

# Quantitative Analysis and Development of New Color Tables for Mountain Ecosystems in Colombia

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## 1. Introduction

Color has always been a fundamental vehicle of communication. An observer, by the means of color pattern perception, creates references, codes, and signals of identity that make him part of his surrounding environment. Nature is the primary source that gives man the ability of differencing millions of color shades, depending on the wave longitude of reflected light. These photometric magnitudes are obtained through factors that correspond to the relative spectral sensitivity of the visual system, based on receptors in the eye that allow the detection of different levels of color intensity.

However, there are other aspects that influence the perception of color. Visual stimuli from the surroundings of a scene and characteristics of natural landscapes derive on different perceptions of the environment. Also, we can find cultural [1] and linguistic [2][3] differences in the perception and recognition of color amongst several demographic groups. Variables such as age [4], gender [5], mental [6] and optical [7] ailments affect the capacity of categorization and identification of color shades.

For this reason, environmental and cultural adaptation plays a critical role when determining color schemes. For instance, Eskimos [8] are able to differentiate a significant amount of white and blue shades, while at the same time they cannot differentiate green color shades. Such conditions bring some interesting questions: What is the influence of the surroundings of a subject in his perception of color? To what extent operates this influence, in terms of his adaptation?

While these are big questions that are already been given attention from different disciplines such as Psychology and Biology, among others, we can contribute to answer these questions by formulating a more specific one that is the object of this study: *What are the representative colors of an ecosystem?*

Color scheme identification and generation deals with the extraction, by an expert or by computer, of the representative colors of a scene. It has many important application fields, e.g. textile, product, interior and exterior design, architecture, and enables the possibility of generating palettes that 1) convey a message 2) can be used for the quantitative analysis of a given scene (e.g. to calculate the amount of deforestation of a given zone using satellite images).

Given the variability of the 'manual' or 'by eye' recollection of these palettes, and its subjectivity given by the factors exposed above, it is desirable to have an unbiased method for color scheme extraction. Nowadays, automated methods for this task are widely used, easing the tasks of generating, selecting, comparing and sharing these palettes. However, these tools for palette generation are based in color extraction of just an image, which rarely holds the whole spectrum of color shades

found in an ecosystem.

Thus, a method for scaling this process to a whole region is needed, in order to get an insight into its variety and richness of colors, as well as opening the door to more detailed analyses. In this paper we will describe, from our experience in a mountain ecosystem, important aspects to take into account in the capture and analysis of several digital images of a given zone, as well as results from this analysis. The case study takes place in a mountain ecosystem at 2600 m., with an ample degree of biodiversity in its forests, offering several shades of green that contrast with environmental phenomena such as mist and rain.

Results of the project helped on achieving a greater understanding of the natural Colombian scenario. Taking color as a perceptual identification tool that emphasizes in communication at various levels, the exercise resulted in daring color tables showcasing the variety of green tones in Colombian ecosystems, with application in several contexts, such as interior design, clothing, urban landscaping, and product design.

## **2. Visual Perception and Extraction of Representative Colors**

The complexity and amount of surrounding information of an environment suggests the need of abstraction mechanisms for a better understanding. Consider the way an expert human observer makes a reconnaissance of a given region. In his search for colors and patterns, the observer tries to capture the dominant colors of the environment. Since we are examining this process of color extraction, and in order to automate certain parts of it, it is useful to first choose a visual search model. These models are based on the notion of *objects of interest* and *distracting objects*. Thus, the effectiveness of this search is mediated by several factors, such as the density (number of objects) of each type, as well as luminance conditions on a given instant.

With an interesting view in this subject, Ramachandran [9] compares human perception to machine visual detection. The author considers that images are inherently ambiguous, and perception ‘fills the gaps’ caused by this ambiguity with additional information that is outside of the image, e.g. previous knowledge from the observer. Despite the author’s focus on moving images, he argues that the human visual and cognitive system can be seen as a ‘bag of tricks’ that contains adaptive heuristics that have been developed through millions of years of trial and error, in order to resolve specific problems.

With this in mind, we can examine certain aspects of vision and detection: De Vries [10] studies the nature of object detection based on the movements of the human eye. The author examines *Saccadic* movements, which are a quick movement of both eyes in the same direction, with the purpose of processing and rapidly constructing a mental map of a scene. This eye movement is supported by two strategies: stimuli-based *saccades*, and goal-based *saccades*.

### **2.1. Digital Capture of Color Shades**

We can represent these *saccades* made by an expert by using a digital camera and a post-processing of the resulting images under any of the known and widely used image processing algorithms [11]. These algorithms, such as k-means clustering, or

pixel-to-pixel average (Fig.1), are context-free algorithms, i.e. they do not consider other images as related, and do not prioritize the different regions of interest of an image. For instance, consider Fig. 1. There is a forest in the middle of the picture, which is our main region of interest. However, we would also like to consider (to a lesser extent) the grass region of the image, as it also makes part of the environment. Moreover, there are details (such as the clouds and foggy mountains) that we certainly do not want to consider in our analysis.



Fig. 1 – Sample image from a mountain ecosystem. Sky, fog and grass greatly influence the average colors of the image.

Thus, a generic image approach is not very useful to our problem (Fig. 2), as the average colors of the scene are clearly influenced by the white firmament, resulting in ‘washed’, i.e. light colors. In order to propose a method for color extraction, we have to consider aspects observer, taking into account factors such as his field of view. Then, we have to assess the ecosystem and its surroundings, picking representative zones for analysis. Finally, there are some considerations in terms of the image quality and sampling.

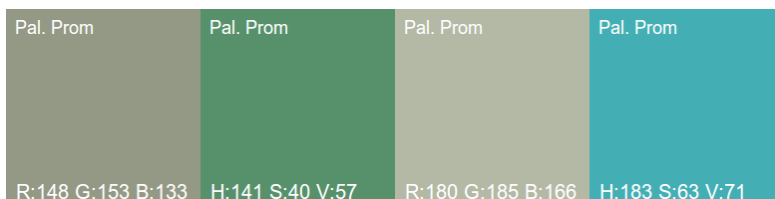


Fig. 2 – Corresponding Global Average palette from Fig. 1.

## 2.2. The System of Study

An ecosystem is composed by a large number of subsystems that share a breadth of similar properties, such as flora, fauna, vegetation coverage, and microclimates, among others. This is a challenge in countries such as Colombia, which presents more than 300 ecosystems [12].

### 2.2.1. Location and trajectory



Fig. 3 – Sequence of five distances starting on a given scene (rightmost image). Note the changes in illumination.

It is certainly difficult to capture in just an image the richness of colors and shapes from an ecosystem. Even if we consider a set of representative scenes, it is difficult to grasp the different tonalities present if we do not consider its surroundings.

### 2.2.2. Region of Interest

Aspects such as the climate and weather of the ecosystem have an impact in the illumination of a scene, and in consequence, of the perception and manifestation of color. In our case, our region of interest is the high mountain forest, which is characterized by its dark green and brown colors. However, as we scale our process to involve several locations of this forest, each one with a set of distances, and in a larger frame of time, it is inevitable that some unwanted or less important elements appear in a photo.

For instance, as the observer enters e.g. a clear field on a forest (Fig. 1), the firmament and grass occupy a large region of an image. As described in Sec. 2.1, this affects the outcome of the analysis. Given that we do not want to discard this image, as it offers a glimpse on the surroundings of the zone, we need mechanisms for the detection of these less important regions of an image.

## 2.3. Image Considerations

Until now, we have discussed external aspects that revolve around the acquisition of images of a given ecosystem. However, there are some methodological issues in the processing of these images:

### 2.3.1. Resolution and Sampling

We must pay attention to the quality of an image at the different stages of analysis. When scaling an image, it is necessary to consider 1) the interpolation algorithm used for scaling, as well as 2) the resolution of the scaled image. Given that less pixels are representing the same scene, pixels of the scaled image must accurately represent the values of a neighborhood of pixels from the original image. The way on which a neighborhood is transformed into a pixel in the scaled image is the interpolation algorithm (See Fig. 4).



Fig. 4 – Nearest Neighbor vs. Bicubic Interpolation.

On the scaling factor, Fig. 5 shows a comparison of the histograms of the original image and a scaled one, where the reader can see the distortion in the RGB channels. It is therefore necessary to choose a resolution between 1600x1200 and 800x600 pixels, allowing a lighter image processing without significantly sacrificing color frequencies.

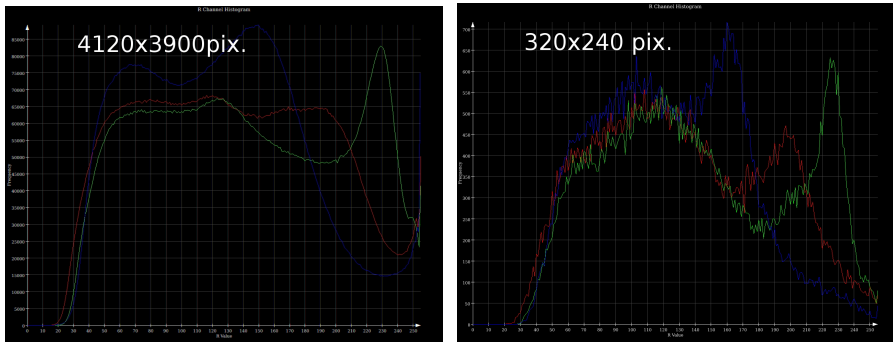


Fig. 5 – Histograms of a photograph, where we can see the distortion in the frequency of RGB values.

### 2.3.2. Variations in Lighting

Given that we are photographing uncontrolled environments, there are some variations in the amount of light of the scene (e.g. a passing cloud, occasional fog). Taking several images of the same scene, and combining them a posteriori can minimize the impact of these issues. However, this combination brings additional challenges (Fig. 6), such as the movement of the objects in the scene (e.g. wind in the foliage of trees), as well as unwanted movement of the camera when shooting.



Fig. 6 – Overlapping of three samples taken from the same scene, taken two seconds apart each one.

### **3. Methodology**

After taking into account the different issues in the capture and processing of these images, we describe a method for obtaining the representative colors. It involves three principal activities, namely Capture, Digital Processing and Assessment.

#### **3.1. Capture**

Images should be taken with a neutral (35-50 mm) focal length, resembling the human vision. High or Low-angle shots should not be used, as they distort the scene. Also, short (less than 1/250 second) shutter speeds are favored, as they offer defined contours of the objects in the scene.

As we are interested in sampling a considerable range of the ecosystem, there should be a marked set of zones. Each zone follows a path (Fig. 3) that should be subdivided in a set of equally distributed points (e.g. each 20 meters in a 100 meter path). This allows us to get a glimpse to a given spot and its surroundings. Each point of a given zone should be sampled several times, in order to compensate sudden changes in illumination and small movement.

#### **3.2. Digital Processing**

After the capture, we can start analyzing the color information of each image, and combine the result with the analysis. This sub-process is conformed by several tasks: 1) the preparation (normalization) of the images, 2) the partition of each image into channels of a given color space, 3) Segmentation of each channel by regions of

interest, and 4) Analysis of each segment. The output of this sub-process is average color information of the ecosystem that is the input for the next stage, *Assessment*.

### 3.2.1. Image Normalization

As described in the capture of the images, it is desirable to get several *samples* of a given *scene* to compensate sudden changes in illumination. This introduces a new problem, which is the synchronization of these samples (see Section 2.3.2). Here we can take advantage of an Image Registration algorithm [14][15], which seeks to minimize the difference between the samples. This involves the rotation and cut of the samples until the overlapped images are similar to each other, pixel to pixel (See Fig. 7).

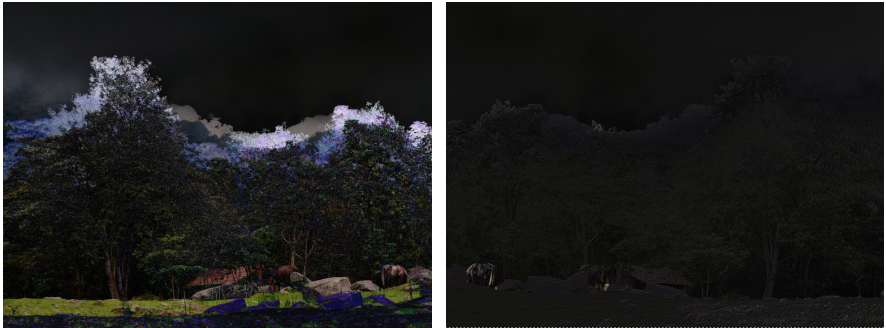


Fig. 7 – Images that represents the difference between (i.e. the subtraction of) three samples. Darker is better. **Left:** before Registration. **Right:** after Registration.

Optionally, all images can be scaled to a reasonable resolution (e.g. 1200x900 pixels, see Section 2.3.1). By reducing the number of pixels to be analyzed, the processing time of the images is also improved, without affecting significantly their histograms.

### 3.2.2. Channel Partition and Concavity Analysis

Each individual image is then separated into a set of grayscale images, each representing a channel in a desired color space, such as RGB or HSV (see Fig. 8 and 9). Each grayscale image represents the intensity of a given channel (e.g. red). Histograms of each of the partitioned images are extracted and a characterization of the histogram takes place, by searching peaks and valleys, with the aim of optimizing the next step, the segmentation of the image into regions of interest.

### 3.2.3. Segmentation

As described in Section 2, there are areas of an image that are more interesting than others. Thus, each grayscale image partitioned into Regions of Interest (ROI). For instance, the forest section (middle) of Fig. 1 is the most significant one, while a the grass section (bottom) would be of secondary interest, and the sky area (top) would be the least significant.

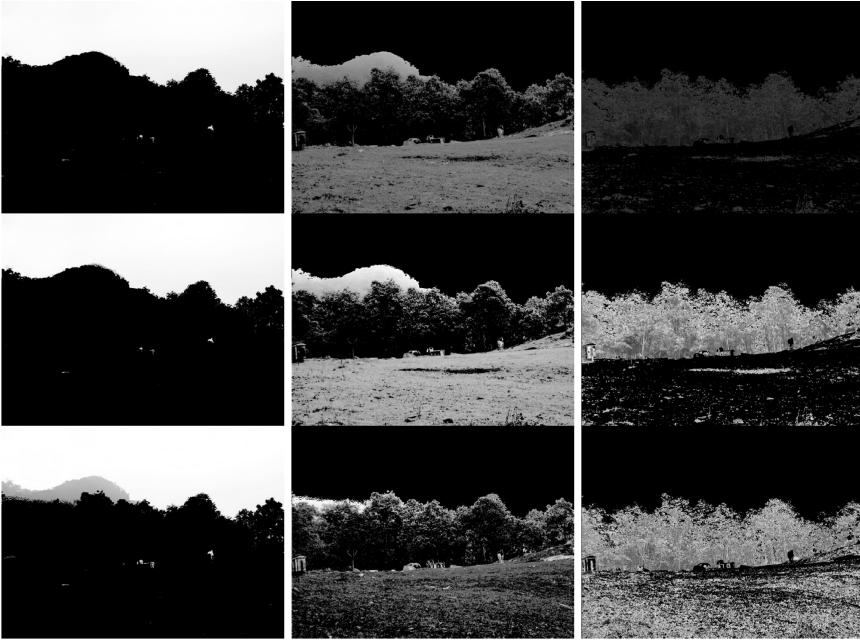


Fig. 8 – Channel partition (rows) and Region of Interest Segmentation (columns) of an individual scene in the **RGB** color space.

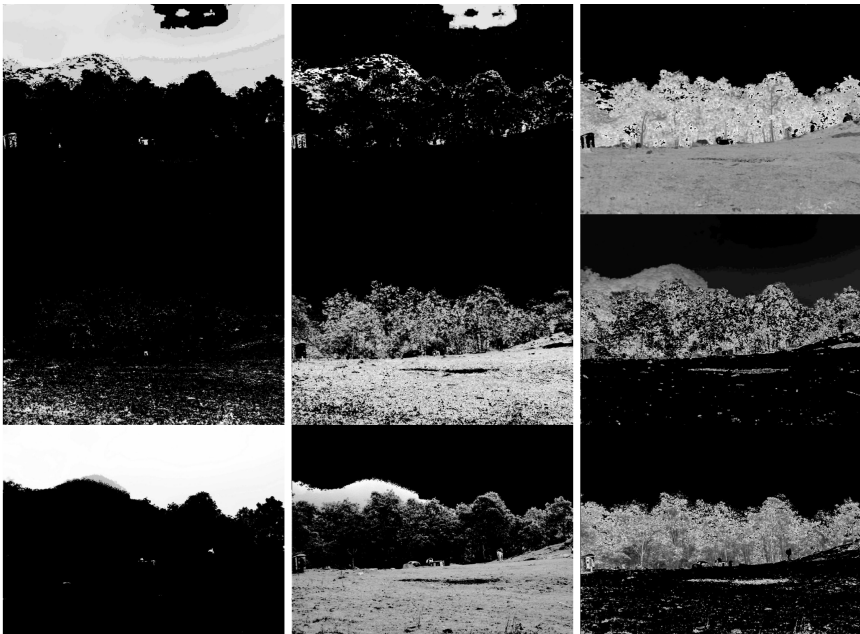


Fig. 9 – Channel partition (rows) and Region of Interest Segmentation (columns) of an individual scene in the **HSV** color space.



### 3.2.4 Segment Analysis

In order to obtain tentative color schemes from an image, we calculate the average, maximum and minimum intensities of every channel within each of the segments (the nine images of Fig. 8 and 9). With this information, we can obtain a set of colors that are representative to one image, that is, a *sample* of a *scene*.

After obtaining the representative colors of every image, we can merge this color information into a matrix that contains the consolidated color values, divided by zone, distance, channel, and region of interest.

### 3.3. Assessment

Finally, to obtain tentative color palettes of the ecosystem, we can process the matrix and assign weights to several criteria, e.g. the Regions of Interest found in the previous step, as well as additional information such as luminance.

Also, we can manipulate how the color information is combined, e.g. by considering only the maximum (or even average) color values of the images. This allows the proposal of several color palettes, assigning values that represent the contribution of each weight (e.g. sky, grass and forest regions of the image) to the resulting palettes.

## 4. Case Study: Chicaque National Park

We start from the photographic registry (Table 1) of an Andean Forest ecosystem, where we picked up three zones that most represented the terrain and flora of the ecosystem. For each zone, we selected a scene each 20 meters on a 100 meter range. Finally, for each distance, three samples were taken, resulting in a total of 45 photos that will be the object of our analysis.

Each image was taken with a Nikon D800 Full-Frame camera, with a focal length of 35 mm, aperture 5.6, and a resolution of 4928x3264 pixels and a RGB color profile. Intensities vary depending on the distance and environmental factors, tending to brighter registries on large distances, mostly caused by the apparition of firmament.

| Scene | Shots | Distance | Light intensity (lumens) | Height | Time of Day |
|-------|-------|----------|--------------------------|--------|-------------|
| 1     | 3     | 100m     | > 20.000 lux             | 2,220  | 10:53       |
| 2     | 3     | 80m      | > 20.000 lux             | 2,210  | 10:50       |
| 3     | 3     | 60m      | > 20.000 lux             | 2,208  | 10:47       |
| 4     | 3     | 40m      | 10.250 lux               | 2,202  | 10:44       |
| 5     | 3     | 20m      | 16.580 lux               | 2,147  | 10:36       |
| 6     | 3     | 100m     | 8.700 lux                | 2,186  | 11:12       |
| 7     | 3     | 80m      | 15.450 lux               | 2,196  | 11:10       |

|    |   |      |            |       |       |
|----|---|------|------------|-------|-------|
| 8  | 3 | 60m  | 12.800 lux | 2,194 | 11:06 |
| 9  | 3 | 40m  | 14.300 lux | 2,187 | 11:03 |
| 10 | 3 | 20m  | 19.300 lux | 1,188 | 11:00 |
| 11 | 3 | 100m | 5.000 lux  | 2,193 | 12:32 |
| 12 | 3 | 80m  | 8.200 lux  | 2,135 | 12:31 |
| 13 | 3 | 60m  | 9.700 lux  | 2,173 | 12:29 |
| 14 | 3 | 40m  | 9.200 lux  | 2,165 | 12:22 |
| 15 | 3 | 20m  | 11.800 lux | 2,142 | 12:20 |

Table 1 – Image capture of the three zones

Images resulting from the *Capture* were then processed using VTK and MeVisLab, two Image Processing and visualization frameworks.

#### 4.1. Results

The Assessment resulted in three tetra-chromatic palettes (see Fig. 10) that were generated using different criteria, but preserving the weights given to each Region of Interest. Sky and mist were ignored, while grass had a weight of 15% and the forest of 85%.

|                   |                   |                   |                   |
|-------------------|-------------------|-------------------|-------------------|
| Pal. Prom Normal  | Pal. Prom Normal  | Pal. Prom Normal  | Pal. Prom Normal  |
| R:81 G:90 B:69    | H:84 S:16 V:31    | R:121 G:133 B:104 | H:132 S:41 V:47   |
| Pal. MaxMaxMinMin | Pal. MaxMaxMinMin | Pal. MaxMaxMinMin | Pal. MaxMaxMinMin |
| R:118 G:134 B:118 | H:115 S:29 V:42   | R:82 G:81 B:56    | H:93 S:27 V:21    |
| Pal. Lum--++      | Pal. Lum--++      | Pal. Lum--++      | Pal. Lum--++      |
| R:44 G:48 B:37    | H:46 S:9 V:16     | R:149 G:164 B:128 | H:161 S:50 V:57   |

Fig. 10 – Final palettes. **Top**: Average. **Middle**: Maximums and Minimums. **Bottom**: Maximum and Minimum luminance.

The first palette is obtained by getting the average colors of each image. The second one, by getting maximum and minimum RGB and HSV values, and the last one, by getting the shades with maximum and minimum luminance.

## 5. Conclusion

Extraction of the representative colors of an image is a widely used technique for generating color schemes. However, this is constrained to carefully selected images, where all the regions of these images are considered equal. In addition, this process does not scale for larger environments, as partial results of each scene are not combined.

In this paper we describe some of the factors that make this process a difficult one, and outline a method for scaling the extraction of representative colors to wider extensions. This involves the capture of several samples of multiple scenes on the terrain, as well as their digital processing. This method is applied to a mountain ecosystem, and resulting color schemes provide an overview of the representative colors of the environment.

Benefits of the automation of the analysis of the captured images include more accuracy in the extraction of the representative colors, as well as flexibility in the selection of color palettes by several factors.

This research opens the gates to a deeper analysis of ecosystems, and research opportunities include the extraction of representative shapes and patterns of such ecosystem.

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