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Perceptual display strategies of hyperspectral imagery based on PCA and ICA

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ABSTRACT

This study investigated appropriate methodologies for displaying hyperspectral imagery based on knowledge of human color vision as applied to Hyperion and AVIRIS data. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) were used to reduce the data dimensionality in order to make the data more amenable to visualization in three-dimensional color space. In addition, these two methods were chosen because of their underlying relationships to the opponent color model of human color perception. PCA and ICA-based visualization strategies were then explored by mapping the first three PCs or ICs to several opponent color spaces including CIELAB, HSV, YCrCb, and YUV. The gray world assumption, which states that given an image with sufficient amount of color variations, the average color should be gray, was used to set the mapping origins. The rendered images are well color balanced and can offer a first look capability or initial classification for a wide variety of spectral scenes.

Keywords: Hyperspectral Imagery, Visualization, Opponent Color Spaces, Human Color Vision

1. INTRODUCTION

Hyperspectral imagers that can measure spectra at more than 200 narrow, contiguous bands have been developed in recent years. With the increasing number of bands which extend to near, short-, mid-, and long-wave infrared and ultraviolet spectral regions, the remotely sensed hyperspectral imagery provides finer spectral resolution, yet presents challenges for data visualization techniques for display of the information content of such datasets since there are many more bands than can be displayed on a tristimulus display.

Traditionally, one can map three widely spaced bands to display R, G, B channels in hopes that they are minimally correlated and able to capture large-scale image variations, for example, one can present a long-, mid-, and short-wave visible band as an RGB image to approximate what a human observer would see. Since these bands are spectrally separated, they are likely to be minimally correlated. When the chosen three bands are highly correlated, decorrelation stretch algorithm[1] can be used to remove the inter-channel correlation and enhance (stretch) the color separation in the final image. Another conventional approach is to choose three specific bands to highlight a particular spectral feature, for example, the absorption peak of water. For this highly specialized mapping, it is possible to predict the perceived color for highlighted materials but may overlook other important spectral signatures.

To take more than three bands into account, the number of bands can be extended to cover the visible region of the spectrum. A true color image can be constructed by using human color matching functions. However, how can the hyperspectral information from a portion of the spectrum not perceived by humans be presented in a manner that is more easily understood? With the similar idea of constructing a true color image, a false color image may be constructed by using three linear spectral weighting functions[2] on hyperspectral imagery, such as stretched human color matching functions, Gaussian functions, piece-wise linear functions, etc.

Another approach related to human color perception is based on the intensity-hue-saturation (IHS) model.[3] In this method, intensity represents the amount of light and can be defined as the maximum value of the spectral distribution or a measure integrating the signal in each band such as the mean value of signals in all bands; hue corresponds to the dominant wavelength of the spectral and can be expressed as its mean wavelength; and saturation can be measured by a

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parameter that describes how the distribution peaks around hue, such as the standard deviation. Once IHS components are obtained from the spectral data, they can be transformed to RGB for display.

The above approaches take into account the trichromatic theory of human color vision or perceptual color attributes to some degree, but do not take into account the statistics of the scene. Due to very close spectral sampling of hyperspectral sensor, hyperspectral imagery is generally highly correlated between bands. The dimensionality of such data set may be reduced by some data projection approaches and some interesting subsets of the original data may be obtained and then used as a visualization tool. PCA is a widely used method for such a purpose. One typical approach for presenting PC images in a pseudocolor display is to directly map the first three PCs into display R, G, B channels. However, the direct mapping method maps the orthogonal PC data into non-orthogonal display channels, which does not take advantage of knowledge about human color vision. In order to create images that present the rich information available from spectral sensors in a readily interpretable manner, it was thought helpful to incorporate knowledge of human color processing into display strategies for spectral imagery.[4] As an attempt of such approach,[4] Tyo, et al. mapped the first three PCs into HSV conical space with a method of manually locating the origin by identifying pixels with spectral characteristics that can be assumed to lie in the same direction within the cone.

This study investigates the application of color and human vision system in visualization of high-dimensional remote sensing products and develops PCA- and ICA-based visualization schemes based on principles of human vision and color perception for more efficient data presentation and interpretation.

2. BACKGROUND

It is well known that the human vision system processes color by means of an achromatic channel and two opponent-chromatic channels, which is called the opponent-color model of human color perception. One mathematical explanation for the reasons of the opponent color encoding was based on a PC analysis of the spectral sensitivities of the three types of photoreceptors.[5] It was demonstrated that the achromatic, red-green opponent, and yellow-blue opponent color processing channels represent statistically non-covariant information pathways. Performing a similar PC analysis on hyperspectral imagery that are often highly correlated between bands, uncorrelated output bands can be produced. This is done by finding a new set of orthogonal axes that have their origin at the data mean and are rotated so the data variance is maximized. The PCs are the eigenvectors of the correlation or covariance matrix, and the transformed PC bands are linear combinations of the original spectral bands and are uncorrelated. The first PC accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. Generally, the first 3 PC bands can explain more than 95% of the entire variance. A display strategy can be developed by mapping the first three uncorrelated orthogonal PCs to an opponent color space.

As opposed to uncorrelated orthogonal PCA, ICA is a statistical and computational technique that extracts independent source signals by searching for a linear or nonlinear transformation that minimizes the statistical dependence between components.[6] It finds a non-orthogonal coordinate system in any multivariate data that minimizes mutual information among the axial projections of the input data. The directions of the axes of this coordinate system are determined by both second-order and higher-order statistics of the original data. The goal of ICA is to perform a transform that makes the resulting source outputs as statistically independent of each other as possible. ICA has also been considered as a method to analyze natural scenes. Much interesting research[7,8] has been conducted to investigate the spatial and chromatic structures of natural scenes by decomposing the spectral images into a set of linear basis functions using ICA. Wachtler, et al.[8] applied ICA to hyperspectral images to determine an efficient representation of color in natural scenes. Their finding suggests that non-orthogonal opponent encoding of photoreceptor signals leads to higher coding efficiency and is a result of the properties of natural spectra. This may be another explanation for why the human vision system processes color via opponent channels. Therefore, in addition to PCA, ICA may be used to reveal the underlying statistical properties of color information in natural scenes.

Because of their underlying relationships to the opponent color model of human color perception, PCA and ICA were used in this study to reduce the data dimensionality in order to make the data more amenable to visualization in three-dimensional color space.

3. DATA PROCESSING AND PERCEPTUAL RENDERING

Two sets of data were used in this study for initial analysis. One is an urban[9] image of an area near San Francisco from the Hyperion[10] sensor on the Earth Observing 1 (EO-1) spacecraft. This sensor can image a 7.5 km by 100 km land area per image in 220 spectral bands ranging from 0.4 to 2.5 μm with a 30-meter resolution per pixel. With removal of some bad bands, only 196 spectral bands were used. The other one is a spectral subset of the 1995 overflight of Cuprite Mining District, NV from the AVIRIS sensor. This sensor has 224 spectral bands also ranging from 0.4 to 2.5 μm in wavelength. The data used in this study is from the ENVI software package and only covers 50 equally spaced spectral bands from 1.99 to 2.48 μm (AVIRIS bands 172 to 221). For both datasets, the radiance data was used in the following PCA and ICA processing.

The PCA was implemented in MATLAB using functions *cov* to calculate the covariance matrix and *pcacov* to do the eigen analysis. For the Hyperion data, the percentage of the variance explained by the first three PCs is 74.56%, 21.54%, and 1.95%, respectively, resulting in a total of up to 98.05% of the entire variance. For the AVIRIS data, the first three PCs contained 98.51% of the entire variance with the first PC explained 90.00%, the second PC 6.35%, and the third PC 2.16%. The ICA was accomplished using the free JadeICA package,[11] which includes a MATLAB program that implements off-line ICA based on the (joint) diagonalization of cumulant matrices.

Shown in Figure 1 are the images by directly mapping the three PCs and ICs to display R, G, B for both data sets. This conventional mapping method for presenting PC images in a pseudocolor display solves the problem of seemingly arbitrary choice of bands to map into an RGB image. Since the PCs and ICs sample the entire spectral space, prominent spectral features will be more likely included in the final color image and the PC-based method also reduces the chance of any feature being completely missed. However, the drawback of the direct mapping method is that the orthogonal PC data is mapped into non-orthogonal display channels, and it does not take advantage of knowledge about human color vision.[4]

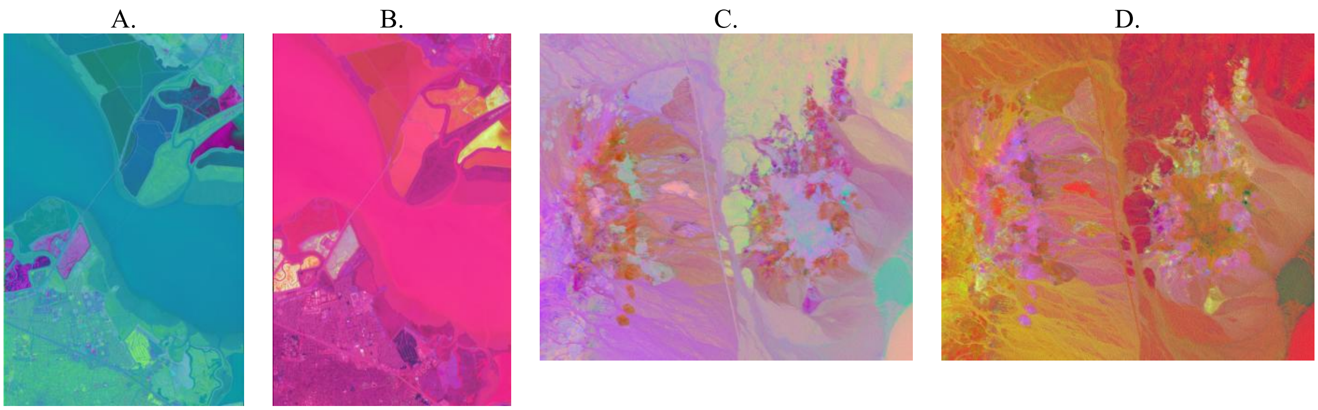

Figure 1. Images by directly mapping the first three PCs or ICs to display R, G, B. A. PCA on Hyperion. B. ICA on Hyperion. C. PCA on AVIRIS. D. ICA on AVIRIS.

In order to create images that present the rich information available from spectral sensors in a readily interpretable manner, it would be helpful to incorporate knowledge of human color processing into display strategies for spectral imagery. This study explored PCA and ICA-based perceptual visualization strategies by mapping the first three PCs or ICs to several opponent color spaces including CIELAB, HSV, YCbCr, and YUV.

It has been widely recognized that to specify and control color representations in perceptual terms is more intuitive and may make such representation more accurate and effective.[12] Ideally, a uniform color space, dependent on the color discriminating ability of the human visual system, is desired so that perceived differences in color accurately reflect numerical data differences. However, considering that the error due to uniformity may be minor compared to the much larger and systemic errors caused by the effect of spatial induction, which can alter the apparent lightness, hue, or saturation of a surrounded color quite substantially, exact uniformity of the color space is unlikely critical. Here, four opponent color spaces were chosen both for investigating different options and for comparison. CIELAB is a widely accepted device independent perceptual color space derived from experiments on the perception of just-noticeable color differences. In CIELAB space, the lightness axis is defined as orthogonal to the two opponent color axes. Hue and Chroma can be defined using the two opponent color axes. Using CIELAB, one can also specify the reference illumination. HSV is a commonly used model in computer graphics applications. In this model, value (lightness) is decoupled from the color information that is described by hue and saturation. It is more intuitive than display RGB model. YCrCb is the standard for DVD video. It is the method of color encoding for transmitting color video images while maintaining compatibility with black and white video. In this color space, Y is the luminance component and Cr and Cb are the chrominance components. This model uses less bandwidth and has advantages in signal compression. YUV is another widely used color space for digital video in which the Y channel contains luminance information while the U and V channels carry color information. This model is very similar to YCrCb in that they both separate chrominance from luminance but they are not identical.

The underlying relationships between PC and IC analysis of hyperspectral imagery and the opponent color model of human color perception suggest an ergonomic approach for display of the data, in which the first PC or IC is mapped to the achromatic channel while the second and third PCs or ICs are mapped to the red-green and yellow-blue chromatic channels in a color space, respectively. Specifically, for each color space, the mapping strategy is as following:

1) For CIELAB: $PC_1 \to L^*$, $PC_2 \to a^*$, $PC_3 \to b^*$
2) For HSV (as in Tyo, etc.[4]): $\text{atan}(PC_3/PC_2) \to H$, $\sqrt{PC_2^{\,2} + PC_3^{\,2}}\,\big/PC_1 \to S$, $PC_1 \to V$
3) For YCrCb: $PC_1 \to Y$, $PC_2 \to Cr$, $PC_3 \to Cb$
4) For YUV: $PC_1 \to Y$, $PC_2 \to U$, $PC_3 \to V$

Given the mapping strategies, one important problem still remains in the practical implementation: That is, in order to make a good visualization of the data with enhanced visual appearance, how does one set the mapping origin? In color science, there is a gray world assumption[13] about the general nature of color components in images that states that given an image with sufficient amount of color variations, the average color should be a common gray. This assumption is generally made for color balance and color constancy problems, but it may be a choice for the setting of mapping origins. Therefore, rather than directly mapping the origin in PCA or ICA space into the origin in specified color space or manually setting the origin by supervised method,[4] with the gray world assumption, an automatic method is to set the mean value of the PCA or ICA data as the origin in PCA or ICA space. Then a piecewise linear mapping was performed. After the mapping, stretching (normalization) or clipping may be applied when necessary in order to fit the display gamut. The resulting images in different opponent color spaces are shown in Figures 2-5. Figure 2 is for the Hyperion data with PCA processing and Figure 3 is for the Hyperion data with ICA processing. Figure 4 is for the AVIRIS data with PCA processing and Figure 5 is for the AVIRIS data with ICA processing.

4. OTHER VISUALIZATION TECHNIQUES

In addition to the perceptual renderings of the hyperspectral imagery based on PCA and ICA, several other common methods were also implemented in this study. The results from these techniques are shown in Figure 6 and 7 and can serve as a baseline for comparison purposes.

The images shown in Fig. 6A and Fig. 7A are three widely spaced bands (see Fig. 6 and Fig. 7 captions for band wavelengths) mapped to display R, G, B channels. This method is simple and convenient, but the drawbacks are that there are many possibilities for choosing the three bands that will result in different color renderings. Spectral features that do not overlap with the chosen bands will not be presented in the final image. There is no statistical analysis being considered for choosing the three bands in this method.

The images shown in Fig. 6B and Fig. 7B used the same three bands as in Fig. 6A and Fig. 7A, but were obtained by applying the decorrelation stretch algorithm. This algorithm[1] first finds the linear transformation that results in decorrelated vectors based on scene statistics, then performs a contrast stretching in the transformed space by forming a stretching vector according to the eigenvalue vector, and then transforms back to form the final output image which is color enhanced. This method is best suitable to the case where the three input bands have joint Gaussian (or near Gaussian) distribution. If the distribution of the input channels is strongly bimodal (or multimodal), the decorrelation stretch will be less effective and will result in images with less diversity of colors. Another limitation of the decorrelation stretch algorithm is in that it also uses only three of the available bands to generate the output image, which will necessarily result in information loss as all three-band representations do. Comparing Fig. 6B and Fig. 7B with Fig. 6A and Fig. 7A, it is seen that the images are color enhanced by the decorrelation algorithm.

Shown in Fig. 6C is a “true color” representation of the Hyperion imagery constructed by applying human color matching functions to the visible spectral bands. (The method was not applied on the AVIRIS data because there are no visible bands included in the available 50 bands). This approach is based on the trichromatic theory of human color vision. It is known that there are three types of receptors in human eyes, which are approximately sensitive to the short, medium, and long wavelength regions of the visible spectrum. Given the receptors’ spectral sensitivities, the stimuli’s spectra, and the spectral power distribution of illumination, the color of the stimuli can be calculated. The rendering of the color on a display can be done by display colorimetric characterization or by utilization of standard color space such as sRGB. This method can create consistent natural representations of spectra imagery as a human observer would see, which may facilitate understanding and analysis of the scene. It may also be useful for visualizations incorporating the fusion of information on a base layer that is visually relevant to the scene.

Linearly stretching the human color matching functions to cover the whole spectral range is another approach to form a color representation as shown in Fig. 6D and Fig. 7C. In fact, the human color matching functions is just one set of all possible linear spectral weighting functions, though it may be the most meaningful one with respect to human visual system interpretation of natural scene. Shown in Fig. 6E and Fig. 7D are results using Gaussion functions as the weighting functions. This method may work well if the weights were adjusted appropriately or may result in images with poor contrast and diversity of color. It might be helpful to interactively adjust the parameters of the weighting functions.

Fig. 6F and Fig. 7E represent images from the IHS model.[3] This method is simple and may produce consistent color composites. However, it is only able to display the global characteristics of spectral distributions.

5. DISCUSSION

The perceptual mappings explored here capitalize on the underlying relationships between the PC and IC channels in hyperspectral imagery and the opponent color-processing model of human vision system. The first PC or IC channel, which generally contains high spatial information, is mapped into the achromatic channel, and the second and third PC or IC, which generally contains low spatial information, is mapped into the two opponent chromatic channels. The fact that the contrast sensitivity function in the achromatic channel is band-pass in nature and sensitive to higher spatial frequencies while the chromatic channels are low-pass in nature with lower frequency cut-offs has the implication that the achromatic channel is critical in carrying relatively high spatial frequency information while the chromatic channels are critical for carrying low spatial frequency information. Therefore, this mapping strategy nicely matches the spatial frequency structures of the PC and IC images with the spatial sensitivity of the corresponding channels.

With the abilities of capturing the underlying cluster structure of a high-dimensional data, the PCA and ICA based mapping strategies provide an easy way to perform first-order unsupervised classification. The resulting images are segmented spatially based on the projection of the local radiance distribution into the first three basis vectors. Materials with significant spectral differences will be mapped into colors that are well separated while materials with similar spectral features will be mapped into similar colors. However, it is possible that this mapping method may not be able to distinguish some closely related materials that can be differentiated by some other processing. The rendered images are best suited to large-scale features, not for identifying small, isolated targets because of their litter effect on the overall covariance matrix.[4] Since the mapping is only for visualization purpose, it is not a classifier or a feature detector and it does not make decisions. It only offers a way for an analyst to take a first look at the data. By visually inspecting the images, analyst’s attention may be directed to appropriate area of interest for furthering processing and analysis.

Both PCA and ICA use the in-scene statistics to compute the basis vectors. It is likely that the most important features can be highlighted for the particular imagery. The images from the perceptual rendering are well color-balanced. The color attribute saturation is equivalent to a confidence measure while the hue is equivalent to a material classification.

The disadvantages of the perceptual rendering strategies are: 1. Due to the three dimensional nature of human color vision, it is inevitable that any three channel representation of high dimensional spectral data will result in information loss. 2. Because of the use of in-scene statistics, the derived basis vectors are scene dependent, which makes the mapping not scene invariant. 3. As the range of wavelengths increases, it might be necessary to have more than three components to capture an equivalent amount of variance in the data.

6. CONCLUSIONS

Perceptual rendering schemes based on PCA and ICA were discussed. An automatic method for setting the mapping origin has been developed based on the gray world assumption. The resulting images are well color balanced and can differentiate between certain types of materials. They offer a first look capability or initial unsupervised classification without making any formal decisions for a wide variety of spectral scenes. The initial look at the data or initial classification feature can form a backdrop for displays of the results of more sophisticated processing.

Several other commonly used visualization techniques were also implemented. The set of resulting images provides a way to go back and forth to make visualization of the data set more thorough or material classification more obvious. To evaluate the usefulness of different strategies, psychophysical experiments may be conducted in the future by asking observers (data analysts) which rendering is more useful. It is expected that the results would show strong data dependency.

Though the resulting images may be visually appealing, they may assign different hues for pixels that are identified as belonging to the same class. It is expected that a good visualization technique based on PCA or ICA should be able to illustrate the cluster feature of PCA or ICA. Based on the knowledge of the perception and understanding of different color attributes,[14] it is desired to have a different hue for each class. Therefore, supervised mapping schemes may be further explored by examining scatter plots of PCA or ICA data and the corresponding classification map from other advanced classification algorithms, with the goal of showing a certain class with a certain hue while maintaining a good hue separation among classes.

As Tyo., etc. pointed out,[4] it is desirable to develop a general set of basis vectors that can capture a large amount of spectral information and be applicable to a variety of imageries so that standard mapping could be developed in a manner more intuitive to observers. However, the question still remains open as to whether a general set of basis vectors can be derived.

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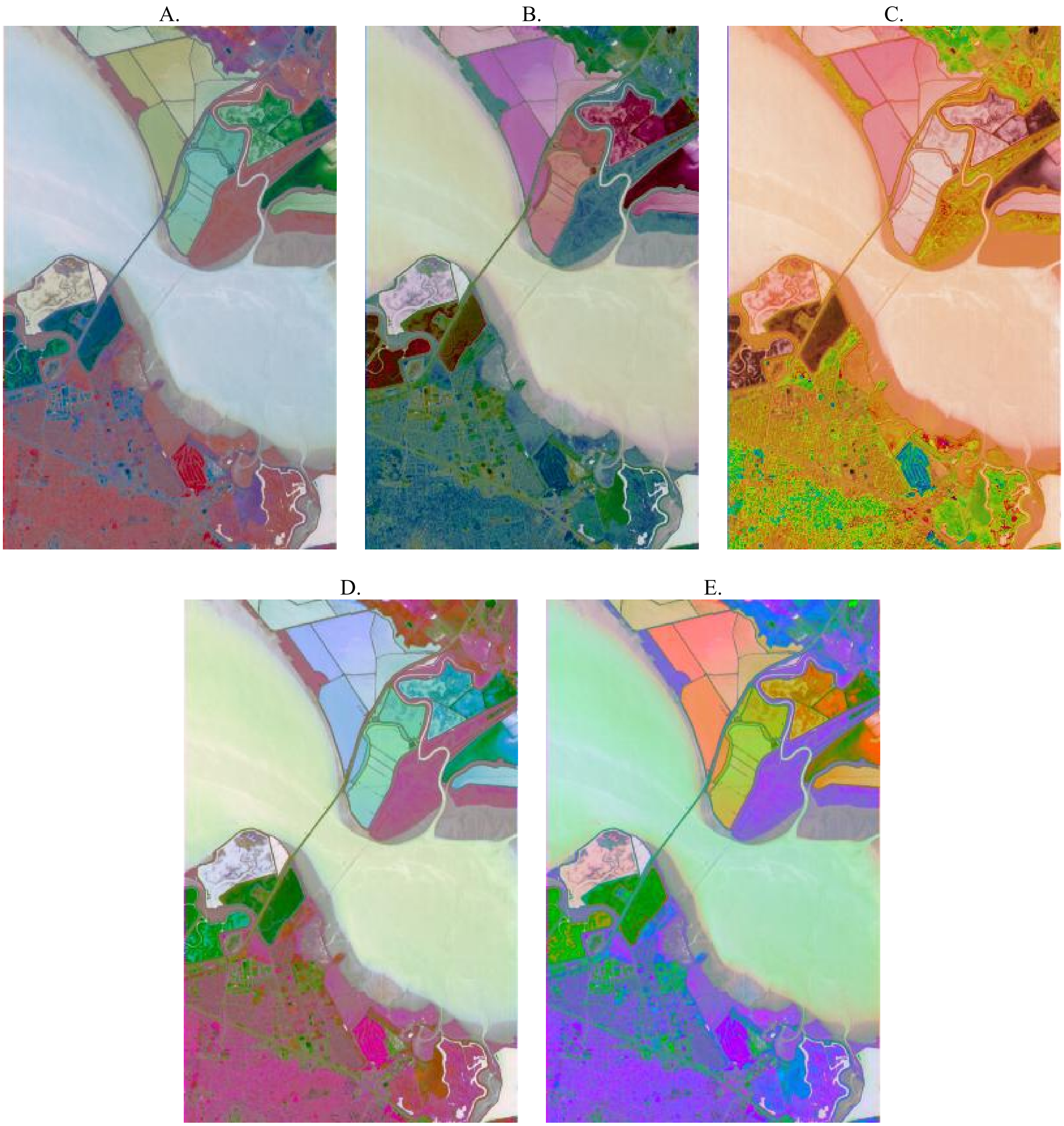

Figure 2. The rendering images in different color spaces for the Hyperion data processed by PCA. A. PCA to CIELAB. B. PCA to HSV with clipping S. C. PCA to HSV with normalizing S. D. PCA to YCrCb. E. PCA to YUV.

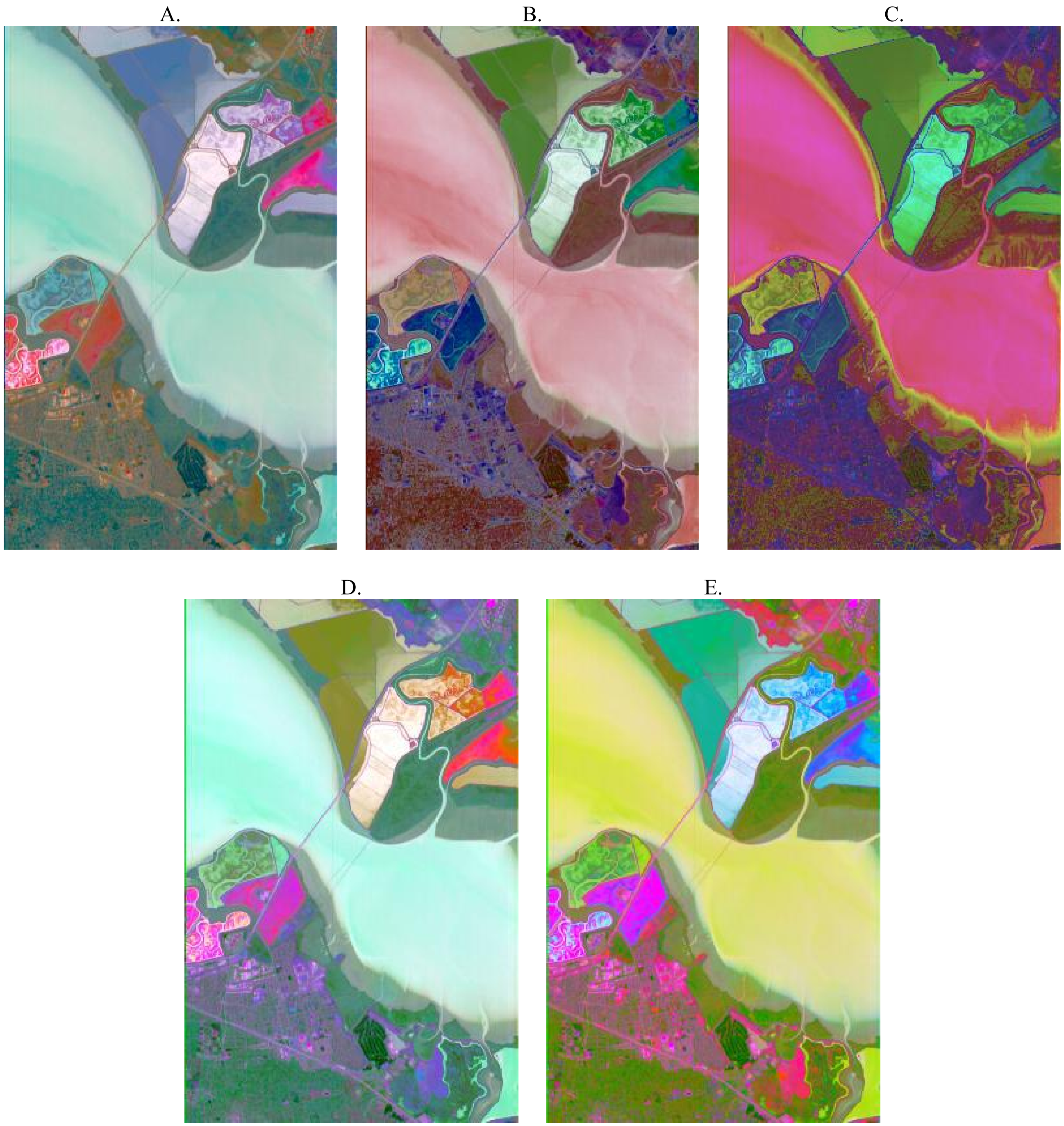

Figure 3. The rendering images in different color spaces for the Hyperion data processed by ICA. A. ICA to CIELAB. B. ICA to HSV with clipping S. C. ICA to HSV with normalizing S. D. ICA to YCrCb. E. ICA to YUV.

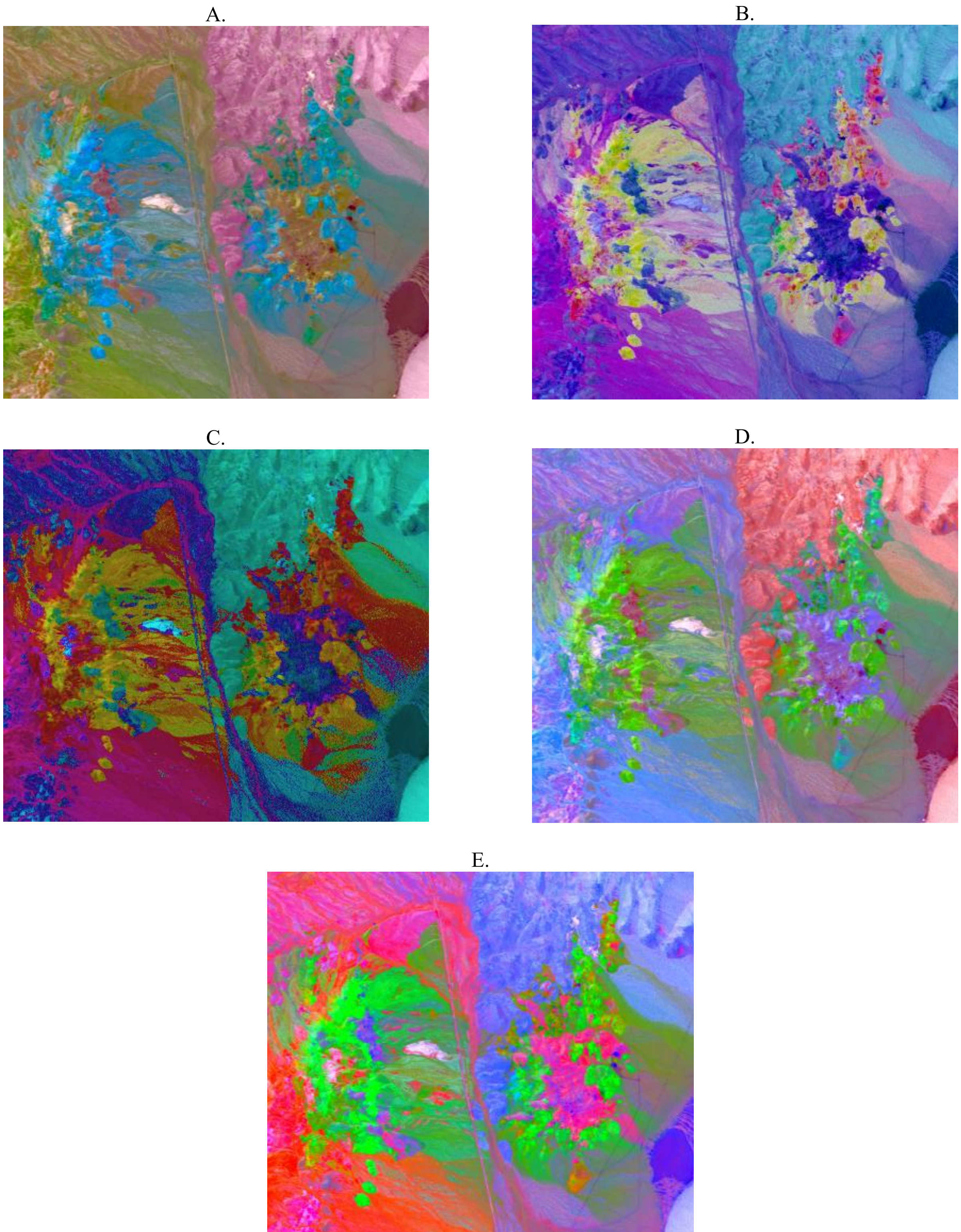

Figure 4. The rendering images in different color spaces for the AVIRIS data processed by PCA. A. PCA to CIELAB. B. PCA to HSV with clipping S. C. PCA to HSV with normalizing S. D. PCA to YCrCb. E. PCA to YUV.

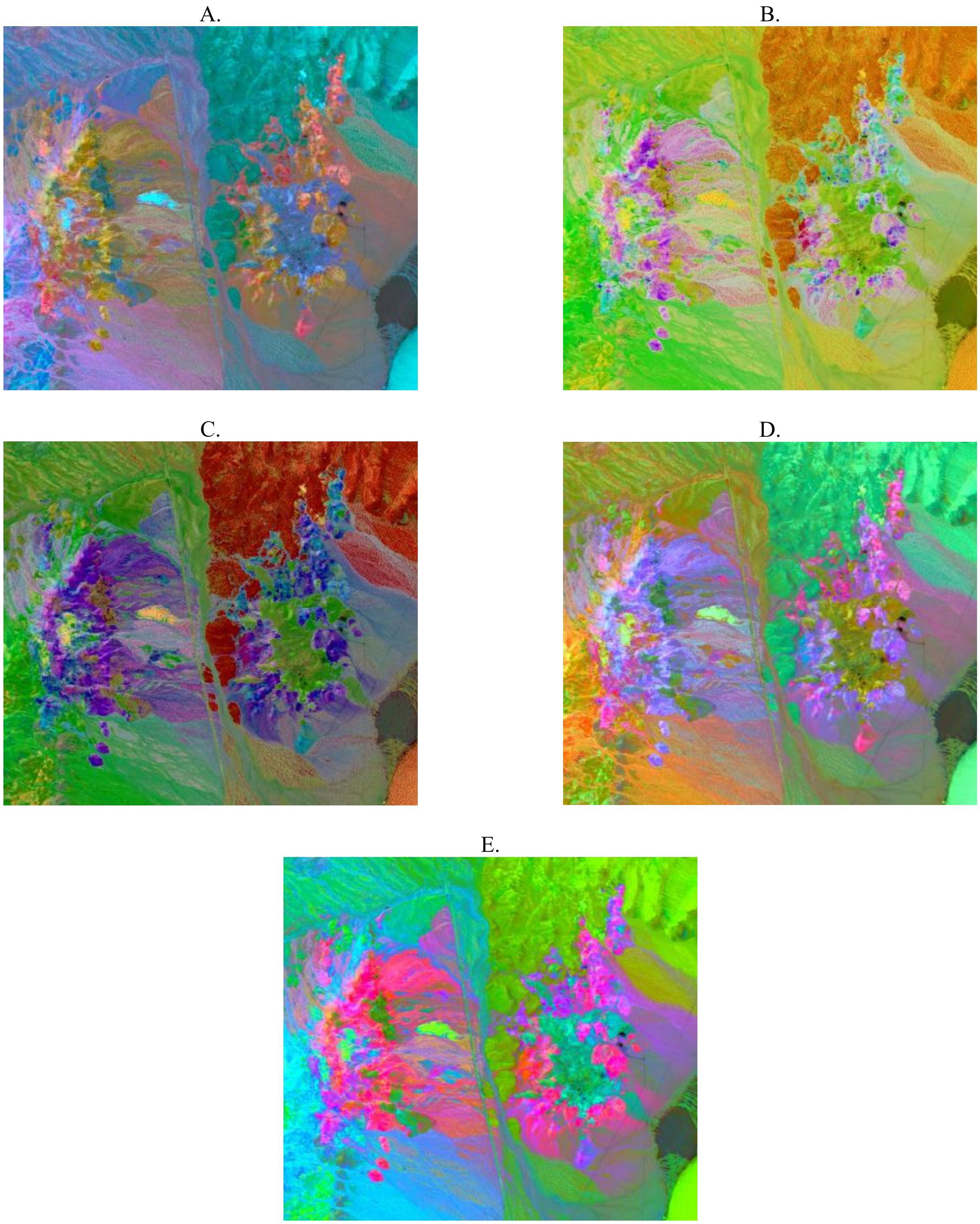

Figure 5. The rendering images in different color spaces for the AVIRIS data processed by ICA. A. ICA to CIELAB. B. ICA to HSV with clipping S (directly using translated ICs to calculate S and H). C. ICA to HSV with Clipping S (first mapping ICs to opponent space, then calculate S and H). D. ICA to YCrCb. E. ICA to YUV.

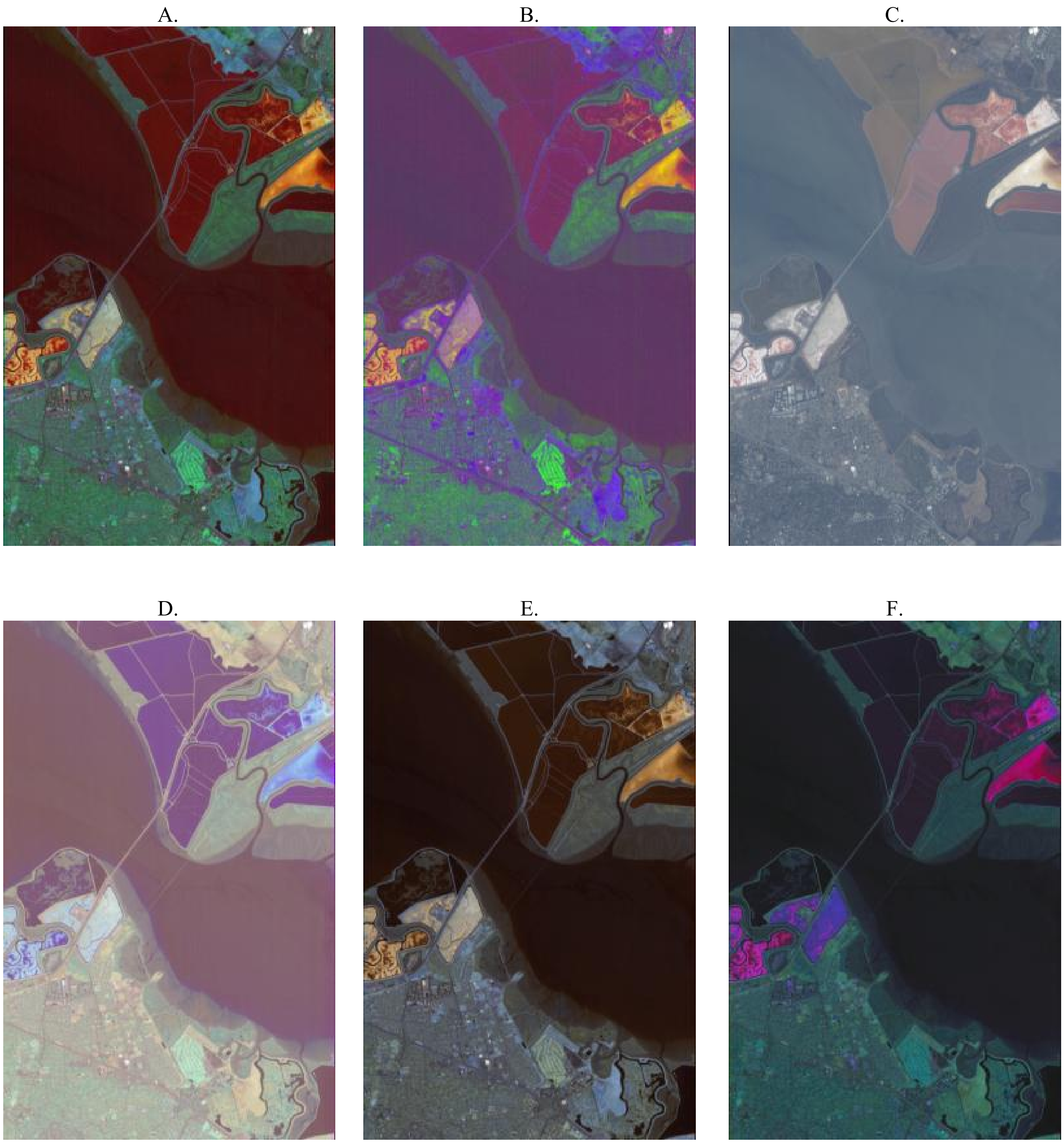

Figure 6. Resulting images from several different visualization methods for the Hyperion data. A. Three widely spaced bands at $\lambda_1 = 0.569\mu m, \lambda_2 = 1.033\mu m, \lambda_3 = 1.639\mu m$. B. Decorrelation stretched version of A. C. The true color image constructed using human color matching functions in the visible bands. D. Stretching the color matching functions and applying to the whole spectrum. E. Gaussian functions as spectral weighting. F. IHS model.

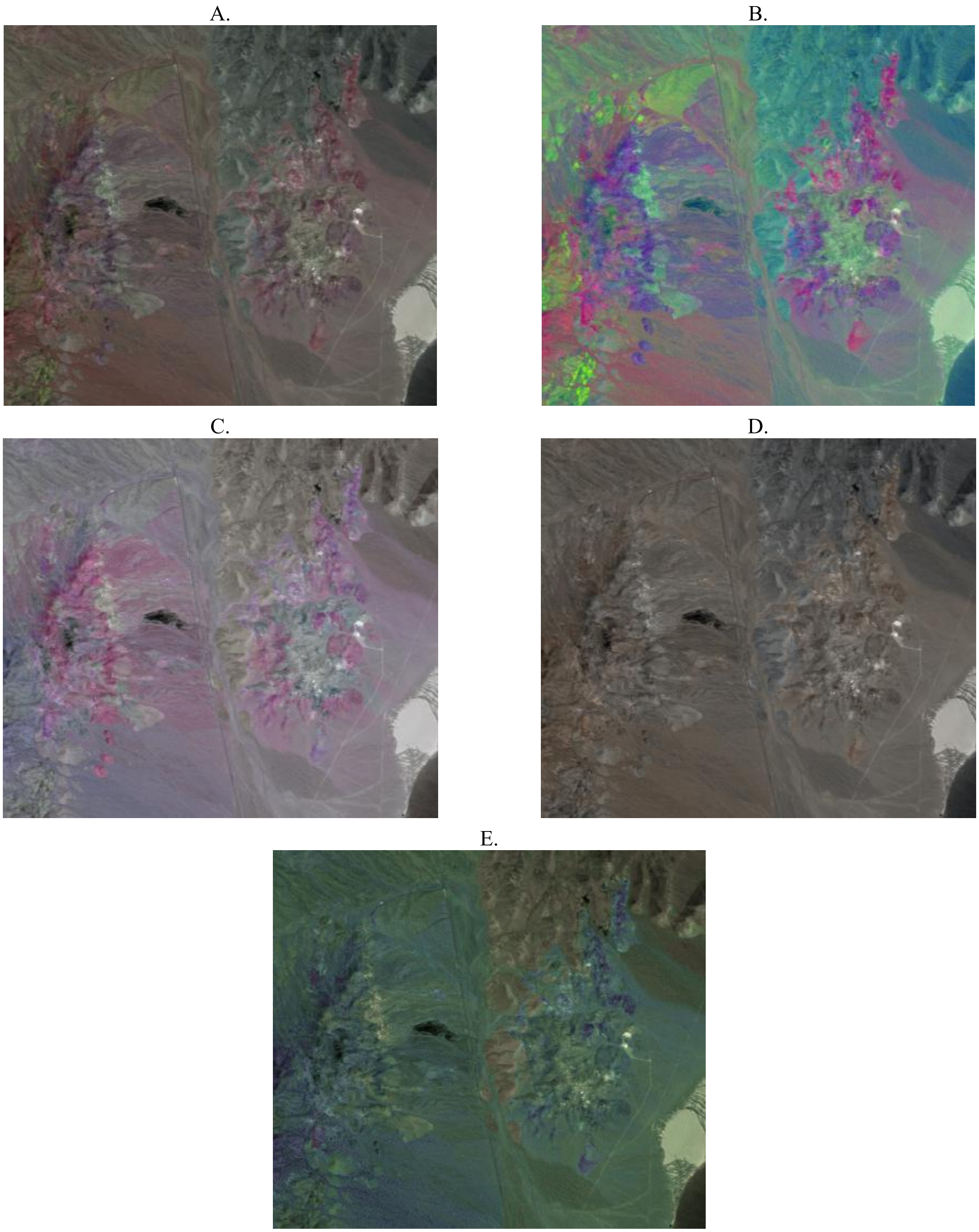

Figure 7. Resulting images from several different visualization methods for the AVIRIS data. A. Three widely spaced bands at $\lambda_1 = 2.101\mu m, \lambda_2 = 2.2008\mu m, \lambda_3 = 2.3402\mu m$. B. Decorrelation stretched version of A. C. Stretched color matching functions as spectral weighting. D. Gaussian functions as spectral weighting. E. IHS model.