-to-mid D complexity (between $D = 1.1$ - 1.5) for contour (Hagerhall, Purcell, & Taylor, 2004) and cluster fractals (Spehar et al., 2003; Taylor, Spehar, Van Donkelaar, & Hagerhall, 2011). In particular, one study (Spehar, Walker, & Taylor, 2016) explicitly compared visual appeal for cluster and contour stimuli comparable to those used in our current study and found similar peak visual appeal ratings for low-to-mid D complexity for both types. Robles, Liaw, Taylor, Baldwin, and Sereno (2020), found similar preferences in adults and children as young as three years of age for statistical and exact fractals with preference for statistical fractals peaking at low to mid complexity and that of exact fractals peaking at higher complexities.

Taylor (2006) found that exposure to low-to-mid D fractals also reduced physiological indicators of stress. Hagerhall et al. (2008) then used qEEG responses to examine how the brain responds to fractal images of varying D . Subjects’ alpha and beta responses were largest when $D = 1.3$. Fractals of this dimension corresponded with the largest alpha waves in the frontal region, suggesting that these images were the most relaxing to view. The largest beta response in the parietal area also corresponded with this fractal dimension, indicating spatial processing activity. This could correspond to the frontal-parietal attention network, which would indicate that this fractal dimension is particularly able to hold our attention (Hagerhall et al., 2008). This pattern of activity supports the concept that images of $D = 1.3$ elicit a particularly strong cognitive reaction relative to other fractal dimensions. Juliani, Bies, Boydston, Taylor, and Sereno (2016)

demonstrated a direct impact on cognitive performance, with participants navigating most effectively in 3D virtual fractal landscapes of a low to mid-level fractal complexity.

Taken together, the above results inform the fractal fluency theory (Taylor et al., 2011; Taylor & Spehar, 2016; Taylor et al., 2018), which states that an aesthetic experience originates from enhanced processing of fractal patterns that we are most frequently exposed to in nature's scenery (either through evolutionary exposure or through our lives). Rim, Kardan, Krishnan, Bainbridge, and Berman (2024) suggest that processing natural scenes requires less cognitive resources than processing urban scenes, further supporting this theory. In addition to advancing the fundamental science of the visual system and its relationship to natural scenery, the fractal fluency theory also has important practical applications such as those outlined in the Biophilia movement (Wilson, 1984), which seeks to improve human well-being by incorporating natural stimuli into the built environment. In particular, fractals have been proposed as a potential source of biophilia's previously established health benefits – which include stress-reduction (Ulrich et al., 1991), improved affect for individuals with depression (Berman et al., 2012), and attention restoration (Kaplan & Kaplan, 1982; Berman, Jonides, & Kaplan, 2008). Incorporating fractal patterns into built spaces has reflected these findings (Abboushi, Elzeyadi, Taylor, & Sereno, 2019; Abboushi, Elzeyadi, Van Den Wymelenberg, Taylor, Sereno, & Jacobsen, 2021). For example, Abboushi et al. (2019) found a shift to higher D values for preference and interest when complex fractal patterns were surrounded by the less complex Euclidean space of the built environment.

In the natural world we rarely encounter solitary fractal stimuli. Instead, we often process layers of fractals, each with its own unique pattern and complexity. For example, when moving through a natural scene, a viewer might see a layer formed by a forest of trees of $D = 1.5$, a layer of clouds of $D = 1.3$ peeking through the trees, and a background layer formed by a mountain ridge of $D = 1.2$. Therefore, natural stimuli would be better represented with layered

fractal stimuli. While there is a rich background of research in aesthetic evaluation of fractals, no research has been conducted to evaluate well-controlled layered synthetic fractal stimuli. Therefore, the current research behaviorally evaluates how we process layers of fractal information, referred to here as “composite fractal environments”, to address this research gap in the literature.

We first conducted a literature review of fractal research measuring the complexity of natural objects to examine the efficacy of fractal fluency theory. Fractal fluency theory postulates that humans are especially responsive to objects of low-to-mid range complexity ($D = 1.3-1.5$) because the average fractal dimension of natural objects is within this range. While it is functionally impossible to completely characterize the complexity and prevalence of natural objects, this literature review takes steps to chart the frequency of occurrence of fractal complexity found in nature by examining the measured D value of natural objects across different fields of study over the course of several decades (1967-2024). The literature review summarizes the D values of a wide variety of types of natural object that are on a scale visible to the naked human eye, such as the patterns of clouds, trees, lightning, riverbeds, mountain ridges, and rock formations. The highest number of types of natural fractal object were found for bins $D = 1.3$, with the median landing squarely in $D = 1.3$ (see *Fig. 2.2*). While this preliminary review of natural objects does not capture the full variety and prevalence of natural objects, it is an important step in validating fractal fluency theory.

Next, we performed an experiment to examine the behavioral correlates of a novel type of fractal - composite fractals. To understand the components influencing visual appeal, this experiment had participants rate three types of fractals common in natural scenery – contour, cluster, and composite fractals. Composite fractals were created which combine one of each of the first two types of fractals, to resemble an abstracted natural landscape. Understanding the typical visual appeal of each type of fractal independently allows us to better understand the

variables which might influence visual appeal for the composite fractals. In accordance with fractal fluency theory, we predict that the more the composite fractals resemble a natural scene, the higher visual appeal ratings they will illicit. As our literature review revealed, in nature, mountains tend to be of low complexity, while clouds are more variable in their complexity. Therefore, we expect that the highest visual appeal ratings will correspond with composite stimuli containing a low complexity contour fractal and a cluster fractal that falls within the natural range of complexity in clouds.

2. Methods

2.1 Literature Review

The literature review focused exclusively on images of natural fractal objects, and measured fractal dimension between $D = 1.0$ and 2.0 . The full range of fractal dimensions was split into ten separate bins of 0.10 increments. If an object's fractal dimension ranged across multiple bins it was represented in each bin it encompassed. When multiple papers were found measuring the same object, the range was updated if measurements occurred outside of the original measurement range, however each object is only represented in a bin once. For example, if one paper listed the fractal dimension of clouds as $D = 1.4 - 1.5$ and another listed it as $D = 1.5 - 1.6$, clouds would be represented once in the 1.4 , 1.5 , and 1.6 bins, respectively.

2.2 Behavioral Experiment

2.2.1 Participants

A power analysis determined that a repeated measures experiment anticipating a small to moderate effect size would require approximately 90 participants. The experiment consisted of two groups of participants, with 36 participants in the first group and 51 participants in the second group for a total of 87 participants (66.3% female, 32.6% male, and 1.1% indicated an

identity outside the binary of male and female). The average age of the participants was $M = 21.34$, $SD = 3.43$. Both groups completed 4 blocks of trials, with the order of the first and second blocks switched between the 2 groups, as well as a brief survey at the end of the testing session. Group 2 participated in an additional fifth block of trials. Participants were paid \$10 an hour for participation or received course credit. The experiment took approximately 30 minutes and participants were either paid five dollars or granted half a credit. All participants were recruited from the Psychology and Linguistic Departments' Human Subject pool at the University of Oregon. Informed consent was acquired following a protocol approved by the Institutional Review Board at the University of Oregon (RCS approval code: 06192011.063, expiration date: 11/04/2024), and all measures were performed in accordance with relevant guidelines and regulations for research involving human subjects as approved by this review board.

2.2.2 Stimuli

The stimuli for this experiment were sets of random midpoint displacement fractal images generated using an algorithm described by Fournier, Fussel, and Carpenter (1982), which allowed us to specify D (for details see Bies et al., 2016b). The number of iterations was set to ten. The stimuli, which were presented against a gray background, were 2100 x 2100 pixels in size. The experiment was created with the program PsychoPy (OmicX) and was conducted using Apple computers.

The experiment utilized four categories of fractal stimuli presented in 4 or 5 blocks. The first two categories contained one type of fractal pattern each. The first category consisted of contour fractals (*Fig. 2.3a*). The second category consisted of cluster fractals (*Fig. 2.3b*). The third and fourth categories were comprised of composite fractal stimuli that combined a contour fractal as well as a cluster fractal, such that the contour fractal aligns with the bottom of the image, and the

cluster fractal comprises the background of the image. The stimuli in the third category consist of five seeds, with five distinct fractal dimensions within each seed (1.1, 1.3, 1.5, 1.7, 1.9). Each image in the third category of stimuli is comprised of fractals such that the contour and cluster fractals within each individual image share the same seed and fractal dimension (*Fig. 2.3c*). Like the third category, the fourth category of stimuli was comprised of a contour fractal and a cluster fractal of the same seed, however the fractal dimension of each fractal pattern varied within the image (*Fig. 2.3d*). The fourth category of stimuli is separated into three types of fractal combinations with different D -values on the top and bottom parts of the image (top/bottom): low/high, high/low, and same- D combinations. For the composite fractals, the cluster was medium gray so that the contour and cluster portions were perceived as two separate patterns, as opposed to a single continuous black pattern.

2.2.3 Measures

Qualitative Responses. Qualtrics (SAP) was used to create a brief post experiment survey, which was conducted to discern if the images used in the experiment reminded the participants of particular natural objects (see *Fig. 2.4*). Participants gave free responses about their impressions. If the answer corresponded to multiple categories it was counted for all applicable categories.

Demographics. Demographics were measured via a Qualtrics survey. The participants were asked their age and gender.

2.2.4 Design

The experiment consisted of two parts and utilized a within subjects design. Each of the first four blocks of the experiment used a unique factorial design. The first three blocks had participants perform a two alternative forced choice (2AFC) task, where they were asked to choose which stimulus they preferred when presented with two side-by-side images of the same

seed, but differing fractal dimensions. An AFC task was used here to directly compare the preference curves of cluster, contour, and same- D composite stimuli. The independent variables were fractal dimension (5 levels) and fractal-type (contour fractals, cluster fractals, same- D composite fractals). The dependent variable was the proportion of patterns with preferred D s. There were 10 pairings of D within a seed and 5 seeds, resulting in 50 total trials. Trials were presented in random order. For the fourth block, the participants were asked to rate the beauty of the stimuli on a slider that ranged from zero to one. The stimuli consisted of composite patterns with D -values on the top and bottom. A slider method, as opposed to AFC, was used to examine precise differences in preference based on the relationship between the cluster and contour fractal dimension. There were 25 possible top/bottom D -value combinations and 5 different seeds resulting in a total of 125 stimuli. Stimuli were presented in random order. The independent variables for this block were the fractal dimension of the contour and cluster fractals, the average fractal dimension of the ensemble, and the range of the combination, which consists of three levels: Low-High (low/high and high/low combinations), Low-Medium (low/medium and medium/low combinations), and Medium-High (medium/high and high/medium combinations). Another independent variable that was examined was the direction of the combination, which had two levels, top- $D >$ bottom- D , and top- $D <$ bottom- D . The dependent variable for block four was the beauty rating.

Part two of the experiment replicated the procedure of part one, except that the cluster block and the contour block were switched to eliminate any order effects. Additionally, part two included an extra block where the participants rated a mixture of all fractal types: cluster, contour, same- D composite, different- D composite (split into top- $D >$ bottom- D and bottom- $D >$ top- D). Forty stimuli were presented for each of these categories. For the single fractals (clusters and contours) and same- D composites five fractal dimensions ($D = 1.1, 1.3, 1.5, 1.7, 1.9$) were presented for eight different seeds. For different- D composites each possible

combination of fractal dimensions was presented for two seeds. Participants were asked to rate each of the 160 stimuli on a slider scale ranging from zero to one. In this block the independent variable was fractal type and the dependent variable was beauty rating. The goal of this analysis was to examine if some types of fractals were more visually appealing regardless of fractal dimension. The data for parts one and two were aggregated for all sections except the mixed slider task, which was only present in part two.

2.2.5 Procedure

A researcher conducted this experiment in one session that lasted approximately thirty minutes. The experiment consisted of an experimental portion followed by a survey portion. In the experimental portion the participants were first asked to choose between two images using the “Z” key to indicate their preference for the left image, or “M” key to indicate their preference for the right image (blocks 1-3). In the fourth block of the experiment, participants were asked to rate the image on a slider from zero to one, with zero indicating least beautiful and one indicating most beautiful. For the second group of participants, a fifth block was presented in which participants were asked to rate a mixture of fractal images on a slider from zero to one, with zero indicating least beautiful and one indicating most beautiful. The instructions for the experiment were given verbally by the experimenter, programmed into the experiment, and printed next to the computer for reference. After the experimental portion of the study had concluded, the participants were asked to complete a brief survey. The survey showed five examples of stimuli from the third block of the experiment (composite fractal images with the same fractal dimension and seed). Participants were asked if the top or bottom portion of each image reminded them of anything (see *Fig. 2.4*), and if so, they were asked to describe what they were reminded of. Demographic data was also collected through this survey.

3. Results

3.1 Literature Review

We reviewed 56 articles (see Table 1), encompassing 125 bins. The results indicated that the median fractal dimension of natural objects visible to the naked human eye is $D = 1.3$, and the mode fractal dimension is $D = 1.3$ (see Fig. 2.2). These results lend credence to fractal fluency theory, indicating that many natural objects do in fact fall within a mid-to-low range of complexity. However, it should be noted that this literature does not take the prevalence of natural objects into account. For example, an individual is much more likely to see trees and clouds in their everyday lives than coral, glaciers, or lightning strikes.

3.2 Behavioral Experiment

3.2.1 Alternative Forced Choice Task

We performed a 3x5 ANOVA with fractal-type (contour fractals, cluster fractals, same- D composite fractals) and fractal dimension (1.1, 1.3, 1.5, 1.7, 1.9) as within subjects factors. The assumption of sphericity was violated for fractal type and fractal dimension, as well as the interaction between fractal type and fractal dimension ($(\chi^2(2) = 2434.21, p < .001, \chi^2(9) = 427.93, p < .001, \text{ and } \chi^2(35) = 492.60, p < .001)$), so the degrees of freedom were altered with a Greenhouse-Geisser correction ($\epsilon = 0.50, 0.33, \text{ and } 0.39$). The results indicated that there were no main effects of fractal type, $F(1, 86) = 1.51, p = .22, 90\% \text{ CI } [0, 0.09], \eta_p^2 = 0.02$. However, there was a main effect of fractal dimension, $F(1.31, 112.82) = 5.90, p < .05, 90\% \text{ CI } [0.01, 0.14], \eta_p^2 = 0.06$. The interaction between fractal type and fractal dimension was also significant, $F(3.15, 270.52) = 21.22, p < .001, 90\% \text{ CI } [0.13, 0.26], \eta_p^2 = 0.20$ (see Fig. 2.5).

The 2AFC task block which had participants choose between contour fractals of varying complexity, found significant differences in visual appeal between each individual fractal dimension (Fig. 2.5, “Contour” condition). A series of paired t-tests, with false discovery rate

(FDR) correction was applied to the p -values to account for family-wise error rates, as described in Benjamini and Hochberg (1995). Results showed significant differences between the proportion of stimuli preferred for each level of fractal dimension for contour fractals (see *Table 3a* “Contour” condition for t-tests, adjusted p -values, and effect sizes). Overall, the results indicated a strong preference for lower complexity contour fractals, with preference peaking at $D = 1.1$.

The results for the 2AFC task for cluster fractals were strikingly different to those of contour fractals (*Fig. 2.5*, “Cluster” condition). A series of paired t-tests, with false discovery rate (FDR) correction applied to the p -values, showed that there were significant differences between the proportion of stimuli preferred for $D=1.1$ vs. 1.3, 1.5, and $D = 1.7$. However, there was no significant difference between the proportion of $D = 1.1$ vs. $D = 1.9$ stimuli preferred. Similarly, there were significant differences between the proportion of stimuli preferred for $D = 1.3$ vs. 1.5 and $D = 1.7$, but not for $D = 1.3$ vs. $D = 1.9$. Additionally, there was no significant difference between the proportion of $D = 1.5$ vs. $D = 1.7$ or $D = 1.9$. There was a significant difference between the proportion of $D = 1.7$ and $D = 1.9$ stimuli preferred see *Table 3b* “Cluster” condition for t-tests, adjusted p -values, and effect sizes. Overall, these results indicate a preference for mid to high complexity cluster fractals, with visual appeal peaking at $D = 1.7$.

The third block of the 2AFC task introduced composite fractals consisting of a contour fractal and a cluster fractal combined into one image (*Fig. 2.3c*). Both fractals in the composite image were of the same seed and fractal dimension. When comparing composite fractals across D -levels, significant differences were found in visual appeal between some, but not all, fractal dimensions of same- D composite stimuli (*Fig. 2.5*, “Same- D Composite” condition). A series of paired t-tests with false discovery rate (FDR) correction applied to the p -values, determined that there were not significant differences between the proportion of $D = 1.1$ vs. $D = 1.3$, $D = 1.5$, and $D = 1.7$. There was a significant difference between the proportion of $D = 1.1$ and D

= 1.9 stimuli preferred. There were no significant differences when comparing $D = 1.3$ vs. $D = 1.5$. However, there were significant differences between $D = 1.3$ vs. $D = 1.7$ and $D = 1.9$. The difference between preference for stimuli of $D = 1.5$ vs. $D = 1.7$ and $D = 1.9$ was significant, as was that of $D = 1.7$ vs. $D = 1.9$, (see *Table 3c* “Same D Composite” condition for f-tests, adjusted p-values, and effect sizes). Overall, the results indicated a stronger preference for low-to-mid complexity composite fractals. In sum, the 2AFC portion of the study revealed strikingly distinct patterns of visual appeal depending on fractal type.

Additionally, a series of paired t-tests adjusted for multiple comparisons showed significant differences between the probabilities of choosing individual fractal dimensions among the fractal groups, such that the proportion of time the fractal dimension was selected varied among contour, cluster, and same- D composite stimuli (see *Table 4*). For $D = 1.1$ stimuli, there were significant differences between contour and cluster stimuli, cluster and composite fractal stimuli, and contour and composite fractal stimuli. For $D = 1.3$ stimuli, there were significant differences between contour and cluster stimuli and cluster and composite fractal stimuli, but no significant difference between contour and composite fractal stimuli. For $D = 1.5$ stimuli, there were significant differences between contour and cluster fractal stimuli and contour and same- D composite stimuli, but no significant difference between cluster stimuli and same- D composite stimuli. For $D = 1.7$ stimuli, there were significant differences between every group: contour and cluster fractal stimuli, cluster and same- D composite stimuli, and contour and same- D composite stimuli. Finally, for $D = 1.9$ stimuli, there were significant differences between contour and cluster stimuli and cluster and composite fractal stimuli, but no significant difference between contour and same- D composite stimuli.

3.2.2 Slider Task

The slider task (Block 4; *Fig. 2.3d*) examined the impact of varying the relative complexity

of the top and bottom portions of the composite fractals. The analyses examined how the relationship between the range of the top and bottom fractal dimensions (i.e., the specific combination of low, medium, or high complexity), as well as the direction of that relationship (i.e., whether the top- D was equal to, greater than, or less than the bottom- D) impacted visual appeal. Data from one participant was removed from this section for failure to use the entire slider range.

Data were analyzed using a 2x3 ANOVA with direction (top $D <$ bottom D , top $D >$ bottom D) and range (low-medium, medium-high, low-high) as within subjects factors. Results indicated the variable of range violated sphericity ($\chi^2(2) = 160.57, p < .001$), so the degrees of freedom were subsequently adjusted with a Greenhouse-Geisser correction ($\varepsilon = .54$). The interaction between range and direction did not violate sphericity ($\chi^2(2) = 3.10, p = .21$). Results showed that there were significant differences in visual appeal based on the direction of the relationship, $F(1, 84) = 145.57, p < .001$, 90% CI [0.53, 0.70], $\eta_p^2 = 0.63$ (Fig. 2.6a), as well as the range of the combination, $F(1.08, 90.54) = 16.47, p < .001$, 90% CI [0.06, 0.27], $\eta_p^2 = 0.16$ (Fig. 2.6b). Additionally, there was a significant interaction between the direction and range of the fractal relationship, $F(1.93, 162.05) = 66.74, p < .001$, 90% CI [0.35, 0.52], $\eta_p^2 = 0.44$ (Fig. 2.6c).

Regarding the main effect of direction (Fig. 2.6a) the average rating for top $D >$ bottom D composite fractals was significantly greater than the top $D <$ bottom D combinations ($M = 0.62$, $SD = 0.12$ vs. $M = 0.38$, $SD = 0.14$), $t(84) = 12.14, p < .001$, $d = 1.32$.

The interaction between range and the direction of the relationship between the D of the top and bottom portions (Fig. 2.6c) was striking, with the high and low combinations being the most and least preferred depending on the direction of the relationship ($M = 0.68$, $SD = 0.16$ for high/low vs. $M = 0.32$, $SD = 0.18$ for low/high), $t(84) = 12.12, p < .001$, $d = 1.32$. The highest visual appeal rating overall was for the combination of high complexity cluster fractals and low

complexity contour fractals (i.e., high/low) ($M = 0.68$, $SD = 0.16$), followed closely by medium/low combinations ($M = 0.62$, $SD = 0.19$), and high/medium combinations ($M = 0.52$, $SD = 0.18$).

When examining the top- $D <$ bottom- D combinations (Fig. 2.6c, left side), participants rated low/medium combinations significantly more visually appealing on average ($M = 0.48$, $SD = 0.14$) than medium/high combinations ($M = 0.35$, $SD = 0.21$), ($t(84) = 4.71$, $p < .001$, $d = 0.51$) and low/high combinations, ($t(84) = 7.20$, $p < .001$, $d = 0.78$). Medium/high combinations were not rated significantly more visually appealing than low/high combinations ($M = 0.32$, $SD = 0.18$), ($t(84) = 2.77$, $p = .10$, $d = 0.30$).

For the top- $D >$ bottom- D combinations (Fig. 2.6c, right side), participants rated medium/low combinations significantly more beautiful on average than high/medium combinations ($M = 0.62$, $SD = 0.19$ vs. $M = 0.52$, $SD = 0.18$) ($t(84) = 3.21$, $p < .05$, $d = 0.35$); high/medium combinations were rated significantly less visually appealing on average than high/low combinations ($M = 0.52$, $SD = 0.18$ vs. $M = 0.68$, $SD = 0.16$) ($t(84) = -7.05$, $p < .001$, $d = -0.76$); and medium/low combinations were similarly rated as significantly less beautiful than high/low combinations on average ($M = 0.62$, $SD = 0.19$ vs. $M = 0.68$, $SD = 0.16$) ($t(84) = -4.11$, $p < .01$, $d = -0.45$).

A correlation matrix indicated a significant correlation between bottom- D value and visual appeal rating $r(25) = -.93$, $p < .001$. Top- D was not significantly correlated with visual appeal rating, rating $r(25) = .28$, $p = .17$. However, average- D was significantly correlated with visual appeal, rating $r(25) = -.46$, $p < .05$. Of course, both bottom- D and top- D were significantly correlated with average- D , rating $r(25) = .71$, $p < .001$, introducing multicollinearity issues. A regression analysis with top- D , bottom- D , average- D , and combination type (top- $D >$ bottom- D , top- $D <$ bottom- D , and top- $D =$ bottom- D) as predictors of visual appeal explained a striking

96% of variance in visual appeal, $R^2 = .96$, $F(3, 21) = 169.31$, $p < .001$. It was found that top- D was a significant predictor of visual appeal ($\beta = .24$, $p < .001$), as well as bottom- D ($\beta = -.90$, $p < .001$). When top- D and bottom- D were considered, combination type was not a significant predictor ($\beta = -.10$, $p = .06$), and average- D accounted for so little variance that it was removed completely from the model. These results indicate that the relationship between the top and bottom- D values is the key to explaining visual appeal, with higher values of top- D in combination with lower values of bottom- D predicting higher levels of visual appeal.

3.2.3 Mixed Slider Task

A one-way repeated measures ANOVA was performed to examine the impact of fractal type on visual appeal. The assumption of sphericity was violated for fractal type ($\chi^2(9) = 102.52$, $p < .001$), so the degrees of freedom were altered with a Greenhouse-Geisser correction ($\varepsilon = 0.61$). The results found significant differences between fractal types, $F(2.45, 120.02) = 38.29$, $p < .001$, 90% CI [0.34, 0.50], $\eta_p^2 = 0.44$ (see *Fig. 2.7*).

A series of paired t-tests with a false-discovery rate (FDR) correction applied to p -values showed that while top- $D >$ bottom- D composites were rated highest in visual appeal out of all fractal types, they was not rated significantly higher than cluster fractals ($M = 0.61$, $SD = 0.12$ vs. $M = 0.55$, $SD = 0.18$) ($t(49) = 1.96$, $p = .06$, $d = 0.28$). However, top- $D >$ bottom- D composites were rated significantly higher than same- D composites fractals ($M = 0.61$, $SD = 0.12$ vs. $M = 0.47$, $SD = 0.10$) ($t(49) = 11.92$, $p < .001$, $d = 1.69$), contour fractals ($M = 0.61$, $SD = 0.12$ vs. $M = 0.39$, $SD = 0.14$) ($t(49) = 8.76$, $p < .001$, $d = 1.24$), and bottom- $D >$ top- D composites ($M = 0.61$, $SD = 0.12$ vs. $M = 0.36$, $SD = 0.13$) ($t(49) = 12.20$, $p < .001$, $d = 1.73$).

Additionally, cluster fractals were rated significantly higher than same- D composites ($M = 0.55$, $SD = 0.18$ vs. $M = 0.47$, $SD = 0.10$) ($t(49) = 2.78$, $p < .01$, $d = 0.39$), contour fractals ($M = 0.55$, $SD = 0.18$ vs. $M = 0.39$, $SD = 0.14$) ($t(49) = 6.08$, $p < .001$, $d = 0.86$), and bottom- $D >$

top- D composites ($M = 0.55$, $SD = 0.18$ vs. $M = 0.36$, $SD = 0.13$) ($t(49) = 6.34$, $p < .001$, $d = 0.90$).

Same- D composites were rated significantly higher than contour fractals ($M = 0.47$, $SD = 0.10$ vs. $M = 0.39$, $SD = 0.14$) ($t(49) = 3.61$, $p < .01$, $d = 0.86$) as well as bottom- $D >$ top- D composites ($M = 0.47$, $SD = 0.10$ vs. $M = 0.36$, $SD = 0.13$) ($t(49) = 9.30$, $p < .001$, $d = 1.32$). Contour fractals were not rated significantly higher than bottom- $D >$ top- D composites ($M = 0.39$, $SD = 0.14$ vs. $M = 0.36$, $SD = 0.13$) ($t(49) = 1.30$, $p = .20$, $d = 0.18$).

3.2.4 Qualitative Survey

The qualitative survey asked participants to identify what the top and bottom portion of the image reminded them of (see *Fig. 2.4*). Responses were spontaneous. The response groupings were determined post-hoc based on the most prevalent responses for each category (contour vs. cluster fractals). Each response reported by more than two participants was set as a category. For contour fractals most responses fell within six categories: Mountains/hills, trees, natural material (e.g., grass), humanmade material (e.g., skyscrapers), graphs/data (e.g., plot of a time-series described as a “signal”), and static (e.g., visual snow). For cluster fractals most responses fell within three categories: Clouds/sky, maps/continents, and art/paint. For responses that spanned multiple categories (e.g., a hill with trees) the response was tallied in both categories. Responses that didn’t correspond to any category were included in the total count and categorized as “other”. The results of the questionnaire (see *Table 5a*) indicated that for contour fractals, low-to-mid range fractal dimensions tend to remind individuals of mountains and/or hills, mid-range fractals ($D = 1.5$) were most likely to remind participants of trees, in addition to mountains/hills. As fractal dimension increased ($D = 1.7$ or $D = 1.9$) participants were much more likely to be reminded of inorganic humanmade materials, graphs/data, and static.

For the top portion of the image (the cluster fractal), participants reported strikingly different

impressions (see *Table 5b*). Notably, participants were most likely to report that the top fractal reminded them of clouds/the sky for every fractal dimension, but as the fractal dimension increased to 1.9, participants were much more likely to report specifically they were reminded of the night sky. Additionally, as fractal dimension increased participants were much more likely to report being reminded of paint or art.

4. Discussion

This study of composite fractal environments yielded a striking series of important results. The literature review showed the median fractal dimension of natural objects visible to the naked human eye is $D = 1.3$, and the mode fractal dimension is $D = 1.3$ (see *Fig. 2.2*). The alternative forced choice portion of the experiment found that there were significant differences in preference across D between contour and cluster fractals (*Fig. 2.5*). There was a significant visual preference for contour fractals of lower complexity. This corresponds with previous findings that low-to-mid fractal dimension corresponds to greater preference for contour fractals (Hagerhall, Purcell, & Taylor, 2004). Additionally, this corresponds with the findings cited in the literature review. Keller, Crownover, and Chen (1987) and Mark and Aronson (1984) found that mountains have a fractal dimension ranging between 1.10-1.29 D . Additionally, the hillslopes measured in Lathrop and Peterson (1992) ranged between 1.00-1.29 D . Contour fractals of $D = 1.1$ were the most preferred, followed closely by contour fractals of $D = 1.3$. In the post-experiment qualitative survey, 77.53% of participants reported that the $D = 1.1$ fractals reminded them of mountains or hills, while 84.27% of participants reported that the $D = 1.3$ fractals reminded them of hills or mountains. Overall, these results indicate a strong visual preference for lower complexity contour fractals, which aligns with the original hypotheses of this study (that low complexity contour fractals would elicit higher visual appeal ratings), as well as previous research (Spehar et al., 2003).

Additionally, the alternative forced choice portion found that visual preference peaked at $D = 1.7$ for cluster fractals. However, the variation in visual appeal was not as starkly defined for cluster fractals as for contour fractals. While visual appeal peaked at $D = 1.7$, there was still comparable visual appeal for cluster fractals of $D = 1.5$ and $D = 1.9$. The post-experiment questionnaire of the composite fractals found that cluster fractals of $D = 1.7$ most likely reminded participants of clouds and/or the sky, with 51.69% of participants reporting accordingly. However, the majority of responses indicated that cluster fractals reminded participants of the sky/clouds more than anything else regardless of D -value. This supports our hypothesis that visual appeal for cluster fractals would be more variable, as the fractal dimension of clouds is more variable than that of mountains. Several studies measuring the fractal dimension of clouds found that the complexity ranges from $D = 1.10$ - 1.69 (Batista-Tomás, Díaz, Batista-Leyva, Altshuler, 2016; Bies, Taylor, and Sereno, 2015; Lohmann, Hammer, Monahan, Schmidt, Heinemann, 2017; Luo & Liu, 2007; and Rys & Waldvogel, 1986). However, our results contradict previous findings which show that visual appeal peaks between $D = 1.3$ - 1.5 for cluster fractals (also referred to as “coastline” fractals) (Spehar et al., 2003; Taylor et al., 2011; Spehar & Taylor, 2013), although there are often significant individual differences in preference with one subgroup preferring midrange complexity and others preferring high or low complexity (Spehar et al., 2016). Additionally, previous research on fractals in a built environment found that visual interest peaked for fractal light patterns of $D = 1.5 - 1.7$ (Abboushi, Elzeyadi, Taylor, & Sereno, 2019).

The results of the slider task further illuminated the nature of this relationship, demonstrating a high visual appeal for composite fractal environments when the cluster fractal was of higher complexity than the contour fractal (*Fig. 2.6a,c*). These results align well with fractal fluency theory since in nature a mountain ridge is usually of lower complexity than the sky. Additionally, when the Range (Low-Medium, Medium-High, Low-High) and Direction (Top $D <$ Bottom D , Top $D >$ Bottom D) of the combinations were considered, there was a significant interaction

between these factors (see *Fig 2.6a-c*). The most preferred stimuli overall were the clusters and high/low combinations when the cluster fractals were of higher complexity and the contour fractals were of lower complexity. Conversely, the least preferred stimuli were the contours and high-low combinations with low complexity cluster fractals and high complexity contour fractals. These findings indicate that simple contrast between fractal dimensions or number of layers does not determine visual appeal, but the relationship between the specific types of fractals is critical.

Additionally, it was shown that the bottom D value has a higher impact on visual appeal overall than the top D value. This is likely because participants showed moderate preference for most D values in the cluster fractal, but a clear dislike of high complexity contour fractals. This could also be because the contour fractals were black, while the cluster fractals were white and gray. The lower contrast between the white and gray parts of the cluster fractals could have allowed for greater tolerance of variation in D values for cluster fractals, while the high contrast of the black contour against the white and light gray background may have led to higher complexity contour fractals being perceived as overwhelming.

5. Conclusion

Overall, the results of this study largely support our hypotheses. The strong visual appeal for composite fractal environments with higher complexity cluster fractals relative to the contour fractal mirrors the properties of natural environments.

6. Implications and future directions

The lack of previous research conducted on composite fractals made it difficult to predict how the preference for individual fractals (i.e., contour and cluster fractals alone) would influence preference when the fractals were combined into one single image. Our research creates a basis for future research on composite fractal environments. While our research did shed light

on the perception of multiple fractals in one space, it was limited to examining two fractals, while a natural scene is often composed of numerous fractals of differing levels of complexity. Future research should expand our ability to simulate nature by incorporating additional layers and types of fractals. For example, Owen, Rowland, Philliber, Sereno, Taylor (2024) combined cluster and contour fractals with branching fractals (similar to rivers and trees) to simulate natural scenes.

Additionally, most natural environments are not in gray scale, and therefore the color palette of this experiment was not true to that of a natural scene. To reflect nature more closely, future studies should examine not only the effect of contrast between layers but move from gray scale to a more diverse range of colors. Systematically varying the gray scale of the composite fractals is another reasonable progression. This will allow us to control for contrast and compare the simulated contrast to that of reality. If it is true that most natural scenes consist of multiple fractals, then it would stand to reason that we would be able to more fluently process and therefore prefer stimuli that better reflects this natural order. Overall, future research on composite fractals should aim to nudge these simulated environments to closer approximations of natural environments (c.f., Owen et al., 2024).

7. References

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Fractal Dimension (D)	Natural Objects
1.00 - 1.09	Coastline ^{10, 33, 35, 58} , creek ⁵¹ , deciduous tree (broadleaf) ^{36, 54} , dunes ¹⁵ , hillslope (glacial) ²⁹ , leaf outline (American basswood, American elm, English elm, ginkgo, pepper) ^{7, 44, 57} , leaf veins ⁷ , lighting ⁴⁸ , river channel ^{20, 41, 49} , river network ²⁵ , rock ridge ¹⁰
1.10 - 1.19	Coastline ^{10, 16, 21, 22, 35, 46, 47, 58} , clouds (cumulonimbus) ² , creek ⁵¹ , deciduous tree ⁵⁴ , dunes ¹⁵ , evergreen tree ⁵⁴ , leaf outline (eggplant, red oak, sugar maple, tomato, white oak) ^{7, 44, 57} , leaf veins ⁷ , lighting ^{39, 48} , meadow silhouette ⁴⁵ , mountains ²⁴ , mudcracks ⁵⁶ , river channel ^{20, 41, 49} , rock surface (palisades) ⁶
1.20 - 1.29	Clouds (cirrus, cumulus) ⁰ , coastline ^{10, 22, 33, 35, 58} , creek ⁵¹ , deciduous tree ⁵⁴ , forest patch (small) ²⁷ , glacier ⁹ , evergreen tree ⁵⁴ , hillslope (fluvial) ²⁹ , leaf veins ⁷ , leaf outline (grapevine, silver maple, white oak) ^{34, 57} , lighting ^{39, 48} , macroalgae (Chondrus crispus) ¹⁷ , mountains ³⁷ , mudcracks ⁵⁶ , river channel ^{41, 49} , river network ²⁵ , rock surface (palisades) ^{6, 10} , tree ring indexes ³¹
1.30 - 1.39	clouds (cirrus, cumulus, hail) ^{2, 0, 32, 50} , coastline ^{10, 16, 22} , deciduous tree (sycamore) ⁴⁰ , evergreen tree ⁵⁴ , evergreen shrubs ⁵⁴ , forest patch (large) ²⁷ , forest silhouette ⁴⁵ , ivy ⁴⁰ , leaf veins ⁷ , leaf outline (grapevine) ³⁴ , lighting ^{39, 48} , macroalgae (Lomentaria articulata) ¹⁷ , mountains ³⁷ , mudcracks ⁵⁶ , palm tree ⁵⁴ , plateau ²⁹ , river channel ⁴¹ , river network ²⁵ , rock surface (glacial) ⁶ , tree ring indexes ³¹
1.40 - 1.49	Caves ¹³ , clouds (alto-, cirro-, and strato-Cumulus) ^{0, 30} , coastline ²² , deciduous shrub (barberry) ⁴⁰ , deciduous tree (ash, downy birch, silver birch, weeping elm) ⁴⁰ , evergreen shrubs ⁵⁴ , fire scars ³¹ , leaf veins ⁷ , leaf outline (grapevine) ³⁴ , lighting ⁴⁸ , macroalgae (Laurencia pinnatifida) ¹⁷ , mudcracks ⁵⁶ , palm tree ⁵⁴ , river network ^{25, 51} , rock fractures ¹⁹ , roots ⁵³ , tree ring indexes ³¹
1.50 - 1.59	Clouds (alto-, cirro-, and strato-Cumulus) ^{0, 30} , cloud field ³⁰ , coastline ^{10, 16, 22} , deciduous vine (Virginia creeper) ⁴⁰ , fire scars ³¹ , forest patch (large) ²⁷ , leaf outline (grapevine) ³⁴ , lichen ⁵² , mudcracks ⁵⁶ , rock fractures ¹⁹ , river network ^{25, 42, 43, 51} , rock surface (Hamilton) ^{6, 10} , roots ⁵³ , seagrass ¹ , treeline ²⁴ ,
1.60- 1.69	Coastline ^{10, 22, 46} , coniferous tree (cypress, yew) ^{36, 40} , coral (Anacropora spinosa) ³⁸ , clouds ³⁰ , fire scars ³¹ , leaf outline (black locust, oriental planetree, red mulberry) ³ , mudcracks ⁵⁶ , rock fractures ¹⁹ , river network ^{25, 28, 43, 51} , rock surface (bedding, c-plume, s-plume) ⁶ , sea anemone ⁸ , sea sponge ²³
1.70 - 1.79	Broccoli ²⁶ , coastline ^{10, 22} , coral (Eusmilia fastigiata) ³⁸ , deciduous shrub (cotoneaster) ⁴⁰ , evergreen shrub (Asparagus plumosus) ^{11, 54} , leaf outline (common serviceberry, ficus, peach, slippery elm, white oak) ³ , mineral dendrites ¹² , mudcracks ⁵⁶ , river network ^{14, 25, 28, 42, 43, 51} , smoke ⁴ , tree ring widths ⁵⁵
1.80 - 1.89	Cauliflower ²⁶ , evergreen shrub (Asparagus plumosus) ¹¹ , leaf outline (American hornbeam, eastern redbud) ³ , mudcracks ⁵⁶ , river network ^{14, 25, 42, 51} , roots (maize) ¹⁸
1.90 - 1.99	river network ^{14, 25, 51}

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Table 2.1: Table of natural objects per 0.1 change in fractal dimension, with the sources for the natural fractal object measurements numbered and listed below.

	Low ($D \leq 1.5$)	High ($D \geq 1.5$)	Entire Range ($D = 1.1-1.9$)
Lower /Higher	Low/Medium (1.1/1.3;1.1/1.5;1.3/1.5)	Medium/High (1.5/1.7,1.5/1.9,1.7/1.9)	Low/High (1.1/1.7,1.1/1.9,1.3/1.7,1.3/1.9)
Higher /Lower	Medium/Low (1.3/1.1,1.5/1.1,1.5/1.3)	High/Medium (1.7/1.5,1.9/1.5,1.9/1.7)	High/Low (1.7/1.1,1.9/1.1,1.7/1.3,1.9/1.3)

Table 2.2: Definitions for Block 3 slider task stimulus groupings. The various Top- D /Bottom- D stimulus combinations are grouped into Lower- D /Higher- D and Higher- D /Lower- D subgroups to examine visual appeal in relation to the Top/Bottom D -value combinations.

Table 3a: Paired T-tests for Contour Alternative Forced Choice Portion					
	1.1 <i>D</i>	1.3 <i>D</i>	1.5 <i>D</i>	1.7 <i>D</i>	1.9 <i>D</i>
1.1 <i>D</i>		$t = 2.418$ $p < 0.05^*$ $d = 0.259$	$t = 4.509$ $p < 0.001^{***}$ $d = 0.483$	$t = 5.120$ $p < 0.001^{***}$ $d = 0.549$	$t = 4.880$ $p < 0.001^{***}$ $d = 0.523$
1.3 <i>D</i>			$t = 5.028$ $p < 0.001^{***}$ $d = 0.539$	$t = 5.236$ $p < 0.001^{***}$ $d = 0.561$	$t = 4.846$ $p < 0.001^{***}$ $d = 0.520$
1.5 <i>D</i>				$t = 3.961$ $p < 0.001^{***}$ $d = 0.425$	$t = 3.637$ $p < 0.01^{**}$ $d = 0.390$
1.7 <i>D</i>					$t = 2.140$ $p < 0.05^*$ $d = 0.229$
Table 3b: Paired T-tests for Cluster Alternative Forced Choice Portion					
	1.1 <i>D</i>	1.3 <i>D</i>	1.5 <i>D</i>	1.7 <i>D</i>	1.9 <i>D</i>
1.1 <i>D</i>		$t = -3.939$ $p < 0.001^{***}$ $d = -0.422$	$t = -3.978$ $p < 0.001^{***}$ $d = -0.427$	$t = -3.524$ $p < 0.01^{**}$ $d = -0.378$	$t = -1.965$ $p = 0.068$ $d = -0.211$
1.3 <i>D</i>			$t = -2.934$ $p < 0.01^{**}$ $d = -0.315$	$t = -2.555$ $p < 0.05^*$ $d = -0.274$	$t = -0.772$ $p = 0.474$ $d = -0.083$
1.5 <i>D</i>				$t = -1.546$ $p = 0.149$ $d = -0.166$	$t = 0.655$ $p = 0.538$ $d = 0.070$
1.7 <i>D</i>					$t = 2.488$ $p < 0.05^*$ $d = 0.267$
Table 3c: Paired T-tests for Same-<i>D</i> Composite Alternative Forced Choice Portion					
	1.1 <i>D</i>	1.3 <i>D</i>	1.5 <i>D</i>	1.7 <i>D</i>	1.9 <i>D</i>
1.1 <i>D</i>		$t = -1.288$ $p = 0.226$ $d = -0.138$	$t = 0.337$ $p = 0.749$ $d = 0.036$	$t = 1.564$ $p = 0.148$ $d = 0.168$	$t = 2.649$ $p < 0.05^*$ $d = 0.284$
1.3 <i>D</i>			$t = 1.661$ $p = 0.125$ $d = 0.178$	$t = 2.763$ $p < 0.05^*$ $d = 0.296$	$t = 3.831$ $p < 0.001^{***}$ $d = 0.411$
1.5 <i>D</i>				$t = 2.968$ $p < 0.01^{**}$ $d = 0.318$	$t = 4.276$ $p < 0.001^{***}$ $d = 0.458$
1.7 <i>D</i>					$t = 4.132$ $p < 0.001^{***}$ $d = 0.443$

Table 2.3: A series of paired T-tests with a false-discovery rate (FDR) correction applied to p -values to control for family-wise error rates. One asterisk indicates $p < 0.05$, two asterisks indicate $p < 0.01$, three indicate $p < 0.001$. The effect sizes in the form of Cohen's d are also reported.

<i>D</i> Value	Contour vs. Cluster	Contour vs. Same- <i>D</i>	Cluster vs. Same- <i>D</i>
1.1	t = 7.285 p < .001*** d = 0.781	t = 3.325 p = .001** d = 0.356	t = -4.672 p < .001*** d = -0.501
1.3	t = 5.422 p < .001*** d = 0.581	t = 1.336 p = .185 d = 0.143	t = -4.462 p < .001*** d = -0.478
1.5	t = -3.359 p = .001** d = -0.36	t = -3.068 p = .003** d = -0.329	t = 0.321 p = .749 d = 0.034
1.7	t = -7.499 p < .001*** d = -0.804	t = -3.021 p = .003** d = -0.324	t = 4.875 p < .001*** d = 0.523
1.9	t = -4.179 p < .001*** d = -0.448	t = -0.816 p = .417 d = -0.087	t = 3.908 p < .001*** d = 0.419

Table 2.4: A series of paired t-tests comparing fractal dimensions between categories in the alternative forced choice task with a false-discovery rate (FDR) correction applied to *p*-values to control for family-wise error rates. One asterisk indicates $p < 0.05$, two asterisks indicate $p < 0.01$, three indicate $p < 0.001$. The effect sizes in the form of Cohen's *d* are also reported.

Table 2.5a: Contour Qualitative Survey Results

	Mountains/ Hills	Trees	Natural Material	Humanmade Material	Graphs/Data	Static	Other
1.1 <i>D</i>	74.71%	13.79%	12.64%	3.45%	0%	0%	2.30%
1.3 <i>D</i>	84.27%	20.22%	5.62%	2.25%	2.25%	0%	5.75%
1.5 <i>D</i>	58.43%	34.83%	3.37%	12.36%	0%	4.49%	4.60%
1.7 <i>D</i>	14.61%	22.47%	3.37%	4.49%	28.09%	4.49%	17.65%
1.9 <i>D</i>	1.12%	26.97%	4.49%	13.48%	30.34%	6.74%	18.60%

Table 2.5b: Cluster Qualitative Survey Results

	Clouds/Sky	Maps/Continents	Art/Paint	Other
1.1 <i>D</i>	45.98%	43.68%	3.37%	10.34%
1.3 <i>D</i>	53.93%	37.08%	2.25%	9.20%
1.5 <i>D</i>	47.19%	43.82%	2.25%	8.05%
1.7 <i>D</i>	51.69%	6.74%	17.98%	25.58%
1.9 <i>D</i>	47.19%	1.12%	17.98%	28.74%

Table 2.5: Distribution of responses from the post-experiment qualitative survey. Participants were asked what the (a) bottom (contour) and (b) top (cluster) portions of composite images reminded them of. Responses were spontaneous. Categories were defined as objects mentioned by more than two participants.

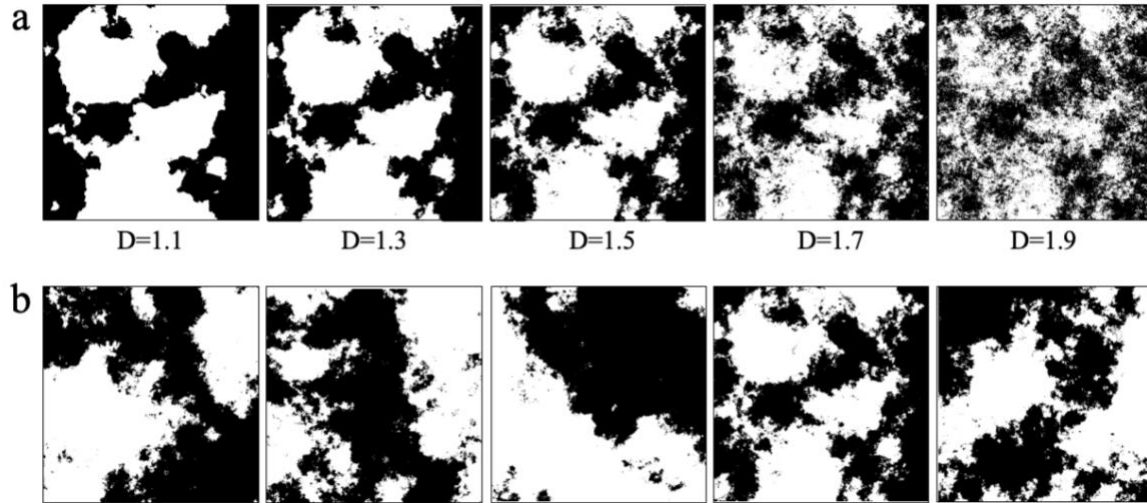


Fig. 2.1: Fractal stimuli. (a) The full range of fractal dimension for a single seed, where $D = 1.1$ is the least complex and $D = 1.9$ the most complex. (b) Five seeds of $D = 1.5$.

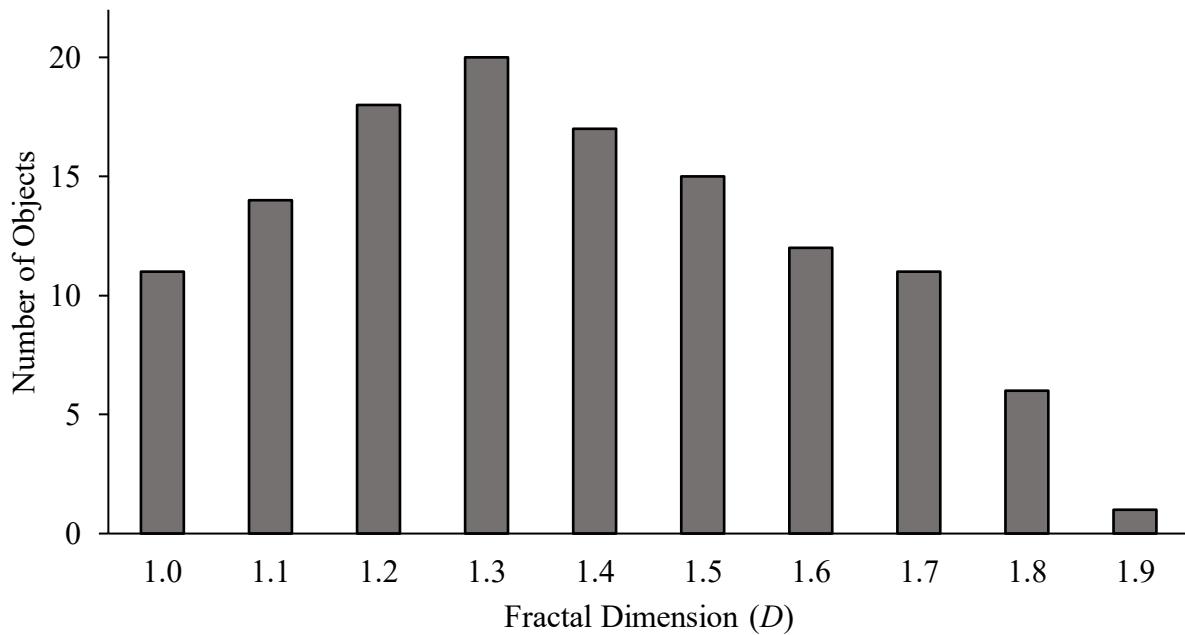


Fig. 2.2: Histogram of natural objects by fractal dimension.

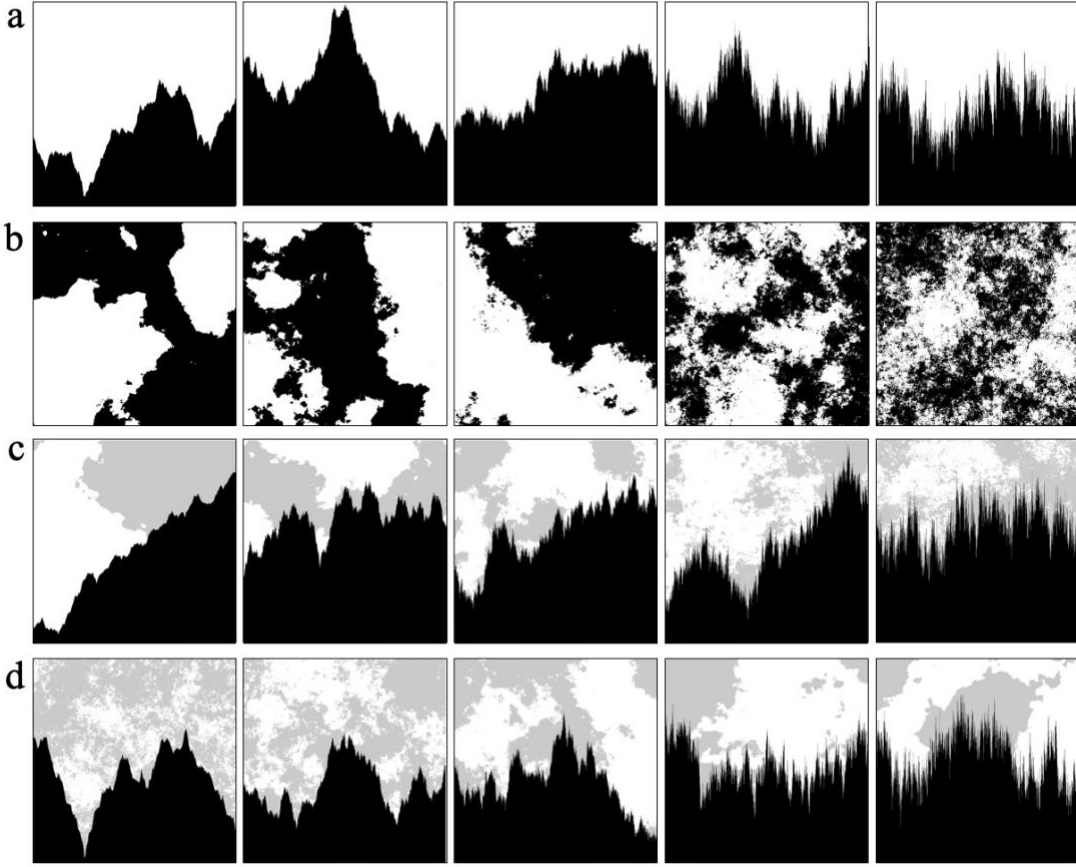
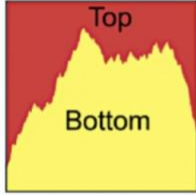


Fig. 2.3: Example stimuli for the first 4 blocks of the experiment. (a) Block 1 or 2: contour stimuli. D -values are 1.1, 1.3, 1.5, 1.7, and 1.9 respectively. (b) Block 1 or 2: cluster stimuli. D -values are 1.1, 1.3, 1.5, 1.7, and 1.9 respectively. (c) Block 3, combined contour and cluster same- D stimuli. D -values are 1.1, 1.3, 1.5, 1.7, and 1.9 respectively. (d) Block 4: combined contour and cluster different- D stimuli. The complexities of the contour fractals are $D = 1.1, 1.3, 1.5, 1.7$, and 1.9 from left to right, while the complexities of the cluster fractals are $D = 1.9, 1.7, 1.5, 1.3$, and 1.1 from left to right.

The following images have different parts – a TOP portion and a BOTTOM portion.
You will be asked if the top or bottom parts of each figure remind you of something that is familiar to you.







1) The bottom part of this image reminds me of:

2) The top part of this image reminds me of:

Fig. 2.4: Qualitative perception survey example. The survey presented five same- D composite fractal stimuli. D -values ranged from low to high complexity (1.1, 1.3, 1.5, 1.7, 1.9).

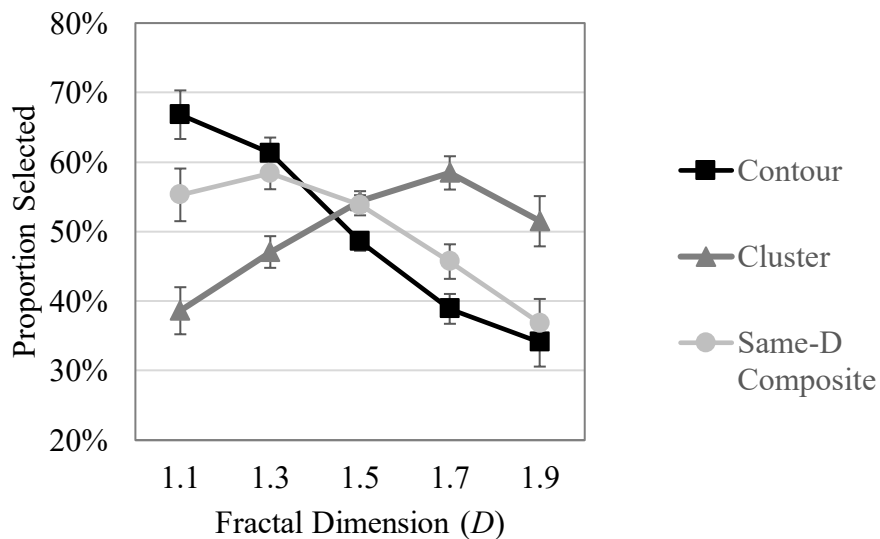


Fig. 2.5: Comparison of two alternative forced choice (2AFC) Blocks 1-3 for the proportion of the time that each fractal dimension was selected for three different fractal types (contour, cluster, and same- D composite fractals). Error bars represent ± 1 standard error of the mean (SEM).

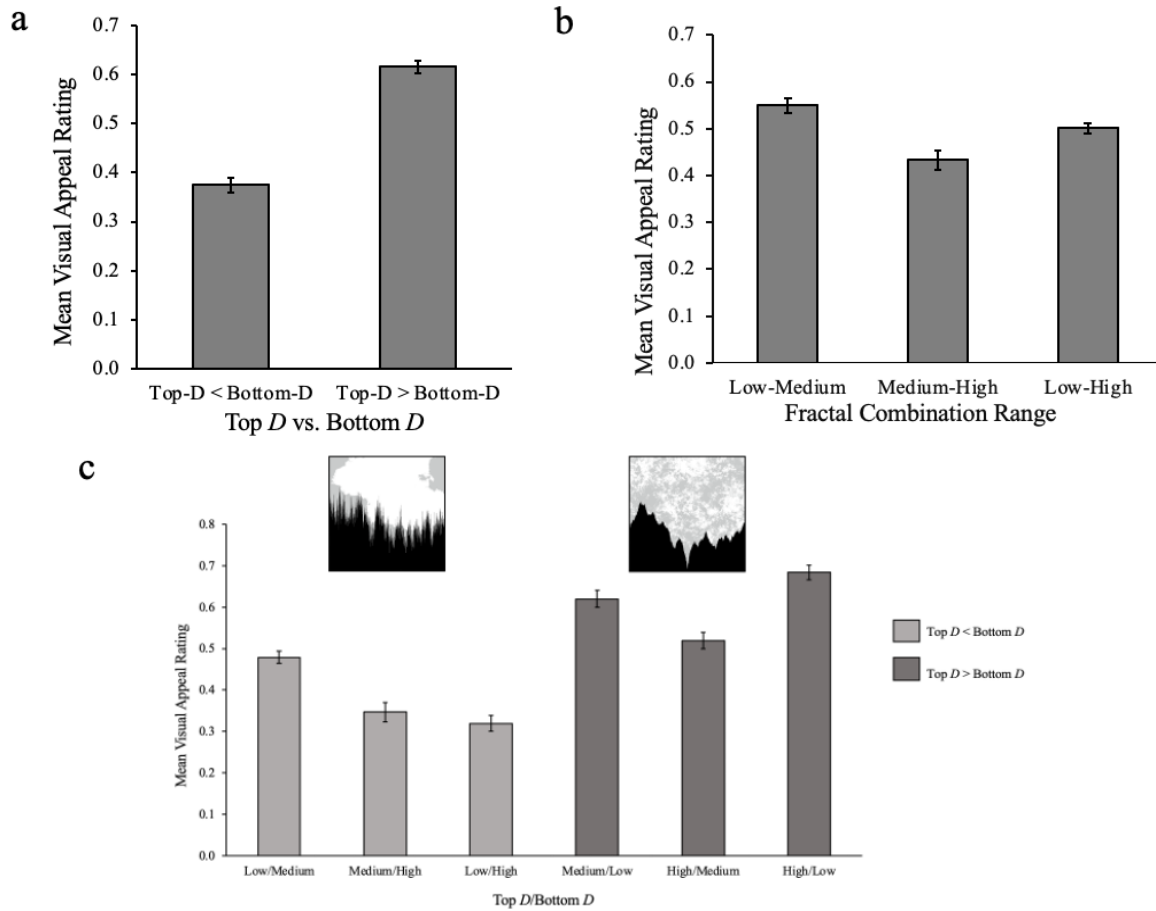


Fig. 2.6: Slider task (Block 4; *Fig 2.3d*) results. (a) Mean visual appeal rating, on a scale from 0-1, is plotted as a function of the direction of the fractal relationship (i.e., the relationship between the D -values in the 2 parts of the stimulus), where “Top- D ” refers to the D -value of the top, cluster portion of the stimulus and “Bottom- D ” refers to the D -value of the bottom, contour portion of the stimulus. (b) Mean visual appeal rating, on a scale from 0-1, is plotted as a function of the range of fractal relationship (D -values) between the top and bottom portions of the stimuli. Range is defined as the level of contrast being combined (Low-Medium, Medium-High, or Low-High). Both polarities (lower/higher and higher/lower) are encompassed in the combinations (e.g., Low-Medium stimuli refer to composite fractals where the top is of low complexity and bottom is of medium complexity, or vice versa). See *Table 1.2* for specific definitions. (c) Mean visual appeal rating, on a scale from 0-1, is plotted for composite fractals with different Top and Bottom D -

values. The figure inserts are example composite stimuli with Top- $D < \text{Bottom-}D$ (left) and Top- $D > \text{Bottom-}D$ (right). Error bars represent ± 1 SEM.

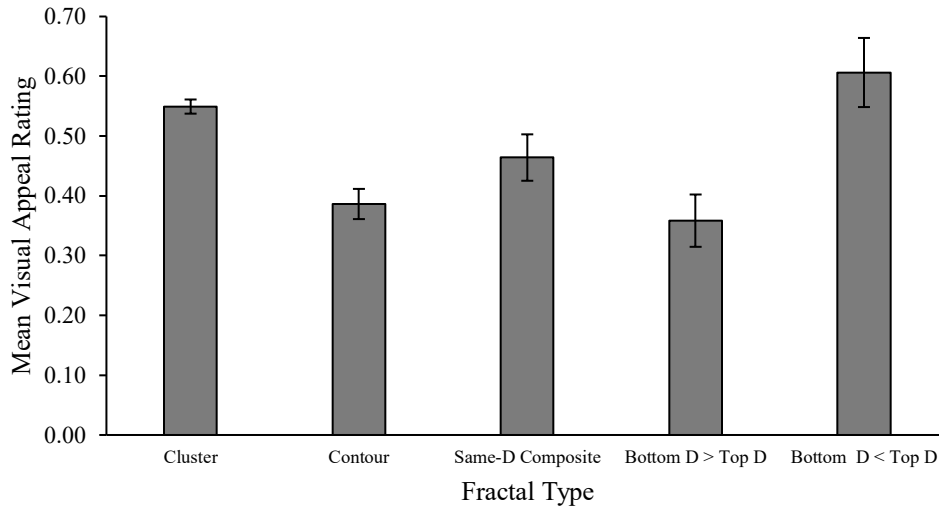


Fig. 2.7: Mixed slider task comparing mean visual appeal rating different types of fractals, contour, cluster, same- D composite, and different- D composite (split into bottom $D < \text{top } D$, and bottom $D > \text{top } D$), on a scale from 0-1. Error bars represent ± 1 SEM.

CHAPTER III

Magic Seeds: The Influence of Composition and Pareidolia on the Perception of Fractals

1. Introduction

What distinguishes one maple tree from another? Why do some cumulus clouds draw our gaze, but not others? Humanity's collective eye is undeniably attracted to natural imagery. Intuitively this makes sense. Our visual systems evolved to efficiently process natural scenes. One of the overarching structural characteristics of natural objects is their fractal properties. Fractals, first described by Mandelbrot (1978), are defined by their self-similar nature. A tree is fractal, for example, because the same general pattern repeats at different scales – the trunk splits into large branches, which split into smaller branches, which split again into twigs. A host of natural objects are fractal in nature. From macrostructures like coastlines (Mandelbrot, 1967) and watersheds (Schuller, Rao & Jeong, 2001), to microstructures such as neurons (Smith et al., 2021) and the bronchioles of the lungs (Weibel, 1991), nature often utilizes this efficient self-similar mechanism.

While fractal properties are prevalent in nature across scales, they are abundant in natural objects visible to the naked human eye. This is vital because these are the objects our visual systems evolved to process. Features such as mountain ridges (Mark & Aronson, 1984), clouds (Bies, Taylor, & Sereno, 2015), and lightning (Miranda & Sharma, 2016) are fractal.

Natural environments have been linked with broader psychological benefits. A meta-analysis of the relationship between natural environments and physiological stress reduction found a small to moderate effect overall (Gaekwad, Moslehian, & Roös, 2023). Videos of nature facilitate significantly more stress reduction than videos of urban environments (Ulrich, Simons, Losito, Fiorito, Miles, & Zelson, 1991). Similarly, research examining differences between

walking in nature and urban settings found that nature walks were associated with decreased negative affect (e.g., stress and rumination), preservation of positive affect, and increased working memory performance (Bratman, Daily, Levy, & Gross, 2015). Electroencephalography (EEG) studies have shown that videos of nature prompted increased alpha wave activity, which are associated with feelings of wakeful relaxation and internalized attention (Grassini, Segurini, & Koivisto, 2022).

While there is a rich history of natural fractal scenes eliciting positive effects, there is similar research showing the benefits of computer-generated fractal patterns. When generating fractal images researchers can control for variables such as the fractal dimension (D), which quantifies complexity. For two-dimensional fractal images, D -value ranges between one and two, with values closer to one indicating lower complexity and values closer to two indicating higher complexity. Fractal patterns also fall on a spectrum between statistical and exact structure. Exact fractals repeat the seed pattern perfectly across iterations, while statistical patterns introduce an element of randomness such that the patterns are similar across iterations but not exact. Bies, Blanc-Goldhammer, Boydston, Taylor, and Sereno (2016) found that preference increased with complexity for exact fractals for most participants, but there was a subgroup that preferred low complexity exact fractals. When examining EEG responses to statistical fractals, participants exhibited increased alpha wave activity, indicating that static natural images may be sufficient to induce the psychological benefits associated with exposure to nature (Hägerhäll, Laike, Küller, Marcheschi, Boydston, & Taylor, 2015).

Because our visual systems evolved to process natural objects, multiple studies have shown that human beings display a particular aesthetic affinity for statistical fractals in the low to mid-range of complexity (1.3-1.5 D) (Spehar et al., 2003; Taylor, Spehar, Van Donkelaar, & Hagerhall,

2011; Spehar, Walker, & Taylor, 2016). This low to mid-range of complexity is theorized to encapsulate the average fractal dimension of nature, which is supported by the literature review of measurements of fractal complexity of natural objects conducted by Owen, Robles, Bies, Taylor, & Sereno (in preparation). Exposure to low-to-mid D fractals resulted in reduced physiological indicators of stress (Taylor, 2006). When examining the neural response to varying fractal dimensions with qEEG, subjects' alpha and beta responses were largest when $D=1.3$ (Hagerhall et al., 2008). Additionally, Robles, Liaw, Taylor, Baldwin and Sereno (2020) found that children as young as three exhibit adult fractal preferences.

Our general affinity for fractals, particularly of low to mid complexity, informs the fractal fluency theory (Taylor et al., 2011; Taylor & Spehar, 2016; Taylor et al., 2018) which states that an aesthetic experience originates from enhanced processing of fractal patterns that we are most frequently exposed to in nature's scenery (either through evolutionary exposure or through our lives). Studies on aesthetics in general have found that natural images tend to evoke the highest aesthetic ratings, and have more self-similar properties (Forsythe, Nadal, Sheehy, Cela-Conde, and Sawey, 2011). Overall, the study found that fractal dimension accounted for 30% of variance in judgements of beauty of natural scenes, and 19% of variance of judgment of the beauty of abstract art (Forsythe, Nadal, Sheehy, Cela-Conde & Sawey, 2011). While aesthetic engagement may seem like a trivial goal on the surface, several studies have linked aesthetic engagement to increased activity in the reward pathways (Brown, Gao, Tisdelle, Eickhoff, & Liotti, 2011; Yue, Vessel, & Biederman, 2007). Aesthetic pleasure has even been linked to profound psychological and physiological benefits such as pain reduction (Tommaso, Sardaro, & Livrea, 2008).

While the influence of fractals and visual complexity on aesthetics has been thoroughly explored, one element that has not been studied is the impact of seed on visual perception. This is

likely because the seed is perhaps the most abstract factor that influences the structure of fractal patterns. The seed is the element in the pattern that repeats. In an exact fractal pattern, such as an H-tree, the element in the pattern repeats perfectly across scales. In the H-tree the seed is the “H” itself. In a statistical fractal pattern, due to the randomness inherent to statistical fractals, the element that repeats is not an exact shape, but rather a statistical pattern or distribution. Thus, the average properties are similar across scales.

The seed is the element of a fractal pattern that makes it unique from other patterns of the same type and complexity. Just like how each tree, even within the same genus and species, has a distinct pattern, a fractal pattern can have the same level of complexity but a distinct structure. While fractals are prevalent in nature, out of context the patterns appear abstract, for example in Pollock’s drip paintings (Taylor, Micolich, & Jonas, 1999).

Previous literature has examined the visual appeal of abstract art. While abstract images can appear random, composition plays a vital part in the visual perception of abstract art. For example, abstract paintings positioned in the orientation intended by the artist tend to elicit greater appeal (Bai, Guo, & Jia, 2019). The design principle of simplicity has also been scientifically validated. When quantified as a lack of visual clutter researchers found a significant negative correlation between visual clutter and aesthetic appeal (Redi & Pova, 2013). Another study specifically examined pareidolia (i.e., the perceptual tendency to impose meaning on ambiguous stimuli) in fractal patterns finding that images at fractal $D = 1.3$ elicited the highest number of percepts at the fastest response rate (Bies et al., 2016a).

While the field has a strong sense of the power of fractal patterns in general, as well as the role of complexity in visual aesthetics, the impact of the seed on the perception of fractal images has been largely overlooked. The current study aims to investigate whether 1) some seeds

are preferred across participants, 2) some seeds are disliked across participants, and 3) these preferences can be attributed to compositional elements, pareidolia, or other factors. In accordance with previous fractal research, we expect to see the highest preference for low-to-mid level complexity stimuli ($D = 1.1-1.5$). Overall, we expect to find a subset of seeds that are rated highly across participants, and a subset of seeds that are rated low across participants. Previous research (Bies et al., 2016b) has shown that human subjects experience the most pareidolia when viewing low-to-mid level complexity fractal stimuli which corresponds with peak preference ($D = 1.1-1.3$). Due to these findings, we hypothesize that pareidolia will be the most prevalent explanation for high ratings.

2. Method

2.1 Participants

A power analysis determined that a repeated measures experiment anticipating a small to moderate effect size requires approximately 90 participants for adequate power. The experiment consisted of 78 participants. Two participants were excluded from data analysis due to binary rating patterns (all ratings were 0 or 1).

The experiment took approximately forty-five minutes and participants were compensated with research credit. All participants were recruited from the Psychology and Linguistic Departments' Human Subject pool at the University of Oregon. Informed consent was acquired following a protocol approved by the Institutional Review Board at the University of Oregon, and all measures were performed in accordance with relevant guidelines and regulations for research involving human subjects as approved by this review board.

2.2 Stimuli

The stimuli for this experiment were sets of random midpoint displacement fractal images generated using an algorithm described by Fournier, Fussel, and Carpenter (1982), which allowed us to specify D (for details see Bies et al., 2016a). The number of iterations was set to ten. The stimuli, presented against a grey background, were 2100 x 2100 pixels in size. The experiment was created with PsychoPy (OmicX) and Python and was conducted on apple computers. One hundred unique seeds were generated at five fractal dimensions (1.1, 1.3, 1.5, 1.7, 1.9) for a total of 500 unique stimuli.

2.3 Measures

Qualitative Responses. Participants first completed a slider task (see below) which was used to quantify the visual appeal of 500 unique stimuli, followed by a survey which was created within the PsychoPy (OmicX) program to collect qualitative data on the reasoning behind the aesthetic ratings. For each participant, the top five rated seeds and the bottom five rated seeds (collapsed across fractal dimension D) were presented again to the participant. The participants were asked to describe what they liked or disliked about each seed. An image of the seed across the five fractal dimensions was displayed above the prompt. The reasoning for the ratings were dummy coded as composition related (e.g., referencing line, space, balance, etc., such as they liked the diagonal structure), pareidolia (e.g., it looks like a starry sky, it looks like a bunny, it reminded me of home), lack of pareidolia (e.g., it didn't remind me of anything, I couldn't make sense of it), affect (e.g., it made me feel uneasy, it gave me the creeps), and over/under stimulation (e.g., it was too much, not enough). If the explanation spanned multiple categories, the entry was coded as belonging to each category it encompassed, with the value divided by the number of categories. For example, if a participant said they liked a seed because it was well balanced and

looked like clouds, 0.5 would be tallied toward composition and 0.5 toward pareidolia. A distinction was made between participants reporting too much black or white in an image which were categorized as composition related (because it referred specifically to color balance) and responses indicating that the image in general was over-stimulating or under-stimulating (e.g., there's too much going on; there's not enough going on) which were coded as stimulation based. *Demographics.* Demographic information was collected through University of Oregon's SONA website.

2.4 Design

The experiment consisted of two parts and utilized a within subjects design. The first part was a slider task which was used to quantify the visual appeal of 500 unique stimuli. Stimuli were presented in random order. Participants were asked to rate each stimulus on a scale of zero to one, with values closer to zero indicating lower visual appeal and values closer to one indicating higher visual appeal (see *Fig. 1*). The independent variables examined were the fractal dimension, which had five levels (1.1, 1.3, 1.5, 1.7, and 1.9 *D*), and seed which had 100 levels. The dependent variable was beauty, operationalized in this experiment as visual appeal.

The second portion of the experiment presented participants with their five top rated and five lowest rated seeds, averaged across fractal dimensions. Participants were asked to give qualitative feedback on why they found each seed appealing or unappealing.

2.5 Procedure

A researcher conducted this experiment which lasted approximately 45 minutes. The experiment consisted of a rating section followed by a qualitative feedback section. Participants were asked to rate the image on a slider from zero to one, with zero indicating lowest visual appeal

and one indicating highest visual appeal. The instructions for the experiment were given verbally by the experimenter and programmed into the experiment.

After the rating portion concluded, participants were presented with their five highest rated seeds and five lowest rated seeds and asked to explain why they did or did not like those patterns. Once the experiment concluded participants were debriefed and awarded credit.

3. Results

1.1 Preference for Fractal Stimuli Across Dimension

Ratings were Z-score normalized to account for individual rating styles. To determine the effect of fractal dimension on preference, we performed a one-way repeated measures ANOVA with 5 levels of stimulus complexity ($D = 1.1, 1.3, 1.5, 1.7, 1.9$) using participants' average normalized preference ratings for each level of complexity (D). Mauchly's test indicated that the assumption of sphericity was violated, $\chi^2 = 504.60$, $p < .001$. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = 0.30$). While ratings were highest for lower fractal dimensions ($D = 1.1, 1.3$) those differences were not significant: $F(1.20, 90.05) = 1.31$, $p = 0.263$, $\eta p^2 = 0.02$ (see *Fig. 2*). Follow up paired t-tests showed no significant differences between any level of comparison (see *Table 1*).

To determine the effects of rating time on fractal dimension, we performed a one-way repeated measures ANOVA with 5 levels of stimulus complexity (D) using participants' average response times for each level of complexity. Mauchly's test indicated that the assumption of sphericity was violated, $\chi^2 = 160.45$, $p < .001$. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = 0.48$). The results show that there was a significant effect of complexity (D) on response times, $F(1.89, 141.70) = 6.55$, $p = 0.002$, $\eta p^2 = 0.08$ (see *Fig. 3*). Examining differences in rating time by fractal dimension showed a general

trend that response time was longer for low to mid complexity fractal dimensions ($D = 1.1 - 1.5$). Follow up paired t-tests showed significant differences between $D = 1.9$ and every other level, as well as between $D = 1.7$ vs. $D = 1.5$ (see *Table 2*).

1.1.1 Subgroup Preferences Across Dimension

To determine whether the observed trend in preference for fractal stimuli across dimension could be better explained as a combination of multiple discrete subgroup patterns of responses, we performed a two-step cluster analysis and tested for an interaction between the subgroup preferences and D . First, we performed a hierarchical cluster analysis using Ward's method to separate individuals into groups using their preference ratings for each level of D . The resultant agglomeration matrix indicated a two-cluster solution. We then performed k -means clustering analysis to form 2 groups. These cluster analysis techniques are described in more detail in Norušis (2011).

We investigated whether there was an interaction between cluster-membership and D by performing a mixed ANOVA with 5 levels of D and 2 groups. Mauchly's test of sphericity indicated that the assumption of sphericity had been violated, $\chi^2 = 243.03$, $p < .001$. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = 0.47$). The results show that there was a significant main effect of fractal dimension, $F(1.89, 139.53) = 7.75$, $p < .001$, $\eta p^2 = .095$. There was also a significant interaction between D and group, indicating distinct preference curves for each cluster, $F(1.89, 139.53) = 190.72$, $p < .001$, $\eta p^2 = .72$. *Figure 4* shows that one group of participants (53%) prefers higher D fractals, with preference ratings increasing as D increases. In contrast, preference ratings for the other group (47%) decrease as a function of D . This refines our interpretation of the sample's average preferences.

Polynomial contrasts showed a significant linear trend for fractal dimension, $F(1, 74) = 9.49, p < .05, \eta^2 = 0.11$, as well as a significant cubic trend, $F(1, 74) = 18.73, p < .001, \eta^2 = .20$. The interaction between fractal dimension and subgroup showed a significant linear trend, $F(1, 74) = 282.90, p < .001, \eta^2 = .79$, as well as a significant cubic trend, $F(1, 74) = 23.79, p < .001, \eta^2 = .24$.

The impact of fractal dimension and cluster-membership on normalized aesthetic ratings was further verified through multivariate tests. Fractal dimension continued to be a significant main effect, $F(4, 71) = 5.63, p < .001, \eta^2 = 0.24$, and the interaction between fractal dimension and cluster continued to be highly significant, $F(4, 71) = 68.53, p < .001, \eta^2 = .79$.

1.2 Seed Effects

To examine if some randomly generated seeds were more liked or disliked across individuals, we first calculated the five top and bottom rated seeds from the normalized ratings across participants (see *Figs. 5 and 6*). We then averaged the ratings for the top five rated seeds, bottom five rated seeds, and all other seeds for each individual participant's normalized rating data. The top and bottom rated seeds were highly similar but not identical between raw and normalized ratings (see *Table 3*). We performed a 2-way repeated measures ANOVA comparing normalized preference ratings by rating category (3 levels [Top 5, middle, Bottom 5]) and fractal dimension (5 levels). Degrees of freedom for each F-test are reported with Greenhouse-Geisser correction when assumptions of sphericity have been violated, as determined by $p < 0.05$ for Mauchly's test.

The results show that there was not a significant main effect of fractal dimension, $F(1.28, 96.30) = 0.40, p = 0.58, \eta^2 = .005$; there was a significant main effect of seed group, $F(1.21, 91.02) = 25.15, p < .001, \eta^2 = .25$; and no significant interaction between fractal dimension and seed group, $F(5.94, 445.16) = 0.32, p = 0.92, \eta^2 = 0.004$ (see *Fig. 7*).

Paired samples *t*-tests showed that each preference group's normalized ratings were significantly different from the others (see *Table 4*). A series of paired *t*-tests comparing the ratings for each individual seed between cluster groups (i.e. comparing the average rating of each seed collapsed across fractal dimension between cluster groups) found that five seeds were rated significantly differently between the high-*D* and low-*D* preferring subgroups after *p*-values were corrected for family wise error rates with the Benjamini-Hochberg procedure (see *Fig. 8*).

1.3 Qualitative Responses

While the quantitative data give us insight into whether some seeds are rated significantly higher or lower on average, the qualitative data allowed us to dive into the rationale behind the aesthetic ratings. Sixty-five participants were asked to explain what they particularly liked/disliked about their top five and bottom five rated seeds.

When justifications are broken down for each of the top and bottom five rated seeds, we see that for the top five rated seeds the dominant justification was split between compositional elements and pareidolia (see *Table 5a*). For the bottom five rated seeds, compositional elements were the dominant justification (see *Table 5b*).

When justifications are collapsed across the top rated versus bottom rated seeds, clear differences emerge (see *Table 6*). For the top-rated seeds, composition elements and pareidolia explained equivalent proportions of data (40.4% and 44.6%). For the bottom rated seeds compositional elements were the most common justification (47.3%), distantly followed by stimulation (15.4%), lack of pareidolia (12.1%), presence of pareidolia (9.7%), and affective explanations (6.7%).

4. Discussion

Overall, the results of this study support the idea that the fractal seed pattern plays a small but significant role in determining preference. While the top and bottom five rated seeds were significantly different than all other seeds, the effect sizes were small indicating a small role in aesthetic preference of cluster fractal patterns. The normalized ratings across fractal dimension aligned with previous research (Spehar et al., 2003; Taylor, Spehar, Van Donkelaar, & Hagerhall, 2011; Spehar, Walker, & Taylor, 2016), showing preference peaking at low to mid-levels of complexity, despite the differences in ratings between fractal dimensions not showing significance before the cluster analysis (*Fig. 2*). Additionally, response time was longer for low to mid complexity fractal dimensions (*Fig. 3*).

Previous research has shown individual differences in aesthetic preference for fractal dimension of statistical fractals. Street, Forsythe, Reilly, Taylor, and Helmy (2016) found that female participants tend to prefer higher complexity fractals ($D = 1.6$) compared to male participants ($D = 1.2$). Robles et al. (2021) also found individual differences in the perception of fractals, discovering subgroup trends for perceptual ratings of preference, refreshing, and relaxing. Spehar, Walker, and Taylor (2016) also found distinct preference groups, with one preferring higher complexity, one lower complexity, and one displaying the classic curve with preference peaking at mid-level complexity.

In accordance with this previous research on aesthetic preference for fractal complexity, we found individual differences in fractal preferences. One cluster exhibited a strong preference for low complexity fractal patterns ($D = 1.1, 1.3$), and one showed a strong preference for high complexity fractal patterns ($D = 1.7, 1.9$) (*Fig. 4*).

The qualitative coding of the post hoc justifications of top and bottom rated seeds also revealed interesting and somewhat unexpected results. As predicted, pareidolia was the mechanism that explained most justifications for highly rated seeds across participants, however compositional elements were almost equivalently prevalent as a justification for preference. For the lowest rated seeds across participants pareidolia was not a prevalent justification, and neither was a lack of pareidolia. Instead disliking the composition was the most prevalent justification for low preference ratings overall. When directly comparing the top five rated seeds to the bottom five rated seeds, highly rated seeds seem to be less clustered compared to low rated seeds (see *Figs. 5 and 6*). To gain more neutral insight, we compared the top and bottom rated seed with the OpenAI tool ChatGPT. This artificial intelligence is trained on a massive dataset and refined with Reinforcement Learning for Human Feedback, and therefore is a useful tool to gain insight into compositional differences in seeds. When asking ChatGPT to compare and contrast the top and bottom rated seeds for compositional elements the model described the top rated seed as having stronger balance, contrast, use of negative space, and several areas of visual interest (OpenAI, 2025). The bottom rated seed was described as bottom-heavy, with denser areas of contrast and less dynamic (OpenAI, 2025).

One of the most common compositional justifications for ratings was liking/disliking the dominance of the black/white portions of the image. However, the number of pixels of black and white were balanced for each stimulus. On average there was less than a 1% difference in the number of black vs. white pixels. This suggests that the reported justification may not be the true reason behind the rating, but the most salient justification available to the participant. Due to the post hoc nature of the justifications, it is possible that the participants lacked insight into the true

reasons behind their ratings. In fact, one of the most common qualitative responses categorized as “other” was the participant reporting they did not know why they liked or disliked a stimulus.

The ubiquitous nature of fractal stimuli may have played a role in the patterns of justifications. Because cluster fractals are reminiscent of many natural objects such as clouds, canopies, foliage, lichen, and coastlines, there’s a possibility that the patterns felt familiar, but participants struggled to connect that familiarity to a specific object.

5. Conclusion

Overall, the results of this study showed significant differences between the top five rated seeds, bottom five rated seeds, and all other seeds. There were two distinct clusters for preference, with one group strongly preferring low complexity fractal dimension stimuli and the other strongly preferring high complexity fractal dimension stimuli. While we expected pareidolia to be the main justification for high ratings, we instead found the dominant justification for both high and low ratings was related to composition.

6. Implications and Future Directions

The current research illuminates the impact of seed, specifically seed composition, on aesthetic preference for fractal stimuli. The findings show that seed has a small but significant impact on overall aesthetic preference. The implication for biophilic design is that the choice of seed should be examined before designs are utilized in a space.

Future studies should use compositional elements to preselect seeds likely to illicit particularly high and low ratings and compare those curated seeds to randomly generated seed compositions. This would further validate the impact of seed on overall aesthetic preference by allowing for preregistration of seed specific hypotheses. Another intriguing direction would be to

rotate the top and bottom rated seeds and examine if the orientation changes the preference ratings for fractal stimuli.

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	$D = 1.1$	$D = 1.3$	$D = 1.5$	$D = 1.7$	$D = 1.9$
$D = 1.1$		$t = 0.43$ $p = 0.74$ $d = 0.05$	$t = 1.56$ $p = 0.35$ $d = 0.18$	$t = 1.48$ $p = 0.35$ $d = 0.17$	$t = 0.78$ $p = 0.55$ $d = 0.09$
$D = 1.3$			$t = 2.14$ $p = 0.35$ $d = 0.25$	$t = 1.72$ $p = 0.35$ $d = 0.20$	$t = 0.79$ $p = 0.55$ $d = 0.09$
$D = 1.5$				$t = 1.07$ $p = 0.48$ $d = 0.12$	$t = -0.01$ $p = 0.99$ $d = -0.00$
$D = 1.7$					$t = -1.11$ $p = 0.48$ $d = -0.13$

Table 3.1. Paired t-tests for normalized ratings by fractal dimension (D). P-values are corrected for family wise error rates with the Benjamini-Hochberg procedure. Effect size is calculated as Cohen's d.

	$D = 1.1$	$D = 1.3$	$D = 1.5$	$D = 1.7$	$D = 1.9$
$D = 1.1$		$t = -0.29$ $p = 0.77$ $d = -0.03$	$t = -1.38$ $p = 0.25$ $d = -0.16$	$t = 0.71$ $p = 0.53$ $d = 0.08$	$t = 2.64$ $p < .05^*$ $d = 0.30$
$D = 1.3$			$t = -1.66$ $p = 0.17$ $d = -0.19$	$t = 1.02$ $p = 0.39$ $d = 0.12$	$t = 3.20$ $p < .001^{***}$ $d = 0.37$
$D = 1.5$				$t = 3.00$ $p < .01^{**}$ $d = 0.34$	$t = 5.20$ $p < .001^{***}$ $d = 0.60$
$D = 1.7$					$t = 3.28$ $p < .01^{**}$ $d = 0.38$

Table 3.2. Paired t-tests for response time (s) by fractal dimension (D). P-values are corrected for family wise error rates with the Benjamini-Hochberg procedure. Effect size is calculated as Cohen's d. *Indicates significance of $p < 0.05$, **Indicates significance of $p < 0.01$, and ***Indicates significance of $p < 0.001$.

Rank	Type	Seed	Mean Rating
Top 5	Normalized	74	0.14
Top 5	Normalized	40	0.13
Top 5	Normalized	73	0.12
Top 5	Normalized	28	0.11
Top 5	Normalized	94	0.11
Top 5	Raw	40	0.51
Top 5	Raw	74	0.50
Top 5	Raw	28	0.50
Top 5	Raw	43	0.49
Top 5	Raw	94	0.49
Bottom 5	Normalized	35	-0.15
Bottom 5	Normalized	34	-0.11
Bottom 5	Normalized	15	-0.10
Bottom 5	Normalized	48	-0.10
Bottom 5	Normalized	54	-0.10
Bottom 5	Raw	35	0.43
Bottom 5	Raw	34	0.43
Bottom 5	Raw	5	0.44
Bottom 5	Raw	48	0.44
Bottom 5	Raw	54	0.44

Table 3.3. Top and bottom rated seeds for the normalized rating data versus the raw rating data.

The top five most and least preferred seeds remained largely the same between rating categories.

	<i>t</i> -Value	<i>p</i> -value	Cohen's d
Top 5 vs. Bottom 5	5.40	< .001	0.62
Bottom 5 vs. Other	-3.65	< .001	-0.42
Top 5 vs. Other	6.15	< .001	0.71

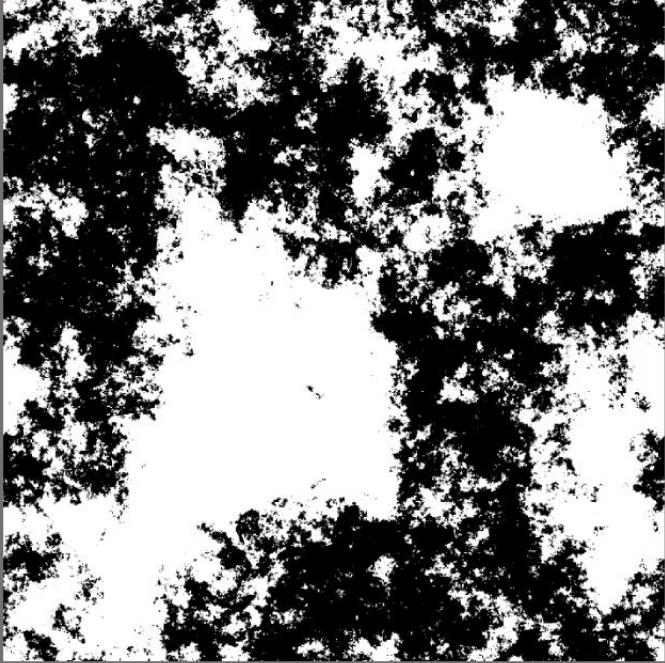
Table 3.4. Paired *t*-tests for each seed group. *P*-values have been adjusted for family wise error rate. Effect size is reported as Cohen's d.

Table 5a: Top Five Seed Qualitative Justifications						
	Composition	Pareidolia	Lack of Pareidolia	Affective	Stimulation	Other
31	50%	0%	0%	0%	0%	50%
28	50%	25%	0%	25%	0%	0%
2	37.5%	37.5%	0%	0%	25%	0%
74	16.7%	66.7%	0%	0%	0%	16.7%
83	66.7%	33.3%	0%	0%	0%	0%
Table 5b: Bottom Five Seed Qualitative Justifications						
	Composition	Pareidolia	Lack of Pareidolia	Affective	Stimulation	Other
5	44.4%	5.6%	16.7%	11.1%	11.1%	11.1%
35	90%	0%	10%	0%	0%	0%
34	50%	0%	20%	0%	10%	20%
1	64.3%	14.3%	0%	0%	7.1%	14.3%
15	87.5%	0%	0%	12.5%	0%	0%

Table 3.5: This table breaks down the reasoning by dummy code for the top and bottom five rated seeds (normalized rating) averaged across participants.

Distribution of Justifications for Top vs. Bottom Normalized Rated Seeds						
	Composition	Pareidolia	Lack of Pareidolia	Affective	Stimulation	Other
Top 5	40.4%	44.6%	0%	1.8%	2.0%	11.1%
Bottom 5	47.3%	9.7%	12.1%	6.7%	15.4%	8.7%

Table 3.6. Comparison of qualitative justification for ratings by category (Top 5, Bottom 5).



How visually appealing do you find this image?

0 ————— 1

Least visually appealing Most visually appealing

A red downward-pointing triangle is positioned on the horizontal line, approximately one-third of the way from the left (0) towards the right (1).

Figure 3.1. The interface used to rate each stimulus. Ratings ranged from zero to one with values closer to zero indicating lower visual appeal and values closer to one indicating higher visual appeal.

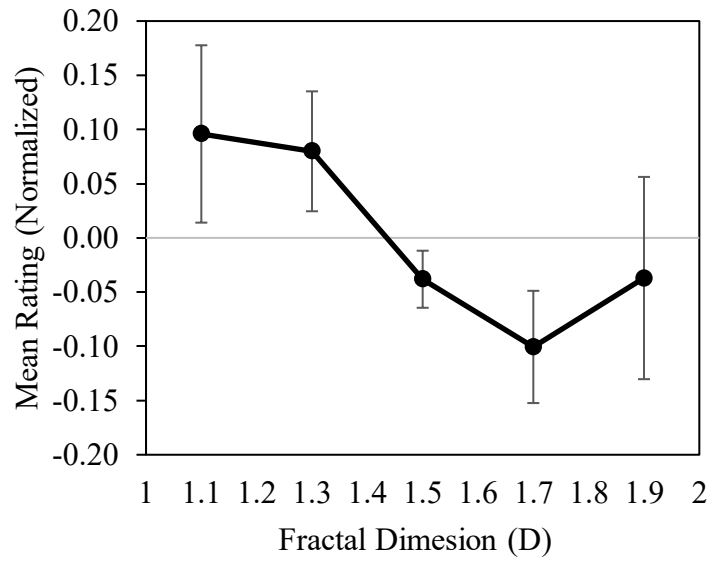


Figure 3.2. The mean normalized rating by fractal dimension (D). Error bars indicate ± 1 SEM.

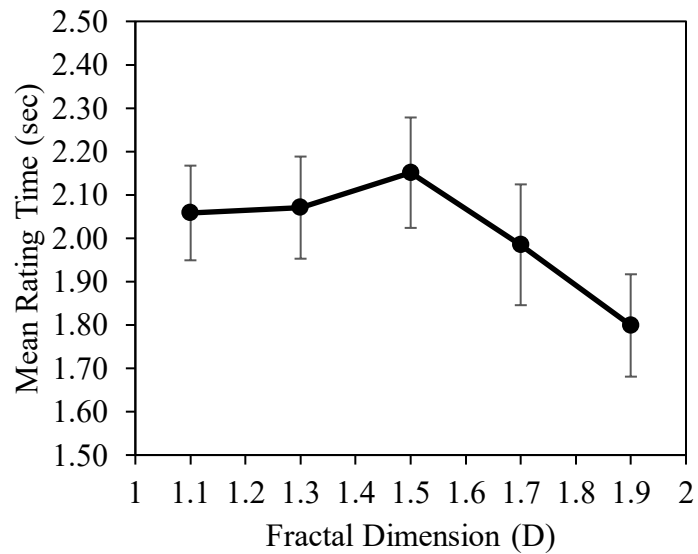


Figure 3.3. The mean response time (in seconds) by fractal dimension (D). Error bars indicate ± 1 SEM.

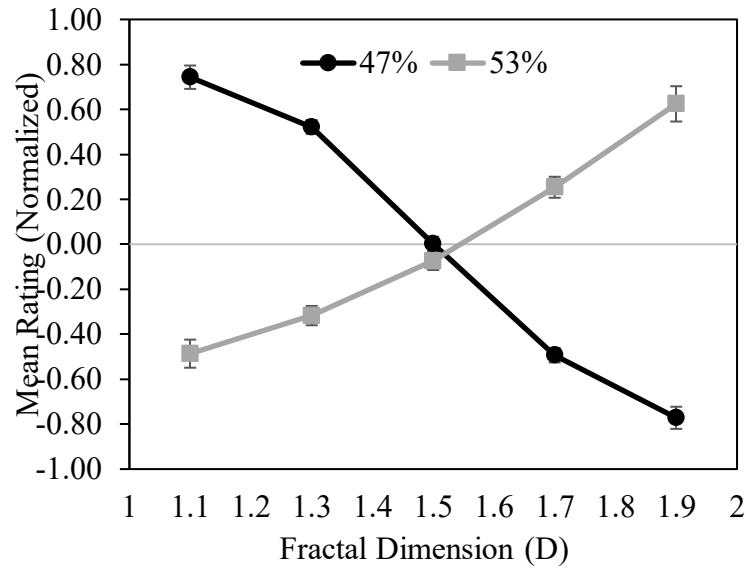


Figure 3.4. The mean normalized rating per fractal dimension for participant subgroups. Error bars indicate +/-1 SEM.

Seed	Mean Rating	Fractal Dimension (D)				
		1.1	1.3	1.5	1.7	1.9
31	0.15					
28	0.12					
2	0.12					
74	0.11					
83	0.10					

Figure 3.5. The top five rated seeds based on mean normalized ratings across participants. The highest rated fractal dimension for each seed is outlined in red.

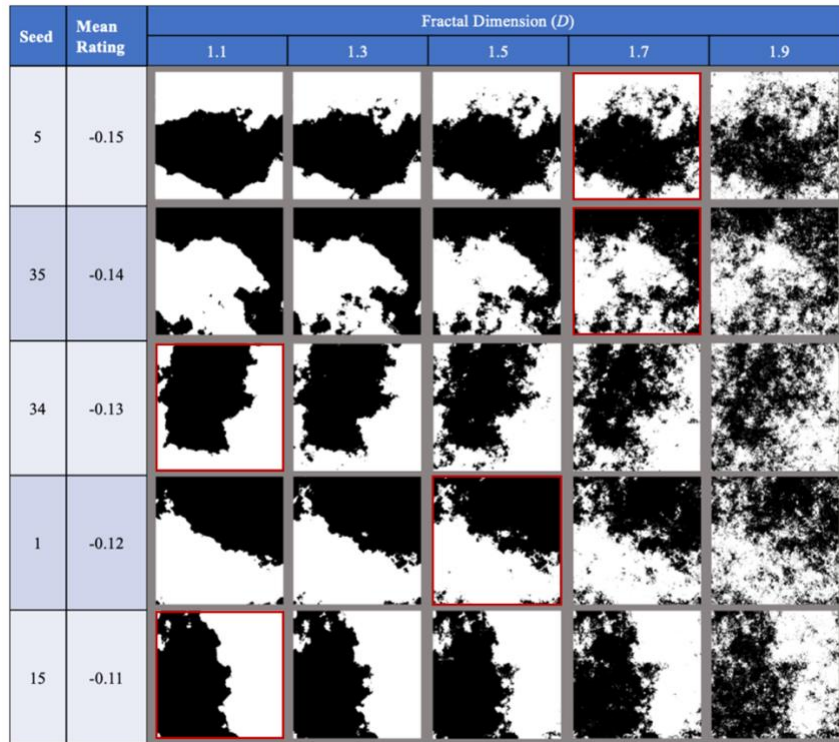


Figure 3.6. The bottom five rated seeds based on mean normalized ratings across participants.

The lowest rated fractal dimension for each seed is outlined in red.

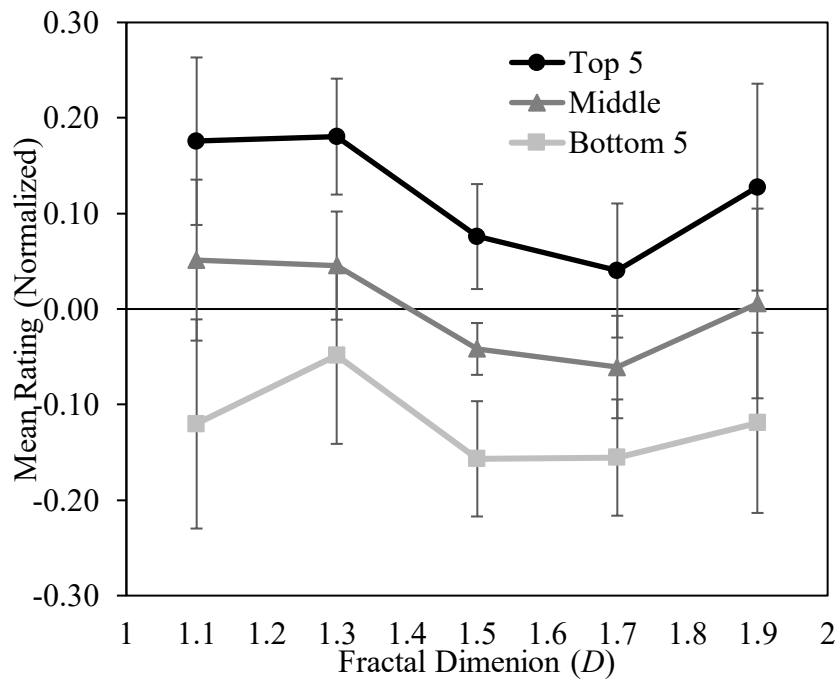


Figure 3.7. Line graph displaying the average normalized rating differences between seed group by fractal dimension. Error bars represent ± 1 SEM.

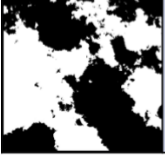
	High- <i>D</i> Preferring	Low- <i>D</i> Preferring	<i>t</i> -score	<i>p</i> -value	Cohen's <i>D</i>
	-0.33	0.17	-5.14	< .001	-0.48
	-0.21	0.13	-3.86	< .01	-0.36
	-0.14	0.16	-3.73	< .01	-0.30
	0.28	-0.09	4.55	< .01	0.38
	0.10	-0.18	3.79	< .01	0.28

Figure 3.8. Seeds rated significantly differently between subgroups (High-*D* preferring vs. Low-*D* preferring). The fractal dimension displayed for each seed above is $D = 1.3$. *P*-values are corrected for family wise error rates with the Benjamini-Hochberg procedure. The first column shows the seed that was rated differently between subgroups. Column two displays the average seed rating for the high-*D* preferring subgroup, column three displays the average seed rating for the low-*D* preferring subgroup.

Chapter IV

The Impact of Value and Contrast on Aesthetic Perception of Fractals

1. Introduction

The natural world is largely composed of self-similar patterns known as fractals. Fractal geometry was first conceptualized by the famed mathematician Mandelbrot (1978) to quantify the rough self-similar patterns of the natural world, which are difficult to quantify through traditional Euclidean geometry. Natural objects such as mountains, coastlines, rock surfaces, clouds, and lichen are fractal (Lathrop & Peterson, 1992; Jiang & Plotnick, 1998; Brown & Scholz, 1985; Batista-Tomás, Díaz, Batista-Leyva, & Altshuler, 2016; Shorrocks, Marsters, Ward, & Evennett, 1991).

While human connection to nature is invaluable in itself, there is also a rich array of psychological benefits to viewing natural scenery. When viewing videos of natural versus urban scenery Ulrich, Simons, Losito, Fiorito, Miles, and Zelson (1991) found that nature videos facilitated significantly more stress reduction. Bratman, Daily, Levy, and Gross (2015) compared walking in nature and urban environments, and linked nature walks to preservation of positive affect, and increased working memory performance. Electroencephalography (EEG) studies have shown that viewing both videos of nature and computer-generated fractals are associated with increased alpha wave activity, which in turn is associated with wakeful relaxation and internalized attention (Grassini, Segurini, & Koivisto, 2022; Hägerhäll, Laike, Küller, Marcheschi, Boydston & Taylor, 2015). Overall, a meta-analysis performed by Gaekwad, Moslehian, and Roös (2023) examining the impact of nature on stress relief found a small to moderate effect.

Human beings show a particular affinity for fractals compared to other types of visual stimuli. Forsythe, Nadal, Sheehy, Cela-Conde, and Sawey (2011) found that natural images have more self-similar properties and participants preferred natural images more than other types of images. While fractals are characterized by their self-repeating properties, the level of precision in that repetition is one factor that varies between fractal patterns. A fractal that repeats perfectly across scales such as in mandalas or snowflakes are known as exact fractals. Most fractal patterns found in nature are statistical fractals, meaning that the fine structure resembles the broad structure but does not repeat perfectly. One prevalent example is trees. The branching of the twigs resemble the branching of the individual limbs which resemble the tree as a whole. For statistical fractals the repetition is approximate, not perfect. Research on aesthetic preference for exact fractal patterns by Bies, Blanc-Goldhammer, Boydston, Taylor, and Sereno (2016) found that preference increased with complexity for exact fractals for most participants, but there was a subgroup that preferred low complexity exact fractals. Statistical fractal patterns also show subgroups for complexity preference. However, preference generally peaks for statistical fractal patterns at low to mid-levels of complexity ($D = 1.1-1.5$) (Spehar et al., 2003; Taylor, Spehar, Van Donkelaar, & Hagerhall, 2011; Spehar, Walker, & Taylor, 2016).

The affinity for fractal patterns, particularly those in the low to mid-range of complexity informs the fractal fluency theory (Taylor et al., 2011; Taylor & Spehar, 2016; Taylor et al., 2018) which states that an aesthetic experience originates from enhanced processing of fractal patterns that we are most frequently exposed to in natural scenes (either through evolutionary exposure or through our lives), this ease of processing in turn leads to a pleasurable aesthetic experience.

In most research on fractal patterns two types of computer-generated statistical fractal stimuli are utilized. “Contour fractals” feature self-repeating structure embedded in lines and resemble

natural features such as mountain ridges or the silhouette of grass. “Cluster fractals” consist of various sizes of amorphous shapes and resemble features such as clouds and coastlines (see *Fig. 1*). The complexity of fractal images is quantified as fractal dimension (D). For two-dimensional fractals D ranges between 1.0 - 2.0 with values closer to one indicating lower complexity, and values closer to two indicating higher complexity. Research by Westheimer (1991) and Spehar et al. (2015) on the relationship between fractal dimension and visual appeal shows that appeal peaks for both cluster and contour patterns at a low to mid level of complexity ($D = 1.1-1.5$).

While we find a universal trend in preferences for fractal dimension several studies also show individual differences in the perception of fractals. Research by Street, Forsythe, Reilly, Taylor and Helmy (2016) examining individual differences in preference for fractal dimension shows that female participants tend to prefer higher complexity fractal stimuli ($D = 1.6$) compared to male participants ($D = 1.2$). Robles et al. (2021) also found individual differences in the perception of fractals, discovering subgroup trends for perceptual ratings of preference, refreshing, and relaxing. Spehar, Walker, and Taylor (2016) also found distinct preference groups, with one preferring higher complexity, one lower complexity, and one displaying the classic curve with preference peaking at mid-level complexity.

Research on the descriptor “naturalness” has shown that images appearing more natural elicit higher assessments of visual appeal. Smith, Goodmon, and Hester (2018) explored aesthetic responses to landscapes and found that photographs with more natural scenery were rated more visually appealing than those incorporating humanmade content. Additionally, the preferred fractal dimensions for cluster and contour fractals aligns with the complexity of the natural objects that participants associated with the abstract stimuli. For example, research by Owen, Taylor, and Sereno (submitted) showed that when combining a cluster and contour fractal into a

composite image, participants preferred lower complexity contours ($D = 1.1-1.3$) reminiscent of mountains or hills, but higher complexity cluster fractals ($D = 1.3-1.7$) which aligned with the more variable complexity of clouds.

While visual appeal of fractal patterns has been examined extensively in relation to fractal dimension, other elements known to be pivotal for visual perception have not been examined, particularly color. Although natural scenes are rich in color, research on aesthetic and psychophysiological responses to computer-generated fractal patterns has focused almost exclusively on monochromatic stimuli. This gap in the literature makes sense. Color is a difficult perceptual beast to quantify as it is not truly one variable but a combination of hue, saturation, and brightness or value. The current study takes the first step to bring fractal stimuli into technicolor by investigating two elementary elements relating to color: value and contrast. Previous research by Schloss and Palmer (2011) examining the general relationship between aesthetics and contrast has shown that more similar hues are greater in harmony, but this relationship has not been explored in fractal stimuli.

It would stand to reason that the most preferred level of value and contrast would be the most natural, particularly for contour fractals. The darker bottom portion of contour fractals tend to resemble mountains and hills, and therefore we expect to find that the darkest values (black and dark grey) for the bottom portion of the image will be most preferred for the contour stimuli (see *Fig. 1 left* and *Fig. 2A*). Because weather and light conditions render all levels of contrast natural for contour stimuli, naturalness may not be a valid method for hypothesizing about preference for these stimuli. However, high levels of contrast for contour fractals would correspond to clear daytime skies and therefore would be associated with greater chances of survival. Consequently, we hypothesize an increase in preference with increasing contrast for contour fractals.

For cluster fractals the most natural contrast and value would depend on which natural object the participants are associating the pattern with. Therefore, for cluster fractals we may expect to see higher preference for high contrast patterns, as they make the patterns more distinguishable. The ability to differentiate natural objects within an environment could potentially increase the likelihood of survival and therefore we hypothesize we'll see the highest preference for high contrast images.

2. Method

2.1 Participants

A power analysis determined that a between subjects design anticipating a moderate effect size requires approximately 128 participants for adequate power. The current experiment collected data from 224 participants. Data was excluded from analysis if more than ten responses in a row were identical, so the final sample included 123 participants. Demographic data showed the sample was 67.21% female, 31.15% male, with 1.6% preferred not to disclose their biological sex. The average age of the participants was $M = 19.03$, $SD = 1.04$.

The experiment took approximately forty-five minutes, and participants were compensated with course credit. Participants were recruited from the Psychology and Linguistic Departments' Human subjects pool at the University of Oregon. The current study utilized the protocol approved by the University of Oregon's Institutional Review Board to acquire informed consent. All measures were conducted in accordance with the guidelines and regulations for human subjects as approved by the review board.

2.2 Stimuli

The stimuli for the current study were generated with the midpoint displacement method described in Fournier, Fussel, and Carpenter (1982), which allowed us to specify D (for details

see Bies et al., 2016b). The number of iterations was set constant at ten. The stimuli were presented against a dark grey background that was distinct from every other shade of grey used in the study. The images were 1600 x 1600 in size. The original images were generated in black and white. Adobe Photoshop was used to change the black and white pixels in the stimuli to different shades of grey, referred to as value. Value was divided into five levels, with one representing white, five representing black, and two, three, and four representing shades of grey. The shades of grey were equally spaced such that two was 25% black 75% white, three was 50% black, 50% white, and four was 75% black, 25% white. Overall, this resulted in 20 combinations of value.

The experiment was created with PsychoPy (OmicX) and data was collected on the online platform Pavlovia. Five seeds were generated for cluster stimuli, and five unique seeds were generated for contour stimuli. Each seed was presented at five fractal dimensions ($D = 1.1, 1.3, 1.5, 1.7, 1.9$), and twenty possible value combinations, for a total of 1000 unique stimuli (500 contour and 500 cluster fractals) (see *Fig. 2*).

2.3 Design

We used a between subjects design, with half the participants rating cluster fractals and the other half rating contour fractals. The conditions were identical except for the type of fractal presented. For each condition the 500 stimuli were presented in randomized order. Participants were asked to rate each stimulus on a slider for visual appeal on a scale of one to five (see *Fig. 3*). One represented the lowest level of visual appeal, and five represented the highest level of visual appeal. The within subjects' independent variables examined were fractal dimension, which was five levels ($D = 1.1, 1.3, 1.5, 1.7, 1.9$), background value (five levels), and foreground value (five levels). In contour fractals the foreground refers to the lower mountain-like area and

the background refers to the upper sky-like area (see *Fig. 1*). In a cluster fractal the background and foreground are ambiguous, so the foreground is set as the black area in the original image, and the background is the white area. The dependent variable was beauty, operationalized in this study as visual appeal.

2.4 Procedure

Conditions one and two were conducted in separate sessions with unique participants, but the procedure was identical. These conditions were conducted online and lasted approximately 45 minutes each. Each condition began by obtaining informed consent and collecting demographic information. Instructions directing participants to rate each stimulus and to take care to utilize the entire slider scale were presented before the rating portion. Participants were presented with the stimulus and asked to rate it on a slider ranging between one and five, with one indicating low visual appeal and five indicating high visual appeal. After the rating portion concluded participants were debriefed about the study and excused. Their participation was recorded, and they were awarded credit.

3. Results

3.1 Fractal Dimension and Visual Appeal

A two-way 2x5 mixed ANOVA with stimulus type (contour, cluster) as a between subjects variable and fractal dimension ($D = 1.1, 1.3, 1.5, 1.7, 1.9$) as a within subjects variable was utilized to examine the impact of fractal dimension on visual appeal between fractal types. Degrees of freedom for each F-test are reported with Greenhouse-Geisser correction when assumptions of sphericity have been violated, as determined by $p < 0.05$ for Mauchly's test.

Results indicated no significant main effect of fractal type, $F(1, 121) = 0.09, p = 0.77, \eta^2 = 0.001$. There was also no significant main effect of fractal dimension, $F(1.13, 136.86) = 2.23, p =$

0.14, $\eta^2 = 0.02$. However, there was a significant interaction between fractal dimension and fractal type, $F(1.13, 136.86) = 9.85$, $p < 0.01$, $\eta^2 = 0.08$ (see *Fig. 4*).

Follow up one-way ANOVAs examining differences in visual appeal between levels of fractal dimension for cluster and contour fractals independently showed distinct results. Results for the cluster fractals indicated no significant difference in visual appeal ratings based on fractal dimension for cluster fractals, $F(1.13, 85.08) = 1.93$, $p = 0.17$, $\eta^2 = 0.03$.

Results for the contour fractals indicated significant differences in visual appeal ratings based on fractal dimension for contour fractals, $F(1.12, 51.31) = 8.95$, $p < 0.01$, $\eta^2 = 0.16$. Follow up paired *t*-tests with *p*-values corrected for family wise error rates with the Benjamini-Hochberg procedure showed significant differences between all levels except $D = 1.1$ vs. 1.3 and $D = 1.7$ vs. 1.9 (see *Table 1*).

To determine if there was an effect of biological sex on preference for fractal dimension, we performed a mixed 2x5 ANOVA with sex as a between subjects variable and fractal dimension as a within subjects variable. Results indicated a significant main effect of biological sex on aesthetical appeal, $F(1, 119) = 7.71$, $p < 0.01$, $\eta^2 = 0.06$. (see *Fig. 5*). Results indicated no significant difference in visual appeal ratings based on fractal dimension, $F(1.12, 133.31) = 0.59$, $p = 0.46$, $\eta^2 = 0.005$. There was also no significant interaction between biological sex and fractal dimension, $F(1.12, 133.31) = 0.08$, $p = 0.81$, $\eta^2 = 0.001$. Overall males tended to rate all stimuli higher than their female counterparts, regardless of fractal dimension (*D*).

3.2 Value and Visual Appeal

We utilized a 2x2x5 mixed ANOVA with fractal type (cluster or contour) as a between subjects variable, and region (foreground or background) and value (1-5) as within subjects variables. Again, degrees of freedom for each F-test are reported with Greenhouse-Geisser

correction when assumptions of sphericity have been violated, as determined by $p < 0.05$ for Mauchly's test.

There was no significant main effect of fractal type, $F(1, 120) = 0.06$, $p = 0.80$, $\eta^2 = 0.001$. There was also no significant main effect of region (foreground or background), $F(1, 120) = 0.14$, $p = 0.71$, $\eta^2 = 0.001$ or value, $F(1.95, 234.16) = 0.31$, $p = 0.73$, $\eta^2 = 0.003$. The interaction between region and value was significant, $F(2.30, 275.59) = 4.93$, $p < .01$, $\eta^2 = 0.04$. The interaction between region, value, and fractal type was also significant, $F(2.30, 275.59) = 6.06$, $p < .01$, $\eta^2 = 0.05$. Results indicate the influence of value on aesthetic appeal is different depending on the region as well as the fractal type (see *Fig. 6a* and *6b*). Specifically, the interaction between fractal type and value differed across the 2 levels of the region factor (foreground and background). For foreground stimuli, preference was lower for low (lighter) values of the contour fractals compared to the cluster fractals. In contrast, for background stimuli, preference was lower for high (darker) values of the contour fractals compared to the cluster fractals. Hence, relative to the cluster stimuli there was lower visual appeal for contour stimuli with a light foreground (lower part of the image) or a dark background (higher part of the image).

To analyze whether the general lightness or darkness of the images impacted visual appeal we also investigated overall value, which was calculated as the sum of the foreground and background values. This resulted in seven levels of overall value. We performed a 2×7 mixed ANOVA with fractal type (cluster or contour) as a between subjects variable and overall value (1-7) as a within subjects variable. Results showed a significant main effect of overall value, $F(1.16, 213.78) = 3.20$, $p < .05$, $\eta^2 = 0.03$. The interaction between overall value and fractal

type was not significant, $F(1.16, 213.78) = 0.08$, $p = 0.90$, $\eta p^2 = 0.00$ (see *Fig. 7*). Results indicated highest aesthetic appeal for moderate-to-high overall value (i.e., darker values).

3.3 Contrast and Visual Appeal

When comparing aesthetic preference for different combinations of foreground and background value we start to see the relationship between contrast and aesthetic rating. Heat maps indicated that for cluster fractals aesthetic appeal increased as foreground and background values diverged (i.e. as contrast increased) (see *Fig. 8a*). For contour fractals the highest aesthetic preference was also for high contrast images, but there was a distinct preference for stimuli where the foreground “mountain” portion was darker in value than the background “sky” portion (see *Fig. 8b*).

For the cluster fractals contrast was calculated as the absolute value of the foreground value subtracted from the background value. For example, the contrast for a black and white cluster fractal would be calculated as $5 \text{ (black)} - 1 \text{ (white)} = 4$. For cluster stimuli the background and foreground are not distinguishable, so inverted value combinations are equivalent. For contour fractals the inverted values were meaningful (i.e. BG 1, FG 5 looks like a black “mountain” against a white “sky”, while BG 5, FG 1 looks like a white “mountain” against a black “sky”). This resulted in four distinct levels of contrast for each stimulus type.

First, we examined the impact of fractal type, contrast, and fractal dimension on visual appeal with a 3-way $2 \times 4 \times 5$ mixed ANOVA. Fractal type (contour, cluster) was a between subjects variable, and contrast (1-4, with 1 being the lowest contrast and 4, the highest contrast) and fractal dimension ($D = 1.1, 1.3, 1.5, 1.7, 1.9$) were within subjects variables. Degrees of freedom for each F-test are reported with Greenhouse-Geisser correction when assumptions of sphericity have been violated, as determined by $p < 0.05$ for Mauchly’s test.

Results showed a significant main effect of contrast, $F(1.22, 147.98) = 3.95, p < .05, \eta^2 = 0.03$; no significant main effect of fractal dimension, $F(1.13, 136.91) = 2.64, p = 0.10, \eta^2 = 0.02$; and no significant main effect of fractal type, $F(1, 121) = 0.17, p = 0.68, \eta^2 = 0.001$. In addition, there was a significant interaction between fractal dimension and fractal type, $F(1.13, 136.90) = 0.19, p = 0.71, \eta^2 = 0.002$ (see *Fig. 4*); a significant interaction between contrast and fractal dimension, $F(7.30, 883.10) = 2.08, p < .05, \eta^2 = 0.02$ (see *Fig. 9*); and no significant interaction between contrast and fractal type, $F(1.22, 147.98) = 0.19, p = 0.71, \eta^2 = 0.002$ (see *Fig. 10*). Finally, there was no significant 3-way interaction between contrast, fractal dimension, and fractal type, $F(7.30, 883.10) = 0.41, p = 0.90, \eta^2 = 0.003$.

The results show that visual appeal tends to increase as contrast increases. Independent samples *t*-tests showed this effect is comparable between cluster and contour fractals, except for contrast level 3, which was rated significantly higher for cluster than contour fractals (see *Fig. 10* and *Table 2*). Follow up paired *t*-tests comparing levels of contrast showed the only levels of contrast rated significantly differently were level 1 vs. levels 2 and 3 (see *Table 3*). The interaction between contrast and fractal dimension (*Fig. 9*) indicates that the relationship between fractal dimension and visual appeal depends on the level on contrast. Specifically, the trend for relatively higher visual appeal ratings for lower compared to higher fractal dimensions is more pronounced for higher contrast stimuli.

Because the direction of contrast is meaningful for contour fractals, we performed a 2x4 repeated measures ANOVA for contour stimuli with direction (positive and negative) and contrast (1-4) as within subjects variables. Given that contrast was defined as background value minus foreground value, positive direction indicated that the bottom foreground portion was lighter in value than the upper background portion, negative contrast indicated the opposite.

Results showed a significant main effect of direction, $F(1, 46) = 5.75, p < .05, \eta^2 = 0.11$ (see *Fig. 11*). This indicates that contour fractals where the foreground (lower portion of the image) is a darker value than the background (upper part of the image) tend to be rated higher in visual appeal. Follow up t-tests comparing inverted levels of contrast (e.g., level -4 vs. level 4) showed significant differences only for level -1 vs. level 1 (see *Table 4*). Results also indicated no significant main effect of contrast, $F(1.12, 51.44) = 0.99, p = 0.33, \eta^2 = 0.02$ and no significant interaction between direction and contrast, $F(3, 138) = 0.51, p = 0.67, \eta^2 = 0.01$.

4. Discussion

The current study found a rich and layered relationship between fractal dimension, value, contrast, and visual appeal ratings. Firstly, we found that fractal dimension was a significant factor in visual appeal ratings for contour fractals, but not cluster fractals. There was a significant interaction between fractal dimension and fractal type, such that visual appeal remained relatively flat with fractal dimension for cluster fractals but decreased for contour fractals (see *Fig. 4*). This finding was unexpected as most literature examining the relationship between fractal dimension and visual appeal shows that preference peaks at low to mid-levels of complexity for both contour and cluster fractals ($D = 1.1-1.5$) (Spehar et al., 2003; Taylor, Spehar, Van Donkelaar, & Hagerhall, 2011; Spehar, Walker, & Taylor, 2016).

The sample was predominantly female (67%), however no significant differences were found in preference for fractal dimension based on sex, despite previous research showing differences in aesthetic preference for fractal dimension based on biological sex, with biological females preferring higher complexity ($D = 1.6$) than biological males ($D = 1.2$) (Street et al., 2016). Instead, we found that males tended to rate all stimuli higher than females regardless of fractal dimension (D) (see *Fig. 5*).

When examining the impact of the value of the foreground and background on visual appeal we found a significant interaction between region, value, and fractal type (see *Fig. 6a* and *6b*). Specifically, the effect of fractal type and value on preference depended on region. For foregrounds, contour fractals were less preferred at lighter values than cluster fractals; for backgrounds, contour fractals were less preferred at darker values. Overall, contour stimuli were less appealing than cluster stimuli when the foreground was light or the background was dark. This complex relationship is further explored in the contrast findings. We also found a significant main effect of overall value (the summed foreground and background values), which indicated peak visual appeal for an overall value of six, which corresponds with the highest contrast stimuli. The low overall value stimuli (i.e., stimuli that were lighter in overall value) were rated much lower than their darker high overall value counterparts (see *Fig. 7*).

We found that contrast had a small but significant impact on visual appeal ratings for fractal patterns. As predicted, the most aesthetically appealing patterns were of high contrast (*Fig. 10*). We also found an interaction between fractal dimension and contrast (*Fig. 9*) suggesting that the link between fractal dimension and visual appeal varies with contrast level. Specifically, the preference for lower over higher fractal dimensions is stronger in high-contrast stimuli. Finally, we found that contour fractals where the bottom “mountain” portion was darker in value than the upper “sky” portion were rated significantly higher than the inverse (*Fig. 11*). This aligns nicely with the value results and our hypothesis that contrast preferences may be related to the survivability of the environment. High contrast allows easier navigation of an environment, however a darker mountain against a lighter sky indicates a warmer daytime setting while a lighter mountain against a darker sky indicates a colder nighttime setting.

The current study allows us to take further steps in understanding the factors contributing

to the perception of fractal images. While we know that fractality and complexity are vital factors in aesthetic appraisal, the other visual elements, particularly those related to color such as hue, saturation, and value, have not yet been investigated. This is vital as aesthetic ratings of fractal images tend to increase with their adherence to nature (Forsythe, Nadal, Sheehy, Cela-Conde, and Sawey, 2011; Owen, Taylor, & Sereno, submitted; Twedt, Rainey, and Proffitt, 2019). Nature is not monochromatic but rich in color. These results lay the groundwork to examine colored fractal patterns, which would adhere much more closely to natural stimuli than the greyscale stimuli currently used.

While increasing aesthetic appeal may seem like a superficial goal, aesthetic engagement has been linked to profound psychological and physiological effects. Brown, Gao, Tisdelle, Eickhoff and Liotti (2011) and Yue, Vessel, and Biederman (2007) found aesthetic engagement was linked to increased activation in the brain's reward pathways. Tommaso, Sardaro, and Livrea (2008) linked positive aesthetic experiences with pain reduction. Incorporating fractal patterns into our daily environment through biophilic design, has the potential to bring the positive effects of viewing nature into urban and indoor environments. Individuals in the United States already spend very little time outdoors. According to the National Human Activity Pattern Survey (NHAPS) Americans spend 92.4% of their time inside, with 86.9% spent in enclosed buildings and 5.5% in enclosed vehicles (Klepeis et al., 2001). These statistics will only become more dramatic as the full effects of climate change reach fruition, creating an infinitely growing need to simulate natural spaces in indoor spaces.

5. Conclusion

Overall, the results of these experiments showed significant differences in aesthetic appeal based on the level of contrast. Aesthetic ratings increased with the level of contrast for both

cluster and contour fractals. Visual appeal was significantly higher for contour fractals where the bottom “mountain” portion was darker in value than the upper “sky” portion.

6. Implications and Future Directions

The current research highlights the role of value and contrast on the perception of fractal patterns. The findings show that value has a small but significant impact on aesthetic preference, with aesthetic appeal increasing with contrast. While we expect that the appeal of high contrast fractal patterns comes from the saliency of the edges and the evolutionary implications, the current research did not examine the qualitative reasoning or neurophysiological mechanisms underlying participants preferences.

Future research should examine the qualitative reasoning behind participants preference for high contrast fractal imagery and utilize neuroimaging methods to compare fractal perception at different levels of contrast. In addition, now that the preference for high contrast stimuli has been established, color can be introduced as a simpler variable since hue can be held constant while saturation and brightness are varied.

7. References

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	$D = 1.1$	$D = 1.3$	$D = 1.5$	$D = 1.7$	$D = 1.9$
$D = 1.1$		$t = 0.68$ $p = 0.50$ $d = 0.10$	$t = -2.83$ $p < .05^*$ $d = -0.16$	$t = 3.06$ $p < .01^{**}$ $d = -0.20$	$t = 2.80$ $p < .05^*$ $d = 0.41$
$D = 1.3$			$t = 3.62$ $p < .01^{**}$ $d = 0.53$	$t = 3.49$ $p < .01^{**}$ $d = 0.51$	$t = 3.09$ $p < .01^{**}$ $d = 0.45$
$D = 1.5$				$t = 2.83$ $p < .05^*$ $d = 0.41$	$t = 2.27$ $p < .05^*$ $d = 0.33$
$D = 1.7$					$t = 0.81$ $p = 0.47$ $d = 0.12$

Table 4.1. Paired t-tests for ratings by fractal dimension (D) for contour fractals. P-values are corrected for family wise error rates with the Benjamini-Hochberg procedure. Effect size is calculated as Cohen's d . *Indicates significance of $p < 0.05$, **Indicates significance of $p < 0.01$.

	Cluster 1 vs. Contour 1	Cluster 2 vs. Contour 2	Cluster 3 vs. Contour 3	Cluster 4 vs. Contour 4
t -value	$t = 0.01$	$t = 1.14$	$t = 2.44$	$t = 1.64$
p -value	$p = 1.00$	$p = 0.31$	$p < .05^*$	$p = 0.14$
Cohen's d	$d = 0.00$	$d = 0.02$	$d = 0.05$	$d = 0.04$

Table 4.2. Independent samples t-tests comparing contrast between cluster and contour fractals.

P-values are corrected for family wise error rates with the Benjamini-Hochberg procedure.

*Indicates significance of $p < 0.05$.

	<i>Level 1</i>	<i>Level 2</i>	<i>Level 3</i>	<i>Level 4</i>
<i>Level 1</i>		$t = -3.76$ $p < .01^{**}$ $d = -0.34$	$t = -3.22$ $p < .01^{**}$ $d = -0.29$	$t = -2.11$ $p = 0.07$ $d = -0.19$
<i>Level 2</i>			$t = -2.03$ $p = 0.07$ $d = -0.18$	$t = -1.05$ $p = 0.35$ $d = -0.10$
<i>Level 3</i>				$t = -0.17$ $p = 0.86$ $d = -0.02$
<i>Level 4</i>				

Table 4.3. Paired t-tests for ratings by contrast levels collapsed across fractal type. P-values are corrected for family wise error rates with the Benjamini-Hochberg procedure. Effect size is calculated as Cohen's d. *Indicates significance of $p < 0.05$, **Indicates significance of $p < 0.01$.

	Contrast -1 vs. 1	Contrast -2 vs. 2	Contrast -3 vs. 3	Contrast -4 vs. 4
<i>t</i> -value	$t = -2.66$	$t = -2.250$	$t = -2.13$	$t = -1.76$
<i>p</i> -value	$p < 0.05^*$	$p = 0.05$	$p = 0.05$	$p = 0.08$
Cohen's <i>d</i>	$d = -0.39$	$d = -0.33$	$d = -0.31$	$d = -0.26$

Table 4 4. Paired t-tests for ratings by contrast levels and direction for contour fractals. P-values are corrected for family wise error rates with the Benjamini-Hochberg procedure

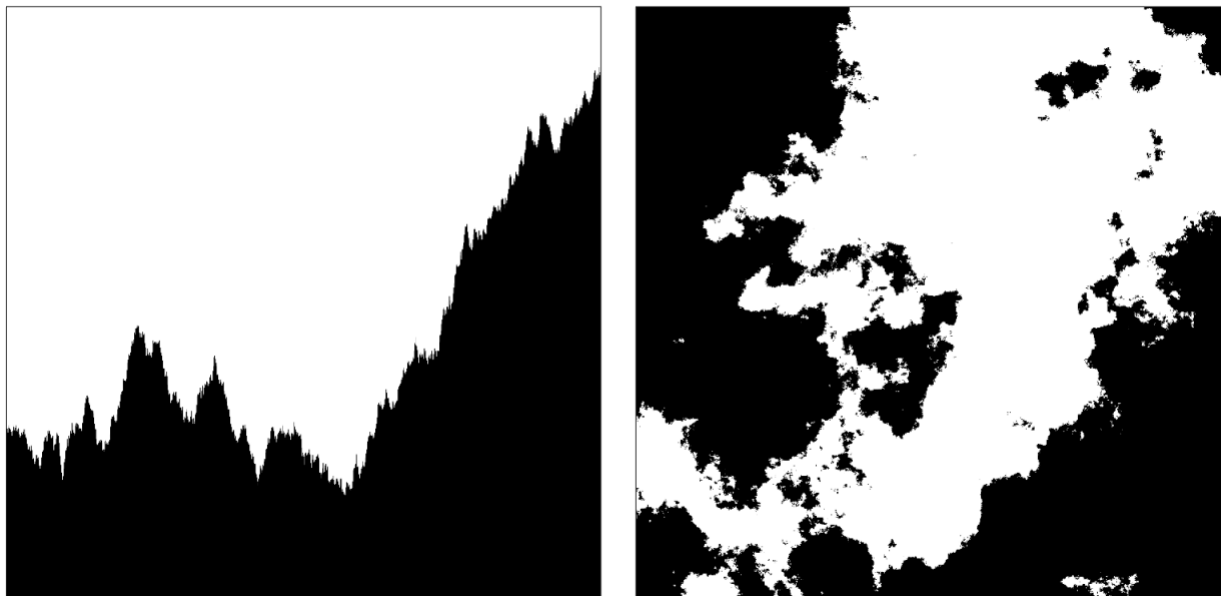


Fig. 4.1. A contour fractal (left) and a cluster fractal (right) of $D = 1.3$ at peak contrast. The contour fractals are created by taking a vertical slice through a 3-dimensional (3D) fractal surface and assigning one value (e.g., white) to all points above the contour and a different value (e.g., black) to all points below the contour. The cluster fractals are created by taking a horizontal slice through the midpoint of a fractal surface and assigning one value (e.g., white) to all points above the midpoint and a different value (e.g., black) to all points below the midpoint.

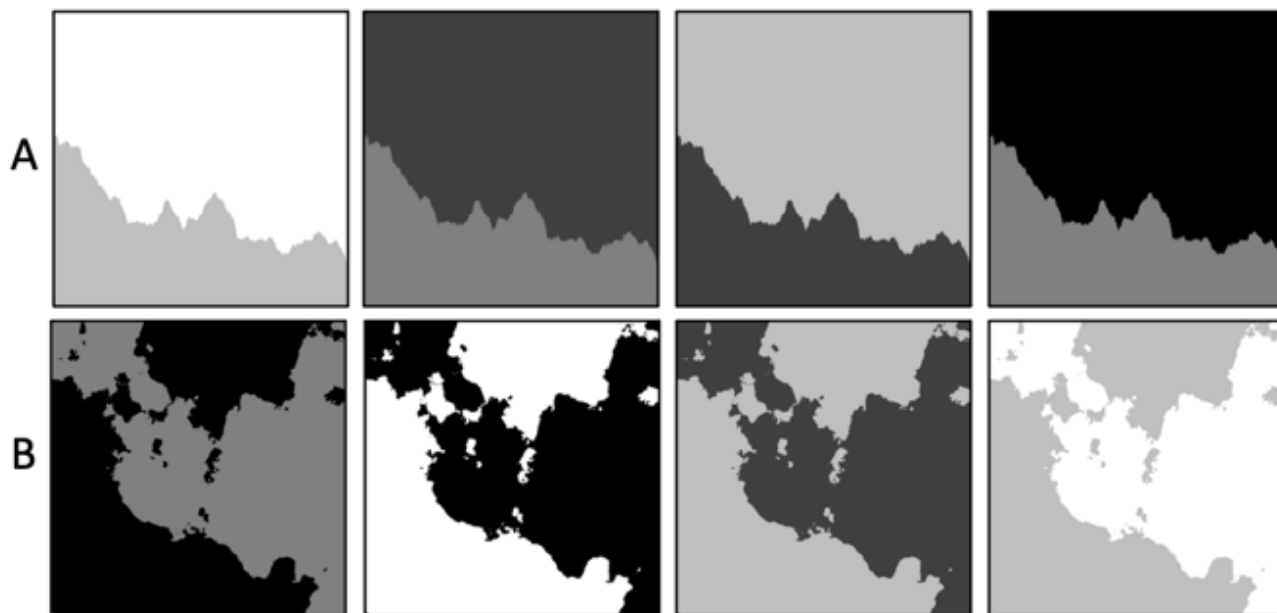


Fig. 4.2. Stimuli examples for A) randomized value contour fractals and B) randomized value cluster fractals.

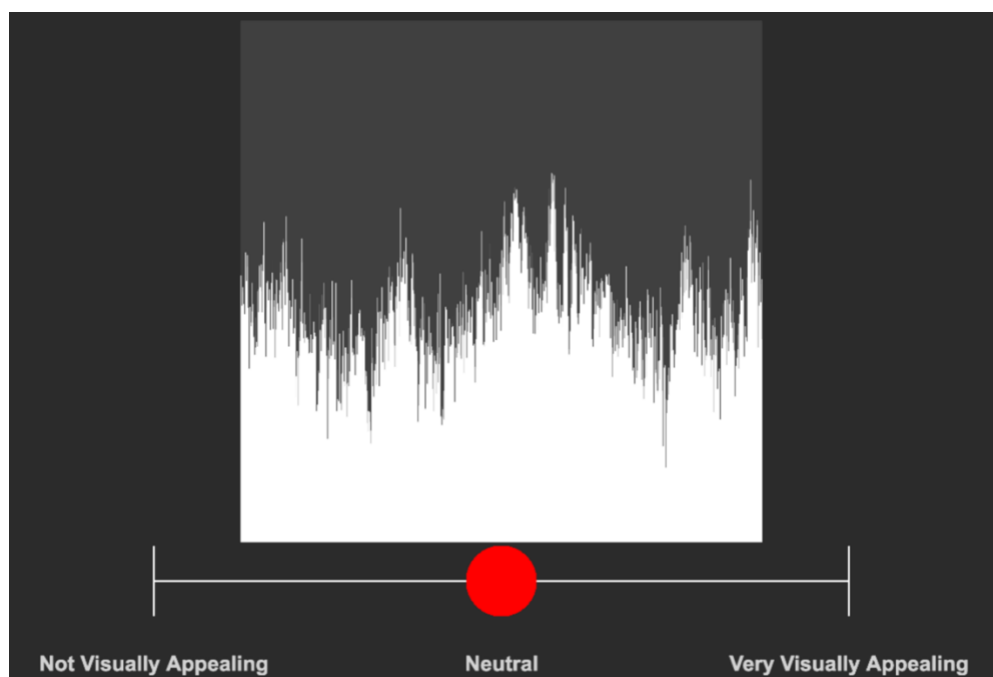


Fig. 4.3. An example of a contour fractal trial. The slider ranged between not visually appealing to very visually appealing.

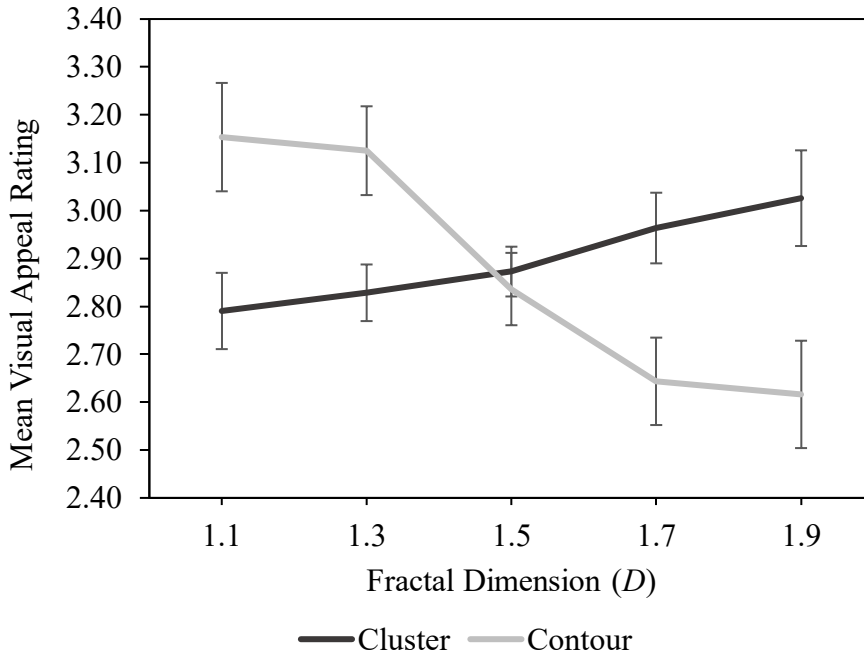


Fig. 4.4. The mean rating by fractal dimension (D) split by cluster and contour fractals. Error bars indicate +/-1 SEM.

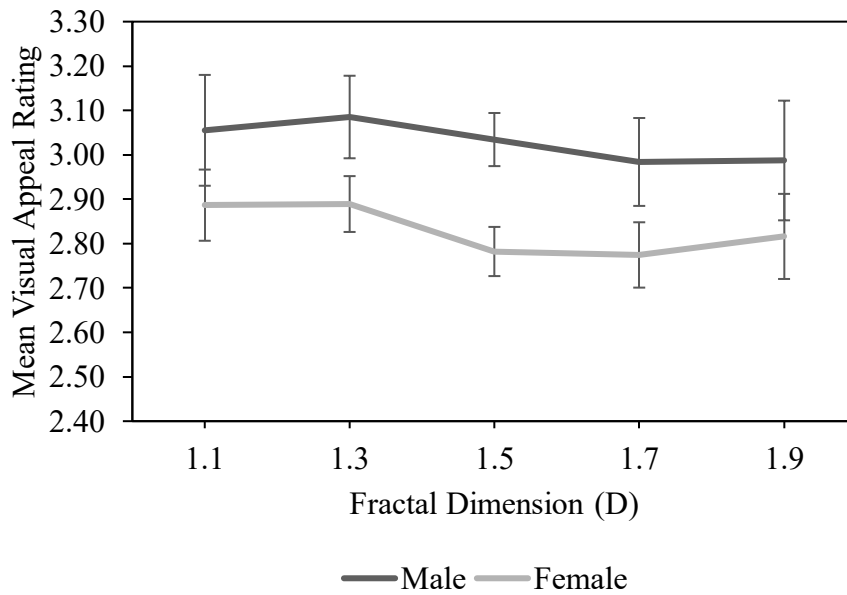


Fig. 4.5. Mean visual appeal rating by fractal dimension divided by biological sex. Error bars indicate +/-1 SEM.

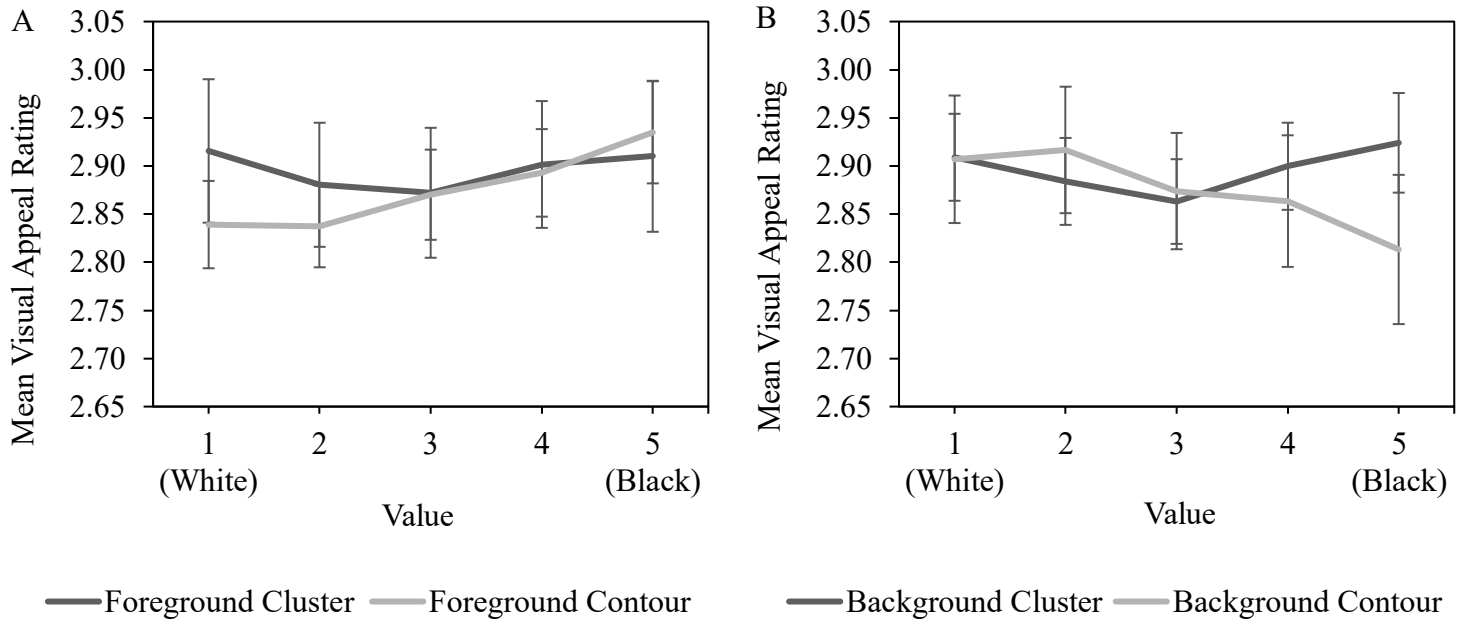


Fig. 4.6. Mean visual appeal rating by value. The relationship is shown for A) foreground value and B) background value. Error bars indicate +/-1 SEM.

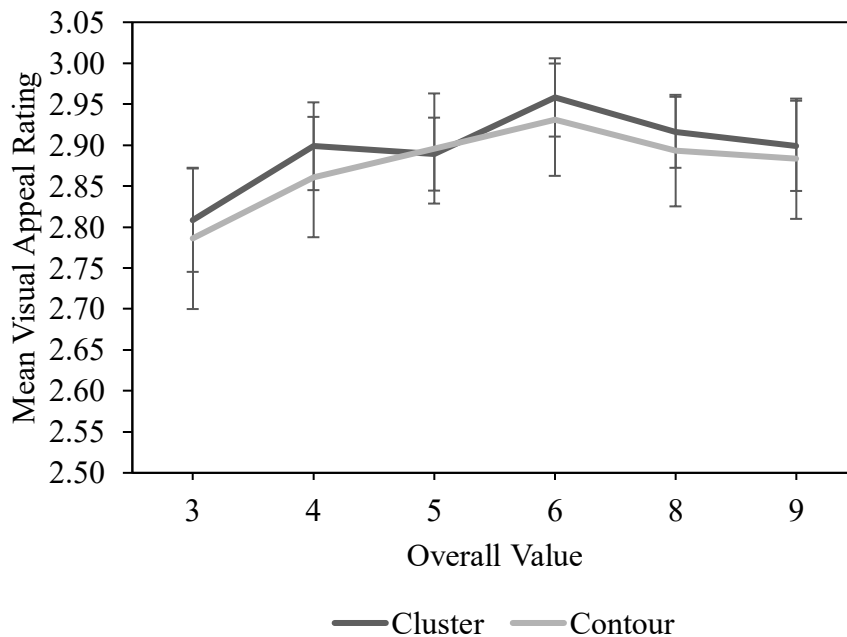


Fig. 4.7. The mean rating by overall value split by cluster and contour fractals. Error bars indicate +/-1 SEM. Lower overall value indicates lighter shading, higher indicates darker shading.

A) Cluster Heat Map							B) Contour Heat Map						
	Background Value							Background Value					
Foreground		1	2	3	4	5	Foreground		1	2	3	4	5
	1		2.81	2.89	2.97	2.99		1		2.77	2.82	2.88	2.89
	2	2.8		2.81	2.94	2.98		2	2.8		2.81	2.89	2.85
	3	2.91	2.81		2.86	2.91		3	2.91	2.93		2.83	2.82
	4	2.96	2.95	2.87		2.83		4	2.96	2.99	2.92		2.7
	5	2.96	2.96	2.89	2.82			5	2.96	2.98	2.95	2.86	

Fig. 4.8. Heat maps examining average rating, based on the mean aesthetic ratings for each combination of foreground and background values for A) cluster and B) contour fractals.

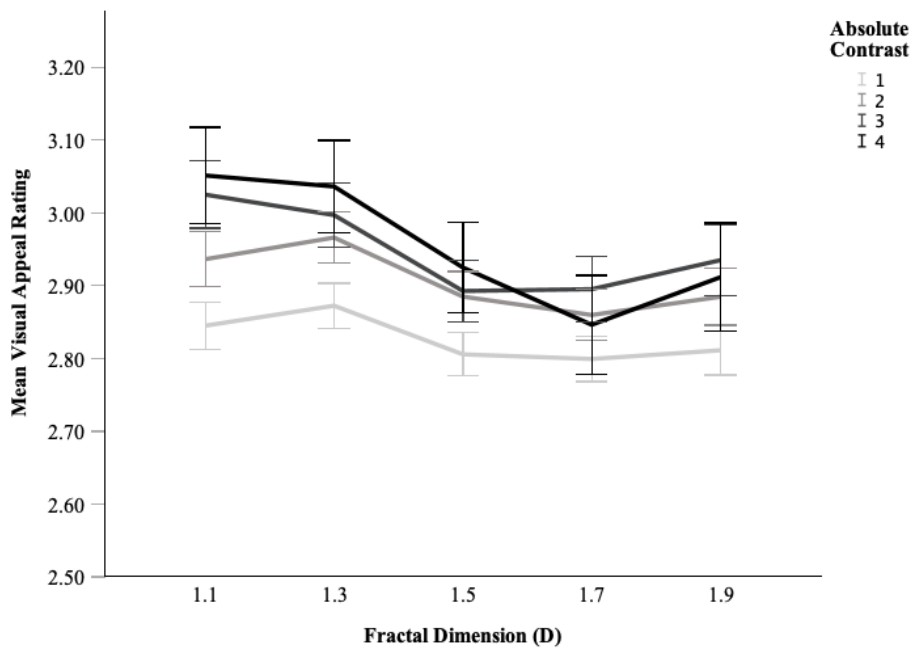


Fig. 4.9. The mean rating by fractal dimension (D) and level of contrast one indicating the lowest level of contrast four indicating the highest. Error bars indicate ± 1 SEM.

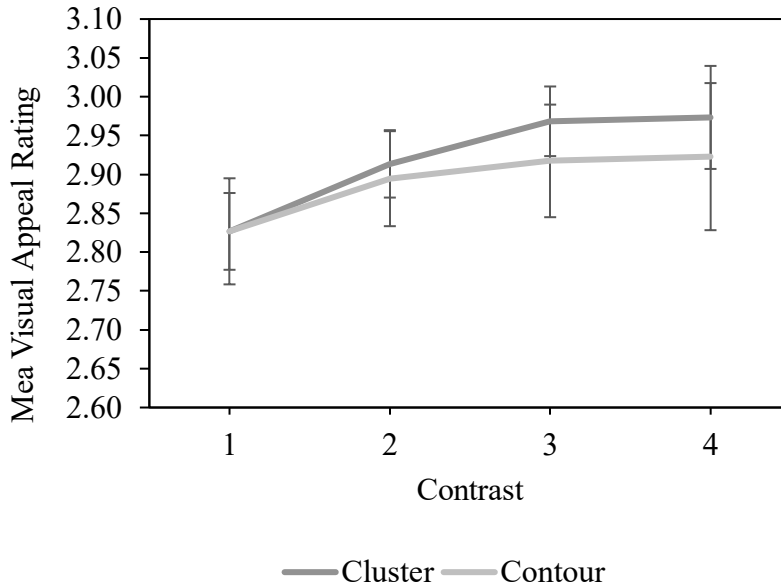


Fig. 4.10. The mean rating by level of contrast with one indicating the lowest level of contrast four indicating the highest. Error bars indicate ± 1 SEM.

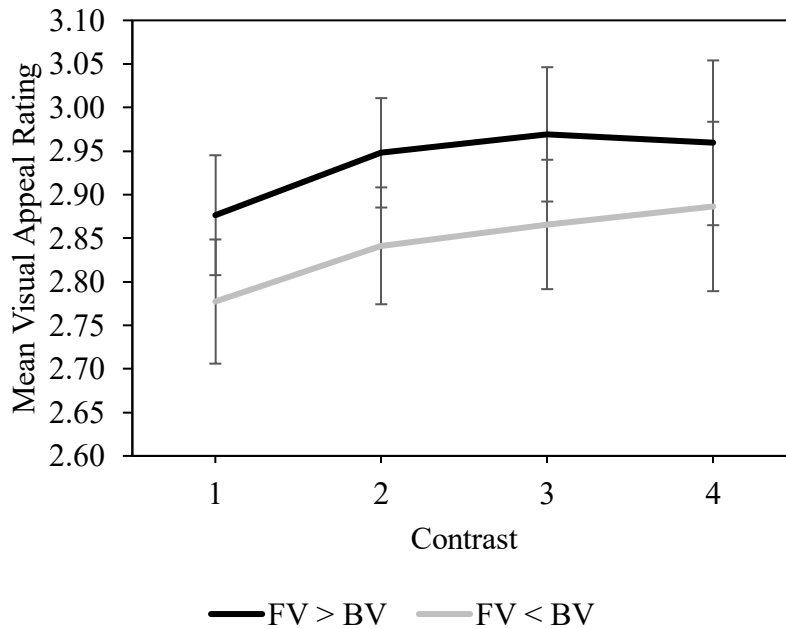


Fig. 4.11. The mean rating by level of contrast and direction for contour fractals with one indicating the lowest level of contrast four indicating the highest. Error bars indicate ± 1 SEM. FV indicates foreground value, BV indicates background value.

CHAPTER V

GENERAL DISCUSSION

The architecture of the natural world is etched in fractal geometry. From the dendritic branching of neurons to the characteristic forking of vasculature, and even the macrostructure of galaxies, natural forms overwhelmingly embody the self-similar properties of fractals (Smith, Marks, Lange, Sheriff, & Neale, 1989; Liew et al., 2008; Coleman & Pietronero, 1992). Exposure to natural stimuli is consistently linked to positive psychological benefits including stress reduction, decreased negative affect (particularly anxiety and rumination), preservation of positive affect, and increased working memory performance (Ulrich, Simons, Losito, Fiorito, Miles, & Zelson, 1991; Bratman, Daily, Levy, & Gross, 2015). The more general effect of nature on the human psyche shows a significant association between measures of nature-connectedness and well-being (Howell, Dopko, Passmore, and Buro, 2011). The meta-analysis conducted by Gaekwad, Moslehian, and Roös (2023) found exposure to natural environments had a small to medium effect on reducing physiological stress.

The neurological mechanisms behind the positive psychological impact of natural stimuli are related to increased alpha wave activity which is associated with wakeful relaxation and internalized attention (Grassini, Segurini, & Koivisto, 2022). Increased alpha wave activity has also been linked to exposure to statistical fractal stimuli, indicating that fractality is a signature of natural patterns (Hägerhäll, Laike, Küller, Marcheschi, Boydston & Taylor, 2015). These findings also indicate that static natural images may be sufficient to induce the positive effects of nature.

While fractality is an essential element of natural patterns, it is also a vital component of aesthetics. Natural images tend to be rated more beautiful than other imagery, and possess more

fractal properties (Forsythe, Nadal, Sheehy, Cela-Conde, & Sawey, 2011). The same study found that fractal dimension accounted for 30% of variation in the perception of beauty in natural scenes and 19% of variance in the perception of beauty for abstract art (Forsythe, Nadal, Sheehy, Cela-Conde, & Sawey, 2011).

Several studies have highlighted the variables that impact our perception of fractal patterns. Euclidean context alters ratings of interest and excitement of fractal patterns, but not ratings of visual appeal, engagement, complexity, or relaxation (Robles, Gonzales-Hess, Taylor, & Sereno, 2023). Fractal light patterns in indoor spaces showed that mid to high level complexity ($D = 1.5-1.7$) elicited high levels of visual interest (Abboushi, Elzeyadi, Taylor, & Sereno, 2019). Applying fractal structure to solar panels increases visual appeal and subsequently eases the incorporation of this method of renewable energy (Roe et al., 2020).

Throughout fractal research, the pervasive argument contends the human affinity for fractal patterns lies in their abundance in nature (Taylor & Spehar, 2016). Biophilic design and architecture is built on the idea that incorporating natural components into built environments can bring the positive benefits of natural scenes indoors ((Wilson, 1984). It would follow that we could heighten this effect by further tailoring the elements of simulated fractal patterns to reflect the properties of nature. While the impact of fractal dimension and exact versus statistical recursion has been examined in depth, several elements such as the impact of layering, seed, value, and contrast have been largely ignored (Bies, Blanc-Goldhammer, Boydston, Taylor & Sereno, 2016a; Hägerhäll, Laike, Küller, Marcheschi, Boydston & Taylor, 2015; Sprott, 1993; Spehar et al., 2003; Taylor, 2006; Taylor et al., 2011; Spehar and Taylor, 2013).

The current research focused on maximizing the external validity of fractals as a method to simulate natural stimuli by 1) examining how layering contour and cluster fractals to create a

composite fractal scene alters aesthetic perception, 2) analyzing the impact of seed on the perception of cluster fractals and the qualitative reasoning behind those aesthetic decisions, and 3) examining how altering value and contrast for contour and cluster fractals influences aesthetic perception of fractals.

Composite Fractals and the Impact of Layering on Fractal Perception

Fractal patterns are ubiquitous in nature. However, within a natural space we rarely view a single fractal pattern, but instead view layers of fractal patterns. There may be layers of foliage differing in complexity, or a mountain ridge overlying a cloudy sky. While layering fractal patterns to simulate natural scenes had been explored in Owen, Rowland, Philliber, Sereno, & Taylor (2024), the visual appeal of composite fractals composed of contour and cluster fractals and their subsequent relationship to fractal dimension had not yet been explored.

Therefore, chapter two of this dissertation aimed to quantify the impact of layering on fractal perception. For the sake of parsimony, we began by superimposing a contour fractal over a cluster fractal. The results revealed several striking findings. Preference peaked at much lower levels of complexity ($D = 1.1-1.3$) for contour stimuli, than for cluster stimuli ($D = 1.7$). This contradicted previous findings which show a strong preference for cluster stimuli of low to mid-level complexity ($D = 1.1-1.5$) (Hagerhall, Purcell, & Taylor, 2004; Spehar et al., 2003; Taylor, Spehar, Van Donkelaar, & Hagerhall, 2011; Spehar, Walker, & Taylor, 2016).

For the composite fractals there was a strong preference for combinations where the contour fractal was of lower complexity than the cluster fractal. Qualitative data validated these findings supporting fractal fluency theory. Participants displayed a strong preference for fractal patterns that reminded them of natural stimuli. Lower complexity contour stimuli were more likely to remind participants of natural features such as mountains or tree lines, while higher

complexity contours were more likely to remind participants of inorganic materials. For cluster stimuli participants were most likely to be reminded of clouds regardless of the level of complexity. However, as fractal dimension increased participants were more likely to be reminded of art/paint or other objects. Additionally, the literature review conducted on natural fractal objects showed that the mean and median fractal dimension of natural objects visible to the naked human eye is $D = 1.3$, further validating the fractal fluency theory.

The Influence of Seed on Fractal Aesthetics

Chapter three explored the impact of randomly generated seeds on aesthetic appeal. While we know that preference varies even for abstract compositions and consumer design (Bai, Guo, & Jia, 2019; Redi & Pova, 2013), little to no research had been conducted to examine the role seed plays in aesthetic preference for fractal patterns. Notably, Sprott, J.C. (1993) found that some randomly generated fractal patterns displayed greater preference than others, but the subset of patterns was relatively small and the qualitative reasoning behind preference was not explored.

In accordance with past research on individual differences in fractal perception, we found two distinct preference clusters for fractal dimension, with one clearly preferring high complexity fractals and the other preferring low complexity fractals (Street et al., 2016; Spehar et al., 2016). Some seeds were more polarizing than others, with five showing significantly different ratings between preference clusters.

This project examined qualitative and quantitative feedback for 100 unique seeds across five fractal dimensions to examine if some seeds were consistently rated significantly higher/lower than others across participants, and if there were distinct seed preferences was there an underlying reason. The findings showed that the top rated five seeds and bottom five rated

seeds were rated significantly differently across participants than the 90 middle seeds. The justification for the ratings were much more likely to fall under the umbrella of composition (e.g., balance, symmetry, order) than pareidolia for both the top rated seeds and bottom rated seeds. Overall, the results indicated that seed has a small but significant role to play in the aesthetic appeal of fractal images. These findings are particularly vital for biophilic design and architecture, as some randomly generated seeds may inherently possess more aesthetic value than others. Therefore, the selection of seed should be carefully curated to reflect the most universal preference to maximize the positive impact biophilic design aims to capture.

The Role of Value and Contrast on the Perception of Fractals

While the appeal of fractal patterns is largely argued to be due to their adherence to natural stimuli, one element that has been sorely lacking in this realism is color. Chapter four took the first step in introducing the complex variable of color by systematically varying the value of foreground and background for cluster and contour stimuli and examining how value and the interplay between values (i.e., contrast) influences aesthetic perception of fractal patterns.

Contrary to most previous research, the current study found that preference was relatively flat for the different complexity stimuli for the cluster portion of this experiment (Sprott, 1993; Spehar et al., 2003; Taylor, 2006; Taylor et al., 2011; Spehar and Taylor, 2013). Previous research has found female participants tend to prefer higher complexity fractal patterns than their male counterparts (Street et al., 2016), however we found no differences in visual appeal ratings based on fractal dimension between biological sexes. We did find that male participants tended to rate stimuli higher across all fractal dimensions compared to female participants.

For cluster stimuli we found striking significant results indicating that aesthetic appeal increased with the level of contrast, such that the most highly rated images were black and white. There was no significant interaction between fractal dimension and contrast, indicating that participants did not display increased tolerance for complexity when images were of low contrast. We expect the mechanism behind these findings may be that the clear boundaries of high contrast cluster fractals could aid in survival.

For contour stimuli aesthetic appeal increased with contrast as well, however when contrast was collapsed across directions this effect was muted compared to that of cluster fractals. When we examined the impact of direction and contrast on aesthetic appeal (i.e., a darker lower “mountain” foreground against a lighter “sky” background, vs. a lighter lower “mountain” foreground against a darker “sky” background) we found aesthetic appeal was significantly higher for contour stimuli where the lower foreground portion was a darker value than the upper background value.

This research contributes novel insight into the field of fractal perception by dissecting how value and contrast influence aesthetic preference for cluster and contour fractals. While low or mid contrast may be more prevalent in natural stimuli, high contrast fractals tended to elicit higher ratings.

Broader Implications

While maximizing aesthetic preference for fractal patterns may appear to be a shallow goal on the surface, there are profound psychological and physiological benefits to viewing natural fractal patterns. These benefits range from stress reduction to increased positive affect, decreased rumination, and increased working memory performance (Ulrich, Simons, Losito,

Fiorito, Miles, & Zelson, 1991; Bratman, Daily, Levy, & Gross, 2015). The underlying structure that characterizes natural patterns is fractality.

However, the amount of time that human beings spend in nature is surprisingly limited. Klepeis et al. (2001) found that human beings spend remarkably little time in our natural environment. Americans spend 92.4% of their time indoors (86.9% within enclosed buildings and 5.5% in enclosed vehicles) (Klepeis et al., 2001). With natural spaces being destroyed at an exponential pace by human development and the ever-increasing impact of climate change, the need to effectively simulate natural environments indoors will only continue to grow. Therefore, our ability to replicate the positive psychological benefits associated with nature in built spaces and determine which factors are necessary to maximize those benefits is paramount.

Limitations & Future Directions

The main limitation on the current series of studies lies in the demographics of the samples. All studies relied on the human subjects' pool at the University of Oregon, and therefore samples were composed of individuals likely to adhere to the W.E.I.R.D demographic (i.e., Western, Educated, Industrialized, Rich, Democratic) as described in Henrich, Heine, & Norenzayan (2010). Additionally, because the subject pool drew largely on psychology undergraduate students the samples tended to include more biological female participants than male. These demographics are not representative of the world at large and therefore limit us in our ability to generalize the current findings across wider samples.

Future research will focus on expanding our understanding of factors contributing to the perception of fractal patterns, particularly color. Now that value and contrast has been thoroughly examined, a project to quantify the impact of hue and saturation is a natural next step. Research

on fractal seeds would benefit from eye-tracking studies to see which parts of the composition attract the most visual attention.

Furthermore, by enhancing our ability to simulate natural stimuli artificially we can expand into applied work as well. For example, incorporating fractal imagery in enclosures for individuals (both human and animal) with limited access to natural spaces. Additionally, we can utilize fractal patterns as distractors from Euclidean shapes to mimic the visual search for footprints employed during search and rescue missions to create training exercises that can be completed in indoor settings.

General Conclusion

The current dissertation furthers our understanding of how aesthetic elements influence the perception of fractal patterns. The studies presented in the current dissertation have contributed novel insight to the field of cognitive psychology, building on the existing knowledge and theory on the perception of computer-generated fractals in several vital areas. We utilized quantitative and qualitative methodology to determine how layering, seed, value, and contrast influence the perception of computer-generated fractals.

Enhancing our understanding of factors influencing the visual perception of fractal patterns offers key insight into the visual properties of natural stimuli. These findings highlight potential considerations for biophilic design and architecture to maximize the associated benefits.

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