



Pantropical dynamics of 'intact' rain forest canopy texture

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ABSTRACT

Aside from deforestation and selective logging, mature tropical rain forests appear to be in a state of near-term flux. At plot scales over a 20-year period, forest inventory data (representing areas < 750 ha) have shown stands to be accumulating above-ground biomass pantropically while displaying signs of increasing turnover. To assess whether or not such disequilibrium is manifest at broader spatial scales (i.e. coarser grain sizes and larger extents), we performed a change detection analysis of landscape texture (i.e. the organization of reflective properties), in satellite images of closed-canopy tropical rain forests considered to be anthropically undisturbed. Here we show that fractal properties of pixel spectral values depicting low and high levels of photosynthetic

activity underwent significant shifts from the 1970s to the 1980s. Following expectations for aggrading forests, canopy texture became more random throughout the tropics. Although subject to periodic disturbance events such as natural exogenic perturbations and/or synchronous die-off, which should produce no consistent trend, these forested landscapes across the globe exhibited similar dynamics at fine temporal (decadal) intervals. Such biophysical changes (representing areas > 1000 000 ha) directly affect atmospheric boundary layer conditions and could have implications with respect to biodiversity and carbon cycling in these systems.

Key words Canopy, fractal, global change, lacunarity, satellite imagery, spatial pattern, texture, tropical rain forest.

REMOTE SENSING FOREST HETEROGENEITY

Mature forested landscapes have been described as shifting mosaic steady-state or quasi-equilibrium systems (Shugart, 1998). At a scale of hectares, forest structure is depicted as a heterogeneous mixture of patches in different stages of gap-phase replacement. Yet, landscape properties such as above-ground biomass (represented as a statistical aggregation of patch elements) are considered to be relatively constant, as are the proportions of each successional stage (Smith & Urban, 1988). However, tree inventory data spanning 1976–96 (Phillips *et al.*, 1998) and ecosystem model pro-

jections spanning 1980–95 (Tian *et al.*, 2000) have shown mature tropical forests to be in a state of disequilibrium, accumulating above-ground carbon. Related studies, based on a globally distributed set of 0.1 ha plots, indicate a global increase in mortality and recruitment rates (Phillips & Gentry, 1994; Phillips, 1996), although these results may have been influenced by biases inherent in permanent plot sampling (Phillips & Sheil, 1997).

Efforts to monitor change in broad-scale vegetation patterns using satellite-based remote sensing have largely focused on the presence/absence of vegetation due to deforestation/afforestation, natural disturbance/recovery or ecotonal shifts (Skole & Tucker, 1993; Tanner *et al.*, 1998; Houghton *et al.*, 2000). Although detailed information regarding internal tropical rain forest heterogeneity has

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been derived (Tuomisto *et al.*, 1995), less conspicuous alterations due to increased turnover (Phillips, 1996) or general degradation, such as those resulting from selective logging, have been undetectable (Stone & Lefebvre, 1998; Nepstad *et al.*, 1999) using commonly available satellite imagery and traditional methods of analysis. Such subtle, yet extensive changes may affect carbon flux estimates (Potter, 1999) and general ecosystem functioning (Phillips, 1997).

In this study, we focus on remotely sensed texture of tropical rain forests as measured by spatial heterogeneity in pixel tones. Within a forested system, texture is a pattern produced through a complex amalgam of canopy processes: spatial differences in tree species, phenology, crown density, canopy gaps, canopy architecture and topographically produced shadows. Although often neglected, or purposefully avoided, spatio-temporal variability in ecological signals is being used to improve discrimination among tropical forest classes (Nelson *et al.*, 2000; Saatchi *et al.*, 2000) and may provide a means to measure forest biodiversity (Innes & Koch, 1998) and monitor the health of broad-scale ecological systems (Kratz *et al.*, 1995).

During forest stand development, fine-scale (1–10 m) textural pattern dynamics in remotely sensed images correspond to changes in canopy structure (Cohen *et al.*, 1990). At coarser scales, comparable to Landsat Thematic Mapper (TM) pixel resolution (i.e. 30 m), spatial patterns of forest reflectance values do not exhibit auto-correlation (Cohen *et al.*, 1990). This follows spatially explicit gap model results of forest structure (Weishampel *et al.*, 1992; Weishampel & Urban, 1996). Although the spatial distribution of tonal values is random at these scales, the contrast of pixel-to-pixel or patch-to-patch reflectance increases, in part due to the formation of canopy gaps, as stands mature. This discrepancy among different aged stands, i.e. from young to mature to old-growth, decreases with larger grain sizes.

As the areal extent of the study area increases, non-random patterns appear as environmental influences, e.g. edaphic (Tuomisto *et al.*, 1995) and topographic characteristics (Weishampel *et al.*, 2000), affect forest composition, structure and reflectance. If the forested landscape is in a quasi-equilibrium state, with dynamics driven by periodic endogenous tree falls, there should not be an

apparent difference in the textural signatures over time. However, if the forest is aggrading and the frequency of canopy gaps rises, as found for developing stands, and if the subsequent increase in variance of tonal properties masks non-random environmental-related patterns, texture patterns should become more random. Similarly, such an increase in gap formation could be driven exogenously by changes in global climatic patterns, e.g. drought from El Niño Southern Oscillation (ENSO) episodes.

METHODS

Bitemporal image sampling and processing

The National Aeronautics and Space Administration (NASA) Landsat Pathfinder Humid Tropical Deforestation Project was assigned to map global deforestation for the humid tropics for three decades, the 1970s, 1980s and 1990s. Landsat Multispectral Scanner (MSS) images from the 1970s and 1980s and Landsat TM images from the 1980s and 1990s were acquired for four regions, designated Central Africa, Legal Amazon (i.e. within Brazil), Outer or Pan Amazon (i.e. non-Brazilian) and Southeast Asia (Fig. 1a). These coverages represent approximately 75% of all tropical rain forests.

At the time of the present study, the Pathfinder Project landcover classification of Landsat TM scenes had not been completed. We selected thirty-five Landsat MSS scene pairs from the four regions based on the presence of > 98% forest cover within the area of scene overlap and the temporal differences between pairs (Fig. 1, Table 1). Inter-annually, pairs were separated, on average by 11 years (1974–85). During this period there was a sharp increase in mean annual turnover as measured in permanent sample plots distributed worldwide (Phillips, 1996, 1997). To reduce phenological differences, intra-annual differences between selected pairs were less than 3 months apart. Scene acquisition times were comparable (within 90 min) due to similarity in orbit geometry of the different Landsat satellites, thereby reducing shadow effects caused by daily sun angle changes. Scene pairs were co-registered using common ground control points that resulted in minimal distortion; the average root mean square error associated with the geometric transformation

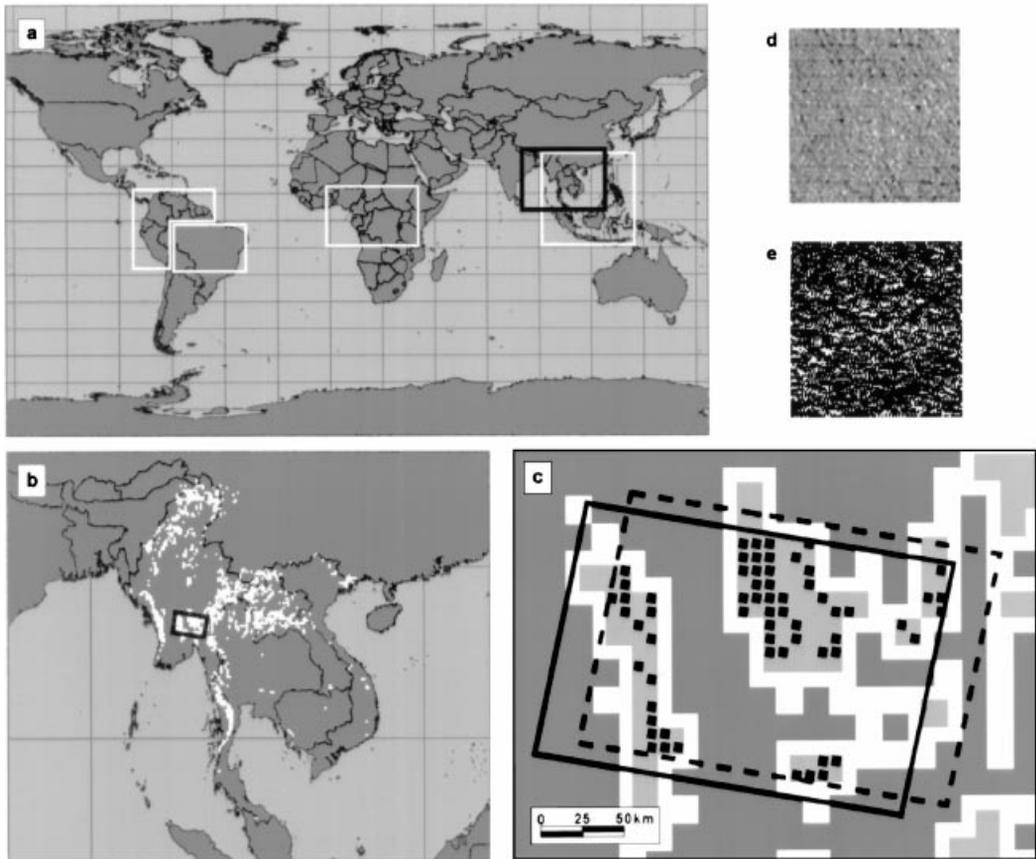


Fig. 1 Sampling of Landsat MSS imagery. (a) Regions (Central Africa, Legal Amazon, Outer Amazon, and Southeast Asia) from the NASA Landsat Pathfinder Humid Tropical Deforestation Project are designated by the white borders. (b) Portion of the Southeast Asian region designated by the black rectangle in panel a. The lightest grey areas represent intact forested areas categorized as 0% deforested with > 98% cover. (c) Buffered regions of intact forest. Randomly distributed 100×100 pixel subsets (black squares) located within the intersecting area of the 1970s (dashed) and 1980s (solid) scenes designated by the black rectangle in panel b. (d) Subset of continuous NDVI measures from a 1980s image. Lighter shades represent higher values. (e) Binary version of the image in panel d. Pixels from the highest NDVI quartile in each row are white.

Table 1 Spatio-temporal information of Landsat MSS scenes and samples

	Central Africa	Legal Amazon	Outer Amazon	Southeast Asia
> 98% rain forest cover (km ²)	191 232	1557 760	450 816	253 952
Number of scene pairs	8	9	11	7
Average scene interval	1974–86	1974–86	1975–85	1973–85
Absolute average day difference*	32(2)	32(–19)	45(14)	32(25)
Number of 100×100 pixel subsets	36	121	66	19
Total area examined (km ²)	1593	4114	2920	841

* Numbers in parentheses represent the average day difference (1970s–1980s).

was < 0.065 of a pixel in Cartesian co-ordinate space. Landsat MSS pixels are 56 m across-track and 79 m along-track.

To limit our study to closed-canopy forests undisturbed by known cutting, we overlaid 16×16 -km grids of 1980s coverage data developed by the Pathfinder Project on intersected areas of the 1970s and 1980s scenes to locate grid cells categorized as 0% deforested with $> 98\%$ forest cover based on 1980s image and field information. Although most of the forested areas (with the exception of those located in the western half of the Legal Amazon; Ropelewski & Halpert, 1987; NOAA, 1994) were subjected to drought effects associated with the 1982–83 ENSO event between scenes (Table 1), the high levels of canopy cover suggest that they were either not exposed to extensive natural disturbance (e.g. fire or blow-down) or rapidly recovered from such during this time period. For the purpose of this study, these areas were classified as intact. To avoid differences due to microclimatic alterations, encroachment and other edge effects that may extend as far as 5 km into the forest (Laurance, 2000), we buffered 8 km inward from the edge of these regions. This buffer also eliminated small patches of intact forest that may be subject to biomass loss (Laurance *et al.*, 1997) and reduced the area to less than a quarter of its original extent. Within these areas, 100×100 pixel windows were randomly sampled without replacement until approximately half of each remaining area was covered. Thus, given the MSS pixel dimensions, each subset was 4424 ha. Each subset was examined visually to remove those areas with cloud cover, cloud shadows and open water, which could produce changes from drought, flooding or river channel migration (Kalliola *et al.*, 1992). This selection process, which in part was an attempt to reduce bias associated with many permanent plot studies, reduced the sample area to $< 0.4\%$ of the total intact forest area (Table 1).

Radiance values from channels 2 (red) and 4 (near infrared, NIR) were calculated from digital number values using postcalibration dynamic ranges for the Landsat MSS satellites series (Markham & Barker, 1987). These were converted to Normalized Difference Vegetation Index [NDVI, i.e. $(\text{NIR} - \text{red})/(\text{NIR} + \text{red})$] values to emphasize vegetative (greenness) properties. High NDVI values are associated with photosynthetically active can-

opies, corresponding to the shift from low reflectivity in the red portion to high reflectivity in the NIR portion of the electromagnetic spectrum. This spectral index has been widely used to characterize rain forest phenology (Justice *et al.*, 1985; Tanner *et al.*, 1998) and has the benefit of reducing spectral differences caused by topographic variation (Holben & Justice, 1981). However, compared to other plant communities, seasonal fluctuations of NDVI in tropical rain forests are minimal (Justice *et al.*, 1985).

Textural pattern analysis

Image striping — horizontal bands created by the malfunction of an MSS detector — required that spatial patterns be analysed only across pixel rows, which is feasible because striped data are valid in terms of their within-line contrast (Lillesand & Kiefer, 2000). Two spatial pattern metrics along each row were calculated, fractal dimension and lacunarity. In the general power-law formula $F(x) = Lx^D$, D is the fractal dimension and lacunarity (L) is the multiplicative prefactor (Mandelbrot, 1983; Sugihara & May, 1990). The average fractal dimension of a subset was calculated using the continuous NDVI values, which vary between -1 and $+1$, following the variogram method (Palmer, 1988; Vedyushkin, 1994). Lacunarity reflects the distribution of gap sizes in data; the greater the range in gap size distribution, the more lacunar the data. To measure lacunarity, we used a gliding box algorithm that analyses deviations from translational invariance of an image's mass distribution (Plotnick *et al.*, 1993, 1996). Following previous remote sensing studies (Henebry & Kux, 1995, 1997; Weishampel *et al.*, 1998), we replaced the continuous NDVI values along each row with binary-valued quartiles to quantify texture. Although lacunarity could be used to analyse continuous NDVI values, an analysis of the quartiles is more robust. Furthermore, rescaling to quartiles attenuates radiometric effects caused by solar angle and atmospheric differences. Lacunarity was estimated as the ratio of the variance of the number of occupied sites to the square of the mean number of occupied sites within a window.

Texture measures have long been used for image analysis and many powerful measures (e.g. entropy, contagion, contrast, etc.) are based on

the co-occurrence matrix (cf. Musick & Grover, 1991). Co-occurrence measures do not assess the texture of the image directly; rather, they assess patterns that arise in the matrix formed by the juxtaposition of particular tonal values or classes. Furthermore, the formulations of the co-occurrence matrix and its associated measures assume spatial stationarity, which is a property rarely encountered in imagery of natural landscapes. There are myriad forms of deviation from spatial stationarity and any of these deviations can bias measures that rely on an assumption of stationarity. Lacunarity measures, in contrast, are designed to quantify spatial nonstationarity and they measure it directly from imagery. The degree of deviation from spatial stationarity can serve as a powerful probe into complex spatio-temporal dynamics observed in image time series (Henebry & Kux, 1997).

To test for non-random behaviour of the textural differences, we used Monte Carlo sampling. Lacunarity differences between 1000 paired 100×100 randomly permuted quartile maps provided confidence envelopes to compare with the average differences found in the subsets. Following the row-by-row quartilization of the scene subsets each 100 pixel-long row possessed twenty-five occupied locations.

Results

Spatial patterns along pixel rows of continuous NDVI (Fig. 2) and binary quartile values were non-random, as indicated by $D < 2$ (Palmer, 1988). Because each 100-pixel row covers roughly 5.6 km, it was expected that environmental patchiness would yield a non-random distribution of reflectance values. As found in an earlier study focusing on Peruvian rain forests (Weishampel *et al.*, 1998), deviations from randomness were more prevalent in the lowest and highest NDVI quartiles than the middle values. Pantropically, fractal dimensions between the bitemporal NDVI subsets were significantly ($P < 0.001$) higher in the 1980s than the 1970s, based on paired *t*-tests. On a regional basis, fractal dimensions for all regions but Southeast Asia were significantly ($P < 0.05$) higher in the 1980s. These fractal dimensions were comparable to that based on canopy top heights for an old-growth stand in Central America (Weishampel *et al.*, 2000). The average fractal dimensions for

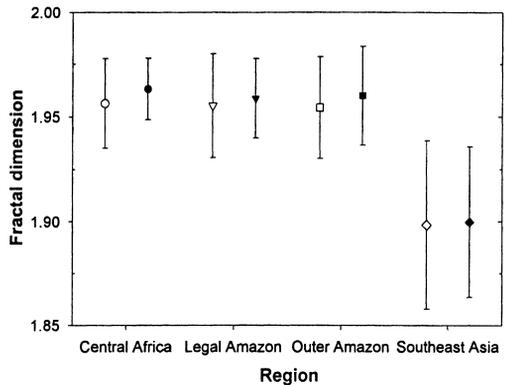


Fig. 2 Average fractal dimensions for NDVI subsets for the 1970s (white markers) and 1980s (black markers). Extensions represent ± 1 standard deviation.

Southeast Asia for both time periods were considerably lower than those for the other regions, perhaps due to fewer samples. This increase in D signifies an increase in spatial independence or an approach towards white noise. This would be expected if reflectance values correspond to spatially random, prevalent increases in forest growth and increasing, but still fairly infrequent, canopy gap formation. The former would produce higher variances of NDVI values and the latter would produce scattered pixels with lower NDVI values.

Lacunarity differences in the lowest and highest NDVI quartiles differed significantly ($P < 0.05$) from random (Fig. 3). Moreover, patterns of these textural differences were fairly consistent among the different tropical regions. On average, clumping of low NDVI pixels was more pronounced in the 1970s at scales ranging from two to seven pixels (112–392 m) and in the 1980s at scales ranging from ≈ 35 –55 pixels (1960–3080 m). Clumping of high NDVI pixels was more pronounced in the 1970s at scales ranging from two to four pixels (112–224 m) and in the 1980s at scales ranging from ≈ 22 –70 pixels (1232–3920 m). For both low and high NDVI values, the general trend was a shift from smaller to larger aggregations. Perhaps related to the fractal dimensions of continuous NDVI values the distribution of smaller aggregations became more randomly organized, whereas the larger aggregations became less so.

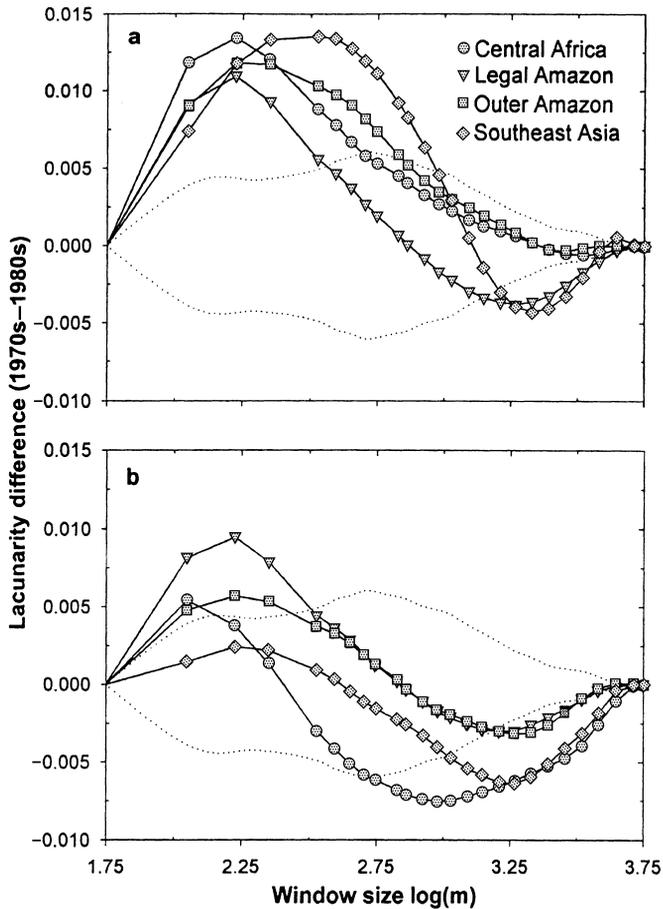


Fig. 3 Average change in lacunarity. Differences for (a) low and (b) high NDVI quartiles for the sampling regions. Dotted lines represent ± 2 standard errors of average lacunarity differences from the random quartile maps.

Discussion

The consistency of the trend across regions suggests that these patterns are unlikely to be directly related to human disturbance, i.e. deforestation or selective logging. These changes may instead reflect a global, more uniformly distributed phenomenon, such as a fertilizing effect from increasing atmospheric CO_2 or nitrogen deposition, as speculated by Phillips (1996, 1997) with respect to the observed higher stand turnover rates. In addition, these systems are sensitive to climatic change (Bazzaz, 1998) and most of the sampled regions were affected by the 1982–83 ENSO. Given the dynamic nature of tropical rain

forests, localized changes due to other exogenous (e.g. atmospheric downburst) and endogenous (e.g. gap formation due to normal tree senescence and mortality patterns) disturbances were anticipated. However, for the 242 subsets (representing $> 15\,000\text{ km}^2$), differences in spatial patterns were not expected to be directional. However, because the Landsat sensor spatial resolution is not optimal for monitoring fine-scale natural (i.e. single treefall) or anthropogenic (i.e. selective logging) gap-level processes and pixel values and texture convolve a host of target properties (Cracknell, 1998), it is difficult to derive the biophysical mechanisms that could explain these emergent behaviours.

Although designated as closed-canopy, potential factors that could induce spectral changes at the scale of the sensor and thus affect spatial patterns include synchronous dieback and re-growth, as found in bamboo-dominated forests, synchronous phenologies such as leaf drop, or rapid recovery from a large disturbance such as fire or downburst that can yield expanses of liana covered forests (Nelson, 1994). However, these dynamics are believed to occur at decadal to century temporal scales. Furthermore, the fact that these forests are accumulating biomass (Phillips *et al.*, 1998) indicates that they have not achieved the quasi-equilibrium state expected with mature forested landscapes. Thus, these aggrading properties may also correspond to developing or mid-successional spatial patterns (Manrubia & Solé, 1997). As stands age and gaps form, variance in tonal patterns become more apparent due to differential growth and shadows (Cohen *et al.*, 1990; Weishampel *et al.*, 1992).

It is unlikely that the observed spatial differences can be attributed to methodological problems caused by atmospheric variation. Although decadal changes in average NDVI values can be attributed to differences in haze, atmospheric effects would need to occur heterogeneously within pixel rows rather than homogeneously spread across the entire scene subset to affect fractal and lacunarity patterns. Although the 1970s scenes were from Landsat 1 and 2 and the 1980s scenes were from Landsat 4 and 5, the sensors were essentially identical (Lillesand & Kiefer, 2000). However, the instantaneous field of view or ground resolution of the earlier Landsats was 79 m and for the earlier versions was 82 m. To what extent such differences would influence textural patterns is unknown, but given the robust nature of lacunarity analysis, we expect little significant effect.

If these changes in spatial heterogeneity cannot be attributed to sensor differences, they indicate a rapid, widespread change in the organization of these forested systems. Along similar lines to the studies showing biomass (Phillips *et al.*, 1998) and turnover (Phillips, 1996) increases, the possible causes are debatable (Sheil, 1995). Whether these patterns represent general system degradation (Phillips, 1997) or transient developmental stages (Manrubia & Solé, 1997), as well as whether these dynamics are externally or internally driven, is a matter of speculation. Thus, how these changes

could affect the ecological interrelationships within these biodiverse areas is uncertain. Changes in NDVI texture could imply changes in crown density or canopy architecture that could relate to or produce changes in growth, recruitment or mortality of individual trees. In addition to biotic implications, landscape textural patterns represent biophysical properties such as albedo and aerodynamic roughness, and therefore changes may affect boundary layer conditions and climate-ecosystem feedbacks (Hayden, 1998). Given the importance in terms of biodiversity and carbon cycling, explanations for these mesoscale dynamics need to be pursued as scientists are becoming increasingly challenged to monitor these forested systems. With the availability of long-term finer resolution imagery of these forests from optical, radar and laser remote sensing instruments (DeFries & Belward, 2000), questions of whether these changes are continuing, and what the underlying mechanisms are, may be answered.

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