Characterizing Canopy Gap Structure in Forests Using Wavelet Analysis

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Summary

1. The wavelet transform is introduced as a technique to identify spatial structure in transect data. Its main advantages over other methods of spatial analysis are its ability to preserve and display hierarchical information while allowing for pattern decomposition.
2. Two applications are presented: simple one-dimensional simulations and a set of 200-m transect data of canopy opening measurements taken in 12 stands dominated by *Pseudotsuga menziesii* ranging over three developmental stages.
3. The calculation of the wavelet variance, derived from the transform, facilitates comparison based on dominant scale of pattern between multiple datasets such as the stands described.
4. The results of the analysis indicate that while canopy pattern trends follow stand development, small to intermediate disturbances significantly influence canopy structure.

Key-words: spatial analysis, gap pattern, forest heterogeneity

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Introduction

Many ecological studies use data collected along transects to examine the spatial characteristics of biotic or abiotic variables. An important objective of such studies is the quantification of the spatial and temporal pattern of the variable of interest, e.g. the structural heterogeneity of forest vegetation at the landscape and within-patch scales (Turner *et al.* 1991).

Fourier spectral analysis has been successfully applied to characterize periodic behaviour in both temporal and spatial data (Platt & Denman 1975; Ford & Renshaw 1984; Kenkel 1988). Although there are many ecological processes that resemble a sine or cosine function in structure, vegetation pattern can appear to be a mixture of periodic and aperiodic components. Such a pattern often occurs where there have been several processes at work over time (e.g. disturbance, establishment and competition) or where the dominant processes or events vary in scale (e.g. changes in topography and microclimate along a biogeographical gradient). As a result, the description of the composite signal and the identification of a specific subpattern can be quite difficult. Because it assumes that a periodic pattern occurs uniformly across the data, Fourier spectral analysis may not always be the most appropriate technique to detect non-uniform patterns in the data (i.e. irregular features or non-stationarity in the data; Priestley 1981).

A second method, related to spectral analysis, is variography. The principal tool of variography, the semi-variogram, is a graphical representation of the spatial variability of the data and is linearly related to the autocorrelation function (Journel & Huijbregts 1977). Both are measures of spatial correlation as a function of the distance between two points. Like Fourier spectral analysis, the semi-variogram provides information on the global average of structure in the data. Whilst it excels in the description of an average structural dimension, the semi-variogram has limited capabilities for the detection of local features deviating from the mean (Cohen, Spies & Bradshaw 1990). The interpretation of the semi-variogram becomes difficult when a multi-scale structure in the data is encountered.

In this paper, we present a technique known as the wavelet transform which can be used to quantify spatial structure as a function of scale and position along a one-dimensional transect (Daubechies 1988). The wavelet transform has three main advantages over previous methods: (i) it acts as a local filter, the dimensions of which do not need to be specified a priori; (ii) the magnitude of the signal can be directly related to position along the transect; and (iii) the analysing wavelet may be chosen to suit the given data form and study objectives. By comparison of the resultant transform at discrete spatial scales, the size, location, magnitude and number of various components of pattern along the transect can be identified. Because position is retained after the analysis, individual and sets of individual events may be related to higher-order patterns, thereby elucidating hierarchical structure. This scale-by-scale analysis is suited for the detection of local features of aperiodic data that may be overlooked by other methods such as Fourier spectral analysis. Unlike the semi-variogram and other stochastically based methods, the wavelet transform does not require stationarity of the data. (A data set may be considered non-stationary if the statistical properties of the data change with location, e.g. when the mean changes with distance along the transect.) Because it preserves locational information whilst effecting a scale-by-scale decomposition of the data into separate spatial components, the wavelet transform may serve as a useful addition to the more commonly used spatial methods.

A quantity derived from wavelet analysis, the wavelet variance, is discussed as a means by which the dominant mean scales (i.e. patch size or scale of features) of the data are determined. The efficacy of the wavelet transform employed for the purposes of spatial discrimination is illustrated with two simulated transects and canopy gap data collected from 12 coniferous forest stands located in the Cascade Mountains of Oregon and Washington, USA.

Wavelet analysis

WAVELET TRANSFORM

The wavelet transform is a collection of convolutions of the data function, $f(x_i)$, (where x_i is distance along the transect) with a windowing function (or 'wavelet') $g(x/a)$ for a given range of scales, a, centred at locations x_j along the transect. It is defined in the discrete case as:

$$W(a,x_j) = \frac{1}{a}\sum_{i=1}^{n} f(x_i)\, g\left(\frac{x_i - x_j}{a}\right).$$

The analysing wavelet can be visualized as a window of a fixed dimension, a, which moves along the data transect as x_i varies. When the wavelet encounters a feature in the data with a like shape and dimension, the absolute value of the transform is high. There are several possible choices for the wavelet function given that certain admissibility requirements are met (Daubechies, Grossman & Meyer 1986; Mallat 1988). Two analysing wavelets are considered here: the Mexican Hat and the Haar (Daubechies 1988). The Mexican Hat function has

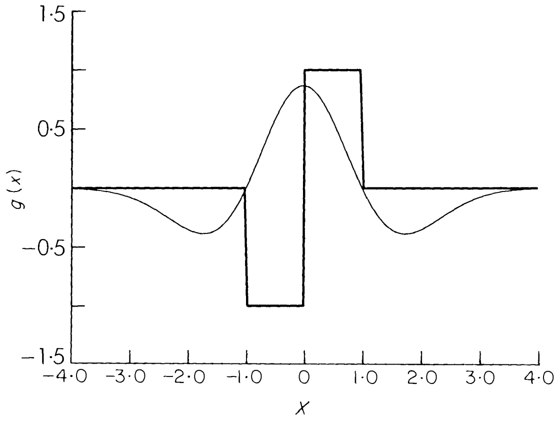

Fig. 1. The Mexican hat (solid line) and Haar (heavy solid line) analysing wavelets, $g(x)$, localized around x.

been chosen such that the range of the function spans (−4 to 4) when a is taken to equal 1 and $g(x)$ is centred at zero (Fig. 1):

$$g(x) = \frac{2}{\sqrt{3}}\pi^{-\frac{1}{4}}(1 - 4x^2)\exp\left(-\frac{4x^2}{2}\right).$$

The Mexican Hat function is an appropriate function to use for revealing patterns in the data characterized by peak and trough events that have symmetrical shapes similar to the Mexican Hat wavelet. In contrast, the Haar analysing wavelet, given its resemblance to a step function, has been found useful in the detection of edges and gradients (Fig. 1; Gamage 1990). As illustrated below in the first example, each wavelet will provide a slightly different perspective on the data. The appropriate choice of the specific wavelet will therefore depend on several factors: the structure of the data, the goals of the analysis, and computational considerations.

SIMULATED EXAMPLE

A simple example was simulated to illustrate the type of information the wavelet transform may provide for the analysis of transect data. A canopy transect characterized by a series of 10-m gaps was generated (Fig. 2a). The transect represents a schematic simplification of forest canopy gap structure where the function $f(x_i)$ corresponds to percentage canopy opening and x_i are points along the transect at 1-m intervals. In this example, the forest canopy is composed of 10-m-wide patches of relatively open gaps alternating with relatively closed, 10-m-wide closed canopy segments superimposed onto a step-function. Whilst the overall 'gap' structure remains consistent across the transect, the data are non-stationary, i.e. the mean is not constant due to the step-function trend. The first half of the data is centred at 5% gap opening whilst the second half of the data is translated and centred at 25% gap opening. This difference in gap intensities between

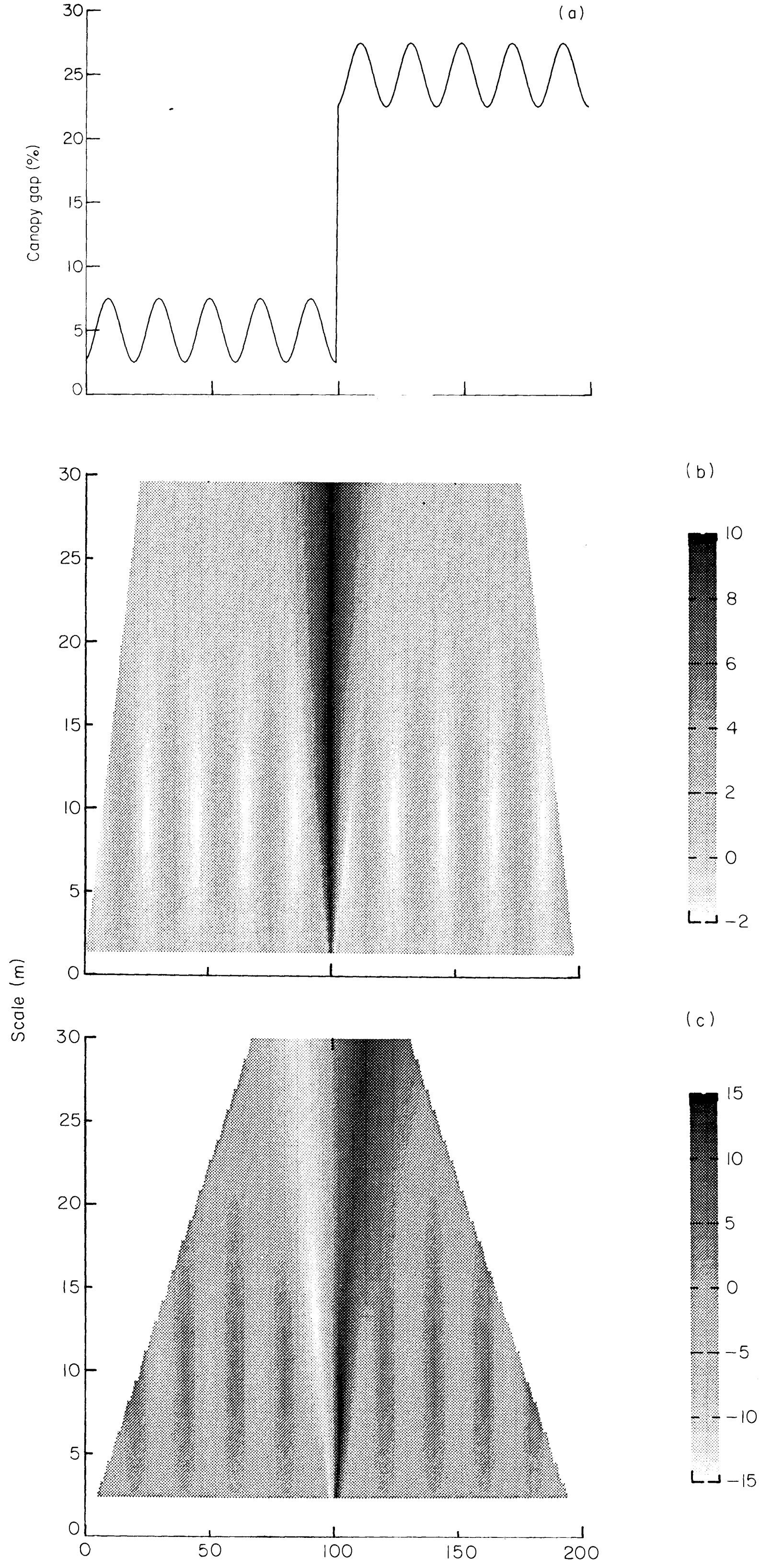

Fig. 2. (a) Simulated forest canopy gap transect of simple pattern plotting percentage gap opening against distance along the transect. (b) Haar wavelet transform and (c) Mexican Hat for data in (a). The grey-scale indicates values of wavelet transform. The vertical axes in (b) and (c) correspond to the scale of the pattern. Viewing nearly parallel to the plane of the page emphasizes the transform structure.

the first and second halves of the data might represent the result of a non-uniform disturbance which has affected only one portion of the transect. Thus, the overall pattern can be viewed as the sum of two scales of pattern resulting from two separate processes.

The wavelet transform calculated from the simulated transect data using the Haar wavelet detects the periodic pattern (Fig. 2b). The 10-m half-period is evinced by the regular series of alternating white (troughs) and grey (peaks) features along the transect centred at the scale of 10 m. The presence of the step-function trend is reflected in the dark, diffuse band centred at 100 m. The extreme values of the transform occurs at 10 m, i.e. the approximate width of the 'canopy gaps'. Note that $W(a, x_j)$ is calculated only for a certain portion of the transect at each scale. This truncation is performed so that the wavelet transform is calculated only at points where the span of the analysing wavelet is contained within the range of the data. The length of transect available for analysis decreases with a corresponding increase in the size of the analysing wavelet and scale.

The transform is also calculated using the Mexican Hat for the same transect shown in Fig. 2a (Fig. 2c). The Mexican Hat transform of the simulated data is similar to the Haar transform with the exception of the response to the step-function trend. The Mexican Hat detects the asymmetry of the 'step' as reflected in the juxtaposition of a white to dark grey band. A second difference between the two transforms is that the length of the transect resolved by the Mexican Hat is less than that of the Haar wavelet; the Mexican Hat requires a greater span for a given scale than that of the Haar. This loss in resolution of larger features may be quite significant at times and thereby influence the choice of analysing wavelet.

WAVELET VARIANCE

Because the wavelet transform is a function of both scale and location, the interpretation of the resultant two-dimensional transform may be quite difficult for complex patterns. One way to facilitate analysis and comparison between data sets is to calculate the wavelet variance function:

$$V(a) = \frac{1}{n} \sum_{j=1}^{n} W^2(a, x_j),$$

where n is defined as the length of the data vector (Gamage 1990). The wavelet variance is simply the average of the squares of the wavelet coefficients at every point along the transect for a given scale, a. The variance is a function of the scale, number and relative magnitudes of the features comprising the data. Higher values of the variance at a given scale reflect the presence of a greater number of peaks and a greater intensity of the signal, or both. In this case, the intensity is proportional to percentage canopy opening. Scales where large values of wavelet variance are centred correspond to scales in the data which strongly dominated the overall pattern.

If a transect characterized by two scales of nested pattern is generated (i.e. individual 4-m-wide peaks cluster to form larger 20-m events alternating with solid 20-m-wide peaks; Fig. 3a), a more-complex wavelet transform results (Fig. 3b). The transform preserves both the nested and simple structure in the data; the wavelet transform locally identifies the single 4-m-wide peaks within a larger 20-m-wide event. This appears in the wavelet transform as a series of small, single events arrayed across the transect lying directly beneath the larger-scaled 20-m peaks on the wavelet transform. This wavelet transform has the appearance of nested folds. The hierarchical structure is more easily observed if the figure is viewed nearly parallel to the plane of the page.

The wavelet variance of the multi-scale pattern shows two distinct peaks centred at 4 m and 18 m (Fig. 3c). The broad peak centred at 18 m reflects the cluster of smaller peaks and the wide, solid peaks. The dispersed character of the peaks is the result of the differences in the forms of the analysing wavelets from the sinusoidal data function. It is instructive to compare the wavelet variance with the transform to discern the two types of wide larger-scale peaks. We now extend the discussion to a more-complex set of data composed of periodic and aperiodic components, namely forest canopy gap data, and examine the utility of the wavelet transform in distinguishing forest canopy structure as measured by gap distribution and size.

Application to forest canopy transects

The spatial pattern of canopy density in forests reflects the disturbance and developmental history of the stand and acts as an important control over growth and establishment in the understorey. The pattern of canopy density is frequently simplified into a classification of canopy gaps and non-gaps, where both the presence and size of gaps are considered to be ecologically important features of the stand. Most gap studies set minimum gap sizes and do not characterize variations in densities of the 'closed' portions of the canopies between the gaps. The gap paradigm has been criticized because it ignores variations in the density of non-gap canopy areas which may be important to understorey response (Lieberman, Lieberman & Peralta 1989). A more objective view of the canopy density pattern of a forest requires a systematic sampling scheme with fine spatial and canopy density resolution.

Wavelet analysis was performed on canopy density measurements taken along twelve 200-m transects to

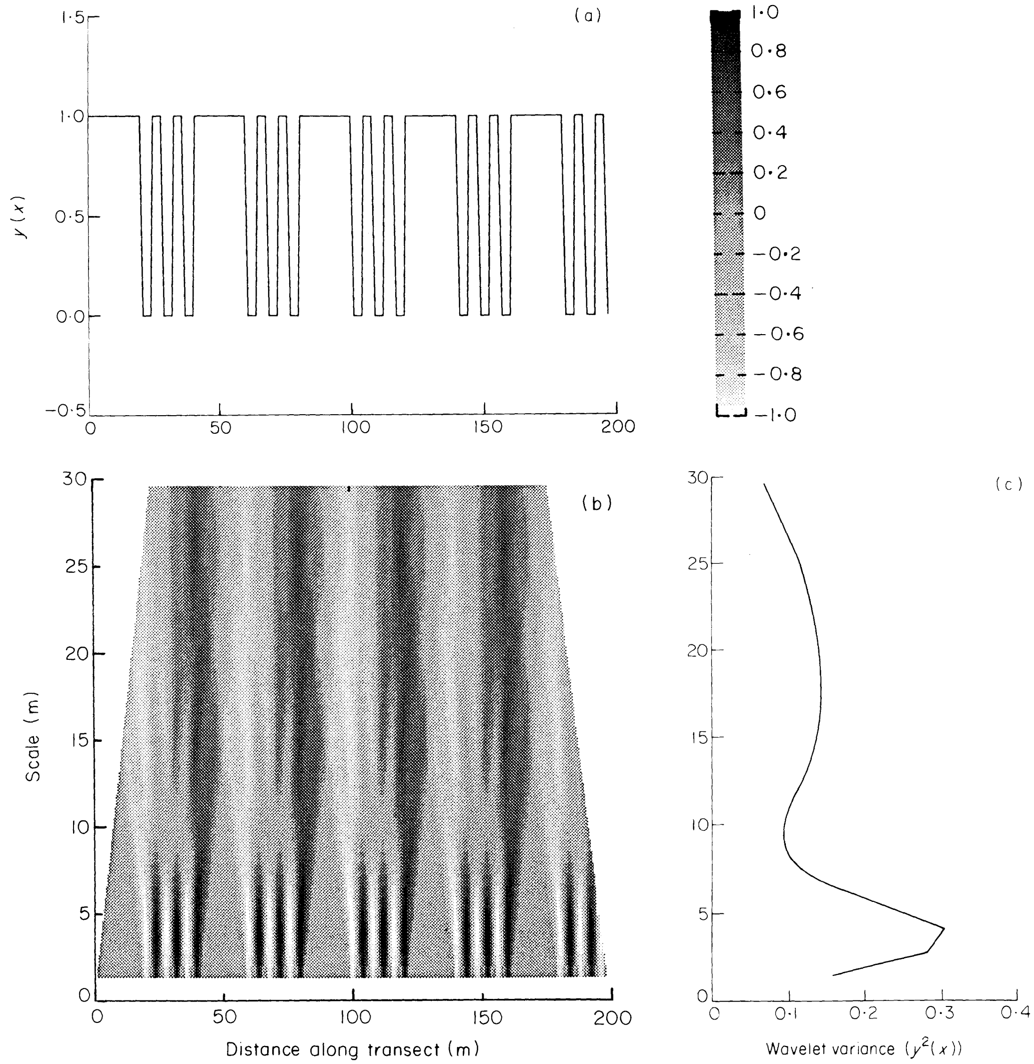

Fig. 3. (a) Simulated transect of nested, two-scale pattern. The vertical axis corresponds to the value of the function $y(x)$ (arbitrary units) as a function of distance along the transect (m). (b) Wavelet transform and (c) wavelet variance of data in (a). The grey-scale indicates values of wavelet transform. The horizontal axis in (c) corresponds to wavelet variance ($y^2(x)$) as a function of the scale of the pattern (m).

characterize spatial patterns of canopy density in relation to stand age and structure. Whilst any study based on a one-dimensional analysis of a two- or three-dimensional pattern is intrinsically weak, the use of transects allowed a greater number of stands to be sampled; decreased dimensionality offered sampling of four stands per age class.

STUDY SITES

Transects selected from three broad age classes of *Pseudotsuga menziesii* (Mirb.) Franco (Douglas fir) and *Tsuga heterophylla* (Raf.) Sarg. (western hemlock) stands in the western Cascade Range of Oregon and Washington, USA were established. Canopy opening measurements were taken at 1-m intervals along 200-m transects in four stands from each of the following dominant tree age classes: young (<80 years), mature (80–200 years), and old growth (>200 years). The 12 stands are denoted O1, O2, O3 and O4, in the case of the four old-growth stands, M1, M2, M3 and M4, for the mature stands, and Y1, Y2, Y3 and Y4 for the young stands.

The stands were selected to be representative of the range of stand conditions observed in a regional study of forest development and structure (Table 1; Spies & Franklin 1990). Within each stand, an area of similar slope, aspect, topography and soils was identified and a single transect was sampled along the slope contours from a randomly selected starting point. Data on percentage canopy opening were obtained at 1-m intervals along the transect using a moosehorn with bubble levels (Mueller-Dombois & Ellenberg 1974). Percentage closure classes from 0% (closed canopy) to 100% (gap) were recorded in 20% increments. Gaps are defined as any part of the canopy at least 1 m wide where the measured value (percentage canopy opening) is positive.

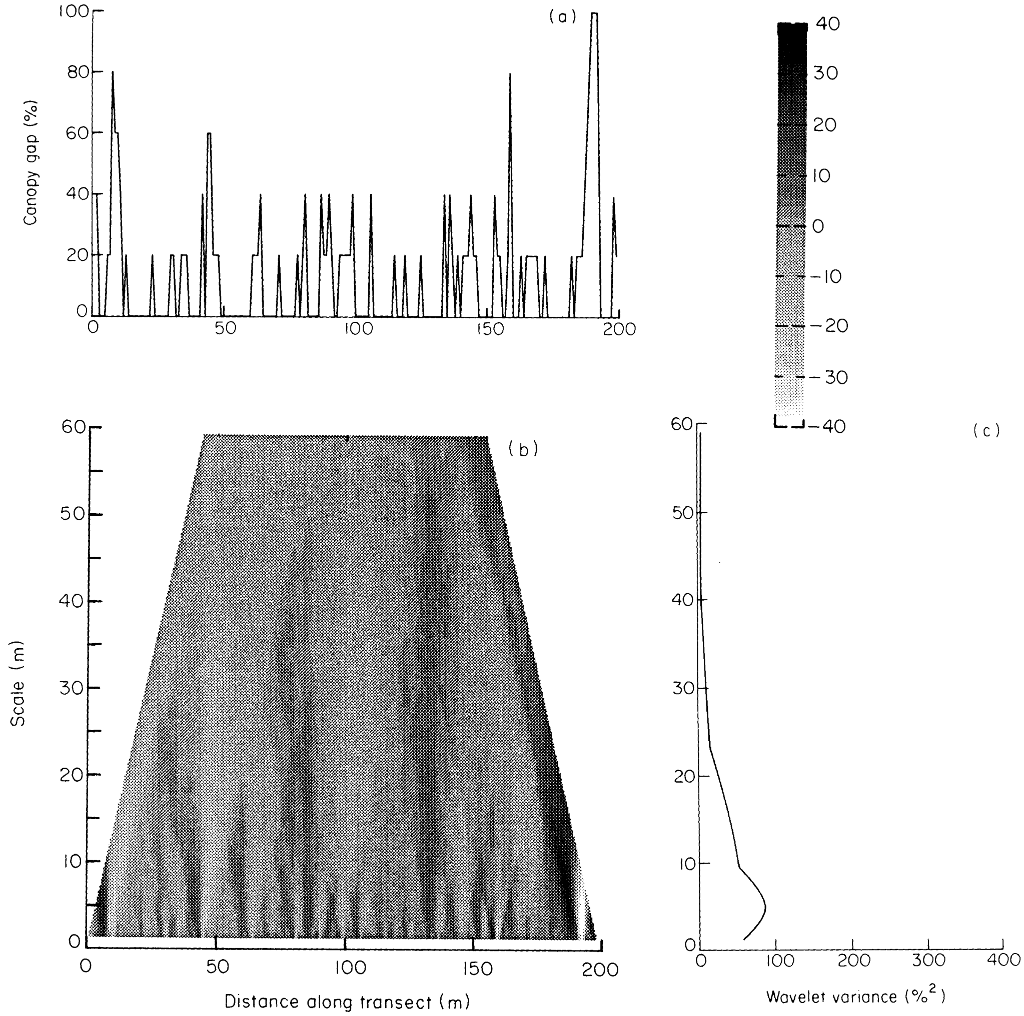

Fig. 4. (a) Transect of forest canopy gaps of a young (75-year-old) stand (Y1) established in a *Pseudotsuga menziesii* stand. The vertical axis corresponds to percentage canopy opening (gap) as a function of distance along the transect (m). (b) Wavelet transform and (c) wavelet variance of gap data in (a). The grey-scale indicates values of wavelet transform. The horizontal axis in (c) corresponds to wavelet variance (%^{2} canopy gap) as a function of the scale of the pattern (m).

WAVELET ANALYSIS

Three stands were chosen for detailed discussion to illustrate how canopy gap patterns were extracted from the data using wavelet analysis. The three stands represent the spectrum of canopy patterns and types found in the analysis. Stand Y1 is fairly typical of many young stands with dense, uniform canopies; canopy closure is continuous and punctuated with small (2–6-m) areas of low-density (predominantly <40% opening) canopy gaps (Fig. 4a). The corresponding wavelet transform shows three faint clusters of gaps of low amplitudes centered at 40, 90 and 150 m (Fig. 4b). The wavelet variance is low in amplitude across all scales with the greatest contribution from gaps <5 m in size (Fig. 4c). Thus, according to the wavelet analysis, the stand canopy is characterized by low-intensity gaps (where intensity corresponds to the percentage canopy opening) and lacks distinct gap structure at all scales except diffuse gaps <5 m in diameter.

In contrast, a transect through an old-growth stand (stand O1) shows a canopy comprised of several sizes of gaps ranging from 2 to 30 m in size (Fig. 5a). These gaps are greater than 60% open on average. The gaps cluster in two main groups centered at 40 and 110 m with two minor groups at 50 and 120 m (Fig. 5b). These clusters are most easily perceived when the transform is viewed near-parallel to the plane of the page. Overall, the amplitude of the transform is much greater than that of the younger, more-homogeneous canopy (Fig. 4). The variety of gap sizes is reflected by high wavelet variance values across a broad range of scales between 5 and 30 m (Fig. 5).

A third transect sampled from a second young stand (Y4) illustrates the signature of disturbance on canopy gap structure (Fig. 6a). The combination of

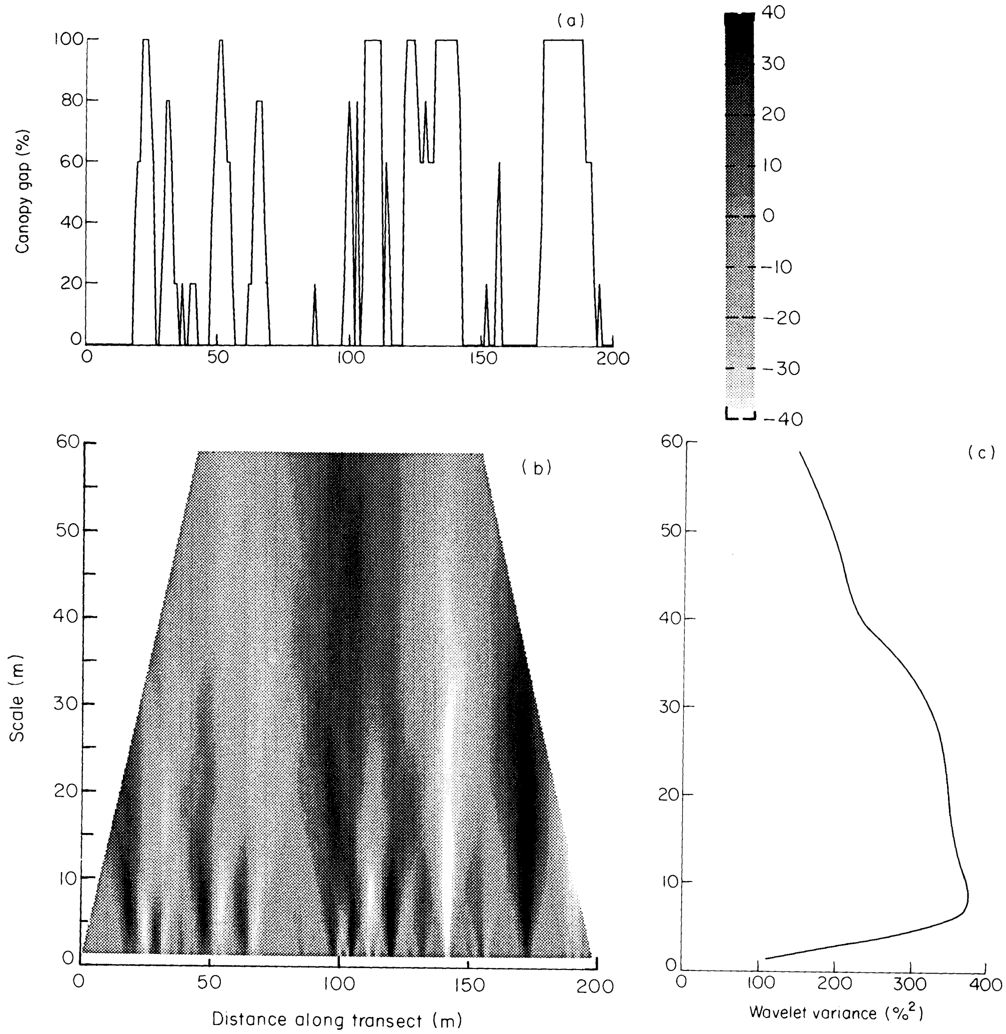

Fig. 5. (a) Transect of forest canopy gaps of an old-growth (400–600-year-old) *Pseudotsuga menziesii* stand (O1). (b) Wavelet transform and (c) wavelet variance of gap data in (a). The grey-scale indicates values of wavelet transform. The horizontal axis in (c) corresponds to wavelet variance (%^{2} canopy gap) as a function of the scale of the pattern (m).

pre-crown closure, patchy disturbance and areas of thin soils have increased the contrast in the canopy structure. This stand lacks the very large gaps of the old-growth stand described above and is instead dominated by low-intensity, 1–2-m-wide and high-intensity, 5–10-m-wide gaps (Fig. 6b). The wavelet variance shows a strong contribution from features 1–7 m in scale as evidenced by the peak centered at 5 m (Fig. 6c). The wavelet variance is distributed evenly at scales >10 m. Whilst visual inspection of the transect data suggests two dominant gap sizes, a double peak is lacking in the corresponding wavelet variance. Although the 1–2-m-diameter gaps form a strong component of the canopy structure (as evidenced by the high variance value), their intensity is low (i.e. the percentage canopy opening is 20% on average) relative to the intensity of the larger gaps. In contrast, the majority of larger gaps (>60% open) caused by disturbance or site condition dominate the wavelet variance.

The wavelet variance is a measure of the contribution of pattern at each given scale to the overall pattern. In the present context, a high wavelet variance at a given scale shows that the gaps are either numerous or very open and of a given width, or both. The presence of peaks in the wavelet variance indicates dominance of a feature at the given scale. For instance, the single strong peak in Fig. 6c reflects the strong dominance of gaps ranging from 4 to 6 m in size. A non-zero variance at greater scales reflects the contribution of other gap sizes to the signal. Canopy transects characterized by broad, high wavelet variance or the presence of two or more peaks indicates the presence of gaps across several scales relative to stand dimension (e.g. Fig. 5). On the other hand, a low variance and/or lack of distinct peaks in the wavelet variance indicate a stand marked by a canopy lacking a multi-scale gap pattern (e.g. Fig. 4).

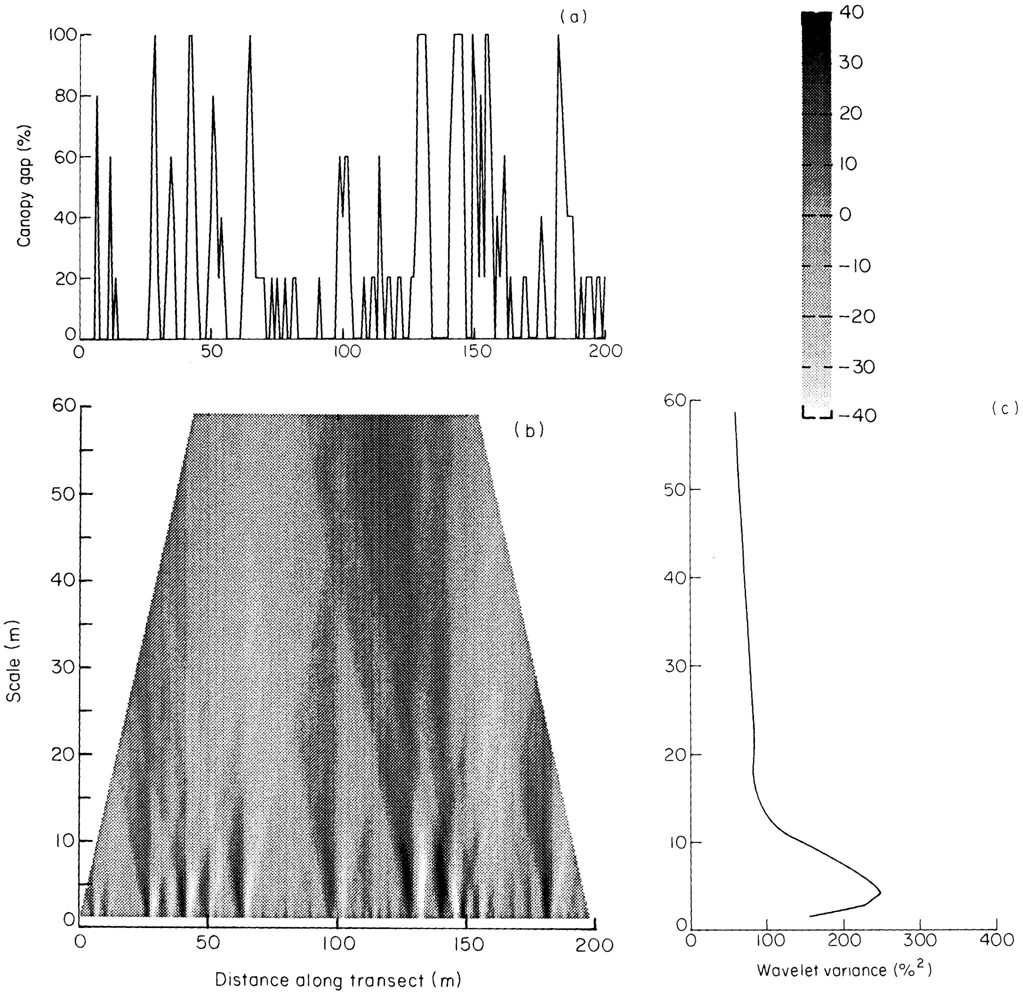

Fig. 6. (a) Transect of forest canopy gaps of a young (43-year-old) *Pseudotsuga menziesii* disturbed stand (Y4). (b) Wavelet transform and (c) wavelet variance in (a). The grey-scale indicates values of wavelet transform. The horizontal axis in (c) corresponds to wavelet variance ($\%^2$ canopy gap) as a function of the scale of the pattern (m).

CANOPY PATTERNS ALONG A CHRONOSEQUENCE

The wavelet variance of the 12 transects representing 12 stands from three forest age classes were calculated (Fig. 7). Trends of canopy pattern among age classes are present, although variation within age classes is high. Old-growth stands (stands O1–O4) tended to have higher wavelet variance amplitudes and pattern at several scales. In general, the young stands (stands Y1–Y4) tended to have wavelet variances of lower amplitudes and a finer pattern. The mature stands (stands M1–M4) exhibited characteristics intermediate to both old-growth and young stands depending on their individual histories.

The wavelet variances can be classified into four general groups based on their curvilinear form. The wavelet variances of Group I (O1, O2, O3 and M3) have peaks in the range 5–30 m and are high in amplitude either across several scales (O1) or dominated by two strong peaks (O1 and O2). These stands have large gaps and a diverse canopy structure as a result of their advanced stage of development. Stand M3, an older mature stand, has experienced mortality from a root rot (*Phellinus weirii*) and bark beetles in the last 20 years. These conditions have created the relatively intense and larger scale of gaps rendering its gap signature more similar to the canopy structure of the old-growth stands.

Group II (Y1, Y2, M2 and M4) is characterized by low-intensity (diffuse) gaps of fairly small size (<8 m). These stands have relatively closed, homogeneous canopies that are typical of many young and mature *Pseudotsuga menziesii*/*Tsuga heterophylla*. Competition mortality, most often affecting single, relatively small canopy trees, has been the primary form of tree death in these stands. Small gaps between crowns may result from branch abrasion of adjacent swaying crowns or as the result of the death of intermediate and suppressed canopy trees. The low-intensity gaps of these stands are areas of thin crowns or crown fringes that are incompletely covered by branches and leaves.

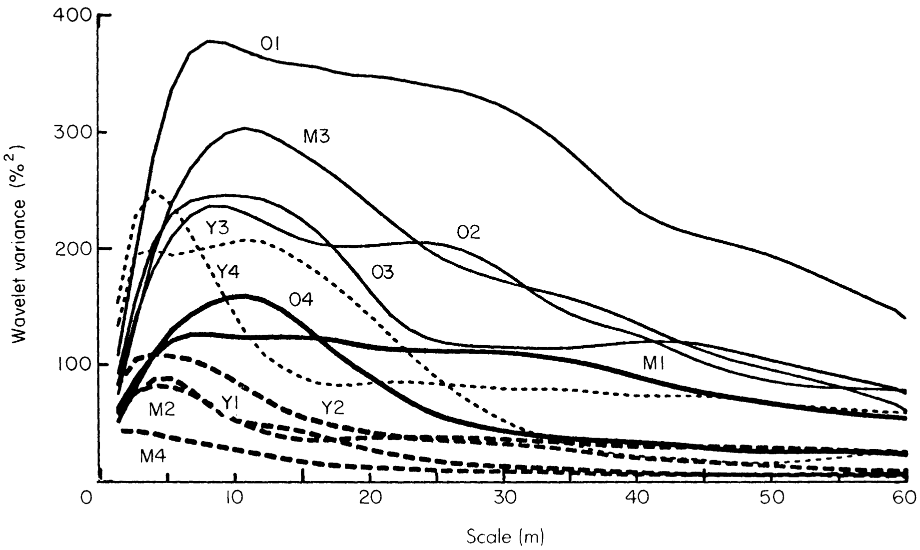

Fig. 7. Composite plot of wavelet variances calculated for canopy gap transects established in 12 *Pseudotsuga menziesii* stands representing three age classes: young, mature and old-growth. The 12 wavelet variances are grouped according to similar structure. Solid lines correspond to group I (multi-scale, open gaps (5–30 m)), heavy dashed lines to group II (small (<8 m), diffuse gaps), light dashed lines to group III (small to moderately sized (4–15 m), open gaps), and heavy solid lines to group IV (moderately sized, diffuse gaps). The vertical axis corresponds to wavelet variance (%^{2} gap opening) as a function of the scale of the pattern (m).

Group III (Y3 and Y4) exhibits the highest wavelet variance of any of the stands at the scale of 2 m. The wavelet variance of stand Y4 has a single, strong peak at 5 m. Whilst stand Y3 has a peak at 4 m, it is less dominant than the second peak at 12 m. The canopies of both these stands are characterized by numerous small, but moderately open gaps. The canopy of stand Y4 is still in the process of closing in some portions with small gaps formed by relatively open crowns and spaces between adjacent tree crowns (Table 1). Stand Y3 is a also a young with small pockets of *Phellinus weirii* that are expanding within the stand in addition to the smaller gaps.

Each of the two remaining stands, comprising Group IV (O4 and M1), has a wavelet variance distinct from any of Groups I–III. Stand O4 has a dominant peak in the range 8–12 m, similar to Group I stands, but lacks the higher-scale patterns found in their wavelet variances. This young old-growth stand retains a high density of large, canopy *Psendotsuga* and *Tsuga*. The canopy has not yet been broken up by gaps formed by the death of the larger canopy trees or groups of trees: a condition typical of many old-growth stands (Spies, Franklin & Klopsch 1990). The wavelet variance of stand M1 (a 140-year-old stand) suggests the canopy pattern is characterized by moderately intense gaps at scales >6 m. These gaps may represent areas of low-density canopy where crowns are sparse and small spaces occur between crowns.

Table 1. Stand characteristics of transect sites studied in the Western Cascade Range, Oregon and Washington. Young stands are denoted Y1–Y4, mature stands M1–M4, and old-growth stands O1–O4

Stand	Stand age (years)	Stand condition*
Y1	75	uniform *Pseudotsuga–Tsuga* canopy, no evidence of disease
Y2	70	thin *Pseudotsuga* canopy, windthrow mounds and thin soil
Y3	75	uniform *Pseudotsuga* canopy with large root-rot pockets
Y4	43	*Pseudotsuga* canopy still closing, patchy disturbance and high site variability
M1	130–140	homogeneous canopy of predominantly *Pseudotsuga* with some *Tsuga*
M2	130–140	mixed *Pseudotsuga–Tsuga* canopy, moderate levels of root rot and canopy openings
M3	145	porous *Pseudotsuga* canopy resulting from bark beetles and disease, no *Tsuga*
M4	160	closed, *Tsuga*-dominant canopy
O1	400–600	*Pseudotsuga* canopy over multi-age *Tsuga* and *Thuja*
O2	400–600	distinct, two-layer canopy of *Pseudotsuga–Tsuga*
O3	350–500	canopy composed of *Pseudotsuga* over *Tsuga*, low productivity site with many openings, no evidence of disease or recent fire
O4	250–275	intact, uniform *Pseudotsuga–Tsuga* canopy

* Species: *Tsuga heterophylla*, *Pseudotsuga menziesii*, *Thuja plicata* Donn.

The canopy wavelet variances of the 12 stands reveal that gaps occur across a wide range of intensities and scales. In many cases, the stands were characterized by very small gaps or by relatively large, low-intensity gaps. These types of gaps can be considered as the canopy background for large, more-intense gaps which are the focus of most gap studies. The relative importance of large, intense gaps to understorey dynamics may be determined in part by the context of the canopy, its characteristic scales and intensities of openings. In this sense, canopies should not be viewed as 'Swiss cheese' (Lieberman, Lieberman & Peralta 1989), but rather as complex structures of variable densities and patch sizes which are not only a function of the processes of stand development, but also disturbance history and local site conditions.

Conclusions

Changes in heterogeneity and pattern with scale are common to many ecological systems. Differences in scale–heterogeneity relationships can be used to characterize ecological systems and provide insight into processes that determine pattern at the stand and landscape scales. There are three main applications for which spatial methods may be used in such studies: (i) the description and characterization of spatial pattern; (ii) testing and confirmation of hypotheses regarding spatial pattern; and (iii) exploration and discovery of new information. The objectives of the study and the properties of the data will determine the most appropriate method of analysis. We have attempted to illustrate the utility of the wavelet transform as an additional method for the use of pattern analysis and quantification. The wavelet transform has the ability to expand transect data into constituent multi-scale components while preserving location along the transect. The graphical representation of this spatial decomposition of the data allows for the examination of hierarchical pattern and non-uniform structure.

A variant of the wavelet transform, the wavelet variance, quantifies the contribution of each signal component at a given scale to the overall pattern and facilitates comparison between multiple data sets. The wavelet variance is a useful method to compare two or more sets of data to characterize relative differences and similarities of scales of pattern. Because the wavelet variance is both proportional to the number and intensity of a feature of a given scale, a peak in the wavelet variance may indicate either a large number of low-intensity gaps and/or the presence of a number of high-intensity (very open) gaps. For this reason, it is important to examine the original data transect and wavelet transform to identify the source of the peak. The combination of the wavelet variance and transform can be used to detect non-stationarity in the data and identify domains of relative spatial homogeneity.

As with other techniques such as spectral analysis, the resolution capabilities of the wavelet transform are limited by the transect length and sampling density. Longer transects relative to resolution scale are needed for a more complete description of the hierarchical structure of the data. This restriction is important to bear in mind during the formulation of sampling designs. For longer transects at a given spacing of the data, the graphical display of the wavelet transform allows resolution of the transect into distinct sub-domains based on pattern scale and frequency.

We have illustrated the capabilities of the wavelet transform to describe forest canopy structure using gap data. The wavelet transform was able to discriminate different canopy gap structures between stands based on gap size and intensity. Whilst it is acknowledged that a one-dimensional analysis of an intrinsically complex, three-dimensional phenomenon, i.e. gap structure, may be simplistic, certain patterns and trends emerged consistent with the ecology. Using this limited set of data, canopy gap structure was inferred to be generally correlated with stand age. Deviations from the general trend can be directly linked to events in stand history and site conditions. We have found that the wavelet transform is an effective technique for the analysis of spatial phenomenon. It is a method which has numerous potential applications particularly in studies of landscape ecology where several scales of pattern may be present.

Acknowledgments

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