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ORDERING OF TIME-DIFFERENCE INFORMATION FROM REPEATED SPATIAL IMAGERY

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Abstract

Our goal is to exhibit a time-differenced multiband spatial field in factored form so as to emphasize the spatially structured signal differences and isolate the spatially unstructured noise. The method we use is a variant of the MAF procedure described in Switzer and Green (1984). The MAF procedure (Min/Max Autocorrelation Factors) is a general purpose technique which extracts p orthogonal linear combinations or factors of the p-variate data which have maximal to minimal spatial autocorrelation. We present two examples of MAF-processed time-difference imagery. The first example is from an area in the Okanogan Highlands province of Washington state; the second is from the western Carson Desert, Nevada. Both examples were generated from Landsat MSS image pairs.

Introduction

Several authors (Lodwick, 1979, 1981; Byrne et al., 1980; Ingebritsen and Lyon, 1984) have applied standard principal components analysis (PCA) to the problem of detecting and classifying temporal change in remotely-sensed imagery. Each of these studies involved geographically registered Landsat multispectral scanner (MSS) imagery. Lodwick (1979) looked at seasonal changes using the first two principal components (PCs), by differencing the PC scores between images or by using linear regression across a number of images. Byrne et al. treated two Landsat images of the same area as a single eight-channel data set, and noted that PCA of the augmented data set generated higher order PCs that contained information about temporal change. Ingebritsen and Lyon showed that the method of Byrne et al. often leads to specific types of change-related PCs, which they referred to as "Δbrightness" and "Δgreenness" in analogy to Kauth and Thomas' (1976) "brightness" and "greenness".

Each of these previous methods has been shown to provide useful information about temporal change; however, they do not take advantage of the data-compression and ordering properties of PCA, because they do not operate directly on the time-change information. We suggest applying PCA and the Min/Max Autocorrelation Factors (MAF) process (Switzer and Green, 1984) directly to time-difference imagery.

Either standard PCA or MAF process can be used to order and reduce multispectral time-difference information. Standard PCA produces decorrelated variables that are ordered based on a simple variance criterion, while the MAF process produces decorrelated variables that are ordered on the basis of spatial autocorrelation.

For the special case of multispectral systems in which all frequency bands have the same noise variance, both methods effectively separate the noise and signal components of an observation vector. However, if the signal-to-noise ratio is not constant between bands, the variance criterion of standard PCA will not necessarily isolate the noise component.

The MAF procedure, on the other hand, is a generally effective method of isolating noise. For this reason, and for the sake of brevity, we emphasize the MAF analysis in this paper. Since PC score images are produced in the course of the MAF algorithm, it is straightforward to refer to both the PC and MAF images during interpretive processing.

Methodology

Let $Z_1(x)$ be the p-variate spatial field at time 1 defined for the lattice of pixels at location x belonging to the spatial domain D of interest. Let $Z_2(x)$ be the corresponding spatial field at time 2 on the same domain D. The p components of $Z_1(x)$ and $Z_2(x)$ are the energy measurements in the p selected wavelength bands (channels) for the pixel at location x measured at time 1 and time 2 respectively.

It will be immaterial whether or not these energy measurements have been previously rescaled (linearly) to give constant variance across D for each channel, provided the same rescaling has been applied at both times. Indeed, any fixed nonsingular matrix transformation of the p-variate field, e.g., to raw or rescaled factor scores, will not affect the final results of this paper, provided the same transform has been applied to the images at both time points.

Let $Z_D(x) \equiv Z_2(x) - Z_1(x)$.

$Z_D(x)$ is the p-variate time-differenced field on the domain D. The goal is to exhibit this difference field in such a way as to emphasize the spatially structured signal diferences and isolate the spatially unstructured noise. The method we use is a variant of the MAF procedure described in Switzer and Green (1984). The MAF procedure is a general purpose technique which extracts p orthogonal linear combinations or factors of the p-variate data which have maximal to minimal spatial autocorrelation.

The rationale for the appliction of MAF to time-differenced spatial imagery is as follows: Those linear combinations of the p channels which had no signal change across the image between time 1 and time 2 should exhibit pure noise. We suppose that noise characteristically shows little spatial coherence; therefore, the minimal autocorrelation factor is taken to be an optimal representation of a pure noise component. Conversely, the signal change which has the greatest degree of spatial coherence should emerge as the maximal autocorrelation factor.

There are at least two kinds of time change which the MAF procedure cannot possibly detect without further modification. First, if the time change is a *constant* increment or decrement in the signal across the whole image, then this situtaion is indistinguishable to MAF from a zero increment, i.e., no signal change at all. One can find other methods to easily distinguish this case but they will not be discussed here. Second, if the time change is spatially very spotty, i.e., only affecting isolated pixels or very small groups of pixels, then MAF will also have difficulty distinguishing this situation from the no-change situation. However, spotty changes are likely to be better detected by special purpose algorithms as opposed to the general purpose MAF procedure.

Examples

We present two examples of MAF processed time-difference imagery. The first example is from an area in the Okanogan Highlands province of Washington state; the second is from the western Carson Desert, Nevada. Both examples are generated from Landsat MSS image pairs. In each case preprocessing steps included geographic registration of a 256 by 512 pixel subscene, resampling (using bicubic interpolation), and generation of a difference image. The difference data were normalized to unit variance.

MAF weights for the two examples are given in Table 1, along with the results of standard PCA for purposes of comparison. The MAF vectors are described in terms of the original data space. In general, the maximal and minimal PC are roughly correlated with the corresponding MAF factors, although we should not customarily expect such a high degree of correspondence.

The Okanogan Highlands imagery (Fig. 2) includes the area in and around Midnite Mine, a large open pit uranium mine. The images used in this example were acquired August 8, 1973 and July 29, 1980. Changes between the two dates are related primarily to expansion of the mine area, differences in the condition of the vegetation, and soil moisture differences.

Table 1. MAF and PCA Weights

Okanogan Highlands Example

		Band 4	Band 5	Band 6	Band 7
	1	1.56	3.59	.59	-.92
MAF	2	-.62	-1.32	2.15	2.64
Weights	3	-.79	-1.45	4.75	-3.54
	4	-.496	4.82	-.10	.02
	1	.31	.32	.32	.24
PC	2	-.46	-.43	.32	.74
Weights	3	-.68	-.21	1.86	-1.34
	4	-2.10	2.30	-.37	.18

Carson Desert Example

		Band 4	Band 5	Band 6	Band 7
	1	-.72	-1.48	.71	2.20
MAF	2	1.12	.44	.28	.00
Weights	3	.14	-1.58	3.88	-2.72
	4	-3.34	3.10	1.09	-.93
	1	.27	.28	.28	.26
PC	2	-.73	-.61	.43	.93
Weights	3	-2.40	3.04	-1.51	.87
	4	-1.88	.82	3.23	-2.45

MAF 1 shows the area of expansion as an anomalously bright area in the center of the image. The area that had been mined by 1973 is the roughly horseshoe shaped area of moderate tone encircled by the area of expansion. Although MAF 1 and PC 1 are highly correlated, MAF 1 distinguishes the area of expansion more explicitly. The loading pattern for PC 1 is relatively uniform, while MAF 1, $[1.56 \quad 3.59 \quad .55 \quad -.92]$, is mostly heavily weighted on the bands in which the area of expansion is most distinct from its surroundings (see Fig. 1).

Thus MAF 1 maps the area as two large, spectrally distinct, relatively homogeneous units, by emphasizing the differences between the area of expansion and the remainder of the image.

MAF 2, $[-.62 \quad -1.32 \quad 2.15 \quad 2.64]$, is less straightforward to interpret. It is only moderately correlatd with PC 2, which clearly responds to changes in green biomass. Outside the mine area, MAF 2 also responds to changes in green biomass, but its map shows quite a bit of spatial variability in the mine area itself. A pond near the north end of the mine, within the area of expansion, appears as a dark anomaly, as does the pre-1973 mine area, perhaps due to greater soil moisture at the time of the 1980 image. The area of expansion, aside from the pond, is moderate to bright in tone.

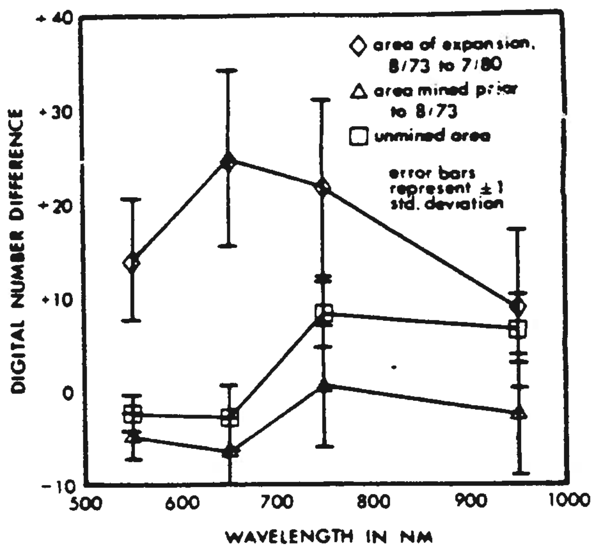


Figure 1 Selected Average Spectra from Okanogan Highlands Difference Image

MAF 3 and MAF 4 contain little or no useful spatial information from an interpretive standpoint and represent the successfully isolated noise components. MAF 3, in particular, does identify and enhance systematic banding, which suggests that it could potentially be used to isolate and remove this type of noise. MAFs 3 and 4 are highly correlated with PC 3 and PC 4. Thus, as anticipated for this type of imagery, both methods apparently provide noise separation.

The Carson Desert imagery (Fig. 3) includes much of the wetland created by the terminal sink of the Carson River. The imagery used in the example was acquired May 26, 1973 and August 6, 1973. Change during this period was primarily related to a decline in water level, changes in green biomass, and the appearance and disappearance of salt efflorscence.

In this example, MAF 1 is highly correlated with PC 2 and MAF 2 is highly correlated with PC 1, i.e., the ordering with respect to the spatial criterion is different than the variance ordering.

MAF 1, $[-.72 \quad -1.48 \quad .71 \quad 2.20]$, highlights areas that changed from shallow water to mudflats or moderately deep water to shallow water, and wetland areas where green biomass increased. The relatively few dark anomalies include some small ponds in which the amount of suspended sediment has decreased (near the Carson River distributary system, on the west side of the image), and areas outside the wetland where the amount of green biomass has decreased.

MAF 2, $[1.12 \quad .44 \quad .28 \quad .00]$, highlights areas that changed from mudflats or very shallow water to dry land, and areas where a salt crust developed. Areas where salt efflorescence decreased or disappeared are shown as numerous and distinct dark anomalies.

As in the Okanogan Highlands example, systematic banding is enhanced by MAF 3 and MAF 4. In this case, however, MAF 3 also contains spatial information that is useful in interpretive processing, while MAF 4 generally isolates noise. MAFs 3 and 4 are only moderately correlated with PCs 3 and 4.

Figure 2 Okanogan Highlands Example

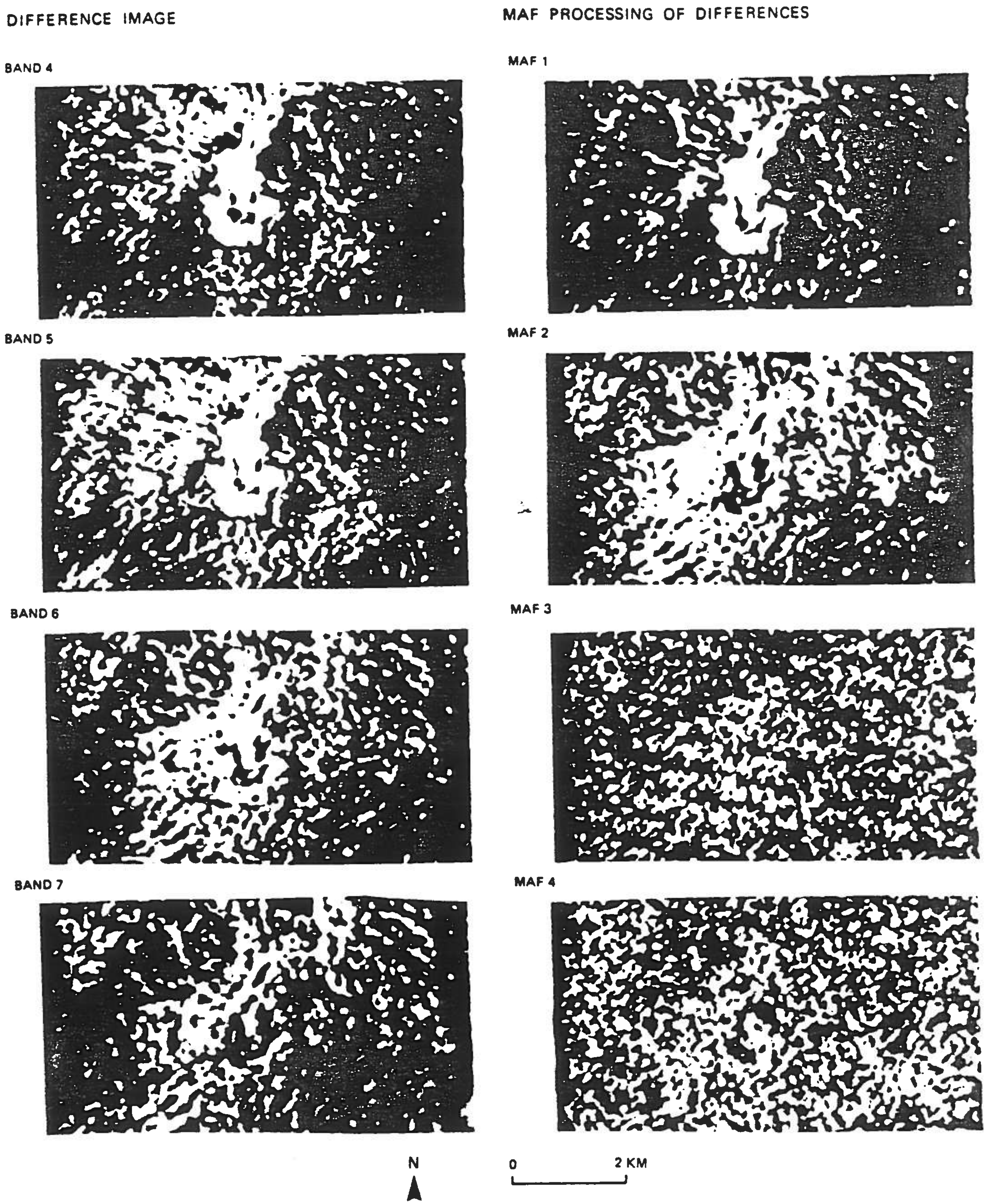
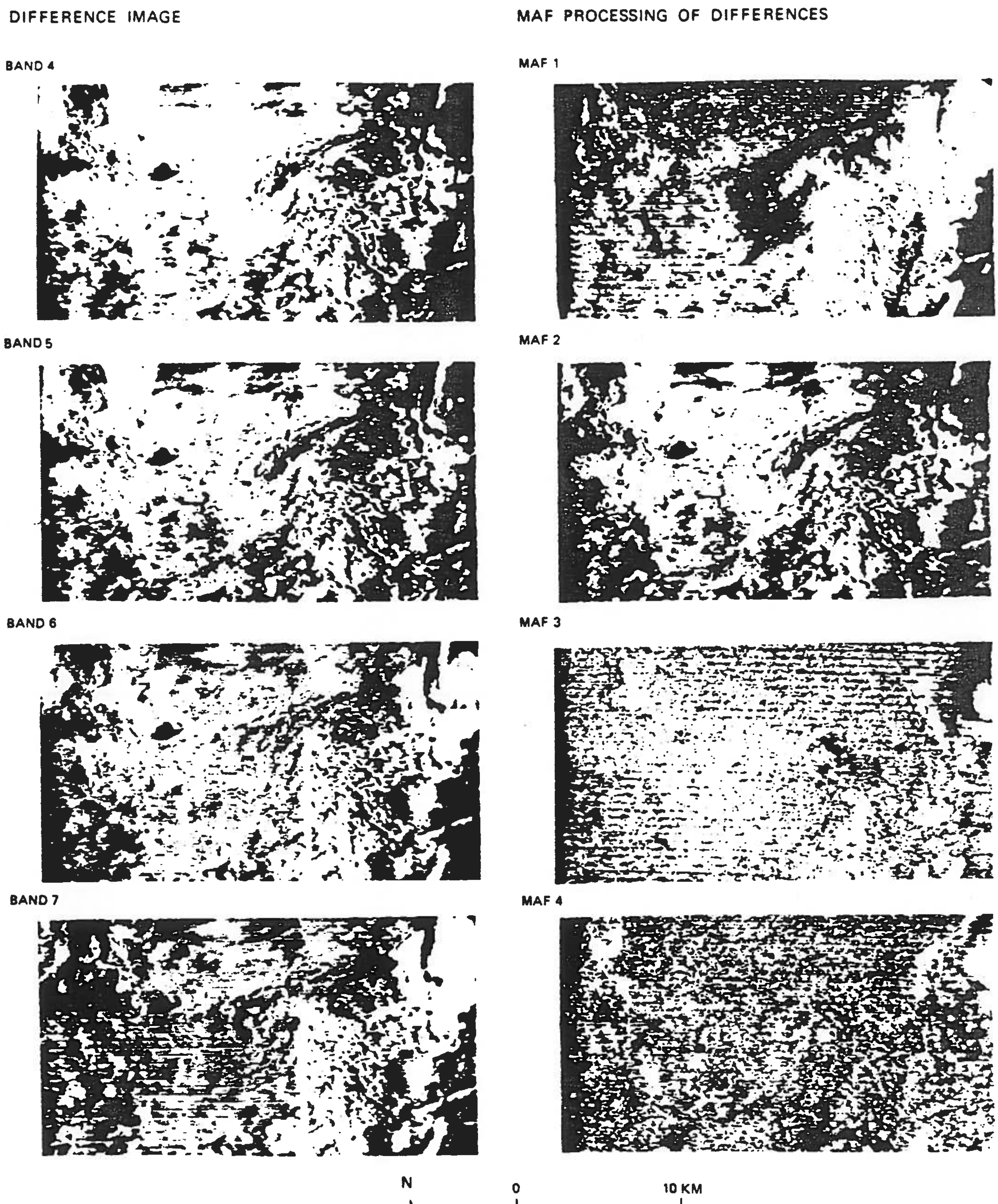


Figure 3 Carson Desert Example



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