Chapter 2
Characterising the spatial heterogeneity of a landscape[1]

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Abstract

Success in understanding spatial heterogeneity (i.e., patchiness) in the landscape and how it relates to other ecological patterns relies on its accurate characterisation. In this study, the intensity (i.e., the maximum variance exhibited when a spatially distributed landscape property such as vegetation cover is measured with a successively increasing window size or scale) and the dominant scale (the scale at which the intensity is displayed) as descriptors of spatial heterogeneity are defined and quantified. A variogram and a wavelet transform are shown to quantify the dominant scale and intensity of spatial heterogeneity, first in one-dimensional (1D) artificial transects with known characteristics, and secondly in two-dimensional (2D) remote sensing imagery. The results demonstrated that the grain (or observation scale or scale of measurement) does not necessarily coincide with the dominant scale of spatial heterogeneity. However, the converse that grain must be less than dominant scale must be true. This implies that the dominant scale and intensity of spatial heterogeneity need to be considered when relating ecological patterns such as wildlife distribution to spatial heterogeneity.

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2.1 Introduction

Understanding spatial heterogeneity (i.e., the patchiness) in the landscape and its influence on other ecological patterns is a central problem in ecology, particularly landscape ecology (Turner 1989, Pickett and Rogers. 1997). The fundamental issue in this regard revolves around the definition and quantification of spatial heterogeneity in a way that is objective and ecologically relevant. Thus, the success in understanding how spatial heterogeneity relates to other ecological patterns relies on its accurate characterisation (McGrigal and Cushman 2002).

Traditionally, spatial heterogeneity has been quantified from remote sensing imagery by using two basic approaches: (a) the direct image approach, where straight reflectance or reflectance indices are used to quantify spatial heterogeneity, using the original pixel size of the image (Goodchild and Quattrochi. 1997), and (b) the cartographic or patch mosaic approach, where the image is subdivided into homogeneous mapping units through classification (Gustafson 1998). The first approach assumes that spatial heterogeneity is displayed at the constant pixel size of the image and, in this case, it is only the reflectance values that change in space. The limitation of this approach is that it ignores the dominant scale (see next paragraph for details on the dominant scale concept), thereby introducing subjectivity. Alternatively, using the patch mosaic approach to quantify spatial heterogeneity assumes a collection of discrete patches. Based on this approach, characterisation of spatial heterogeneity is highly dependent on the initial definition of mapping units by the researcher (Turner 1989). The limitation of this approach is that patches have abrupt boundaries and the variation within the patches is assumed to be irrelevant (McGrigal and Cushman 2002). The patch mosaic model is parsimonious and has therefore become the operating paradigm. It is particularly valid where landscape patches have crisp boundaries, as with the regular landscapes of Europe (Pearson 2002). However, the model poorly represents spatial heterogeneity in landscapes that are characterised by gradients rather than discrete patches, for instance in savanna landscapes (Pearson 2002), and this leads to both loss of information and the introduction of subjectivity. Nevertheless, alternative approaches for defining and quantifying spatial heterogeneity that are based on continuous environmental variation remain underdeveloped.

In this study, a new approach to define and quantify the spatial heterogeneity of continuously varying landscape properties such as vegetation cover, based on intensity and dominant scale, is developed. Intensity is defined as the maximum variance exhibited when a spatially distributed landscape property is measured with a successively increasing window size or scale. For example, measuring the variance in percent canopy cover along a 100 m long transect in a tree plantation with 10 m wide tree stands (with uniformly high canopy cover) that evenly interchange with 10 m wide bare ground (with zero canopy cover) at a successively increasing window size, starting from 1 m up to 100 m, would yield the maximum variance at a window size of 10 m. This maximum variance is the intensity of spatial heterogeneity. It is this scale or window size where the maximum variance in the landscape property is measured that is defined as the dominant scale of spatial heterogeneity. In other words, intensity and dominant scale of spatial heterogeneity are properties of a landscape that are inseparable and in this case, the dominant scale of spatial heterogeneity coincides with the dominant patch dimension (i.e., size of tree stands and bare ground) while intensity coincides with the maximum degree of contrast in vegetation cover between the bare ground and the tree stands. Note that our definition of scale follows that of Levin (1992) and Rietkerk*, et al.* (2002) who define scale as the window or dimension (e.g., m, km, m^2, km^2) through which the landscape may be observed either in remote sensing images or by direct measurement in the field. In this study, scale is treated as a linear dimension, e.g., m, km. We therefore propose that spatial heterogeneity must be defined and quantified using both intensity and the dominant scale. Of course, grain (i.e., the initial observation scale or window size at which the data is collected) and extent (i.e., the size of the study area) limits the range of the dominant scale that can be detected (Wiens 1989).

In this study, we propose that variograms and wavelet transforms can be used to quantify dominant scale and intensity of spatial heterogeneity. Variograms are a geostatistical measure used to determine the average decrease in similarity (also called semivariance) as the distance

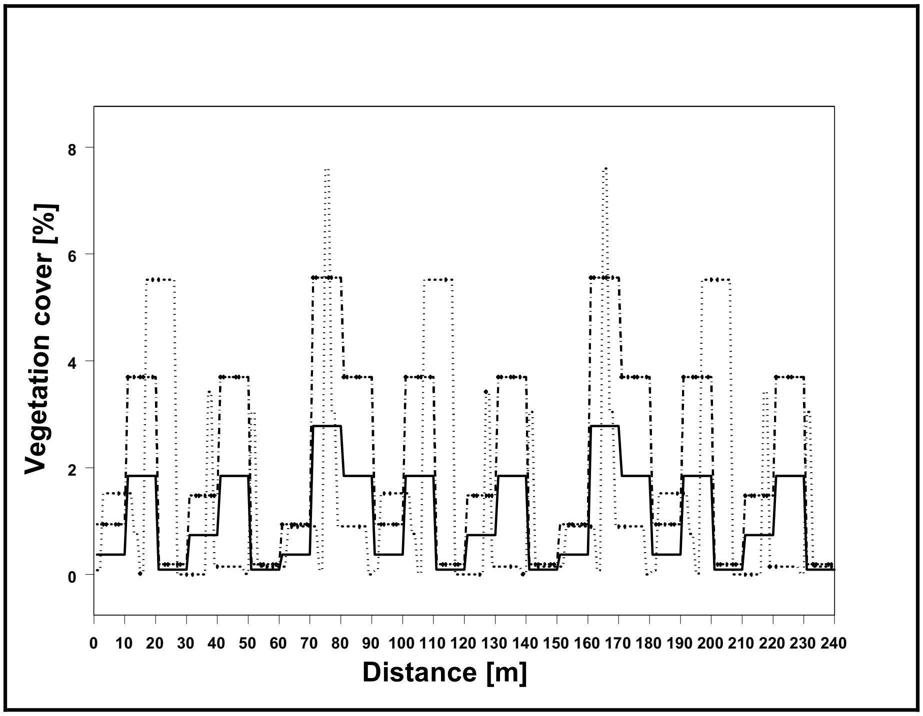

Figure 2.1: Artificial transects simulating vegetation cover with different dominant scales or intensity of spatial heterogeneity. Transects A (-) and B (-·-) have the same dominant scale of spatial heterogeneity (10 m), but transect B has a higher intensity than transect A. Transect C (······) has two dominant scales of spatial heterogeneity (2 m and 10 m).

of separation between points in space increases, and they were originally developed to measure the optimal scale of variability in the landscape (Rietkerk*, et al.* 2000). The wavelet transform is a relatively new tool, initially developed in mathematics during the 1980s for analysing the variance of a signal on a scale-by-scale basis (Graps 1995). To the best of our knowledge, virtually no work has used both variograms and wavelet transforms to quantify spatial heterogeneity from the perspective of dominant scale and intensity.

The aim of this study was to demonstrate the use of the variogram and wavelet transform in quantifying spatial heterogeneity in order to understand continuously varying landscape properties from the perspective of dominant scale and intensity. The hypothesis was that spatial heterogeneity can be quantified from the perspective of dominant scale and intensity by using variograms and wavelet transforms. First, we used the two methods (variogram and wavelet transform) to quantify the spatial heterogeneity of one-dimensional (1D) artificial transects with known characteristics. Secondly, we applied the methods to two-dimensional (2D) remote sensing images of different landscapes (i.e., a regular landscape in Europe and a savanna landscape in Africa).

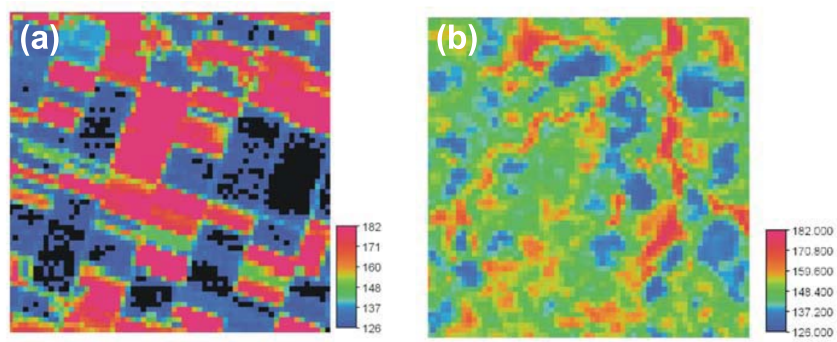

Figure 2.2: The NDVI images derived from Landsat TM imagery (same pixel size or grain of 30 m) of the northern Netherlands (a) and northwestern Zimbabwe (b) study sites. Low NDVI values indicate low vegetation cover while high NDVI values indicate high vegetation cover.

2.2 Materials and methods

Artificial transects

To evaluate the dominant scale and intensity information inherent in variograms and wavelets, spatial heterogeneity was simulated in three transects (fig. 2.1). The artificial transects were sampled at a grain (i.e., the observation scale) of 1 m and an extent (i.e., the transect length) of 240 m. In transect A and transect B, the dominant scale of spatial heterogeneity is 10 m, i.e., maximum variance occurs at a window size or scale of 10 m. However, transect B has higher intensity than transect A, i.e., there is a higher variance in transect B than transect A at the dominant scale (i.e., 10 m). Transect C shows two dominant scales of spatial heterogeneity, namely 2 m and 10 m.

Remote sensing imagery

Two 1.92 km by 1.92 km test sites representing contrasting landscapes were selected in the north of the Netherlands and in the northwest of Zimbabwe. The Netherlands was selected because it has landscapes that are dominated by near regular agricultural fields, comparable with the artificial transects. In contrast, the Zimbabwe study site is in a savanna landscape characterized by a heterogeneous mixture of agricultural fields and natural vegetation. Savanna is defined as a heterogeneous sub-tropical vegetation type co-dominated by woody plants and grasses (i.e., in some places trees are arranged in scattered patches that are dominated by grasslands, or vice versa (Scholes 1997)). The centres of the study sites are defined by the geographical coordinates 53° 05’ 24”N, 5° 38’ 24”E, and 17° 18’ 35”S, 28° 38’ 59”E respectively.

The normalised difference vegetation index (NDVI) images were derived from Landsat TM images acquired on 5 May 1992 for the northern site and 6th of November 1999 for the Zimbabwe site. NDVI is defined as:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{2.1}$$

where *NIR* and *R* are the spectral reflectance values in the near infrared and the red. Data were normalised to the range of 0 to 255 in order to facilitate data handing in image processing software. NDVI was used because it is an established index for estimating vegetation quantity (Walsh*, et al.* 1997, Walsh*, et al.* 2001) and it is a continuous representation that can be analysed for the dominant scale and intensity of spatial heterogeneity using variograms and wavelets. The Landsat TM images have a spatial resolution of 30 m, which means the grain is 30 m. Fig. 2.2 shows the NDVI images of the two study sites.

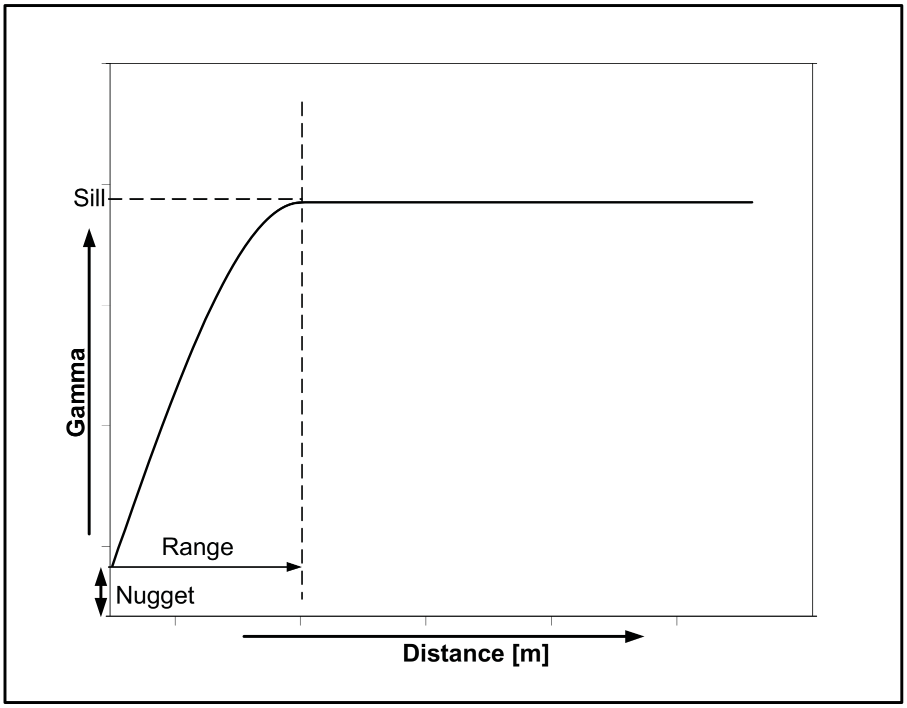

Figure 2.3: The three parameters (i.e., nugget, the range and sill) of the variogram used to measure dominant scale and intensity.

Characterising spatial heterogeneity using a variogram

In this study, the intensity and dominant scale of spatial heterogeneity were quantified for z(x) (i.e., the transects (fig. 2.1) and the NDVI images (fig. 2.2)), using the variogram (fig. 2.3) and its main structural parameters, the sill and the range (Curran 1988) respectively. The error or the non-spatial variance is characterised by the nugget (fig.2.3). The sill is the level at which the variogram becomes flat, and it exists if the process being analysed is stationary. A spatial process is stationary when only the distance that separates points in space explains the difference in value between them. The range is used to measure the scale of spatial correlation, which is the maximum distance at which spatial correlation is

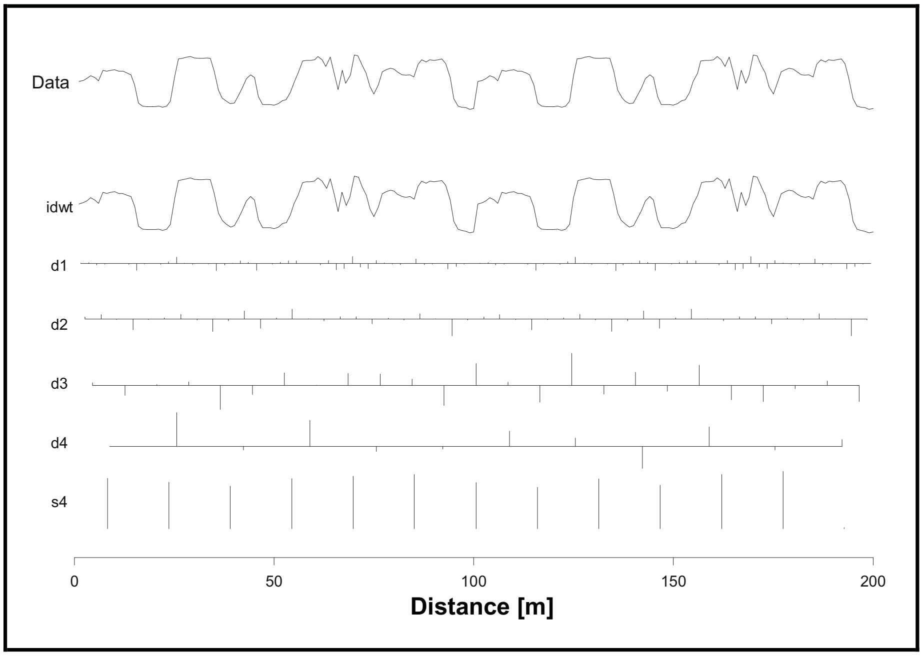

Figure 2.4: The Haar wavelet transform showing wavelet coefficients of four scale levels. Idwt is the data function reconstructed using inverse discrete wavelet transform. The d1…d4 are detail wavelet coefficients at levels $j = 1 \ldots j = 4$, and S4 are the smooth wavelet coefficients at level $j = 4$. The absolute value of a coefficient is a measure of the magnitude of contrast in the function.

present and beyond which spatial correlation is absent. The sill can measure intensity because it quantifies the maximum degree of contrast between points that are the distance of the range apart. The following formula was used to calculate the variogram $\gamma(h)$:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x_i) - z(x_i) + h \right]^2 \qquad (2.2)$$

where $N(h)$ is the number of observation pairs separated by the distance h, z is the value of the regionalised variable at spatial position x_i, and $z(x_i + h)$ is the value of the regionalised variable at distance h from x_i (Treitz and Howarth 2000). The variograms were calculated using a maximum lag of one-third of the total distance covered by a data function (Cohen, *et al.*

1990) and the theoretical variogram models were fitted using a non-linear least squares method. Variograms for the NDVI images were calculated in the vertical (north-south), horizontal (east-west) and diagonal (northeast-southwest and northwest-southeast) directions in order to account for anisotropy, which is the tendency for variogram parameters to change with direction.

Characterising spatial heterogeneity wavelets

Wavelet energy (Bruce and Hong-Ye. 1996) was used to quantify the dominant scale and intensity of spatial heterogeneity in transects and NDVI images. The analysis of wavelet energy begins with a wavelet transform (in this study a Haar wavelet was used), which is defined as the convolution of two wavelet functions (i.e., the *smooth* $\phi(x,y)$ and *detail* $\varphi(x,y)$ functions) and a data series $f(x,y)$ (i.e., $\langle f(x,y)\phi_J(\mathrm{x,y})$, and$\langle f(x,y)\varphi_j(\mathrm{x,y})$ respectively) at successive scales, each being (2^j) (i.e., j = 0,1,2…J). A wavelet transform result in a set of coefficients where each coefficient is associated with a scale level, j = 0,1,2…J and a particular location. Note that formal treatment of wavelets has been handled exhaustively elsewhere (Mallat 1989, Ogden 1997). Wavelet energy is, however, explained below.

Fig. 2.4 illustrates the results of a wavelet transform where wavelet coefficients can be positive or negative but the absolute coefficient value measures the magnitude or degree of contrast in $f(x,y)$ at a specific location at 2^j .

In this regard, wavelet energy was calculated as a second moment of the wavelet transform, defined as the sum of the squared individual coefficients of a band at 2^j, divided by the sum of the squares of all the coefficients in $\hat{f}(x,y)$:

$$E_j^d = \frac{1}{E}\sum_{k=1}^{n/2^j} d^2 j(x,y),\, j = 1,2,3...J \tag{2.3}$$

where $d_j(x,y)$ are wavelet coefficients at j and position (x,y), E is the total wavelet energy of $\hat{f}(x,y)$, and $n/2^j$ is the number of data points at j. Then, wavelet energy values were plotted against scale, and the local maxima in the wavelet energy represented the intensity of spatial heterogeneity, while the corresponding scale values represented the dominant scale(s) of spatial heterogeneity. Details were used in the analysis because they are more scale-specific. For example, details in the NDVI image at j = 1 capture vegetation patches of between 30 m and 60 m in dimension. In contrast, smooths can capture only scales that are equal to or greater than 2^j.

2.3 Results

Table 2.1 summarises the variogram and wavelet parameters illustrating the intensity and dominant scale of spatial heterogeneity for both the artificial transects and NDVI images of The Netherlands and Zimbabwe sites. The results in table 1 are described together with fig. 2.5 to fig. 2.9 in the paragraphs below.

Table 2.1: The variogram and wavelet energy parameters of the artificial transects and The Netherlands and Zimbabwe sites

Data	Orientation	Variogram Nugget	Variogram Nugget 95 % CL	Variogram Sill	Variogram Sill 95%CL	Variogram Range (m)	Variogram Range 95 % CL	Wavelet energy maxima	Wavelet dominant Scale(s) (m)
Transect A		0.11	0.01	0.99	0.01	9.73	0.09	0.11600	16
Transect B		0.41	0.03	3.80	0.03	9.81	0.08	0.12300	16
Transect C		0.44	0.09	3.86	0.09	12.24	0.40	0.18; 0.15	4; 16
Netherlands	Horizontal	-32.12	6.90	602.56	6.96	302.48	3.83	0.00230	480
Netherlands	Diagonal	-0.56	0.10	6.53	0.10	263.266	3.22	0.001100	480
Netherlands	Vertical	-27.81	11.12	594.25	11.14	199.42	3.79	0.004700	240
Zimbabwe	Horizontal	6.75	0.95	50.77	0.95	90.78	1.74	0.000386	120
Zimbabwe	Diagonal	4.87	0.82	54.18	0.82	259.10	4.25	0.0001; 0. 0017	120; 480
Zimbabwe	Vertical	45.18	3.73	45.18	0.80	120.02	2.30	0. 000260	120

Fig. 2.5 and table 2.1 describe the results of the variogram and wavelet analysis of spatial heterogeneity of the artificial transects. As noted earlier, it is important to note that since wavelets jump scales by 2^j, the wavelet energy maxima at j represents the intensity that corresponds to the dominant scales between j and j-1. With this in mind, we can proceed to observe that the wavelet-derived dominant scale (i.e., the scale margin at which the wavelet energy showed the highest maxima) coincided with the dominant scale depicted by the variogram (variogram range) for transect A and transect B. Particularly, we can observe that the wavelet energy local

maxima coincides with a dominant scale of 16 m, meaning that the dominant scales between 8 m and 16 m are represented, which coincides with the estimated variogram range of 9.82 m. Therefore, it is observed overall that both methods depict the dominant scale of spatial heterogeneity, namely 10 m, and the intensity that resembles the spatial heterogeneity present in both transects. However, the variogram range for transect C coincides only with the wavelet energy maxima describing the larger dominant scale, namely 10 m. Furthermore, a look at the two local wavelet energy maxima that represent the two dominant scales of spatial heterogeneity in transect C, shows that the 2 m dominant scale of spatial heterogeneity coincides with the highest intensity compared with the 10 m dominant scale of spatial heterogeneity. Moreover, the differences in intensity are reflected consistently by the variogram sill and peak wavelet energy. It can also be observed that the dominant scale is greater than the grain, namely 1 m.

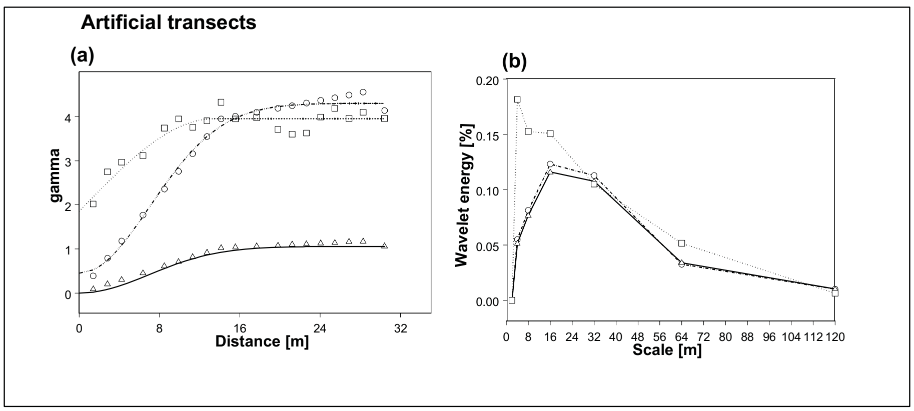

Figure 2.5: The variogram (a) and wavelet energy (b) functions describing spatial heterogeneity in artificial transects A (△), B (❍) and C (☐).

In addition, fig. 2.6 and table 2.1 show the results of the variogram and wavelet analysis of spatial heterogeneity of the north Netherlands image. It can be observed that in the horizontal (east-west) orientation, the dominant scale of spatial heterogeneity quantified using a variogram range (i.e., 302 m) coincides with the wavelet-based dominant scale of spatial heterogeneity that peaks at 480 m (i.e., representing dominant scales of 240 m – 480 m). Also, in the diagonal (northeast-southwest and northwest-southeast) orientation, the dominant scale of spatial heterogeneity quantified using a variogram range (i.e., 263 m) coincides with the wavelet-based dominant scale that peaks at 480 m (i.e., also representing dominant scales of 240 m – 480 m). Finally, in the vertical (north-south) orientation, the dominant scale of spatial heterogeneity quantified using a variogram range (i.e., 199 m) also coincides with the wavelet-based dominant scale that peaks at 240 m (i.e., representing dominant scales of 120 m – 240 m). Moreover, there is relative consistency between the intensity of spatial heterogeneity, i.e., the variogram sill and peak wavelet energy values. Both the variogram sill and maximum wavelet energy values consistently characterise intensity of spatial heterogeneity because both are highest in the vertical (north-south) orientation, medium in the horizontal (east-west) orientation and lowest in the diagonal (northeast-southwest and northwest-southeast) orientation. Furthermore, the dominant scale of spatial heterogeneity measured using both variograms and wavelets is greater than the grain of Landsat TM, namely 30 m.

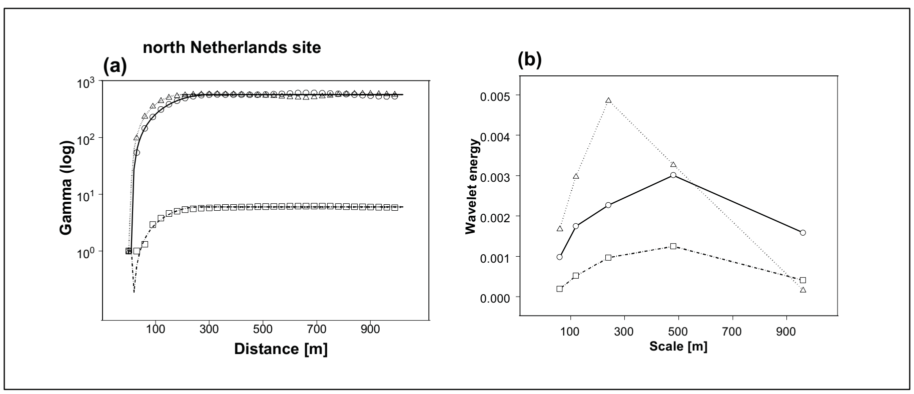

Figure 2.6: The variogram (a) and wavelet (b) functions describing the spatial heterogeneity of the north Netherlands NDVI image in the horizontal (east-west) (○), and diagonal (northeast-southwest and northwest-southeast) (□) and vertical (north-south) (△) orientations.

The spatial distribution of wavelet energy of the north Netherlands image, whose sum constitutes the intensity of spatial heterogeneity and the dominant scales of spatial heterogeneity illustrated in fig. 2.6 and table 2.1 is described in fig. 2.7. Based on fig. 2.7, it can be observed that the highest wavelet energy values in the images coincide with two dominant agricultural field sizes in different orientations, i.e., between 240 m and 480 m in the horizontal (east-west) and diagonal (northeast-southwest and northwest-southeast) orientations, and between 120 m and 240 m in the vertical (north-south) orientation.

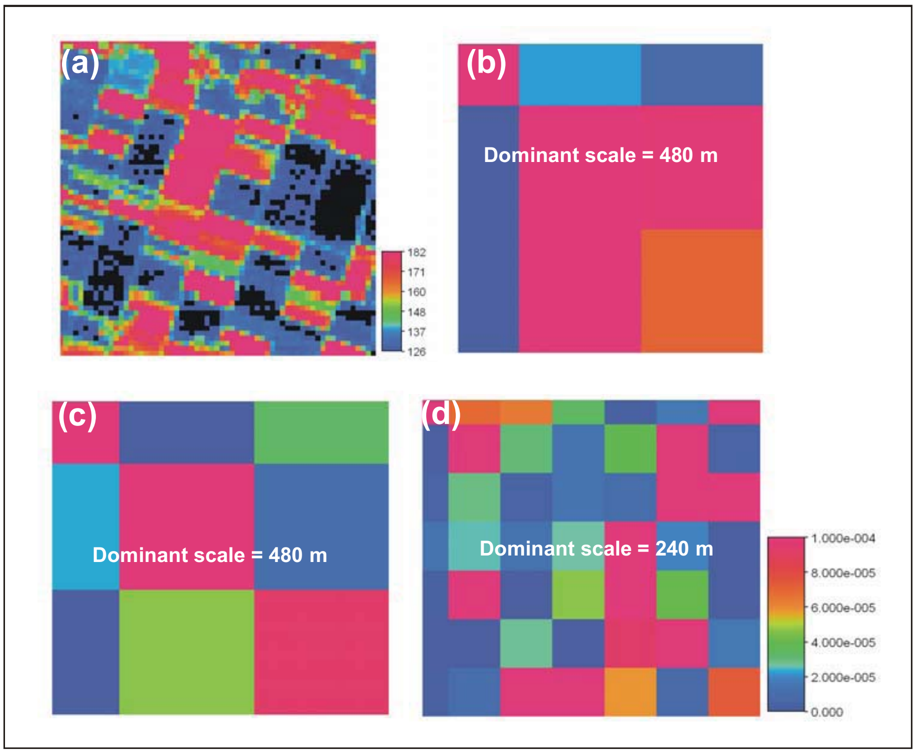

Figure 2.7: The north Netherlands site showing the (a) original NDVI image and the wavelet energy images that make up the most dominant scales of spatial heterogeneity in the (b) horizontal (east-west), (c) diagonal (northeast-southwest and northwest-southeast) and (d) vertical (north-south) orientations.

Moreover, fig. 2.8 and table 2.1 show the results of the Zimbabwe site. The vertical (north-south) and horizontal (east-west) orientations depict a single dominant scale of spatial heterogeneity, shown by the single peak (or maximum) in the wavelet energy. The variogram range coincides with the wavelet-derived dominant scale of spatial heterogeneity, namely 60 m to 120 m. The diagonal (northeast-southwest and northwest-southeast) orientation shows the presence of two dominant scales of spatial heterogeneity, depicted by two wavelet energy maxima. However, in the diagonal (northeast-southwest and northwest-southeast) orientation, the highest wavelet energy maximum is at 480 m. It can be further observed that, in the diagonal (northeast-southwest and northwest-southeast) case, the variogram range coincides with the wavelet energy peak depicting the larger dominant scale of spatial heterogeneity, namely 240 m to 480 m. In addition, there is a similarity in the relative order of variogram sill and peak wavelet energy values (i.e., in intensity for the three different orientations). The variogram sill and the local maxima in wavelet energy are highest in the horizontal (east-west) orientation, medium in the vertical (north-south) orientation and lowest in the diagonal (northeast-southwest and northwest-southeast) orientation. The dominant scale of spatial heterogeneity measured using both variograms and wavelets is also greater than the grain of Landsat TM, namely 30 m.

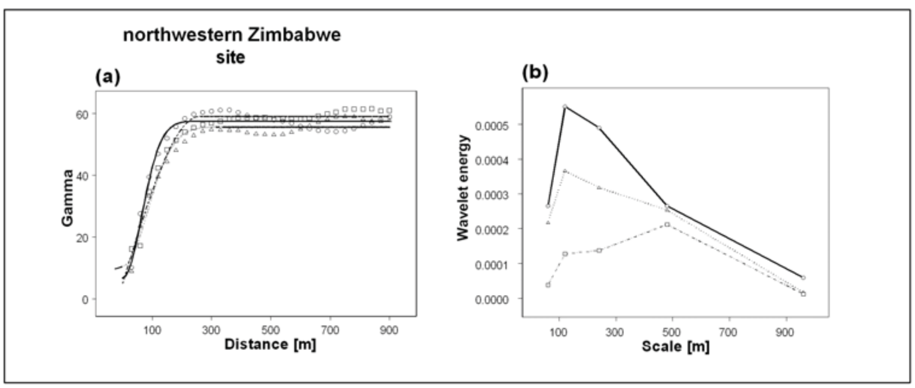

Figure 2.8: The variogram (a) and wavelet (b) functions describing the spatial heterogeneity of the northwestern Zimbabwe NDVI image in the horizontal (east-west) (○), and diagonal (northeast-southwest and northwest-southeast) (□) and vertical (north-south) (△) orientations.

Fig. 2.9 shows the spatial distribution of wavelet energy of the Zimbabwe image, whose sum constitutes the intensity of spatial heterogeneity and the dominant scales of spatial heterogeneity illustrated in fig. 2.8 and table 2.1. For the diagonal (northeast-southwest and northwest-southeast) orientation, only the highest intensity that coincides with the largest dominant scale of spatial heterogeneity is shown. It can be observed that the highest wavelet energy values in the images coincide with different patch dimensions from different orientation.

2.4 Discussion

The results presented in this paper indicated that variograms and wavelet transforms could both quantify spatial heterogeneity from the perspective of dominant scale and intensity. Variograms and wavelets yielded similar outcomes when a single dominant scale of spatial heterogeneity was present (i.e., the distance at which the sill and peak wavelet energy are observed). However, in the presence of more than one dominant scale of spatial heterogeneity, the variogram range coincided with the largest wavelet-derived dominant scale (i.e., the largest scale at which a peak in the wavelet energy is observed). In addition, the relative values of intensity were similar between variograms and wavelets in instances where the variogram range and the wavelet dominant scale coincided. The results were consistent with the fact that wavelets are localised (i.e., wavelet transform can characterise localised dominant scales of spatial heterogeneity) whereas variograms are global in nature (i.e., variograms characterise only the largest dominant scale of spatial heterogeneity) (Dale and Mah. 1998). Furthermore, given a situation when the researcher desires to test the presence of more than one dominant scale and intensity of spatial heterogeneity, our results imply that wavelets are more suited for that purpose compared with variograms.

Moreover, it is important to note that the interpretation of the dominant scale and intensity of spatial heterogeneity based on variograms and wavelet transforms is different. The intrinsic assumption upon which the variogram was calculated (i.e., that differences in the values of a landscape property between two points in space is a function of the distance separating them) enables us to conclude that the dominant scale measured by the variogram range represents both the predominant patch dimension in the landscape and the distance between different patches. On the other hand, using a wavelet transform to estimate the first-order properties of spatial data enables us to deduce the dominant scale of spatial heterogeneity only in relation to the patch dimension at which the wavelet energy is recorded. It is important to consider these issues when these methods are used to characterise spatial heterogeneity as a prelude to analysing other ecological patterns.

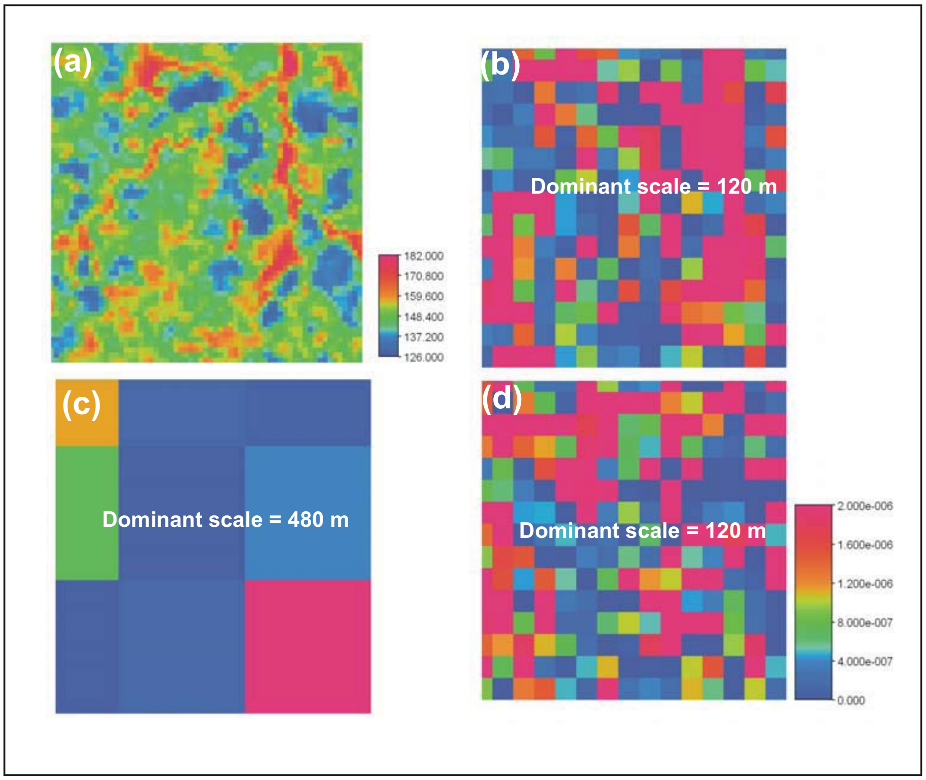

Figure 2.9: The Zimbabwe site showing the (a) original NDVI image and the wavelet energy images that make up the most dominant scale of spatial heterogeneity in the (b) horizontal (east-west), (c) diagonal (northeast-southwest and northwest-southeast) and (d) vertical (north-south) orientations.

In addition, the results in this study indicated that with the wavelet transform the patches that contribute to the measured intensity of spatial heterogeneity and the corresponding dominant scale of spatial heterogeneity could be extracted and visualised (figs. 2.7 and 2.9). In contrast, the intensity and the dominant scale of spatial heterogeneity quantified from the variogram sill and variogram range respectively, constitute the overall statistic that describe the average landscape conditions but cannot be extracted and visualised (Ettema and Wardle 2002). Therefore, we can deduce that wavelets not only provide a global summary of the intensity and dominant scale of spatial heterogeneity, but also provide an explicit spatial distribution of the spatial features that constitute both the intensity and the dominant scale of spatial heterogeneity.

Furthermore, the results indicated that both the variogram and the wavelet transform could be useful in characterising the dynamics of spatial heterogeneity. The three transects in fig. 2.1 (transects A, B and C) could be conceptualised as two possible ways in which spatial heterogeneity in a landscape vary: transect A and transect B show differences (only) in intensity of spatial heterogeneity, whereas transect A or transect B and transect C show differences in both dominant scale and intensity of spatial heterogeneity (fig. 2.1). Pickett and Rogers (1997) point out that one of the most important insights into patchiness or spatial heterogeneity in the landscape is that it is changeable, owing either to natural disturbance such as droughts and floods or to human management factors such as land use management regimes, and that this may occur at various dominant scales. Consequently, the results in this study indicate that variograms and wavelets can also be applied in characterising differences in the intensity and dominant scale of spatial heterogeneity either in a single landscape over time or between different landscapes, in space.

The results indicated that the grain does not coincide with the dominant scale of spatial heterogeneity. For example, the grain of the artificial transects (fig. 2.1) was 1 m, yet they had different dominant scales of spatial heterogeneity. Similar observations applied to the NDVI images (fig. 2.2). Both images had a grain or spatial resolution of 30 m, yet the dominant scales of spatial heterogeneity are more than 30 m (figs. 2.6 and 2.8). However, the converse that grain must be less than dominant scale must be true. Therefore, we deduce that it is important that either a variogram or a wavelet transform should be used to quantify spatial heterogeneity before any further ecological analysis is conducted with the data. This could improve the study of ecological patterns in relation to spatial heterogeneity. For example, it could improve the explanation of ecological patterns such as wildlife distribution. This has traditionally been explained by relating it to spatial heterogeneity, which reflects the grain, rather than to the dominant scale and intensity of spatial heterogeneity (Legendre 1998), that reflect meaningful ecological entities that may influence the response of specific organisms in the landscape.

The results have demonstrated that variograms and wavelets can be used to characterise the dominant scale, as well as the intensity of spatial heterogeneity in "cultural" landscapes and in "natural" landscapes. In this regard, the Netherlands site typically represents a cultural landscape where landscape patches can be clearly identified and the Zimbabwe site largely represents a natural landscape where the boundaries between landscape patches are subtle (fig. 2.1). The ability to characterise spatial heterogeneity, particularly in natural landscapes, is critical, because this is where issues such as the conservation of diversity in wildlife species are of crucial importance. In other words, the ability to characterise spatial heterogeneity in natural landscapes enables the determination of patch gradients that are more difficult to identify using conventional methods such as the patch mosaic model (Pearson 2002). Therefore, we can deduce that variograms and wavelet transforms are invaluable for characterising the dominant scale, as well as the intensity of spatial heterogeneity in different landscapes, including landscapes that are characterised by subtle patch boundaries, i.e., where gradients are prevalent. Future research will focus on empirically determining the relationships between the dominant scale and intensity of spatial heterogeneity and other ecological patterns such as wildlife distribution.

2.5 Conclusions

Landscape properties often vary continuously, being characterised by gradients (e.g., the Zimbabwe site), rather than being a collection of discrete patches (e.g., the Netherlands site). In this regard, the direct image and the patch mosaic approaches to the analysis of spatial heterogeneity, although essential, may limit advances in ecology, the former by ignoring the dominant scale property in spatial heterogeneity and the latter by ignoring both the dominant scale and intensity properties of spatial heterogeneity. Based on the results, a number of conclusions recommendations were made. Firstly, we concluded that a variogram and a wavelet transform could quantify the dominant scale and intensity of spatial heterogeneity, as well as changes in the dominant scale and the intensity of spatial heterogeneity. Secondly, we concluded that the dominant scale of spatial heterogeneity measured using a variogram range represents both the predominant patch dimension in the landscape and the distance between different patches. Alternatively, using a wavelet transform to estimate the first-order properties of spatial data enables us to deduce the dominant scale of spatial heterogeneity only in relation to the patch dimension at which the wavelet energy is recorded. Thirdly, we concluded that the grain or observation scale does not coincide with the dominant scale of spatial heterogeneity, implying that the dominant scale and intensity of spatial heterogeneity may need to be considered when relating ecological patterns such as wildlife distribution to spatial heterogeneity. However, the converse that grain must be less than dominant scale must be true. Fourthly, we observed that both variograms and wavelet transforms are invaluable for characterising the dominant scale, as well as the intensity of spatial heterogeneity in different landscapes, even those with subtle patch boundaries. However, with wavelets, patches that constitute the dominant scale and intensity of spatial heterogeneity can be extracted and visualised. Finally, we observed that the results of this study provide a necessary preamble to the determination of empirical relationships between the dominant scale and intensity of spatial heterogeneity and other ecological patterns such as wildlife species distribution and redistribution.