New Approaches to the Use of Lacunarity Analysis to Characterize Canopy Spatial Heterogeneity

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Overview

DESDynI (or comparable active sensor mission) will provide the potential for characterizing the dynamics of ecosystem structure in landscapes dominated by herbaceous as well as woody species and in wetlands, croplands, grasslands, and shrublands. There is significant value in the analysis of SAR image time series: (1) to detect radiometrically persistent features; (2) to characterize the seasonalities of backscattering and how they relate to the land surface phenologies revealed by passive (and eventually active) optical methods; and (3) to establish baseline expectations from which to assess the magnitude and significance of change, disturbance, or unusual events for habitat monitoring and biodiversity modeling. As lacunarity analyses are well-suited to spatio-temporal characterization of both radar and lidar data, there is high synergistic potential for application to DESDynI data.

Lacunarity Analyses for Image Series

Lacunarity is a scale-dependent property of spatial heterogeneity. As with many multi-scale spatial metrics, the index (or indices) used to estimate lacunarity results from the interaction of the object under study with a series of sampling windows of varying size (and/or shape). The kernel around which various lacunarity indices are built is the sampling distribution of mass density (Plotnick et al. 1993; 1996). Lacunarity indices measures of the deviations of mass density from translational (and rotational) invariance across spatial dimensions.

Lacunarity is sensitive to spatial ***density*** and spatial ***configuration***. However, most implementations of lacunarity indices do not take into account specific mass configurations that occur within the sampling window; rather, sensitivity to configuration emerges from extensive sampling.

Sampling builds a frequency distribution of the mass distribution or occupancy at each window size (w_{ij}). The frequency distribution is normalized into a probability distribution and the ***lacunarity index*** (LI) is constructed from the moments of this empirical sampling distribution.

$$LI(w_{ij}) = 1 + variance(w_{ij}) * mean(w_{ij})^{-2} \quad [1]$$

Higher lacunarity indicates a more sparse, more clumped distribution within the map.

Much of the earlier work on lacunarity focused on the analysis of binary patterns in maps (Allain & Cloitre 1991; Plotnick et al. 1993; Henebry & Batista 1994; Kux & Henebry 1994a,b; Henebry & Kux 1995; Henebry & Su 1995; Krug & Henebry 1995; Plotnick et al. 1996; Henebry & Kux 1996, 1997; Cheng 1997). If the data are binary, then a ***complementary lacunarity index*** (*cLI*) can be calculated on the 0's rather than on the 1's (Kux & Henebry 1994a). Lacunarity gives different results for complementary patterns (Dale 2000); thus, using both LI and cLI, it is possible to construct a ***normalized lacunarity index*** (NLI; Kux & Henebry 1994a; Dougherty & Henebry 2001):

$$NLI(w_{ij}) = 2 - \{LI(w_{ij})^{-1} + cLI(w^{ij})^{-1}\} \quad [2]$$

The NLI facilitates comparisons among different datasets because it scales from 1 to 0. How? When the sampling window size equals the spatial resolution of the data, the inverse of the LI equals the proportion of 1-valued pixels and, similarly, the inverse of the cLI equals the proportion of 0-valued pixels. Thus, the sum of these inverses equal unity.

If an image or a map can be divided into distinct classes that are non-overlapping, then NLI can be generalized to multinomial data. Ordinal, interval, and ratio scaled data can be handled through assignment to non-overlapping classes and generation of ordered binary maps. For example, an image histogram can be divided into four areas of roughly equivalent mass by slices at the quartiles and forming four binary images (Henebry & Kux 1995). Other schemes to partition the mass distribution of the image are possible (Dougherty & Henebry 2002). Furthermore, a lacunarity index can be calculated for each map class and then normalized by a generalization of [2]:

$$NLIk(w_{ij}) = k - \{\Sigma_{(n=1..k)} LI_{[n]}(w_{ij})^{-1}\} \quad [3]$$

where *k* is the number of non-overlapping classes into which the image area is partitioned.

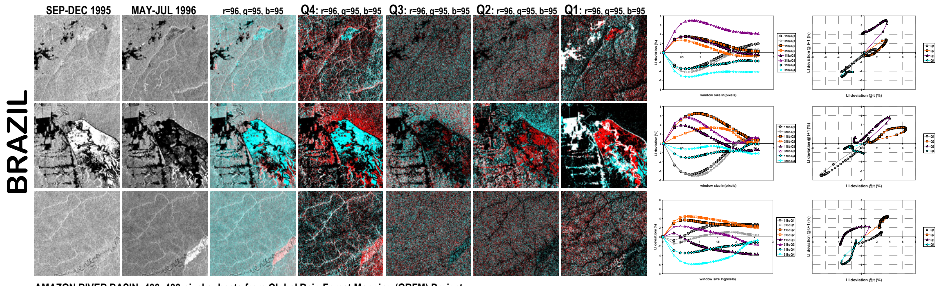
Random maps exhibit a lack of persistent spatial structure under multi-scale windowing (i.e., correlation length approaches zero) and thus low lacunarity. To form binary maps from SAR data, quartiles are determined and four binary quartile maps are generated. Here only Q1 and Q4 are analyzed, the quartile maps representing the lowest and highest backscattering in the scenes. Details of the analysis and additional scenes can be found online (Henebry & Kux 1997).

Against what reference can specific lacunarity decays be evaluated? A neutral model of lacunarity can be built around the expectation of a self-similar decay for each class. In other words, the expectation of the neutral model is that the proportional contribution of a particular slice at w=1 (or grain size) to the total lacunarity will remain constant as w approaches data extent. Deviations from the neutral model decay can then be evaluated:

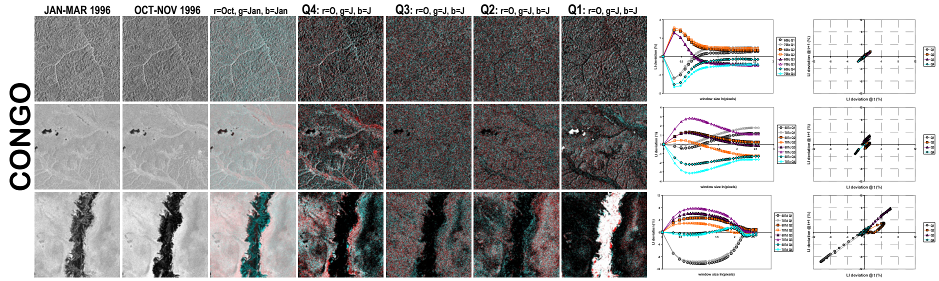
$$LIdev = \{LI_{[s]}(w_{ij})^{-1} * (\Sigma_{(n=1..k)} LI_{[n]}(w_{ij})^{-1})^{-1}\} - \{LI_{[s]}(w_{11})^{-1} * (\Sigma_{(n=1..k)} LI_{[n]}(w_{11})^{-1})^{-1}\} \quad [4]$$

where *k* is the number of non-overlapping classes into which the image area is partitioned and *s* is the specific class of interest. The window size at which maximal deviation occur (positive or negative) indicates the significant scale of pattern. **Negative deviations from self-similar scaling indicate clumping; positive deviations from self-similar scaling indicate dispersion. A pattern can be clumped at one scale and disperse at another, and the converse.** Application to one-dimensional data (transects) are a straightforward simplification. Application to 3-D data are rare in the remote sensing literature and two investigations (Frazer et al. 2005; Kirkpatrick & Weishampel 2005) are motivated by LIDAR retrievals of canopy structure.

Deviations from rotational invariance can be assessed by using two sampling windows with equal area but complementary oblong shapes (w_{1j} & w_{i1}) and forming an ***anisotropy ratio of the lacunarity index*** (ARLI; Kux & Henebry 1994b). Normalized, scaled, and deviation index versions can be built up from the ARLI to explore the anisotropies of lacunarity across several image quantiles or map classes.



AMAZON RIVER BASIN: 400x400 pixel subsets from Global Rain Forest Mapping (GRFM) Project. JERS-1 (L-HH) data from GRFM tiles 118 & 318



CONGO RIVER BASIN: 400x400 pixel subsets from Global Rain Forest Mapping (GRFM) Project. JERS-1 (L-HH) data from GRFM tiles 608 & 708 (top) and 607 & 707 (middle, bottom).

Graphs in the left column display the lacunarity index deviations from self-similar scaling for each quartile for both periods. Ordinate scaling varies to emphasis subtle changes.

Graphs in the right column display a spatio-temporal phase plot of LI deviations. Trajectories close to the 45° axis exhibit little change in spatial heterogeneity between periods. Axis scaling is consistent within basins to compare dynamic ranges.

Negative deviations indicate clumpiness at those spatial scales. Positive deviations indicate dispersion at those spatial scales.

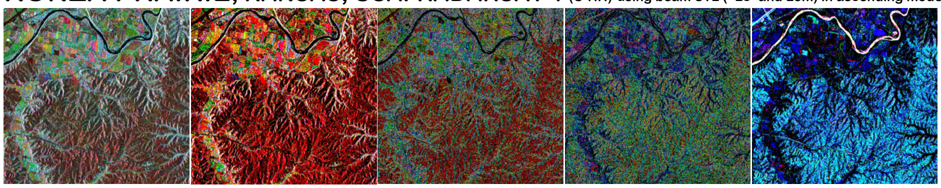
Q2 and Q3, that together constitute the middle 50% of values, exhibit positive deviations at finer spatial resolutions and can shift into the negative region at coarser spatial resolutions. Speckle noise dominates these quartiles.

Q1 and Q4, the extremes of the backscatter values, exhibit positive deviations at finer resolutions that can shift to positive at coarser scales.

Note how the Q4 composites capture in just 2 bits the key spatial pattern evident in the full resolution multidate composite. Note also how the Q1 slice for 607/707d hides the floodplain changes evident in the SAR composite.

Quartile slicing is presented as an example rather than a recommendation. Histogram cutpoints should be driven by system understanding and study objectives.

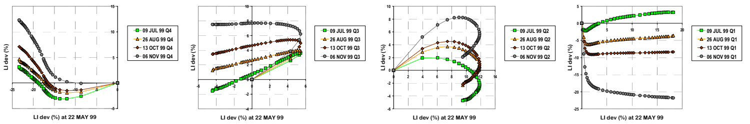
KONZA PRAIRIE, KANSAS, USA: RADARSAT 1 (C-HH) using beam ST2 (~28° and 25m) in ascending mode.



Multi-date composites:
Red = 22 MAY 99
Green = 26 AUG 99
Blue = 06 NOV 99

Composites from left to right:
Image, Q4, Q3, Q2, Q1

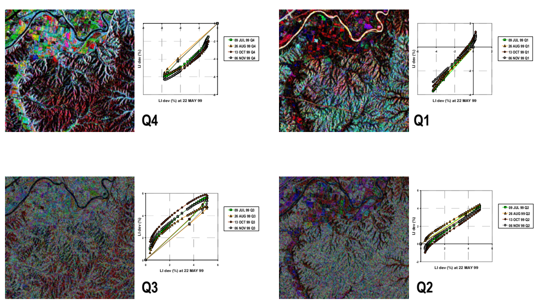
Quartile slicing based on entire series.



Most notable in this image series is the seasonal direction of the spatial pattern of backscatter. In Q1 the movement is to increased aggregation as the season progresses. In contrast, Q2, Q3, and Q4 all move to increased dispersion as the vegetated landscape senesces.

Note also the shifts in dispersion to aggregation in Q2, Q3, and Q4 at the coarser sampling windows and how this changes through the season.

KONZA PRAIRIE: RADARSAT 1, ST2A with quartile slicing per image.



Note the difference in spatio-temporal phase plots between as a result of slicing the quartiles based on the histogram of each date versus the histogram determined by the entire image series. Spatio-temporal dynamics of backscattering are better revealed in this landscape using the seasonal histogram described by the entire image series as the basis for quartile slicing.

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Acknowledgments: **This line of research was previously supported by NSF DEB 96-96229, ESA ERS-2 AO project, and a NASA RADARSAT ADRO 1 project. JERS-1 Images Copyright (c) 1992-1998 NASDA/MITI. Courtesy of the Global Rain Forest Mapping (GRFM) Project. Current travel and research activities supported by the NASA LCLUC program.**

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