Analysis of Change in Piñon-Juniper Woodlands Based on Aerial Photography, 1930's-1980's

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Abstract—We conducted an analysis of land cover change in selected piñon-juniper woodlands of New Mexico and Arizona, using aerial photographs from the 1930's through the 1980's. Both increases and decreases in woodland cover were observed. Fractal dimensions of woodland patches and cover-type changes were analyzed following the method of Krummel and others (1987). The analysis failed to identify the scale of anthropogenic disturbance, although land cover change is clearly due in part to human activity. The analytical method may be an insensitive indicator in these woodland systems because the fractal properties of both natural vegetative cover and human-induced changes are subject to topographic constraints.

Piñon-juniper woodlands are a common vegetation cover type in semi-arid regions of North America. In the southwestern United States, the association is typically composed of either *Pinus edulis* (Engelm.) Sarg. or *Pinus monophylla* Torr. & Frem. in conjunction with various species of *Juniperus*, most commonly *J. monosperma* (Englem.) Sarg., *J. osteosperma* (Torr.) Little, or *J. scopulorum* Sarg. In Mexico, a variety of other piñon pine and juniper species can be important woodland components.

Various processes, both natural and anthropogenic, lead to changes in the spatial distribution of piñon-juniper woodlands over time. Important among these are (1) establishment of seedlings during periods of favorable climatic conditions, (2) mortality of seedlings or adult trees during drought conditions, (3) invasion of junipers into grassland in response to overgrazing and/or fire suppression, (4) removal of trees by humans as a result of fuelwood harvesting, chaining for rangeland management, or clearing of land for urban or agricultural uses.

One focus of landscape ecology is the development of quantitative techniques for the analysis spatial patterns and the changes in such patterns over time. Krummel and others (1987) used a perimeter-area scaling method to determine the fractal dimension of deciduous forest patches in the lower Mississippi River floodplain of the United States. Their results showed a low fractal dimension (1.2) for small patches (<55.7 ha) with an abrupt transition to a higher fractal dimension (1.5) for larger patches (>100.4 ha). This was interpreted as indicating that anthropogenic processes play a dominant role in shaping small forest fragments, while natural processes subject to topographic constraints determine the shape of larger forested areas. On the basis of this result, Krummel and others (1987) suggested that the fractal dimension of vegetated patches could be monitored routinely as an indicator of landscape condition, with abrupt shifts to lower values indicating anthropogenic disturbance.

We have applied the method of Krummel and others (1987) to quantify patterns and changes in selected piñon-juniper woodlands of Arizona and New Mexico, USA. Using aerial photography, we calculated the fractal dimension of woodland patches at each study site at various times within a period extending from 1935 through 1988. Additionally, by comparing consecutive photographs, patches representing changes in land cover (i.e., loss or gain of woodland) could be delineated. We extended the methodology of Krummel and others by performing an analysis not only of the woodland patches themselves, but also patches representing changes in woodland cover over time. On the basis of our results, we find only equivocal support for the notion that the method can be used to routinely monitor anthropogenic disturbance in these landscapes. Our analysis points out several methodological issues which require more intensive study before the applicability of this technique to diverse landscape types can be properly assessed.

Materials and Methods

Four U.S. Geological Survey 1:24000 scale quadrangles were selected as study areas for this research. This is a subset of a set of approximately 30 study areas under investigation in a study of woodland/grassland ecotones (Milne and others 1996). The four quadrangles selected for the current analysis were chosen to represent a variety of climatic conditions, being arrayed along a longitudinal gradient of primarily winter precipitation in the west to a more bimodal pattern of winter and summer precipitation in the east. Panchromatic aerial photographs covering each quadrangle were obtained through the Earth Data Analysis Center at the University of New Mexico. Information on the locations of the quadrangles and the dates of the photography used is summarized in table 1.

In: Finch, Deborah M.; Whitney, Jeffrey C.; Kelly, Jeffrey F.; Loftin, Samuel R. 1999. Rio Grande ecosystems: linking land, water, and people. Toward a sustainable future for the Middle Rio Grande Basin. 1998 June 2-5; Albuquerque, NM. Proc. RMRS-P-7. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

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Table 1—Study areas and dates of aerial photography. Quadrangle names refer to U.S. Geological Survey 1:24000 maps.

Quadrangle name	Latitude	Longitude	Photograph dates
El Dado Mesa, NM	35° 22' 30"N	107° 22' 30"W	1935 1952 1988
Pine Canyon, NM	35° 15' 00"N	108° 07' 30"W	1935 1952 1987
Sandia Park, NM	35° 07' 30"N	106° 15' 00"W	1935 1951 1976 1987
Toothpick Ridge, AZ	36° 37' 30"N	112° 22' 30"W	1953 1981

Photographs were digitized using an 8-bit Hewlett Packard Scanjet IIc flatbed scanner at a resolution such that each individual pixel represented 2.5 x 2.5 m on the ground. Images were transferred from the original TIFF format to the VIFF format of the Khoros system (Konstantinos and Rasure 1994, Rasure and Williams 1991) and then to ASCII format for input to Grass 4.1 in which scanned images were mosaicked together and geographically rectified to the UTM coordinate system.

From imagery covering each 7.5 minute USGS quadrangle, a 1200 x 1200 pixel (3.0 x 3.0 km) subimage was extracted for analysis. The approximate position of the subimage within the quadrangle was determined randomly, by partitioning the quadrangle into four quadrants, and randomly determining the quadrant from which to extract the subimage. Exact location of the subimage was chosen by the analyst, with an effort made to minimize the inclusion of heavily shadowed areas within the subimage, since dark shadows can lead to errors in the subsequent classification.

The gray-scale subimages were classified into two classes corresponding to wooded areas and grasslands by interactively setting a gray-scale threshold and comparing the classified subimage to the original gray-scale subimage. This interactive procedure appeared to produce results which were as good or better than automatic classification schemes, such as k-means cluster analysis (Tou and Gonzalez 1974, p.94). A histogram equalization of the gray-scale was performed on some images to enhance their contrast prior to classification (Jensen 1996, p.150).

Changes in land cover were detected by overlaying classified subimages from successive dates. However, since successive images cannot be expected to be rectified with exact pixel-to-pixel accuracy, some allowance must be made to avoid falsely classifying slight mis-rectifications as actual changes in cover. This was done by defining a 4-pixel (10 m) wide buffer zone at each woodland/grassland interface. The buffer was created using a morphological edge detection algorithm, which involved convolution with a kernel defined to produce a two pixel thick external edge surrounding each woodland or grassland patch (Giardina and Dougherty 1988). Thus defined, the external edges of woodland and grassland patches adjoin, yielding a buffer four pixels in thickness. Change in land cover was inferred only when a definitely classified pixel (i.e., outside the buffer) of one type (woodland or grassland) is definitely classified as the opposite type at a succeeding date. Overlays of the classified subimages (with buffer zone) produced maps of patches representing land cover change, both woodland converted to grassland and vice versa. Edge extraction and overlaying of subimages was done using the Khoros system (Konstantinos and Rasure 1994, Rasure and Williams 1991).

Fractal dimensions were calculated using a C program written by one of the authors (Johnson). Following the methodology of Krummel and others (1987), patches were ordered by size and regressions of log patch perimeter on log patch area were performed in a sliding window containing a constant number of patches, N. Separate regressions were performed for each possible window, ranging from the N smallest patches to the N largest patches. Krummel and others (1987) employed a window size of N = 200 patches. We performed regressions with window sizes of N = 50, 100, and 200 patches for each study area. The fractal dimension, D, was computed as two times the slope of the regression (Hastings and Sugihara 1993, pp.48-50, Lovejoy 1982).

Results

The amount of land surface showing a definite change in cover type is summarized in table 2 for each subimage at each time interval. The values in table 2 do not include any changes which occurred in the buffer zone of the patches defined in subimages, therefore, short distance (<10 m) shifts in patch boundaries will be undetected. Thus, the values in table 2 probably represent lower bounds on the area of land cover which changed over each time interval. Each subimage depicts an area of 900 ha. The areas exhibiting definite change in cover type over any given time interval comprise only a few percent of the total area in the subimage. The net effect of the changes can be either an increase or a decrease in woodland, depending upon the location and the time interval.

Patches of land surface which underwent a definite change in land cover showed a strongly skewed distribution of sizes,

Table 2—Land surface areas exhibiting definite change in subimages from each study site during each time interval. Positive values of net change represent in increase in woodland cover, negative values represent a decrease.

Study site	Time interval	Grassland to woodland	Woodland to grassland	Net change in woodland
El Dado Mesa	1935 - 52	15.0 ha	5.0 ha	+10.0 ha
	1952 - 87	15.2 ha	8.2 ha	+7.0 ha
Pine Canyon	1935 - 52	1.5 ha	3.6 ha	2.1 ha
	1952 - 86	7.3 ha	3.2 ha	+4.1 ha
Sandia Park	1935 - 51	16.1 ha	29.4 ha	13.3 ha
	1951 - 76	23.2 ha	5.0 ha	+18.2 ha
	1976 - 87	2.5 ha	20.3 ha	17.8 ha
Toothpick Ridge	1953 - 80	2.6 ha	16.4 ha	+13.8 ha

with many more small patches than large ones. For instance, in the Sandia Park subimage during the 1935-51 interval, the size of the patches representing land cover change ranged from 1 pixel (6.25 m^2) up to 2631 pixels (16,400 m^2), but with the median patch size near the lower end at 4 pixels (25 m^2). Similar distributions were observed at other locations and at other intervals.

Sliding-window regressions were performed to evaluate the scale-dependence of the fractal dimension of woodland patches in all subimages. Only the 1935 Sandia Park subimage displayed a clear scale dependence (fig. 1a). The pattern was qualitatively similar to that observed by Krummel and others in their study: a low fractal dimension for small patches, with an abrupt shift to a higher dimension for large patches. However, most subimages displayed no clear shift in fractal dimension. The 1951 Sandia Park subimage is typical: the variation in estimates of D for small patches is accompanied by a substantial drop in the R^2 of the regression, and thus cannot be interpreted as clear evidence for a scale-dependent shift in fractal geometry (fig. 1b).

Typical results of performing a sliding-window regression to compute the fractal dimension of the patches representing definite changes in land cover are presented in figure 2. As can be seen, the fractal dimension is relatively constant at a value of approximately 1.5, independent of mean patch size. This is true for both patches representing woodland converting to grassland, and vice versa. The only suggestion of a shift in the value of D is an increase for very small patch sizes (<75 pixels, i.e., <0.045 ha). However, the increasing values of D are accompanied by a decreasing R^2 for the regression model, indicating a poorer fit. The same pattern illustrated in figure 2 (namely, a constant D 1.5 except for a possible increase at small patch sizes) was evident at all study sites at all time intervals.

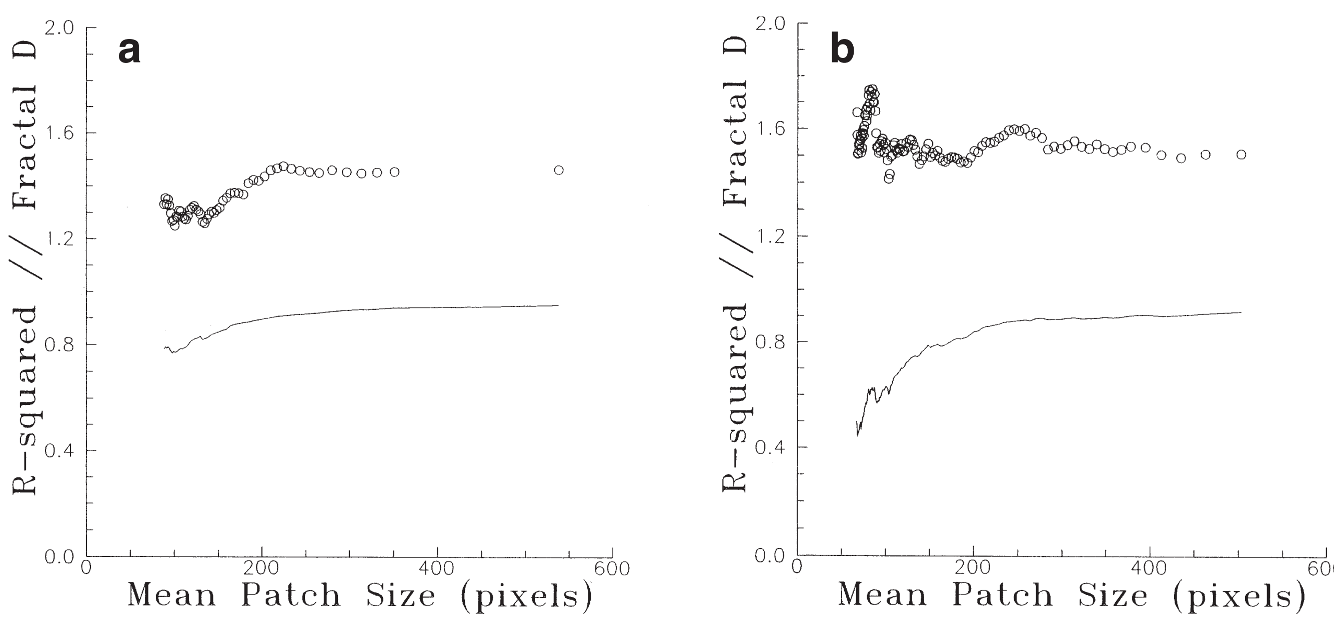

Figure 1—Upper curve: Fractal dimension as a function of mean patch size, computed using a sliding window of 100 patches. Lower curve: R^2 for each regression. Results are for the Sandia Park subimage. (a) woodland patches in 1935. (b) woodland patches in 1951.

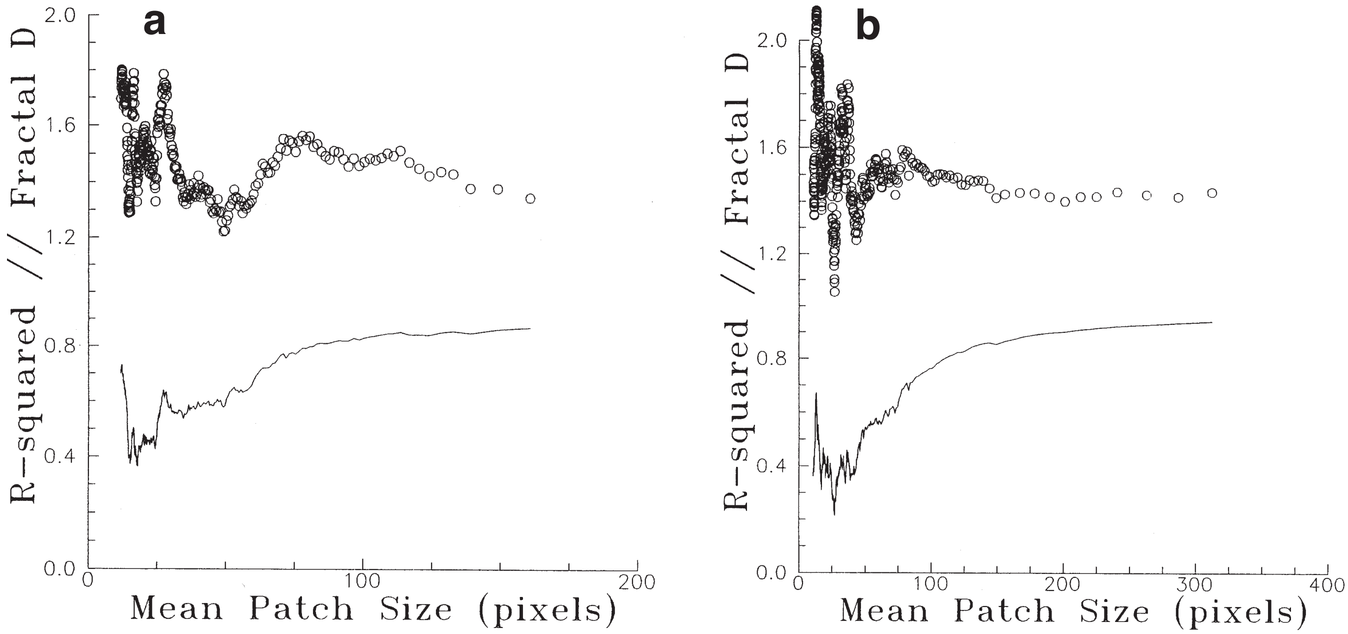

Figure 2—Upper curve: Fractal dimension as a function of mean patch size, computed using a sliding window of 100 patches. Lower curve: R^2 for each regression. Results are for the Sandia Park subimage during the interval from 1935 to 1951. (a) patches representing definite grassland converted to definite woodland. (b) patches representing definite woodland converted to definite grassland.

Discussion

The changes in cover over time presented in table 2 are consistent with a conceptual model of a slowly shifting mosaic of vegetation in the landscape (Pickett and White 1985, Remmert 1991, Watt 1947, Wu and Loucks 1995). On the time scale of decades, patches of former grassland are converted to woodland as conditions appropriate for juniper establishment are encountered, and conversely, patches of former woodland are lost as trees die due to natural causes or are removed by human activities. On a regional scale, piñon-juniper woodlands may be in a dynamic steady-state (sensu Bormann and Likens 1979) in which the proportion of the landscape covered by woodland is constant over time, except for stochastic fluctuations. Alternatively, there may be an overall increasing or decreasing trend in the amount of woodland cover, as the landscape adjusts to climatic trends and changes in human land use patterns. The data set used in this study is too small to distinguish between these alternatives. However, the methods developed here could be employed to address the issue. Resolution of this question would settle a long-standing debate.

When the fractal dimension of woodland patches is examined, the usual pattern observed was a value in the range of 1.5-1.6, with larger fluctuations (and low R^2) at small patch sizes. Only in the case of the 1935 Sandia Park subimage was there a pattern consistent with a systematic shift in fractal dimension as a function of mean patch size. Visual inspection of the original gray-scale images strongly suggests that anthropogenic disturbance occurs in other subimages, but such disturbance is not detectable on the basis of a routine application of the method of Krummel and others (1987).

Extension of the method to analyze patches representing changes in woodlands between successive photographs did not improve our ability to detect anthropogenic disturbance. In all such analyses, the fractal dimension appeared relatively constant with a value near 1.5. The only observed fluctuations occurred at very small patch sizes. However, these fluctuations were always accompanied by substantial reductions in the R^2 of the regression, indicating a lack of conformity to the power-law scaling, thereby making any interpretation difficult.

One bias that might affect our estimation of fractal dimensions, particularly at small patch sizes, is an effect discussed by Milne (1990). When fractal dimensions are calculated from a perimeter to area ratio, the maximum value for any possible arrangement of N pixels varies in a sawtooth pattern as a function of N, and is often below the theoretical maximum of 2.0. This effect is most pronounced when N is small. In a test of the impact of this bias on our results, we calculated a normalized fractal dimension as follows:

$$D_{norm} = 2(D/D_{max})$$

where D_{norm} is the normalized fractal dimension, D is the fractal dimension from the usual perimeter-area relationship, and D_{max} is the maximum fractal dimension for any arrangement with the same number of pixels as the given cluster. Note that the normalized fractal dimension will always have maximum value of 2.

As expected, the greatest effect of this adjustment was at small patch sizes. However, over the range of patch sizes used in our analyses, the effect was not large, and did not qualitatively change the nature of the graphs of fractal dimension vs. mean patch size. Specifically, fluctuations in the graph at small patch sizes which were evident when the usual fractal dimension was plotted were still evident when the normalized fractal dimension was used (data not shown). If anything, the amplitude of the fluctuations was somewhat greater when the normalized fractal dimension was employed. Since the normalized fractal dimension did not change the interpretation of our results, only data based on the usual definition of fractal dimension were presented here.

The fact that the fractal dimensions of both the woodland patches and the patches representing change hover near a value of 1.5 is suggestive. Topographic surfaces, particularly mountainous areas such as our study sites, typically have a fractal dimension $D_{surface}$ 2.5 (Mandelbrot 1983). If piñon-juniper woodlands were restricted to elevations above some fixed threshold, one would expect the resulting pattern to have a fractal dimension $D_{woodland} = D_{surface} - 1 = 1.5$. Of course, in the real world, slope and aspect effects modify the lower elevational ecotone of piñon-juniper woodlands, but these effects may not change the fractal dimension much. Thus, the fact that most patches have fractal dimensions near 1.5 is consistent with the hypothesis that the distribution of woodlands, and changes in woodlands, are strongly constrained by topography.

It may be reasonable to assume that even the patterns of anthropogenic disturbance in these ecosystems may be largely determined by topographic constraints. The Mississippi floodplain forests analyzed by Krummel and others (1987) were probably essentially continuous prior to human disturbance. Thus, any edges arising from human activity are likely to be simple in shape, and to leave fragments with low fractal dimension. Piñon-juniper woodlands in mountainous terrain, on the other hand, are fragmented in their natural condition. Human activity may result in the removal of patches, or parts of patches, of woodland. Yet even in a highly disturbed piñon-juniper system, most of the edges would still be topographically influenced. This effect is due to a combination of (1) the large number of natural edges controlled by topography, and (2) the tendency of human removal of trees to follow elevational contours when there is substantial topographic relief. Because both natural processes and human activities are influenced by topography, a shift in fractal dimension may not occur.

Although topographic constraints could account for the difference between our results and those of Krummel and others (1987), there are several methodological problems that might also have influenced our results or their interpretation. First, our results could be influenced by errors in the initial classification of the gray-scale images into woodland and grassland cover types. Most problematic are probably shadows, since the true vegetation cover in heavily shadowed areas cannot be ascertained, and dark areas of shadowed grassland may be misclassified as woodland. Shadows are most pronounced in areas of high topographic relief, and the degree of shadowing and positions of the shadows may change from photograph to photograph depending upon the season and time of day. Thus, shifts in shadows could be misinterpreted as changes in woodland.

The second potential source of error is mis-rectification of the images between dates. If there is mis-rectification, the patches in one image will be shifted in position relative to their location in the other image. A change map computed from such mis-rectified data will show many falsely identified changes outlining the perimeters of all the patches. Such an effect is visually apparent if change maps are computed without first defining a buffer zone. However, with the 10 m buffer zone, such outlining of all patches is no longer apparent. Thus, we conclude that the buffer used in this study is sufficient to eliminate most or all of the false inferences of change due to mis-rectification.

Finally, our computation of the fractal dimension of clusters could be affected by the use of the morphological algorithm used to define the buffer. The morphological algorithm essentially expands the width of the interface between woodland and grassland patches. In so doing, the perimeters of the remaining clusters may tend to smoothed, and this effect might be most noticeable for small patches. If so, the fractal dimension of patches after the buffer is defined should be lower that their original fractal dimension, with small patches being particularly affected.

The work of Krummel and others (1987) is frequently cited as an example of human impact on landscape pattern, but few other studies have applied the same methodology. Perimeter-area relationships are frequently used to compute fractal dimensions in analyses of landscape pattern, but the dependence on mean patch size is usually not examined (for example, O'Neill and others 1988, Turner 1990). Some papers have employed modifications of the Krummel and others (1987) methodology. For instance, Turner and others (1991) describe a method they call the "variance staircase" which is related to a fractal dimension. Meltzer and Hastings (1992) employed "rolling regressions" to calculate the size-related fractal properties of grass patches in a rangeland in Zimbabwe, based on fit to a hyperbolic size distribution. Vedyushkin (1994) reported scale-dependent fractal dimensions for remotely-sensed data (normalized difference vegetation index, NDVI, and thermal infrared radiation, TIR) for a forest in central Russia, based on a box-counting procedure. Although these studies can be viewed as generally supportive of the hypothesis that landscape patches display size-related shifts in their fractal dimension, they do not constitute independent support for the specific methodology of Krummel and others (1987). Krummel and others (1987) suggest that their "technique should be of particular interest to the analysis of remotely sensed data, as it provides a simple metric, D, that indicates the scale at which processes are occurring on the ground." However, the published evidence for such utility is still appears to be based on the analysis of a single map representing one portion of the Mississippi floodplain.

Our results, based on applying the methodology of Krummel and others (1987) to piñon-juniper woodlands in the southwestern United States, raise questions about the general utility of the method for detection of anthropogenic disturbance. The possibility must be considered that scale-dependent variations in the fractal dimension of patches may only serve as good indicators of certain types of anthropogenic disturbance, or may only be useful in certain landscapes. Further investigation is needed to determine the scope over which this methodology can be routinely used to detect anthropogenic disturbance.

Acknowledgments

We thank T.F.H. Allen for his insightful comments on a poster presentation of our results. This research was supported by USDA Forest Service, Rocky Mountain Research Station, Albuquerque, NM through Cooperative Agreement No. 28-C4-880 to Drs. Johnson and Milne.

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