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Empirical Evaluation of Route-Based Landscape Experiences

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EMPIRICAL EVALUATION OF ROUTE-BASED LANDSCAPE EXPERIENCES

by

Garet Openshaw

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF LANDSCAPE ARCHITECTURE AND ENVIONMENTAL PLANNING

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ABSTRACT

Empirical Evaluation of Route-Based Landscape Experiences

by

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Methods of landscape visual analysis have evolved significantly due to the development of new methods and technology. In the assessment of visual quality, viewsheds remain the most common form of geospatial analysis. However, this method only provides a partial assessment, missing valuable information that informs planning decisions. This thesis explores an alternative visual analysis method, visual magnitude, through systematic modeling (Chapter 2) and empirical validation of the efficacy of this method (Chapter 3).

Chapter 2 asks, is there an optimal sampling rate of viewpoints along a route that can increase efficiency in running a visual magnitude analysis and still accurately represent the environment? Through the use of digital elevation models and three separate routes we tested multiple viewpoint sampling distances from 1 to 100-meters along our route. The resulting visual magnitude analyses were then compared in excel to analyze the trade-off between our sampling distance and amount of data lost. We found for visually sensitive areas, a 30-meter sampling distance produced optimal results.

Chapter 3 encompasses an application and visual analysis of routes with varying

scenic quality. In this study we used the optimal sampling distance of 30-meters to extract visual magnitude values for 15 different environments. These values are then compared to scenic rating values that we collected though a survey where participants saw videos of the same 15 envrionments and rated their scenic quality. We saw results that indicate this tool strongly correlated to our survey participants scenic quality ratings, indicating that this tool can be used to understand and predict preferred visual landscape experiences within Utah. Additionally, we saw indications that topography, individual and demographic variables all play a significant role in how survey participants rated the scenic quality of road-based experiences.

From this entire study, we can suggest to professionals that they can run these types of visual analyses in a more efficient way. With the results from optimizing the viewpoint sampling rate and the relationship between scenic quality ratings and the VM tool, this tool can be used as a proxy to begin to understand how people view the quality of landscapes they are experiencing.

(139 Pages)

PUBLIC ABSTRACT

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This thesis explores a method of visual analysis that aims to create a more in-depth understanding of how individuals see and visually perceive their environment. Here we explore a geospatial tool, called Visual Magnitude, to assess road-based experiences. We aimed to provide evidence of a relationship between the tool and scenic rating preferences from a survey. The content of this thesis is split between two articles. The first article, contained in Chapter 2, focuses on optimizing the selection of viewpoints along route-based envrionments. In this study we ask the question is there an optimal sampling rate of viewpoints along a route that can increase efficency in running a visual magnitude analysis and still represent accurately represent the envrionment. We found that for visually sensitive areas, a 30-meter sampling distance produced optimal results. For other landscapes a 50-meter sampling distance poduced resonable results in both sampling points and retained raster area.

The second article, contained in Chapter 3, is an applied visual magnitude study where we use the optimal sampling distance of 30-meters to extract visual magnitude values for 15 different envrionments. These values are then compared to scenic rating values that we collected though a survey where participants saw videos of the same 15 envrionments and rated their scenic quailty. By doing this we were able to provide

emperical evidence that the visual magnitude tool can be a way to predict best visual experiences within Utah.

With the results from these studies we can make suggestions to professionals on how they can better use this GIS tool. These suggestions include sampling distances for multiple envrionments and the potential for this tool to be used as a poxy when attempting to interpret how landscapes observers feel about them. This additional infromation will help planners in understanding and making decisions more informed planning decisions along roadways and surrounding areas that have the highest potential impact on observers. By using this tool planners can assess where those areas are and the amount of impact that positive or negitive planning decisions will have on observers.

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CHAPTER 1

INTRODUCTION

Our world is experienced in a dynamic and ever changing fashion, yet when assessing visual quality, most attempts still focus on static assessments. With advancements in technology we are able to more easily close the gap between these circumstaces. This research explores using the ArcPro GIS Visual Magnitude Plugin to simulate a route-based perspective as a means to a evaluate the visual experience an observers has as they move through a space. This is one of many new tools being developed to help planners evaluate landscapes more effectivly.

Visual analysis is an important field within the realm of landscape architecture and planning because of how heavily people rely on visual information for judgements of scenic quality, safety and decision making. Understanding the visual impact of development of cities, roadways, scenic byways and even conservation is required by law from the federal government though the NEPA Act of 1970. This act requires companies to analyse the potential effects that projects would have on the environment, including visual effects. However, these analyses are only as good as the tools that they are conducted with. Most visual analyses are conducted use singular viewpoints in selected areas, but some installations require a more in-depth analysis that is based on a route type approach (e.g., roadways, scenic byways, transmission lines). Large scale planning, which visual magnitude was first adapted for by the Forest Service (Iverson, 1985), needs need sampling points that provide a more sequential and holistic picture of the environment. Even though visual magnitude provides a deeper insight of visual analysis

than the viewshed, there are no examples of studies that explore sampling distances and what the most representative measure could be. A study like this would help provide the beginning of a basis for professionals to expand and conduct visual analyses in a dynamic fashion in spaces that are meant to be experienced dynamically.

Once we knew how sampling should be approached for these dynamic experiences, we wondered about the validity of the results of the visual magnitude tool expressing how people were experiencing these dynamic spaces. Again, there was very little basis to build on that looked at route-based experiences. However, with increasing importance on visual quality of environments being pushed by expansion, continuing development, and renewable energy projects more tools and expertise in this field is going to be in an ever-increasing demand.

A viewshed analysis, which is the most used visual analysis by planners (Davidson et al., 1993), only provides information about areas on the landscape that are either visible or not. This rudimentary binary outcome does not offer a means to assess nuances about how individuals perceive different qualities of the landscape, including the topographic relationship of the land to the viewer. Nevertheless, we see these analyses being frequently used in instances of high visual impact by professionals (Barendse et al., 2016; de Almeida Rodrigues et al., 2018; Poudyal et al., 2010; Sullivan et al., 2012).

There have been numerous developments of alternatives to the binary viewshed that have explored areas like assessment of ocean blue space (Qiang et al., 2019), visualscapes (Llobera, 2003), visual exposure (Domingo-Santos et al., 2011), cumulative viewsheds (Wheatley, 1995), archaeological elements (Čučković, 2015), wind infrastructure (Gibbons, 2015), visual pollution (Chmielewski et al., 2016), landmark

visibility in urban areas (Bartie et al., 2010) and work on expanded viewsheds (Fisher, 1992, 1995). One of the older methods explored is called visual magnitude (Iverson, 1985) from which the ArcPro GIS Visual Magnitude Plugin was adapted. While (Iverson, 1985) provided the first application of visual magnitude to landscape assessment, its roots extend far earlier. In fact, early references and calculations of visual magnitude are demonstrated by astronomers and physicists in the 19th century (and perhaps earlier). They used visual magnitude to assess celestial bodies to determine distances or even ages of stars. Early calculations focused primarily on the magnitude of light eminating from stars, which provided a means to calculate distance from earth. These measures could be done using a range of tools, including photography to measure the amount of space (and light) that a celestial body reflected or produced.

In the landscape planning application, visual magnitude provides a similar result, but varies in that the calculation focuses on the amount visible area of an area on the surface of the earth, relative to the total area visible to the human eye. The result is an absolute measuring, theoretically ranging from 0 (not visible) to 1 (completely occupying a viewer's entire visible area). To calculate visual magnitude, slope, aspect, and distance relative to the viewer are used (Chamberlain & Meitner, 2013). For this study, we adopt the average weighted visual magnitude (Chamberlain & Meitner, 2013), which also considers the number of times a surface area is seen. In this calculation, the visual magnitude values are averaged across all viewpoints in which the area is visible. We aim to provide evidence that the tool providing this measure can be used to provide a deeper understanding of large scale and route-based visual analyses.

The potential applications of this tool to be used as an effective proxy for

professionals is the basis of this thesis study. We aimed to dive deeper into the applications of this tool by finding the answer to two questions though two separate but related studies: (1) what is the trade-off between the number of sample points and the accuracy of the average weighted visual magnitude model, referred to hereafter as visual magnitude? and (2) can the visual magnitude tool inform us which scenic byways or other roadway environments contain the best experience for vehicle-based viewers? These two questions are addressed in two separate articles which are contained in Chapters 2 and 3 of this thesis.

Chapter 2 consists of an article exploring the first question of viewpoint sampling distances and the resulting trade off in model accuracy when increasing the sampling distance. The article contained in this chapter was published as a peer reviewed article as a part of the Visual Stewardship Resource Conference in 2021, except for minor edits for additional clarity and some additional research that was not finished prior to the articles publication. This additional infromation is contained in sections 3.4 and 3.5 and helps to enrich the initial study by looking at an additional area of differing topography and adding additional measurements at a 1-meter sampling distance for each environment.

Chapter 3 takes results from the previous chapter and uses it in an applied visual analysis study. In this article we collected visual magnitude values pulled from 15 different envrionments and explored how they relate to scenic ratings. Scenic ratings were collected though a survey published at Utah State University through Quadratics software collecting scenic ratings for the 15 previously mentioned envrionments as well as some independt infromation to assess the influece of outside variables on their ratings. This study has yet to be published.

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CHAPTER 2

OPTIMIZING VIEWPOINT SELECTION FOR ROUTE-BASED EXPERIENCES: FINDING A THRESHOLD BETWEEN SAMPLING RATE AND MODEL ACCURACY[1]

Abstract

Viewsheds and visual analysis are critical in understanding our relationship with surrounding landscape, especially when experienced along a route. The presence and use of geospatial visual analyses techniques have existed for decades with one of the earliest as the viewshed analysis. There has been tremendous progress toward the optimization, accuracy, and techniques for these analyses. This paper is intended to further previous work by addressing shortfalls with the lack of empirical work conducted on viewshed analysis and viewpoint optimization for landscape planning, particularly focused on the identification of route-based experiences.

The purpose of this study is to identify the optimal trade-off between the number of viewpoints needed to represent an experience (e.g., highway route) and the accuracy of a visual magnitude analysis, which is an extension of the standard viewshed analysis. In this study, we focused on exploring the trade-off functions expressed in a mountainous and flat environment. The study was conducted to compare the two extremes in topography and see if and how their differences influence the trade-off between model accuracy and the sampling of viewpoints along a route.

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[1] Authors: Openshaw, Garet K., & Chamberlain, Brent C.

To conduct this analysis, we employed a Visual Magnitude Plugin using publicly available DEM and roadway data. We generated a one-mile-long segment of a route for each environment and systematically discretized the route by varying the sampling distance intervals from 10-meter to 100-meter. In addition to the different environments, we compared the difference between an equal interval distance and a pseudo-random interval. Results show a linear decrease in the correlation of the visual magnitude model, with minor differences between the mountainous and flat environments. Comparing a 10-meter base sampling distance with 30-meter and 50-meters, the correlation coefficients were above 0.9 and 0.7, respectively. This suggests that for route-based analyses using visual magnitude, reducing the sampling rate can produce equivalent results with far less time and precision.

Keywords: viewshed, visual magnitude, viewpoint selection, accuracy, GIS

Introduction

The presence and use of viewshed analyses in landscape assessment has existed for decades (O'Sullivan & Turner, 2001; Smardon et al., 1986), with a variety of research on the use, optimization, and limitations of viewshed conducted in the late 90's (Fisher, 1992, 1993, 1996). In the past couple decades, there has been a surge in extending the traditional binary viewshed to more nuanced forms and applications including the assessment of oceanic blue space (Qiang et al., 2019), visualscape (Llobera 2003), visual exposure (Domingo-Santos et al., 2011), cumulative viewsheds (Wheatley 1995), the identification of key archaeological elements (Čučković, 2015) and identifying the impacts to housing prices from wind energy infrastructure (Gibbons, 2015).

There have also been significant efforts to optimize viewsheds in a geographic information system to improve the reliability of the analysis, the sampling techniques, and the speed with which the analysis completed. For instance, Starek et al. (2020) used a simulated annealing technique to identify optimal locations for locating viewsheds to maximize the visible area using laser scans. Earlier, Gao et al (2011) and Cauchi-Saunders (2015) developed optimal approaches to viewsheds using Graphics Processing Units (GPU) with dramatic improvements over CPU-based algorithms. Andrade et al. (2011) has also provided a more efficient CPU-based algorithm.

Approaches to improved efficiency can greatly reduce the amount of time it takes to render a specific analysis. However, reducing the time it takes to conduct the analysis is only one part of the equation – the other is selecting which viewpoints should be a part of the analysis. Within the literature, there seems to be less of a focus on selecting optimal *and* appropriate viewpoints for landscape planning, instead there tends to be a focus on either the optimal number of viewpoints for a large area for maximum coverage *or* in selecting representative key observation points (KOPs). For instance, Shi and Xue (2016) provide a technique for reducing the number of viewpoints for the maximum coverage over an entire area (total viewshed), assuming that peaks are the ideal viewpoints for maximum coverage. Likewise, Wang and Dou (2019) take a similar approach toward applications where total viewshed is the key issue. However, there is limited research on systematic techniques, particularly those assessed with empirical field that identifying how to select optimal key observation points, with a recent exception by Palmer (2019) that addresses this shortfall. These limitations are compounded by Chamberlain and Meitner (2013) who argue that a singular KOP may not be adequate for

representing landscapes that are experienced as a journey (route-based) rather than overrepresenting singular observation points.

Even though there has been progress with variations of different viewshed analysis developed, single KOPs with a standard viewshed remains a central aspect of visual quality assessment. Unfortunately, there are plenty of indications that show how standard, binary viewsheds lack important information about the way we perceive landscapes (Chamberlain & Meitner, 2013; Ervin & Steinitz, 2003).Simply put, while the viewshed provides information on visibility, this is only a superficial layer of information that is not thorough enough. The result of this lack of depth is being felt by professionals as they are trying to fill that gap though the use of other tools that explore results that are beyond a simple binary output as mentioned earlier.

Unlike the viewshed which creates a basic binary raster image of what areas of the landscape are seen and unseen, the visual magnitude tool aims to create a measure of physical measure visual impact of a landscape on observers. This is accomplished though calculations that determine the amount of space that an area takes up in an observer's visual field. This visual impact index is created from measurements of slope, aspect, distance, and the number of times seen. The added depth of information from this analysis highlights landscape areas that are highly susceptible to impact from alteration and visual disruption. By isolating these areas in analyses professionals can make a case for the protection of these areas from a visual standpoint and have better data to inform land management decisions from a visual standpoint.

The inspiration for this paper stems from: the lack of empirical work conducted on viewpoint optimization for landscape planning, particularly focused on the

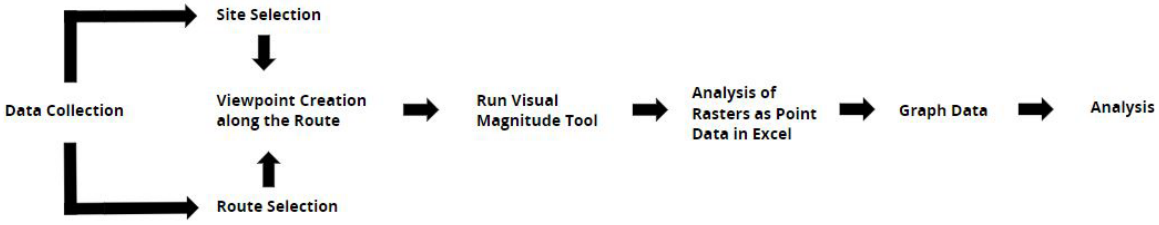
identification of route-based experiences. To address these shortfalls, we asked two key research questions. (1) What is the trade-off between the number of sample points and the accuracy of the visual magnitude model? (2) Further, can we identify an optimal trade-off between the number of viewpoints needed to represent an experience and the accuracy of visual magnitude analysis? To answer these questions, we developed a systematic approach toward analyzing visual magnitude models in two distinct landscapes, using various sampling techniques with results highlighting the differences and errors between the sampling techniques.

Methods

The objectives for the study are to: (1) develop a repeatable process that can be validated further by other researchers, (2) assess the effectiveness of a random versus interval viewpoint sampling technique, and (3) compare outcomes of a mountainous and flat landscape. Figure 2.1 gives an overview of the process we used to conduct this study. This process was utilized for both terrain types, as well as both viewpoint reduction methods. The process included the following steps: (1) data collection, (2) site and route

Figure 2.1

Methodological Process Overview



selection, (3) creation of viewpoint measures, (4) running the Visual Magnitude Plugin tool, (5) image analysis and correlation, and (6) creation of graphs for correlation and other analysis.

Data Collection

All data obtained for this study were retrieved from the Utah Automated Geographic Reference Center (AGRC). These included transportation data for Roads and Highways and digital elevation models (DEM) for terrain. ESRI ArcPro software package was used to manipulate and analyse the geospatial data.

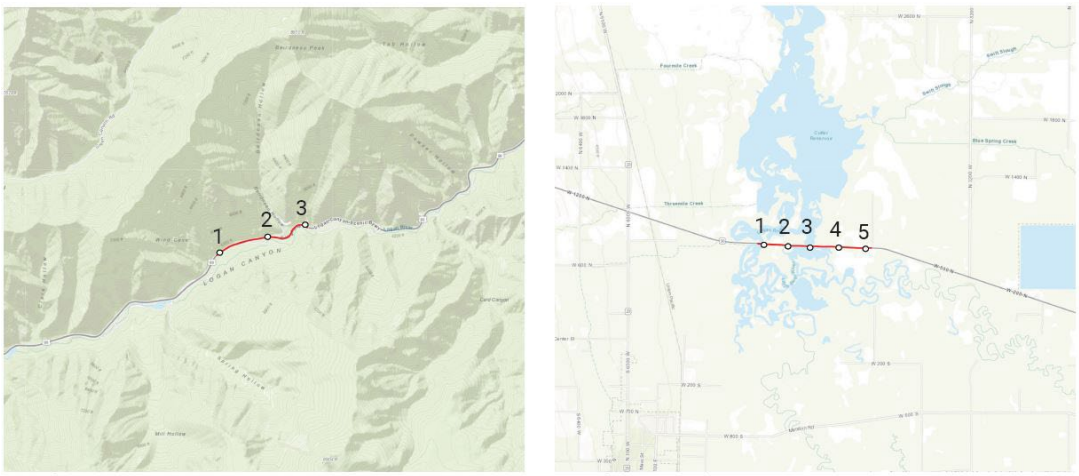
Site and Route Selection

The selection of sites was guided by the authors' knowledge of the study's region, which consists of two large mountain ranges and an extensive valley. To minimize potential impacts from urban development, sites were selected from places that fit the topographic demands and are designated for minimal infrastructure development. Figure 2.2 shows the specific site and contact of the environment surrounding the route.

The first site selected, Logan Canyon, is within the Cache National Forest just east of Logan, UT and is very mountainous area. The other site is along the Utah highway SR30 just outside of Benson, UT, where there is a large wetland on either side of the roadway and near popular local and regional recreational areas. Figure 2.3 shows the images along the selected routes and gives visual context of the environment that observers experience.

Figure 2.2

Mountainous (left) and Flat (right) Study Site Overview



Study Site- Mountainous Environment Study Site- Flat Environment

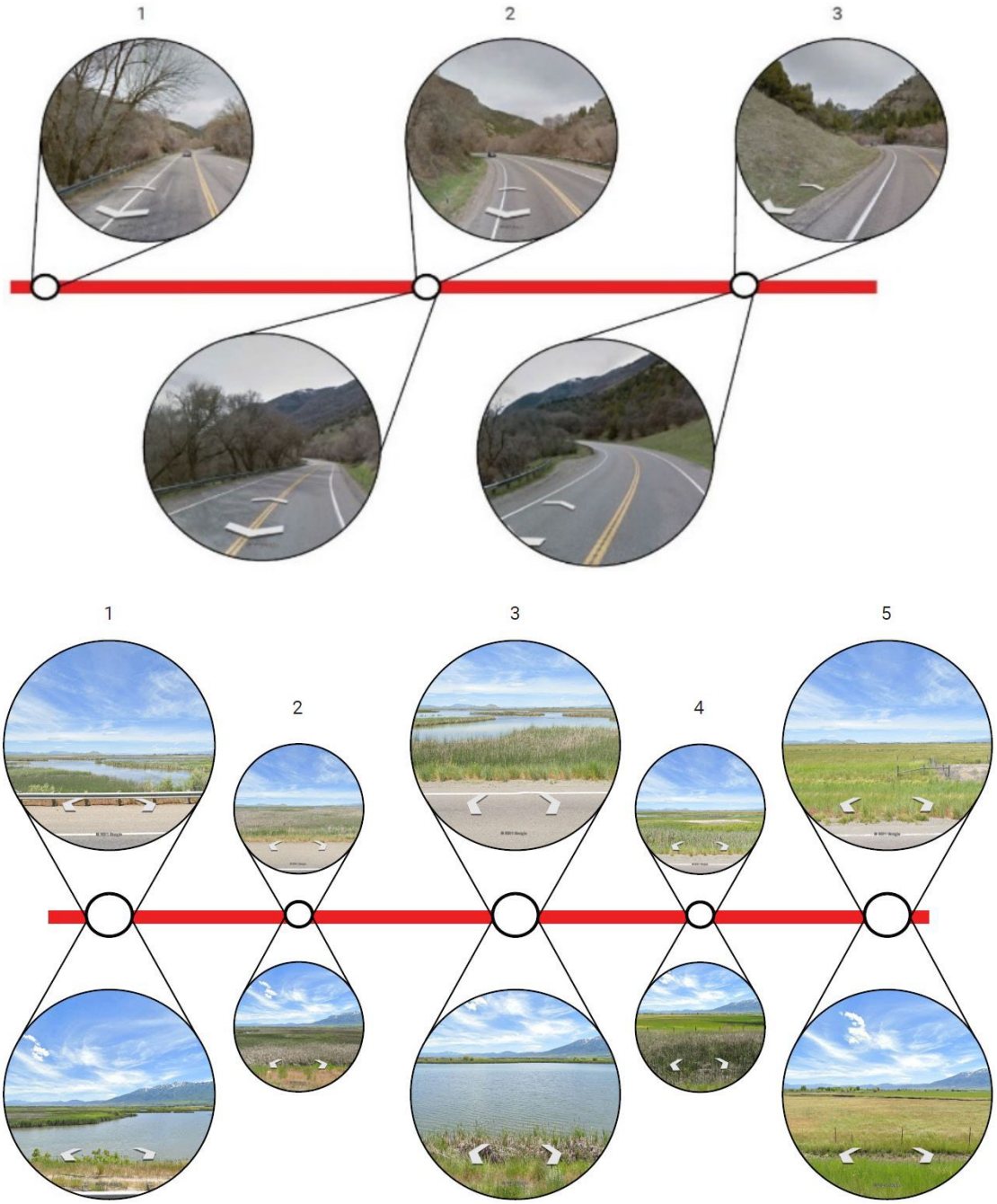
provided sufficient terrain for our flat environment site. Both selected routes are located A 1-mile-long route was selected from each site to compare and contrast the differences of the effects of topographical properties on visual magnitude.

Generating Viewpoints

A visual magnitude analysis was run across various sampling intervals, and with two sampling techniques: equal interval and randomized (explained in detail later). Following Chamberlain and Meitner (2013) we use a 10-meter resolution DEM with 10-meter sample distance along each route section. The initial 10-meter sampling distance was used as a base to create the remaining sampling variations. Additional viewpoint intervals along the route include 20, 30, 40, 50, and 100 meters. After selecting our created route, we used the Generate Points tool in ESRI's ArcPro to create points at a 10-meter distance. We then built a model to select the sample interval for the equal interval

Figure 2.3

Site Images Along Our Study Route Giving Visual Context of the Surrounding Environments



Note. The first image (top) shows the mountainous environment which is in Logan Canyon just east of Logan, UT, and the other image (bottom) showcases the flat environment.

technique and used a random number generator to select five different viewpoint samples for the randomize sampling technique. The random generator assigned a percentage to each viewpoint so that the sampling frequency (e.g., 50% at 20m, 25% at 40m) selected similar number of viewpoints relative to the equal interval stratification.

This resulted in 168 viewpoints at 10-meter distance, and over 84 viewpoints at 20-meter distance in our mountain environment. In the equal interval sample these viewpoints were spread every 20-meters, while for the random sample we selected the same number of viewpoints scattered throughout the 10-meter distances (resulting in some gaps of greater than 20-meters). Generating viewpoints at these distances will help us gather an understanding of the degree that we can see the surrounding environment when viewpoints are generated in a randomized fashion along a route.

Running the Visual Magnitude Tool

The Visual Magnitude Plugin (Chamberlain & Cook, 2019) was used to conduct the analyses. The plugin requires, at minimum, two input datasets: DEM and viewpoints. The DEM was clipped to a 3-kilometer site, which provides a reasonable radius around the one-mile route to ensure a high variety of visual magnitude values. Each of the different combinations of viewpoint sample techniques and intervals were conducted separately, and the procession time foreach was recorded. The output of the analysis is a single, 1-band, floating point tiff file.

Statistical Analyses

The Visual Magnitude Plugin produces an objective normalized value from 0 to 1

for each cell of the raster output, making comparisons somewhat straight-forward. For this study, efforts focused on conducting a Pearson correlation coefficient to identify how each of the different interval and sampling techniques compared to one another. However, before this analysis could be produced, data needed to be adjusted because of the differences in the total visible area (some intervals resulted in more visible area than others). To accomplish this, we built an analysis mask that combined all visual magnitude outputs into one raster where there were no null values in one or more outputs (a null value indicates not visible and cannot be analyzed in a coefficient). The mask was used to extract the visual magnitude values for each visible cell across all analyses, ensuring that the same cell was being compared across outputs. To conduct Pearson correlation, each raster cell value was extracted into a one-dimensional dataset and analyzed. Additionally, we noted the total missing values (not part of the mask contained within the 3-kilometer site) for each analysis that were not part of the base, 10-meter interval. These were included as error of the difference between total visible area though the percent of land area that was left between each of the rasters. The combination of the Pearson correlation and the error provides an effectiveness snapshot of each different sampling technique.

Results

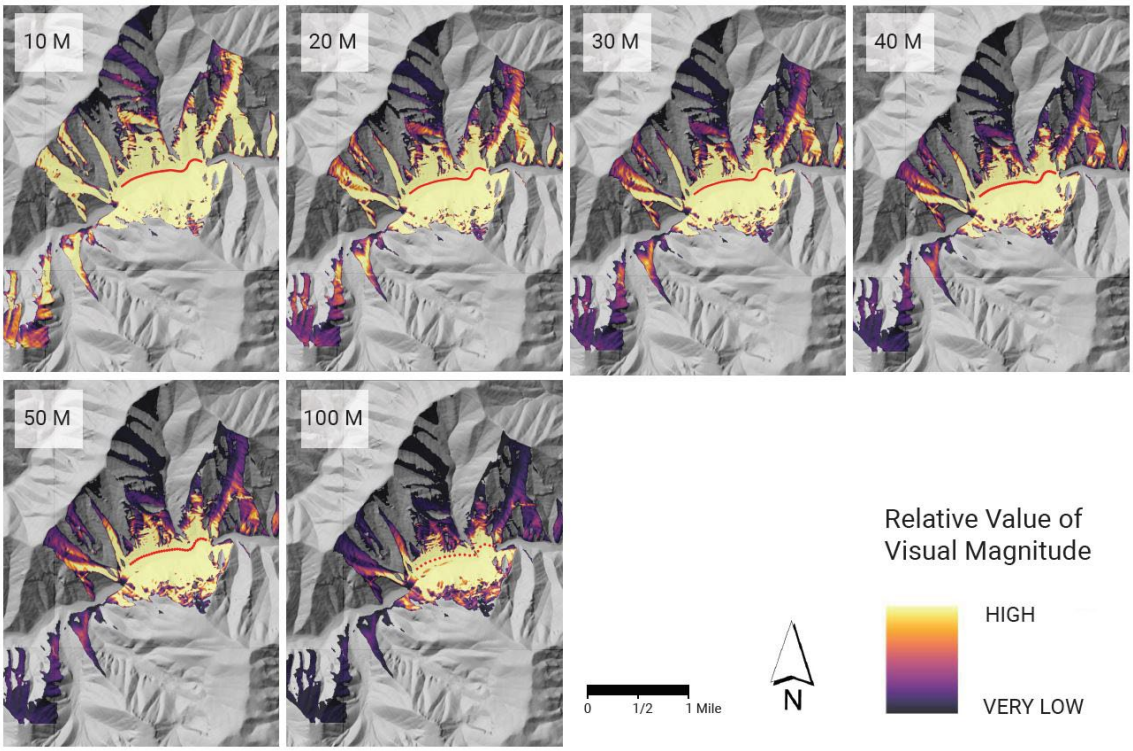
All statistical data were analyzed in MS Excel, where we compared the number of viewpoints, processing time, and the total area percentage error, with accompanied graphs. Additionally, all maps developed were conducted using ESRI ArcPro. These results are provided below for each of the different study sites. Correlations are reported as positive (they are actually a negative relationship between the two variables studied).

Mountainous Environment Interval Results

Figure 2.4 showcases the total visual magnitude for each of the equal interval analysis. The one-mile route is presented, but the scale of the image is too small for the sampling interval to be noticed, except for the 100-meter condition. The same legend was used to produce the output, resulting in an expected shift from the extent to which high values and low values are represented with each interval. This is expected because with greater number of viewpoints, the higher the visual magnitude values for each cell will become (increasing the number of times it is seen from each sampling point) relative to the lower sampling interval using the same legend.

Figure 2.4

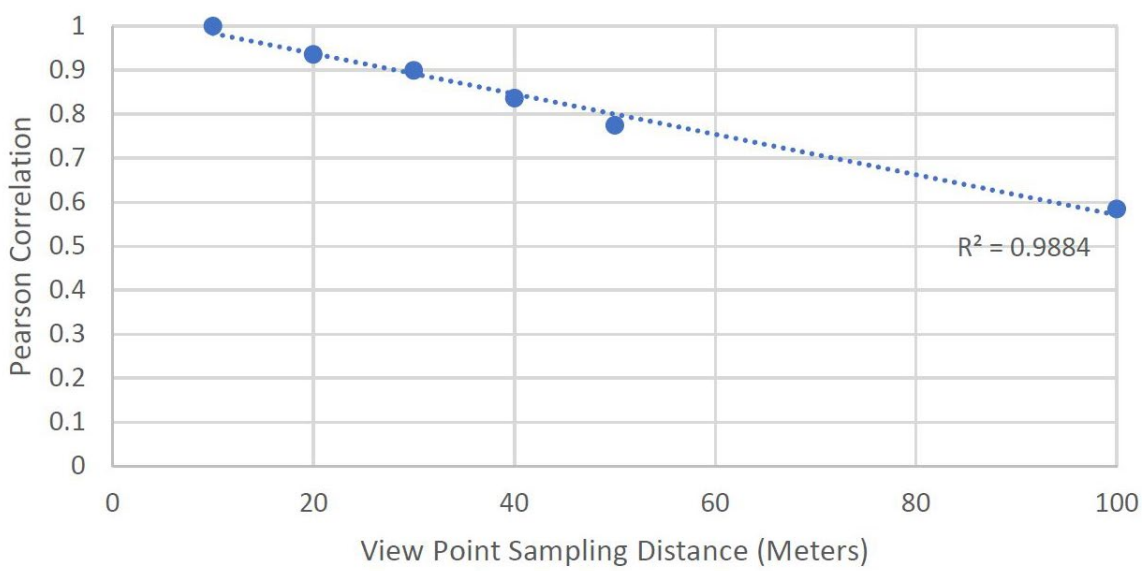
Mountainous: Equal Interval Viewpoint Reduction Method Visual Magnitude Outputs



The visualization of the data appears to show a difference in the results according to the legend, with higher impacts being represented by the smaller sampling distance. However, the key question for this paper focuses on the relative differences, as measured through the correlation coefficient as the legends may not best represent the full story. Figure 2.5 shows the correlation between our interval viewpoints as we moved through our interval distance reduction process. As indicated, there is a gradual reduction in correlation between our 10-meter measure and all other resulting measures. The R^2 value, which is being used to analyze the strength of our models, is at 0.9884, indicating a very strong linear relationship as we reduce the number of viewpoints. The overall trend is negative and linear, providing a strong indication of predictability for how a reduction in

Figure 2.5

Correlation Graph of Mountainous Environment Equal Interval Viewpoint Reduction Method



sampling will impact the result. The slope is y = -0.0046x + 1.0292, or roughly for every 1-meter increase in sampling distance, a correlation reduction of just over 0.31%.

Table 2.1 provides the difference for each of the sample equal interval distances, relative to the 10-meter base analysis. This table indicates the accuracy of the visible area, using our 10-meter sampling model as a base and assuming that it is accurate, identifying how much less of the area was visible because of increased sampling distance. Here the loss is about 0.06% of total visible area per 1-meter increase in sampling distance.

Table 2.1

Mountainous Environment Equal Interval Viewpoint Reduction Method Results

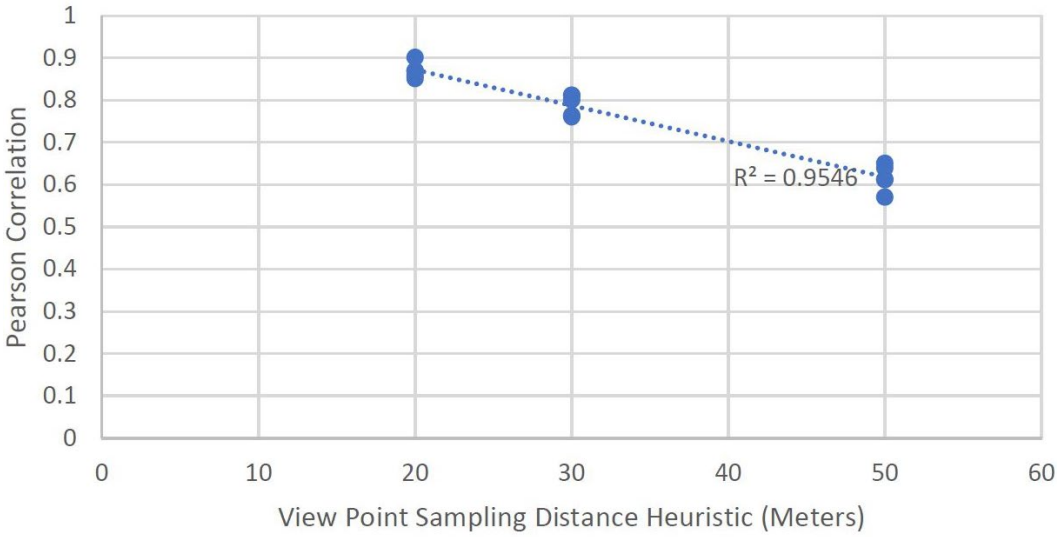
VP distance	VM raster correlation	% of total area	# of VP
10 M	1.00	100	168
20 M	0.94	98	84
30 M	0.90	97	56
40 M	0.84	97	42
50 M	0.77	95	33
100 M	0.58	94	17

Mountainous Environment Random Results

Figure 2.6 shows the results from the random viewpoint reduction method resulting in variation of correlation values between 5 to 10% for each viewpoint distance sampling interval. Each dot on the graph corresponds to one of the random viewpoints selection sets. Overall, the randomized viewpoint routes returned correlation values lower

Figure 2.6

Correlation Graph Mountainous Environment Random Viewpoint Reduction Method



than their corresponding interval measures. The correlation between our randomized measures has a R^2 value of .9546, which remains high, but the slope is nearly double that of the equal interval technique at a roughly 0.065% loss of correlation per meter increase in sampling distance.

Table 2.2 provides the error difference for each of the sampling distances. The correlation differs more substantially than the equal interval, even for the best of the five randomly selected samples for each interval. The difference in total area is similar to the equal interval sampling, with some of the randomly generated samples performing slightly better and some slightly worse. Still the total area difference is negligible.

Flat Environment Interval Results

Results from the equal interval flat environment demonstrate a similar overall negative trend as we reduce our viewpoints from our 10-meter measure to 100-meter.

Table 2.2

Mountainous Environment Randomized Reduction Method Results

Set	VP distance	VM raster correlation	% of total area
Set 1	20 M	.90 to .85	99% to 97%
Set 2	30 M	.81 to .76	99% to 96%
Set 3	50 M	.65 to .57	95% to 93%

Figure 2.7 showcases the relative change in visual magnitude value for the study area. Here there is a similar visual effect as in Figure 2.4. In Figure 2.8 the correlation values remain high for most of the loss in sampling distance, with roughly a 0.41% reduction in correlation for each meter increase in sampling distance. The R^2 value is 0.9838, also suggesting a high degree of predicted correlation loss over distance.

Figure 2.7

Flat: Equal Interval Viewpoint Reduction Method Visual Magnitude Outputs

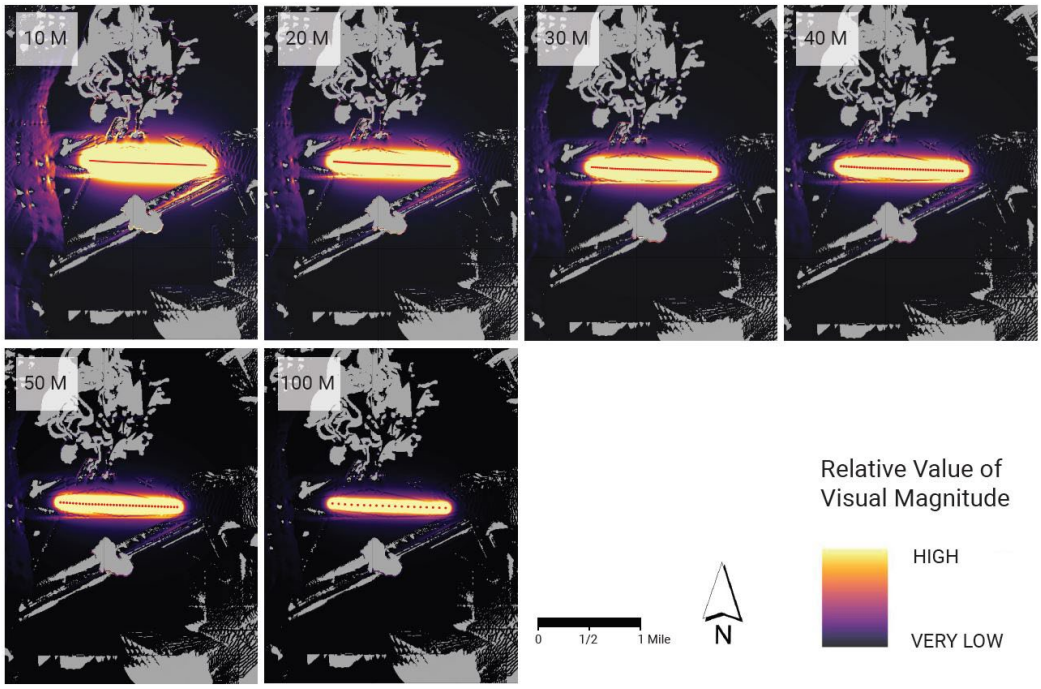


Figure 2.8

Correlation for Flat Environment Equal Interval Viewpoint Reduction Method

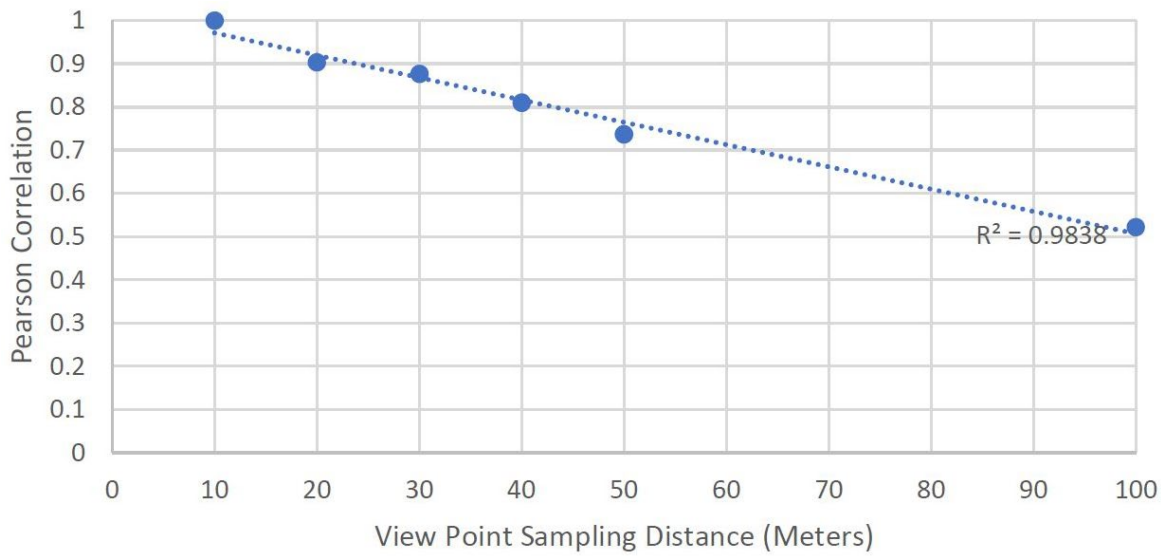


Table 2.3 is also expectedly similar to Table 2.1, with the loss in total area being relatively minor as the sampling distance increases. In this study area, the total area loss is actually less than within the mountainous study area.

Table 2.3

Flat Environment Equal Interval Viewpoint Reduction Method Results

VP distance	VM raster correlation	% of total area	# of VP
10 M	1.00	100	186
20 M	0.90	99	94
30 M	0.88	98	63
40 M	0.81	98	47
50 M	0.74	97	38
100 M	0.52	95	19

Hilly Environment Interval Results

This is an additional site that was selected for this study but not included in the published paper. This area is a hilly environment located just south of Collinson, UT. The surrounding terrain is filled with undulating hills and a river section that cuts through the hills to the north of our selected route. This area is mostly farmland but with the presence of the river the area also attracts recreationists. This additional area provided us with a topographical middle ground between the Mountainous and Flat sites.

The results seen from this area show an expected negative trend in correlation as we decrease the number of viewpoints. Figure 2.9 showcases this trend for the hilly study area. In Figure 2.10 the correlation values remained high again, with a resulting $R^2 = 0.91$ indicating a very strong relationship.

Figure 2.9

Hilly: Equal Interval Viewpoint Reduction Method Visual Magnitude Outputs

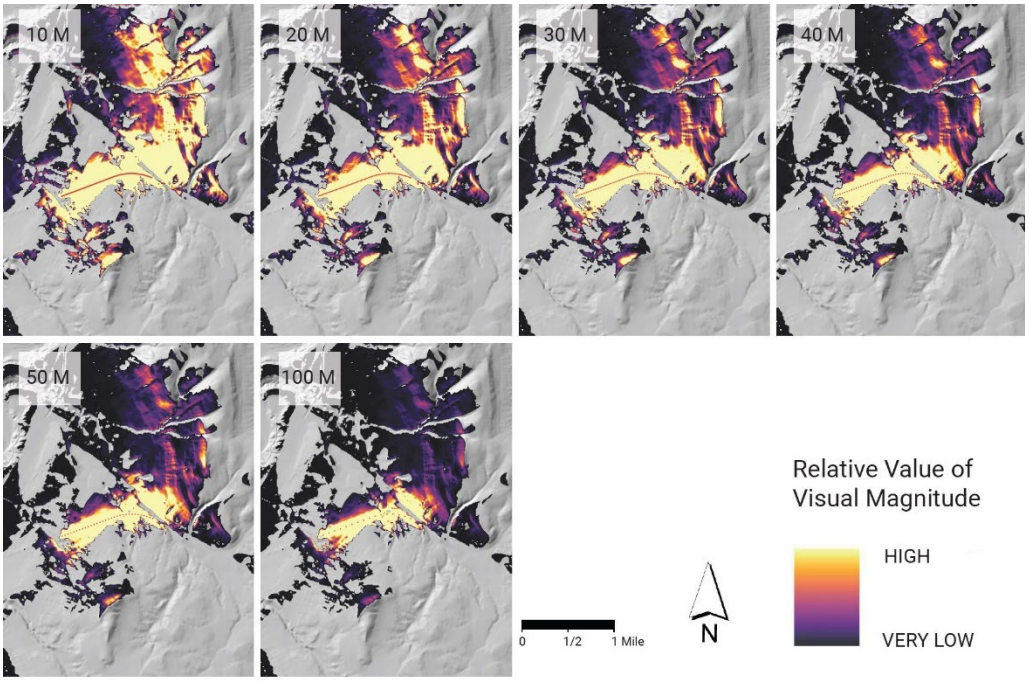


Figure 2.10

Correlation for Hilly Environment Equal Interval Viewpoint Reduction Method

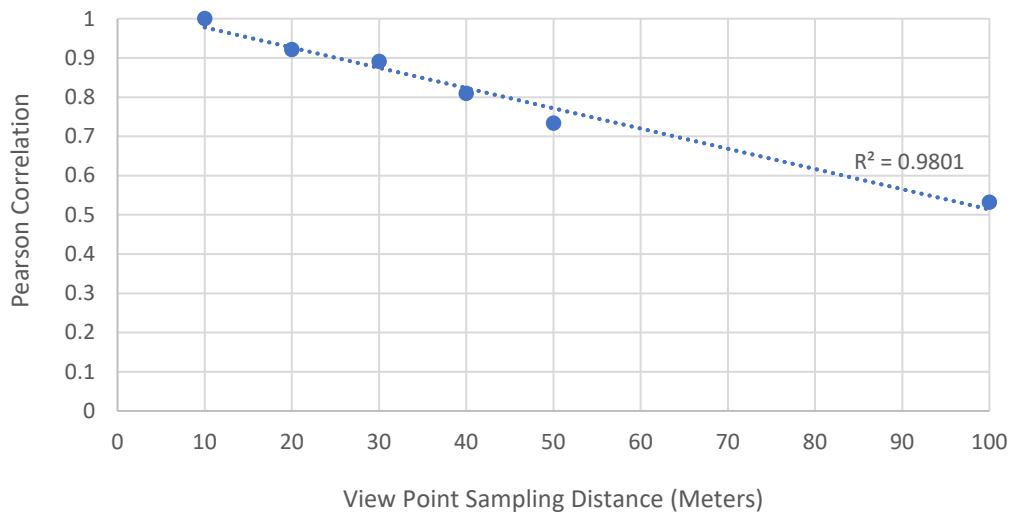


Table 2.4 shows a continuing trend previously seen our other two areas. For each interval, there is average of 5% reduction of the correlation coefficient for every 10m interval increase. However, there is very little loss of total area seen, averaging less than 0.5% per 10-meter interval increase. Around our recommended sampling distance of 30 meters, we see a correlation of .89 with only 1% loss of total area seen. These results correspond with results from the other two environments.

Table 2.4

Hilly: Equal Interval Viewpoint Reduction Method Visual Magnitude Outputs

VP distance	VM raster correlation	% of total area	# of VP
10 M	1.00	100	159
20 M	0.92	99	80
30 M	0.89	99	54
40 M	0.81	98	40
50 M	0.73	98	32
100 M	0.53	96	16

One Meter Measures

The following figures were created after doing an additional sampling distance for every 1-meter. After adding this additional measure to our Pearson correlation analysis, the data maintains a strong R^2 values for all environments. With the addition of another sampling distance there is an increase in all the R^2 values from changing the base sampling distance from 10-meters to every 1-meter shown in Table 2.5. Figures 2.11-2.13 show the change in correlation between each environment for every sampling distance.

Table 2.5

Hilly: Equal Interval Viewpoint Reduction Method Visual Magnitude Outputs

Environments	*R* value before 1 meter	*R* value after 1 meter
Mountainous	.9546	.9918
Hilly	.9801	.9846
Flat	.9838	.9863

Figure 2.11

Mountain Environment Correlation Analysis with 1-Meter Sampling Distance

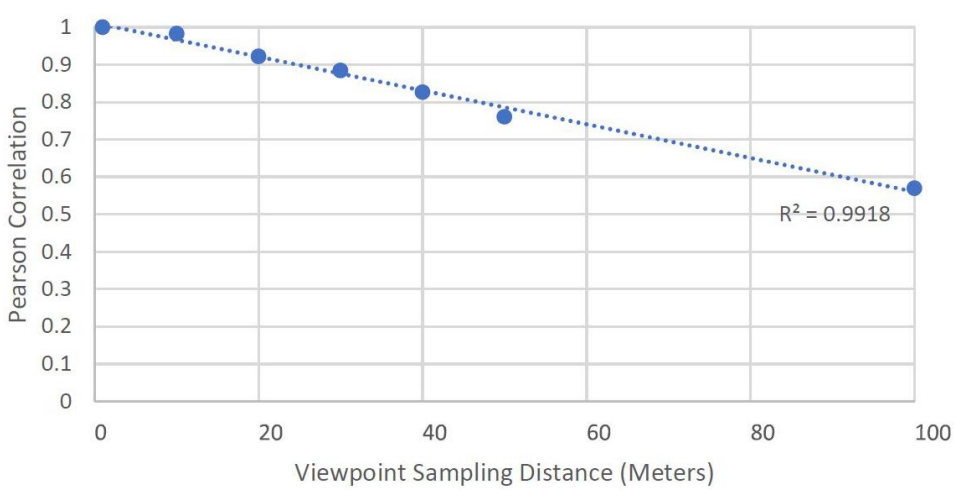


Figure 2.12

Hilly Environment Correlation Analysis with 1-Meter Sampling Distance

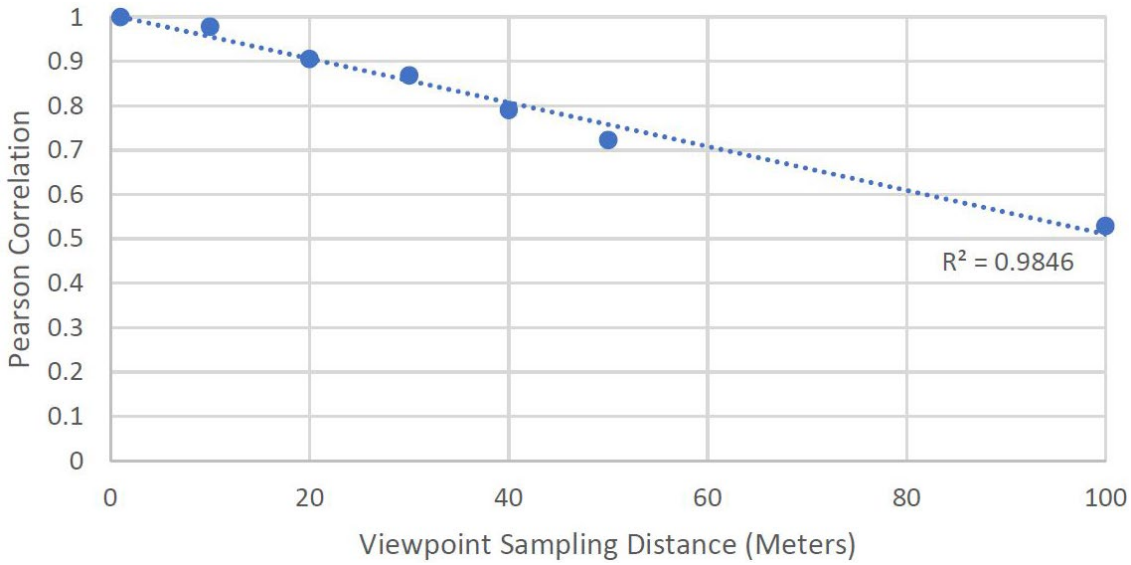
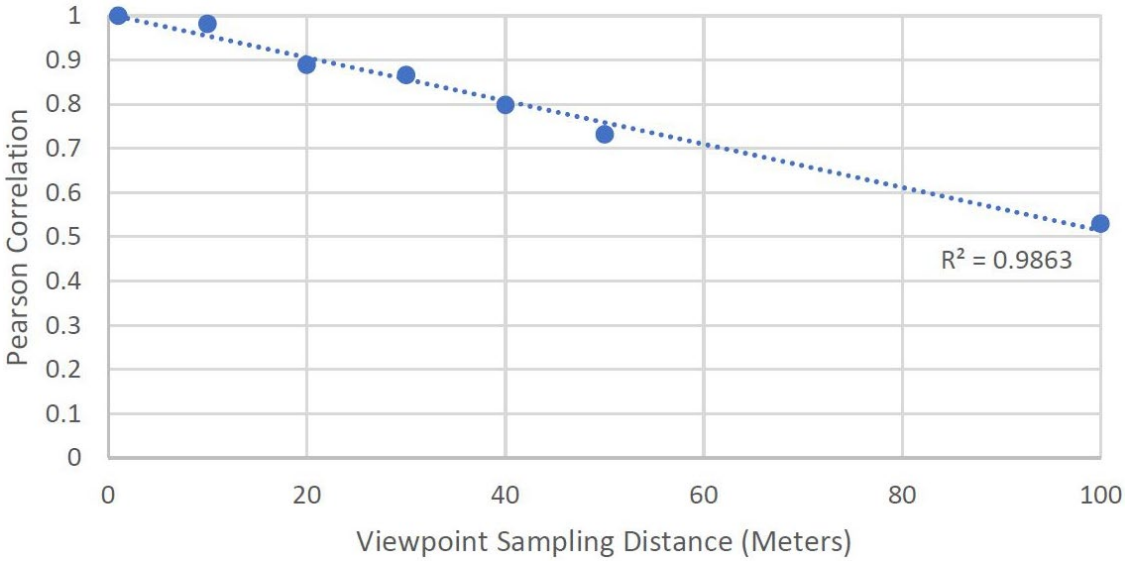


Figure 2.13

Flat Environment Correlation Analysis with 1-Meter Sampling Distance



Discussion

For this paper we sought to provide empirical evidence to address unanswered optimization questions for site selection of route-based experiences. We set out to discover the relationship between the number of sample points and the accuracy of the visual magnitude model, as well as the optimal point at which this trade-off could be exploited. The following is a discussion on the outcomes of our findings and recommendations for future research.

When we set out to analyze the differences in sampling techniques (equal interval versus random), we had not anticipated a result where all samples performed worse than the equal interval technique. We suspect running additional random samples could produce at least one higher correlation than the equal interval but doing so negates the usefulness in practice due to the amount of time needed to find a high preforming random sample of viewpoints. The substantial variation of correlation with the random sample is not worth exploration. Our recommendation is to maintain and equal interval stratification of viewpoints along a route.

With the random versus equal interval sampling analysis completed, we moved toward identifying the extent to which terrain would alter the outcome. The selection of two very distinct landscapes provided a means to compare differences and perhaps come away with reasonable recommendation for the sampling frequency. As indicated the overall correlation and R^2 values are high across both study areas. The Pearson correlation reduction is linear within the sampling distances analyzed, thought this would likely fall off dramatically. Extending this sampling distance could be an interesting

research exercise, but from a localized planning perspective it is likely wise to maintain a higher correlation coefficient greater than the 100-meter sampling distance.

The primary goal of this research endeavor was to identify if there was an optimal point between the trade-off of viewpoint sampling distance and the correlation of visual magnitude values. The data demonstrate a negative linear relationship between these two variables, making the recommendation slightly harder than if there was some inverted logarithmic relationship where there was a clearer indication of a tipping point. So, before making a blanket recommendation, we explore the relevant context from which to make our claim. Our data analyzed the 10-meter interval as the base. While this is an arbitrary number it represents an observation every half-second for someone driving 45 MPH along our routes (similar to speed limits). Thus, it is expected the frequency of this sampling rate is likely to encompass the range of visual diversity an individual would see along this route. Further, 10 meters was also the resolution of the digital elevation model. For future analyses where the experience may be slower, it would be worth considering analyses with sampling distances as smaller intervals. For instance, if this type of analysis were to be conducted as a hiking trail, a 1-meter interval would be appropriate as a base comparison because this is representative of a walking pace. Nevertheless, the scenic and landscape experience from our roadway example provides some indication that correlation coefficient does not drop off rapidly. Even adding the additional results from the hilly environment and the 1-meter measures, our findings were consistent across both of the other two environments.

To interpret findings, we conducted a Pearson Correlation *r* and followed recommendations from various fields that provide insight into the meaning of the results.

. The results provide a correlation of the average visual magnitude values across all viewpoints, essentially comparing the topographical response to viewpoint sampling distances. So, while these data sit squarely within the physical sciences, the interpretation of these data fall within the realm of psychological sciences because we are most interested in how individuals perceive topography. To this end, we recognize there are different interpretations between the physical and social sciences regarding Pearson's *r*. In social sciences, interpretation of *r* is somewhat well defined, with 0.9 said to be very high (e.g., Mukaka, 2012), 0.7 is strong or high positive (e.g., Ratner, 2019). However, when considering these data as test-retest reliability (Koo & Li, 2016), the interpretation of correlation changes, with 0.5 – 0.75 as moderate or reliability, 0.75 – 0.9 as good reliability, and 0.9 or greater as excellent reliability. However, a test-retest reliability study should be conducted with comparable sampling frequency across different times or individual samples. In our application where values are averaged across samples, this is not a conventional test of reliability.

Based on these interpretations we make two recommendations (here we assume a large area visual analysis). If the environment is highly sensitive to visual impacts, aim for a 30-meter interval (near 0.9 correlation), while for other landscapes, a 50-meter interval seems reasonable (near 0.7 correlation). Both substantially reduces the number of our viewpoints by 66% (30-meter) and 80% (50-meter), while balancing both the interpretation of social science correlation and reliability benchmarks. Further, it should be noted that these sampling distances also maintains the total area error of 96%, meaning that only 4% of area is not visible when sampled at 50-meters, compared to 10-meters. This is likely of minimal concern, because the lost areas of visibility tend to be

skewed toward further distances, which individually have a much lower visual magnitude.

Until a new optimization technique for selecting viewpoints along a route emerges, we believe an equal interval sampling technique will provide consistent and accurate results across a range of landscapes. We do see some opportunities to refine and enrich this study. These include increasing the variety of environments, and differing terrains, including a hilly environment for medium sized elevation change and urban environment to evaluate the influence of the built environment. We would also like to see additional measures of viewpoints explored. A range of greater than 3-kilometer could be useful to explore for open expansive environments. Additionally, we are curious the extent to which correlation changes most rapidly at various distances away around the route. Could it be that viewpoint selection could be optimized for different distances where visual features or impacts may be most readily observed? Further, how might these results be modified using different raster resolutions for the digital elevation model? To address these questions, we recommend further analysis into a systematic comparison of viewpoint sampling, raster resolution and analyses that consider correlations, where distance may be considered a covariate. For now, this research offers provides a foundation from which these additional explorations could be produced. There may certainly be more optimal approaches to route-based viewpoint selection, but a one-size-fits all optimization could be challenging given the variety of localized conditions.

Conclusion

This study was created to help professionals process visual impact analyses more

efficiently for route-based conditions. Additionally, the study aimed to identify the extent to which accuracy of a visual magnitude model altered based on sampling distances for viewpoints along the route. This study was conducted in two distinct landscapes: mountainous and flat wetland areas. We created a systematic way to analyze how these environments impacted the outcome and the role of different sampling techniques. The analysis was conducted using a 10-meter DEM (publicly available data) and roads. Our findings suggest that 30-meters is an ideal sampling distance interval for highly sensitive environments, whereas 50-meter still produces a strongly correlated result for other landscapes. These recommendations establish a baseline, whereby future empirical studies can begin. We have identified the trade-off between the number of viewpoints being used along a highway route and the accuracy of the visual magnitude tool outputs. The result of this study carries promising results for the field of visual analysis and with the exploration of other environments, data resolutions and other variables mentioned in the discussion section the necessary input data can further optimized.

Acknowledgements

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CHAPTER 3

PREDICTING SCENIC QUALITY OF UTAH ROADS

Abstract

In this study we investigate whether visual magnitude metrics can predict scenic quality ratings. Our results indicate a statistically significant, strong correlation between these measures. For each site, we produced a skewness metric that evaluated the distribution of visual magnitude values across the visual extent of each drive. Drives that were skewed to a higher number of very small visual magnitude values predicted lower scenic quality compared with drives that were less skewed. The less skewed the visual magnitude analysis and wider the distribution of the standard deviation indicated higher ratings, with higher standard deviation providing the strongest relationship to scenic ratings. Additional analyses were conducted, including reviewing the relationship of different individual demographic and experiential characteristics. Results indicated differences in gender and age, with women and younger participants giving scenic quality ratings that were lower overall compared to other participants. With these results we have a greater understanding of the potential applications of the VM tool to conduct dynamic impact analysis of environments in a more detailed and efficient way and how this measure relate to how people perceive the scenic quality of environments.

Keywords: visual magnitude, scenic ratings, correlation, route-based, scenic quality, video experience, survey

Introduction

Spatial and visual analysis are important tools for planners in understanding and evaluating our surroundings. With technological advancements, these types of analyses often are being generated utilizing GIS computer software (Davidson et al., 1993). By using a viewshed analysis, which is the most common form of visual analysis (Davidson et al., 1993), planners can evaluate the extent of visual exposure an observer has to an environment. Techniques like this are often used by planners for management and assessment of landscapes (Daniel, 2001; Germino et al., 2001; O'Sullivan & Turner, 2001; Palmer, 2004; Smardon et al., 1986). Information and maps generated using these types of geospatial analysis software is used to help planners make informed planning decisions. However, there are limits to the amount of data created and the extent of understanding that is gained from utilizing these techniques of visual analysis. This is primarily due to the binary nature of the returned analyses. There has been an increasing importance in exploring visual analysis (Gobster et al., 2019) outside of the traditionally used viewshed to more specific uses, including the assessment of visualscapes (Llobera, 2003), visual exposure (Domingo-Santos et al., 2011), visual pollution (Chmielewski et al., 2016; De Montis & Caschili, 2012) and cumulative viewsheds (Wheatley, 1995). All these different visualization methods help planners gain a deeper understanding of the visual quality of a landscape and allow for better planning decisions.

Many of these types of new visualization techniques and tools use specific point data that focuses on areas of high visual value or impact. The viewshed tool produces an analysis of visibility as a raster analysis. Here, the slope of each cell is calculated, relative

to the viewer, and any cell further away from the viewpoint must have a slope higher than cells closer to the viewpoint along a line of sight. If the more distant cell is determined to have a higher slope, it is indicated in the final viewshed with a value of one (visible). The viewshed tool has been used to support land management decisions, but it lacks important information about how viewers see the landscape. In this case, the viewshed assumes visibility is the same across any visible cells on the raster. Instead, there are alternative techniques that use the same raster analysis but provide measures of how much each cell is visible within an observer's field of view. For instance, one of the alternatives to a binary viewshed is called visual magnitude. Visual magnitude measures and accounts for the visibility of each cell relative how much space that area on the landscape occupies an observer's view. This providing a range from 0 (not visible) to 1 (completely occupying all visible area to the human eye). These measures provide a range of visibility and can be compared across cells and landscapes because the calculation is an absolute value.

The first study to argue for the importance of route-based assessments using visual magnitude came from Brent Chamberlain in 2013, exploring a scenic area in British Columbia. This study focused on evaluating an experience using the Visual Magnitude ArcGIS Plugin (VM) tool and the different possible outputs to help inform landscape management decisions. The visual magnitude tool uses a combination of metrics including slope, aspect and number of times seen to create a visual analysis output that depicts the degree of impact and visibility of an environment to viewers (Chamberlain & Meitner, 2013). Outside of this study there has been little work done to empirically evaluate the efficacy of the visual magnitude tool and its analysis technique.

This study focuses on answering the following questions: can the visual

magnitude tool inform us which scenic byways or other roadways which are rural or more natural environments contain the best experience for vehicle-based viewers and to what extent can an averaged visual magnitude output correlate to public scenic ratings of highway experiences? To answer this, we collected empirical data from ratings of rural roadways, including scenic byways, and correlated these with VM metrics of the same environments. This was done by first collecting the VM outputs of the environment and then creating a hyper lapse video of the same environments for rating by an audience. Those ratings were then compared against the VM outputs, and the extent of their correlation was graphed and analysed. Throughout this study we will refer to different sites, routes or environments that are being measured, these words are being used interchangeably to refer to the road and its surrounding environment.

This study aimed to improve the understanding of how we are experiencing landscapes from a vehicle-based perspective, the visual impacts of an environment based on a route context and provide information on the extent of the visual magnitude tool to be able to accurately represent those environments. We can see to the extent that the visual magnitude tool can predict preferred exposure and scenic rating preferences for environments.

Background and Literature Review

Technology and Visual Assessments

Our understanding of the world and its processes relies heavily on visual information. This makes sight a crucial tool in collecting information from landscapes for personal understanding and to inform decision making (Kaplan et al., 1998). To visualize

scenic quality, planners use visual analysis to help them quantify aesthetic quality of environments (Arriaza et al., 2004; Daniel, 2001). These visual tools assist in analysis and planning of environments. Most of these analyses are conducted using key observation points (KOPs) where certain areas of the landscape are selected to be used as the origin of a visual analysis to assess the visibility of a large area or selecting representative key observation points of visually desirable areas. This method has several shortcomings including providing a limited, static representation of dynamic experiences and overrepresenting single points (Chamberlain & Meitner, 2013). In circumstances where more area is included in the visual analysis, more viewpoints are needed to ensure adequate coverage of the entire area. Each additional viewpoint requires more than a trivial amount of effort, necessitating time, data preparation and computer processing for each analysis. This is one of the reasons KOPs are used a proxy for a broad assessment for continuous experiences. Alternatively, it would be useful to have a technique that could assess hundreds or thousands of viewpoints and simultaneously provide a metric to assess overall aesthetic quality. Visual magnitude, offered in (Chamberlain & Meitner, 2013) provides this opportunity. Unfortunately, there has been no systematic recommendation to indicate the trade-off between how many viewpoints and the accuracy of the visual analysis to identify an optimal number of sampling points until our previous study was conducted (Openshaw & Chamberlain, 2021) or distances needed to represent a route-based experience.

With the advancement of technology, visual analysis planning has shifted from our roots of only having photography for collecting visual information to being able to use geospatial software. Historically, visual assessments and visualizing changes in the

landscape begin with modelling and ink drawing techniques developed by the Egyptians and Chinese around 2500 B.C (Zube et al., 1987). These processes were developed further for landscape architects and planners by Humphry Repton and his creation of "Red Books" in the 1700s. This was a technique used by Repton where he would paint a landscape in its current form and then paint the landscape again with his suggested changes helped develop the field of scenic visualization (Raphael, 2021; Zube et al., 1987). From there the field of visual analysis evolved significantly when cameras were invented. Planners began taking and analysing photographs to document landscape quality. Those images could then be used in public settings to gain a deeper understanding of preferred landscapes through ratings (DePriest, 2018; Palmer, 2004; Wright, 1974) but the accuracy of this method often lead to understanding of only small parts of the entire picture reducing the validity of their ratings of the environment that they were attempting to evaluate (Palmer & Hoffman, 2001). Development of computers and software programs once again lifted the development of visual analysis to new heights. With this advancement planners can now create models that allow us to have a deeper understanding of topography, visibility, quality, and what elements potential observers and users of the landscapes might experience.

One of these commonly used visual analysis tools for planners is the Viewshed (Davidson et al., 1993). A viewshed analysis allows planners to identify areas that carry significant visual weight and allows for the mapping of areas of visual exposure according to a defined point that the landscape is being viewed from. Viewsheds, created using commercial GIS software, creates only a simple binary output (P. F. Fisher, 1996). A viewshed will assign the landscape a value of either one, the area is visible, or 0, the

area is not visible from your chosen viewpoint or KOP. The result is a geospatial raster image that illustrates areas that are visually exposed to viewers. This type of visual analysis is limited in the information that it can provide, and some experts suggest that using only one type of visualization method does not provide enough context to give a sufficient understanding of the landscape (Chamberlain & Meitner, 2013; Ervin & Steinitz, 2003). Many variations of non-binary analysis tools have been developed to give a more in depth understanding and perspective to the visual inventory and analyses processes to inform planning. Some examples of these tools include ocean blue space (Qiang et al., 2019), visualscapes (Llobera, 2003), visual exposure (Domingo-Santos et al., 2011), cumulative viewsheds (Wheatley, 1995), archaeological elements (Čučković, 2015), wind infrastructure (Gibbons, 2015), visual pollution (Chmielewski et al., 2016), landmark visibility in urban areas (Bartie et al., 2010), and work on expanded viewsheds (P. F. Fisher, 1992, 1995).

Historically visual magnitude was a measure used in Astronomy to calculate the visibility of stars and how faint of an object the human eye can see (Schaefer, 2000). However, it was realized that this method of visualization could be applicable to analyse the visibility of landscapes. With the development of computer-generated visual magnitude, the Forest Service identified it as an important tool to help them make land use calculations and decisions in the late 1970s although it was not documented in research until 1985 (Iverson, 1985). Chamberlain and Meitner (2013) proposed another method using this analysis technique by utilizing a specialized tool they had been developing for physical landscape-based impact assessments called Visual Magnitude (VM). This GIS plugin tool provides a unique way to assess how topography and

distance interact through a continuous space like a route or drive. This tool helps us to understand the amount of impact that the landscape visually by deriving a calculation of how much space (measured in pixels in images and cells in GIS raster outputs) is being occupied by elements or areas of the landscape in our vision throughout a route. This GIS tool calculates the relative distance between the viewer and a location, as well as the relative slope and aspect of the terrain at that location relative to the viewers angle of observation. Further, it includes the number of times each space is seen (Chamberlain & Meitner, 2013). It then generates a single value for each specific raster cell representing the space. The higher the value of that cell, the greater the calculated impact on an observer. A higher number means that the cell is closer to the viewpoint, the aspect of the environment is more directly facing the viewer and/or the slope is greater. All these factors make the amount of potential visual impact increase, but it has yet to determine how this technique is related to scenic quality.

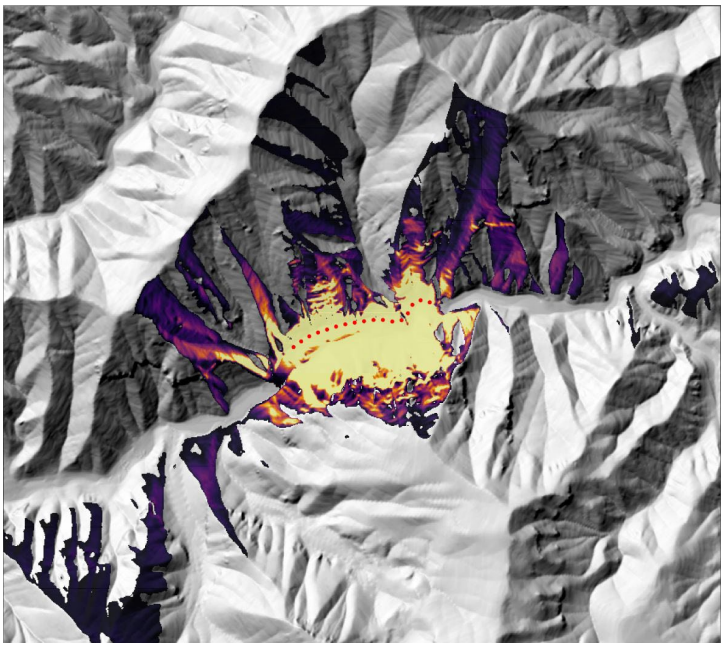
Figures 3.1 and 3.2 indicate the difference in the type of information that is being relayed in the same area of Logan Canyon using the same route. Figure 3.1 is a viewshed analysis, this analysis indicates only areas along the route that are visible. Figure 3.2 is our average weighted visual magnitude analysis (conducted at 30-meters) which indicates the amount of space each of these cells is taking up visually in the view of observers giving an indication of the more sensitive areas. Areas that are yellow show areas that are taking the highest amount of space in our visual field and have the highest degree of impact and black showing areas that take up the smallest amount of space but are still visible and contain the lowest amount of visual impact. In a ground truthing study conducted in 2019, it showed that the Visual Magnitude Plugin was able to accurately

Figure 3.1

Viewshed Analysis of a Portion of Logan Canyon

Figure 3.2

Visual Magnitude Analysis of a Portion of Logan Canyon (100-meter sampling distance)



correlate to real word conditions when comparing the tools outputs when compared to photographs of the environment being studied (Chamberlain & Cook, 2019). While visual magnitude is only one of many tools used to assess visual quality of an area, the potential of this tool has yet to be explored in depth.

Our Evolving Exposure to Nature

How people see, understand, and interpret nature and its appeal to them has been a subject of research for a long time. People are drawn to places that they see as having a high visual value to them. There sometimes is a detachment of the understanding of beaty between experts and non-experts (Daniel, 2001; Zube et al., 1982) and how they interpret or evaluate aesthetic quality. However, many people have tried to create rating systems to evaluate landscape aesthetics and quality (Linton, 1968; Palmer, 2004; Wright, 1974) and accepted the quantification of visual quality as a measure of its resource value (Gillespie, 1971; Linton, 1968).

Our health behaviours are shaped by how we live (Twardzik et al., 2018). Exposure to natural environments offer many benefits that can increase humans' well-being through physical, emotional, mental and spiritual restoration, and stress recovery in terms of allostatic load (Haluza et al., 2014), or the cumulative burden of stress and life. However, with lifestyle changes, many of us are spending a significant amount of time away from nature. This detachment from nature has and will continue to impact our quality of life (QOL). However, we experience landscapes from the roadway now more than ever and driving for pleasure has often been one of the highest recreational activities in the USA (Cordell, 2008; Draper & Petty, 2001; Hallo & Manning, 2009). Even with

this increased travel amount we are experience a continuing detachment from nature. This gives us a unique opportunity to create and protect beautiful driving experiences (O'Neill, 2007). We utilize vehicles to help us to get from one place to another, giving us this opportunity to re-expose ourselves with natural environments and increase our QOL with the positive effects nature has on us from the roadway. This highlights the importance of experiences of nature that are now happening from vehicles. Traveling a scenic byway is one of the principle means of experiencing a linear landscape (Crafts, 1995).

Traveling along roadways is a unique way to experience landscapes both scenic and not, often at the discretion of the observer. Recognition of scenic environments and drives though the scenic byway system is a way that the State and Federal governments can increase and justify creating stronger protections for these environments and their resources when they have been identified as notable sites. There is a significant amount of land set aside for transportation purposes that takes us through a variety of scenic quality of environments which gives an opportunity for a variety of experiences. The more important sites that receive more exposure could then be a target for preservation policies to maintain their intrinsic values.

The Scenic Byway System

The scenic byway system was established beginning in 1989 with the Scenic Byways Act and the first report being published in 1991 (Sipes et al., 1997). Congress also passed the Intermodal Surface Transportation Efficiency Act (ISTEA) which helped to create funding for the scenic byway system (Selin & Chavez, 1995). As defined by the

legislation (U.S. Code, Title 23, Section 162), a “scenic byway” is recognized as “roadways having outstanding scenic, historic, cultural, natural, recreational, and archaeological qualities” (Clay & Smidt, 2004; Gustafson, 2009). Simply put, these selected sections of roadway and surrounding landscape showcases the most beautiful or most enjoyable experiences (Denstadli & Jacobsen, 2011), preserve our more scenic roadways, and promote tourism (Brunswick, 1995; Selin & Chavez, 1995) for everyone to have the opportunity to see the unique environments that are offered by that area. With vehicle-based experiences being a primary mode of transportation and recreation that influences the way that we are now experiencing nature. Protecting our scenic byways and the beautiful scenery that envelops the expansive roadway systems has never been more important.

For a roadway to be recognized as a Scenic Byway, it must contain at least one of these six designated intrinsic qualities: scenic, recreation, natural, historical, cultural, or archaeological value worth preserving and protecting in its current form (Kelley, 2004). A status of All American Road is given to a roadway environment that contains multiple of those qualities. A scenic byway system that contains a diverse supply of these qualities sees success in providing unique experiences and strengthens its value as a tourist and recreational attraction (Kelley, 2004). These beautiful sections of road and their vistas face several threats, the most common being development (Kelley, 2004) development especially unplanned puts the qualities of the scenic environment at risk of losing the value that the environment holds. Effective planning (Yu et al., 2007, 2007) and understanding of the value of these sensitive routes and their environments is key to ensuring the protection of the unique experiences they hold. A continual growing number

of both state and national byways (Kelley, 2004) indicates an importance of this resource to the population of the United States and illustrates the success of the National Byway System.

It is our goal to use technology to create and represent a visual experience of both scenic byways and regular roadways to study the vehicle-based experiences that these routes are creating. Using technology to represent a virtual experience is not a new technique (Bishop, 1997; Bishop & Bruce Hull, 1991; Clay & Gimblett, 1998; Daniel, 1992; House et al., 1998) and can be used to represent a real-world experience (Daniel, 2001) for analysis.

Why Utah as a Study Site?

A vital part of Utah's economy depends on having vibrant and beautiful landscapes to draw people in for tourism. Utah is situated at an intersection of multiple major ecoregions giving it the opportunity to offer a wide variety of landscapes from Alpine Forests to Deserts. This biodiversity brings a significant desire for people to come and see what Utah has to offer. The state contains five National Parks, ranking it third among the nation even though it is only the 13th largest state. Utah also contains eight nationally designated scenic byways and 18 state designated scenic byways which lay the scene for visiting some of the most unique scenic vistas in the world.

In conjunction with tourism, Utah is also advertising itself as a place that has something for everyone in terms of recreational services, whether that occurs through the "Greatest Snow on Earth", the Rocky Mountains, over 2,000 lakes and 89,000 miles of streams. Tourism greatly influences Utah's economy with visitors spending $10 billion

(Leaver, 2019). Utah's travel and tourism industry accounted for approximately 141,500 jobs in 2019, which is about 1 out of every 11 jobs being supported by visitor spending, a 4% increase year-over-year (Leaver, 2019). The Utah State Tax Commission reported a 10.7% increase in spending on amenities from 2018 to 2019 (Leaver, 2019).

For these reasons we selected Utah as our study site. Visual aesthetics and maintaining a sense of scenic beauty and awe are valued highly in Utah, and with projected population growth Utah needs to be able to make a case for protecting its natural amenities and maintaining its important economic use of resources for recreational and tourism activities.

Review of Previous Study of Sampling Distances

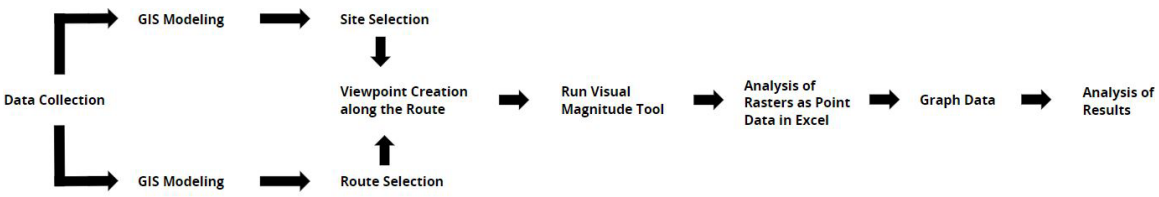
This thesis was originally developed as two distinct studies, the first as a modelling exercise in visual magnitude assessment sampling and the second as an empirical analysis of the sampling in conjunction with the relationship to aesthetic ratings and visual magnitude. The first study is contained in Chapter 2 but directly influenced the sampling method of this study. For this reason, it seemed pertinent to include a short methodological review of the previous study.

The purpose of the previous study (Openshaw & Chamberlain, 2021) was to identify a threshold between viewpoint sampling interval and the resulting correlation of visual magnitude raster outputs. By doing this we aimed to be able to identify an optimal sampling distance. Our hypothesis, which was confirmed, was that we would see an overall negative correlation trending towards 0 between increased sampling distance and resulting correlation of visual magnitude outputs. We also expected to see topography,

(mountainous, hilly, flat environments) play a role in the total amount of data that the visual magnitude rasters will display due to increased distance of visibility. Figure 3.3 outlines the methodology framework being used to accomplish this objective.

Figure 3.3

General Methodology Part 1



The first set of data that we needed to accomplish this objective was a Digital Elevation Model (DEM) of the areas of interest, then we clipped the DEMs down to the study site which encompassed a 3-kilometer extent to capture the optimal viewing area (Emerging Technology, 2019; Krisciunas & Carona, 2015; Roland, 2019). We decided that a DEM at a 10-meter resolution was sufficient to meet the amount of detail we need while looking at a 3-kilometer surrounding distance (Emerging Technology, 2019; Krisciunas & Carona, 2015; Roland, 2019). The second data set collected was roadway information, which was downloaded at the state level and then paired down to one mile segment in length for our study routes. Both datasets were found at the Utah Geospatial Resource Center (UGRC) website for download.

We wanted to address the question of finding a viewpoint threshold to optimize representing an experience. This was done by selecting three environments that contain differing topography and selecting a mile long route through the environments. Much of

this process was automated using the ModelBuilder function in GIS. After selecting our routes and creating viewpoints at different sampling distances we had the data we needed for the VM tool. After running the VM tool we obtained raster outputs for each of the different sampling distances (10, 20, 30, 40, 50, and 100-meters). To make these rasters comparable we applied a mask of the lowest common area, or the cells of the raster that are visible on every output raster, of all of the rasters and keep only that area for analysis. This allowed us to extract point data for each cell across the different sampling distances and then compare the numerical difference between the rasters. Using Excel, we inserted those cell ID numbers and corresponding values to run a Pearson correlation analysis. After this we were able to plot the change in cell values between the VM outputs and the sampling distance, showing the steady decline in correlation over sampling distances increased. With these results we were able to view the trade-off between the sampling distance in the visual magnitude analysis and the time required for calculation, allowing us to find an optimal sampling distance to apply in out next study.

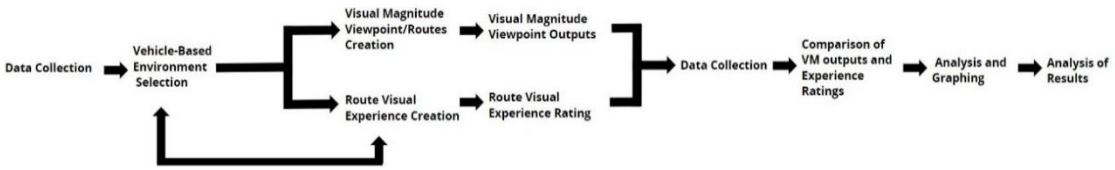
Methods

In this study we asked the question can the visual magnitude tool inform us which scenic byways or other natural or rural roadway envrionments contain the best experiences for vehicle-based viewers? More specifically, to what extent can the visual magntiude tools output correlate to public scenic ratings of highway experiences? In order to answer the our questions for this study, we created the methological framework in Figure 3.4 to guide our the process of what type of data needs to be collected, how this information was used to create routes and extract visual magnitude values, collection of

scenic rating preferences, evaluating the results and providing an analysis to answer our research question.

Figure 3.4

General Methodology Part 2



Data Collection

There were three primary data sources that were used to collect our needed data: (1) Google Street View imagery, (2) geospatial data from the Utah UGRC, and (3) EPA ecoregions data. From UGRC we downloaded highways and roads at the state level, as well as DEM data for the entire state. Unnecessary roads were removed according to the criteria described in the site selection section. The DEMs covered each site at a 10-meter resolution. To create our virtual environment experiences, we downloaded Google Street View images for each of the routes. Additionally, a level three ecoregions map of Utah was downloaded from the EPA. This ecoregion data set was used to associate people's travel experience and exposure to different environment typologies within Utah to see how it may influence their scenic quality ratings.

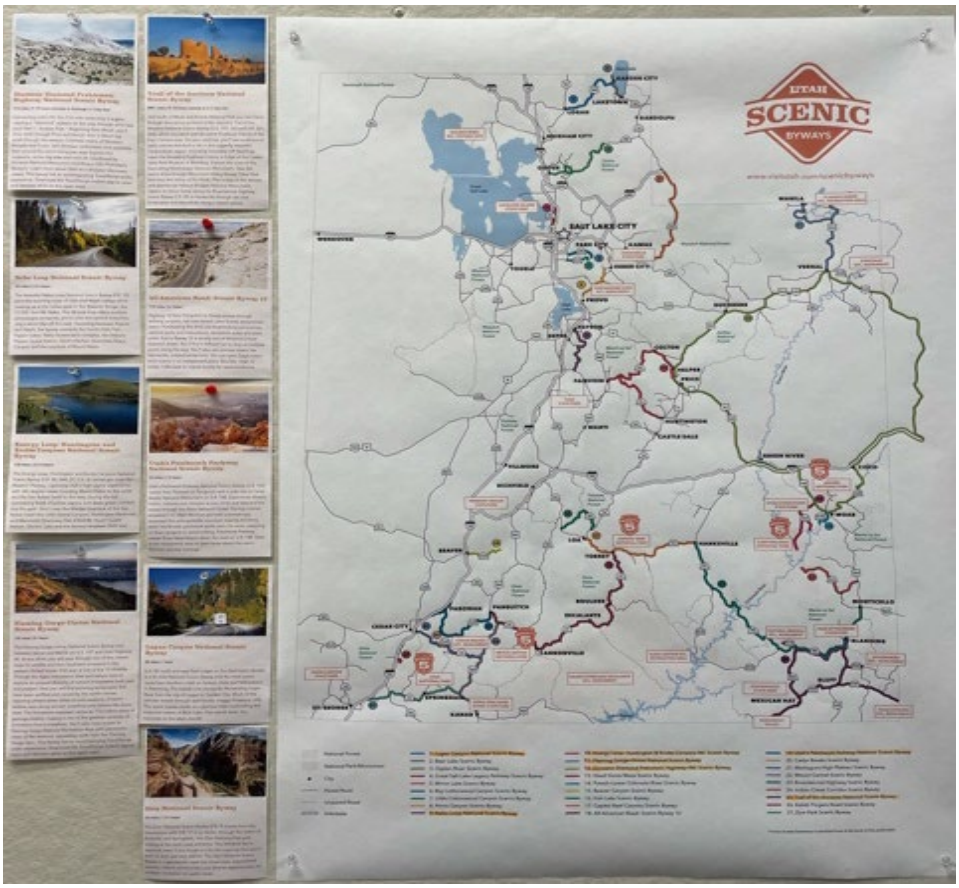
Site Selection

Fifteen distinct routes or drives in Utah were selected for the final analysis out of a total of 24 potential routes. The discovery of and use of routes, started with the initial

selection of 20 sites, which were then filtered. Four more sites were later added to make up the entire 24 potential sites. The selection process that resulted in the final 15 sites is provided below. First, sites were selected across two key categories: (1) availability of quality Google Street view imagery, and (2) site distinction and diversity within the state. Site selection began using the Utah Scenic Byways map (Figure 3.5) which identifies all locations of scenic byways and representative images. Site selection began by identifying different environment typologies and relative proximity to national parks and scenic areas (as these may be more familiar to research participants). Some routes and environments

Figure 3.5

Map of Scenic Byways Available at the Visit Utah Webpage



were be selected for their unique visual quality, their proximity to National Parks, their designation as a National or State Scenic Byway, or because their visual quality and experience appears subjectively poor (to encourage variety to scenic rating values). This was done to ensure that we were able to collect a diverse representation of experiences and eventually receive an equally diverse variety of scenic ratings. Selection was based on these subjective properties, as well as the following criteria.

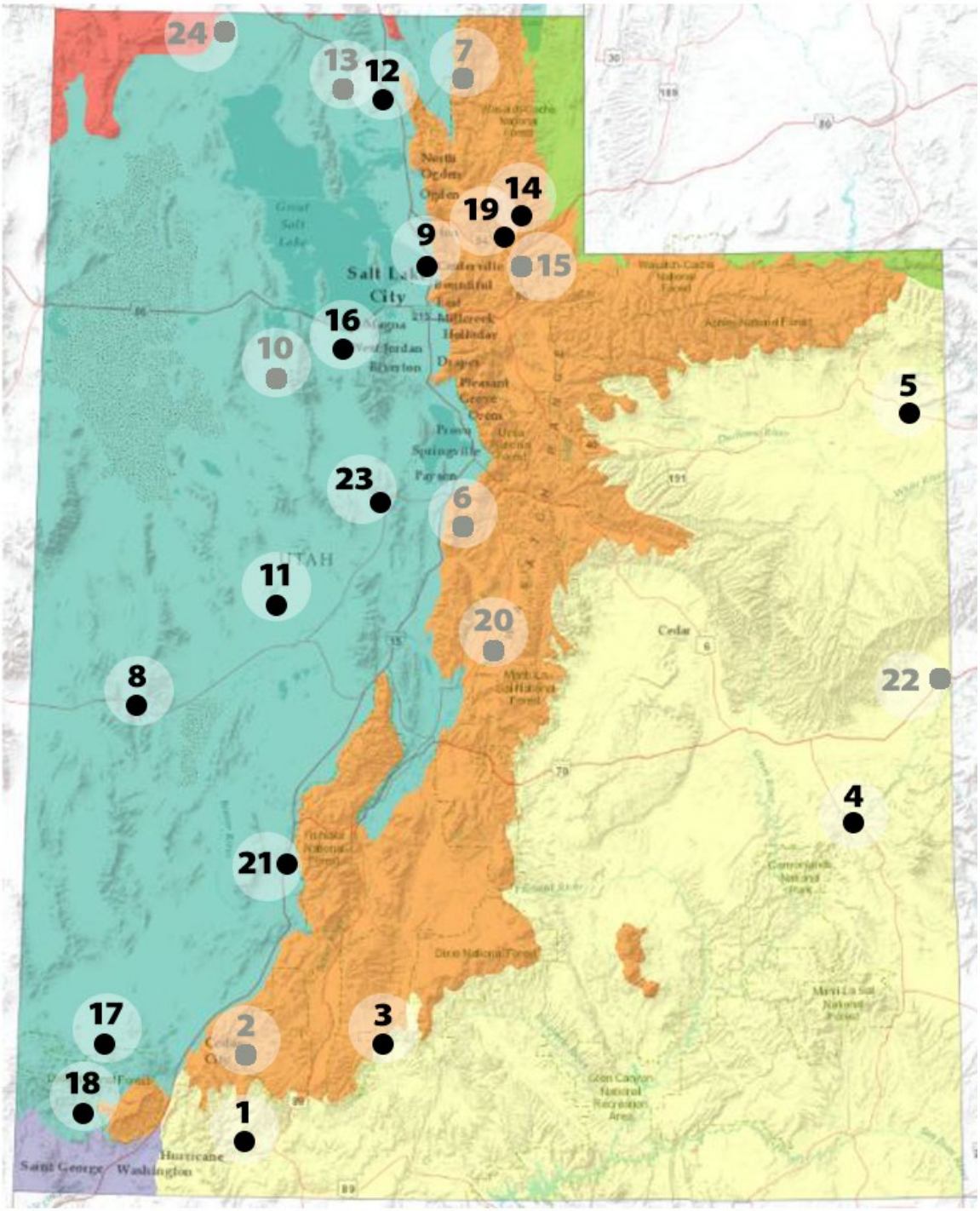
1. Selection of route length was be kept to ONE mile in length
2. Selected roadways were TWO driving lanes in width (with or without painted lines)
3. Selected environments were either be Rural Development or Natural Environments
4. Roadways were contained to the state of Utah
5. Speed limit between 50 and 60 MPH to control the rate of environmental exposure

Figure 3.6 is a map of the final total routes that were identified suitable for this study and the ecoregions of Utah that they were in. Routes that were used in this study can be identified by the black color of the dot and corresponding text, whereas unused routes are grey in color and text.

The conditions of the site that we identified were collected as independent variables due to the seasonality, quality and other factors that could affect the quality of Google Street View images. 20 initial sites were selected to give us a buffer of five sites if the environments or images from Google Maps turned out to be unusable for this study. Due to various factors (quality, etc.), it was concluded that we should exclude the following 5 roadways from the survey- Roads 6, 10, 13, 15 and 20. This left us with our target goal of 15 routes.

Figure 3.6

Suitable Routes for the Study



Note. Routes that were used are shown as black and unused routes are grey.

After beginning the creation of the videos, we again had some issues with getting imagery, or imagery jumping back and forth between roadways and other quality issues. To address this, added several more additional routes and removed others because of missing imagery. In total we ended up creating 24 initial routes for analysis. We maintained our target goal of 15 routes by substituting some of the videos we had issues with alternative routes.

Producing Visual Magnitude Analysis

Using the roadway data and DEMs collected a range of different visual magnitude analyses for each site. The route experience was represented based on a one-mile-long route. The viewpoints used for the analysis were created at a 30-meter distance, following the recommendation of previous research (Openshaw & Chamberlain, 2021). The decision was made to clip our results down to a 3-kilometer extent to focus on the environment that has a more direct impact (Emerging Technology, 2019; Krisciunas & Carona, 2015; Roland, 2019). This gave us two different outputs to compare, one for the full extent or everything seen from the viewpoints and a second at a 3-kilometer extent. The result of the Visual Magnitude outputs was then summarized into the following metrics (see Table 3.1).

Route Simulation and Generation

To collect empirical ratings of each site, forward looking Google Street View images were downloaded and sequenced together to create a seamless streaming hyper lapse video. Each video clip was approximately 10 seconds long, and the variation in time of the videos was a result of the number of images available from Google Street

Table 3.1

Collecting VM Values

Metric	Description
Full Maximum (Max) VM	Maximum visual magnitude value (for all raster cells) across all viewpoints for the entire envrionment that is visible from those viewpoints
3 Km Maximum (Max) VM	Maximum visual magnitude value (for all raster cells) across all viewpoints for a clipped 3-kilometer environment
Full Average (Avg) VM	Average visual magnitude value (for all raster cells) across all viewpoints for the entire environment that is visible from those viewpoints
3 Km Average (Avg) VM	Average visual magnitude value (for all raster cells) across all viewpoints for a clipped 3-kilometer environment
Full Minimumn (Min) VM	Minimum visual magnitude value (for all raster cells) across all 30-meter viewpoints for the entire environment that is visible for those viewpoints
3 Km Minimum (Min) VM	Minimum visual magnitude value (for all raster cells) across 30-meter viewpoints for a clipped 3-kilometer environment
Standard Deviation Values (*SD*)	Distrbution of the values show in the VM outputs
Skewness	Skewness of the values show in the VM outputs

View. Stitching was done through a combination of software and updated python scripts (documented in Appendix A), with the original script can be found at **Error! Hyperlink reference not valid.**. Stitching together images for visual analysis is a common practice for aerial imagery (Liang et al., 2018), panoramas (Li & Lu, 2018), comparing static and dynamic environments (Stamps, 2010) and 3D model creation (Visser et al., 2014). Our video creation used a similar process by stitching together still street view images taken by google into a temporal sequence. These images were then converted into a video format (MP4). This process allowed us to simulate an experience for each environment and share it on a large scale to collect scenic ratings.

During the video sequencing process, we encountered several problems in the

creation the videos of the environment that we had to respond to. By using Google Earth Street View to create our experiences we were limited to the most recent image sequence. This means that some of the imagery was collected by Google at different time periods (ex. Spring versus fall pictures creates different visual feels), with different cameras (pixel resolution) and in different weather situations (blurriness or water on the camera). Images illustrating some of these problems are attached in Figures 3.7, 3.8, and 3.9.

As indicated previously, we concluded that we should initially exclude five roads because these problems. Three additional roads were removed after the video sequencing process began. Even with attempting to control for the previously mentioned imagery situations we were still limited in the amount of control that we had for image detail or

Figure 3.7

Poor Camera Resolution

Figure 3.8

Picture Dates: Spring Photos Before Trees Have Leaves

Figure 3.9

Environmental Factors: Foggy and Blurry Photos

resolution, google image watermarks, blurriness on images due to Googles face blurring software, bugs or water droplets on the camera lens, shadows from the vehicle driving, etc.

Another issue that we encountered was caused by the images being taken by a 360-degree camera, which sometimes resulting in the pulled images being from opposite sides of the road (both oncoming and outgoing traffic lanes). To address this, we had to check the beginning and ending coordinate points for the routes so when we created the videos the vehicle taking the images was driving on the correct side of the road. This required us to use Google Maps on each of the routes and search for indicators of the direction the imaging was taken. We also discovered that if the vehicle taking images drove the same road, back and forth, that those images were not distinguished as being on one side of the road or the other. Images taken from both sides of the road were selected and imported as the same drive. To address this issue, we manually isolated images from one side of the road. However, this process left us with two videos that were half the length of all the others. These two shorter videos were used as validation videos to check viewer attention span and compare environment ratings to the other half of their respective environments.

Survey Design and Participant Recruitment

Generated videos were implemented into a survey interface (Qualtrics) that allows for a participant-based data collection. The survey asked people to rate scenic quality of route-based scenic experience based on their personal preference for each site. This provided a quantifiable number to correlate the qualitative aspect of scenic quality.

The survey instrument is organized into two modules: background data and rating collection. The first, collected preliminary information (independent variables) including participant age, gender, place of origin, education level and travel experience in Utah. Travel experience was used to identify how many of the sites or similar sites participants have traveled to, in order to gauge familiarity with the context of the sites used in this study. This was done by having participants rate familiarity to designated ecoregions, measured at level 3, of Utah. These variables are important to know because they can influence the participant perception of landscape quality from one environment to another. After answering those questions, participants were led though the second module which involved them rating videos of each site. The presentation order of the videos was randomized. Route segments were cut into two videos, each approximately 10 seconds long. Following each video participants were asked to rate the scenic quality of each environment on a scale of 1-10. This method originally developed in the late 70s (Daniel, 1976) is a typical standard for rating scenic quality and is still being used an improved upon (Ribe, 2021).

After the survey was created, we conducted an initial pilot test with six participants, known to the authors. The survey was then reviewed and edited according to their feedback. We added one new block at the beginning of the survey that contained an image of the highest and lowest ranking environments, as well as four average ranking environments. We asked participants to look at these images, which were randomized in order by the survey and without disclosing their various ranking values, asked them to consider how they might rank those environments differently. The aim of the images shown in Figure 3.10 were used to anchor peoples' responses and give them an overview

Figure 3.10

Grounding Images Used in the Survey

Road 1- Context Image

Road 3- Context Image

Road 14- Context Image

Road 5- Context Image

Road 17- Context Image

Road 8- Context Image

of the scope of types and qualities of environments block was to anchor peoples' responses and give them an overview of the scope of types and qualities of environments.

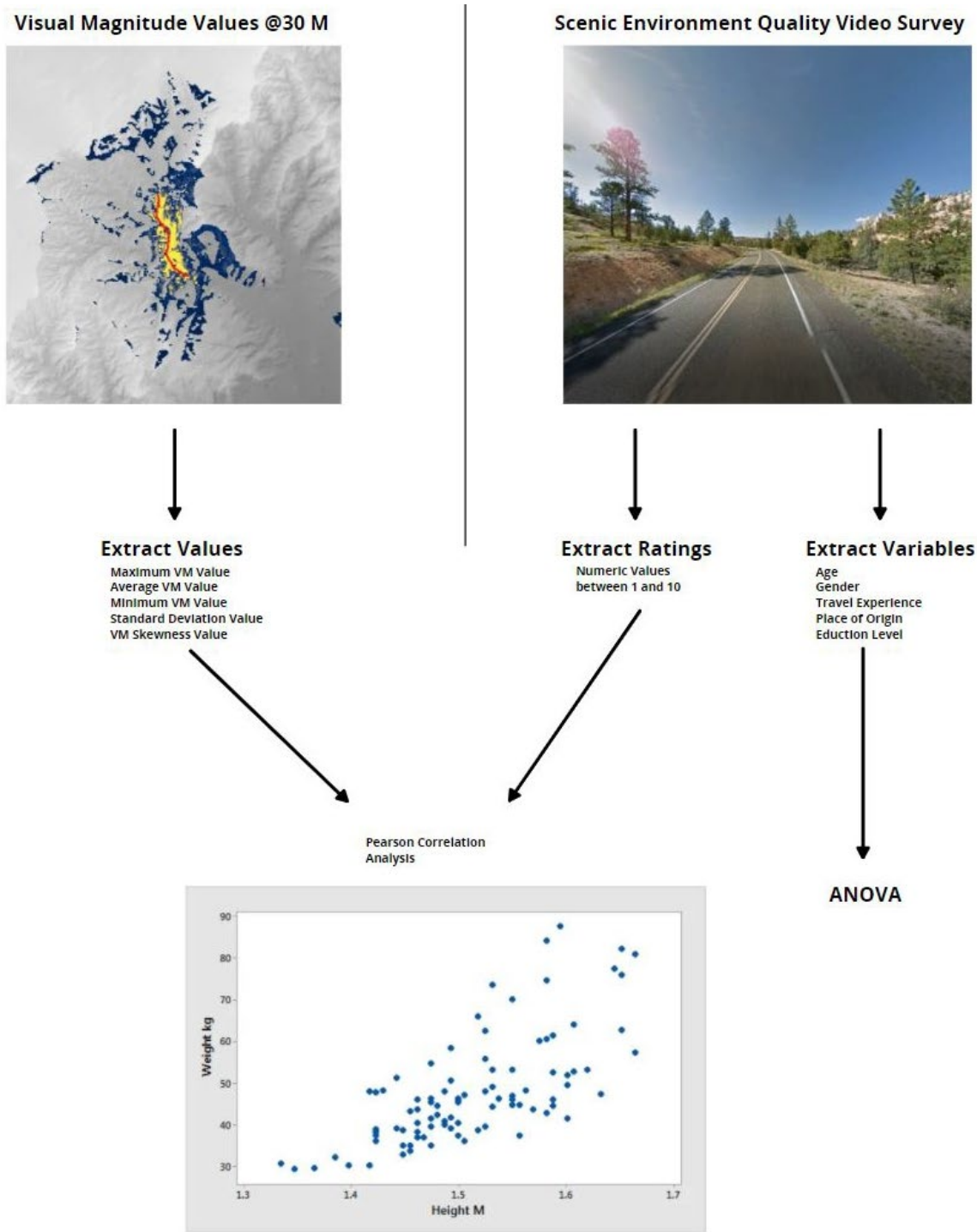
Participants that took part in this study were invited to participate in our study by office administrators and professors from USU, which resulted in our respondents being mostly students. Recruitment was accomplished by advertising through university-wide approved channels (departmental emails and canvas announcements) using a link to the Qualtrics survey. After creating the survey, it was sent out to a group of pilot testers, their feedback informed several small changes to wording and visual display of information. The link to the survey was then distributed though the approved channels to office administrators, professors, and department heads (e.g., some of these departments included English, Mathematics, Agriculture, Psychology, and Education) to be sent out via their graduate and undergraduate emailing lists. We aimed to recruit 40 participants for this study and received just under 50 responses. These responses were then vetted for their reliability by analyzing the standard deviation of their scenic ratings. The one participant whose results were dropped from this analysis had a SD of under 0.5, all other respondents had SD values of nearly .9. This left us with 44 useable results for our analysis. Participants who finished the survey received compensation for their time spent on the survey in the form of $10 cash, which was picked up after the survey had closed.

Analysis Techniques

To analyze the data, we proposed several different statistical tests, as well as platforms. Microsoft Excel and SPSS were used to produce the analyses. Figure 3.11 illustrates how this these results and the following analysis took place.

Figure 3.11

VM Value and Rating Extraction Process



First, results of the values of the VM outputs of the entire perceivable extent by correlating the range of metrics identified in Section 4.2.3 with the ratings for each site. These allowed us to identify a potential relationship between VM and broad scenic ratings of different highway drives. This was assessed by using Pearson correlation.

The other independent variables collected (demographics and site conditions) were used in ANOVA analyses using SPSS software. This allowed us to identify potential variables that predict scenic ratings and how much variation is resulting from those individual variables.

Each of these different types of analyses were used to compare the relationships between the collected visual magnitude values and the scenic ratings of each site. Additionally, these analyses helped us to see the relationship between the independent variables of participants and the scenic ratings and how those variables influenced the outcome of the scenic ratings.

Results

The following results are reported in either scientific notation or ended at the third decimal place for clarity.

Visual Magnitude Results

We collected two different measures for the Visual Magnitude tool. The first measure was the entire visible area of the surrounding environment from the selected route. The second was the visible area seen within a 3-kilometer radius around the selected route. The highest returned output numbers were consistently along the road,

because of the cell's proximity to the viewpoint (distance has an exponential effect on VM and the most impactful element in the analysis). The maximum values did not change when comparing the full extent and the clipped area because of this factor. The lowest values are where we saw the most significant changes. These value changes also caused the average measured visual magnitude values to shift. Additionally, the standard deviation, which refers to the dispersal of the values shown in the raster, between the VM values and the measure of skewness, which tells us the spread or distortion of the values compared to a normal bell curve distribution of values, were also extracted. A higher standard deviation indicates that the values are more spread out, whereas a low value means that the data is clustered around the average value. Skewness is measured in positive or negative trend of the values relative to a normal bell curve, the lower the value, the more normalized the data. With these data, all data are skewed because one of the calculations for visual magnitude is an exponential reduction in value due to distance (or distance squared). All mentioned values for each road are shown in Tables 3.2 and 3.3. The column headings of the table relate to the measures designated for collection (see methodology section "Producing Visual Magnitude Analysis").

Figures 3.12 and 3.13 illustrate the variation of values and changes between the full extent being seen of our sites and the 3-kilometer extent. Between every road there is a decrease to some extent in every environment of the values being seen full extent and the 3 K extent. Roads 4 and 5 show the most significant changes in average value changes when clipped to the 3-kilometer area. The minimum values show that clipping the VM raster caused a decrease of noise and moved the minimum value closer towards 0. Figure 3.4 illustrates the difference between a few of the routes and the range of values

Table 3.2

Visual Magnitude Numerical Outputs for Full Extent

Road number	Full VM max	Full VM avg	Full VM min	*SD*	Skewness
1	0.132	0.001	5.63E-11	0.003	6.389
3	0.200	9.32E-04	7.26E-11	3.68E-03	15.563
4	1.06E-01	4.244E-05	3.38E-14	0.001	39.254
5	3.64E-02	2.30E-05	6.50E-14	3.45E-04	33.425
8	0.031	1.259E-05	1.77E-13	6.00E-05	185.727
9	0.052	1.27E-05	3.80E-13	1.82E-04	108.288
11	0.007	4.10E-07	2.92E-16	7.09E-06	467.0360
12	0.027	3.63E-06	5.62E-14	6.94E-05	169.620
14	0.087	4.46E-04	1.86E-11	1.27E-03	9.819
16	0.013	1.48E-06	2.80E-14	2.20E-05	252.404
17	0.018	1.33E-06	1.25E-14	3.10E-05	151.816
18	0.046	1.11E-05	6.16E-13	1.61E-04	74.918
19	0.105	1.87E-04	6.79E-12	1.32E-03	29.612
21	0.090	7.80E-06	1.65E-14	2.66E-04	147.055
23	0.027	6.01E-06	3.04E-14	7.85E-05	121.831

Table 3.3

Visual Magnitude Numerical Outputs for 3 K Extent

Road Number	3 Km VM Max	3 Km VM Avg	3 Km VM Min	SD	Skewness
1	0.132	0.001	5.19E-10	0.003	6.054
3	0.200	0.001	1.95E-10	0.004	14.102
4	0.106	0.001	8.97E-11	0.001	13.734
5	3.64E-02	1.91E-04	4.83E-13	1.01E-03	11.314
8	0.031	4.26E-05	1.46E-12	1.38E-04	39.603
9	0.052	5.87E-05	4.50E-13	5.09E-04	39.050
11	0.007	4.64E-06	2.29E-12	6.47E-05	51.666
12	0.027	3.77E-05	4.36E-12	3.92E-04	30.192
14	0.087	5.15E-04	8.38E-11	1.35E-03	13.494
16	0.013	1.33E-05	7.52E-13	1.63E-04	34.339
17	0.018	3.87E-05	7.40E-11	1.87E-04	25.681
18	0.046	6.37E-05	4.42E-11	4.48E-04	26.972
19	0.105	2.39E-04	2.18E-10	1.50E-03	26.100
21	0.090	9.70E-05	2.07E-11	1.05E-03	29.024
23	0.027	2.93E-05	5.86E-12	2.15E-04	44.838

Figure 3.12

Average Visual Magnitude Values Between Full and Clipped 3-Kilometer Sites

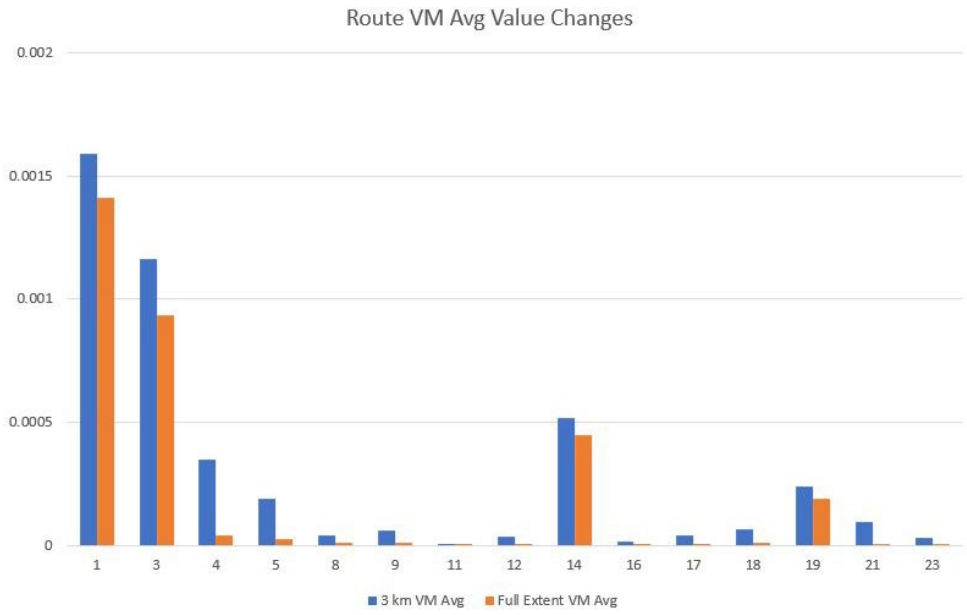


Figure 3.13

Minimum Visual Magnitude Values between the Full and Clipped 3-Kilometer Sites

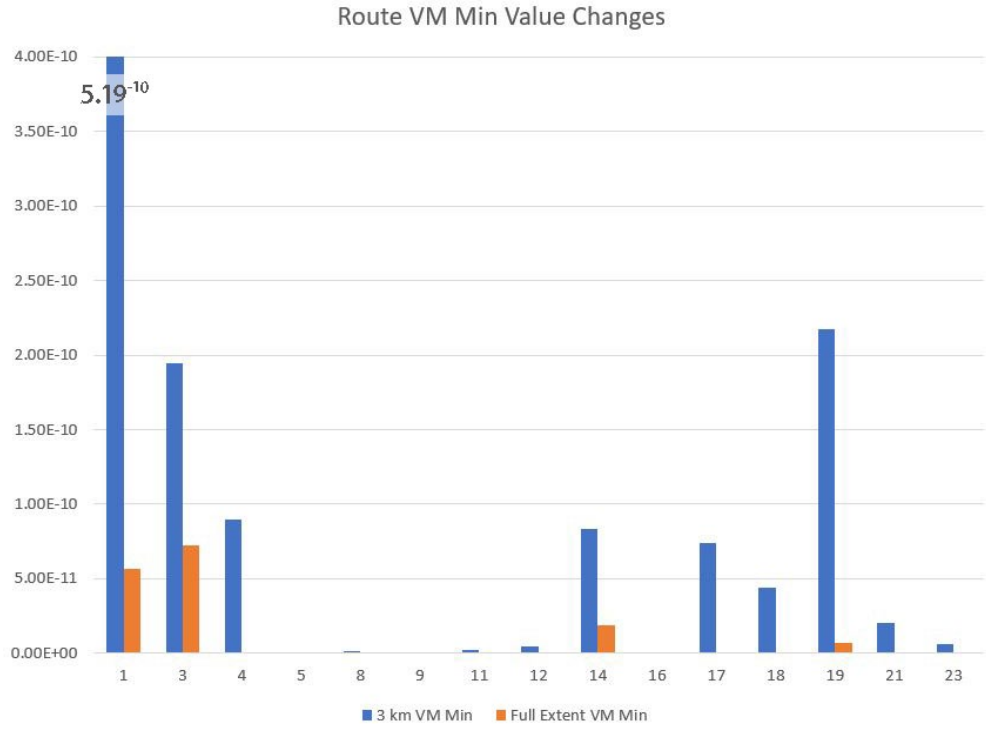
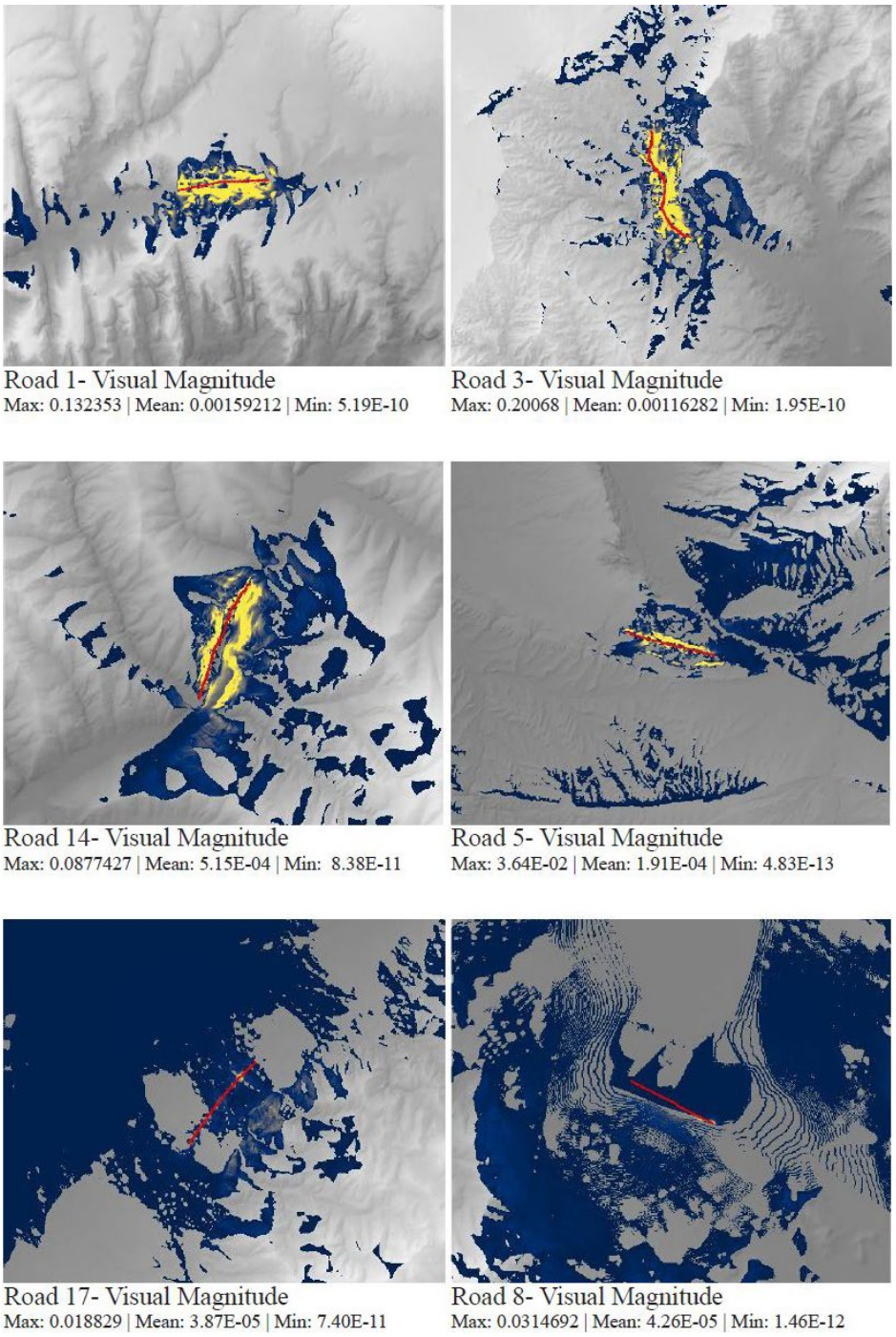


Figure 3.14

Sample Illustrations of Six Routes



Note. These images illustrate some of the most diverse values returned from the visual magnitude tools analysis output as a raster image from GIS for Roads 1 to 6.

found in our analysis. The entirety of our VM measures and context images are found in Appendix B.

Scenic Ratings and Visual Magnitude Relationship Analyses

The values of scenic ratings across the 44 valid responses are noted in Appendix Tables D.1 and D.2 in Appendix D because of the size of the data.

Road ratings varied widely between our values of 1 and 10. Figure 3.15 and 3.16, respectively, show the highest and lowest rated roads. There is a wide variety in the scenic quality of these roads as well as vegetation, terrain, and overall environment.

Figure 3.15

Highest Rated Road

Note. Average scenic rating of 7.9.

Figure 3.16

Lowest Rated Road

Note. Average scenic rating of 3.3.

Descriptive statistics from a Pearson correlation analysis yielded these results using with 660 original data points (scenic ratings for each of the 15 roads per the 44 survey participants) averaged into 15 data points (averaged scenic rating for each of the 15 roads from participants). When analysing the scenic road ratings for each individual participant with the average visual magnitude numbers we saw a correlation of 0.582 illustrated in Figure 3.17 for the full extent. An additional Pearson correlation analysis was run of all scenic ratings averaged for each roadway experience with the average visual magnitude numbers. This analysis showed a Pearson correlation of 0.631 illustrated in Figure 3.18. Additional statistics for the average VM measures analysed in SPSS are shown in Table 3.4.

Figure 3.17

Pearson Correlation Showing the Full Extent Average VM Values and Average Scenic Ratings

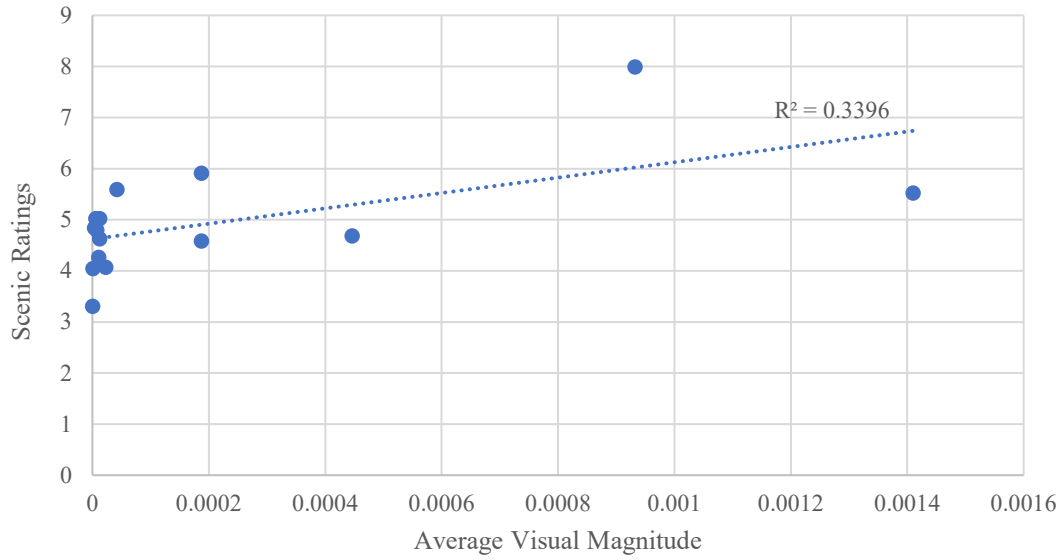


Figure 3.18

Pearson Correlation Showing the 3-Kilometer Extent Average VM Values and Average Scenic Ratings

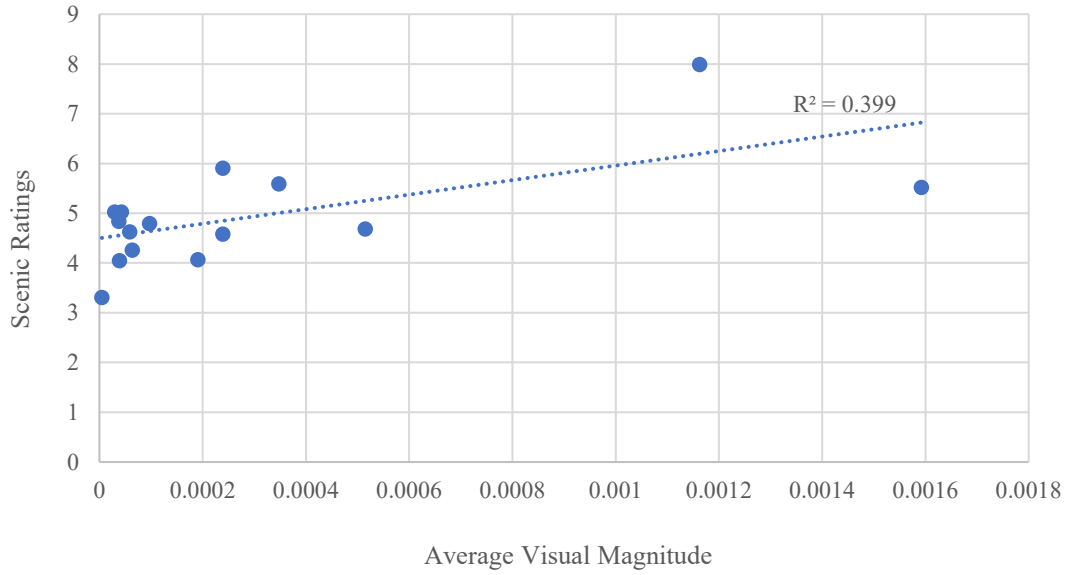


Table 3.4

Pearson Correlation of Average VM Values and Scenic Ratings

VM outputs	Pearson coefficient	Count	*t* statistic	*df*	*p* Value
Full Extent	0.582	15	2.585	13	.022
3 Km Avg	0.631	15	2.937	13	.011

To further understand the variation in values seen in the visual magnitude rasters, we analyzed the standard deviation (*SD*) between those values, in correlation with scenic ratings. We ran an additional Pearson correlation for the full extent which showed a correlation of 0.756 shown in Figure 3.19 and for the 3-kilometer extent a correlation of 0.785 shown in Figure 3.20. Additional statistics for the standard deviation VM measures analysed in SPSS are shown in Table 3.5.

Figure 3.19

Pearson Correlation Analysis of the Full Extent Standard Deviation of VM Values and Scenic Ratings

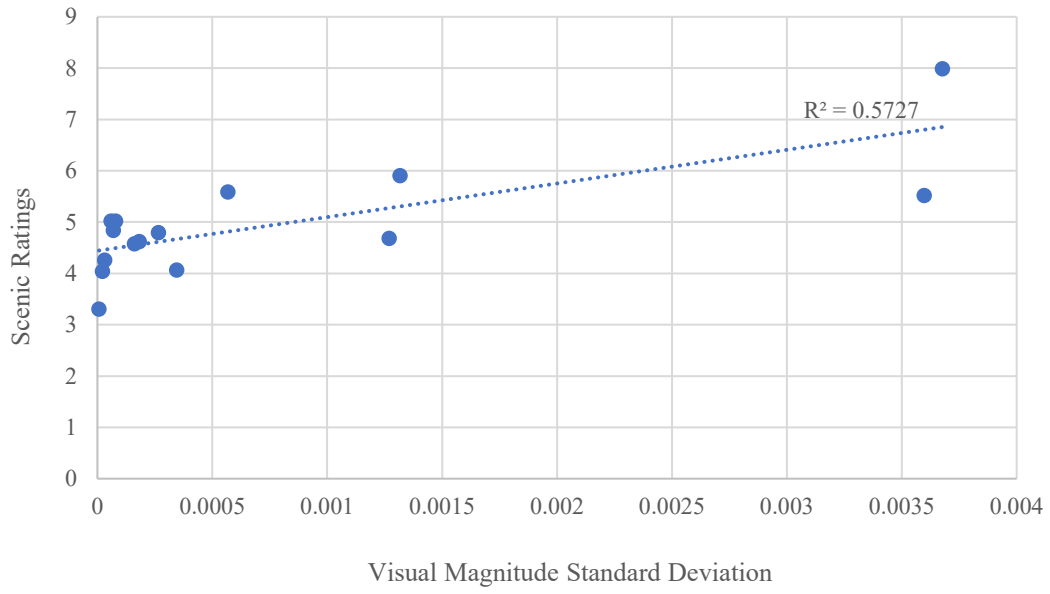


Figure 3.20

Pearson Correlation Analysis of the 3-Kilometer Standard Deviation of VM Values and Scenic Ratings

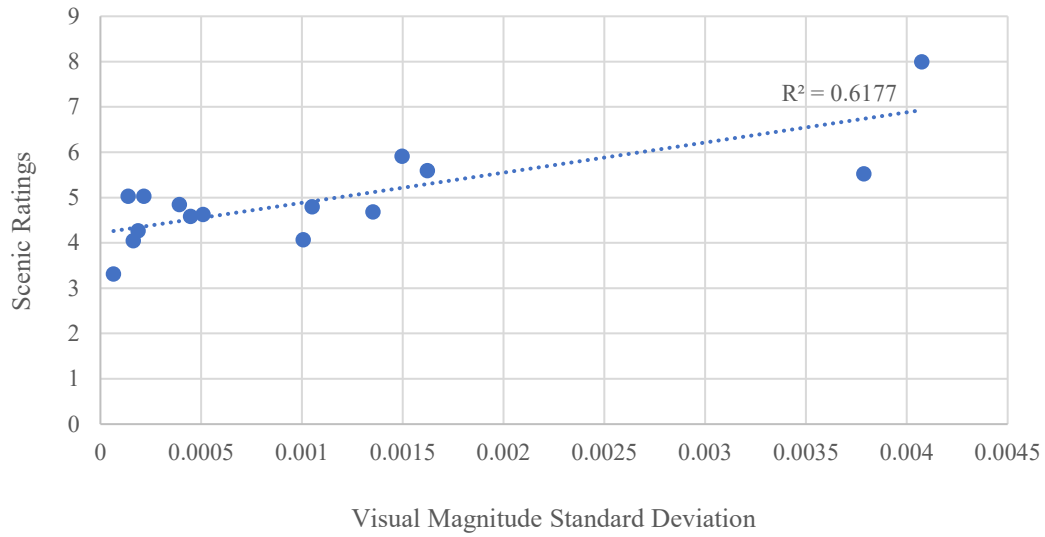


Table 3.5

Pearson Correlation Showing Standard Deviation VM Values and Scenic Ratings

VM *SD* outputs	Pearson coefficient	Count	*t* statistic	*df*	*p* value
Full Extent	0.756	15	4.174	13	0.0011
3 Km	0.785	15	4.582	13	0.0005

We analysed the skewness of the VM rasters, or the spread of the values relative to a normal bell curve. Skewness of the values generated by the visual magnitude tool were analysed at both the full extent and 3-kilometer radius. When comparing the skewness and the scenic ratings for the full extent the correlation value was -0.61 show in Figure 3.21 and at the 3-kilometer outputs showed a correlation of -0.457 shown in Figure 3.22. These results tell us that as the skewness of the VM rasters increase there is

Figure 3.21

Graph of Pearson Coefficient of Skewness for the Full Extent of the VM Rasters

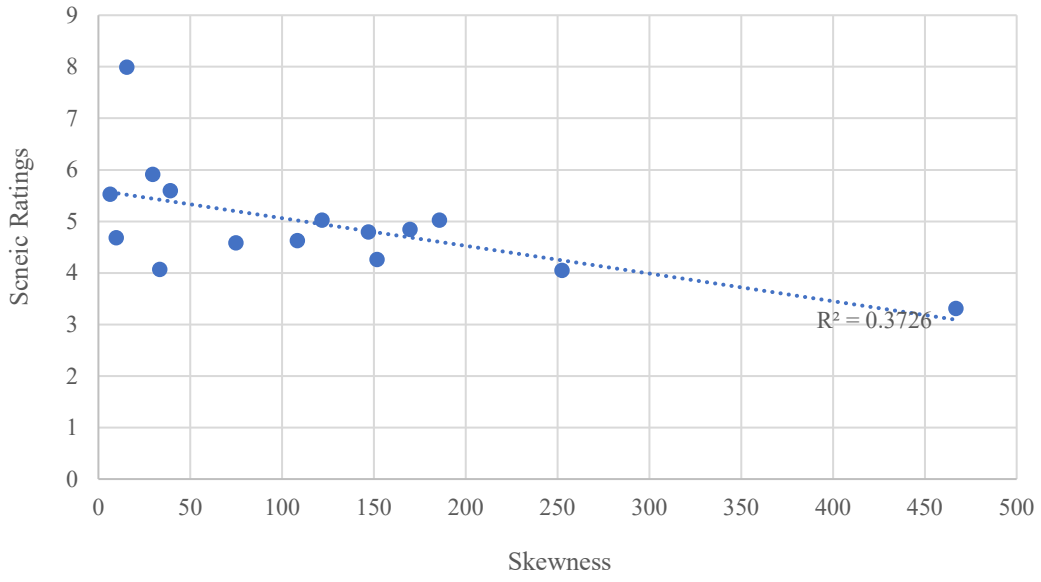
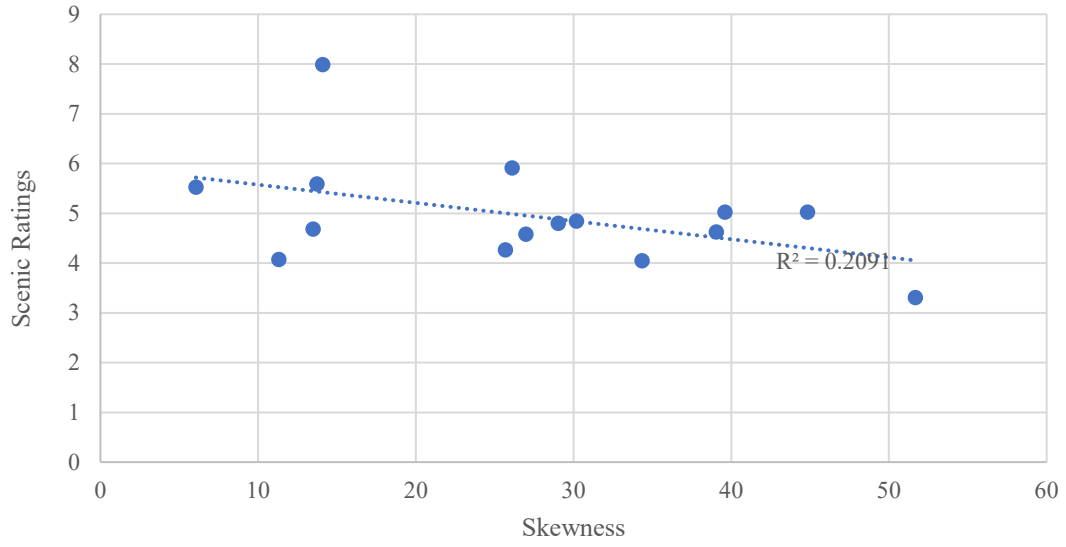


Figure 3.22

Pearson Coefficient Showing Skewness of the 3-Kilometer VM Raster



a related decrease in scenic rating values. Additional statistics for the skewness VM measures analysed in SPSS are shown in Table 3.6.

Table 3.6

Pearson Correlation of Skewness VM Values and Scenic Ratings

VM outputs	Pearson coefficient	Count	*t* statistic	*df*	*p* value
Full Extent	-0.610	15	-2.778	13	.015
3 Km	-0.457	15	-1.853	13	.086

Demographics for Survey Respondents

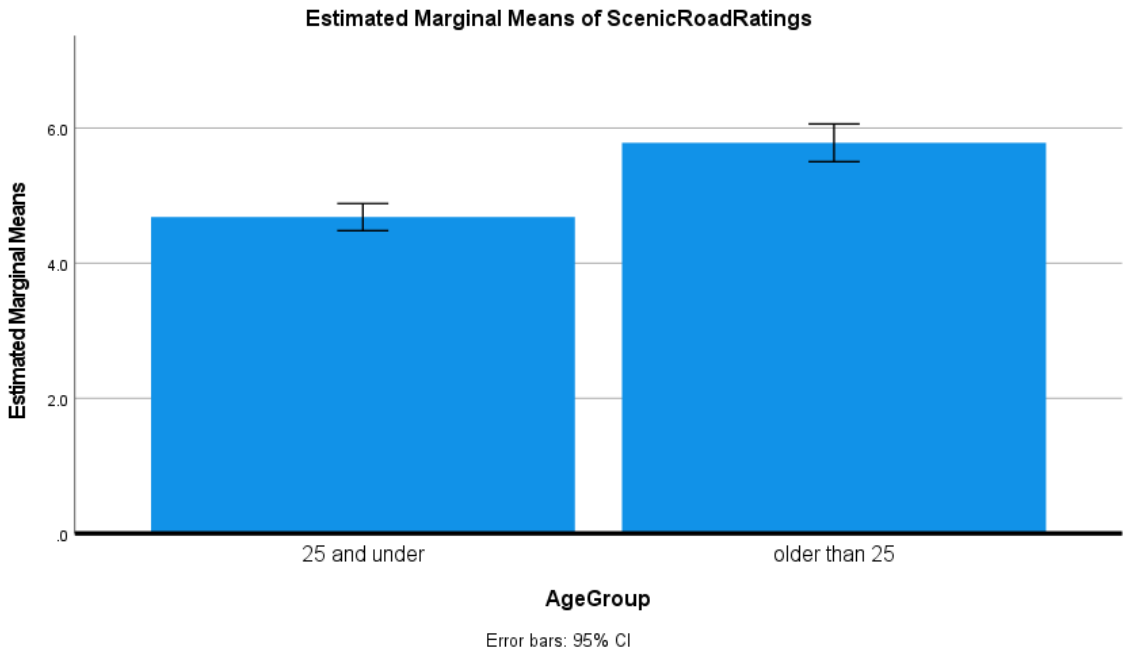
A total of 44 people finished the survey with useable results with analyzing the individual variables including a wide age range from 18 to 48, three gender classifications, varying education levels, varying familiarity with the various ecoregions of Utah, and places of origin. The following subsections break down results further by each independent variable that was collected and analyzed though ANOVA analyses.

Age

The age of survey participants is between 18 and 48, with a mean age of 24.5 years old representing an overall younger demographic. There were 28 respondents who were 25 or under and 14 over the age of 25. To analyze differentiation of age more easily, we created two age groups on either side of the average participant age. This showed that for our scenes, participants over 25 were rating scenic quality higher than participants under 25. ANOVA analysis retuned the following statistics for age, $F(1,1) = 39.47$, $p = .001$, $\eta_p^2 = .06$ with a 95% confidence interval. These results are shown in Figure 3.23.

Figure 3.23

Age Analysis of Participants



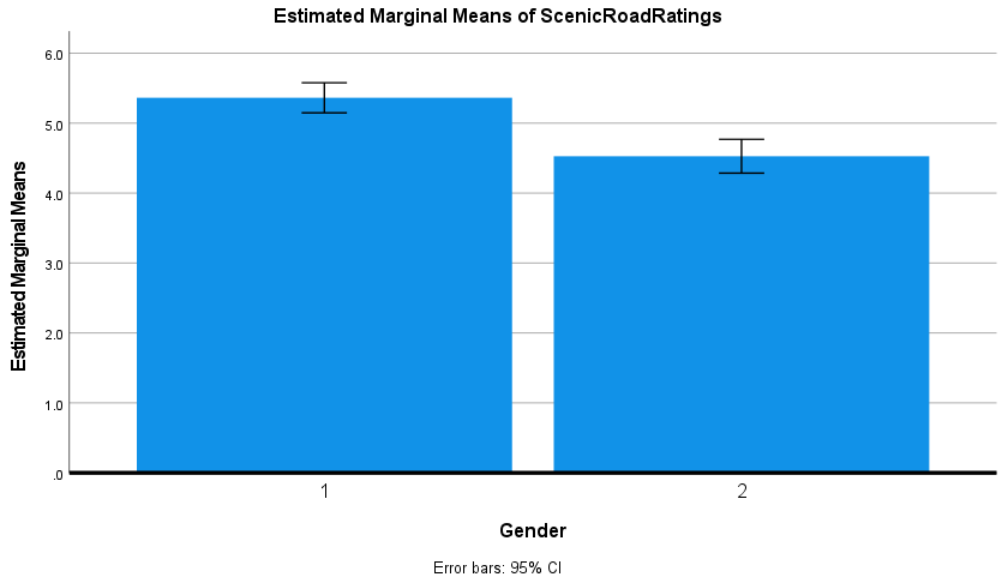
Gender

The response for this question had 3 choices which were Male (1), Female (2) or Other/Non-Binary. These 3 different gender types consisted of 24 males (mean = 5.364, *SD* = 2.159), 19 females (mean = 4.528, *SD* = 1.9710) and 1 non-binary respondent. For these results, we dropped the single participant that indicated their gender as non-binary conforming because of the low sample size. ANOVA analysis retuned the following statistics for gender, $F(1,1)$ 19.65 = , $p = .001$, $\eta_p^2 = .038$ with a 95% confidence interval.

These results that indicate, for our scenes, participants who identified as male rated the road scenic quality higher, while those who identified as female gave lower ratings. These results (Figure 3.24) indicate that gender is statistically significant and accounts for nearly 4% of variance in rating the scenic quality of our drives.

Figure 3.24

Gender Analysis of Participants



Education

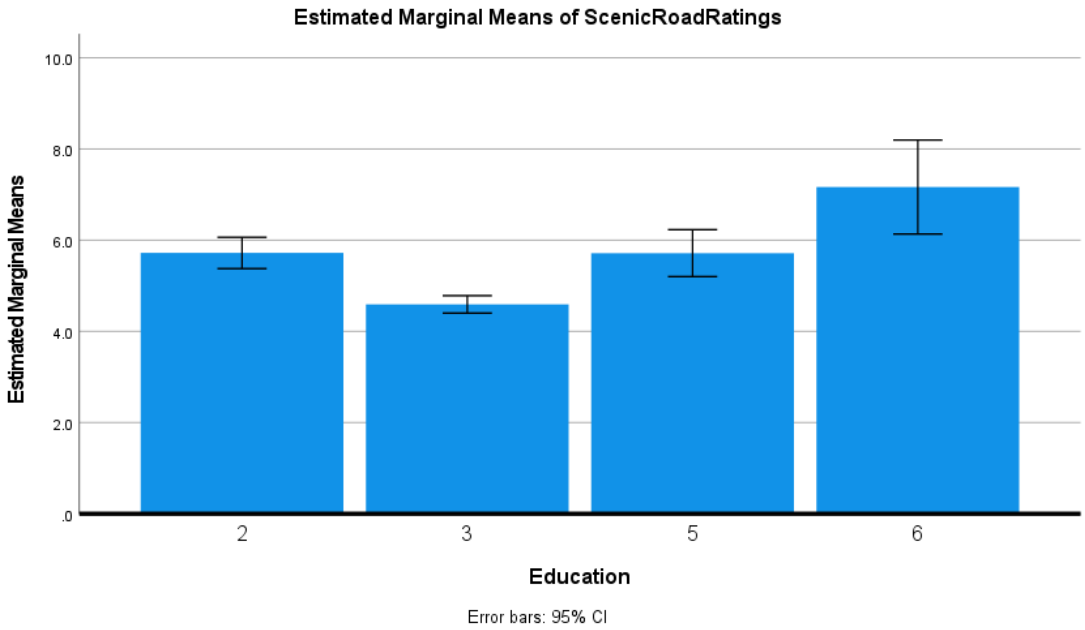
Responses for education level ranging from high school had 10 respondents (mean = 5.722, *SD* = 2.2005), college had 29 respondents (mean = 4.594, *SD* = 2.0224), master's degree had 4 respondents (mean = 5.717, *SD* = 1.6605) and Ph.D. had 1 respondent (mean = 7.167, *SD* = 2.0325). ANOVA analysis retuned the following statistics for education, $F(3,1) = 19.65$, $p = .001$, $\eta_p^2 = .084$ with a 95% confidence interval (see Figure 3.25). However, there is no apparent trajectory of the role that education plays in predicting scenic quality ratings.

Familiarity/Travel Experience

Travel experience was assessed to determine participants' exposure to landscape types though Ecoregions Level Three classification of Utah. For this reason, in our analysis only roads that were completely contained and observed within one ecoregion,

Figure 3.25

Education Analysis of Participants



Note. The shown bar graph illustrates response to education level according to the following values, 2 = Highschool, 3 = College, 5 = Masters, 6 = Ph.D.

leaving 12 of 15 roads. Roads were split via their respective ecoregion and matched with the corresponding scenic ratings for participants. Ecoregion #2 contained seven roads, ecoregion #3 contained two roads and ecoregion #5 contained three roads.

The first test evaluated potential effects of familiarity with a zone (zone rating used as a covariate), the specific zone (the category), the VM skewness value (another covariate) and the scenic road rating (dependent variable). The results from this test show that there is no statistical significance with the zone but that there is a statistically significant findings with the familiarity rating and skewness values compared to scenic ratings. Tests two through four used the same model in SPSS to compare familiarity

between each specific ecoregion (see Appendix C for more data). While the results were statistically significant, they were extremely random.

Place of Origin

Just over half of our respondents, 23 out of 44, stated that their place of origin was outside of Utah. This data was split into two groups, one of participants who were born in Utah and the other of participants who were born outside of Utah. The Shapiro-Wilk (and Kolmogorov-Smirnov) test of non-normality were statistically significant ($p < 0.001$). Thus, a one-way ANOVA was conducted, instead of an independent *t* Test. The ANOVA revealed a statistically significant effect $F(1, 3958) = 15.746$, $\eta^2 = .009$, $p < .001$. The mean for those self-identifying as from Utah is 4.81 and those outside of Utah is 5.08. living in or outside of Utah.

Discussion

In this paper we sought to provide empirical evidence to understand the relationship between visual impact data generated by the Visual Magnitude tool and how people interpret an environments scenic quality. We attempted to discover this relationship by gathering numerical impact values across a variety of different typologies and qualities of environments across the state of Utah. This information was then compared to the results of scenic quality ratings gathered from the survey that were created. The following paragraphs in this section discuss the outcomes, findings, and recommendations for any future research that may build onto the results of this study.

Viewshed analyses were originally created as an impact analysis tool for a single

object (e.g., mining, solar, turbines) and not as a tool to analyze scenic quality along routes. VM, on the other hand, was created expressly for the purpose of evaluating potential visual impact through routes (Chamberlain & Meitner, 2013). However, the tool only generates a numerical value for the degree of potential visual impact, yet there was no direct and empirical explanation for what these numbers mean regarding perception and sentiment. This study aimed to bridge the gap between understanding the relationship between the impact values and how people perceive environments.

Study Process

In this study we wanted to evaluate the extent to which visual magnitude metrics related to individual sense and rating of the scenic quality of highway drives. Evaluation of scenic quality has a long history (Arriaza et al., 2004; Daniel, 2001; Gustafson, 2009; Palmer, 2004; Qin et al., 2008), where numerical values are often used to supplement subjective ratings of scenes. However, someone seeing moves beyond a quantifiable number and instead attempts to represent a broader sense of scenic quality. For instance, an environment with a lot of variation in topography and interesting natural elements is likely to be seen as more picturesque than an environment with little variation, resulting in different scenic rating values. The resulting impact of landscapes of low quality and little variation produces a feeling of indifference and boredom. While numerical ratings of scenes are predominately used to assess landscape, and are subjective, they tend not to be used to evaluate long experiences (e.g., routes or drives).

In an attempt to be more objective and evaluate large areas with a proxy metric for feelings and impressions, we decided using video was the best way to give an overall

impression of an environment, rather than sample static locations. Asking survey participants to rate the scenes enables a quantitative comparison between the feeling and objective measure of visual magnitude. One of the major issues that we ran into surfaced in the process of creating the routes for the video experiences. During this process we ended up creating and eliminating quite a of our selected routes and environments due to unusable imagery from Google. Our original goal was to have 15 different routes to run this study on, but as we began looking at available imagery, we decided it was best to have some extra sites giving us a buffer to be able to discard routes with the worst available imagery.

Even with this buffer of extra routes, we still encountered problems with imagery including graffiti, water droplets, watermarks from Google, random area blurring from Googles privacy algorithm, images suddenly switching lanes, poor resolution of images and the shadow or hood of the vehicle taking the images appearing in the videos. The only way that we may have been able to eliminate this problem would be by driving the routes ourselves, but the timeframe and scope of this project didn't allow for that.

The video experiences were generated with a previously existing, but outdated, python code. Creating the videos themselves took some time, as we had to ensure that the imagery being collected was coming from the correct side of the road, duplicate images were being erased, and correctly ordering coordinate systems for the routes. The resulting images created videos that were able to give viewers a good understanding of the type of environment that the road was in. However, the videos would have been better if we had been able to have a wider field of view, both horizontally and vertically similar to what our eyes may actually see when looking out of a vehicle. Our videos were limited to only

90 degrees which provided a smaller window of the surrounding environment.

This process could be continued for other sites, but it may be best to film the drive directly. This could offer greater control of the quality, timing, and number of images to work with. Otherwise by using this method, you would be at the mercy of the available imagery from Google. It may also be interesting, to experiment with virtual reality with a study like this where observers can view the entire area. This mixed with a more in-depth look at where people want to look and what people want to look at along the road would produce some very interesting results.

Understanding the Relationship of VM Values and Scenic Ratings

In order to assess the relationship of the VM values and scenic ratings we collected a number of measures from GIS including the maximum, average, minimum, standard deviation, and skewness values of the VM rasters. Out of all of these values we used the average, standard deviation, and skewness values in correlation analyses with our scenic ratings. Our original method was to analyze the maximum and minimum values of visual magnitude; however, the tool currently only calculates the highest and lowest VM for each analysis, not for each cell. An analysis of maximum and minimum VM values could be useful if we do a correlation of values by the maximum of each cell but at this point our tool cannot calculate these values. For this reason, we thought that the previously mentioned three metrics would have the best correlation with scenic ratings. When these values were all compared to the scenic ratings, we saw multiple results of strong correlations with multiple metrics. The best results for both the full extent and the 3-kilometer came from the standard deviation measures but both the

average and skewness values showed strong correlations.

Using the average visual magnitude values, we ran statistical analyses of the full extent of what was being measured from our observation points on the road. Our results showed a low correlation between average visual magnitude and scenic ratings (.308). We attribute this is due to the high amount of low visual magnitude values being contained in fringe areas. The decision was made to clip our results down to a 3-kilometer extent to focus on the environment that is having more of a direct impact (Emerging Technology, 2015; Krisciunas & Carona, 2015; Roland, 2019) and remove some of those fringe area that were affecting the correlation value in the full extent analysis. These results showed a stronger correlation value (.632) between the average visual magnitude measures for the full extent and the scenic quality ratings. By removing the very distant visible cells the skewness in the visual magnitude data was reduced, providing a more normal distribution of values that resulted in a stronger correlation with scenic ratings. Our suspicion then, was that people were rating scenes were there were more topographical elements of higher visual magnitude and paying less attention to visible areas in the far distance. Further, that skewness and distribution of VM values played a key role in the relationship with ratings at the full extent.

In another test we assessed the relationship between the VM skewness values and the scenic ratings using a Pearson coefficient of skewness test. This test showed that the scenic ratings correlated stronger with the values of the full extent, rather than the 3-kilometer outputs. These results occurred because of the loss of those extremely small fringe values when we changed our measured extent from full to 3-kilometer. This smaller extent altered the normal distribution of the represented values when compared to

a normal bell curve of values when the values begin on either side of 0, the resulting values are skewed. The more normal the skewed values were (closer to 0 or a normal representation of values), like we saw in the full extent VM measures, the higher the correlation to the scenic value ratings. Our results showed us that the more skewed the VM raster values were the lower the scenic rating values would be.

Our strongest correlation measures come from the standard deviation values. These values resulted in a correlation of 0.756 for the full extent and 0.785 for the 3 K extent. We suspect that the results are so high in this measure because standard deviation provides an effective measure of diversity in visual magnitude throughout the route, suggesting that individuals prefer a wider distribution of values, indicating that people prefer variation in terrain and experience as well as a degree of enclosure, as shown in the variation of visual magnitude values. This seems to be the best metric for creating a highly correlating and accurate predictor of scenic preferences. We suspect this is because the standard deviation value shows the distribution of the values throughout the landscape which more accurately displays the variation of terrain and enclosure which from our results seems to be influencers of our survey participants for their rating of scenic quality. This suggests that very distant landscapes with similar topography as near landscape, tend to be valued much less, though not exponentially less. The results from using this method of standard deviation of the VM raster values indicates to us that VM tool can provide the most accurate and efficient predicting measure of scenic ratings. The evidence that we are seeing from these studies highlights the potential of the VM tool being used to accurately predict scenic preferences.

Variability of Demographics

There are many different variables that influence scenic ratings that could potentially be collected from participants. We collected several variables that we hypothesized would be influential. With the results from the analysis of these variables we can make several inferences about how and why people are perceiving and rating scenic and nonscenic drives throughout Utah.

Gender seemed to play a significant role in ratings, participants that identified as females were giving overall lower ratings lower for our roadway experiences, whereas males tended to rater higher. This conformed our hypotheses that females were more critical of scenic environments. This being one of the first studies conducted in this manner on scenic roadway assessment we did see a difference between genders similar to a previous article (Ode et al., 2009). We would suggest continuing to evaluate the role of gender in scenic ratings of landscapes, as it may have a previously little-known role in ratings.

We wanted to be able to assess the influence of age on people's perception of landscapes (Zube et al., 1983) and how it may differ between a younger and older population. Although our age group of participants was limited to a younger demographic, we still felt like it would still impact scenic ratings because of the distribution of our age results which were from 18 to 48. The results from the age variable analysis showed that younger people, 25 years old and under, were rating our scenes consistently lower. This could be because of limited of travel experience and being unsure of what is "beautiful" because of a lack of other comparable landscapes. It would be interesting to collect ratings from a much larger age distribution, including

participants under 18 and over 50, for comparison.

Our survey question about education did not provide any meaningful outcomes. There were too many educational level options, six in total and four of them that were used, which spread our responses fairly thin. The wording of the question also had a bit too much ambiguity in what level the participant actually was. We could have worded the question more clearly asking for the highest level of education achieved using certifications as a cut off measurement like diploma, bachelors, masters, or PhD. In any future studies, we would want to see a much larger pool of participants with a more defined question to generate the type of information that would help us see if education has a statistically significant impact on scenic ratings.

Familiarity with Utah's six ecoregions was assessed to see if it increased scenic quality ratings because of potential bias towards one area over another (Keane, 1990; Mangone et al., 2021; Svobodova et al., 2010). Our analysis of travel experience consisted of asking people what their familiarity of certain ecoregions throughout Utah. Three of the six ecoregions, Northern Basin and Range, Wyoming Basin and Mojave Basin and Range, were unable to be represented in our study because these ecoregions did not contain roads that met our criteria list, this could be due to outdated data in the UGRC database. We excluded three roadways from our travel experience analysis because of their close proximity of two very different types of ecoregions, for example two roads were within the Central Basin and Range ecoregion but the Wasatch and Uinta Mountain Range were clearly visible and prominent throughout the video experience. This resulted in scenic ratings that could have been from either ecoregion or a combination of both. For a clearer understanding of scenic ratings within specific

ecoregions, only roads that were contained within that ecoregion, without a view of an adjacent ecoregion, were used in our analysis.

By making some alterations to the roadway selection criteria we could have been able to include roads that are contained with the three missing ecoregions. It was difficult trying to find roads that did not see the Wasatch and Uinta Mountain Range ecoregion because of the sheer size of the mountains and the degree of their visibility throughout the state. In future studies, this could be controlled by selecting imagery for videos that only showcased the relevant ecoregion without any other ecoregions in. There were also more roads contained within the Central Basin and Range ecoregion of Utah. One reason for this was because of our criteria and how we selected roads. The other part is that this ecoregion contains most of the western half of Utah, approximately 37% of the state according to the ecoregion GIS layer that was downloaded from the EPA.

Our hypotheses were that the higher the participants familiarity with a zone, the higher the corresponding roads would be rated by participants. Our results suggested that there is no difference in scenic rating with ecoregion type but there is a difference in scenic ratings based on familiarity ratings and skewness. The analysis of our results suggests a random relationship, unfortunately we did not have adequate depth of information to really interpret other nuances of this relationship. The other three tests ran suggest a statistically significant but irregular pattern. With these tests and results, we have concluded that varying levels of familiarity with the ecoregions in Utah does not predict what ratings would be in any of the zones that contained our roads. While there is some relationship, our data was not detailed enough for us to understand the extent or type of relationship between familiarity and scenic ratings. These results may be because

many of these people were already familiar with this landscape, or other similar landscapes (most participants were from the western U.S.). Moving forward it would be interesting to see if familiarity correlates with scenic ratings when we account for visual magnitude.

Participants place of origin was also assessed, 21 people were from Utah and 23 were born outside of Utah. We did identify a statistically significant, albeit small effect for those identifying as from Utah compared to those outside Utah. However, the effect size of this outcome was negligible with less than a small effect. So, while significant, it is unlikely that this is meaningfully different. This is not a surprising because people who took this test are all currently living in Utah and are being exposed to its environment daily. Additionally, many of the participants who were born outside of Utah were from the Intermountain West region of the U.S. This region shares much of the same geographic and ecological environments found in Utah, this factor would greatly affect the sense of scenic quality that may come from someone who lives in a very different region. This focus on Utah ecoregions with ratings from people currently residing in the state or largely coming from within or outside of Utah, does not provide a broader representation of landscape experiences. Thus, we would recommend continuing to evaluate the role that familiarity with, or origin from, may have on scenic ratings overall.

We acknowledge that there are other variables that influence these ratings and in future studies exploration of other variables in the physical environment (e.g., physical environment measures, greenness) imaging variables (e.g., weather or sky conditions, imaging techniques and resolutions) or individual variables (e.g., ethnicity, religious, race) would lead a greater understanding of what variables may further influence scenic

rating decisions. The relationship of those variables and the VM metrics could then be understood and assessed. The assessed variables from this study still carry much weight in the decision-making process, and we would recommend continuing to use these five focus variables in future studies.

Key Take Aways

After this study we can say that the VM tool is a viable analysis tool in predicting the how people may rate the scenic quality of rural road-based environments, especially within the areas that have the highest impact on observes. This underlines the importance of regulating development and thoroughly planning along scenic roadways critical in the impact that they have on observers. These results indicate that there is a statistically significant relationship between the VM tools outputs and scenic ratings, to varying degrees based on the distance of the environment being studied. In future studies we think that exploring how this relationship strength of these two types of data sets might change when looking at different distances. For example, looking from a much closer area like 1-meter or 10-meter distance from the road and how that might correlate to scenic ratings. Also, we would like to see if there is a middle ground between the full extent and a 3-kilometer area that may illustrate a relationship that is more of a middle ground.

There are strong indications that the scenic ratings that we collected from the surveys relate directly to the amount of enclosure that was occurring around the roadway. The environments surrounding the roads that had more topographical change or were more enclosed were rated higher than areas that had no enclosure and were flatter and

open. When it comes to visual quality and aesthetics people prefer diversity in the landscape (García-Llorente et al., 2012; Krause, 2001) including topographical and landscape elements (Qin et al., 2008). This diversity helps to keep them interested in the environments around them. We suspect this is why we observed high scenic ratings on roads that have significant topographical variation close to the viewer, compared to roads that were flat.

There are many other variables or combinations of variables, that influence landscape preferences and scenic ratings (Dearden, 1984), that have the potential to augment the correlation between the VM tool and scenic quality ratings. Other variables that could be explored could be the amount of visible green spaces in the scenes or the amount of perceived naturalness (Ode et al., 2009). These and other additional measures could help us understand more fully what is influencing scenic preferences and ratings and how they night relate to visual magnitude tools assessment of landscapes.

Conclusion

Our primary goal of this study was to show empirical evidence of a relationship between VM values and scenic ratings. We asked the question: Can the visual magnitude tool inform us which scenic byways or other roadway environments contain the best experience for vehicle-based viewers and to what extent can an averaged visual magnitude output correlate to scenic ratings of route-based experiences? Based on what we have seen, this tool can be an accurate predictor of scenic preferences. However, using the averaged visual magnitude values were not the best metric to use to assess the scenic ratings of route-based experiences. The best measure to assess scenic ratings

turned out to be the standard deviation. When using this value we saw the strongest correlation between the two data sets, making it the best predictor metric.

The results of this study will help elevate the professionals conducting visual impacts analyses for route-based environments. We aimed to create an empirical study to understand the relationship between the Visual Magnitude Plugin for GIS and personal preferences in a variety of environmental typologies across the state of Utah. We experimented with creating pseudo-video experiences though extracting images and then sequencing them together for use in a survey. This survey was used to collect scenic quality ratings. These ratings were then compared to the VM tool output to see if there was any underlying relation between the environments with higher VM numbers. Based on the information generated results from this study we have empirical evidence that the visual magnitude tool can inform us of the best environments using the average VM value for closer extents, and the skewness values for the entire extent of the area seen. When analysing vehicle-based routes using this tool will yield strongly correlated results to how people would rate the scenic quality of environments.

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CHAPTER 4

CONCLUSIONS

The results of these two studies has several implications for acedemia and professional practice. The emperical evidence that we have gathered gives significt weight and value to the application and future expansion of this tool and other tools like it. The expansion of nonbinary tools to provide more dynamic pictures and infromation that more closely represent real world envrionments is going to continue, escpecially as our grasp on the concepts and technological capicty continues to increase.

From the results compiled in Chapter 2 furthered our understanding on sampling rates and optimal sampling distances when assessing visual magnitude. This allows for clearer and more efficient measuring techniques when measuring impact of route based experiences on observers. Additionally, the results found from Chapter 3 provide a more statistical foundation for validation of the tool. The statistical analyses between the two different data sets shows that there is a statistically significant relationship between those measures.

The visual magnitude tool was originally created to assess visual impact, but its usefulness is expanding. This tool helps us to understand the amount of space that is being occupied by elements or areas of the landscape in our vision. Our study to understand an optimal sampling rate produced strong results mathematically and indicated that our sampling distances for sensitive areas be 30-meter intervals and 50-meter intervals for other landscapes. However, combined with the results from our scenic

quality we are beginning to see that with the measure of standard deviation from the visual magnitude tool that the amount of variation of values correlates strongly to the scenic quality ratings. Even though mathematically our sampling distance makes sense, because of the additional focus that people place on terrain and additional elements in the landscape capture and influence people's perception of the overall quality of the entire environment. While we still recommend using the sampling distance that we have found, these results could indicate that, in natural and rural environments, we could actually have a wider distance between samplings because overall impression and scenic quality is being heavily influenced by certain details of the landscape.

The results of these studies have led to an interesting additional definition of the visual magnitude tool. Before this study we could say that the visual magnitude tool was just a scientific measure of impact that helps us to understand the amount of space that the landscape and its components are occupying in our visual field based on slope, aspect, and distance. Now additionally, we can say that the visual magnitude tool could be used as a proxy to begin to interpret how people feel about the scenic quality of rural and natural landscapes within Utah with the potential to do the same everywhere. While there is still much to be explored with this tool, this study has created an emperical base to build future studies of visual magnitude and impact analyses.

APPENDICES

Appendix A

Edited Python Code used for Video Sequencing

orderFolder.py

```
import sys
from utils import *
import glob
import os
import time
nameOfRoad = "Road23B"
fileType = ".jpg"
dir_name = 'C:/Users/Scott Johnson/Downloads/street-view-movie-maker-master/street-
view-movie-maker-master/lineup-' + nameOfRoad
# Get list of all files only in the given directory
list_of_files = filter(os.path.isfile,
 glob.glob(dir_name + '/*') )
# Sort list of files based on last modification time in ascending order
list_of_files = sorted( list_of_files,
 key = os.path.getmtime)
basepath = list_of_files[0][:len(dir_name) + 1]

# Iterate over sorted list of files and print file path
# along with last modification time of file
for i, file in enumerate(list_of_files):
 os.rename(file, basepath + str(i))
print("donewithpart1")
for i, file in enumerate(list_of_files):
 os.rename(basepath + str(i), basepath + nameOfRoad + str(i) + fileType)
print("donewithpart2")
```

utils.py

```
from __future__ import print_function
# Some useful Google API documentation:
# https://developers.google.com/maps/documentation/directions/
# https://developers.google.com/maps/documentation/roads/snap

import googlemaps
import urllib.request, os
import numpy as np
import json
import pandas as pd
import polyline
import glob
import subprocess
import math
import scipy
PHOTO_FOLDER = "photos/"

# Adapted directly from Andrew Wheeler:
```

```
# https://andrewpwheeler.wordpress.com/2015/12/28/using-python-to-grab-google-street-
view-imagery/
# Usage example:
# >>> download_streetview_image((46.414382,10.012988))
def download_streetview_image(apikey_streetview, lat_lon, filename="image",
savepath=PHOTO_FOLDER, picsize="640x640", heading=151.78, pitch=-0, fi=".jpg",
fov=120, get_metadata=False, verbose=False, outdoor=True, radius=5):
	assert type(radius) is int
	# Any size up to 640x640 is permitted by the API
	# fov is the zoom level, effectively. Between 0 and 120.
	base = "https://maps.googleapis.com/maps/api/streetview"
	if get_metadata:
		base = base + "/metadata?parameters"
	if type(lat_lon) is tuple:
		lat_lon_str = str(lat_lon[0]) + "," + str(lat_lon[1])
	elif type(lat_lon) is str:
		# We expect a latitude/longitude tuple, but if you providing a string
address works too.
		lat_lon_str = lat_lon
	if outdoor:
		outdoor_string = "&source=outdoor"
	else:
		outdoor_string = ""
	url = base + "?size=" + picsize + "&location=" + lat_lon_str + "&heading=" +
str(heading) + "&pitch=" + str(pitch) + "&fov=" + str(fov) + outdoor_string + "&radius"
+ str(radius) + "&key=" + apikey_streetview
	if verbose:
		print(url)
	if get_metadata:
		# Description of metadata API:
https://developers.google.com/maps/documentation/streetview/intro#size
		response = urllib.request.urlopen(url)
		data = json.loads(response.read())
		return data
	else:
		urllib.request.urlretrieve(url, savepath+filename+fi)
		return savepath+filename+fi

# Gist copied from https://gist.github.com/jeromer/2005586 which is in the public
domain:
def calculate_initial_compass_bearing(pointA, pointB):
	if (type(pointA) != tuple) or (type(pointB) != tuple):
		raise TypeError("Only tuples are supported as arguments")
	lat1 = math.radians(pointA[0])
	lat2 = math.radians(pointB[0])
```

```
        diffLong = math.radians(pointB[1] - pointA[1])
        x = math.sin(diffLong) * math.cos(lat2)
        y = math.cos(lat1) * math.sin(lat2) - (math.sin(lat1)
                        * math.cos(lat2) * math.cos(diffLong))
        initial_bearing = math.atan2(x, y)
        initial_bearing = math.degrees(initial_bearing)
        compass_bearing = (initial_bearing + 360) % 360
        return compass_bearing

def haversine(a_gps, b_gps):
        """
        Calculate the great circle distance between two points
        on the earth (specified in decimal degrees)
        """
        lat1, lon1 = a_gps
        lat2, lon2 = b_gps
        # convert decimal degrees to radians
        lon1, lat1, lon2, lat2 = map(math.radians, [lon1, lat1, lon2, lat2])
        # haversine formula
        dlon = lon2 - lon1
        dlat = lat2 - lat1
        a = math.sin(dlat/2)**2 + math.cos(lat1) * math.cos(lat2) * math.sin(dlon/2)**2
        c = 2 * math.asin(math.sqrt(a))
        km = 6367 * c
        m = 6367000.0 * c
        return m

# Given two GPS points (lat/lon), interpolate a sequence of GPS points in a straight line
def interpolate_points(a_gps,b_gps,n_points=20,hop_size=None):
        if hop_size is not None:
                distance = haversine(a_gps, b_gps)
                n_points = int(np.ceil(distance*1.0/hop_size))
        x = np.linspace(a_gps[0],b_gps[0],n_points)
        y = np.linspace(a_gps[1],b_gps[1],n_points)
        dense_points_list = zip(x,y)
        return dense_points_list
        # else:
        #       print("You forgot to provide a hop parameter! Choose between:")
        #       print(" n_points = number of points to interpolate;")
        #       print(" hop_size = maximum distance between points in meters.")

# Short script to process the lookpoints from the above "interpolate points" function.
def clean_look_points(look_points):
        # Remove points that are the same
        pt_diffs = [np.array(a)-np.array(b) for (a,b) in zip(look_points[:-
```

```
1],look_points[1:])]
	keepers = np.abs(np.array(pt_diffs))>0
	look_points_out = [look_points[i] for i in range(len(keepers)) if
np.any(keepers[i])]
	return look_points_out

# Download street view images for a sequence of GPS points.
# The orientation is assumed to be towards the next point.
# Setting orientation to value N orients the camera to the Nth next point.
# If there isn't a point N points in the future, we just use the previous heading.
def download_images_for_path(apikey_streetview, filestem, look_points, orientation=1,
picsize="640x640"):
	assert type(orientation) is int
	assert orientation >= 1
	for i in range(len(look_points)):
		gps_point = look_points[i]
		if i+orientation >= len(look_points):
			heading = prev_heading
		else:
			heading = calculate_initial_compass_bearing(gps_point,
look_points[i+orientation])
		probe = download_streetview_image(apikey_streetview, gps_point,
filename="", heading=heading, picsize=picsize, get_metadata=True)
		if probe['status']=="OK" and 'Google' in probe['copyright']:
			dest_file = download_streetview_image(apikey_streetview,
gps_point, filename=filestem + str(i), heading=heading, picsize=picsize,
get_metadata=False)
		prev_heading = heading

def get_turn_headings(h1, h2, stepsize=15):
	if h2 < h1:
		h2 += 360
	clockwise = (h2 - h1 < 180)
	if not clockwise:
		h1 += 360
	n_points = np.ceil(np.abs( (h1 - h2)*1.0 /stepsize))
	headings = np.linspace(h1,h2,n_points)
	return np.mod(headings,360)

# def execute_turn(apikey_streetview, filestem, gps_point, h1, h2, picsize="640x640",
stepsize=15):
#	if h2 < h1:
#		h2 += 360
#	clockwise = (h2 - h1 < 180)
#	if not clockwise:
```

```
#                   h1 += 360
#         n_points = np.ceil(np.abs( (h1 - h2)*1.0 /stepsize))
#         headings = np.linspace(h1,h2,n_points)
#         probe = download_streetview_image(apikey_streetview, gps_point, filename="",
heading=headings[0], picsize=picsize, get_metadata=True)
#         if probe['status']=="OK" and 'Google' in probe['copyright']:
#                   for h_i,h in enumerate(headings):
#                             dest_file = download_streetview_image(apikey_streetview,
gps_point, filename="{0}_turn_{1}".format(filestem,h_i), heading=h, picsize=picsize,
get_metadata=False)
#
def generate_download_sequence(gps_points, savename):
         # Create dataframe with GPS points
         pt_list = pd.DataFrame(index=range(len(gps_points)), data=gps_points,
columns=["lat","lon"])
         # Compute basic headings
         headings = [calculate_initial_compass_bearing(pt[0], pt[1]) for pt in
zip(gps_points[:-1],gps_points[1:])]
         pt_list['heading'] = headings + [headings[-1]]
         # Set up probes and collect all in raw form
         pt_list['probe'] = [{} for i in pt_list.index]
         for i in pt_list.index:
                   pt_list['probe'][i] = download_streetview_image("AIzaSyAaFENLZe-
tmLkswnzGXcRqECQZ_5ctmSw", (pt_list["lat"][i],pt_list["lon"][i]), filename="",
heading=pt_list["heading"][i], get_metadata=True)
         # Assign probe items to their own columns:
         probe_items = ['copyright', 'date', 'location', 'pano_id', 'status']
         for p_item in probe_items:
                   pt_list[p_item] = [x[p_item] for x in pt_list['probe']]
         pt_list.to_pickle(savename)
         return pt_list

def create_itinerary_df(gps_points):
         # Create dataframe with GPS points
         pt_list = pd.DataFrame(index=range(len(gps_points)), columns=["lat", "lon",
"heading", "probe", "copyright", "date", "location", "pano_id", "status", "downloaded_1",
"downloaded_array"])
         lats, lons = zip(*gps_points)
         pt_list['lat'] = lats
         pt_list['lon'] = lons
         pt_list['downloaded_1'] = False
         pt_list['downloaded_array'] = False
         # Compute basic headings
         headings = [calculate_initial_compass_bearing(pt[0], pt[1]) for pt in
zip(gps_points[:-1],gps_points[1:])]
```

```
	pt_list['heading'] = headings + [headings[-1]]
	# pt_list['probe'] = [{} for i in pt_list.index]
	pt_list = pt_list.fillna('')
	return pt_list

def probe_itinerary_items(itinerary_df, indlist, apikey_streetview, redo=False):
	assert [i in itinerary_df.index for i in indlist]
	probe_items = ['copyright', 'date', 'location', 'pano_id', 'status']
	for i in indlist:
		if (itinerary_df['status'][i] == '') or (redo):
			print(i)
			probe_result = download_streetview_image(apikey_streetview,
(itinerary_df["lat"].loc[i],itinerary_df["lon"][i]), filename="",
heading=itinerary_df["heading"][i], get_metadata=True)
			# itinerary_df.loc[i]["probe"] = probe_result
			# Assign probe items to their own columns:
			for p_item in probe_result.keys():
				itinerary_df[p_item][i] = probe_result[p_item]

def process_pointlist(pt_list=None, pt_list_filename=None):
	if pt_list is None and pt_list_filename is not None:
		pt_list = pd.read_pickle(pt_list_filename)
	# Remove duplicate / invalid points:
	unique_panos = np.unique(pt_list.pano_id)
	panoid_to_ind = {panoid:pt_list.pano_id.eq(panoid).idxmax() for panoid in
unique_panos}
	keepers = [i for i in sorted(panoid_to_ind.values()) if pt_list.status[i]=='OK' and
'Google' in pt_list.copyright[i]]
	new_list = pt_list.loc[keepers]
	new_list.index = np.arange(new_list.shape[0])
	crit_diff = 5
	turn_indices = new_list.loc[np.abs(np.diff(new_list.heading))>crit_diff].index
	new_rows = []
	for ti in turn_indices:
		h1 = new_list.headings[ti]
		h2 = new_list.headings[ti+1]
		headings = get_turn_headings(h1, h2, stepsize=1)[1:-1]
		tmp_df = pd.DataFrame(np.tile(new_list.loc[ti],(len(headings),1)))
		tmp_df.columns = new_list.columns
		tmp_df.heading = headings
		tmp_df.index = np.linspace(ti+0.01,ti+0.99,len(headings))
		new_rows += [tmp_df]
	final_list = pd.concat([new_list]+new_rows)
	final_list = final_list.sort_index()
	final_list.index = np.arange(final_list.shape[0])
```

```
	return final_list

def download_pics_from_list(item_list, apikey_streetview, filestem, picsize,
redownload=False, index_filter=None):
	print("hello")
	if index_filter is None:
		index_filter = item_list.index
	for i in index_filter:
		row = item_list.loc[i]
		lat, lon, heading, downloaded = row['lat'], row['lon'], row['heading'],
row['downloaded_1']
		if (not downloaded) or redownload:
			download_streetview_image(apikey_streetview, (lat,lon),
filename=filestem + str(i), heading=heading, picsize=picsize, get_metadata=False)
			item_list["downloaded_1"].loc[i] = True

def download_tableaux_from_list(item_list, apikey_streetview, filestem, picsize, fov,
fov_step, pitch, grid_dim, index_filter=None):
	if index_filter is None:
		index_filter = item_list.index
	for i in index_filter:
		row = item_list.loc[i]
		lat, lon, heading, downloaded = row['lat'], row['lon'], row['heading'],
row['downloaded_array']
		download_images_for_point(apikey_streetview, (lat,lon), filestem + str(i),
"./photos/", heading, fov, fov_step, pitch, grid_dim)
		if (not downloaded):
			assemble_grid_of_images(filestem + str(i), "./photos/",
"./photos/composite-{0}-{1}".format(filestem,i), grid_dim, crop_dim="640x640+0+0")
			item_list["downloaded_array"].loc[i] = True

# Download set of zoomed-in views to be composited into a larger image

# Download set of zoomed-in views to be composited into a larger image
def download_images_for_point(apikey_streetview, lat_lon, filestem, savepath, heading,
fov = 30, fov_step = 30, pitch = 15, grid_dim = [4,2]):
	horiz_points = (np.arange(grid_dim[0]) - (grid_dim[0]-1)/2.0) * fov_step
	vert_points = (np.arange(grid_dim[1])[::-1] - (grid_dim[1]-1)/2.0) * fov_step +
pitch
	# horiz_points = np.linspace(-1, 1, grid_dim[0]) * (fov / 90.0)
	# vert_points = np.linspace(max_pitch, min_pitch, grid_dim[1]) * (fov / 90.0)
	# fov_angle_frac = 1.0 * fov / max(grid_dim)
	# fudge_factor = 5
	# assert fov_angle_frac >= 15
	panel_inds = np.reshape(np.arange(np.prod(grid_dim)), grid_dim, 1).transpose()
```

```
	for ix,x in enumerate(horiz_points):
		for iy,y in enumerate(vert_points):
			panel_ind = panel_inds[iy,ix]
			print(panel_ind)
			tmp_heading = heading + x
			tmp_pitch = y
			print(tmp_heading, tmp_pitch)
			download_streetview_image(apikey_streetview, lat_lon,
filename="{0}_{1}".format(filestem,panel_ind), savepath=savepath, picsize="640x640",
heading=tmp_heading, pitch=tmp_pitch, fi=".jpg", fov=fov, get_metadata=False,
verbose=False, outdoor=True, radius=5)

def assemble_grid_of_images(filestem, savepath, outfilestem, grid_dim,
crop_dim="640x640+0+0"):
	panel_inds = np.reshape(np.arange(np.prod(grid_dim)), grid_dim, 1).transpose()
	grid_filenames = [["{0}/{1}_{2}.jpg -crop
{3}".format(savepath,filestem,pind,crop_dim) for pind in pindrow] for pindrow in
panel_inds]
	command_string = "convert " + " ".join([" \( " + " ".join(row+["+append"]) + " \)
" for row in grid_filenames]) + " -append {0}.jpg".format(outfilestem)
	# print(command_string)
	subprocess.call(command_string, shell=True)

# Line up files in order to make a video using ffmpeg.
# ffmpeg requires all images files numbered in sequence, with no gaps.
# However, some images will not have been downloaded, so we need to shift everything
to tidy up gaps.
# Also, some images will be duplicates, and we can remove them.
# Also, a user may want to manually discard images because they are clearly out of step
with the path (e.g., they might be view inside a building, or slightly down a cross-street.)
After manually removing files, re-running this will line up the files.
def line_up_files(filestem, new_dir="./movie_lineup", command="move",
override_nums=None):
	if not os.path.exists(new_dir):
		os.makedirs(new_dir)
	files = glob.glob("./photos/"+filestem+"*.jpg")
	file_nums = [int(filename[9+len(filestem):-4]) for filename in files]
	file_sort = [files[i] for i in np.argsort(file_nums)]
	# First, remove file_nums that represent duplicate files
	file_keepers = prune_repeated_images_from_list(file_sort)
# for i in range(1,len(file_sort)):
# prev_file = file_keepers[-1]
# curr_file = file_sort[i]
# result = os.system("diff " + curr_file + " " + prev_file)
# if result > 0:
```

```
 # file_keepers += [curr_file]
        # Now, shuffle the files into a packed numbering:
        for i in range(len(file_keepers)):
                old_filename = file_keepers[i]
                new_filename = "{0}/{1}{2}.jpg".format(new_dir,filestem,i)
                # print("{0} {1} {2}".format(command, old_filename, new_filename))
                os.system("{0} {1} {2}".format(command, old_filename, new_filename))

# Refactor line_up_files as separate steps:
def line_up_files_with_numbers_script(filestem, numbers, new_dir):
 files = ["./photos/{0}{1}.jpg".format(filestem,num) for num in sorted(numbers)]
 file_keepers = prune_repeated_images_from_list(files)
 copy_files_to_sequence(file_keepers, "./photos/{0}/{1}".format(new_dir, filestem))

def copy_files_to_sequence(list_of_files, new_filestem, command='cp'):
        for i in range(len(list_of_files)):
                old_filename = list_of_files[i]
                new_filename = "{0}{1}.jpg".format(new_filestem,i)
                #print("{0} {1} {2}".format(command, old_filename, new_filename))
                os.system("{0} {1} {2}".format(command, old_filename, new_filename))

def prune_repeated_images_from_list(list_of_files):
        file_keepers = [list_of_files[0]]
        for i in range(1,len(list_of_files)):
                prev_file = file_keepers[-1]
                curr_file = list_of_files[i]
                result = os.path.getsize(prev_file) - os.path.getsize(curr_file)
                if abs(result) > 150:
                        file_keepers += [curr_file]
        return file_keepers

def make_video(base_string, rate=3, video_string=None, picsize="640x640",
basepath="./photos"):
        if video_string is None:
                video_string = base_string
        print("ffmpeg -r {0} -f image2 -s {3} -i {4}/{1}%d.jpg -vcodec libx264 -crf 25 -
pix_fmt yuv420p {2}.mp4 -y".format(9, base_string, video_string, picsize, basepath))
        subprocess.call("ffmpeg -r {0} -f image2 -s {3} -i {4}/{1}%d.jpg -vcodec
libx264 -crf 25 -pix_fmt yuv420p {2}.mp4 -y".format(9, base_string, video_string,
picsize, basepath), shell=True)
#ffmpeg -r 20 -f image2 -s 640x640 -i ./lineup-joshua_tree//joshua_tree%d.jpg -vcodec
libx264 -crf 25 -pix_fmt yuv420p joshua_tree.mp4 -y
```

street_crawl.py

```
import sys
from utils import *
```

```
#from API_KEYS import API_KEY_DIRECTIONS, API_KEY_STREETVIEW

'''Google Street View Movie Maker

Usage is:
	python2 ./street_crawl.py lat1 lon1 lat2 lon2 output_filestem


For example, to make a one-second video of the entrance of Joshua Treet National Park:
	python2 ./street_crawl.py 33.669793 -115.802125 33.671796 -115.801851
joshua_tree

Note: usage requires your own API keys.

'''

def main(lat_lon_A, lat_lon_B, filestem):
	print ("Tracing path from " + str(lat_lon_A) + " to " + str(lat_lon_B))
	# Request driving directions from A to B
	gd = googlemaps.Client(key='AIzaSyAaFENLZe-
tmLkswnzGXcRqECQZ_5ctmSw')
	directions_result = gd.directions(origin=lat_lon_A, destination=lat_lon_B,
mode="driving")
	# Convert driving directions into sequence of GPS points
	print(directions_result)
	path_points = polyline.decode(directions_result[0]['overview_polyline']['points'])
	dense_points = [interpolate_points(pt[0],pt[1],hop_size=3) for pt in
zip(path_points[:-1],path_points[1:])]
	look_points_rough = [item for sequence in dense_points for item in sequence]
	# Remove unnecessary points
	look_points = clean_look_points(look_points_rough)
	print ("For this route, there are " + str(len(look_points)) + " images to
download.\n")
	continue_opt = input('Would you like to download them all Type yes to proceed;
otherwise, program halts.\n')
	if continue_opt not in ['Yes','yes']:
		return
	# Download sequence of images (up to a limit? What's the limit in a day?)
	download_images_for_path("AIzaSyAaFENLZe-
tmLkswnzGXcRqECQZ_5ctmSw", filestem, look_points)
	# Assign images new filenames (and remove bad images)
	print("here" + filestem)
	line_up_files(filestem, new_dir="./lineup-{0}/".format(filestem))
	# Convert sequence of images to video
	make_video(filestem, rate=20, video_string=filestem, basepath="./lineup-
```

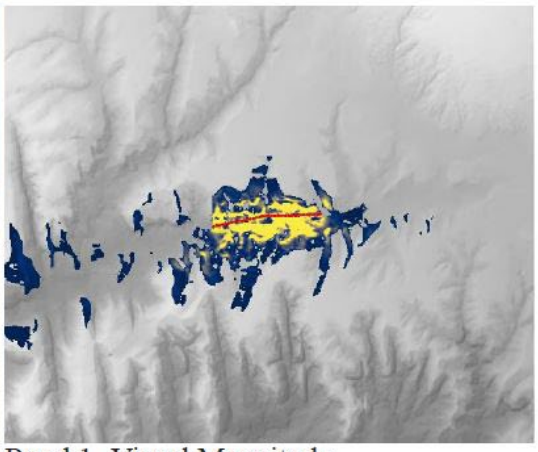
```
{0}/".format(filestem))
        # TODO: Delete downloaded images

if __name__ == "__main__":
        lat_A, lon_A, lat_B, lon_B = [float(x) for x in sys.argv[1:5]]
        filestem = sys.argv[5]
        main((lat_A, lon_A), (lat_B, lon_B), filestem)
```

Appendix B

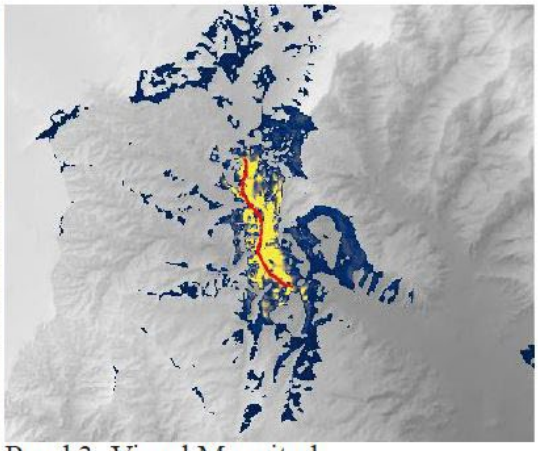
Site Context Images and Visual Magnitude Raster Maps

Road 1- Context Image
Average Scenic Rating: 5.52



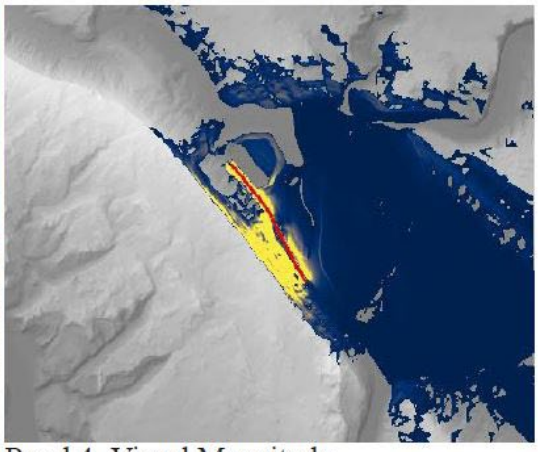
Road 1- Visual Magnitude
Max: 0.132353 | Mean: 0.00159212 | Min: 5.19E-10

Road 3- Context Image
Average Scenic Rating: 7.98



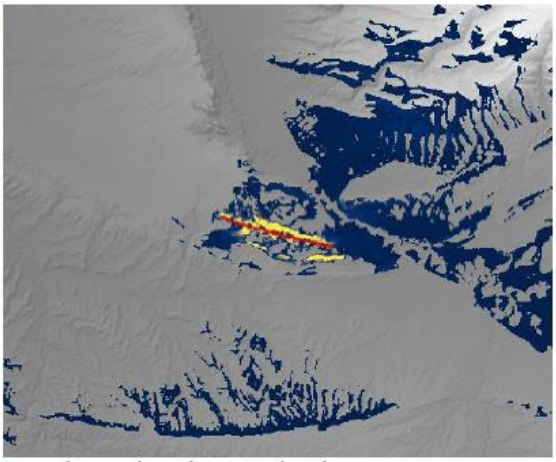
Road 3- Visual Magnitude
Max: 0.20068 | Mean: 0.00116282 | Min: 1.95E-10

Road 4- Context Image
Average Scenic Rating: 5.59

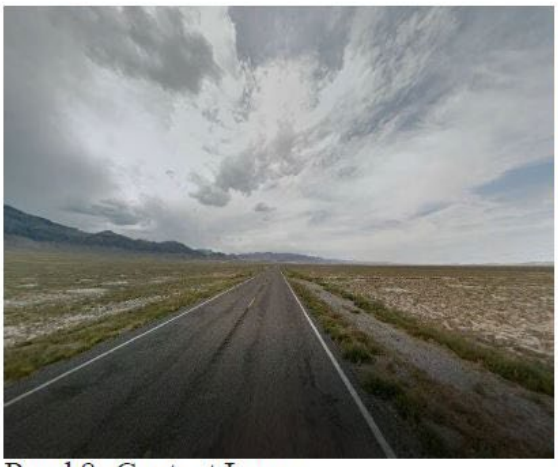


Road 4- Visual Magnitude
Max: 0.106024 | Mean: 0.00034751 | Min: 8.97E-11

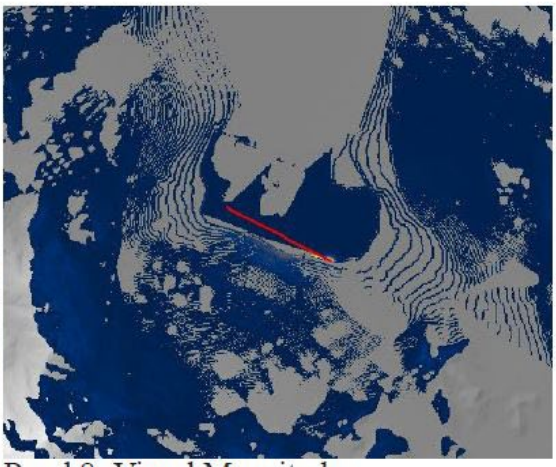
Road 5- Context Image
Average Scenic Rating: 4.06



Road 5- Visual Magnitude
Max: 3.64E-02 | Mean: 1.91E-04 | Min: 4.83E-13

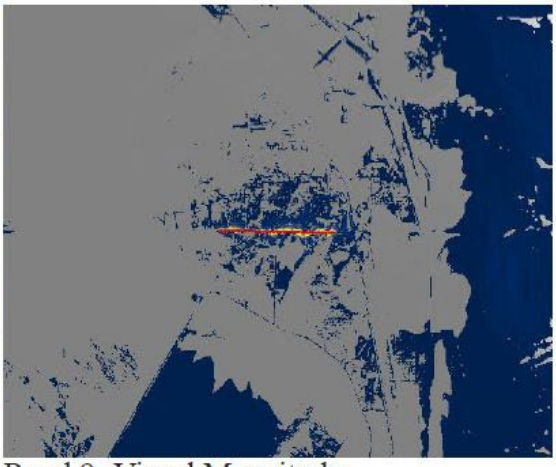


Road 8- Context Image
Average Scenic Rating: 5.02



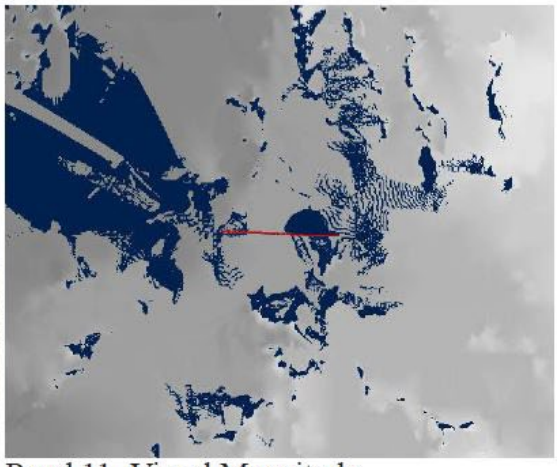
Road 8- Visual Magnitude
Max: 0.0314692 | Mean: 4.26E-05 | Min: 1.46E-12

Road 9- Context Image
Average Scenic Rating: 4.62



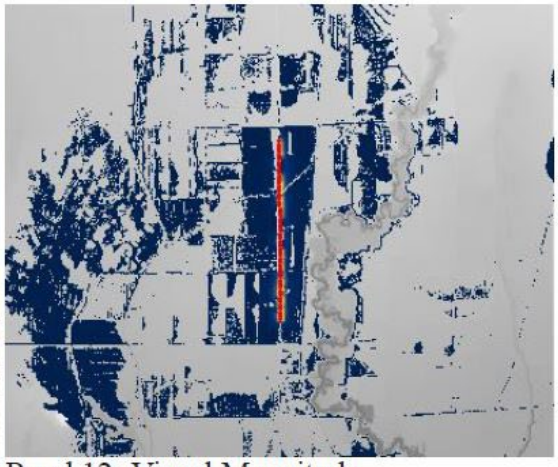
Road 9- Visual Magnitude
Max: 0.0521513 | Mean: 5.87E-05 | Min: 4.50E-13

Road 11- Context Image
Average Scenic Rating: 3.31



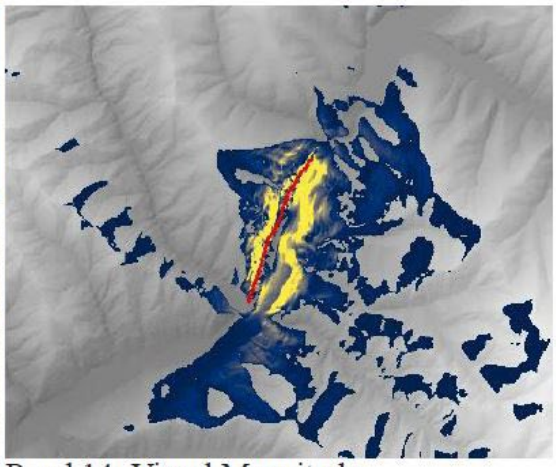
Road 11- Visual Magnitude
Max: 0.0078431 | Mean: 4.64E-06 | Min: 2.29E-12

Road 12- Context Image
Average Scenic Rating: 4.84



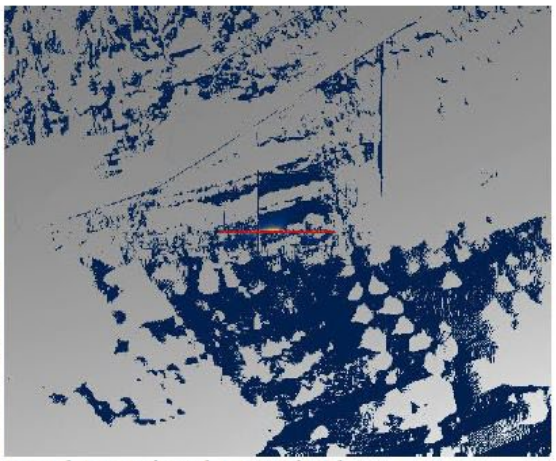
Road 12- Visual Magnitude
Max: 0.0273011 | Mean: 3.77E-05 | Min: 4.36E-12

Road 14- Context Image
Average Scenic Rating: 4.57



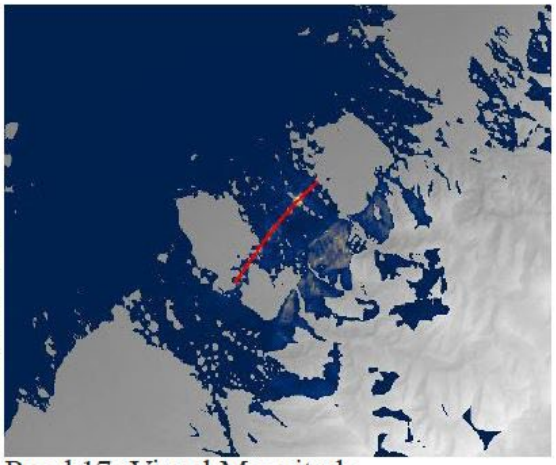
Road 14- Visual Magnitude
Max: 0.0877427 | Mean: 5.15E-04 | Min: 8.38E-11

Road 16- Context Image
Average Scenic Rating: 4.04



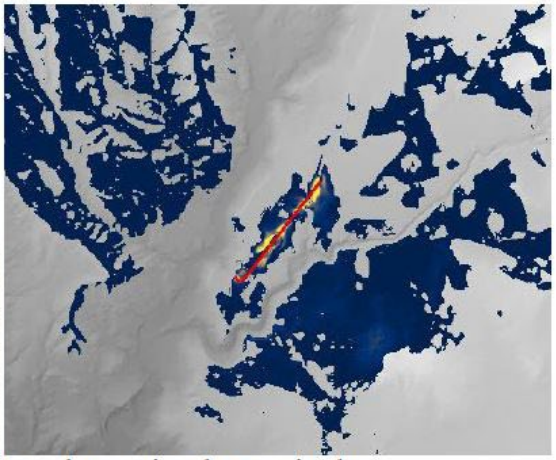
Road 16- Visual Magnitude
Max: 0.0131676 | Mean: 7.52E-13 | Min: 1.33E-05

Road 17- Context Image
Average Scenic Rating: 4.426



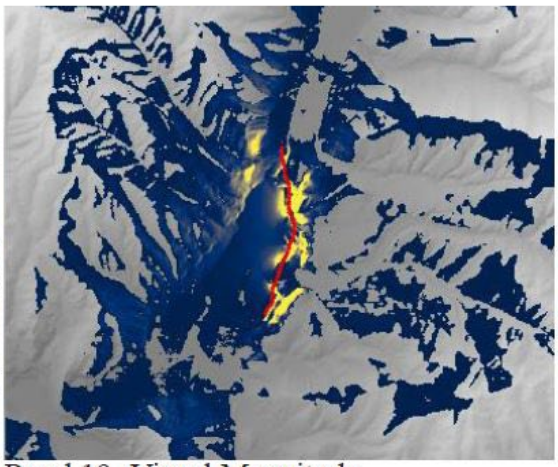
Road 17- Visual Magnitude
Max: 0.018829 | Mean: 3.87E-05 | Min: 7.40E-11

Road 18- Context Image
Average Scenic Rating: 4.57



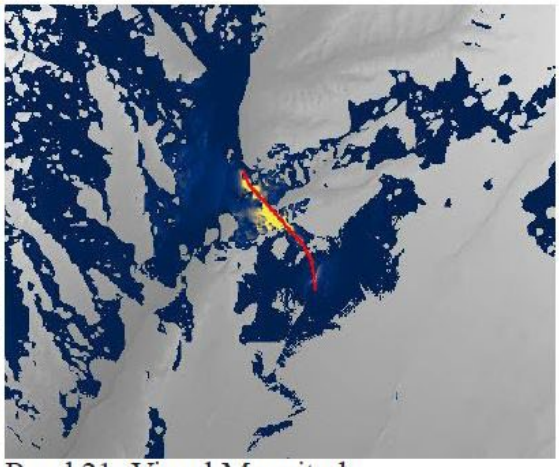
Road 18- Visual Magnitude
Max: 0.0464253 | Mean: 6.37E-05 | Min: 4.42E-11

Road 19- Context Image
Average Scenic Rating: 5.91

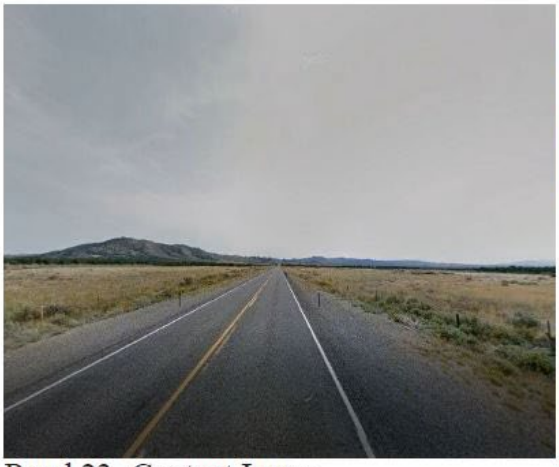


Road 19- Visual Magnitude
Max: 0.105125 | Mean: 2.39E-04 | Min: 2.18E-10

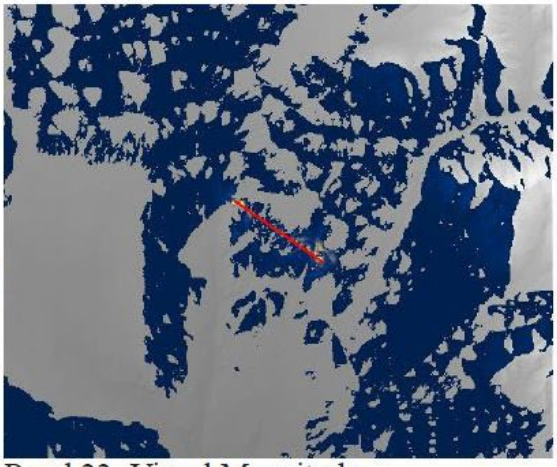
Road 21- Context Image
Average Scenic Rating: 4.79



Road 21- Visual Magnitude
Max: 0.090301 | Mean: 9.70E-05 | Min: 2.07E-11



Road 23- Context Image
Average Scenic Rating: 5.02



Road 23- Visual Magnitude
Max: 0.0277852 | Mean: 2.93E-05 | Min: 5.86E-12

Appendix C

Familiarity and Scenic Ratings Data

Figure C.1

Familiarity with Each Individual Ecoregion (Zone) and Scenic Quality Ratings

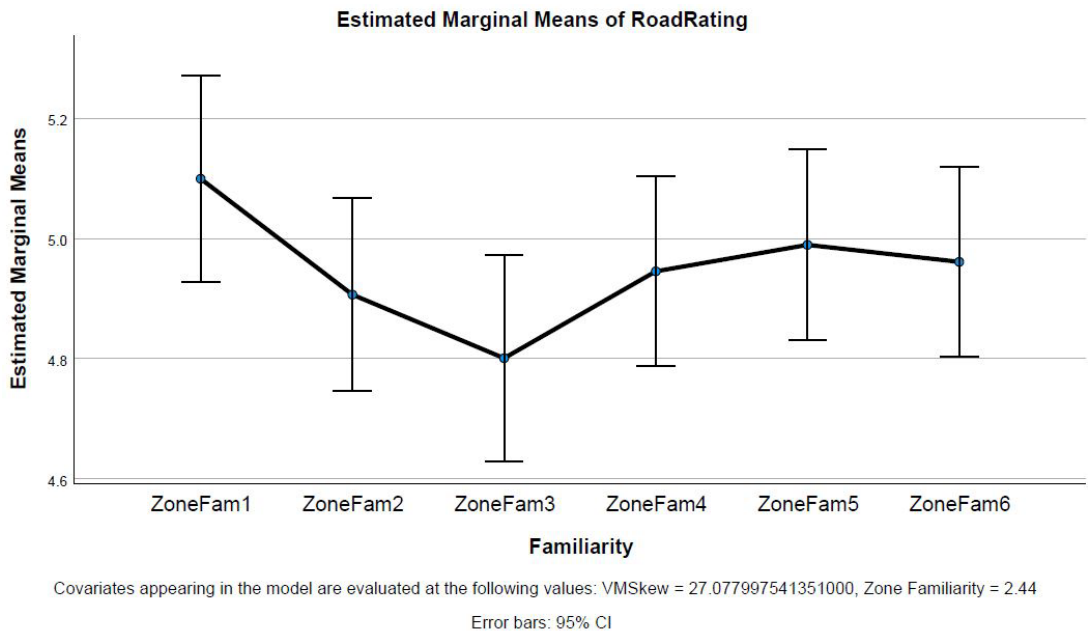


Table C.1

SPSS Statistics for Familiarity with each Ecoregion (Zone) and Scenic Quality Ratings

Source	*df*	Mean square	*F*	*p* value	Partial η^2
Intercept	1	11212.569	2629.881	.000	.400
VM skew	1	879.618	206.312	< .001	.050
Familiarity rating	1	79.434	18.631	< .001	.005
Familiarity	5	4.548	1.067	.377	.001

Figure C.2

Familiarity with Ecoregion (Zone) 2 and Scenic Quality Ratings

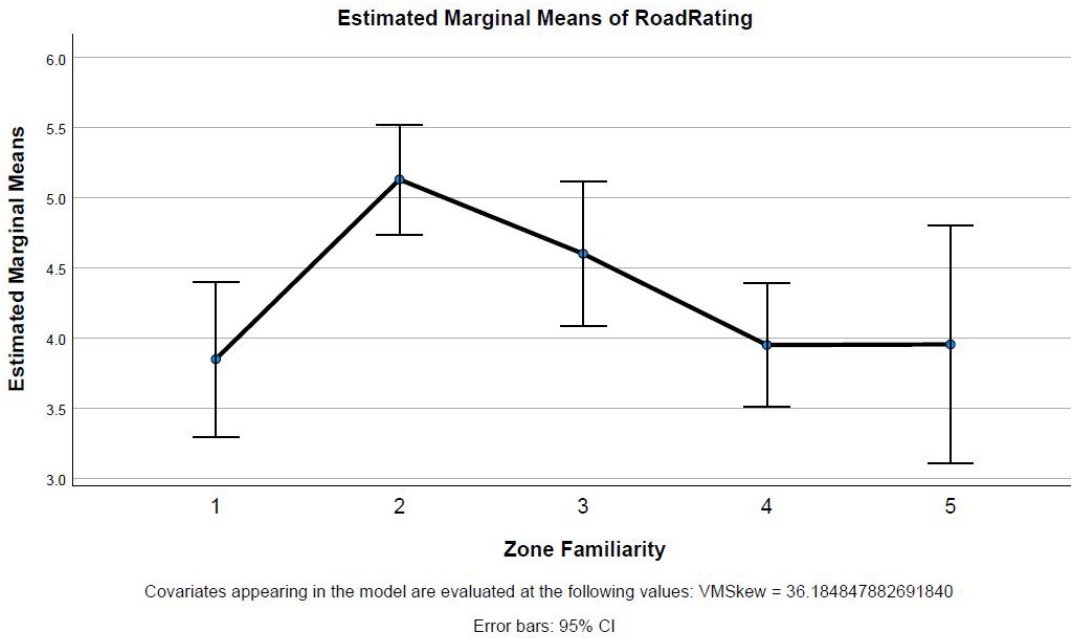


Table C.2

SPSS Statistics for Familiarity with Ecoregion (Zone) 2 and Scenic Quality Ratings

Source	*df*	Mean square	*F*	*p* value	Partial η^2
Intercept	1	423.199	109.369	< *.001*	.270
VM skew	1	8.717	2.235	.134	.008
Familiarity rating	88.589	4	22.147	< .001	.072

Figure C.3

Familiarity with Ecoregion (Zone) 3 and Scenic Quality Ratings

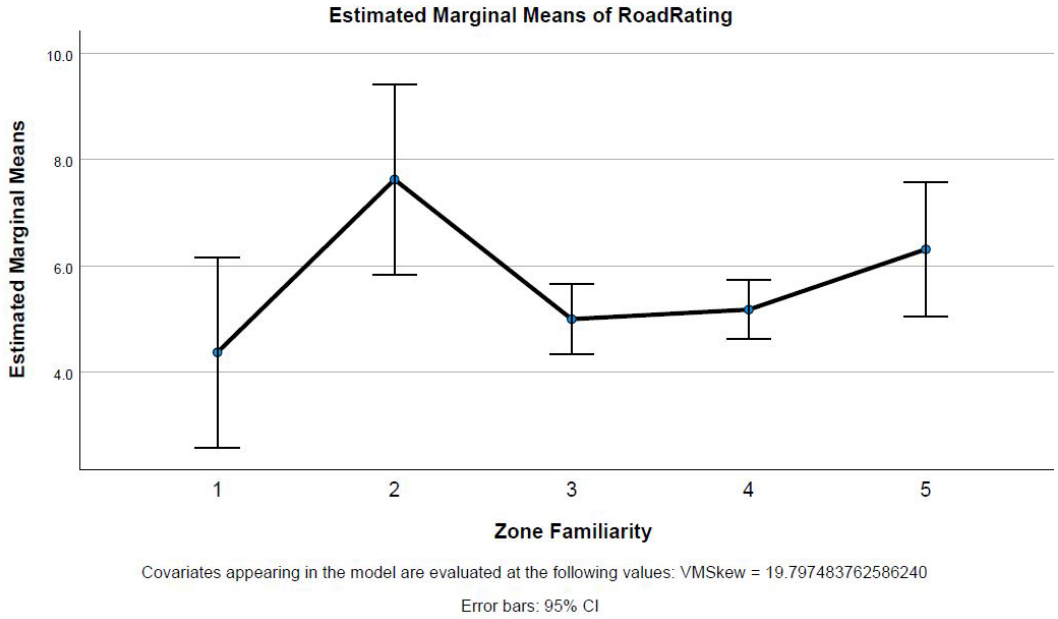


Table C.3

SPSS Statistics for Familiarity with Ecoregion (Zone) 3 and Scenic Quality Ratings

Source	*df*	Mean square	*F*	*p* value	Partial η^2
Intercept	1	102.005	31.550	< .001	.278
VM skew	1	33.136	10.249	.002	.111
Familiarity rating	4	9.141	2.827	.030	.121

Figure C.4

Familiarity with Ecoregion (Zone) 4 and Scenic Quality Ratings

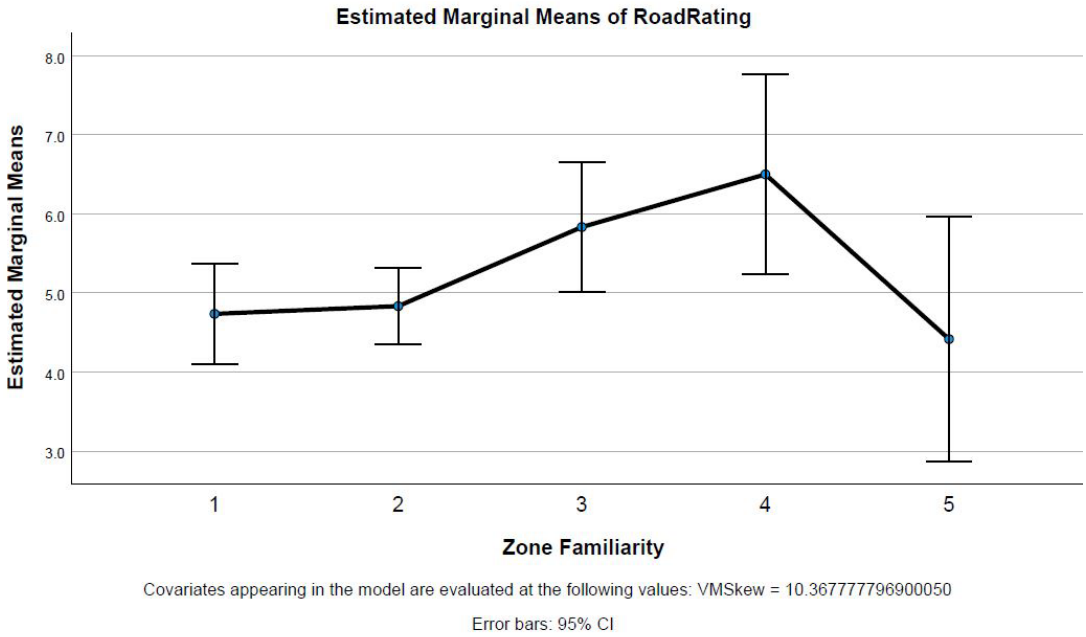


Table C.4

SPSS Statistics for Familiarity with Ecoregion (Zone) 4 and Scenic Quality Ratings

Source	*df*	Mean square	*F*	*p* value	Partial η^2
Intercept	1	339.430	93.061	<.001	.425
VM skew	1	1.879	.515	.474	.004
Familiarity rating	4	10.141	2.780	.030	.081

Appendix D

Scenic Quality Ratings for Each Roadway

Table D.1

Scenic Quality Ratings from the Survey Road 1 to 11

ID	RD 1	RD 3	RD 4	RD 5	RD 8	RD 9	RD 11
1	5	7	5	4.5	5	5.5	4
2	7.5	9	8	3.5	7	1.5	1.5
3	4	6	3	1.5	2	3	1
4	6	8	6.5	6.5	7	7.5	4.5
5	4.5	8.5	6	2	2	4.5	2
6	5	7.5	5.5	2.5	1.5	3	2
7	4.5	6.5	3.5	2	3	3	1
8	7	9	8.5	4	5	5.5	4
9	6.5	7	4.5	3	6	3.5	3
10	5.5	8	3.5	3	2.5	3.5	2.5
11	4	6.5	2	3	3.5	5	2
12	9	10	10	9	7.5	7	7
13	7	9	8	8.5	9	7.5	8
14	6	6.5	2.5	3.5	3.5	5.5	2.5
15	6.5	7.5	7	6	6	6	5
16	5.5	7.5	4	3	6.5	6.5	2
17	4	5	3	2.5	3	4.5	2
18	6.5	9.5	6.5	3.5	7	3.5	1
19	5	8.5	6	3.5	4.5	4.5	3
20	7	9	7.5	7	6.5	5.5	7
21	4.5	8.5	6	3	5	5	1
22	8.5	9.5	6.5	2.5	8	3	3.5
23	3	8.5	6	4.5	5	3	7
24	4.5	8	6	3.5	6.5	5.5	4
25	4	9	2.5	2.5	2	5.5	1
26	6	8	6	5	6.5	5.5	2.5
27	8	10	8	7	8	2	6
28	5	8.5	4	3.5	3	5	1
29	6	8	3	5	2	5	2.5
30	3.5	7.5	3.5	3	5	3.5	2.5
31	8	9.5	9.5	6.5	7.5	8	8
32	2.5	4	4	2	3.5	3.5	1
33	5.5	8	6	3.5	5	5	1.5
34	5.5	9	7.5	5	4.5	4	3
35	4	9.5	5.5	1.5	2.5	1.5	1.5
36	5.5	10	8	6	8.5	3.5	6
37	6.5	8	7	4	5	6	2
38	5	8.5	4.5	2	6.5	3.5	2.5
39	6.5	7.5	7.5	5.5	7.5	7.5	5
40	7	8.5	7	6.5	7.5	7	5
41	3.5	8	4	4	4	4.5	5
42	7	9.5	6	7	7	4	6
43	4.5	7	5	3	1.5	4	2
44	3	3.5	2.5	1	1.5	2.5	1

Table D.2

Scenic Ratings from the Survey Road 12 to 23

ID	RD 12	RD 14	RD 16	RD 17	RD 18	RD 19	RD 21	RD 23
1	6.5	6	4.5	5	4.5	6	4	4.5
2	4.5	4	2	5	5.5	4	5	7
3	3	2.5	2	2	2.5	4.5	3	2.5
4	6	5.5	5.5	5.5	6	6.5	4.5	5.5
5	6	6	4.5	4	5	7	5	5
6	3.5	2.5	3	2.5	4	5	4.5	3
7	3.5	3	2	2	2.5	4	2.5	3
8	5	5.5	4.5	6	5.5	6.5	6.5	6.5
9	3.5	6	2.5	4.5	4.5	4	4.5	5
10	4.5	2.5	4	2.5	4	6.5	3	4
11	4.5	2.5	3.5	2	3.5	5	3	4
12	10	10	8.5	10	10	9.5	10	9.5
13	8.5	9	8	8.5	8	8	8	8.5
14	4	1	4.5	1	3.5	6.5	3	2.5
15	6	6	5.5	6	6	8	6	6
16	5.5	2	5.5	4	4	6.5	3	6.5
17	4	2.5	2.5	2	2.5	4	3.5	2.5
18	3.5	4.5	4	5.5	3	4.5	4	5.5
19	4.5	4	4.5	4	3.5	6	4.5	5.5
20	6.5	6	5.5	6.5	6	7	7.5	7
21	6.5	4.5	5	3.5	2.5	7	4	5.5
22	4	7	4	4	8	6.5	5	6
23	5	6.5	3	6	2.5	7	4.5	5
24	5	5.5	5.5	4	6	6	5.5	4
25	3	2	3.5	1.5	2	4.5	3.5	2.5
26	4.5	6.5	4.5	4.5	6	7	6.5	6.5
27	8.5	7	3.5	8	7.5	8.5	8.5	7
28	2.5	3.5	2	2.5	3	5.5	2.5	4.5
29	3.5	3.5	2	4	4	7.5	4	4.5
30	2.5	3.5	3	4	4	6	4.5	3.5
31	7.5	7.5	4.5	3.5	7	5.5	7.5	7.5
32	2.5	1	3	1.5	1	4	1	2.5
33	3	3.5	3	2	2.5	6	4	3.5
34	5	6	4	3	5	6.5	6	4.5
35	2.5	1.5	2.5	3	1.5	4	4	3
36	6.5	6.5	5	6.5	6	6	6.5	7.5
37	7	2	5.5	3	5.5	6.5	3.5	4
38	3	6	2	6	6	4.5	3	6
39	6	7	6	6.5	5	7.5	7	6
40	6.5	7	6	6	6	7.5	6.5	7
41	5.5	6.5	4.5	5	5	6	7	4.5
42	5	6	4.5	7.5	6.5	5	7	8
43	3	3.5	3	2.5	4	4	2.5	3
44	2	1.5	2	1	1	2.5	2	1.5