Observing Spatial Structure in the Flint Hills using AVHRR Biweekly Composites of Maximum NDVI

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Abstract. The Advanced Very High Resolution Radiometer (AVHRR) offers twice-daily coverage with coarse spatial resolution (1 km pixels). The Normalized Difference Vegetation Index (NDVI), which indicates the degree of green vegetation present within a pixel, can be calculated from the red and near-infrared bands of AVHRR. The EROS Data Center of the U.S. Geological Survey produces a standard dataset on CD-ROM of the biweekly composites of maximum NDVI for the conterminous United States. We extracted from each of the 21 images in the 1991 dataset a 39,633 pixel area corresponding to the Flint Hills, the largest extant region of tallgrass prairie. We measured the temporal dynamics of spatial structure in the image series using lacunarity analysis and scale of fluctuation analysis. Our results capture phenological differences across the Flint Hills and illustrate the importance of measuring the spatial as well as the spectral characteristics of remotely sensed imagery.

Key words: AVHRR, NDVI, spatio-temporal variability, lacunarity, scale of fluctuation, correlation length, tallgrass prairie, Flint Hills, Kansas, Oklahoma

Introduction

Concerns about global change, biodiversity, and ecosystem management have increased attention to the characterization of ecological dynamics across regional landscapes (Turner 1989; Groffman and Likens 1994). A principal difficulty in spatially explicit ecological investigations lies in the knotty problem of rescaling the heterogeneity of processes and patterns found in natural landscapes (Milne 1991). Seldom do either functional representations of nonlinear processes (King et al. 1991) or statistical moments of distributions of spatial patterns (Openshaw and Taylor 1981; Arbia 1989) retain essential characteristics under rescaling operations. Yet there is a strong tendency in ecology to extrapolate findings using the principle of similitude (Iverson et al. 1994). For example, Konza Prairie Research Natural Area (KPRNA), 3700 ha of native tallgrass prairie in northeast Kansas, is intensively studied as representative of the tallgrass prairie ecosystem (Franklin et al. 1990). However, it amounts to only about 0.25% of the area in the Flint Hills, the largest extant expanse of tallgrass prairie. Thus arises the question: how can general ecological findings gleaned at finer scales (spatial, temporal, structural, functional) be rescaled usefully to coarser scales?

Ecological hierarchy theory (O'Neill et al. 1986) notes that lower frequency fluctuations occur at coarser spatio-temporal scales and that the higher frequency fluctuations occuring at finer spatio-temporal scales are constrained by those lower frequency dynamics. In other words, everything ecological (whether process or pattern) is dynamic, but relative disparities in rates of change allow some things to be viewed as the background against which higher-frequency dynamics unfold. Landscape-level remote sensing studies at KPRNA have demonstrated that surrogate measures of canopy phenology are modulated by spatio-temporal forcings of higher frequency (precipitation and grazing) and lower frequency (fire, drought, topography) (Briggs and Nellis 1991; Henebry 1993; Henebry and Su 1993). We expect that several of these factors will be relevant throughout the Flint Hills, but we also expect other factors, such as temperature, to gain explanatory power at the regional scale (Reed et al. 1994).

Scaling up from watershed to regional observations also requires a conceptual shift. At a spatial resolution of 30 m, the canopy is still meaningful as a resolvable scene object; thus, the phenology of the canopy can be observed. At a spatial resolution of 1 km, however, landscape details typically are too blurred to enable canopies is to be well-resolved; thus, we introduce the concept of phenology of the land surface. Implicit to this concept is the assumption of a significant degree of spectral mixing from different land covers. This is not a traditional phenology associated with specific events in a plant's life history; rather, land surface phenology describes the seasonality of reflectance characteristics that are associated with stages of vegetation development (cf. Reed et al. 1994). Mapping Normalized Difference Vegetation Index (NDVI) values back to green biomass, for instance, can be a dubious endeavor (Turner et al. 1992). At this juncture, we need instead to address directly the phenomenology of NDVI and other spectral vegetation indices because these are the only kind of data available at the synoptic, regional level.

Before we seek out the principal processes controlling land surface phenology across the region, we must find appropriate ways to summarize the spatio-temporal complexity of the data. What we describe here is a preliminary investigation of the spatio-temporal variation in reflectance across the entire Flint Hills over a single year. We wish to test the utility of time series of spatial metrics in expressing regional dynamics. Specifically, we assess lacunarity, which is a multiscale index of spatial heterogeneity in binary imagery, and the scale of fluctuation, which is an estimate of correlation length in interval-scaled imagery.

Vanmarcke (1983) developed an approach for characterizing "distributed disordered systems" which is amenable to remote sensing applications. He defined the scale of fluctuation (SOF) of an underlying spatial stochastic process as the parameter that controls the behavior of the process under extended local averaging. Spatial variation is analyzed through averages along transects or across areas. The 1-D SOF is the correlation length: the distance on average required to obtain samples that are statistically independent. Pixels within the correlation length exhibit positive spatial autocorrelation, i.e., their residual variance is less than that expected at random. A longer correlation length implies a more homogeneous landscape; it is effectively an estimate of patch size. Details of the algorithm and implementations for imagery were discussed in Henebry (1993).

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Lacunarity describes the complex intermingling of the shape and distribution of gaps within an image: a highly *lacunar* image exhibits gaps distributed across a broad range of sizes (Mandelbrot, 1983). Lacunarity is an aspect of fractal geometry: lacunarity (L) is the multiplicative prefactor in the general power-law formula of which the fractal dimension is the exponent, $F(x)=Lx^{(D-E)}$. As a measure of spatial heterogeneity, lacunarity quantifies the deviation of a geometric object (e.g., shape, pattern, fractal) from translational invariance and, thus, is well-suited to analysis of natural scenes. Simply stated, lacunarity is sensitive to clumping. Plotnick et al. (1993) discussed details of the algorithm and its applicability to landscape ecology. Implementations for quantitative image analysis were presented in Henebry and Batista (1994), Kux and Henebry (1994a,b), and Henebry and Kux (1995). Seasonal changes in the spatial arrangement of reflectance across land surfaces translates into changes in lacunarity; thus, lacunarity can characterize natural spatio-temporal variability as well as detect change.

We applied these spatial measures to a standard dataset readily available on CD-ROM, the 1991 AVHRR (Advanced Very High Resolution Radiometer) biweekly composites for the conterminous United States (USGS-EDC 1991).

Methods

The 1991 AVHRR biweekly composites produced by the EROS Data Center of the United States Geological Survey is composed of 21 separate 14-day maximum NDVI composites (Table 1) that were generated from nearly 500 NOAA-11 images (USGS-EDC 1991). In addition to 17 biweekly composites that encompass the growing season (March 1, 1991 to October 22, 1991), the months of January, February, November, and December are each represented by a single biweekly composite. The daily observations in the dataset had been calibrated to reflectance, scaled to byte data, and geometrically registered to the Lambert Azimuthal Equal Area map projection. The NDVI, computed from AVHRR bands 1 and 2, had been scaled for byte representation in the range of 0-200, with computed NDVI values of -1.0, 0, and 1.0 being mapped to 0, 100, and 200, respectively. (Subsequent analyses used the byte format, but the results were converted back into the unit interval format for presentation.) NDVI values less than zero indicate clouds, snow, water, and other nonvegetated surfaces, values greater than zero indicate surfaces with vegetated cover.

The boundaries of the Flint Hills were identified visually using a seasonal NDVI composite. An irregular shape of 39,633 pixels then was digitized onscreen and embedded within a rectangular mask of 399 lines with 130 samples per line to extract a consistent region from each 13 Mb composite image of the conterminous US. Two measures of spatial structure, scale of fluctuation and lacunarity, were calculated for each of the resulting 21 NDVI images of the Flint Hills.

Table 1: Biweekly composite periods for 1991

Period	Date of coverage	Day of year
1	01/04 - 01/17	004 - 017
2	02/01 - 02/13	032 - 045
3	03/01 - 03/14	060 - 073
4	03/15 - 03/28	074 - 087
5	03/29 - 04/11	088 - 101
6	04/12 - 04/25	102 - 115
7	04/26 - 05/09	116 - 129
8	05/10 - 05/23	130 - 143
9	05/24 - 06/06	144 - 157
10	06/07 - 06/20	158 - 171
11	06/21 - 07/04	172 - 185
12	07/05 - 07/18	186 - 199
13	07/19 - 08/01	200 - 213
14	08/02 - 08/15	214 - 227
15	08/16 - 08/29	228 - 241
16	08/30 - 09/12	242 - 255
17	09/13 - 09/26	256 - 269
18	09/27 - 10/10	270 - 283
19	10/11 - 10/24	284 - 297
20	11/08 - 11/21	312 - 325
21	12/06 - 12/19	340 - 353

Correlation length was estimated in each NDVI image using a random-walk transect resampling technique (Henebry 1993). Each transect was constructed from a random starting point and each next step was selected randomly with equal probability from among the eight nearest neighbors or remaining in place (viz., 1/9). Transects sampled only the image data; steps into the background matrix were forbidden. The length of each transect was 2593 pixels or 6.5% of the image data. Correlation length was estimated using successive local averaging with a maximum possible smoothing window of 255 and a convergence criterion of 2.5% between successive averagings. The sampling distribution of correlation length resulting from 100 transects was characterized by mean; standard deviation; skewness; and several percentiles (5, 25, 50, 75, 95), from which the coefficient of variation and interquartile range could be calculated.

The lacunarity index described by Plotnick et al. (1993) is defined only for binary data. Interval-scaled NDVI images can be analyzed by deriving a series of binary images based on quantiles of the image histogram (Henebry and Kux 1995). Here we constructed six binary images from each NDVI image corresponding to the following percentile intervals of the histogram: <5, 5-25, 25-50, 50-75, 75-95, >95. For example, pixels having NDVI values greater than the 95th percentile are mapped to white and remaining pixels are mapped to black. The resulting binary image illustrates the spatial distribution of the areas within the Flint Hills that have very high NDVI. This approach defines the percentile intervals relative to each image date, thus enabling an adaptive partitioning of the histogram as it changes during the growing season. Lacunarity was estimated in each of six binary images for each composite date using the complete sampling technique outlined in Plotnick et al. (1993) and a range of square windows that measured from one to 63 pixels on a side.

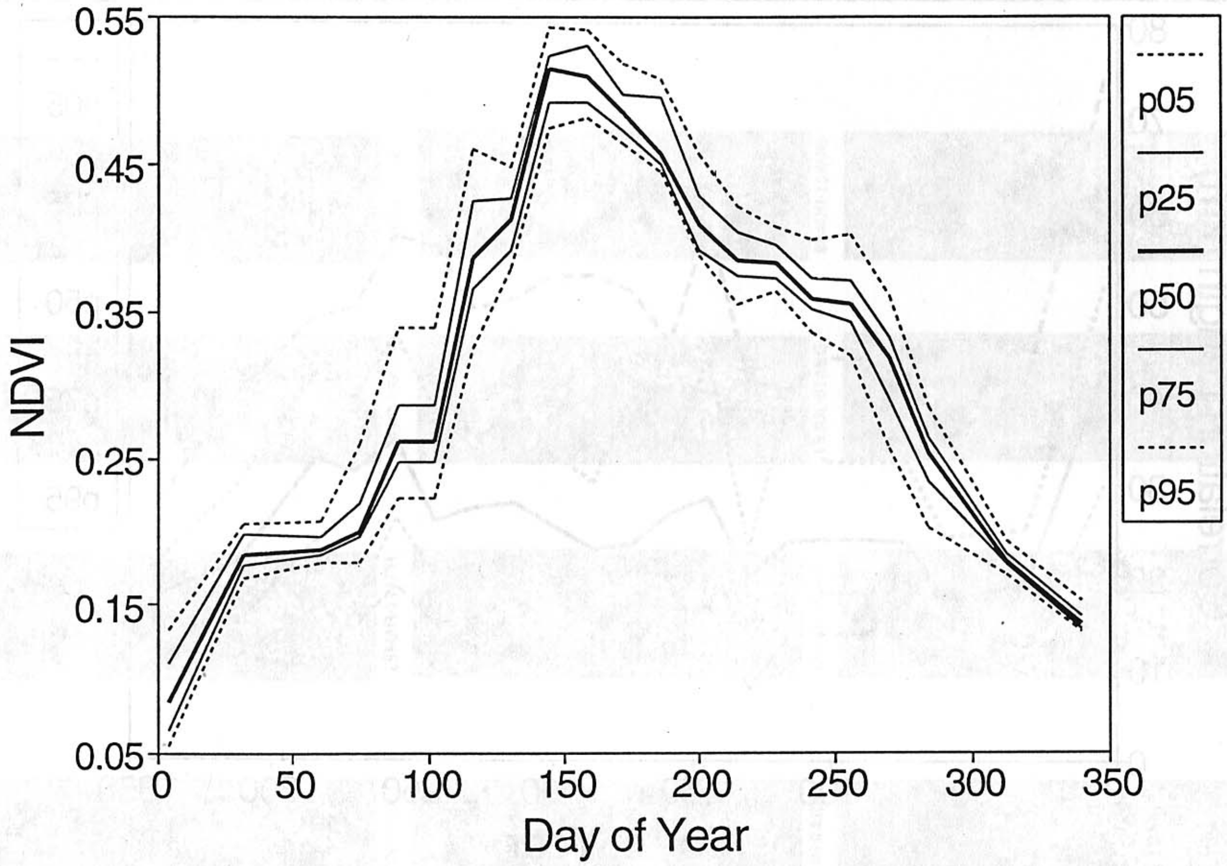

FIG. 1. Normalized Difference Vegetation Index (NDVI) of the Flint Hills during 1991. Median estimate is bracketed by other percentiles of the sampling distribution.

Results

The histogram time series of NDVI in the Flint Hills is illustrated in Figure 1. The seasonality of surface reflectance is clearly evident. The regional variability of NDVI at each date is captured by the percentiles bracketing the median value, e.g., the empirical 90% confidence interval is the area between the dashed lines. Note the pattern of a rapid increase in NDVI soon after day 100 (mid-April), a peak before day 150 (late May), the relatively swift decline in NDVI until a later season phase from about day 225 to day 275 (mid-August to early October). Typically, the peak occurs slightly later and the subsequent decline is more gradual; however, precipitation was below normal during June and July of 1991.

The correlation length time series presented in Figure 2 show no significant seasonality and much variation in the sampling distribution at each date. The median estimate of correlation length is about 25 km, which may result directly or indirectly from climatic factors. Direct effects may include common vegetation responses to precipitation gradients or common storm paths; indirect effects may include land management responses to seasonal temperature gradients and artifactual patchiness from the compositing process.

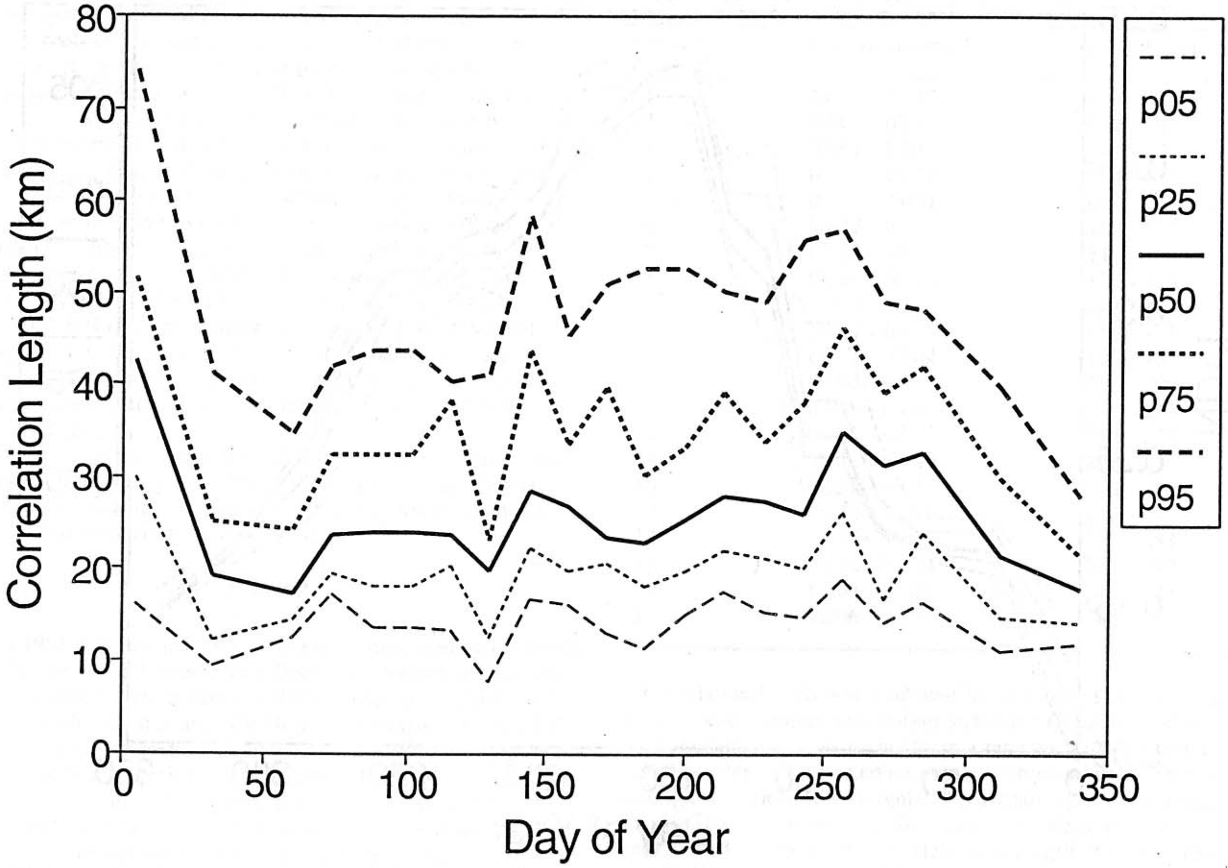

FIG. 2. Correlation length in NDVI images of the Flint Hills during 1991. Median estimate is bracketed by other percentiles of the sampling distribution.

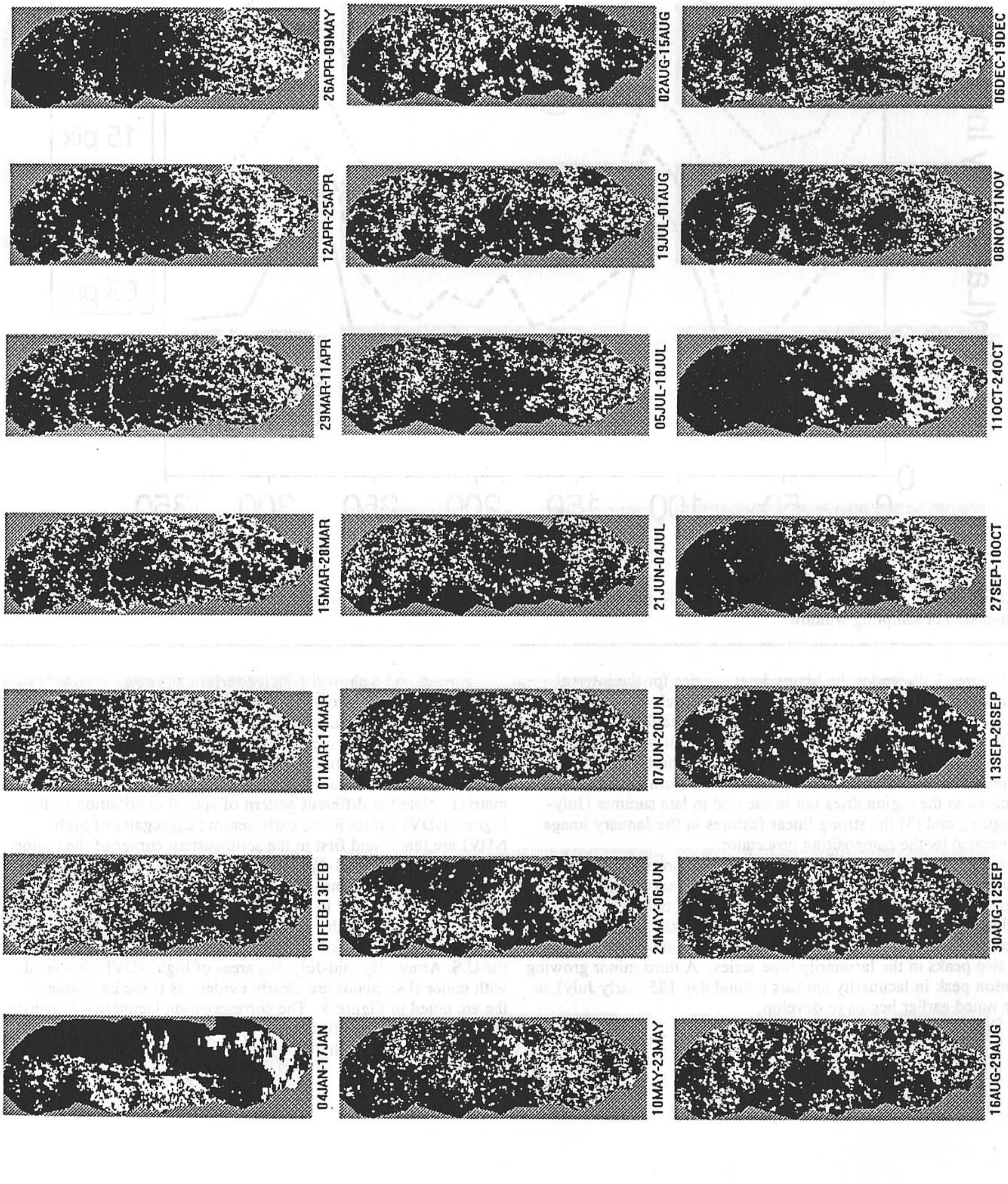

FIG. 3. Binary images formed from NDVI values in the 75th to 95th percentiles.

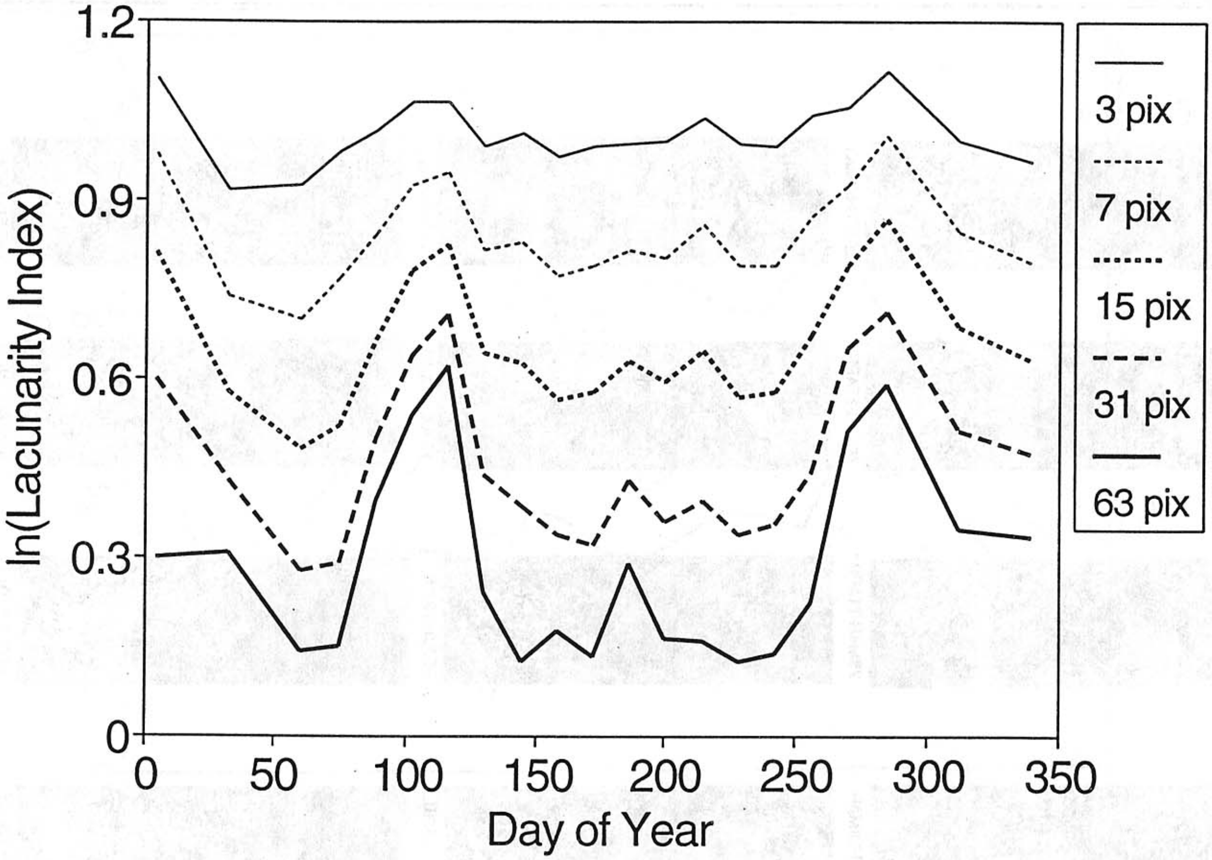

FIG. 4. Lacunarity indices for binary images formed from NDVI values in the 75th to 95th percentiles as a function of day of year and dimension of sampling window.

Figures 3 illustrates the binary image series for the interval containing the 75th to 95th percentile NDVI values. Amidst the spatio-temporal complexity of the data, note the following patterns: (1) definite north-south anisotropy during early (April) and late (October) growing season; (2) development of an arc of comparable NDVI values running clockwise from 12 o'clock to 7 o'clock as the region dries out in the mid to late summer (July-August); and (3) the strong linear features in the January image generated by the compositing procedure.

Figure 4 shows the lacunarity time series corresponding to the data in Figure 3. Note how lacunarity is dependent upon window size and how the seasonality of spatial pattern becomes more evident as larger window sizes are used for estimation. The clumping evident in the image series in April and October appear as two peaks in the lacunarity time series. A third minor growing season peak in lacunarity appears around day 185 (early July), as arc noted earlier begins to develop.

Figures 5 and 6 show the image series and corresponding lacunarity series for the highest 5% of NDVI values. Note that only 5% of the pixels are turned on in this image series as opposed to 20% in Figure 3. Again, temporal compositing leads in January to significant clumping (the density of which is exaggerated in this figure by the lower resolution of the graphical matrix). Note the different pattern of spatial distribution of the highest NDVI values in the early season: aggregates of high NDVI are that found first in the southeastern corner of the region during March into mid-April, shift to the southern tip of the Flint Hills from mid-April into May. Note the diagonal line of high NDVI during late May to early July extending from the north central area to the northwest corner of the region; the northwest extremity of this line is Fort Riley, a 41,000 ha training site for the U.S. Army. By mid-July, the areas of high NDVI associated with major floodplains are clearly evident as is the backbone of the arc noted in Figure 3. The corresponding lacunarity dynamics capture some of these features; specifically, the concentrations of high NDVI in the south during April and October and the January compositing effect.

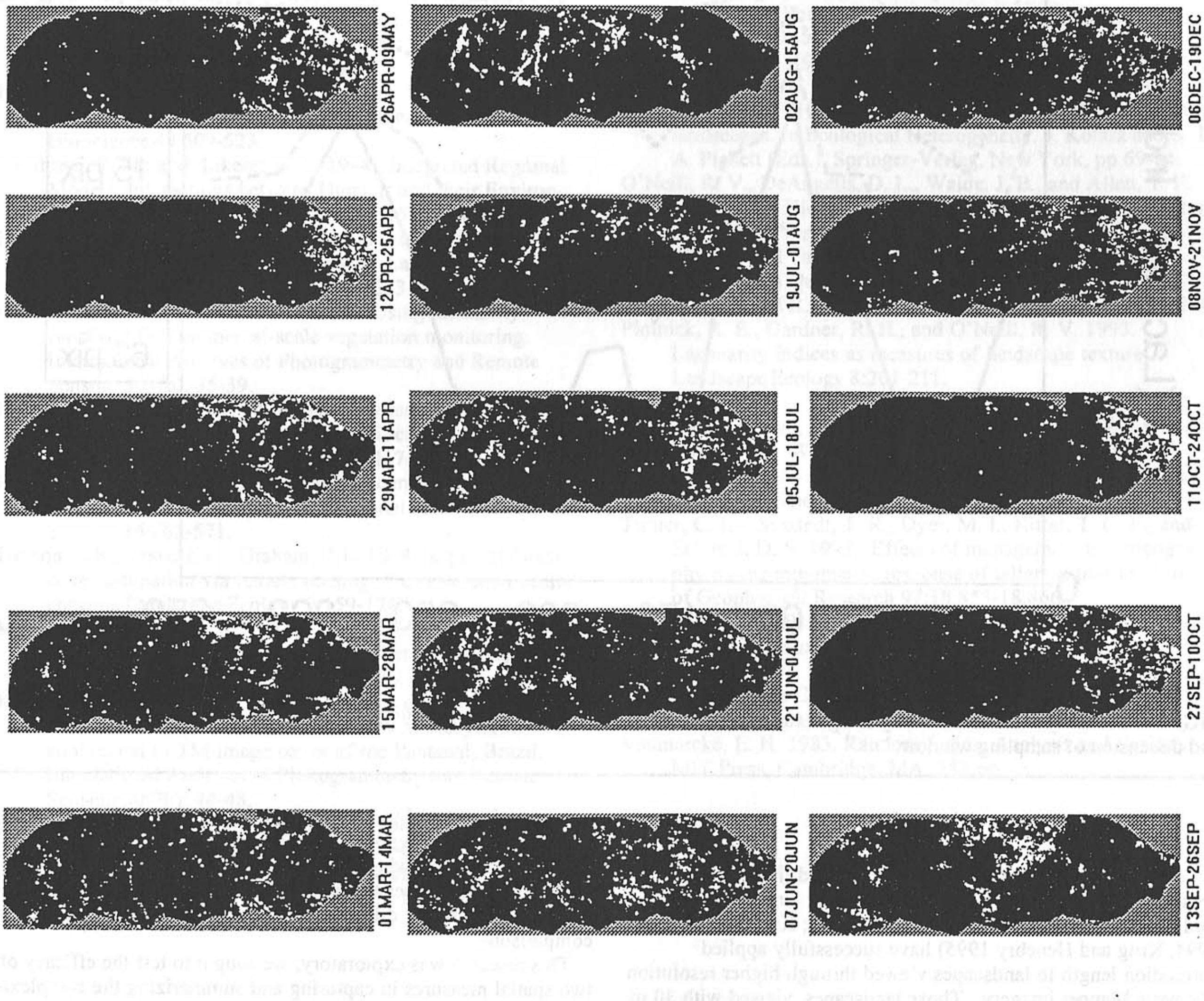

FIG. 5. Binary images formed from NDVI values greater than the 95th percentile.

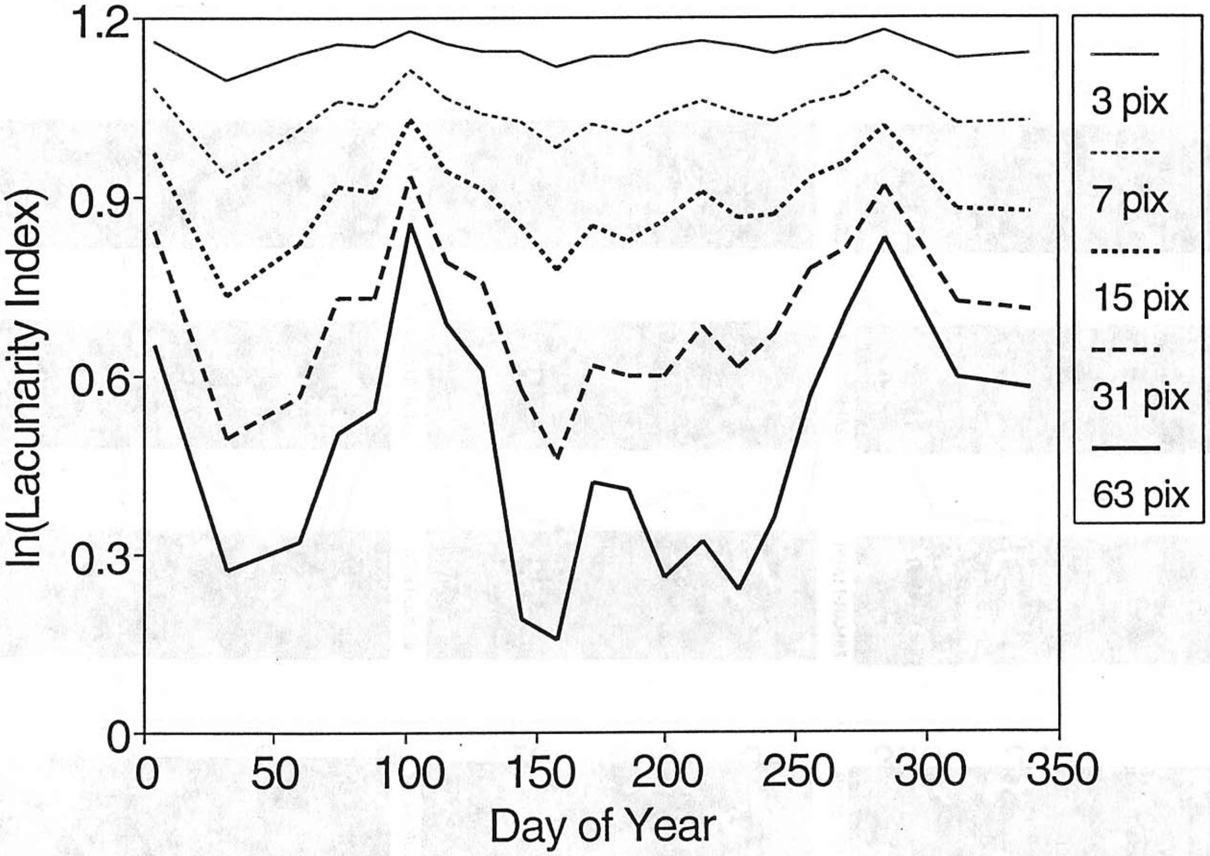

FIG. 6. Lacunarity indices for binary images formed from NDVI values greater than the 95th percentile as a function of day of year and dimension of sampling window.

Discussion

To our surprise, correlation length exhibited little temporal sensitivity to an obviously complex, changing landscape. Prior studies (Henebry 1993; Henebry and Su 1993; Krug and Henebry 1994, Krug and Henebry 1995) have successfully applied correlation length to landscapes viewed through higher resolution Thematic Mapper imagery. Those landscapes, viewed with 30 m pixels, showed stronger internal structure or patchiness of NDVI than did the Flint Hills when viewed through 1 km pixels. We attribute the poor performance of the correlation length to the combination of the broad similarity of land use and land cover in the Flint Hills and the blurring effect of a spatial resolution coarser than the size of most management units. Moreover, correlation length was estimated using a random walk resampling procedure that did not take into account broad latitudinal or longitudintal gradients. A reanalysis using anisotropic estimation procedure might yield better information on the seasonality of correlation length. On the other hand, the median estimate for correlation length in the image series was about 25 km, a scale at which the lacunarity index revealed a significant seasonality in patchiness.

Lacunarity proved to be sensitive to both spatial and temporal patterns in the image series. The ability of lacunarity to respond to early and late growing season clumping in the southern extent of the Flint Hills poses the possibility of calibrating lacunarity to regional temperature differences to facilitate interannual comparisons.

This research was exploratory; we sought to test the efficacy of two spatial measures in capturing and summarizing the complexities embodied in time series of imagery. For the Flint Hills landscape viewed with the AVHRR sensor, lacunarity analysis appears to be superior to scale of fluctuation analysis for eliciting sensitive comparisons. Our next task will be to extend the lacunarity analysis to multiple years and to gather the appropriate climatological data to explore the relationship between lacunarity and measures of temperature fields.

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