Landscape Trajectory Analysis: Toward Spatio-temporal Models of Biogeophysical Fields for Ecological Forecasting

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ABSTRACT: Analysis of image time series can reveal landscape dynamics. The temporal development of spatial patterns holds significant information about ecosystem processes, including the influence of climatic varability, disturbance regimes, and recovery processes. Yet, the tools for the characterization of spatio-temporal structure are few. This position paper is motivated by the following workshop questions: ***"Which kinds of spatio-temporal questions are of interest? What do these data look like? What do investigators want to get out of these data?"*** and ***"Which types of data mining techniques are useful for analyzing biogeophysical data for ecological forecasting?"*** One approach to working the problem presented by spatio-temporal datastreams is to project the data into a metric space with reduced dimensionality and/or enhanced information density. An illustration is offered for consideration.

INTRODUCTION

We are now in an era of intensive earth observation: orbital platforms generate myriad remote sensing datastreams across a range of spatial, temporal, spectral, and radiometric resolutions. The number and variety of "eyes in the skies" are scheduled to increase significantly over the next few years. This veritable data deluge necessitates new ways of thinking about transforming remote sensing data into information about ecological patterns and processes. These datastreams hold the promise for environmental decision support, including ecological forecasting [1,2]. Effective use of remote sensing datastreams to characterize and monitor landscape dynamics requires analysis of the temporal variations in spatial patterns. Yet, there is a critical need for theories and tools that will enable efficient and reliable characterization of spatio-temporal patterns contained in image time series.

We distinguish four main phases in the analysis of image time series [3]:

- change detection--perceiving the differences;
- change quantification – measuring the magnitudes of the differences;
- change assessment – determining whether the differences are significant; and
- change attribution – identifying or inferring the proximate cause of the change.

Conventional change detection strategies can handle only few images at a time, analyzed retrospectively through pair wise comparisons, and there are not feasible to implement with high-volume datastreams at a near-real-time tempo.

A key issue concerns data representation: What constitutes the appropriate units of analysis for time series of images that portray variations in electromagnetic radiation within the context of spatial and temporal coordinates? We assert that georeferenced and temporally located individual pixels are not appropriate. What is of principal scientific interest in image time series are not the pictures themselves but the dynamic of pattern and process that sequences of pictures can portray. Consider the analogy of sparse sampling of individual frames or even frame sequences from a movie. One level of analysis could aim at reconstructing motion from these data but a more sophisticated analysis could aim at reconstructing the plot. Intelligent and informed knowledge discovery in scientific databases must aim at the latter objective – reconstructing plots, comparing plots, identifying unusual plots as well as interesting deviations from typical plots. Some relevant ecological storylines include seasonality in vegetation growth and disturbance effects and recovery across a landscape.

An apt analogy is that weather data are to image data as climate norms are to ecological expectations of land surface dynamics. The climate of a place at a given time of year is operationally defined as the expected meteorological condition conditioned on 30 years of weather observation at that place (or somewhere nearby). Unusual weather conditions, also called climatic anomalies, are identified with respect to this specific observational baseline. In a similar but distinct manner, these ecological expectations would summarize across specific regions the typical temporal development of spatial pattern in biogeophysical fields (e.g., sunlight reflecting from a growing plant canopy or microwaves emitting from a drying watershed). To make ecological forecasting an operational possibility, it is necessary to develop methods to define, establish, and update complex spatio-temporal baselines that will enable prediction of the usual and identification, quantification, and assessment of the unusual. We illustrate here one approach using a standard image time series to derive expected (mean) spatio-temporal trajectories in pattern metric space.

STUDY AREA

We have chosen six contrasting ecoregions of the U.S. according to Omernik's Level III ecoregional delineations [4,5]: Cascades (#4); Chihuahuan Deserts (#24); Nebraska Sand Hills (#44); Western Corn Belt Plains (#47); Southeast Wisconsin Till Plains (#53); and Southern Florida Coastal Plain (#76) (Fig.1).

DATA

As we are describing a new analytical approach, we think it is important to use standardized data products to provide *transparent* technique that enables the repeatability of the analyses by other investigators. We have chosen to use the conterminous U.S. (CONUS) AVHRR maximum Normal Difference Vegetation Index (NDVI) biweekly composites produced for 1990 to 2000 by the USGS EDC [6]. The NDVI has a long history within the remote sensing community as a means of estimating green vegetation density. It exploits the contrast between strong absorption of red light and strong reflectance of near infrared light exhibited by all green vegetation. Compositing daily images to biweekly maxima aims at minimizing cloud cover effects. While these data have a variety of limitations, they constitute as rich and as long a standardized image time series as is currently available at 1 km resolution. We analyzed each NDVI composite for 17 compositing periods across 11 years for a total of 184 images. The image time series ranges from the beginning of March through the end of October for 1990-2000. (The abbreviated 1994 series arises from a satellite failure in September.) As the EDC NDVI composite product has developed over the years, the naming convention and start dates of the biweekly compositing periods have changed. We have crosswalked the nominal compositing dates and the EDC compositing periods to minimize this source of variation.

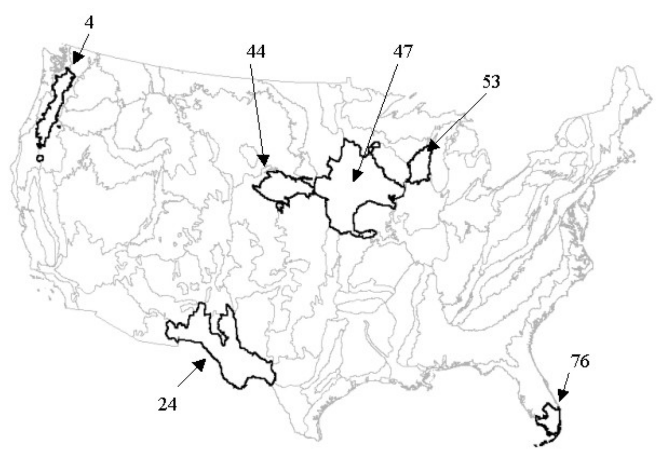

Fig. 1. Omernik's Level III ecoregions and location of study areas.

METHOD

An image time series portraying the same scene can be transformed into a *landscape trajectory* by decomposing the sequence image by image and projecting it as a time-ordered series of coordinates in a pattern metric space [7]. Following the procedure described in [8], we used random walk resampling to estimate correlation length as scale of fluctuation (SOF). Random walk resampling is computationally expensive but it stabilizes estimation of spatial structure under conditions of nonstationarity by measuring the spatial heterogeneity and spatial dependence in a series of transects formed by many independent but repeatable random walks. Each random walk transect nominally sampled 10% of the image area (the actual percentage is less due to the possibility of revisiting pixels).

One thousand (10^3) random walk transects were performed on each image yielding a nominal 100X oversampling. Scale of fluctuation analysis [8,9] estimates the correlation length along the transect through observing the behavior of the weighted normalized variance under extended local averaging. In this context, correlation length indicates the distance needed to travel before reaching a point that is significantly different from the starting point.

Along the same random walk transects, we calculated mean NDVI and another, albeit implicit, measure of spatial structure—the Shannon-Weaver-Wiener diversity index (H') normalized by the maximum possible diversity (H_{MAX}). In the ecological literature, this measure is typically called evenness. H_{MAX} could be calculated several different ways, including using the maximum bandwidth possible from the quantization, or the maximum bandwidth of possible positive NDVI values, or the maximum bandwidth possible given the expressed range of NDVI values encountered in the transect. We chose the last option because it enhances the sensitivity of the measure. Evenness refers to the observed distribution (histogram) of possible values (colors) compared to a uniform (or even) distribution. Higher evenness values (max=1.0) indicate more even distributions; lower values indicate a distribution with a few (or one) dominant colors. Evenness is an implicit measure of spatio-temporal structure because the spatial domain over which the measure is calculated does not vary through time.

A GESTALT OF THE RESULTS

These six ecoregions show clear differences in the strength of the expression of seasonality in the temporal profiles of NDVI (Fig. 2), SOF (Fig. 3), and evenness (Fig. 4). Bivariate plots of NDVI x SOF (Fig. 5), evenness x SOF (Fig. 6), and evenness x NDVI (Fig. 7) illustrate commonalities and distinctiveness among the spatio-temporal dynamics of these ecoregions. While this is not the appropriate forum to parse the nuances of these results, it should be evident that there is enhanced information density in the shape, range, and rotation of these trajectories. For certain broad classes of earth observation applications, trajectories like these may be able to serve as more tractable objects for data mining algorithms. This is an area that we may explore during the workshop.

CONCLUSION

A necessary first step in harnessing remote sensing datastreams for operational terrestrial environmental monitoring, decision support, and ecological forecasting is the development of quantitative expectations of the spatio-temporal dynamics of land surfaces. These expectations will necessarily be linked to particular places defined by specific spatial partitionings, such as ecoregions. While the import and significance of landscape trajectories is not yet well characterized, commonalities will emerge as the past observational record and new image time series are ingested and analyzed. Ecological forecasting using terrestrial remote sensing can advance using data assimiliation in a manner analogous to meteorological forecasting. However, much attention is needed to model and map typical biogeophysical processes to expressed spatio-temporal patterns.

References

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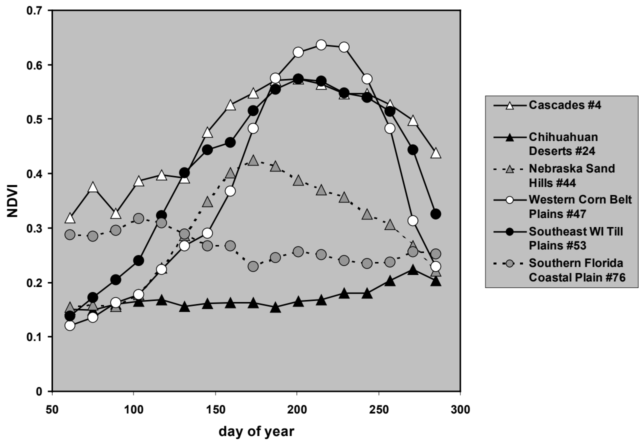

Fig. 2. Mean biweekly NDVI time series for March through October.

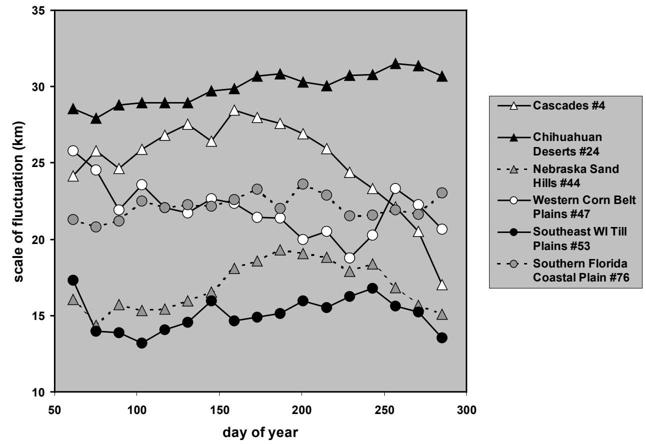

Fig. 3. Mean biweekly SOF time series for March through October.

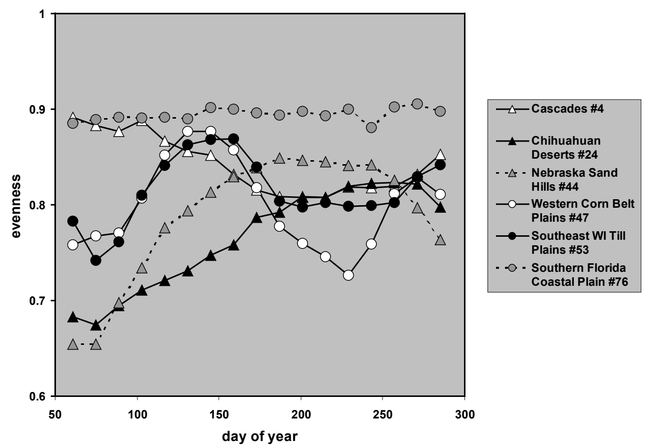

Fig. 4. Mean biweekly evenness time series for March through October.

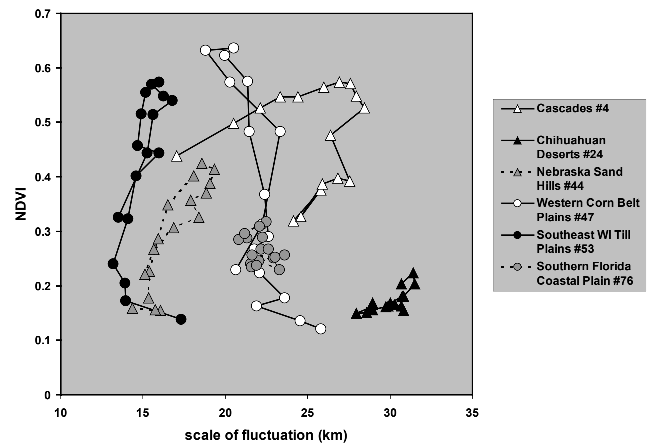

Fig. 5. Expected NDVI x SOF landscape trajectories.

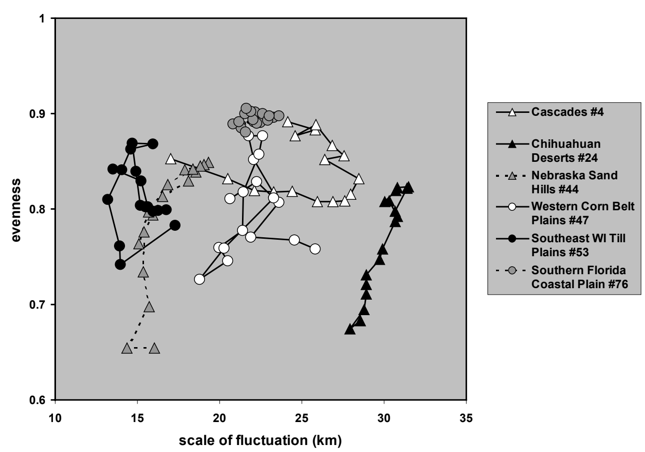

Fig. 6. Expected evenness x SOF landscape trajectories.

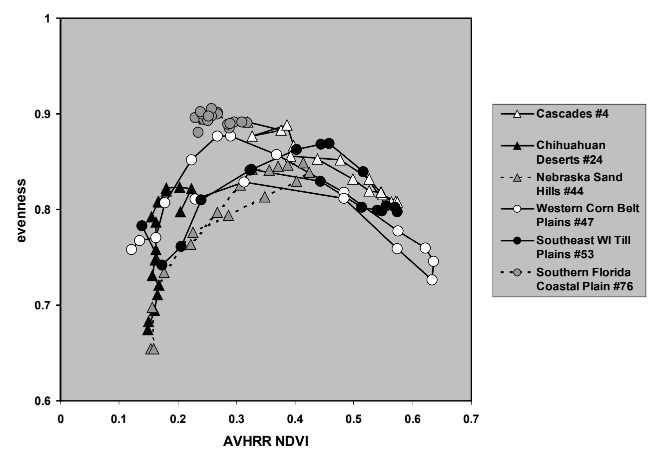

Fig. 7. Expected evenness x NDVI landscape trajectories.