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Assessing Change in the Surficial Character of a Semiarid Environment with Landsat Residual Images

Surficial degradation and vegetation productivity in a semiarid environment are distinguished simultaneously with Landsat MSS residual images.

Abstract: *Landsat residual images have been used to assess the relative change in land quality in a semiarid rangeland in east-central Utah. The residual images are computed as the difference between actual MSS reflectance and MSS reflectance predicted with a linear model of change between two successive Landsat scenes. The residuals represent greater than or less than expected deviations from the linear trend. MSS5, MSS6, and R6,5 residual images appear to be related to significant terrain related features. Regions of degradation and vegetation productivity that result from summer thunderstorm activity are distinguished on residual difference images. Degradation produces greater than expected reflectance in the residual image, while vegetation productivity produces less than expected reflectance. Changes in reflectance due to environmental factors which act fairly uniformly over the landscape are accounted for with the trend of the linear model.*

Introduction

The surficial character of a semiarid environment often develops in response to degradational processes that act to lower the useful productivity of the land. These processes are induced by a combination of human and physical factors, particularly the denudation of vegetation by man and domestic animals, and the infrequent and irregular distribution of precipitation (Johnson, 1977). Consequent effects on erosion, salinity, and vegetation productivity typically persist for long periods of time, and act over large geographic areas (e.g., Bentley *et al.*, 1977). However, other changes in the landscape develop rapidly over short time intervals in response to either single catastrophic events or to precipitation events of moderate intensity which recur relatively frequently (Wolman and Miller, 1960). These changes may occur in isolated locations, and affect the quality of the land only temporarily. Some changes are degradational, which become manifest as rills and gullies, or as broader regions of erosion caused by sheetfloods. Still other changes result in an ephemeral growth of vegetation caused by the immediate availability of soil moisture. Therefore, vegetation productivity may increase while degradation occurs simultaneously nearby in the landscape.

Landsat Multispectral Scanner (MSS) reflectance is used in this study to monitor ephemeral vegetation growth and erosion in a semiarid landscape. However, vegetation is typically so sparse in semiarid grassland-shrub communities that reflectance is dominated by the soil background instead of the vegetation. Changes in vegetation density, therefore, must be distinguished indirectly by monitoring the effect of vegetation change on the soil reflectance. Generally, an increase in vegetation density causes an overall decrease in reflectance, while increased soil exposure caused by sheetfloods usually causes reflectance to increase. The magnitude of change in reflectance due to change in vegetation density is difficult to predict because the change in

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reflectance is dependent on the albedo of the background soil. High albedo soils show a greater decrease in reflectance than low albedo soils with a similar increase in vegetation (Siegal and Goetz, 1977). Dynamic environmental factors also affect changes in reflectance, particularly sun angle, antecedent soil moisture, atmospheric conditions, viewing angle of the sensor, and topographic setting of the terrain. Separating the effects of vegetation from the soil background and distinguishing changes in reflectance that are related to extrinsic environmental factors from actual land quality changes are two fundamental problems in a semiarid environment.

In this study, a reflectance difference model is used to assess land quality changes in a semiarid landscape by examining changes in Landsat MSS reflectance that are greater than or less than expected relative to the general trend in reflectance change between two successive images. This is accomplished by regressing spectral reflectance and spectral band ratios from one scene against the paired values in a successive scene. The regression model is used to represent general change in reflectance between two Landsat scenes that may be caused by environmental factors that affect reflectance uniformly across the landscape. Differences between the actual reflectance and the predicted reflectance in the successive scene represent areas of unexpected change. Residual difference images are then created to illustrate the pattern of change from the regression model.

The results of this change detection technique are compared with the results of albedo difference images, which have been shown previously to be useful in detecting changes in land quality of arid and semiarid environments (Robinove *et al.*, 1981). Albedo difference is an example of absolute change, while residual difference represents change relative to the trend identified by the linear regression model.

Background

Albedo Difference Images

Robinove *et al.* (1981) have shown that the relative annual change in land quality of arid and semiarid environments can be assessed by monitoring changes in albedo estimates of the landscape with the Landsat MSS. Albedo is the ratio of the amount of electromagnetic radiation reflected from a surface to the amount of radiation incident on the surface. The authors concluded from field investigations in the Desert Experimental Range in southwestern Utah that annual changes in albedo, as measured with successive fall-to-fall Landsat images, are related to land quality changes. Most increases in albedo are due to catastrophic events, such as flash floods, which increase soil exposure. Most decreases in albedo are caused by an increase in the annual plant cover. However, other decreases may be related to variation in soil moisture. The albedo difference image developed by Robinove *et al.* (1981) is constructed by subtracting albedo values (computed with Equation 1) of two successive Landsat images.

$$\text{Albedo} = \sum_{k=1}^{4} (B_k - B\text{min}_k)/S_k \sin \alpha \; R_k \qquad (1)$$

where

B_k = MSS Band 4 to 7 Dn's,
$B\text{min}_k$ = minimum reflectance value due to atmospheric backscatter in Band k,
S_k = the average solar irradiance at the top of the atmosphere in mW/cm^2 in Band k,
R_k = factor to convert the Dn's to radiances ranging from 0.0 to 2.48 mW/cm^2/sr, and
$\sin \alpha$ = correction factor which allows calculation of albedo as though the sun were at zenith.

Then images are created by grouping albedo changes into class intervals which can be displayed as black-and-white images. This has proven to be a useful technique for detecting changes in the landscape; however, the model used to construct the albedo images can not fully account for all extrinsic environmental factors that also affect reflectance changes. Indeed, this would be a difficult problem to resolve.

Landsat Residual Difference Images

In this study, an attempt is made to account for the effect of extrinsic factors that act uniformly over the landscape by first computing a linear model of spectral reflectance change from two successive images. The linear change model is a simple linear regression of Landsat spectral reflectance from one image against the spectral reflectance of a successive image (Equation 2).

$$\hat{Y}_{i,j,k} = a_0 + a_1 X_{i,j,k} \qquad (2)$$

where

i and j represent pixel coordinates,
k = spectral band or band ratio,
$\hat{Y}$ = estimated spectral reflectance value, and
X = spectral reflectance value for initial scene.

Differences between predicted reflectance and actual reflectance in the successive image represent changes greater than or less than expected in comparison to the overall change between images. Residual images can be constructed for each Landsat image with Equation 3, and subsequent black-and-white images can be made by grouping changes into class intervals much like the albedo difference image.

$$R_{i,j,k} = Y_{i,j,k} - \hat{Y}_{i,j,k} \quad (3)$$

Landsat digital numbers are transformed into reflectance values with Equation 4 (from Robinove, 1982) before regression. Reflectance is the percentage of radiance to irradiance. With this model, reflectance values account for variation in Landsat satellite sensors, as well as some differences caused by changes in sun angle between successive Landsat images.

$$\text{Reflectance} = \pi/E \sin \alpha \; [\text{Dn}/\text{Dmax}(\text{Lmax} - \text{Lmin}) + \text{Lmin}] \quad (4)$$

where

- E = irradiance in mW cm^{-2} at the top of the atmosphere,
- α = solar elevation,
- Dn = digital value of a pixel,
- Dmax = maximum digital number in band,
- Lmax = radiance measured at detector saturation in mW cm^{-2} sr^{-1}, and
- Lmin = lowest radiance measured by detector in mW cm^{-2} sr^{-1}.

Residual images constructed in this manner attempt to account for changes in reflectance that may be caused by environmental effects that act fairly uniformly over the landscape, such as variation in soil moisture or bidirectional reflectance due to terrain and solar elevation. Positive and negative deviations from the predicted change represent increases or decreases in terrain reflectance greater than or less than expected by the predictive model. Residuals are primarily related to surficial changes in the terrain; however, the effects of terrain, soil moisture, sun angle, and even misregistration of successive scenes can contribute error to the interpretation of residuals. Nevertheless, residual difference images provide an additional change procedure that is based on intuitive statistical rules.

Jupp and Mayo (1982) have previously presented the concept of residual images to assess the spectral heterogeneities in spectral classes, such as constructed through unsupervised clustering. These residual images are made by assigning each Landsat pixel the difference between the actual radiance value in each spectral band and the average radiance value for the class in which that pixel is assigned during classification. This method, however, requires that land cover classes have been classified, whereas albedo difference and residual difference images represent changes without regard for *a priori* classification of landscape units. This study does not address the advantages or disadvantages of multispectral classification as a means to detect changes in semiarid landscapes.

Study Area

Matching subscenes from two successive Landsat images of a cold desert in east central Utah were created to illustrate reflectance patterns from the end of a dry period, 2 July 1977, to the end of an active period of summer thunderstorms on 25 August 1977. Subscenes of the two images were registered to the Universal Transverse Mercator coordinate system with a least-squares model, and resampled to 50- by 50-metre pixels (Graham, 1977). Because perfect registration is difficult to achieve, and any misregistration will affect change detection, a Lanczos digital filter (Hamming, 1977) was applied to both registered subscenes to smooth the effects on reflectance.

Four vegetation units common to the Mancos Shale region of east-central Utah are represented in this study area (Figure 1). The first unit consists mostly of halophytic shrubs and associated species. Saltbush is dominant, particularly mat saltbush (Atriplex corrugata) and shadscale (A. confertifolia). These types are found on a young alluvial deposit (Qay) derived from Mancos Shale. This deposit is generally a heavy gray deposit with relatively high albedo when vegetation density is low. The second unit consists of perennial grasses, particularly blue grama (Bouteloua gracilis) and galleta (Hilaria jamesii) on quaternary sands and gravels (Qco) on gentle slopes. Some annuals and shrubs may be mixed with grasses to produce a lower albedo than the Qay surface. The third unit is a fine Jurassic buff sandstone, the Entrada formation (Je), that contains mixtures or nearly pure stands of nonhalophytic shrubs, mostly fourwing saltbush (A. canescens) and rabbitbush (Chrysothamnus nauseousos). The fourth unit is an upland Jurassic composite composed of several formations, particularly Cedar Mountain shale, and Morrison and Saltwash sandstones. This unit is covered with fairly uniform stands of pinyon-juniper forest (*Pinus edulis-Juniperus utahensis*) and associated understory growth.

Regression as a Change Detection Algorithm

The distribution of a systematic sample of paired observations of Landsat MSS5 reflectance values from the July and August images is presented in Figure 2. Least-squares regression lines for linear, quadratic, and cubic regressions are drawn through these paired samples, along with the line of simple difference (see Table 1). The linear regression line accounts for 51.2 percent of the August variance, while the quadratic and cubic lines both account for 63.6 percent of the variance. Nevertheless, the linear regression describes the relationship between July and August MSS5 reflectance better in this semiarid environment. Because most of the reflectance values occur below values of 0.50, the added inflexions of the higher order polynomials do not appear to provide significantly more information on the change in reflectance over this two-month interval.

MSS5 reflectance exhibits greater variation from the linear regression as reflectance values increase.

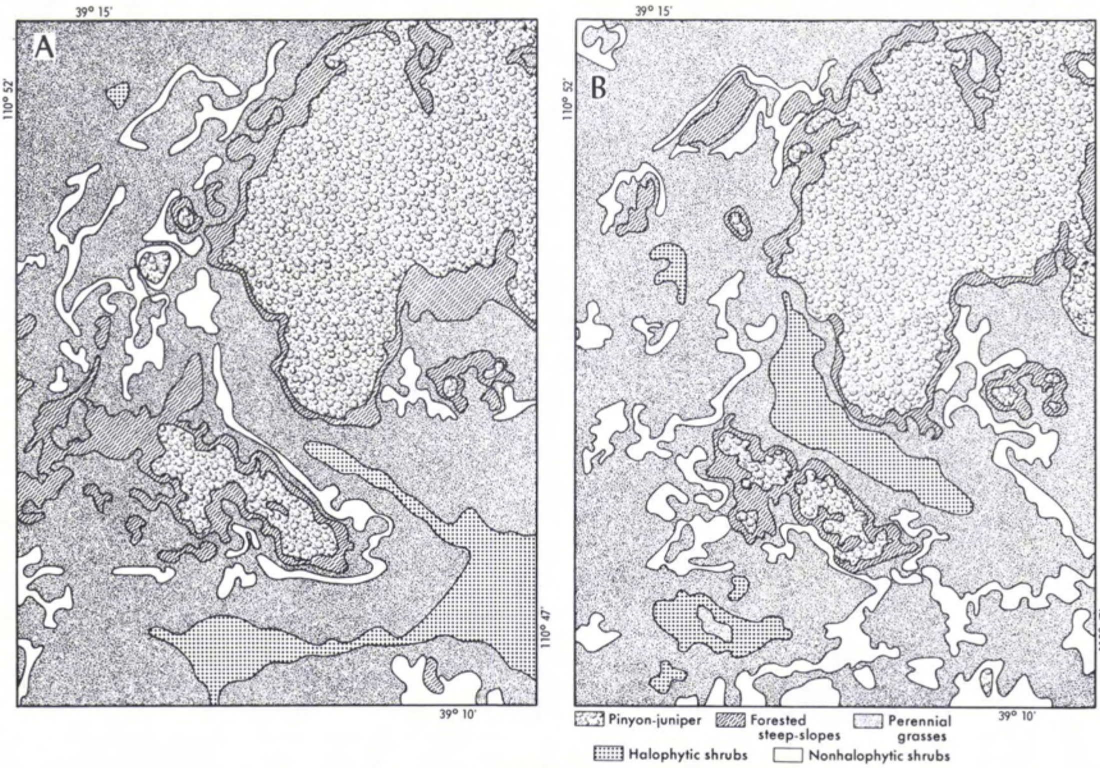

FIG. 1. Vegetation classification derived from Landsat, color IR aerial photographs, and field study.

This may be a problem in detecting changes with residual difference images; however, little variation is apparent in the lower reflectance values. The residual images constructed from this distribution will primarily illustrate change in the relatively high reflectance values. Changes in the higher reflectance values result from increased degradation which acts to increase reflectance, and increased vegetation productivity which acts to decrease reflectance. This appears to be a direct consequence of the total amount of precipitation that has affected this area during this interval between the successive Landsat scenes.

One advantage of regression over simple image differencing with MSS5 to detect change in this semiarid environment also is shown in Figure 2. An image difference between July and August MSS5 reflectance would result in nearly all negative values (below $y = mx$), whereas the linear regression accounts for the general decrease between the successive Landsat scenes. Image differencing can be effective though in environments that exhibit both increases and decreasese in reflectance associated with radical change in surface features. For example, Jensen and Toll (1982) have reported that image differencing is an accurate method for predicting change in the urban fringe where agriculture and range lands are being developed into residential land. Burns and Joyce (1982), in contrast, have demonstrated that regression is ineffective in predicting change that has occurred in the productive alluvial plains of the Mississippi River in southern Louisiana. Regression may have more potential to detect change in semiarid environments because changes in vegetation density are more transitional, causing spectral reflectance to increase or decrease gradually rather than in large increments.

Changes in reflectance can be represented as either relative or absolute changes. Absolute change may be shown for example as a difference in albedo from one time to another, or as a difference in single band reflectance from one time to another. The latter is shown in Figure 2 as the $y = x$ line. Relative change may be shown as the deviation from a predicted value or a value calculated by comparison of the two data sets. This is shown in Figure 2 by the $y = 0.06 + 0.47x$ regression line. Absolute estimates of the rates of degradation or vegetation productivity probably can be made only through direct measurements made *in situ;* however, relative changes in reflectance may provide evidence on the change in condition or quality of the land.

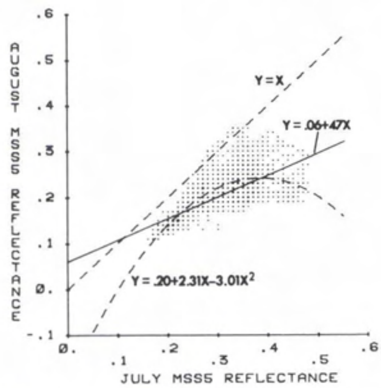

FIG. 2. Sample of MSS5 reflectance from July and August subscenes.

FIG. 3. Landsat albedo image on 2 July 1977.

EXAMPLES OF RESIDUAL AND ALBEDO DIFFERENCE IMAGES

CHANGES DETECTED WITH ALBEDO DIFFERENCE IMAGES

Two albedo images have been constructed for the successive Landsat images with Equation 1 for July (Figure 3) and August (Figure 4). These albedo images are presented to demonstrate the problem of detecting and labelling change in semiarid environments. Considerable change has occurred in the spectral response patterns of these vegetation classes during the interval from 2 July to 25 August. More change has occurred than might be expected because this period is normally characterized by high temperatures, isolated infrequent precipitation, and limited vegetation productivity. Contrary to this usual summer pattern, precipitation events were numerous, as recorded at surrounding stations (Table 2). General observations of vegetation condition were made in the study area during periodic visits from June through August 1977 to verify the mapping units in Figure 1. These observations suggest that an overall growth of summer annuals has occurred. A green flush of herbage was observed, which is consistent with the phenologic response of desert vegetation to summer thunderstorms. Simultaneously, erosion features that developed because of sheet floods were observed along the major drainage corridor of this area. These changes can be seen as classes of albedo change in the albedo difference image in Figure 5. Field transects made at random sites within each vegetation unit indicate that vegetation density has increased, for the most part, where albedo has decreased, while vegetation has been eroded where albedo has increased. This interpretation is consistent with those of Robinove *et al.* (1981) for the Desert Experimental Range.

Some changes in albedo due to changes in sun angle are accounted for with Equation 1; however, bidirectional reflectance change may also affect the albedo difference. For example, a dark linear band oriented nearly north to south at the top-center of Figure 5 shows change due to shadow differences along a steep escarpment. Some differences in atmospheric conditions also are corrected with Equation 1 by subtracting the minimum reflectance associated with atmospheric scatter in each successive image. Otherwise, the atmosphere is considered constant for these two dates.

TABLE 1. RESULTS OF THE LINEAR, QUADRATIC, AND CUBIC REGRESSION OF JULY MSS5 AND AUGUST MSS5 REFLECTANCE

order	r	r^2	$\hat{r}^2$	b_0	b_1	b_2	b_3	SD
linear	0.72	0.51	0.51	0.065	0.470			0.032
quadratic	0.80	0.64	0.64	−0.200	2.308	−3.001		0.027
cubic	0.80	0.64	0.64	−0.252	2.834	−4.750	1.828	0.027

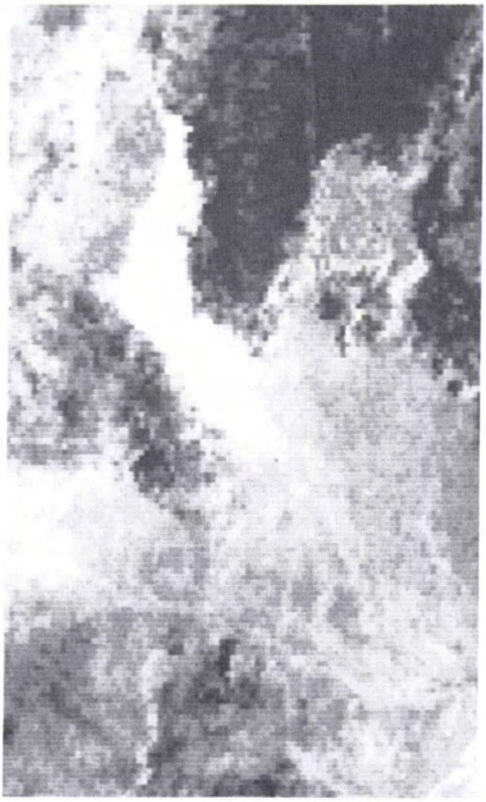

FIG. 4. Landsat albedo image on 25 August 1977.

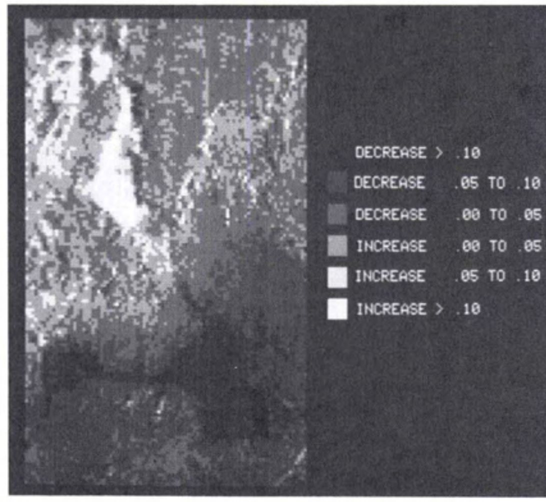

FIG. 5. Albedo difference image.

CHANGES DETECTED WITH RESIDUAL DIFFERENCE IMAGES

The July subscene was regressed against the August subscene one spectral band at a time with a simple linear least-squares model. Individual spectral band ratios described in Table 3 were computed for each subscene, and were regressed in the same manner. The results of these linear regressions are presented in Table 4. A more general summary of the July and August reflectance and band ratio characteristics is presented in Table 5.

In general, these results indicate that approximately half of the variance in individual MSS bands can be explained by the linear regression. This suggests that a general trend exists between the reflectance patterns in the July and August scenes. The relationship between July and August MSS band ratios depends on the combination of bands; for example, the R6,5 regression demonstrates that a general trend is not apparent (0.35), while the R5,4 regression suggests changes are more predictable.

TABLE 2. PRECIPITATION AMOUNT SUMMARY FOR FIVE STATIONS SURROUNDING THE STUDY AREA OVER THE TIME INTERVAL 4 JULY 1977 TO 22 AUGUST 1977

		Amount (mm)				
Event	Date	Hiawatha	Emery	Green River	Hanksville	Thompson
A	July 4	17.53	2.79	14.83	3.05	21.59
	5	4.57				3.05
B	19	1.27	3.30			
	20		3.56			
	21				8.89	
	23		1.27	13.21	0.51	7.62
	24	19.81	17.78	5.08	0.25	3.05
C	Aug 14	4.06			2.03	
	15	0.76		11.68		
	17	22.86	4.83	8.13	0.76	11.68
	18	22.35			1.27	2.03
	19				6.86	28.19
	20		5.08		0.25	
	21		10.67			
	22		6.10			
TOTALS		93.21	55.38	42.93	23.87	77.21

TABLE 3. EQUATIONS USED TO COMPUTE SPECTRAL REFLECTANCE AND SPECTRAL BAND RATIOS FROM LANDSAT MSS DIGITAL NUMBERS

Landsat Reflectance Values

MSS4 = 3.141593/17.70 sin α {MSS4/127.0(2.63–0.08) + 0.08}
MSS5 = 3.141593/15.15 sin α {MSS5/127.0(1.76–0.06) + 0.06}
MSS6 = 3.141593/12.37 sin α {MSS6/127.0(1.52–0.06) + 0.06}
MSS7 = 3.141593/24.91 sin α {MSS7/63.0(3.91–0.11) + 0.11}

where α = 55.0 on 2 July 1977
α = 44.0 on 25 August 1977

Landsat Reflectance Ratios

R5,4 = MSS5/MSS4
R6,4 = MSS6/MSS4
R7,4 = MSS7/MSS4
R6,5 = MSS6/MSS5
R7,5 = MSS7/MSS5
R7,6 = MSS7/MSS6

Landsat Reflectance Index Models

TVI7 = SQRT(MSS7 − MSS5)/(MSS7 + MSS5) + 0.5)
TVI6 = SQRT(MSS6 − MSS5)/(MSS6 + MSS5) + 0.5)

Because R6,5 has been shown to be sensitive to the amount of vegetation (Tucker, 1979; Curran, 1982), this lack of predictable relationship suggests that significant change may have occurred in the vegetation character of the terrain that cannot be explained by the general change that is explained by the linear model. In contrast, the R5,4 regression, which distinguishes best between soil and rock groups (Eliason *et al.*, 1981), indicates that a smaller change has occurred in the surficial character of the soil and rock, as would be expected.

MSS5, MSS6, R6,5, and R5,4 residual difference images are used to examine the relationship between spectral reflectance change and surficial characteristics in this study area. These residual difference images have been selected based on the results of the linear regression, and based on the fundamental relationships that can be expected from these images. Other residual difference images, particularly R7,6 and TVI6, have the potential to represent significant terrain related change; however, the evidence that has emerged in this study indicates that these ratios represent similar terrain related changes as seen in MSS5, MSS6, R6,5, and R5,4.

MSS 5 RESIDUAL DIFFERENCE IMAGE

A residual difference image of MSS5 reflectance has been constructed to illustrate the relationship between a single band reflectance and surficial changes in the landscape. The MSS6 residual difference image could also be displayed; however, the pattern of residuals is nearly identical to the MSS5 residual difference image (see Table 6). Selection of class intervals to display the residual change can be subjective; therefore, intervals have been selected to illustrate classes that are related to significant terrain features. Five percent intervals of reflectance greater than or less than expected from the linear regression have been used in the accompanying image (Figure 6).

In general, three classes of change are depicted in the MSS5 residual difference image: areas that have increased in vegetation cover (decreased reflectance), areas that have been eroded along the major drainage corridor (increased reflectance), and transitional areas that exhibit small deviations from the predicted change. A general decrease in plant cover is consistent with flooding that has occurred in the major drainages. Perennial grasses near the major drainage, but slightly upslope, exhibit an increase in plant cover due to the availability of soil moisture. These areas are distinguished on the re-

TABLE 4. RESULTS OF THE LINEAR REGRESSION OF JULY REFLECTANCE AND BAND RATIOS AGAINST AUGUST REFLECTANCE AND BAND RATIOS.

REFLECTANCE OR RATIO	r	r^2	a_0	a_1	SE
MSS4	0.68	0.46	0.05	0.51	0.0249
MSS5	0.72	0.52	0.06	0.47	0.0313
MSS6	0.71	0.51	0.08	0.47	0.0305
MSS7	0.66	0.44	0.09	0.45	0.0313
R5,4	0.89	0.79	0.22	0.79	0.0368
R6,4	0.83	0.70	0.09	0.94	0.0550
R7,4	0.76	0.58	0.14	0.90	0.0644
R6,5	0.59	0.35	0.24	0.81	0.0614
R7,5	0.70	0.49	0.21	0.85	0.0688
R7,6	0.61	0.38	0.37	0.64	0.0418
TVI6	0.66	0.43	0.17	0.78	0.0651
TVI7	0.77	0.59	0.15	0.81	0.0536

TABLE 5. GENERAL SUMMARY OF THE JULY AND AUGUST REFLECTANCE AND BAND RATIO CHARACTERISTICS IN UTAH STUDY AREA.

	July Reflectance					August Reflectance				
Variable	Mean	SD	Min	Max	Range	Mean	SD	Min	Max	Range
MSS4	0.262	0.046	0.17	0.47	0.24	0.184	0.035	0.12	0.31	0.19
MSS5	0.296	0.069	0.16	0.49	0.33	0.204	0.045	0.11	0.35	0.24
MSS6	0.327	0.066	0.19	0.53	0.34	0.231	0.044	0.14	0.38	0.24
MSS7	0.328	0.062	0.20	0.51	0.31	0.234	0.042	0.13	0.38	0.25
R5,4	1.118	0.092	0.92	1.47	0.22	1.098	0.081	0.85	1.41	0.56
R6,4	1.242	0.083	1.03	1.64	0.61	1.253	0.093	1.04	2.06	1.02
R7,4	1.251	0.088	0.95	1.65	0.70	1.270	0.104	0.94	2.49	1.55
R6,5	1.114	0.053	1.00	1.33	0.33	1.144	0.072	1.01	2.31	1.30
R7,5	1.123	0.085	0.94	1.46	0.52	1.160	0.104	0.93	2.69	1.76
R7,6	1.007	0.035	0.91	1.15	0.24	1.013	0.036	0.80	1.22	0.42
TVI6	0.743	0.016	0.71	0.80	0.09	0.752	0.019	0.71	0.95	0.24
TVI7	0.745	0.025	0.68	0.83	0.15	0.756	0.026	0.68	0.98	0.30

sidual difference image as an increase in reflectance greater than expected from 0.00 to 0.05. In comparison, the albedo difference image suggests that this area has decreased in absolute albedo from 0.00 to 0.05. This change differs from the greater vegetation growth that has occurred near the bottom of the scene, especially in the saltbush communities. The residual difference image indicates the decrease in reflectance of this surface is much greater than expected (0.05 to 0.10, and greater than 0.10). The albedo difference image illustrates this change in absolute terms; indeed, the outline of the saltbush growth is clearly depicted on the albedo difference image. The residual difference image, however, illustrates the areas of relative change, which considers the Qay change in the same class as other areas of similar vegetation growth. The class intervals produce a change image that depicts regions of similar change, rather than absolute change as seen in the albedo difference image. These change images can be seen to correspond to known changes in the semiarid environment that are related to general degradation and vegetation productivity. These relative change maps may be most useful in a management application because the changes in the condition of vegetation can be monitored by examining the relative increases and decreases in reflectance. This is a similar application proposed by Yazdani *et al.* (1981) for mapping the general condition of crops with a Multi-temporal Vegetation Index (MTVI).

Yet the MSS residual difference images do not show the areas of extreme change. For example, an isolated green flush of herbage was readily apparent in the field, but is not evident on the MSS5 residual difference image. For this purpose, the R6,5 residual image was constructed to map changes in extreme vegetation growth.

R6,5 AND R5,4 RESIDUAL IMAGES

The linear regression of R6,5 in July against R6,5 in August illustrates that extreme residuals exist with the linear regression. These residuals are responsible for the low r-squared coefficients in this model. The large residuals, however, are related to the extreme changes in vegetation cover at an isolated location in the northwest part of the study area that has exhibited a green flush of growth on an otherwise dry lakebed. This change is not apparent

TABLE 6. FREQUENCY (%) OF CHANGE FOR ALBEDO AND RESIDUAL DIFFERENCE IMAGES FROM 2 JULY 1977 TO 25 AUGUST 1977.

	DECREASE			INCREASE		
	>0.10	0.05–0.10	0.00–0.05	0.00–0.05	0.05–0.10	>0.10
ALBEDO	10.37	26.93	34.03	21.96	5.06	1.66
MSS5	0.01	2.04	59.59	28.17	8.17	2.11
MSS6	0.01	2.29	57.71	30.40	7.54	2.04

	DECREASE		INCREASE	
	>0.15	0.00–0.15	0.00–0.15	>0.15
R6,5	00.50	53.05	44.83	1.62
	>0.10	0.00–0.10	0.00–0.10	>0.10
R5,4	9.13	47.52	38.44	4.91

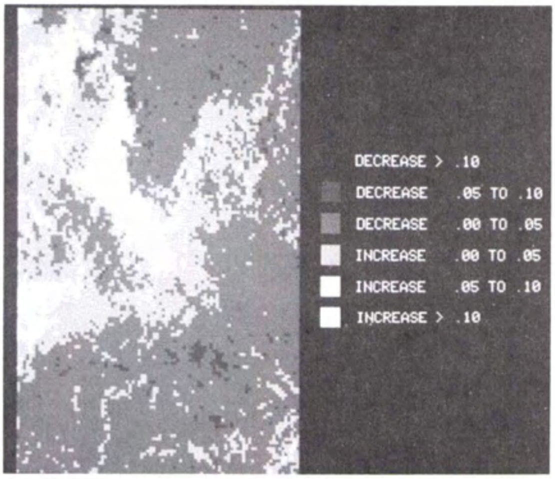

FIG. 6. Landsat MSS5 residual difference image with linear regression model.

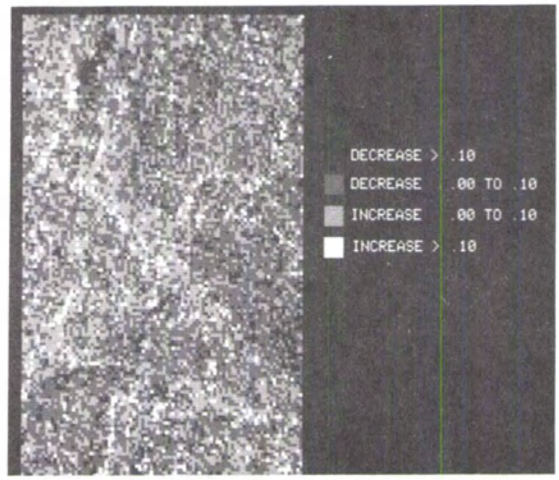

FIG. 8. Landsat R5,4 residual difference image with linear regression model.

on the MSS5 residual difference image or the albedo difference image. Yet the change is obvious on the R6,5 residual difference image as an increase in R6,5 much greater than expected (Figure 7). This residual difference image demonstrates that regression can provide information on the condition of vegetation that the albedo difference image does not illustrate.

The linear regression from R5,4 indicates that little unexpected change has occurred in the R5,4 values from July to August. Because R5,4 distinguishes best between soil and rock units, the change is expected to be predictable. The residual difference image constructed from R5,4 (Figure 8) shows random terrain changes. R5,4 residuals do not appear to be as effective as either the MSS5 or R6,5 residual images, or the albedo difference image for the purpose of monitoring change in the surficial character of this environment.

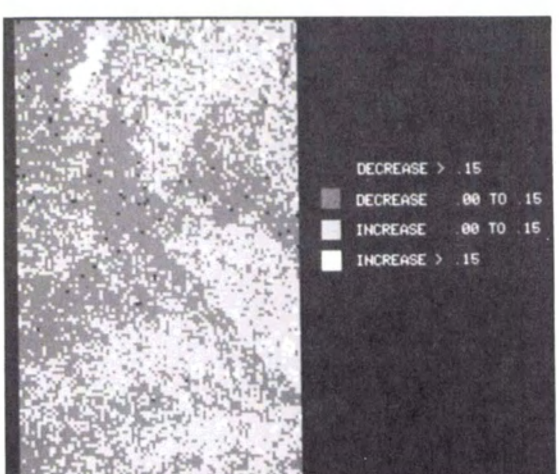

FIG. 7. Landsat R6,5 residual difference image with linear regression model.

SUMMARY OF RESIDUAL DIFFERENCE IMAGES

McDaniel and Haas (1982) have suggested that MSS6 and MSS7 radiance do not vary as much seasonally as the MSS4 and MSS5 radiance in a semiarid environment. This means that the relative sensitivity of band ratios to changes in the character of vegetation should be determined by the responsiveness of the visible bands. The results of this study suggest that MSS5, MSS6, and MSS7 exhibit equal variance and range within a scene (see Table 5). However, MSS5 and MSS7 show more variation between the two successive scenes than either MSS4 or MSS6. MSS4 radiance contributes to the largest band ratio variance in the R7,4 regression. Both MSS5 and MSS6 residual difference images provide effectively the same information, while the R5,4 residual difference image provides less information on the relative change in the surficial character of the environment. R6,5 regression results in large extreme values which represent extreme change in vegetation productivity.

CONCLUSIONS

A procedure to construct residual difference images that are related to relative changes in the surficial character of semiarid environments has been presented. The residual difference image is computed as the difference between actual MSS radiance or band ratio values, and the linear model of change between two successive Landsat images. This method has the advantage that greater than or less than expected deviations from this general trend represent degradation and vegetation productivity. The uniform environmental effects are partially accounted for in the linear model of change.

The linear model used in this study is probably limited to relatively small geographic areas, although this assumption has not been examined in this study. Because precipitation events occur irregularly and in isolated locations during the summer months, a large geographic area could introduce more variability due to the environment than the linear model is able to represent as uniform change.

The residual difference images constructed in this study only represent the relative change in land quality of a semiarid environment. Yet this method provides another tool to assess and monitor spatial trends in vegetation productivity and degradation in a semiarid environment.

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