SPACE, TIME AND STABILITY: Investigating Landscape Responses to Climate Variability in the Southwest

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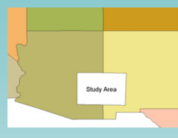
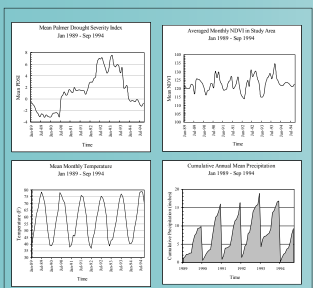
ABSTRACT

Landscape stability and resilience can be conceived as the ability of landscape elements to resist and recover from externally induced change. Remote sensing and climate data sets are a useful source of information for investigating landscape-scale spatiotemporal variability in landscape parameters, a necessary first step for understanding the stability and resilience of vegetation communities across a landscape. This study demonstrates that such landscape parameters can have long temporal persistence (more than 1000 years) by examining correlations between the distribution of prehistoric human settlements and landscape stability estimates generated from modern remote sensing data.

When coupled with climatic data, spatiotemporal data on vegetation productivity permit investigation of the spatial and temporal scales at which change occurs, and the spatial and temporal lags between climatic variability and ecosystem response. These spatial and temporal lags are important factors for modeling human perceptions of and responses to climate and ecosystem change.





Climate variables 1989 - 1994

INTRODUCTION

In this study I use various spatial and temporal analyses to investigate the highly variable landscape of the Mogollon Rim area. The project location is indicated in the figure to the right. In the arid and semi-arid southwest, water and temperature are limiting factors for vegetation productivity, and vegetation is an important factor in the distribution of animal resources. Remotely sensed data on vegetation productivity is thus a useful proxy for resource productivity at a landscape scale. Normalized Difference Vegetation Index (NDVI) data are used, which is a ratio of Red and Infrared wavelength absorption/reflection. NDVI is useful for several reasons. First, because it is a ratioing method, it effectively eliminates the effects of atmospheric scattering. Second, NDVI is directly related to biomass and to vegetation health. Finally, NDVI data are readily available for little or no cost at the scale used in this study. Data from 1989 through 1994 were selected for analysis, because the study area during this time period experiences both a severe drought (Jan 1989 – Aug 1990), and a severe wet period (May 1992- Aug 1993), as shown in the PDSI time series plot to the left.

•Satellite Data: National Oceanographic and Aeronautical Administration (NOAA) 1km resolution Advanced Very High Resolution Radiometer (AVHRR) NDVI monthly composite data, spanning in time from January 1989 until September 1994. NDVI data are already calculated and come georegistered to NAD27 Datum in UTM format.

•Climate Data: PDSI, Precipitation, and Temperature data from NOAA NCDC CIRS Climate Division dataset. These data were collected from several climate division stations in and adjacent to the study area, as illustrated by the red dots on the locator map above.

•Archaeological Data: Site locations from AZ and NM site files, acquired from multiple sources. These data provide fine resolution data on site locations (usually at an accuracy of < 100m). Due to multiple sites being recorded in a single area, the site location data were resampled to a 1km resolution grid of site presence or absence. This minimized the swamping effects that otherwise resulted in the analyses, and are the result of intensive surveys where dozens of small sites and artifact scatters are recorded in areas covering less than just a few kilometers squared.

ANALYSES USED IN STUDY

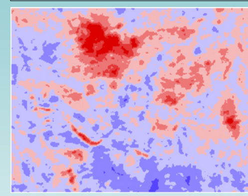
Principal Components Analysis: This is an important first stage of analysis, providing (in this case) primarily qualitative information on seasonal variability in vegetation patterns.

Time Series Analysis: This analysis provides information on temporal patterning in the data, as well as the lags between the various data sets. This information is important for determining the temporal lags between climate and landscape productivity.

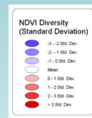
Spatial Analysis: The semivariograms generated for this analysis provide information on the spatial lags over which changes in productivity and landscape stability occur. These values can play an important role in modeling prehistoric landscape use.

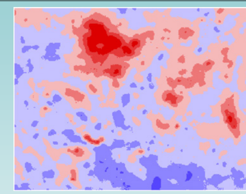
SPATIAL ANALYSIS: Determining Spatial Lags of Stability Patterns

The images below show the process of using kriging and semivariograms to determine the level of spatial autocorrelation in the NDVI Diversity map. The distance at which spatial autocorrelation occurs is a measure of the distance one would have to go to find absolutely no correlation in diversity values. The first image shows the NDVI Diversity map as calculated from the multitemporal NDVI data. Below it is a semivariogram, with an exponential model interactively fitted to the curve. This was performed on a logarithmically and Z-Score transformed data set (shown in the histogram below), since the semivariogram assumes source data that are reasonably normally distributed. Finally, a surface is generated using kriging, based on the model in the semivariogram. The result is shown in the image below right. Comparing this simulated image to the original image provides a means of qualitatively assessing the validity of the semivariogram model.

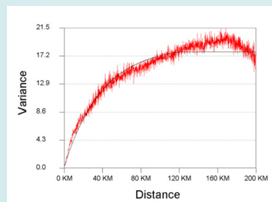


Map of actual NDVI Diversity, measured using ERDAS' Stack Statistics utility.

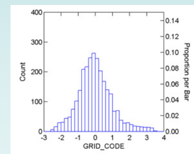




Map of simulated NDVI Diversity, generated with a kriging technique based on the semivariogram model to the left.



Exponential semivariogram of NDVI Diversity data (stability of productivity of biotic communities), omni directional. Nugget = 0, Range = 100km.

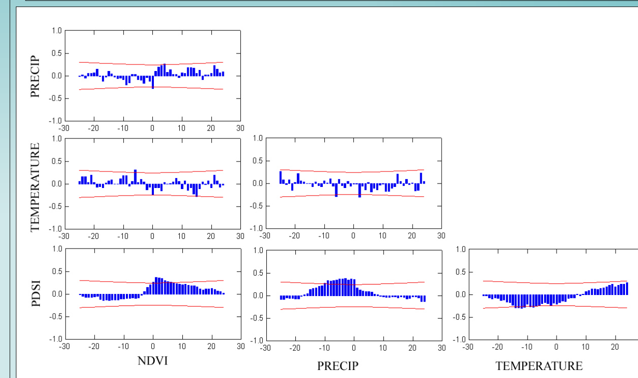


Histogram of Z-Standardized, Log(10) Normalized Diversity Data.

SUMMARY OF RESULTS:
This area of the southwest displays a spatial lag of approximately 100km in diversity of NDVI values. From a human perspective, this indicates that one would have to travel on average 100 km to reach an area whose vegetation behaves in fundamentally different ways (i.e., highly variable versus highly stable vegetation productivity.) These results are based on analysis at both 1km and 5km resolutions, which generated nearly identical semivariograms. This scale is appropriate for Biome-level applications. Finer resolution data would be more appropriate for investigating vegetation associations, and would likely have different spatial lags.

TIME SERIES ANALYSIS (TSA): Determining Temporal Lags of Relevant Variables

I performed a TSA of the climate and remote sensing data for two reasons. First, this provides a means of assessing interrelationships among the variables. Second, this provides measures of the temporal lags associated with variables that influence environmental productivity. The time lag between climate event and environmental effect is important in any consideration of human perceptions of ecosystems. In this analysis, I investigated the temporal distributions of four variables: NDVI, PDSI (the Palmer Drought Severity Index), monthly mean precipitation, and monthly mean temperature. For each variable, I used a Lowess smoothing routine in SYSTAT (tension = 0.5), and then generated a time series and an autocorrelation plot. Since each displayed considerable seasonal variation, I used SYSTAT's "SEASONADJ" routine to remove seasonal effects from the data (using a 12 month periodicity.) New autocorrelation plots were then generated, and first order temporal lags removed from the data. For each variable pair, I then generated cross correlation plots (below, left). While these figures are complex, they do contain important information on the amount of influence among variables, and the temporal lags associated with those effects.

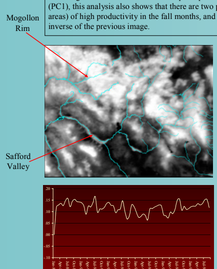


Climate Cross Correlation Plots. graphs above are cross correlation plots (CCF) of seasonally adjusted climate data. There are strong relationships between PDSI and NDVI/Precipitation/Temperature. Horizontal axes indicate positive or negative time lag (in months). Vertical scale indicates correlation. Thus, the bottom left plot shows that PDSI from several months ago influences NDVI in the present, although there is a stronger influence of NDVI now on PDSI about 5 to 6 months in the future. The graph to the right of it shows that precipitation in the last several months strongly drives PDSI.

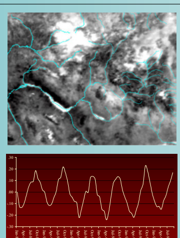
SUMMARY OF RESULTS:
NDVI is most closely correlated with PDSI (previous 2 months), which in turn is driven by precipitation (last 8 months) and by temperature (previous several months). Because temperature and precipitation seem to drive PDSI, and PDSI has a strong correlation with NDVI, I had expected a stronger correlation between precipitation-NDVI and temperature-NDVI. The lack of correlation reflects the cumulative and interacting effects of temperature and precipitation over several months influencing NDVI. In human terms, it seems that there are complicated relationships between temperature and precipitation, but that an understanding of general drought conditions will provide a very good predictor of productivity (NDVI) in two months, and a fairly good predictor of productivity for several months after that.

PRINCIPAL COMPONENTS ANALYSIS (PCA): Linking Pattern to Process

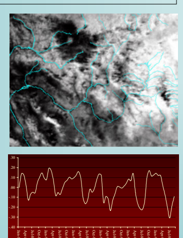
The images below show the first three principal components of the PCA. Aside from obvious differences in general vegetation productivity across the landscape (PC1), this analysis also shows that there are two primary seasonal patterns. PC2 shows an important seasonal cycle in upland and irrigated areas (lighter colored areas) of high productivity in the fall months, and low productivity in the spring months. PC3 shows a cyclical as well as linear trend, that also appears to be a near inverse of the previous image.



Principle Component 1: Average greenness. This is a measure of total productivity over the course of the year, and is similar to a time integrated NDVI map. The image above shows broad bands of greenness that correspond to higher elevation areas along the Mogollon Rim and mountains south of the Gila River.



Principle Component 2: Green in Fall, Brown in Spring. Strong cyclical pattern in component loadings graph. Spatially, the areas that best match this pattern are irrigated agricultural areas along the Gila, and mountainous areas north of the Mogollon Rim.

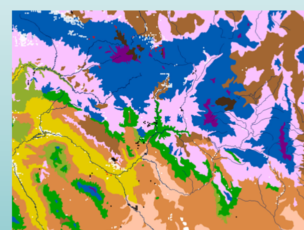


Principle Component 3: Brown in Summer, green in Winter. The graph indicates a cyclical pattern of low NDVI in May-July, with generally high level of NDVI in from late Fall to early Spring. Spatially reflected by SW-NE trend, and upland-lowland trend.

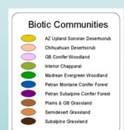
PCA RESULTS SUMMARY:
Principle components two and three show important patterns in cyclical variability that are useful for interpreting the results of the other analyses. The patterns identified above are the result of biophysical processes at the scale of biotic community. Upland and irrigated areas display strong cyclical patterns in NDVI values across time. Another important pattern is apparent in the third principle component, an axis of winter productivity versus summer lack of productivity.

APPLICABILITY ASSESSMENT: Are the results relevant for the past?

One important question that this study hope to answer is whether modern remote sensing and climatic data have any relevance for understanding human-environment interactions in prehistory. Of special concern is that the 1km resolution of the data are at too coarse a scale to say anything meaningful about prehistoric environments. To answer this question, I examined the distribution of archaeological sites (spanning AD 200 – AD 1400) across the landscape, to determine whether the distribution of archaeological sites was non-random with respect to diversity values. I expect a non-random distribution, because prehistoric land-use practices should favor areas that are more stable through time (and thus more predictable). The image below, right shows the distribution of archaeological sites in the study area. Red dots indicate highly diverse ($\geq$ 1.0 standard deviation) locations, Black dots extremely low diversity areas ($\leq$ 1.0 standard deviation) white dots average diversity (intermediate values).



This map shows the distribution of archaeological sites across the biotic communities of the study area. Site locations are colored based on the mean diversity of NDVI in a 5km radius circle around the site. Red=high, white=average, black=low diversity. There are very few sites located in areas whose NDVI changes drastically in response to climatic fluctuations.



Chi-Squared Test, All sites

H_0: Sites are randomly distributed across all three categories.

H_1: Sites are not randomly distributed across all three categories.

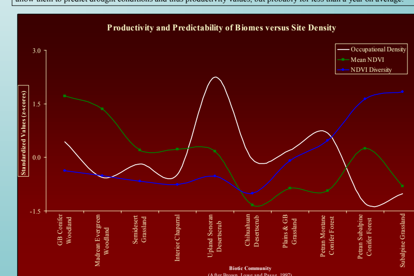
Relative NDVI Stability	OBS	EXP		
High	98	135.0	Chi Squared:	54.2
Average	891	806.1	df:	2
Low	25	77.0	alpha(.01):	9.2

RESULTS:
Since X^2 > alpha (54.2 > 9.2), the null hypothesis H_0 is rejected at the 0.01 level. Prehistoric sites are not randomly distributed with respect to modern satellite-based measures of NDVI diversity.

APPLICABILITY RESULTS:
The data and techniques presented here do provide information that is relevant to landscape stability over the long term. Satellite data are thus a useful addition to studies of past landscapes. The significance test demonstrated that archaeological sites pattern non-randomly with respect to productivity stability as measured by NDVI diversity from satellite data.

RESULTS AND CONCLUSIONS

This study has had four primary purposes. First was to determine the applicability of the data and techniques for investigating past landscapes, and this was affirmed. Second was to investigate the spatiotemporal variability in vegetation productivity as measured by satellite NDVI to determine the overriding patterns in the data that are the output of principal components analysis. Interpreting the first three principal components permitted an elucidation of the underlying biophysical processes that may have generated those patterns. Third, I used spatial analytical techniques to investigate the spatial lags inherent in the calculated diversity map, which demonstrated that there was a maximum 100km distance in spatial autocorrelation of the data. Future analyses should take a subset of the study area and investigate a finer resolution dataset to determine the extent to which the scale of the data determines the resultant spatial lag values. Finally, I used time series analytical techniques to investigate the temporal relationships among the variables that influence the patterns in productivity as measured by NDVI. The results of the analysis suggest that environmental observations by prehistoric peoples who understood their landscape would allow them to predict drought conditions and thus productivity values, but probably for less than a year on average.



This graph displays the density of archaeological sites with respect to Mean NDVI and NDVI Diversity by biotic communities. Each of the values in the plot has been weighted by area, and standardized to a Z-Score to permit simultaneous display. Lower elevation biotic communities are on the left half of the plot, and higher elevation communities on the right half. Interestingly, the lower elevation communities are characterized by higher mean productivity, with lower diversity of values, while the higher elevation communities are characterized by the opposite pattern, with lower mean productivity and higher diversity of values through time. Archaeological site density peaks in communities where mean productivity and diversity are at relatively average values.

PROSPECTS FOR FUTURE STUDY

The results of this study are encouraging, pointing the way to potentially productive future analyses. In addition to further investigation of spatial scaling factors, future work should better investigate the temporal relationships among climate variables. Once these are better understood, it may be possible to use dendroclimatic data as climate proxy to project productivity estimates into the past.

Another promising research avenue involves an investigation of the spatial and temporal lags within individual biotic communities. In this study, I ignored variation within biotic communities, and analyzed the data across the whole study area. However, as the graph to the right shows, there are some potentially important differences in the patterns of productivity (mean NDVI) and stability (NDVI diversity) between different vegetation communities, and this seems to be relevant to the study of prehistoric land-use patterns.

This research is an important first step in examining the resiliency of landscapes. This would be accomplished by applying these techniques to pre- and post-disturbance (whether anthropogenic, natural, or climate-induced) or post-recovery data sets. Since analyses such as these can be applied to areas of different sizes and at multiple scales, this study can serve as a guide to research on landscape stability and resilience in many settings.