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Analysis of Change in Central Texas Using Image Differencing and Unsupervised Classification

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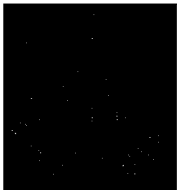
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Albuquerque, New Mexico

ANALYSIS OF CHANGE IN CENTRAL TEXAS USING IMAGE DIFFERENCING AND UNSUPERVISED CLASSIFICATION

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ABSTRACT

An image differencing algorithm was applied to two Landsat MSS scenes in central Texas to assess its ability to identify change in the greater Austin, Texas metropolitan area. Near infrared data from a Landsat MSS scene acquired September 9, 1972 were subtracted from a Landsat MSS scene acquired August 24, 1990 to produce a difference image representing change in and around Austin, Texas covering a twenty year period. Results indicate that use of empirical analysis to visually identify change within a difference image is highly effective. Unsupervised classification of a difference image to identify change is dependent upon time requirements and the sensitivity of the classified image. While an unsupervised classification of a difference image with a small number of classes was shown to be time saving, it was determined to possess less subtle areas of change. Therefore, it became evident that the greater number of classes used resulted in a higher degree of identified subtle areas of change.

INTRODUCTION

Change detection in remote sensing allows an image interpreter to determine temporal alterations, such as deforestation and population growth, in a landscape (Brondizio et al., 1994) Many change detection techniques produce an image making areas of change visible (Collins, 1997). However, difference images can include areas of transition which are difficult for an untrained eye to interpret. These areas simply do not stand out well enough for visual interpretation. This becomes an important issue for the interpreter in communicating or presenting the information to natural resource managers who may not have remote sensing backgrounds. These managers need to have images that readily communicate areas of change. Typically they do not have the luxury of reading a treatise on the subject of image-difference detection. Instead, they seek specific information that allows them to make timely decisions.

The purpose of this project was to analyze a digital image processing technique that will allow areas of change to be enhanced within an image. An image differencing algorithm was applied to the image data to produce a single band image with pixel values potentially ranging from -255 to 255. The difference image algorithm was chosen for its simplicity and ability to produce a black and white image with very dark areas having extreme negative pixel values and very bright areas having extreme positive pixel values, which represent areas of change. (Singh, 1989)

Statistically the pixel value histogram appears Gaussian in nature. (Jensen, 1996) Thresholds of change typically are chosen in numbers of standard deviations from the mean or from the tails (Price et al., 1992).

METHODOLOGY

The area under examination includes portions of northern Travis County, Texas and southern Williamson County, Texas. (Figure 1) This portion of the state, northwest of downtown Austin is in one of the fastest growing regions of the United States. (Texas Department of Economic Development, July 1995). Because of the rapid growth this area

has undergone in the past 20 years, it was chosen for this study based on the authors' knowledge of the local landscape and the ability to produce a difference image with verifiable change.

Two cloudless LANDSAT Multi-Spectral Scanner (MSS) images representing the study area in central Texas were chosen to analyze change. From the full Landsat MSS scenes which were originally acquired in 1972 and 1990 respectively, subset imagery representing the area of interest per year were taken from the full data sets (Figures 2 & 3).

From the extracted subset imagery, the image differencing technique was conducted. This technique involves subtracting the pixel values of one image from another on a pixel-by-pixel basis. Using the near infrared band of both images, chosen for its ability to detect subtle changes in vegetative cell structure typical of areas in and around Austin, Texas, the 1972 subset near infrared image data were subtracted from the 1990 near infrared band. The pixel values in the resulting difference image have a range of -45.0 to 78.0; the mean pixel value is 5.3 with a standard deviation of 7.7. (Figures 4 & 5)

From the resulting difference image, two techniques were used to enhance the areas of change. The first technique utilized was level-slice image enhancement. This method splits an image into a specified number of levels based on pixel values (Figure 6). In this instance six levels were chosen based on our empirical manipulation of the difference image histogram and our visual interpretation of the optimum level to visually identify verifiable change. However, depending upon the degree of change one wishes to display and/or the particulars of the image itself, the interpreter may choose any number of levels.

The second technique utilized was unsupervised image classification. Two classification schemes were used. The first unsupervised classification scheme created six classes within the difference image. Upon classifying the difference image, the classification classes were display on screen and highlighted sequentially to identify those classes that represented change. Two classes that represented negative pixel values and hence change in the difference image were coded blue. Two classes that represented positive pixel values and hence change in the difference image were coded yellow. The other classes that represented areas of no change were coded gray (Figure 7).

Next, an unsupervised classification was performed on the difference image to produce 150 distinct classes. In a similar fashion, the resulting classified image was visually interpreted to identify classes representing change. Three classes representing extreme negative values and hence changes in the difference image were coded blue. Three classes representing extreme positive pixels values and hence changes in the difference image were coded yellow. All other classes, which represented areas of no change, were coded gray. (Figure 8)

RESULTS

The level-slice enhanced image shows areas of change within approximately one standard deviation of the extremes, as either black, denoting negative values or white, denoting positive values. Unchanged areas with pixel values nearest the mean are in the majority and appear in a moderate gray. The most prominent areas of change are Lake Georgetown, found in the black area in the upper center of the image and the rock quarry expansion, seen as large white areas just south of Lake Georgetown. Other areas of significant change include a golf course, near the center of the image, agriculture fields found in the eastern section of the image and various suburban housing developments scattered throughout the image. An analysis of the two classified images shows that the classified

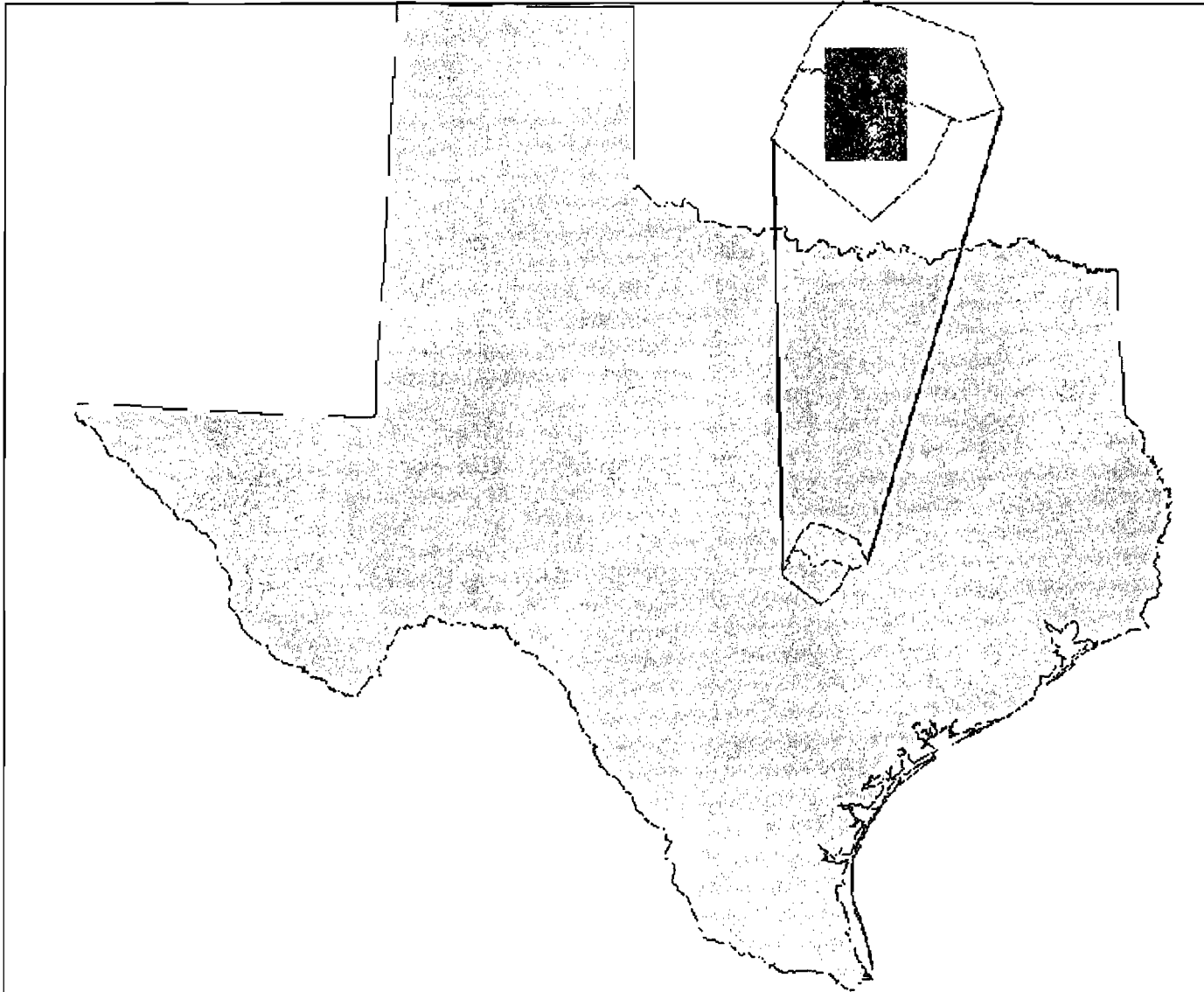


Figure 1: Location of study area, northern Travis County, Texas and southern Williamson County, Texas.

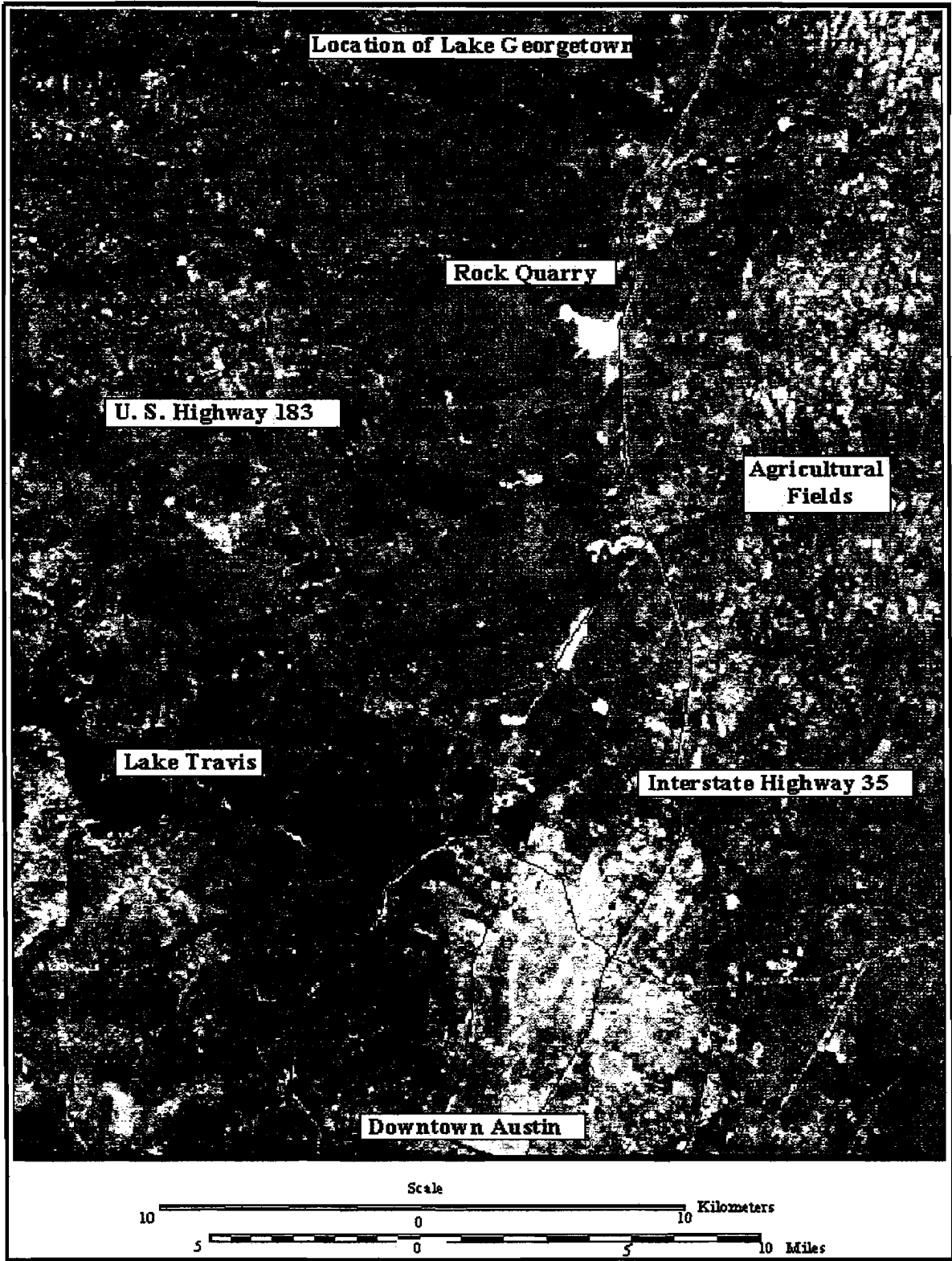


Figure 2: 1972 LANDSAT MSS scene of northern Travis County, Texas and Southern Williamson County, Texas

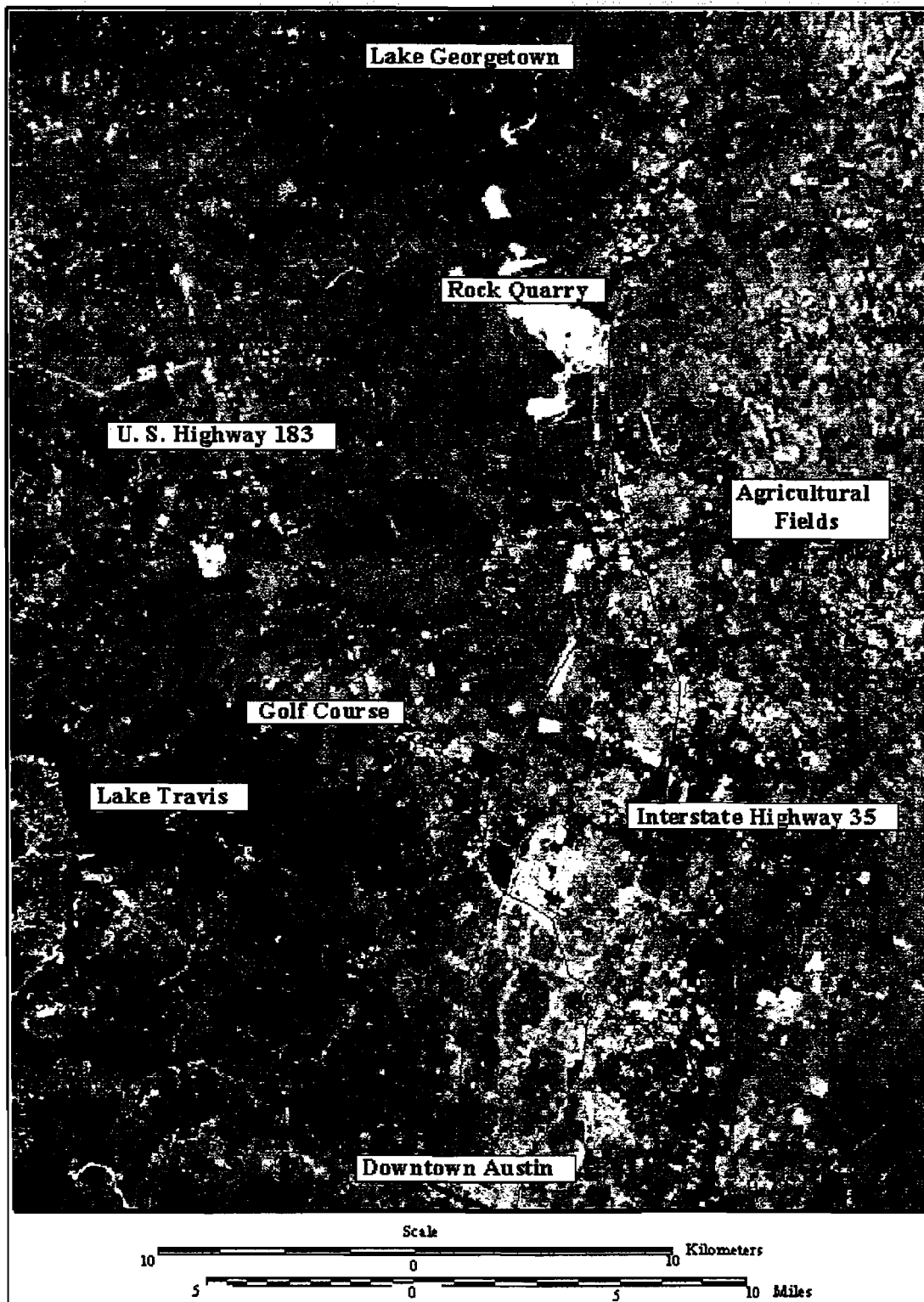


Figure 3: 1990 LANDSAT MSS scene of northern Travis County, Texas and southern Williamson County, Texas.

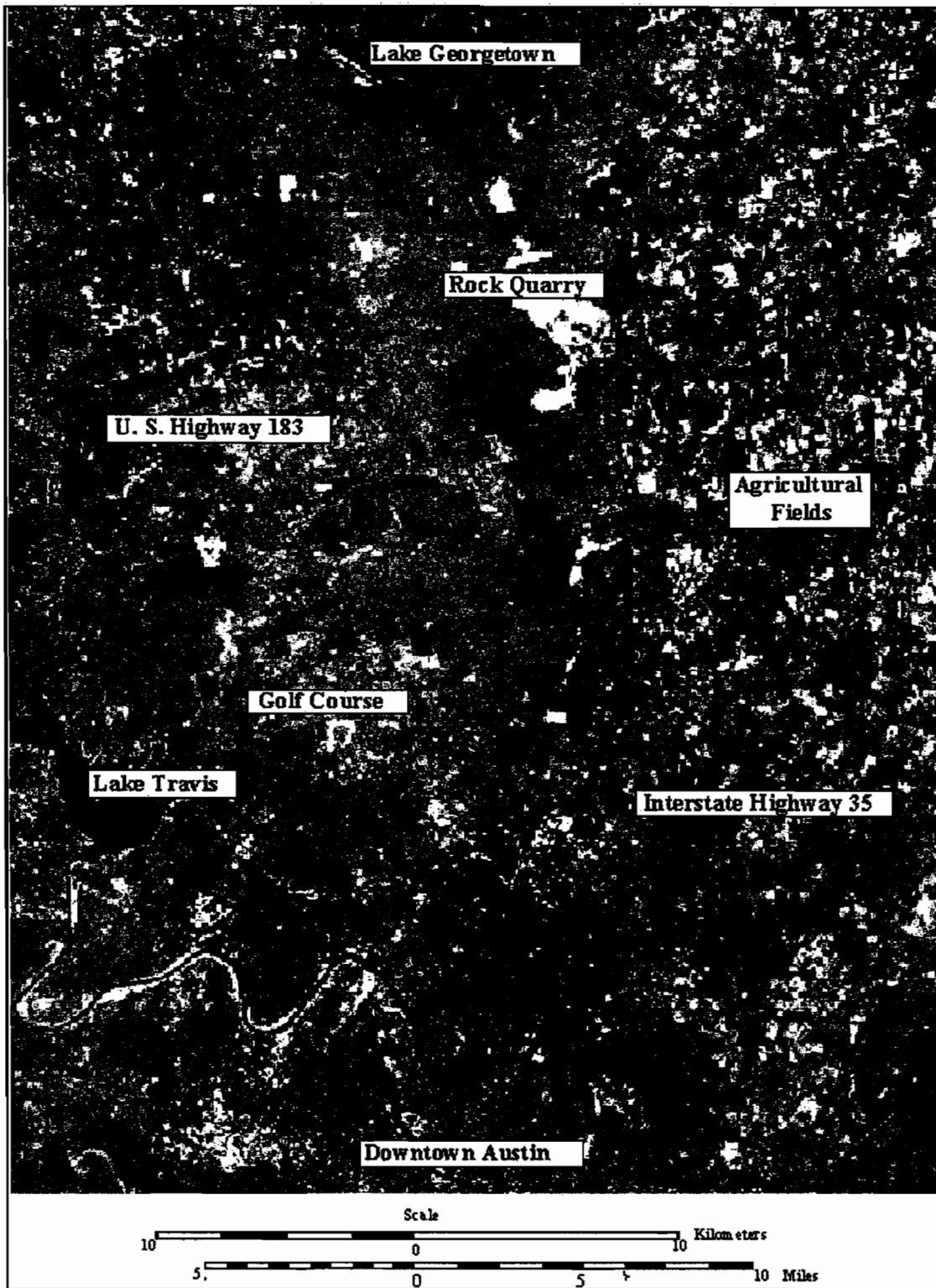


Figure 4: Difference image of northern Travis County, Texas and southern Williamson County, Texas.

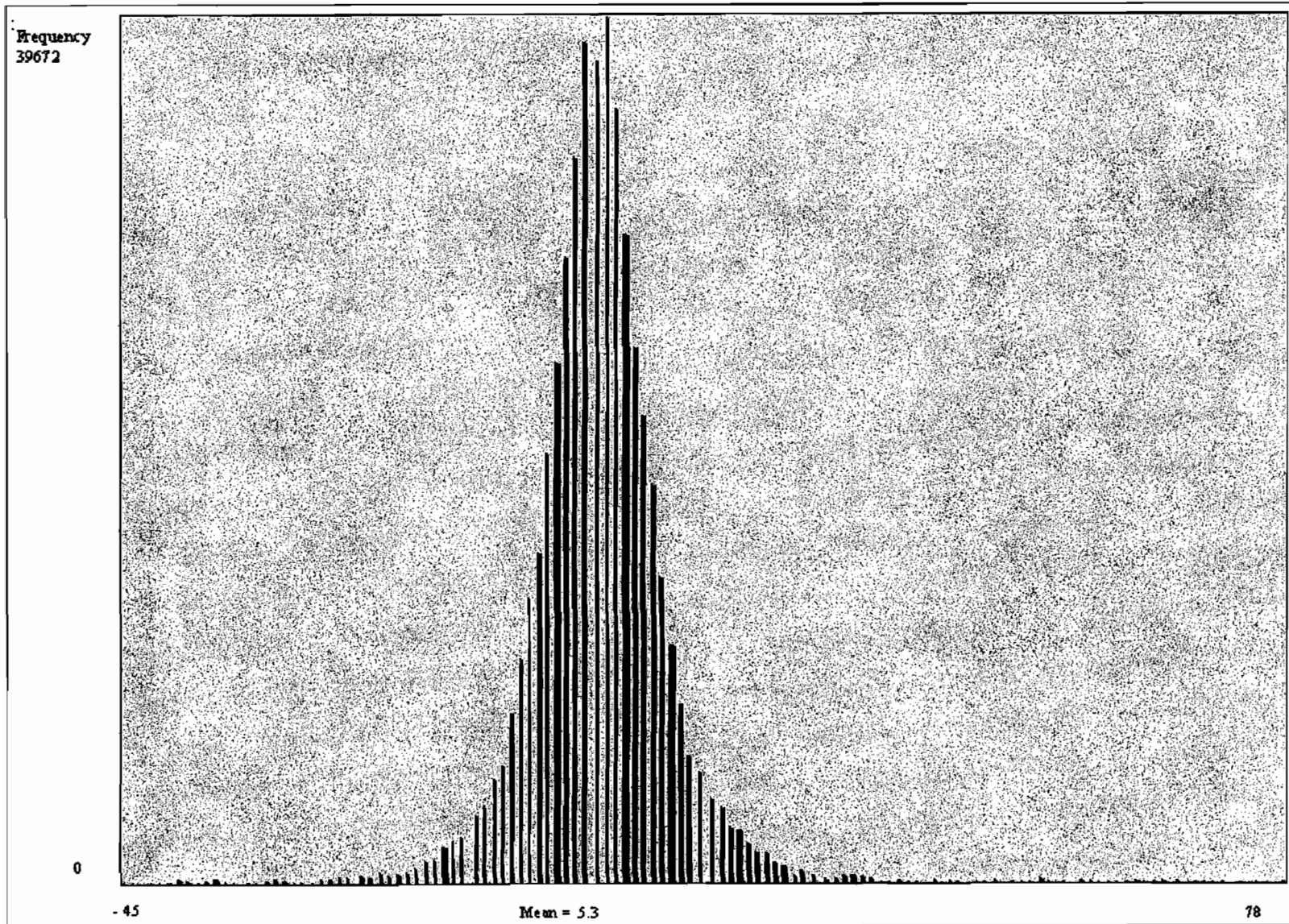


Figure 5: Pixel value histogram of difference image.

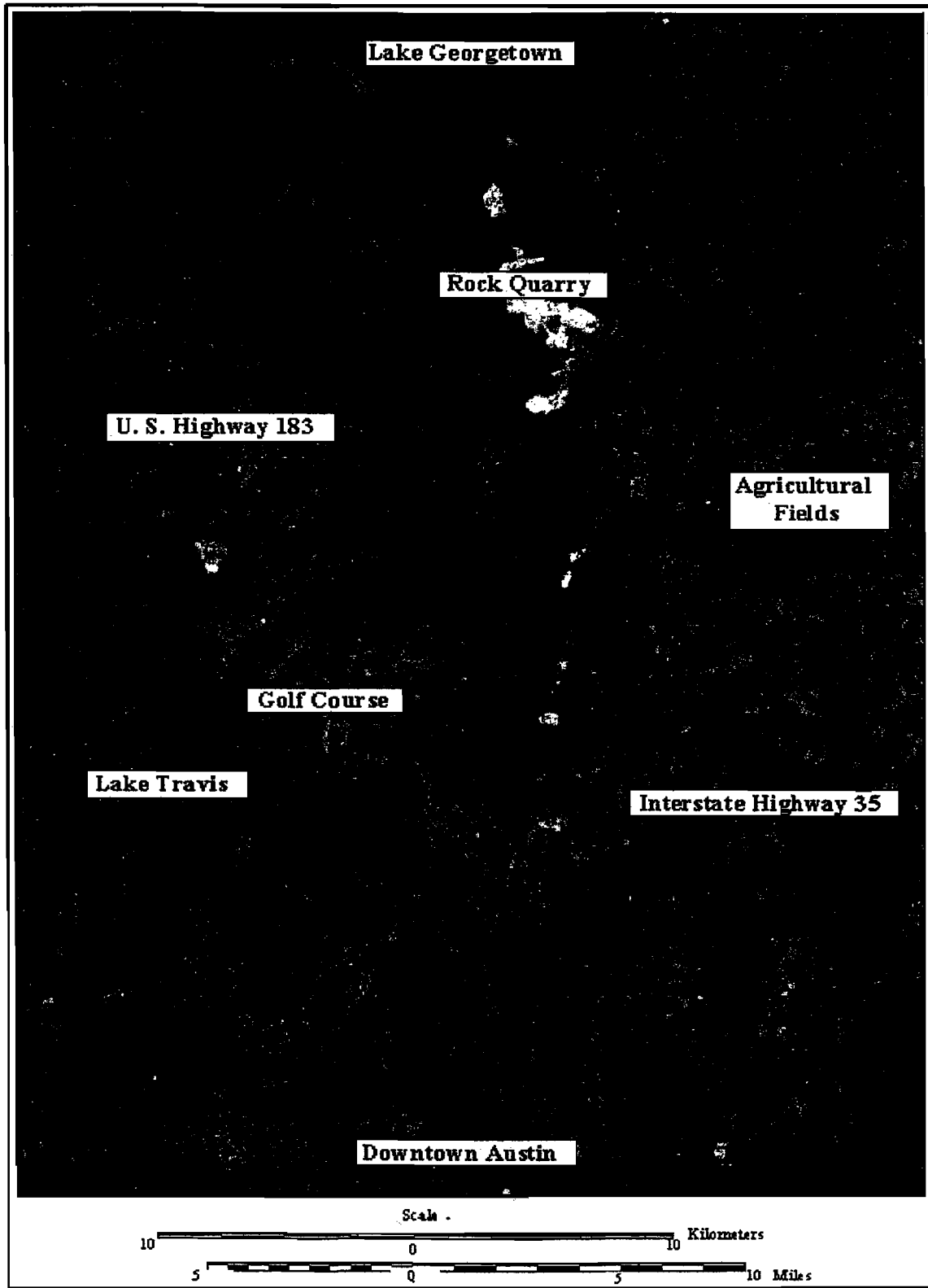


Figure 6: Level slice image enhancement of difference image indicating areas of change.

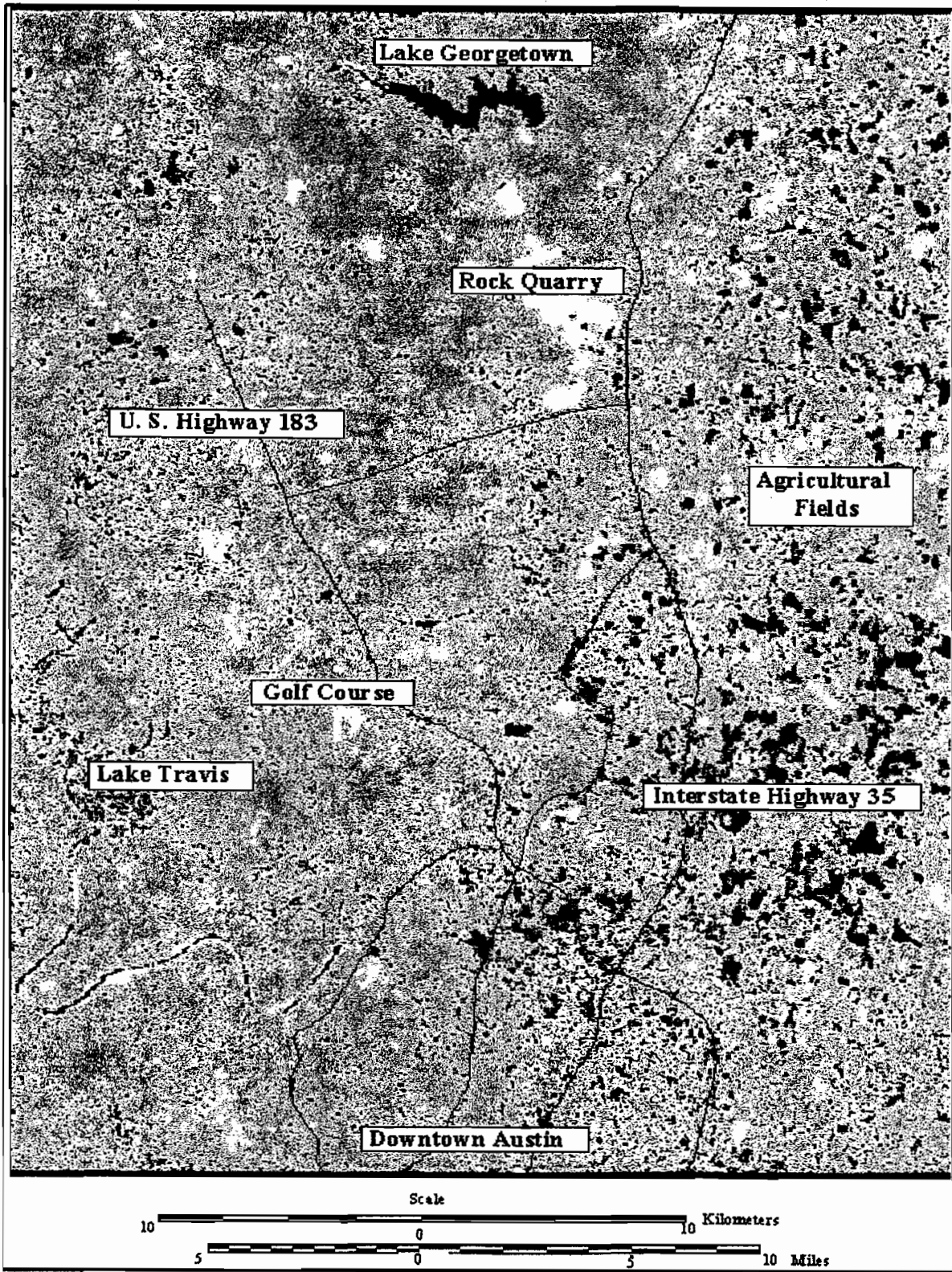


Figure 7: Classification of difference image using 6 initial classes indicating areas of change.

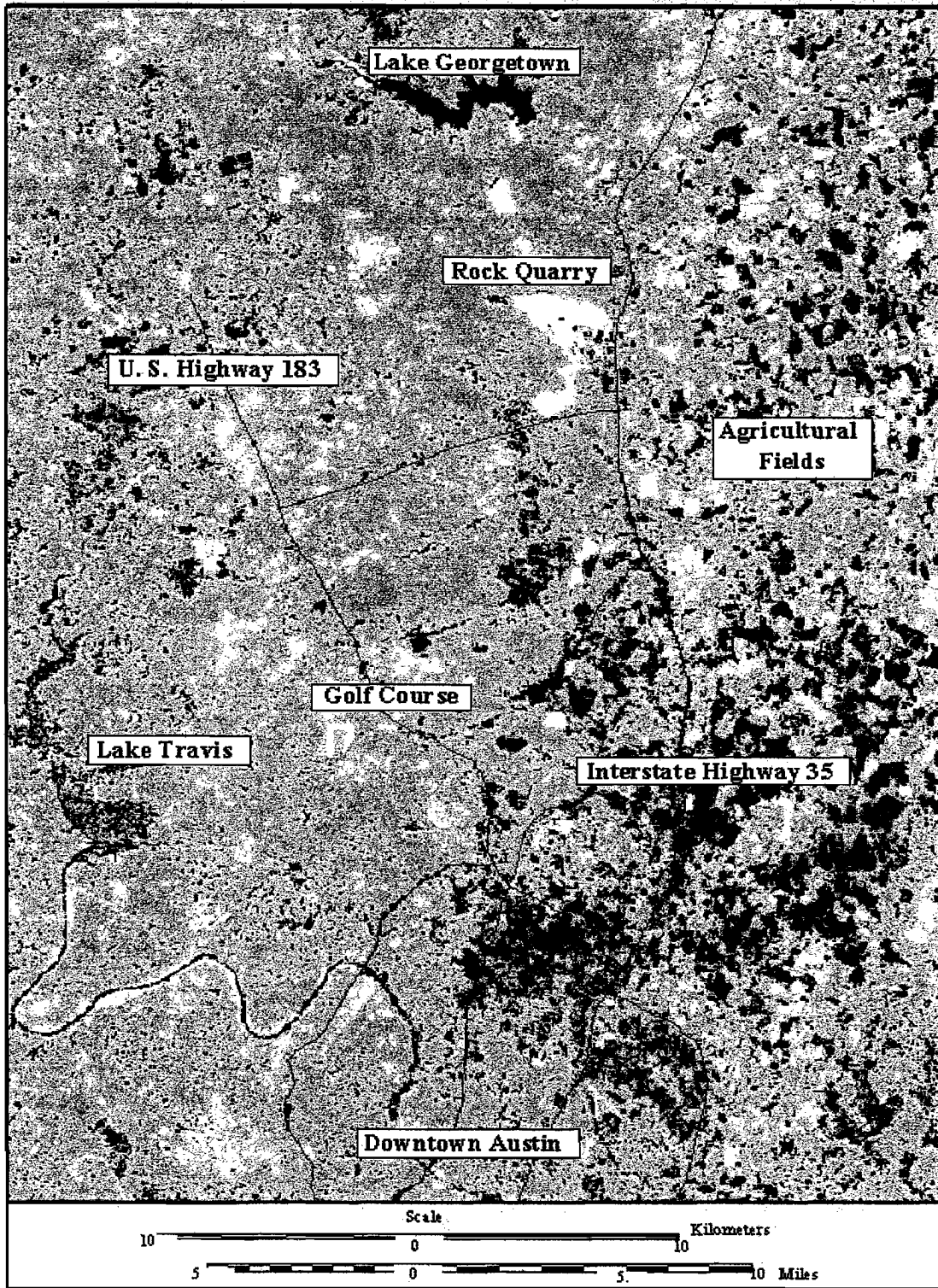


Figure 8: Classification of difference image using 150 initial classes indicating areas of change.

difference image with 150 initial classes was more sensitive to areas of change than that of the classified difference image with 6 initial classes. The difference image with 150 initial classes illustrates, as change, areas of roughly one to three standard deviations of the extremes. The 150 differentiated classes may be overly inclusive as it inaccurately depicts Lake Travis, a 60-year-old reservoir, as an area of change. While the classified difference image with 6 initial classes is time saving, the lack of sensitivity leaves something to be desired.

Which technique an image interpreter chooses depends on what information he or she is attempting to communicate. If the information desired is change at any level, a classified image using many classes would be preferable. If one wishes only to convey change over large areas, an image classification with few classes or level-slice contrast could be the method of choice.

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