Temporal Change Enhancement in Multispectral Images Remotely Sensed from Satellites

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ABSTRACT

The application of principal components analysis to multispectral satellite images is a routine way to present the data in false-color composite images. These composite images include a very high percentage of available information and have no correlation between the displayed colors. The transformation of multispectral image data into its principal components is also an effective way to separate image information from noise. This paper describes a procedure for temporal change enhancement which exploits both the decorrelation and noise isolation properties of the principal components transformation. Using simulated temporal change, this procedure was demonstrated to be more effective than the standard procedures described in the literature. Simulated temporal change as low as one percent of original pixel brightness was easily seen. Changes of less than one percent were difficult to simulate because of integer roundoff. However, a one percent change was sufficient to measure the relative effectiveness of each procedure considered.

Background

Each spectral band in a multiband data set contributes both exclusive and redundant information from a scene. Interband correlation is a good measure of this redundancy. The variable transformation known as principal components analysis (PCA) replaces the original system of highly correlated variables in the image data set with a new system of variables. In the original system, the variables used are the brightness of the image in each individual wavelength band. PCA produces a new system of variables in which each new variable has no correlation with any of the others; therefore, there is no redundancy among these new variables. These new variables are created so that the information contained in a multispectral image can be displayed with as much contrast and detail as possible.

These new variables are called principal components (PCS), and are ranked according to the amount of image detail (information) they contain. Typically, almost all the information in a multispectral image can be found in the three highest ranking PCS. See Figure 1. On the other hand, most of the noise in a multispectral image is cast into the lowest ranking PCS. See Figure 2. PCA therefore not only enhances the amount of detail in an image, but it isolates the noise. We take advantage of both of these properties of PCA when we proceed to enhance temporal change in a multispectral image.

The Genetic Algorithm PCA

The PCA transformation must be done numerically and a variety of algorithms have been employed for enhancement purposes. See Figure 4. The algorithm used in this study[1] is a genetic algorithm and was chosen because of its demonstrated tenacity in resolving the image data into principal components. See Figure 4. Further background on genetic algorithms can be found in the literature[2,3]

Data Used

The image scene was selected for its relevance to some precision agriculture work Utah State University is involved in with Simplot and NASA. A farm a few miles southeast of Rexburg, Idaho, is the focus of this activity. Landsat Thematic Mapper (TM) data from May 2, 1992 were used. Data spanning short time intervals were not available, therefore subtle temporal change had to be simulated. This situation was used to advantage since simulation can be controlled quantitatively to obtain a measure of the performance of various enhancement methods. Simulation also provided qualitative latitude; one could choose what real world process to simulate. In this case, the simulation was of new vegetative growth on bare soil. Six-band spectral signatures of both vegetation and bare soil were taken from surface areas of the May '92 image. These signatures were used to simulate the transition from bare soil to meadow. In effect, simulated new growth of vegetation was "planted" on an image area of bare soil in the form of the familiar "smiley-face" symbol.

Shuffle or Merge Method

This is the method often encountered in the literature[4,5]. With this method, all six bands from each acquisition time are shuffled or merged into a single twelve-band set. The PCA is then performed on this set as if it were from a single acquisition time. The intention is that the othogonalization and enhancement of variation will produce images in which temporal change can be easily recognized. The weakness in this method seems to be in the way the PCA distributes image information and noise throughout the resulting 12 PCS. The six bands from each accession time were the 30-m resolution bands, i.e., bands 1-5, and 7.

This method is initiated by taking all six bands from the unmodified image and stacking on top of these bands the six bands from the image with the simulated " smiley-face" vegetation pattern. The resulting twelve-band image then underwent PCA. The next step was to examine the individual PCS and see if the simulated temporal change could be detected. This method was evaluated with two different PCA algorithms, the genetic algorithm mentioned earlier, and a widely-used algorithm included in the ERDAS IMAGINE software package. The steps in this method are summarized below:

1) Combine all bands from both dates into a single multispectral, multitemporal file.

2) Run a PCA on this combined file.

Cascade Method

Instead of arbitrarily stacking both six-band images and running a twelve-band PCA, we can take advantage of the way PCA separates information from noise and apply PCA to each individual image as an initial step. Once the PCA is performed on an individual image, most of the image noise can be discarded by discarding the lowest-ranking PCS. Only the highest-ranking PCS are retained, and it is in them that most of the information in an image can be found.

The three highest-ranking PCS from each image are combined to form a six-band image and a subsequent PCA is then performed. Finally, the PCS resulting from this cascaded process are examined to see if the simulated temporal change could be detected. The steps in this method are summarized below:

1) Run PCAs on files for each individual date.

2) Combine the three highest-ranking PCS from both dates into a single multi-PC, multitemporal file.

3) Run a PCA on this combined file.

Results

Since we are interested in change only within a certain area, the enhancement of change should be restricted to this area of interest. Both algorithms were set up to ignore the image data outside of the perimeter of the farm. The outline of the farm was that of a semicircle, as shown in Figures 1-4. This outline was the result of a 180-degree overhead pivot irrigation system. Simulated new growth was evaluated at different levels down to the limits of roundoff. Any change in the image on the order of 1/2% would be rounded off to zero change, so the smallest change evaluated was 1%.

Figure 3 shows that when the ERDAS IMAGINE[6] algorithm was used, it was necessary to use the cascade method to detect a temporal change of 1%. The shuffle method could not detect change at this level. The USU ABW algorithm (genetic algorithm) was able to detect 1% change using both the shuffle and cascade methods, but the presentation of the temporal change was clearer and less noisy with the cascade method. See Figure 3.

For comparison, a conventional Tasseled-Cap Transformation[7] was performed on the simulated new growth. The results of the tasseled cap transformation can be compared with those of the cascade method in Figure 4.

Conclusions

The cascaded PCA method described in this paper proved to be effective in the visual enhancement of simulated temporal change. PCA was used initially to separate image information from noise. Noise from each image was then discarded with the low-ranking PCS. Finally, the high-ranking PCS from each image were combined and PCA was performed to enhance the temporal change. The magnitude of the simulated change was adjusted to the point were integer roundoff made the change essentially zero. Any change other than zero, however, was easily detected.

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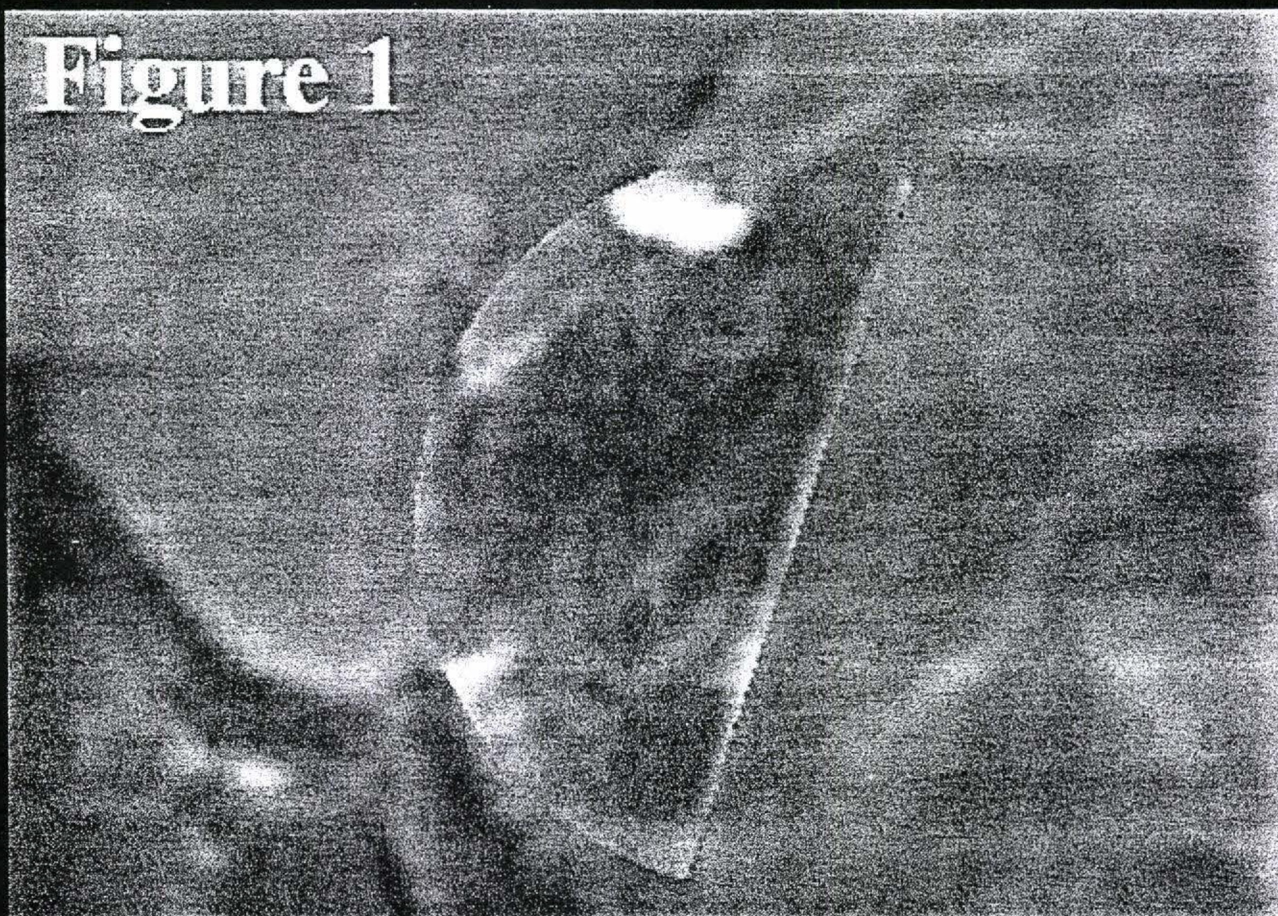
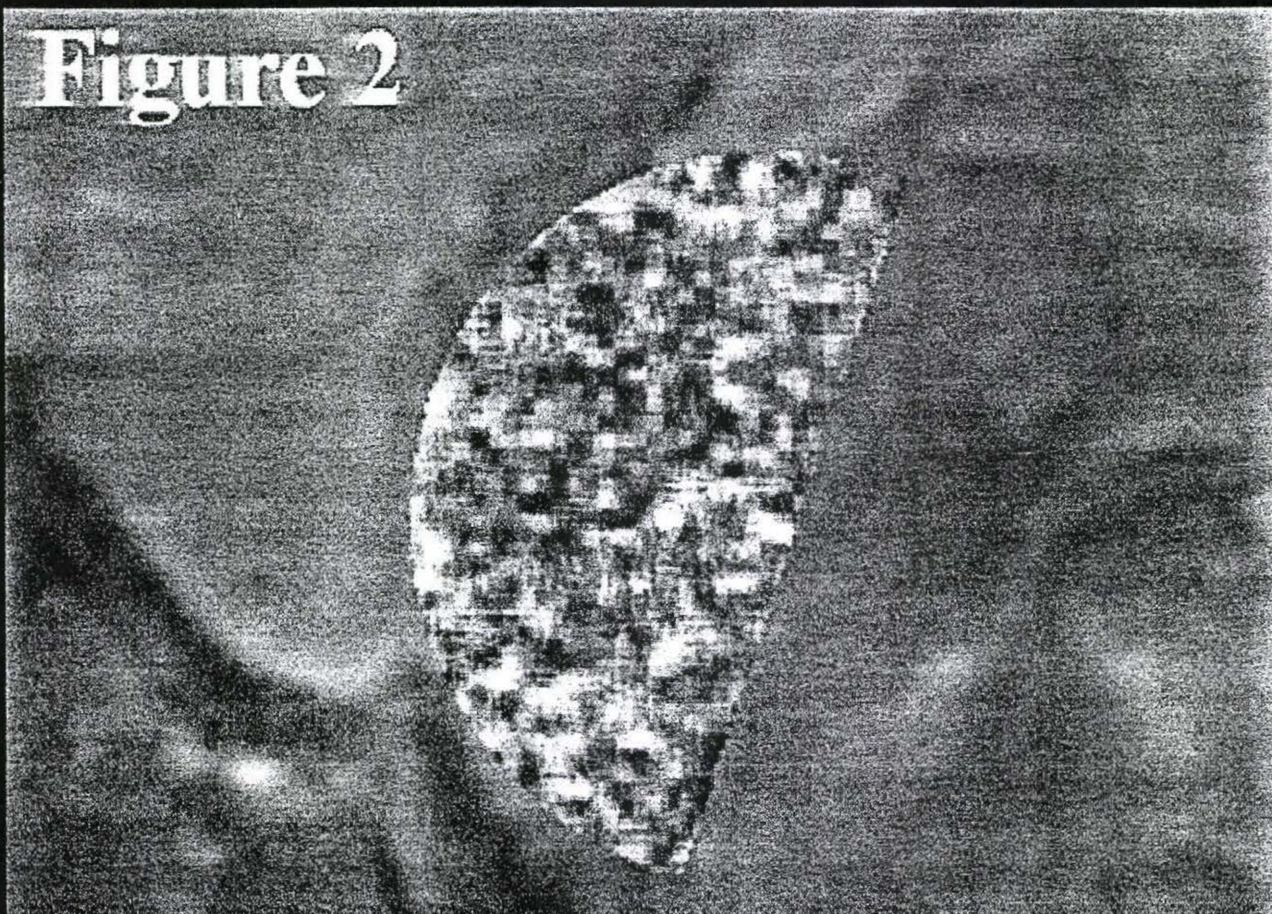
Figure 1



May '92 Unmodified
Principal Components

Red: PC 3
Green: PC 2
Blue: PC 1

ABW



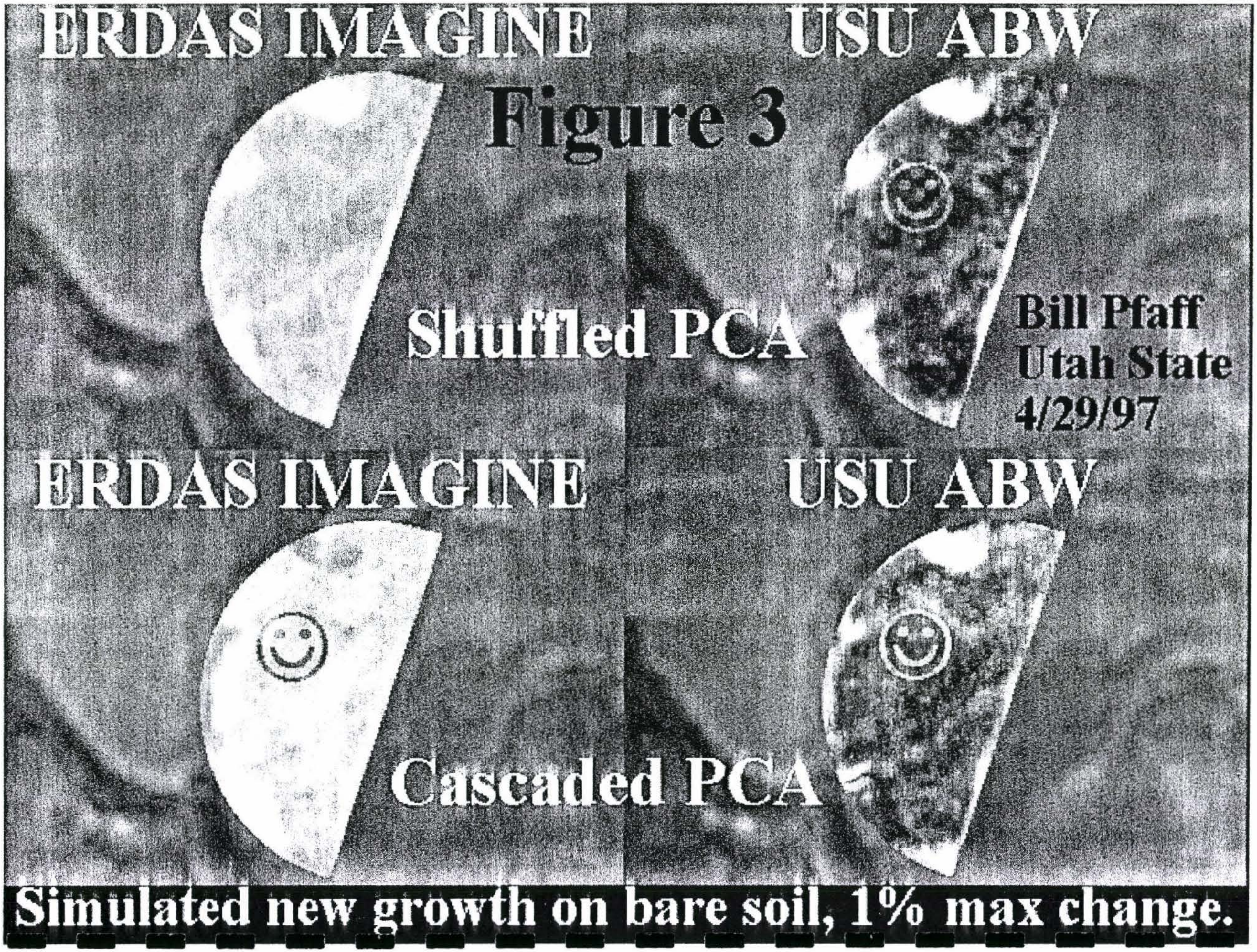
May '92 Unmodified

Principal Components

Red: PC6
Green: PC5
Blue: PC4

Noise

ABW


ERDAS IMAGINE
USU ABW
Figure 3
Shuffled PCA
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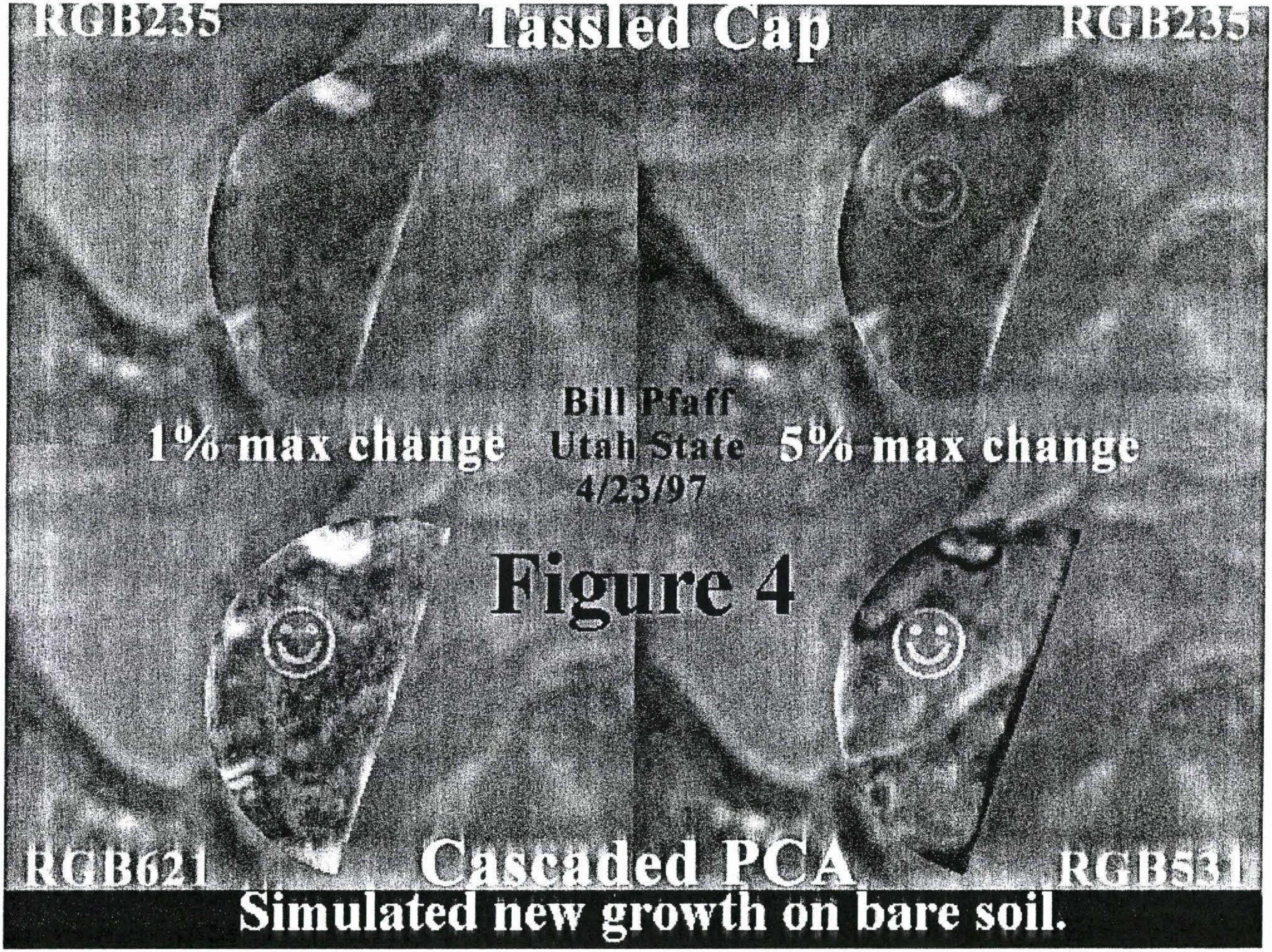
4/29/97
ERDAS IMAGINE
USU ABW
Cascaded PCA
Simulated new growth on bare soil, 1% max change.


RGB235
Tassled Cap
RGB235
Bill Pfaff
1% max change
Utah State
5% max change
4/23/97
Figure 4
RGB621
Cascaded PCA
RGB531
Simulated new growth on bare soil.