Change Detection at Multiple Temporal Scales: Seasonal and Annual Variations in Landscape Variables

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Abstract

Landscape attributes vary at a hierarchy of temporal scales. Temporal aggregation of fine-scale observations is necessary before attempting to detect change in landscape attributes at broader time scales. This paper pursues three goals: (1) to demonstrate the limitations of the classic change detection approach in situations where landscape attributes are characterized by marked seasonal variations; (2) to explore the effect of increasing the frequency of observation on the change detection performances, using a common data aggregation approach; and (3) to test a method which monitors broad time-scale changes in landscape attributes by taking explicitly into account the finer time-scale variations. These issues are explored with data on the landscape spatial pattern of three West African landscapes. The spatial structure of these landscapes is measured from AVHRR data, for a period covering two years. It is shown that seasonal changes in landscape spatial pattern may be much greater than that caused by long-term changes. Therefore, combining information from multiple temporal scales of observation is essential to quantify in a meaningful way the spatial dynamics of landscapes.

Introduction

Most of the world's vegetation is in a constant state of flux at a variety of spatial and temporal scales. These changes are driven by seasonal and interannual climate variations, long-term climatic shifts, vegetation succession, and human or natural disturbances (Hobbs, 1990). The interaction between these changes leads to specific landscape dynamics. A major attribute of a landscape is its spatial pattern, i.e., the arrangement in space of its different elements. The concept of landscape spatial pattern covers, for example, the patch size distribution of residual forests; the location of agricultural plots in relation to natural or cultural features; the shapes of fields; or the number, types, and configuration of landscape elements (i.e., their spatial heterogeneity). Landscape spatial pattern is seldom static due both to natural changes in vegetation and to human intervention. The monitoring of landscape spatial pattern at a variety of temporal scales has several applications (e.g., Turner, 1989). These spatial dynamics interact with ecological processes which have important spatial components, e.g., flows of energy, matter, and information between landscape components; biological productivity; biodiversity; the spread of disturbances; etc. The accurate parameterization of surface processes for climate modeling — e.g., land-atmosphere interactions and vegetative inputs into biogeochemical cycles — also requires a knowledge of the spatial and temporal variability of some land-surface data at the scale of landscapes (Avissar and Pielke, 1989; Henderson-Sellers and Pitman, 1992). Lambin and Strahler (1994b) showed that the detection of land-cover change processes by remote sensing is improved when using both spectral (e.g., vegetation index and surface temperature) and spatial indicators of surface condition. Their study suggested that the detection of interannual changes in landscape spatial structure is more likely to reveal long term and long lasting land-cover changes, while spectral indicators are more sensitive to fluctuations in primary productivity associated with the interannual variability in climatic conditions. The long term monitoring of landscape spatial pattern, in addition to other biophysical variables, might lead to the detection of a greater range of processes of landscape modification (Lambin and Strahler, 1994b).

Before the processes and the ecological impacts of changes in landscape spatial patterns can be understood, the dynamics of landscape pattern must be characterized and quantified in meaningful ways (Turner, 1989). Through its potential for synoptic assessment of the landscape and its sensitivity to vegetation dynamics, remote sensing offers the possibility to analyze changes in spatial structure at the scale of landscapes (e.g., Frank, 1984; Pickup and Foran, 1987; Briggs and Nellis, 1991; Turner and Gardner, 1991; Vogt, 1992).

Multiple Temporal Scales of Change

Changes in landscape spatial patterns are dependent on the spatial and temporal scales of observation (Meentemeyer and Box, 1987; Turner, 1989; Malingreau and Belward, 1992). The importance of the spatial scale of observation for the measurement of landscape spatial structure received much more attention (e.g., Henderson-Sellers *et al.*, 1985; Woodcock and Strahler, 1987; Turner *et al.*, 1989; Nellis and Briggs, 1989; Meentemeyer, 1989) than the effect of changes in temporal scale. Because variations in landscape pattern are related to ecological processes operating at a variety of time-scales, a problem arises in determining the sampling frequency with which to resolve multiple scales of changes in surface characteristics. How can changes in landscape spatial pattern be monitored at broad time-scales when large variations in landscape pattern occur at finer time-scales? For example, seasonal changes in vegetation pattern may be much greater than that caused by some long-term changes in vegetation and, consequently, might obscure the latter.

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Two Approaches to Scaling Up

The issue of changing scales is usually approached differently for the spatial and temporal domains. At the scale of the landscape, the spatial pattern can be characterized in terms of the statistical distribution of patch sizes, shapes, and types, and by the spatial configuration of patches (e.g., Legendre and Fortin, 1989; Turner and Gardner, 1991; Cullinan and Thomas, 1992). For considering larger spatial entities such as regions, the spatial scale of observation can be broadened both in terms of grain — i.e., resolution — and extent. In the first case, the region across which variations in landscape spatial pattern are measured is enlarged. In the second case, each data unit represents a larger area. This spatial aggregation is most commonly performed by averaging the fine grain information. After scaling up spatial observations, fine spatial structures can no longer be perceived (Turner *et al.*, 1989). However, all the information provided in the input data is contributing to the calculation of the aggregated data and is summarized by these. Note, however, that it is not the case with the aggregation functions used for categorical data. Typically, these functions select the most frequent value in a template neighborhood, e.g., modal filter.

For landscape dynamics studies, changes in temporal scale are usually handled differently. When measuring interannual changes in landscape spatial pattern, sequential maps of the landscape are compared. These maps can be derived from aerial photographs and/or satellite data (e.g., van Dorp *et al.*, 1985; Turner, 1990; Dunn *et al.*, 1991). In these studies, only one date is sampled from the finer scale temporal series to represent the years to be compared. Ideally, anniversary dates are selected to control the influence of exogenous factors such as phenological states, soil moisture and sun angle. The data sequence can be compared using classic digital change detection techniques (reviewed by Singh (1989)). This process can be viewed as a scaling up in the temporal dimension from one observation — i.e., the daily scale — to the annual scale, for every year, followed by a comparison of the sampled values at the pluriannual scale. In this approach, the extent of the temporal data increases, the grain remains unchanged, but only a small sample of fine-grain data are extracted from the temporal series, i.e., the sampling rate decreases. In contrast to the aggregation which is performed for scaling up spatially, temporal variations in landscape characteristics at a fine time-scale are not taken into account when analyzing broad-scale temporal series to detect change in landscape attributes by remote sensing or by successive mapping. This approach — i.e., the selection of a few isolated dates for change detection — is appropriate only when it can be assumed that there is no significant seasonal variation in landscape spatial pattern.

Frequency of Observation and Change Detection

When seasonal variations in spatial patterning occur, the detection of interannual changes in landscape spatial pattern might lead to the detection of spurious changes, unless the fine time-scale variations are explicitly accounted for in the detection of broader time-scale variations. If data from only one or a few dates a year are used to measure interannual changes, the obvious undersampling of the temporal series hinders the change detection accuracy: the few dates on which the interannual comparison is based might represent poorly the real landscape pattern. This problem arises even if the intra-annual seasonal variations in landscape spatial pattern are controlled by the sampling design, i.e., through the selection of anniversary dates.

This paper pursues three goals: (1) to demonstrate the limitations of the classic change detection approach in situations where landscape attributes are characterized by marked seasonal variations; (2) to explore the effect of increasing the frequency of observation on the change detection performances, using a common data aggregation approach; and (3) to test a method which monitors broad time-scale changes in landscape attributes by taking explicitly into account the finer time-scale variations. The landscape attribute on which this study is based is spatial structure, calculated from remotely sensed data. The study is based on high temporal frequency remotely sensed data from the Advanced Very High Resolution Radiometer (AVHRR) over a region in west Africa, for a period covering two hydrological years (i.e., years starting from the beginning of the rainy season to the end of the following dry season).

Data

Study Area

The remotely sensed data were extracted from a subscene of Local Area Coverage (LAC) AVHRR data which covers a region across Mali, Senegal, and Guinea (Figure 1). This area extends from the northern edge of the Fouta Djallon, southwest of the scene, to the Sahel, north of the scene. Precipitation varies from about 1,800 mm in the Fouta Djallon to 750 mm in the Sahel. The rainy season normally occurs from June to early October, but is shorter and starts later in the north. The area belongs to the Sudanian phytogeographic zone and, in the northern part, to the Sahelian domain.

Remotely Sensed Data

The daily AVHRR LAC data have a spatial resolution of 1.1 km at nadir, which is well suited to monitor seasonal vegetation dynamics at the scale of the landscape. The AVHRR LAC multitemporal data used in this study were assembled and preprocessed by the Monitoring Tropical Vegetation group, at the Joint Research Centre (Ispra, Italy). Data were acquired by the NOAA-9 and, after November 1988, NOAA-11 satellites. Differences in pre-launch calibration characteristics were compensated for using a procedure described in Vogt (1990). The data included one hundred relatively cloud- and smoke-free, near-nadir view images that were selected from the July 1987 to June 1989 period. The image data were geometrically registred to a master image using ground control points (Grégoire, 1990).

The normalized difference vegetation index (NDVI) was calculated from AVHRR data, as (channel 2 − channel 1)/(channel 2 + channel 1). The NDVI is interpreted as absorbed photosynthetically active radiation, photosynthetic capacity, and minimum canopy resistance (Sellers, 1985). Time integrals of vegetation index data provide estimates of net primary production, leaf area index, and above-ground total dry-matter accumulation (Tucker *et al.*, 1983). Seasonal variations of vegetation indices can be interpreted in terms of vegetation phenology (Justice *et al.*, 1985). The atmospheric contamination and directional reflectance effects were reduced from the annual NDVI data series using the maximum-value composite technique (Holben, 1986), with a one-month compositing period. A more detailed presentation of the study area, the data set, and the pre-processing steps is given in Lambin and Strahler (1994a).

Indicator of Landscape Spatial Pattern

The spatial structure of the landscape was characterized by measuring the variance of NDVI data within a 3- by 3-pixel adaptive moving window applied to each monthly composite image. The adaptive window calculates a texture value for each pixel based on the minimum local variance value from the set of nine 3- by 3-pixel windows that share a common pixel. This technique tends to preserve edges rather than enhance them (Woodcock and Ryherd, 1989). The output of this calculation is a texture image scaled between 0 and 255.

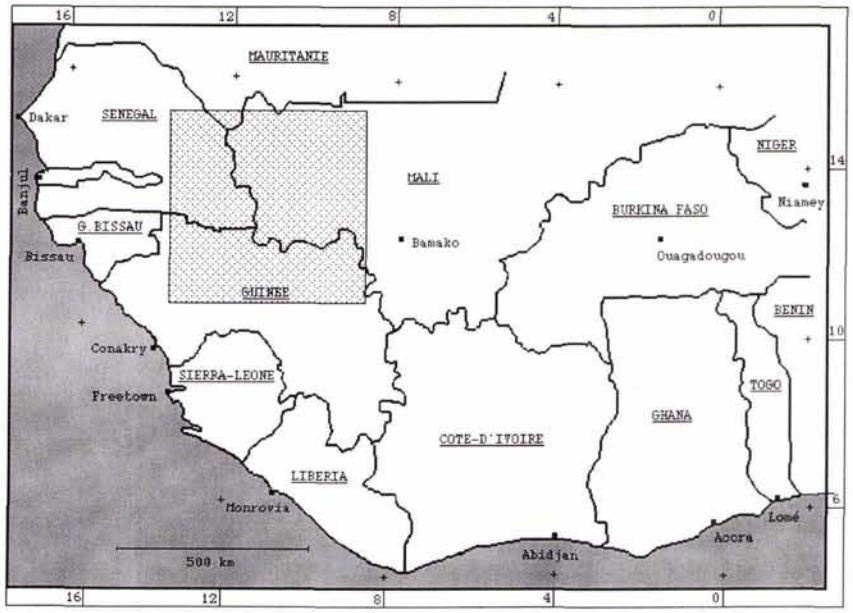

Figure 1. Location of the study area.

The mean value of local variance was computed over three 20- by 20-pixel sample areas, selected from distinct ecoclimatic regions. These mean values are indicators of the average spatial heterogeneity of the landscape for these regions. This procedure was repeated for every monthly composite of the NDVI, for the two hydrological years. This allowed monitoring of seasonal and interannual changes in landscape spatial pattern for the three regions. Because spatial structure is characterized directly from non-categorical NDVI data rather than from a land-cover map (i.e., an interval scale rather than a nominal scale), the measure is not dependent on predetermined landscape units and classification accuracy. A limitation of this approach is that the spatial response function specific to the AVHRR sensor results in dependence between neighboring pixels for LAC data (Belward and Lambin, 1990), which interferes with the measurement of local heterogeneity in image data. The mean local variance should therefore only be used as a relative measure for data from the same sensor. Also note that the local variance measure is dependent on the variance of the image (Woodcock and Strahler, 1987) and, thus, is not strictly a measure of local heterogeneity.

Analytical Procedures

The three sample areas selected from the remotely sensed data belong to different ecoclimatic regions and represent well-defined landscape types: Sahelian from the northern part of the scene, Sudanian from the center, and Guinean from the southern part. The Sahelian landscape is dominated by a herbaceous stratum and is mainly used as rangelands by semi-nomadic societies. The main vegetation types of the Sudanian and Guinean landscapes are, respectively, tree savannah and open forest dominated by deciduous and semideciduous species with an herbaceous stratum. These two regions are cultivated under extensive, traditional farming systems. The three landscape types are also characterized by different seasonal dynamics. These three samples were selected over areas not affected by major, long-term land-cover changes over the 1987-1989 period.

The analysis was performed in four parts. First, the seasonal dynamics of the spatial structure for the three landscape types was analyzed. Second, a classic change detection approach was applied to the data, with different combinations of observation dates. Third, the effect of increasing the frequency of observation and aggregating the observations — independently for each year — before detecting change, was explored. Fourth, the interannual changes in landscape spatial pattern were measured using a technique which compares the seasonal profile of local variance between the two hydrological years.

Seasonal Changes in Landscape Spatial Pattern

The seasonal changes in mean local variance for the three 20- by 20-pixel areas, for the two hydrological years, are displayed in Figures 2, 3, and 4. The first observation is that, for the three landscape types, landscape spatial structure displays seasonal variations. The time-trajectories of mean local variance follow a complex seasonal pattern, with some consistency between landscape types and hydrological years. These variations are driven by the phenological cycle of vegetation, even though it is spatial heterogeneity, not the state of vegetation, which is measured here. The fact that phenological changes are not synchronous and/or not of the same amplitude in neighboring landscape elements leads, at the spatial resolution of AVHRR LAC data, to seasonal variations in landscape spatial pattern.

As it could be predicted on ecological grounds, the annual average of the mean local variance is lowest for the northern Sahelian landscape and highest for the southern Guinean landscape for the two years (Table 1). For most of the year, the grassland landscape is spatially more homogeneous than the tree savannah landscape, which itself is more homogeneous than the open forest landscape. Predictably, the spatial structure of the Sahelian landscape also displays fewer seasonal fluctuations in mean local variance — both in terms of magnitude and frequency — than the two other landscape types. In general, the spatial heterogeneity of the three landscapes is at its lowest during the period of highest vegetation development, which corresponds to the end of the rainy season (September or October, depending on the lati-

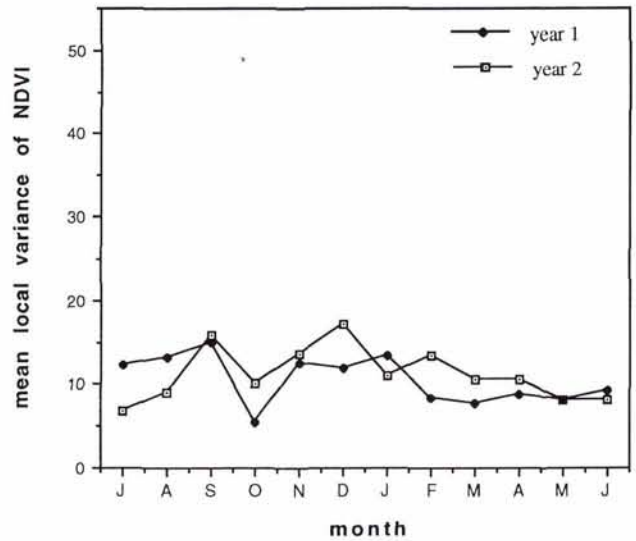

Figure 2. Seasonal dynamics of the spatial structure of NDVI for a Sahelian landscape for the two hydrological years.

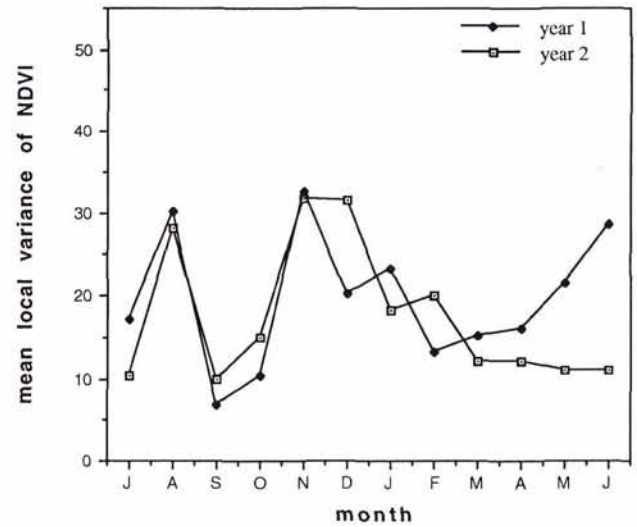

Figure 3. Seasonal dynamics of the spatial structure of NDVI for a Sudanian landscape for the two hydrological years.

tude and the years). Thus, landscape spatial heterogeneity is at its minimum at the period when the NDVI is at its peak. (There is one exception: for the second hydrological year, the Sahelian landscape has a minimum heterogeneity in July, even though the October value is also low.)

These results can be explained by the higher density of the vegetation cover and the higher fragmentation of the Sudanian and Guinean landscapes compared to the Sahelian north, where the herbaceous stratum dominates the landscape. In the southern part of the region, there are more topographic effects than in the Sahel, the human occupation of the land is more intensive and diversified, and the landscape is divided into many small patches of different land uses. These are associated with the presence of valley bottoms, fields, pastures, lateritic duricrusts, savannahs, and open forests. This heterogeneity is masked at the end of the rainy season, when the vegetation is fully developed throughout the landscape. The spatial pattern of the landscape reaches a maximum heterogeneity at the periods of vegetation transition, when each vegetation type is at a different stage of development (June to August), or when the agricultural fields have been harvested while the natural vegetation is still green (November). During the dry season (December to May), the degree of landscape spatial heterogeneity is subject to latitudinal and interannual variations.

It must be emphasized that the observation of seasonal variations in landscape spatial pattern does not necessarily mean that the spatial pattern of actual land-cover classes is changing cyclically. Landscape spatial heterogeneity is measured here on the basis of NDVI data, which is interpreted in terms of vegetation rates and vegetation states, and is closely associated with the phenology of the vegetation cover. These results thus indicate that seasonal variations in NDVI do occur at a different rate for each landscape component, leading to a dynamic spatial configuration of the biophysical attributes of the surface.

Interannual Changes in Landscape Spatial Pattern

The interannual comparison of annual averages calculated from the mean local variance data (Table 1) reveal that, for each of the three landscape types, the averages over the 12 monthly composites, for the two hydrological years, are not much different from one another. (Note that the statistical significance of the equality of the average values cannot be tested because the monthly mean local variances observations are not independent and not normally distributed.) By contrast, the comparison of the shape of the temporal profiles of mean local variance on Figures 2, 3, and 4, reveal that, for the Guinean and Sudanian landscapes, clear interannual differences do exist. A careful analysis of these graphs leads to the following observations:

- For the Sahelian landscape (Figure 2), no interannual differences in mean local variance are observed.
- For the Sudanian (Figure 3) and Guinean (Figure 4) landscapes, interannual differences in spatial heterogeneity are

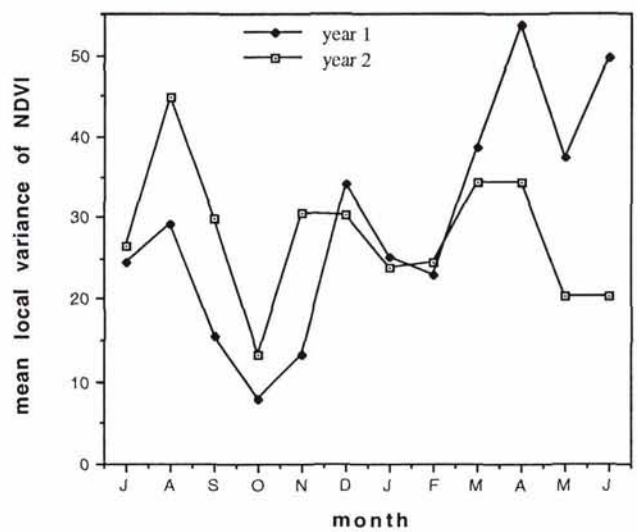

Figure 4. Seasonal dynamics of the spatial structure of NDVI for a Guinean landscape for the two hydrological years.

TABLE 1. AVERAGE MEAN LOCAL VARIANCE (MLV) FOR THE TWO HYDROLOGICAL YEARS

Landscape type	mlv, year 1	mlv, year 2
Sahelian	10.47	11.18
Sudanian	19.61	17.57
Guinean	29.30	27.72

larger and observed essentially during the period of vegetation growth (mid-April to June for these ecosystems). Furthermore, the Guinean landscape also displays large interannual variations during the rainy season.

- For the three landscape types, interannual differences in landscape spatial pattern are at a minimum in September or October, when the spatial heterogeneity is minimum (period of maximum vegetation development) and during the dry season (December to May).

Note again that none of these statements can be tested for statistical significance because the observations — i.e., each 3- by 3-pixel window in the sample areas — are not independent, due to inherent spatial autocorrelation in the landscape and sensor-induced dependency between neighboring pixels.

These changes in landscape spatial pattern can be attributed to differences in the timing of rainfalls between the two years. An early onset of the rainy season at the end of the first hydrological year (ORSTOM, 1991) led to an earlier than usual start of the growing season. Therefore, a greater difference in vegetation states between landscape components, i.e. a larger difference in landscape spatial heterogeneity, is observed at the end of the two hydrological years. The other interannual differences for the Guinean landscape might be related to burning patterns (in November) and cultivation patterns (in August and September).

How can one measure these interannual variations in landscape dynamics? Which method is most appropriate to detect quantitatively these changes?

Measuring Interannual Changes in Landscape Spatial Pattern

The Classic "Anniversary Date" Approach

In the classic approach, observations at anniversary dates are selected from the two years and are compared using a variety of techniques. One of the most widely used and most efficient change detection techniques is univariate image differencing: spatially registered images from two different dates are subtracted, pixel by pixel, to produce an image which represents the change between the two times (Singh, 1989). This method was applied to the mean local variance data from the two hydrological years, for all possible combinations of anniversary dates and non-anniversary dates. For our purpose, using differencing rather than other methods, such as image ratioing or image regression, does not make any difference because the emphasis of this study is on the frequency of observation for interannual change detection, not on the analysis techniques used to delineate areas of significant alterations. Table 2 presents the maximum and minimum magnitude of change detected for all date combinations, for the three landscape types. Because the absolute value of interannual differences in mean local variance depends on the overall magnitude of mean local variance through the years, the difference values are also expressed as the percentage of the average value of mean local variance over the two years.

Results of Table 2 clearly demonstrate that the measurement of the magnitude of change depends crucially on the dates of the two observations being compared. Taking an interannual difference in mean local variance of 30 percent of the average value of mean local variance for the two years as an arbitrary threshold (above which a change can be considered as being significant ecologically), one can see that, for some combinations of dates, no interannual change in landscape spatial pattern is detected while, for other combinations, very large changes are detected. The same conclusion holds for the three landscape types, even though the spatial structure of the Sahelian landscape displays smaller seasonal variations compared to the two other landscape types.

By taking non-anniversary dates into consideration, the number of possible combinations of observation dates increases dramatically, and the range of change magnitudes for different combination of dates is much wider than for anniversary dates. Thus, the comparison of anniversary dates does indeed provide some control over seasonal variations. However, it does not solve the problem that, at certain moments of the year, there are no detectable change, while at other moments, large changes are observable. This situation creates a large dependency of the change detection outcome on the choice of observation dates. In conclusion, while the classic change detection approach can deal successfully with situations characterized by permanent changes of categories, it is not appropriate for situations characterized by seasonal fluctuations in the values of landscape attributes.

Increasing the Frequency of Observation

The problem described above could be thought of as a problem of inadequate temporal aggregation method: fine time-scale variations are not accounted for in the broad time-scale change detection. Taking the spatial aggregation approach as an analogy would suggest increasing the frequency of observation — i.e., the sampling rate — and then collapsing the observations across multiple dates, before attempting to detect change between years. This approach was tested with our data by increasing, step by step, the number of observation dates for the two years. To keep the number of possible combinations of interannual dates to a reasonable level, two constraints were set: (1) only anniversary dates were selected and (2) the observation dates were distributed at regular intervals within a year. It is thought that, with these two rules, the benefit, in terms of change detection accuracy, of increasing the observation frequency is *a priori* maximized. Once the dates have been selected, mean local variance observations at these dates were averaged for each year, and the differences between the average value for the two years were calculated. Table 3 presents the maximum, mean and minimum magnitude of change measured for the three landscape types, for all date combinations allowed by the two constraints. The difference values are also expressed as the percentage of the average value of mean local variance over the two years. The same arbitrary threshold of an interannual

TABLE 2. MAXIMUM (MAX) AND MINIMUM (MIN) DIFFERENCES BETWEEN MEAN LOCAL VARIANCES FOR THE TWO HYDROLOGICAL YEARS, FOR ALL COMBINATIONS OF OBSERVATION DATES. THE NUMBER IN PARENTHESIS ARE THE INTERANNUAL DIFFERENCES EXPRESSED AS THE PERCENTAGE OF THE AVERAGE VALUE OF MEAN LOCAL VARIANCE OVER THE TWO YEARS. IN **BOLD** ARE THE CHANGE MAGNITUDES THAT ARE SIGNIFICANT AT THE 30% THRESHOLD.

	Anniversary dates		Non-anniversary dates	
Landscape type	max	min	max	min
Sahelian	**5.56** (**51.34%**)	0.04 (0.37%)	**11.75** (**108.49%**)	0.04 (0.37%)
Sudanian	**17.52** (**94.24%**)	0.88 (4.73%)	**24.87** (**133.78%**)	0.04 (0.22%)
Guinean	**29.47** (**103.37%**)	1.14 (4.00%)	**40.45** (**141.88%**)	0 (0%)

difference in mean local variance of 30 percent of the average value of mean local variance for the two years is taken to separate between ecologically significant and non-significant changes.

The results demonstrate that the maximum difference between mean local variances for the two hydrological years decreases very rapidly when the frequency of observation increases (Figure 5). Significant interannual changes are only detected for some combinations of one and two observation dates per year (Table 3). The mean difference follows the same trend, but at a slower rate (Figure 6). On the average for all combinations of dates, no significant changes are detected for a frequency of observation higher than one date per year (Table 3). These results can be explained by the fact that, when the frequency of observation becomes high, the averaging of observations obscures any interannual difference in the seasonality of landscape spatial heterogeneity.

An important observation is that, when the frequency of observation increases, the range of interannual differences in mean local variance for the different date combinations decreases sharply (Figure 7). In other words, by adding observation dates, the change detection outcome becomes less dependent on the selection of dates. In conclusion, if increasing the frequency of observation and averaging the observations through the year does not allow detection of interannual changes in seasonality, it does at least control for the exogenous influence of date selection on the detection of change. The influence of the selection of observation dates is paramount for low observation frequencies.

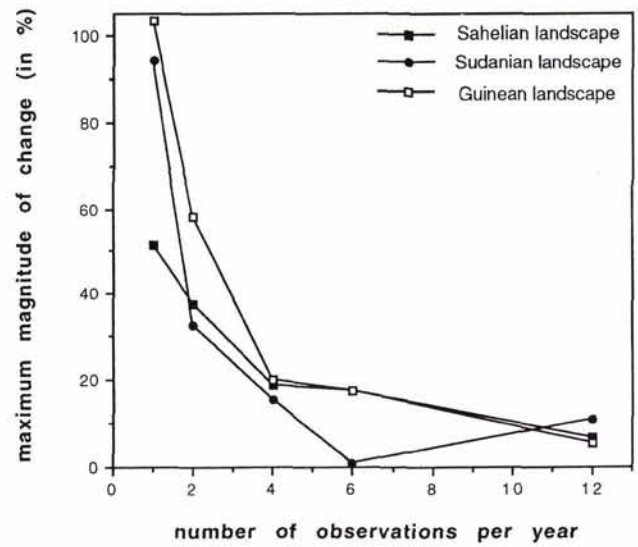

Figure 5. Maximum interannual difference in mean local variance in relation to the frequency of observation.

Multitemporal Change Vector Analysis

Concept

Because a simple measure, such as the difference between the average landscape spatial heterogeneity for large numbers of observations, fails to detect interannual variations in our data, another method to quantify these subtle changes should be applied. Lambin and Strahler (1994a) developed a land-cover change detection approach which explicitly takes into account the seasonal dynamics of landscape spatial structure. The method is based on a comparison of the temporal development curve, or time trajectory, for successive years of remotely sensed indicators derived from high temporal resolution data. When the time trajectory of these indicators over a particular pixel departs from that expected for that pixel, a process of land-cover change can be detected.

The seasonal dynamics of a remotely sensed indicator can be represented, for each pixel, by a point in a multidimensional space, with the number of dimensions of this space corresponding to the number of observations n. The set of values taken by the indicator during a year is defined by a vector. Every year, the coordinates of the position of any pixel in the multidimensional temporal space can be observed. Any change in seasonal dynamics of the indicator between successive years will result in a displacement of the pixel's point in the multidimensional space. This difference in position can be described by a change vector. The magnitude of the change vector measures the intensity of the change in land cover (Lambin and Strahler, 1994a). It is calculated as the Euclidean distance between two points in the n-dimensional temporal space: i.e.,

$$\left[\sum_{i=1}^{n} (I_1 - I_2)^2_i\right]^{1/2}$$

where I_1 and I_2 are the year 1 and year 2 pixel values for the indicator I and i is the observation period during the year (e.g., for monthly composites, $n = 12$).

Results

This calculation was performed for the three landscape types, between the two hydrological years. The resulting

Table 3. Maximum (max), Mean, and Minimum (min) Differences Between Mean Local Variances for the Two Hydrological Years, for Different Combinations of Anniversary Dates. The Number in Parenthesis Are The Interannual Differences Expressed as the Percentage of the Average Value of Mean Local Variance over the Two Years. In **bold** Are the Change Magnitudes that Are Significant at the 30% Threshold.

Number of observations per year	Sahelian landscape			Sudanian landscape			Guinean landscape		
	max	mean	min	max	mean	min	max	mean	min
1	**5.56** (**51.34%**)	2.59 (27.25%)	0.04 (0.37%)	**17.52** (**94.24%**)	**6.33** (**34.05%**)	0.88 (4.73%)	**29.47** (**103.37%**)	**10.94** (**38.38%**)	1.14 (4.00%)
2	**4.06** (**37.49%**)	2.07 (19.08%)	0.44 (4.06%)	**6.04** (**32.49%**)	2.99 (16.09%)	0.08 (0.43%)	**16.56** (**58.07%**)	6.30 (22.10%)	0.03 (0.11%)
4	2.04 (18.81%)	0.99 (9.14%)	0.41 (3.79%)	2.84 (15.27%)	2.05 (11.03%)	1.65 (8.88%)	5.76 (20.20%)	4.50 (15.78%)	3.37 (11.82%)
6	1.92 (17.73%)	1.21 (11.13%)	0.49 (4.52%)	0.13 (0.70%)	0.09 (0.46%)	0.04 (0.22%)	4.97 (17.43%)	3.39 (11.87%)	1.80 (6.31%)
12		0.71 (6.56%)			2.04 (10.97%)			1.58 (5.54%)	

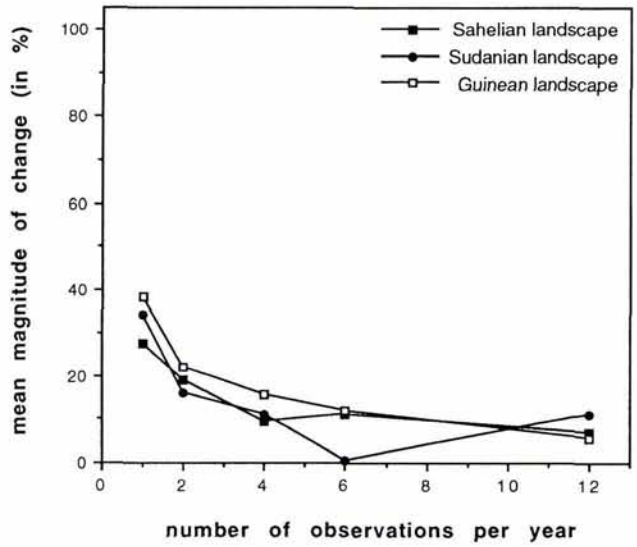

Figure 6. Mean of the interannual differences in mean local variance for different date combinations, in relation to the frequency of observation.

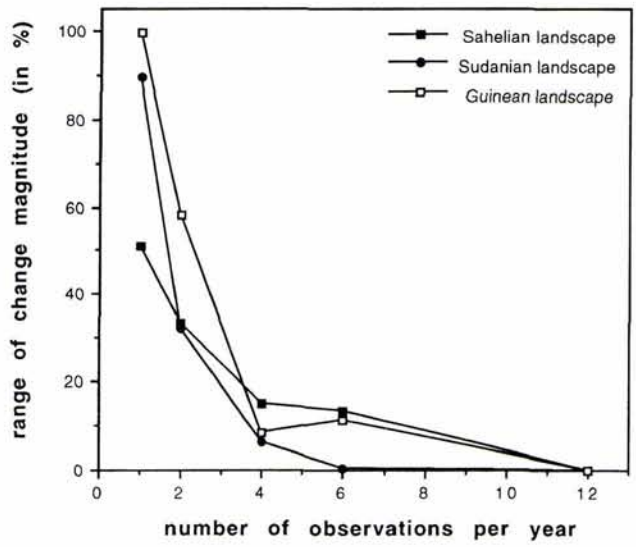

Figure 7. Range of interannual differences in mean local variance for different date combinations, in relation to the frequency of observation.

magnitudes of the change vectors are given in Table 4. As expected, the largest interannual change intensity in landscape spatial heterogeneity is measured for the Guinean landscape, and the lowest intensity for the Sahelian landscape. The Sudanian landscape is characterized by an intermediate value of change intensity. The multitemporal change vector analysis applied to mean local variance data therefore detects interannual changes in the seasonal dynamics of landscape spatial pattern. This approach is particularly useful for the Sudanian and Guinean landscapes, because their seasonal changes in spatial structure are much greater than the change in average values between the two years being analyzed.

Conclusion and Discussion

- Landscape attributes vary at a hierarchy of temporal scales. When a landscape attribute displays seasonal variations, the detection of interannual changes in this attribute must be based on a comparison of its time trajectory between different years rather than on a simple comparison of attribute data derived from single dates. If a comparison of isolated dates is applied, the results vary from the detection of very large changes to no change in landscape attribute, depending on the dates of the images being compared. Temporal "synthesis" of fine-scale observations is thus necessary to detect change in any landscape variable at broader time scales. The aggregation approach used for continuous spatial data — i.e., averaging of the fine grain information — is not a good model to aggregate temporal series of landscape variables for change detection. Collapsing multiple fine-scale observations obscures processes of changes that might be of crucial importance to understand the interactions between climatic change and landscape ecology. Only a method which takes explicitly into account fine time-scale variations in the detection of change at broader time-scales, such as the multitemporal change vector analysis, can successfully grasp the seasonal dimension of interannual landscape change processes.
- The observation of seasonal variations in landscape spatial pattern depends on two factors: (1) the type of landscape under study and the disturbances affecting it (e.g., flooded plain, grasslands subject to periodic fires, or forest permanently cleared), and (2) the method of measurement of landscape spatial pattern. On the second point, if the landscape is classified according to a rigid land-cover scheme, it is unlikely that seasonal changes will be noticed. Indeed, seasonal behavior might be one of the attributes defining land-cover classes. (Note that, when there is a strong seasonal dynamic, the accuracy of the land-cover classification depends heavily on the date(s) of observation because, during periods of phenological transition, some land-cover types might be difficult to distinguish from each other.) But, if landscape spatial pattern is measured in terms of biophysical attributes of the surface (e.g., primary productivity, surface moisture, canopy resistance) or in terms of the spatial pattern in these attributes, seasonal changes in landscape spatial pattern are likely to be observed. Biophysical and structural attributes of the cover types can be represented as continuous variables in space and time, while land-cover maps are made of discrete units. Change detection on the basis of continuous spectral, spatial, or biophysical variables is more accurate than the comparison of sequential classifications (Singh, 1989).
- The question of defining the optimal sampling rate to represent time series, and the question of the methods of aggregation and comparison of two time series, are two distinct issues which should not be confused. This paper mainly deals with the second issue. The first issue is a classic one and is solved universally by the sampling theorem. This theorem states that the rate at which a continuous function is sampled must exceed twice the bandwidth of the function — a sampling rate of twice the bandwidth of the function is referred to as the Nyquist rate. The sampling theorem is not relevant for our test of the multitemporal change vector method because this test was based on the twelve-monthly composites — i.e., the whole time series.
- This study was restricted to two time scales — seasonal and biannual — which are very short compared to the typical scales of modifications in landscape spatial pattern brought

TABLE 4. AVERAGE, FOR THE THREE LANDSCAPE TYPES, OF THE MAGNITUDE OF THE MULTIEMPORAL CHANGE VECTOR

Landscape type	Magnitude of the change vector
Sahelian	12.06
Sudanian	26.98
Guinean	48.57

about either by human activities or long-term vegetation changes. In such a short interval of time, the main interannual change which affected the three landscapes analyzed in this paper was caused by interannual variations in rainfall distribution. A monitoring of landscape spatial pattern over longer periods of time will probably reveal more radical and permanent changes in landscape patterns, such as those related to the permanent clearing of natural vegetation by human activity, vegetation succession, or climatic shift. The multitemporal change vector method could easily be adapted to integrate a larger hierarchy of temporal scales.

- The multitemporal change vector method tested in this paper has high requirements in terms of temporal frequency of the data. Currently, the only remote sensing systems which satisfy this requirement are AVHRR and the DMSP-Operational Line Scanner. Several future satellite sensors in the optical domain will also provide daily coverage of the Earth at a coarse spatial resolution (e.g., the Along-Track Scanning Radiometer-2 of ERS-2, VEGETATION of SPOT-4, the Medium Resolution Imaging Spectrometer of POEM-1, and the Moderate Resolution Imaging Spectroradiometer of EOS-AM).

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