

Evaluating visual channels for multivariate map visualization

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Abstract

Visual differencing, or visual discrimination, is the ability to differentiate between two or more objects in a scene depending on the values of certain attributes. Focusing on multivariate maps visualization, this work examined human's predictable bias in interpreting visual-spatial information and inference making. Moreover, this study seeks to develop and evaluate new techniques to mitigate the trade-off between proximity and occlusion and to enable analysts to explore multivariate maps. Therefore, we developed a multi-criteria decision-making technique for land suitability using multivariate maps, and we carried out a user study where users are tasked to choose the most suitable piece of land to plant grapes. We designed the user study to evaluate mapping a map's layers (variables) to visual channels (Transparency, Hue, Saturation and Brightness/Lightness); two color spaces were used Hue Saturation Value (HSV) and Hue Saturation Lightness (HSL). The categorical variables were mapped to the Hue channel and the quantitative/ordinal variables were mapped to either Saturation, Brightness/lightness, or Transparency channels. Our online user study was taken by 85 participants to test the users' perception of different map visualizations. The statistical analysis of survey responses showed that mapping quantitative layers to the Transparency channel outperformed the other channels, and the use of HSV color space showed a more efficient mapping than HSL, especially for the extreme values in the dataset.

CCS Concepts

•Human-centered computing → Visualization techniques; Geographic visualization; Empirical studies in visualization; Visualization design and evaluation methods;

1. Introduction

Many Multivariate Multidimensional data (MVMD) can be defined as a set of n observations X , where the i th element X_i is a vector with m variables.

$$X_i = (x_{i1}, \dots, x_{im}), i \in (1, \dots, n) \quad (1)$$

Each variable may be independent or dependent on one or more other variables. Independent variables are referred to as multidimensional and dependent variables are referred to as Multivariate. To develop MVMD visualization we should consider several important 'Environment Properties' relating to the configuration of objects' geometry in a visualization environment, which are density, complexity, and interaction; Considering the spatial interaction of objects in the environment is proximity where objects are in such close proximity (without intersecting) that they occlude each other from some viewpoint [ET07]. Thus when trying to visualize different dimensions and/or variables of a scientific data set, we have the same trade-off between proximity and occlusion for designing MVMD visualizations as follows [Pol06]:

1. Multiple View Visualizations:

- (+) Provide separate screen space to represent high dimensional spaces and complex relationships among multiple variables (Elmqvist's 'proximity', Polys's 'Display Space').
- (-) With small multiples we need to hold the info in the mind's

working memory, which is expensive (Working memory is limited in context-switching) and error-prone.

- (-) Relationships between views must be explicit.

2. Overlay Visualization:

- (+) Collapses dimensions onto a single View (enclosure, Viewport Space).
- (-) Perception is difficult due to crowding/density and occlusion; also error-prone.

3. Embedded Visualization:

- (+) Views are embedded in same space as the referent (containment, Object/World Space).
- (-) In the overlaying views perception is difficult due to crowding/density; also error-prone.
- (-) Relationships between views must be explicit.

In this research, we seek to develop and evaluate new techniques to mitigate these trade-offs and to enable analysts to better explore MVMD data sets. In this study we have numerous attributes (dimensions/variables) evenly distributed across a spatial basis (a map), a similar situation to scientific visualizations where we are trying to compose several dimensions/variables into one 'view'. We call this approach composed appearance where:

4. Composed Appearance:

- (+) The contribution of different attributes (layers) can be

weighted and composed into the appearance of a shape (e.g. texture, color) but,

- (-) it may be difficult to perceive the values of or patterns in individual dimensions after they are composed.

Land suitability is one of many domains where multiple attributed variables are spatially registered (geo-located on maps) and serve as criteria for decision-making. Such maps are considered as MVMD, as each map layer represents an independent constraint or variable in the analysis; for example, hydraulic conductivity of soil, slope percent and index of available water are all factors in determining the suitability of land for the agricultural production of a specific crop.

Researchers in this area have developed several techniques to handle such MVMD representations. One popular method is Spatial Multi-Criteria Decision-Making (MCDM). In MCDM, each criterion variable (dimension or layer) is assigned a weight that can be determined according to the adjusted output from pairwise comparisons [CYK13]. The MCDM output should be some accurate classification of the land by those weighted criteria.

For example, how suitable is a piece of land for some crop (highly suitable, suitable, maybe suitable and unsuitable)? The human in the loop might adjust initial weights and choose which variables are included in the analysis; at the end of the classification process, they can view a colored map showing the resulting classes by composing the layers in a single map or viewing each layer as a separate individual map.

Most of these visualizations used the rainbow color map although researchers in the field of visualization tackled the problem of using the rainbow color map for comparison tasks. The main deficiency of the rainbow color map is "it isn't a perceptually ordered color map". For comparison tasks, the used color maps should exhibit perceptual ordering such as the gray scale color map, as the change of data values can be mapped to the luminance change from black to white [BT107, LB04b].

Moreover the rainbow color map is not isoluminant so that the small variations in the data are hidden in one color range, only the big changes are apparent in the borders between two colors. Also the data to color mapping in the rainbow color map confuses the data type representation (quantitative vs. nominal), as different data values are assigned to different colors (hues), as they are different categories although they are different values in the same category [BI07], [LB04a] and [Mor09].

We are evaluating the use of color spaces and color channels to compose multiple variables into a 2D map. As recommended by best practices in data visualization [CMS99], we designed our mapping methods according to data type (quantitative or qualitative) and according to graphical representation rankings by [CM84] and [Mac86] where color is a common representation among all data types (i.e. quantitative, ordinal or qualitative/nominal). We then tested various visual color encodings of data layers as a 2x3x4 (color space x color channel x spectral relative difference) full-factorial, within-subjects experiment with 85 subjects. In this paper we describe our methods, results and discuss the performance implications of representing multiple variables in a 2D map.

2. Related work

The initial work for multivariate data representation was, naturally, the bivariate data representation. One of the most extensively stud-

ied techniques was bivariate color-coding scheme technique for bivariate maps visualization where two variables are represented on one map using two n-class sequential color schemes [Rhe97] and [War09]. However, changes in color dimensions are not independent but likely to interfere perceptually; to overcome this and obtain some degree of separability, [Rhe99] suggested using Hue and Value (Brightness). On the other hand, [BRT95] suggested mapping high spatial frequency information to Hue and low spatial frequency to Lightness. Multivariate data visualization considers the representation of more than one variable. According to Ware [War88], Saturation scales only can be expected to yield a few clearly readable steps for continuous maps.

A visual analytics framework has been developed to explore seismic event catalog data together with satellite imagery data (MVMD) to collect a multi-modal observational dataset [YXG*10]. Their prototype allowed users to visually zoom in on interesting time intervals and spatial regions around seismic events. They have designed their own transfer functions to handle multi-modal observational data; specifically creating color maps for MVMD, which were controlled through parallel coordinates and multidimensional scaling methods. This work is informative for our study as we also used color as a graphical representation for MVMD data.

A year after, Long and Linsen [LL11] tackled the visual analysis of MVMD data based on the evaluation of the data density distribution. They described an interactive exploration system for MVMD data analysis ranging from density computation over an automatic hierarchical density cluster computation to an optimized projection method into the visual space based on star coordinates, where clusters of the hierarchical density clusters are rendered using nested contours or surfaces. We consider their method related to our research as they inspected MVMD, but from information visualization point of view.

Multivariate spatio-temporal data was examined in another study where the variables of time, location, and attributes are represented on tables as data fields.

Multivariate Spatio-Temporal Cube (MSTC) uses 3-dimensional Cartesian coordinates to visually represent the data of a table. The main idea is that each record of the data table is converted to a data plane of two dimensions, i.e. each data tuple of a record is shown as the graphics in a 2-dimensional domain, and then these data planes are arranged along and perpendicularly to the time axis of a 3-dimensional Cartesian coordinate system. MSTC is illustrated with the data table of Napoleon's 1812 Russian campaign. All data of the table is represented on a cube showing visually the great loss on soldiers as well as tragic defeat of the campaign [TN12].

Urness [Urn03] proposed a new method called 'Color weaving', which uses Hue and Saturation, to allow multiple colors to be closely interwoven (instead of being blended) by the assignment of distinct separate hues to individual streamlines. They varied the Saturation of the color at each point according to the value in the corresponding scalar distribution, which allowed each color to encode multiple values in a continuous distribution. Their method assigned color indices to streamlines in an alternating manner that depends on the order in which they are encountered in a deterministic walk through the pixel grid. The result is a multicolored line integral convolution (LIC) image that resembles a tapestry woven with different colored threads. The authors also defined a 'Texture stitching' technique, which allowed faithful preservation of region boundaries in multi-frequency LIC through the use of a post-LIC

merging of selected adjacent regions. They obtained separate LIC textures based on correlated high and low frequency noise input patterns, then combined the results using a binary mask to force adherence to pre-defined boundary curves [Urn03] and [HSKIH07]. Our method is similar to the color weaving method with one difference: that we have categorical data assigned to the hues and quantitative data assigned to Saturation.

Helfman [Hel15] studied 'Hue tinting' for interactive data visualization, he addressed the problem that most visualization systems make it difficult to use Hue variation to identify and compare features in a dataset without distorting the ordered mapping of quantity to brightness variation that encodes the relationships in a data distribution. Like colorizing a black-and-white photograph, 'Hue tinting' lets users use Hue to select, identify, and mark relevant portions of their data without distorting the brightness of the underlying gray scale visualization. He concluded that hue tinting a specific range of data values provides a direct method for validating and compliance testing. His work followed the best practices in the field of data visualization recommended by [War13]. In this paper we are proposing mapping the qualitative data layers to the Hue. On the other hand, Ware proposed the quantitative texture sequence (QTonS) to display data for one of two maps, with a conventional color sequence for the other. The purpose of the QTonS was to create an ordered sequence of textures with an explicitly perceived value associated with a member of the sequence [War09].

Recently, a survey of glyph-based visualization for spatial multivariate medical data emphasized using Parameter Mapping Functions (PMFs) to associate different variables with one or more properties of a glyph e.g., shape, size or color. [ROP11] proposed a classification of glyph properties specifically designed for medical visualization that is based on findings from the perception literature. They classified glyphs the way they communicate the information to be visualized, introducing a more strict differentiation between pre-attentive and attentive glyph properties. In their taxonomy, the pre-attentive stimuli were classified with respect to glyph shapes as well as glyph appearance such as color, transparency, and texture. For example in the context of diffusion tensor imaging (DTI) visualization, mapping tensor information to Gabor textures is optionally combined with mapping the Eigenvector to color and anisotropy to transparency. Thus, anisotropy characteristics are mapped to color, transparency, and texture while directional information is only visualized if it is assessed as reliable based on the relation between the eigenvalues. Using other representations such as textures or glyphs can produce overcrowded maps; in this case study, we focus on the simpler case of composing color space data to visualize multivariate maps.

Kayastha et al. [KDD13] used an MVMD data set similar to our case study (integrating layers such as slope aspect, slope angle, slope curvature, relative relief and land use) to produce a landslide susceptibility map. To generate such a map, they applied the Analytic Hierarchy Process (AHP), a semi-quantitative method in which decisions are taken by weights through pairwise, relative comparisons to reduce inconsistency in the decision-making process. AHP is a heuristic method (an expert-judgment method); however, such techniques may be codified into digital decision making tools that can mitigate human bias.

3. MVMD mapping to visual channels

We ran a 2x3x4 mixed experimental design for color spaces (HSV and HSL), visual channels (Saturation, Brightness/ Lightness and

Transparency (Alpha)) and spectral relative difference (25%, 34%, 50%, and 75%) respectively. We designed our experiment according to the best practices in data visualization recommendations [War13]:

1. Mapping quantitative data to 'ordered' visual elements, such as position, size, and brightness;
2. Mapping qualitative data, such as names and categories, to 'unordered' visual elements, such as shape and color.

This study used a land map consists of different layers, which were classified as categorical, quantitative or ordinal layers according to the variable each layer was representing. For example, the soil-type layer was classified as a categorical layer and the available water was classified as a quantitative layer. Color is a common graphical representation among all data types [Pol14]. We mapped the categorical/qualitative layers to the "Hue" channel of the color space and the quantitative/ordinal layers to another ordinal visual channel such as Saturation, Brightness/Lightness or Transparency (Alpha). In other words, we have a set of layers:

$$L = L_1, \dots, L_m \quad (2)$$

Whereas each $L_i, i \in (1, \dots, m)$ can be either a categorical (L_{ci}) or quantitative (L_{qi}) layer our visualization $V = L \rightarrow C$, where C is the composite map. On the other hand, we denoted the visual channels as follows, Hue as H, Transparency as T, Saturation as S, and Brightness/Lightness as B. For each channel we have a set of values as follows:

$$H = H_1, \dots, H_m \quad (3)$$

$$T = T_0, \dots, T_{100} \quad (4)$$

$$S = S_0, \dots, S_{100} \quad (5)$$

$$B = B_0, \dots, B_{100} \quad (6)$$

We mapped each category in the categorical layer L_{ci} to a certain H_i based on the linear mapping between the gray scale values (0 to 255) and hue values on the color wheel (0 to 360). For each L_{qi} there is a specific weight W_j where $j \in (1, \dots, q)$, q is the number of quantitative layers and $\sum W_j = 1$. To map a number of quantitative layers to a certain visual channel, we weighted the layers and added them as in Equation (7), the resulting image was mapped to either T, S, or B.

$$I = \sum (W_j \times L_{qi}) \quad (7)$$

We examined color spaces that have these visual channels addressable separately, specifically, HSL and HSV (Figure 1 from Wikipedia) keeping in mind that Transparency is a color space independent channel. HSL and HSV color spaces consist of transformed points of RGB color space points, where HSL and HSV models are the transformations of the RGB color model. HSL and HSV models are more convenient way for programmers to specify colors in software than RGB models. In other words, they describe perceptual color relationships more accurately than RGB, while remaining computationally simple. We composed one image from the map variables (layers) by assigning the categorical layer to the Hue channel and the quantitative/ordinal layers to the Saturation, Brightness/Lightness, or Transparency channel. Worth mentioning that mapping the quantitative layers to the Transparency channel will result the same representation as mapping to Saturation if the image background is white while it will be similar to mapping to Brightness if the image background is Black.

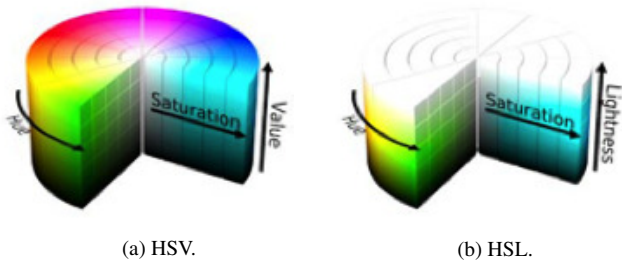


Figure 1: The two color spaces Used in the study.

In this experiment, the hydric Soil Type layer was mapped to the Hue channel. For the experimental conditions, we varied the source of the quantitative layer among Solar Aspect, Digital Elevation, and Available Water. All map layers were 13200X13200 pixel gray scale images, an example of mapping the soil types layer to the Hue and the available water layer to Saturation/Brightness is shown in Figure 2. The a priori hypotheses of this experiment are:

1. Human can visually differentiate between different quantities represented on the map by different Saturation/Brightness scales of the same Hue value.
2. Mapping quantitative data to visual channels in the HSV color space can provide more perceptually accurate representations than those mapped to the HSL color space.

The procedure of mapping data layers to visual channels was accomplished in batch mode using ImageMagick scripts according to the following pseudo code: Input:

1. Map's layers in grayscale color space, one of them should have qualitative/categorical data.
2. The weights assigned to each quantitative layer (should sum up to 1)

Procedure:

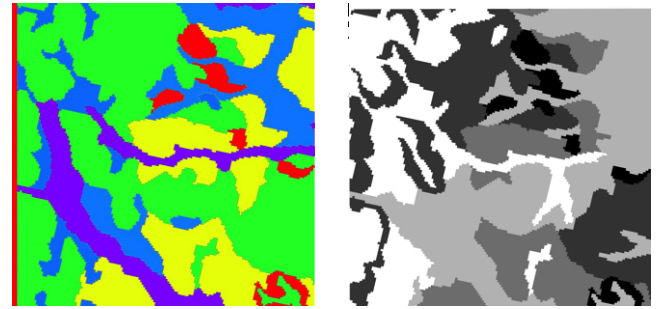
1. For each quantitative layer's image
 - a Multiply the image by its weight.
 - b Map the resulting image to the grayscale color space.
2. Compose the weighted images as one image.
3. Map the resulting image from step 2 to the grayscale color space.
4. Create the final image in the HSV or HSL color space:
 - a Assign the categorical layer's image to the Hue channel
 - b Assign the resulting image from step 3 to the (Saturation, Brightness, Lightness or Transparency) channel
5. Stop

Output:

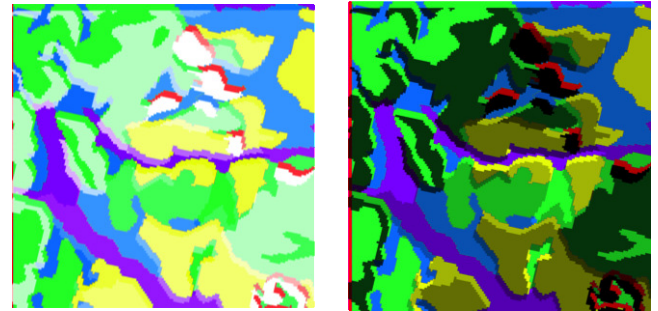
1. Composite image contains all map's layers.

3.1. User study

This study evaluated color use in map reading. In each trial, Participants were presented with a colored map; all maps showed a base soil-type layer, but differed in how they showed the values of the quantitative layer, Figure 3. Each map had two candidate areas of land, which were graphically marked off in equal sized 2 boxes. Subjects were asked to choose which area had the most vivid color



(a) The hydric soil layer, 5 categories are mapped to 5 hues in the Hue channel. (b) The available water layer is represented in the grayscale color space.



(c) The hydric soil and the available water layers are mapped to Hue and Saturation channels respectively. (d) The hydric soil and the available water layers are mapped to Hue and Brightness channels respectively.

Figure 2: Mapping map's layers to the visual channels to represent different map's layers in one image.

(e.g. more water, slope, or solar aspect) and therefore is more suitable for planting. The pair of boxes showed the same soil-type category (represented by the same Hue); the difference between the two boxes varied as follows: there were 4 trials for each condition, the mapped quantitative layer values had relative differences of (25%, 34%, 50%, and 75%) for each pair of boxes respectively. So that that the four relative differences are constant across all conditions setups.

In total, we had 40 samples (trials), 12 samples with the quantitative layers mapped to Brightness, 12 samples with the quantitative layers mapped to Saturation, 8 samples with the quantitative layers mapped to Transparency and 8 samples with the quantitative layers mapped to both Brightness and Saturation.

3.2. Participants

85 participants took the survey, but only 75 participants answered all the questions. The majority of participants were university graduate students (45 females and 30 males). Ages ranged from 19 to 45+, and the median age was the 26-34 range. Although only 3 of the participants answered 'yes' to the question "Have you ever experienced color blindness?" all participants passed the online test for color blindness [Ish87].

3.3. Procedures

This study was administered as a web survey using Virginia.tech.qualtrics.com; the navigation was through a web browser as a desktop application. Each question was presented sequentially

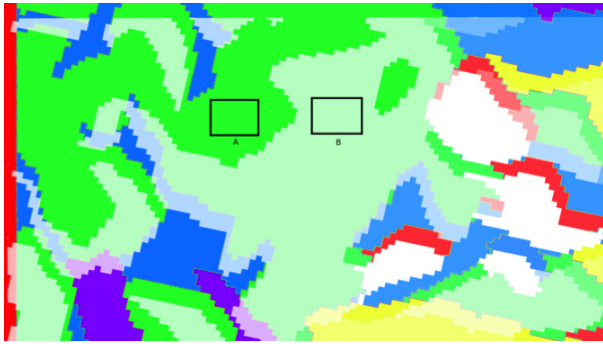


Figure 3: A sample image has the two boxes labeled A & B for the two colors the user should choose between.

in a random order. Participants were asked to judge color differences between two locations on the map (i.e. boxes A and B in Figure 3). They were given trial examples to help them understand the nature of the task.

Subjects were asked to choose which one of the two candidate locations had the more vivid/pure color. For each trial, they were asked to rate the difficulty of their judgment on a (7 point) scale that ranged between 'very easy' and 'very difficult'. Finally, subjects filled out questions relating to their background with map-reading applications. The session lasted approximately 30 minutes for each participant.

4. Results and discussion

4.1. Visual channel comparison

Our hypothesis posed that the Saturation channel was the best visual channel to represent quantitative layers. In order to test this hypothesis, we have run one-way ANOVA tests between Transparency, Saturation and Brightness assuming a null hypothesis that all means are equal with significance level of 0.05.

4.1.1. One-way ANOVA for accuracy

Accuracy here means correctness, which reflects if participants chose the location that has more vivid color (and hence has the higher value of the quantitative layer). According to the resulting p -value < 0.001 , the difference between the three means is statistically-significant. Figure 4 shows that the Transparency channel had the highest (0.93), the average score under the Saturation condition was 0.88, and the Brightness channel had the lowest average (0.59) correctness among the three channels.

The accuracy (correctness) test results showed that mapping quantitative layers to the Transparency channel outperformed the mapping to the other channels. We followed that with T-tests to compare the different mean values of each pair of visual channels. For p -values < 0.001 , Transparency is better than Brightness, and Saturation is better than Brightness. Also, a p -value of 0.004 between Transparency and Saturation shows that Transparency can support more accurate judgments.

4.1.2. One-way ANOVA for difficulty

In the same user study, we asked the participants to rate the difficulty of choosing the location with the highest quantity (the most vivid color). According to the p -value < 0.001 , there are statistically-significant differences in the mean values. Figure 4



Figure 4: One-way ANOVA: Comparing visual channel performance for accuracy and difficulty rating. Error bars represent standard error values.

shows that the Transparency (Alpha) has the highest (5.58) and the Brightness has the lowest average difficulty rating among the three channels (5.08). We followed that with T-tests to compare the difference between all pairwise mean values. For a p -value < 0.001 we can say that Transparency and Brightness have statistically significant different means of 5.58 and 5.08 respectively. Similarly, with a p -value of 0.006, we have strong evidence that Transparency and Saturation are statistically different (5.58 and 5.33 respectively). Also the T-test between Brightness and Saturation gave a p -value of 0.011, which led us to the same conclusion that the Saturation' mean difficulty ratings are higher than the Brightness' mean difficulty rating.

4.2. Color space comparison

In this study we have chosen to use two color spaces to test our approach for mapping the data to visual channels.

4.2.1. Accuracy

To evaluate correctness in the two color-spaces, we performed a T-test with the null hypothesis that the two color spaces means are equal with significance level of 0.05. A p -value < 0.001 indicates a statistically significant difference between the two means. Figure 5 shows that the HSV mean (0.8) is greater than the HSL mean (0.65). Therefore, participants were more accurate in choosing the correct location in the maps when the data was represented in the HSV color space.

4.2.2. Difficulty

To compare the two color-spaces by user ratings of difficulty, we performed a T-test with the null hypothesis: the two color spaces means are equal with significance level of 0.05. The resulting p -value of 0.354 indicates that there isn't enough statistical evidence to prove the difference between the two means (5.3 and 5.1), see Figure 6.

4.3. Color space and visual channel interaction

To test for the effect of the two factors (visual channel and color space) on the responses, we ran a two-way ANOVA test. Visual channel factor includes Saturation and Brightness, while color

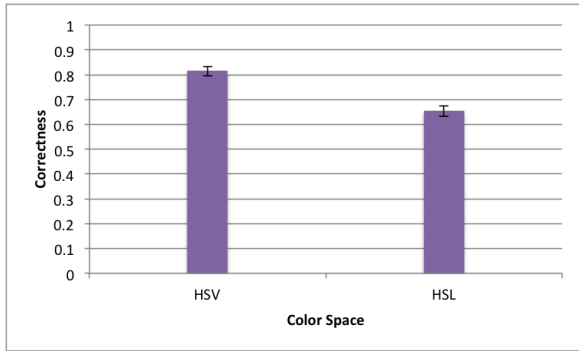


Figure 5: One-way ANOVA: Comparing color space performance for accuracy.

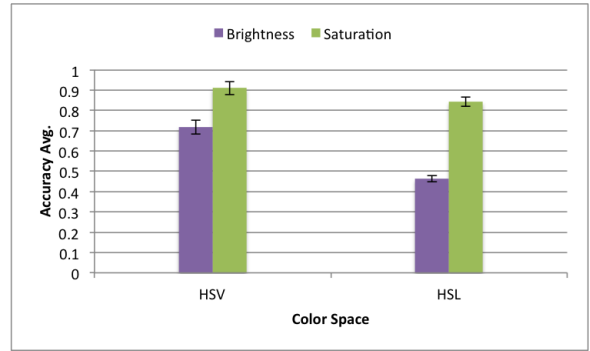


Figure 8: Two-way ANOVA: Visual channel and color space interaction on Accuracy. Error bars represent the standard error values.

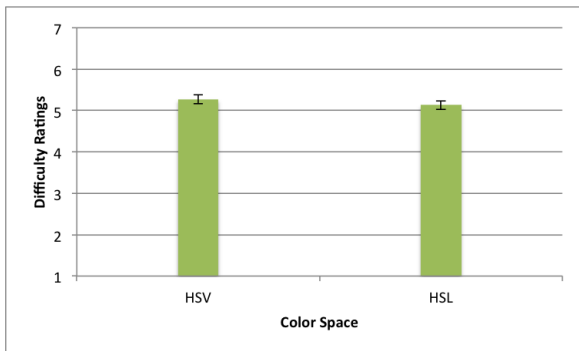


Figure 6: One-way ANOVA: Comparing color space performance for difficulty ratings.

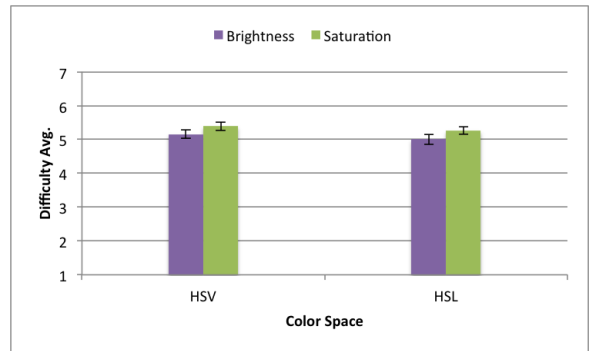


Figure 9: Two-way ANOVA: Visual channel and color space interaction on Difficulty ratings. Error bars represent the standard error values.

space includes HSV and HSL. The set of null hypotheses were: 1) The population means of the visual channels are equal, 2) the population means of the color spaces are equal, and 3) there is no interaction between the visual channel and the color space. The significance level for the test was 0.05, (Figure 7). We couldn't include the Transparency channel in the analysis because it doesn't belong to any of the color spaces. Moreover, it gives the same resulting images as either Saturation or Brightness depending on the image post assigned background (white or black mat).

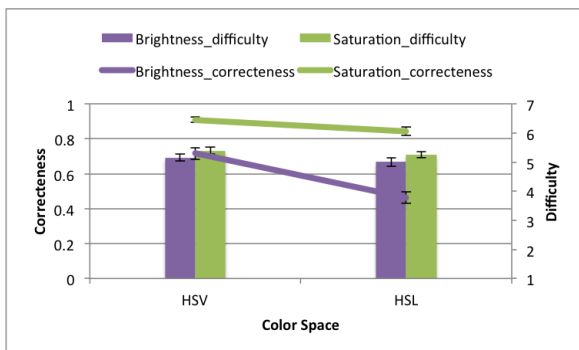


Figure 7: Two-way ANOVA: Visual channel and color space effect on Accuracy and Difficulty. Error bars represent the standard error values.

4.3.1. Two-way ANOVA for accuracy

For the first two null hypotheses the p-values were less than 0.001, so we rejected them. According to the p-value of 0.001, we rejected the third null hypothesis, which means that there was an impact of the interaction between visual channels and color spaces on the Accuracy (Figure 8).

4.3.2. Two-way ANOVA for difficulty

We did the same test on the users' difficult ratings for each trial where they had to choose the location on the map that had greater value of the quantitative layer. For the first null hypothesis (visual channels means are equal), the p-value was 0.01, which means there is a statistical significant difference between Saturation and Brightness. But for the second hypothesis (color spaces means are equal), the p-value was 0.354, which means we don't have enough evidence to verify the difference between HSV and HSL. Also for a p-value of 0.265, we can't reject the third null hypothesis (there is no interaction between the visual channel and the color space); consequently, we didn't have enough statistical evidence to say there is an impact of the interaction between visual channels and color spaces on the difficulty ratings, Figure 9.

4.4. Color space, visual channel and spectral relative difference (SRD) interaction

We ran a three-way ANOVA to test for the interaction of the three factors (color space, visual channel and SRD) on the responses. For this test, the values for the three factors are as follow: HSV and HSL

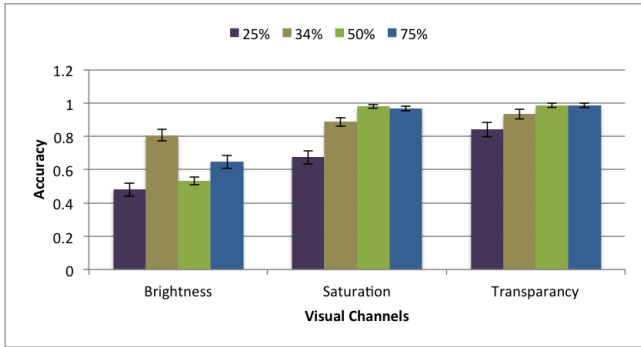


Figure 10: Visual channel and spectral relative difference interaction on accuracy.

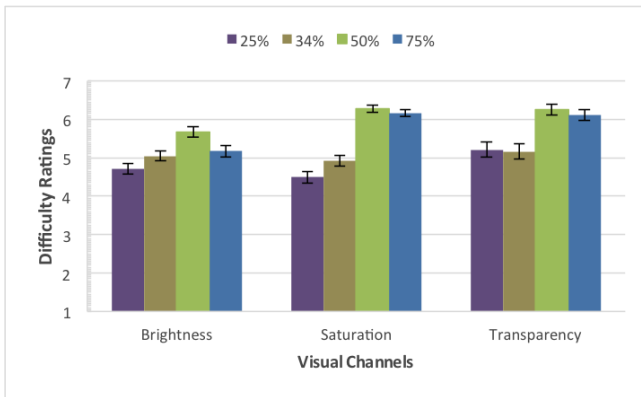


Figure 11: Visual channel and spectral relative difference interaction on difficulty.

color spaces, Saturation, Brightness and Transparency visual channels and (25%, 34%, 50%, and 75%) spectral differences. There was a statistically significant three-way interaction between color space, visual channel and spectral difference, $p < 0.001$.

4.4.1. Visual channel and SRD interaction

For both accuracy and difficulty there was a statistically significant interaction between visual channel and SRD with $p < 0.001$. For correctness (accuracy), Transparency and Saturation channels have the same performance trend: as the spectral relative difference increases the accuracy increases. On the other hand, Brightness accuracy has its maximum in the 34% SRD (Figure 10). For difficulty rating, Brightness and Saturation hit their lowest in the 25% SRD, but Transparency has its minimum difficulty rating with the 34% SRD. Also it is noticed that Transparency and Saturation followed the same trend, with the highest difficulty rating reached in the 50% and 75% SRDs (Figure 11).

4.5. The effect of demographic data on accuracy and difficulty

All participants took a pre-questionnaire containing questions related to some criteria that might affect their performance in the experiment such as gender, age, if they were diagnosed with color blindness, wearing glasses or contact lenses, if they used mobile devices displays to take the survey, and their experience in map reading. We calculated the Spearman correlation coefficients to test for the monotonic relationships between these data and users' performance. According to the Spearman R values in (Table 1) there

were no correlation between any of the demographic data and the user performance for both accuracy and difficulty.

Table 1: Correlation coefficients between demographic data and visual channels performance for correctness and difficulty.

Criteria	Transparency	Brightness	Saturation
Accuracy			
Gender	-0.13	0.02	-0.19
Age	-0.05	-0.24	0.05
Map Reading	-0.04	-0.12	0.04
Wearing Glasses	0.07	0.23	-0.02
Color Blindness	0.24	0.11	0.32
Display Size	-0.17	-0.02	-0.05
Difficulty			
Gender	-0.10	-0.12	-0.04
Age	-0.09	-0.12	-0.07
Map Reading	-0.15	-0.11	-0.17
Wearing Glasses	0.17	0.18	0.14
Color Blindness	0.29	0.16	0.30
Display Size	-0.08	-0.13	0.13

5. Conclusions and future work

We have examined techniques for composing multivariate maps using different visual channels according to data type; according to the results and the user study, we recommend mapping categorical layers to the hue channel and the quantitative layers to the Saturation channel. Although the Transparency channel had the highest mean value for accuracy, it has also the highest mean value for difficulty rating compared to the other channels. The results also showed that using the Brightness channel to represent the quantitative data layers had significantly lower accuracy.

The average values of the difficulty ratings for the three channels ranged from 5 to under 6, which correspond to the 'somewhat difficult', and 'difficult' options on the point scale. One explanation for this result is that participants were anxious about their performance choosing the best location on the map because they didn't receive feedback as to whether they chose the correct answer or not. Comparing the statistical analysis of the accuracy vs. difficulty derived this explanation.

Although the Transparency channel had the largest average value for accuracy, it also had the largest average value for rating difficulty. The opposite happens for the Brightness channel, where the one-way ANOVA and T-test for difficulty results showed that there was a statistical difference between the conditions. Participant's average response for difficulty was closer to "somewhat difficult" option for Brightness and Saturation but closer to "difficult" option for the Transparency channel.

Despite this low subjective rating, the Transparency channel might be attractive because it is a color-space independent channel. However, in this case, mapping quantitative layers to the Transparency channel results in the same images as when the layers were mapped to the other channels of the color space. For example, setting a white background for the resulting image, the Transparency channel yields the same output as the image derived from mapping to the Saturation channel. But setting the background as Black, the derived image is the same as that output from the mapping to the Brightness channel. As the HSL color space ranges from black

to white with the pure colors in the middle, it has the problem of ‘washing out’ the colors at extreme values (i.e. the lowest and highest data values).

According to these study results, we recommend using the Saturation channel to represent the quantitative layers in the HSV color space. The statistical analysis along with the resulting images support the use of this method to represent quantitative values in color spaces and channels.

Our research continues as we search for other graphical representations that can support more variables for visual differencing. Although we didn’t design our hue mapping function to overcome the problem of red-green color perception, we recommend using other color spaces designed for people with red-green color perception deficiencies such as Isolum in [GL13].

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