

Chapter 5

Evaluating a new approach to predict the spatial distribution of elephants from NDVI⁴

Amon Murwira, Andrew K. Skidmore and Jan De Leeuw

Abstract

Spatial heterogeneity (i.e., the patchiness in the landscape) is important for understanding the degree of wildlife species presence in a landscape. Remote sensing provides an invaluable source of data from which spatial heterogeneity can be quantified for the purpose of predicting ecological patterns like wildlife distribution. However, approaches to quantify spatial heterogeneity remain rudimentary. In this study we developed a new approach based on the concepts of 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 dominant scale (i.e., the scale or window size at which the intensity is displayed) to quantify spatial heterogeneity of a normalised difference vegetation index (NDVI) for use in predicting the probability of elephant (*Loxodonta africana*) presence in different sampling units in an agricultural landscape in Zimbabwe. NDVI was estimated from Landsat TM imagery. A novel wavelet transform and a variogram were used to quantify spatial heterogeneity using the new approach. The specific objective was to evaluate whether the new approach can predict elephant distribution better than the usual NDVI average and the NDVI coefficient of variation that assume a constant pixel size or uniform scale. Results showed that the new approach predicted the probability of elephant presence better than the usual NDVI average and the NDVI coefficient of variation that assume a constant pixel size or uniform scale. In fact, wavelet and variogram-derived spatial heterogeneity explained 80 % and 65 % of the variance in the probability of elephant presence respectively, compared with 60 % and 48 % explained by the NDVI average and the NDVI coefficient of variation. Therefore, in this study, we found the intensity and dominant scale of spatial heterogeneity improves upon the usual NDVI average and NDVI coefficient of variation in predicting ecological patterns.

⁴ In review: Remote sensing of Environment

5.1 Introduction

Spatial heterogeneity (i.e., the patchiness in the landscape) has important implications for understanding the spatial distribution of wildlife species that inhabit landscapes (Turner, *et al.* 1997). The spatial distribution of organisms is hypothesised to respond to the patchiness in landscape suitability that reflect, for instance, varying levels of resource availability or varying levels of human disturbance (Johnson, *et al.* 1992). Consequently, spatial heterogeneity is considered a critical determinant of the spatial distribution of wildlife species in the landscape (Ritchie 1997). However, ambiguity still surrounds the approaches to characterise spatial heterogeneity (Sparrow 1999), thereby making the objective characterisation of spatial heterogeneity a critical preamble to understanding spatial distribution patterns of wildlife species.

The quantification of spatial heterogeneity is an empirical approach based on observed data. Therefore, it is a forerunner to the testing of specific hypotheses about ecological patterns (Perry, *et al.* 2002). In this regard, remote sensing provides an invaluable source of spatial data that is useful for the quantification of spatial heterogeneity in the landscape from a continuous landscape property perspective (Kerr and Ostrovsky 2003). Traditionally, ecologists have related the distribution of wildlife species to spatial heterogeneity measured from remote sensing images using the variance measure such as the coefficient of variation calculated from straight reflectance or reflectance indices such as the normalised difference vegetation index (NDVI) at the original pixel size of the image (Tanser and Palmer 1999, Oindo 2001). This approach is herein defined as the direct image approach. However, by assuming only a change in reflectance at constant and arbitrary pixel size across the image, the direct image approach ignores the spatial structure component of spatial heterogeneity (Legendre and Fortin 1989, Legendre 1998, Ettema and Wardle 2002). Consequently, we feel that by ignoring the scale factor, the direct image approach may lack repeatability. This is because landscapes are naturally patchy, and patch dimension is important, as well as the fact that different remote sensing imagery come with different pixel sizes.

In view of the limitations of the direct image approach, in this

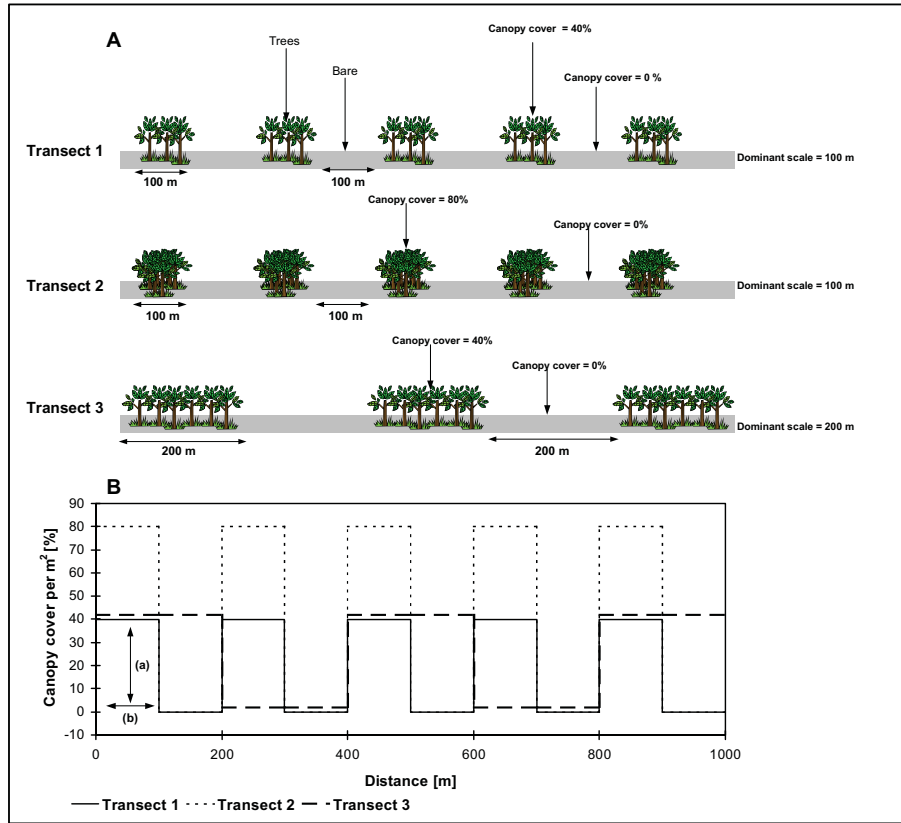


Figure 5.1: Part (A) are transects with alternating spaces of trees and bare ground and part (B) shows the simulation tree canopy cover along each transect assuming that the cover measurements are made after every 1 m (i.e., grain = 1 m) and an extent of 1000 m. For example, the (a) intensity (maximum variance) of transect 1 occurs at (b) a dominant scale of 100 m.

study we propose a new approach to characterising spatial heterogeneity from remote sensing imagery, based on intensity and dominant scale, as a forerunner to predicting the spatial distribution of a wildlife species in a landscape. 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 the 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. 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 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, m², km²) through which the landscape may be observed either in remote sensing images or by direct measurement. In this study, scale is treated as a linear dimension, e.g., m, km. We therefore propose that spatial heterogeneity be defined and quantified using both the 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 (overall size of the study area) limits the range of the dominant scale that can be detected (Wiens 1989).

In order to further clarify the centrality of intensity and dominant scale in the definition of spatial heterogeneity, we present a simulated example of tree canopy cover that is measured along three artificial transects (fig. 5.1). The three artificial transects stretch over 1000 m and the tree canopy cover was measured at an interval of 1 m. The sampling interval of 1 m defines the grain (i.e., the initial observation scale) while 1000 m defines the extent (i.e., the transect length). In this example, the transects 1 and 2 have a dominant scale of spatial heterogeneity of 100 m, i.e., a maximum discontinuity between high canopy cover and low canopy cover occurs after every 100 m whereas transect 3 has a dominant scale of 200 m. If we consider, transects 1 and 2, the dominant scale of spatial heterogeneity is equal, but the intensity of spatial heterogeneity is different and transect 1 and transect 3 have equal intensity of spatial heterogeneity but have different dominant scales of spatial heterogeneity. We see that characterizing spatial heterogeneity in this example is not complete if only

either intensity or dominant scale of spatial heterogeneity is considered. Thus, we propose that both the intensity and dominant scale be used to describe spatial heterogeneity as a forerunner to analysing ecological patterns such as the spatial distribution of elephants.

In this study we investigated whether the spatial heterogeneity of NDVI analysed from the intensity and the dominant scale perspective can predict the probability of elephant (*Loxodonta africana*) presence in the landscape better than the usual direct image approach based on NDVI average or the NDVI coefficient of variation that both assume a uniform scale in the landscape. A windowed variogram and a wavelet transform were used to characterise the intensity and dominant scale of spatial heterogeneity (Murwira and Skidmore, 2003). Thus, we also tested whether spatial heterogeneity estimated from variograms can predict the probability of elephant presence in the landscape better than spatial heterogeneity estimated from a wavelet transform or vice versa. We based our analysis on different land units (sampling units) defined by intersections of ward (administrative unit) and vegetation class boundaries in the agricultural landscape of the Sebungwe in Zimbabwe. The Landsat TM imagery of 19 October 1984 was used to estimate NDVI. The elephant data were obtained from point location data from the analyses of Sebungwe aerial surveys by Cumming and Lynam (1997) and made available by WWF in Harare. The African elephant was selected in this study because it is a keystone species that is threatened by the expansion of human activities, thereby constituting a serious conservation problem in Africa (Hoare and Du Toit 1999).

5.2 Materials and methods

Study area

The study was based on the Sebungwe region in Zimbabwe (fig. 5.2). The Sebungwe has undulating topography with the average elevation of between 700 – 800 m above sea level. The region is characterised by a single wet season (November to March) with a mean annual rainfall of 680 – 700 mm, as well as a long dry season (April to October). Savanna woodlands and grasslands characterise the main natural land cover. The

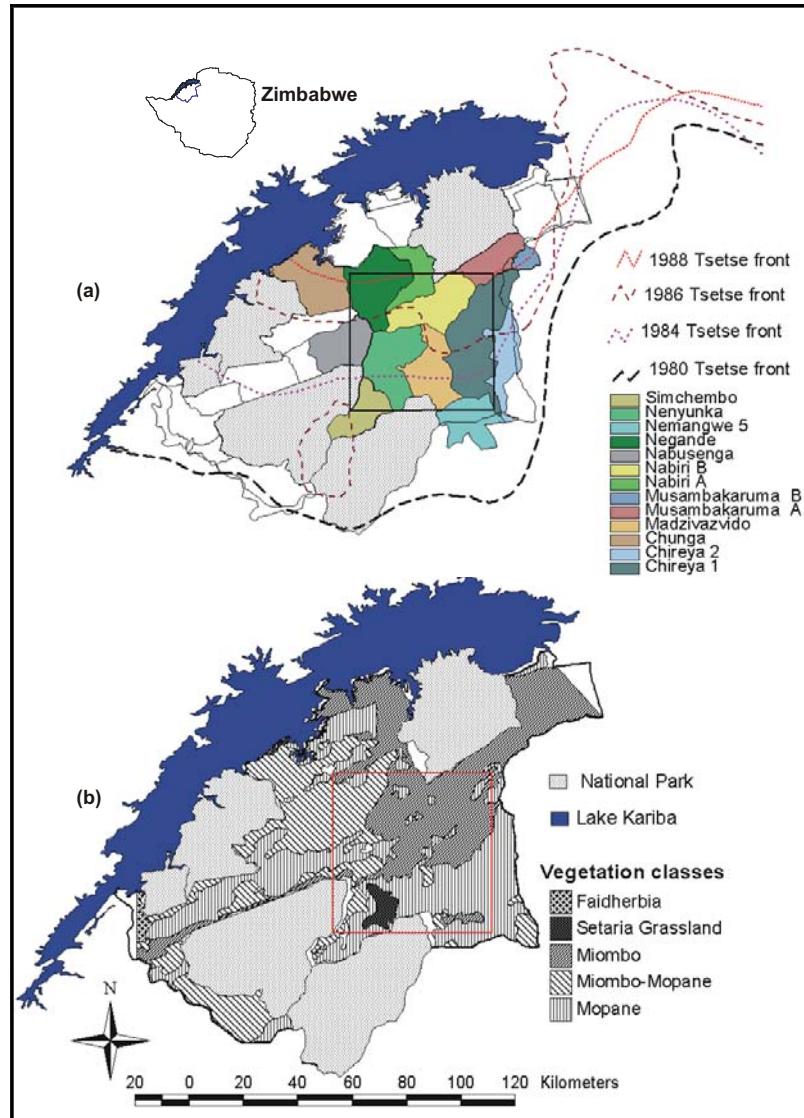


Figure 5.2: The location of the Sebungwe region in Zimbabwe and (a) the wards, national parks and the history of the progression of tsetse eradication (source: Tsetse and Trypanosomiasis control branch, Harare) and (b) the physiognomic-floristic vegetation classes in the communal lands based on (Timberlake and Nobanda 1993). The square box is a 61 km x 61 km area selected for this study.

natural cover types include, Miombo woodland dominated by *Brachystegia spp.* and *Julbernardia globiflora*, Mopane dominated by *Colophospermum mopane*, *Faidherbia* woodland dominated by *Faidherbia albida*, Miombo-Mopane with co-dominance of *Brachystegia spp.* and *Julbernardia globiflora* and *Colophospermum mopane*, as well as *Setaria* grasslands dominated by *Setaria incrassata*, *Ischaemum afrum* and *Dicathium papillosum* (Timberlake, *et al.* 1993) (fig. 5.2b). The floristic-physiognomic vegetation units do not change over time, representing the vegetation classes that would be there in an undisturbed environment (Timberlake, *et al.* 1993). Therefore, the boundaries do not change within a matter of decades.

The Sebungwe consists of five wildlife reserves, interspersed with communal lands (fig. 5.2a). The communal lands have varying degrees of agriculture within the natural vegetation units and varying degrees of elephant presence. Communal lands are a land category that are characterised by collective or community land ownership and they are subdivided into administrative or management units called wards (fig. 5.2a). In the communal lands elephant presence is affected by ecological conditions, and also poaching and human disturbance rather than by conservation measures or laws like those enforced in wildlife reserves. In other words, in communal lands elephants are present provided there are necessities such as enough cover and water available. Elephants have to cross the communal lands when moving between the wildlife reserves.

In the Sebungwe landscape evolved from a complex of different historical forces linked to the eradication of tsetse fly (*Glossina* sp.) and the related changes in land use (fig. 5.2a). Historically, the Sebungwe region was home to both tsetse fly and a wide range of wildlife species until the 1960s when the tsetse belt began to continually dwindle as a consequence of the tsetse eradication programme that was meant to enable livestock ranging and arable agriculture, thereby relieving population pressure from elsewhere in the country. As tsetse fly was progressively destroyed since the 1960s, the valley began to be increasingly occupied by farmers (Cumming and Lynam 1997). By the mid-1980s immigration had accelerated and the threat of arable agriculture on the persistence of

wildlife began to increase in parts of the Sebungwe (Cumming and Lynam 1997).

This study is based on a 61 km x 61 km landscape mainly covering the communal lands (fig. 5.2). This study area was considered large enough for studying the spatial distribution of elephants in the Sebungwe. Specifically, elephants in the Sebungwe region have an estimated range of between 83 km² to 263 km², approximating a horizontal length scale (horizontal dimension) of 9.1 km and 16.2 km, respectively (Guy 1976a, Dunham 1986). This makes the extent of the study area, i.e., 3721 km², which is at least 14 times the estimated range of the elephant in the Sebungwe large enough to study elephant distribution.

Determining individual sampling units

The individual sampling units for analysing elephant-spatial heterogeneity relationships in this study were defined by an intersection of ward boundaries and floristic-physiognomic vegetation class boundaries (Timberlake, *et al.* 1993) (fig. 5.2b). The floristic-physiognomic vegetation class map (fig. 5.2b) describes the potential vegetation classes, and is therefore constituted by floristic units that are considered constant over time (Timberlake, *et al.* 1993). Also, by using sampling units that incorporate floristic-physiognomic vegetation classes and wards, our aim was to incorporate variation due to management and ecological factors respectively. In this study, a ward with, e.g., three vegetation classes would yield three sampling units whereas a ward with a single vegetation class would yield one sampling unit. The sampling units were obtained by crossing the ward and vegetation class maps in a Geographical Information system (GIS). Fig. 5.3 shows the sampling units that were used in this study and their respective area in square kilometres.

Elephant data

The data on the spatial distribution of elephants were determined using respectively, a GIS based combination of 1981-1983 point data sets. These data were obtained from the point location data from the analyses of Sebungwe aerial surveys by Cumming and Lynam (1997) and made available by WWF in Harare. The recordings of the elephant sightings were made within 0.5 minute segments (≤ 1 km) along the flight path with an aircraft travelling at approximately 120 km per hour and the sightings

could be up to 250 m on either side of the aircraft (Cumming and Lynam 1997), suggesting that the worst case of locational error in these surveys would be closer to 500 m. The aerial surveys were carried out in the dry season, i.e., between August and October of the relevant years. This was considered an appropriate period for studying the effect of spatial heterogeneity on elephant distribution because the crop fields are fallow during the dry season. Crop fields tend to attract the elephants outside their normal natural range, thus making wet season (October to March) data less reliable for assessing the effect of spatial heterogeneity. In other words, an area that can be suitable for the elephant in the dry season can safely be assumed to be suitable in the wet season.

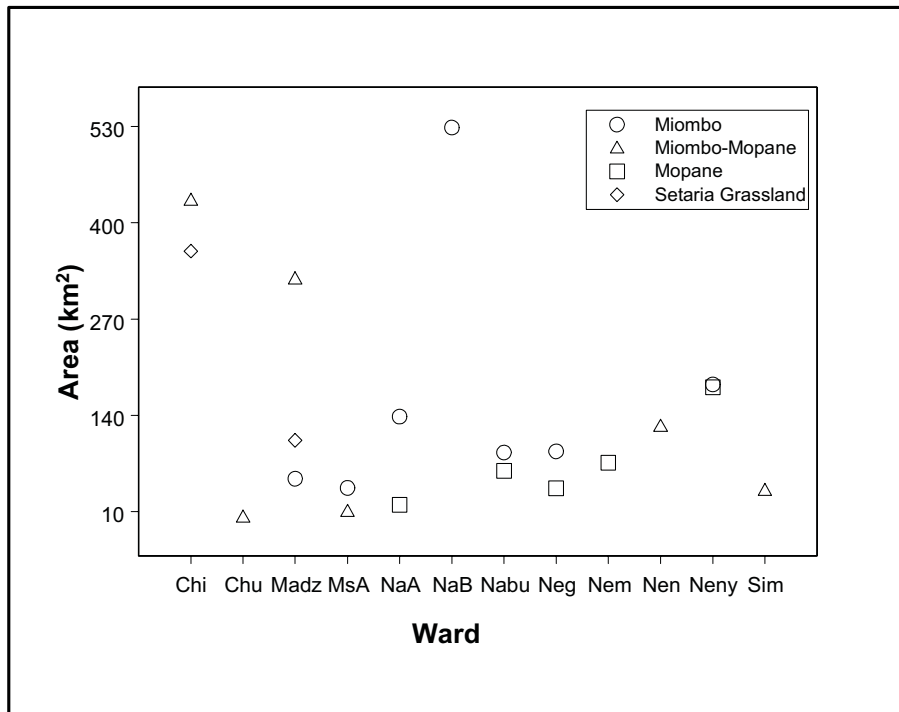


Figure 5.3: Sampling units (intersection of wards and vegetation classes) used in the regression of the probability of elephant presence on the dominant scale and intensity of spatial heterogeneity based on the early 1980s and the early 1990s data (Chi = Chireya 1, Chu = Chunga, Madz = Madzivavzvido, MsA = Musambakaruma A, NaA = Nabiri A, NaB = Nabiri B, Nabu = Nabusenga, Nem = Nemangwe 5, Neg = Negande, Neny = Nenyunka and Sim = Simchembo).

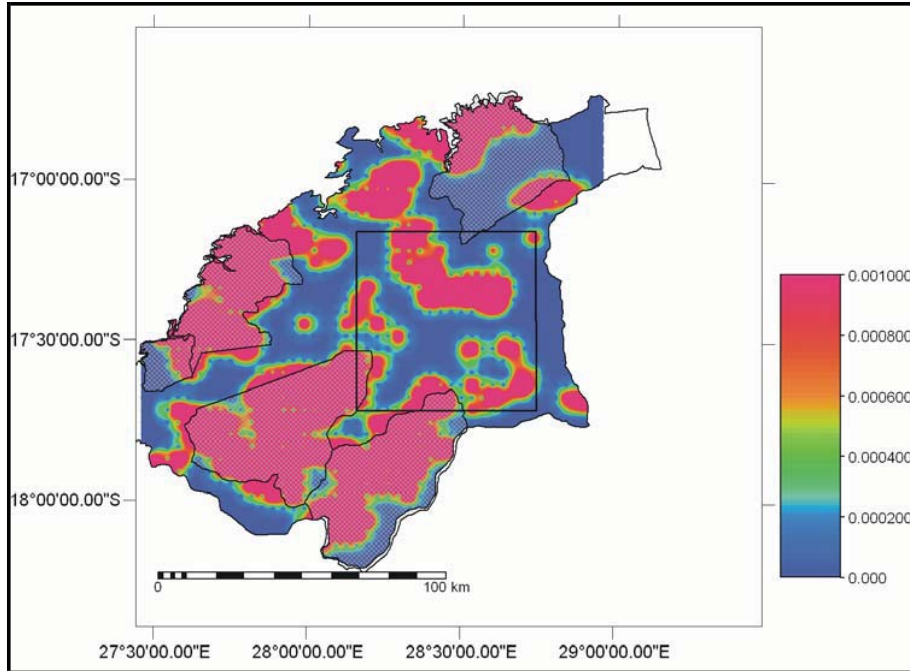


Figure 5.4: Map showing the probability of elephant presence within a 3 km radius in the Sebungwe in 1981-83 and the 61 km by 61 km square box shows the area used in this study.

We considered the elephant distribution map of our study area R as a spatial point pattern (Diggle 1983). Each point where elephants were observed is called an event. We calculated the first-order intensity function $\lambda(x)$ for the elephant point map to give an expected number of events per unit area (Fotheringham, *et al.* 2000):

$$\lambda(x) = \lim_{r \rightarrow 0} \frac{E(N(C(x,r), X))}{\pi r^2} \quad (5.1)$$

where $E(N)$ is the expected number of events in the study area considered and $C(x,r)$ a circular sub-region of R located at x with a radius r . A kernel function was used in this study with radius r equal to 3000 m based on an exploratory analysis in S-PLUS software (Lam 2001). This kernel radius was also large enough to overcome any locational errors in elephant

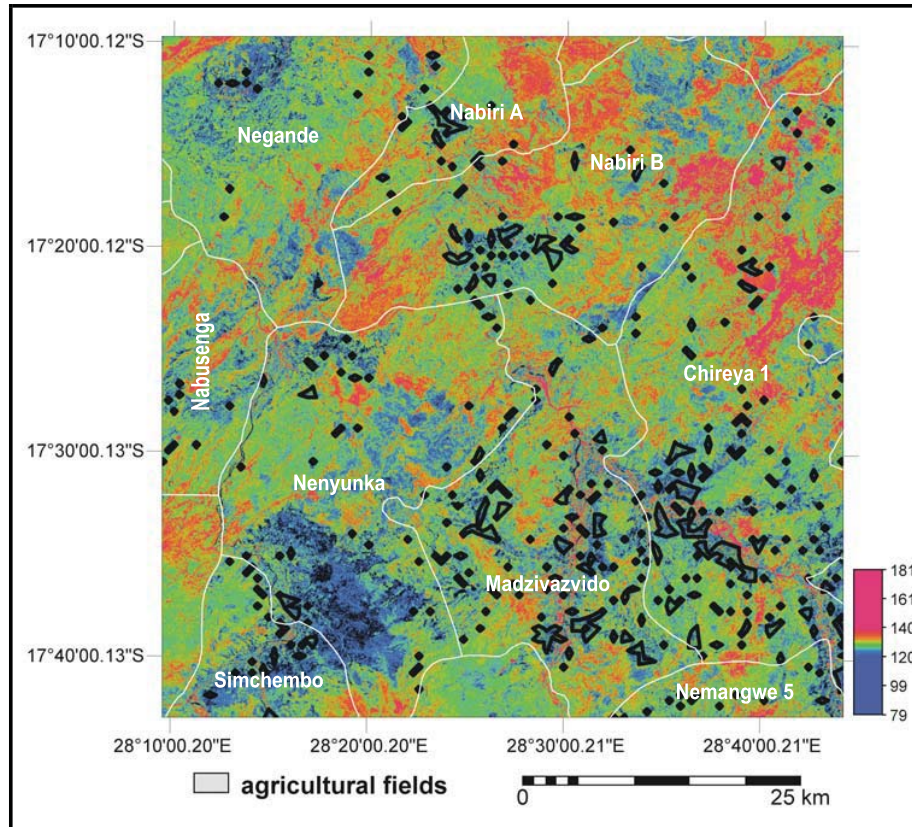


Figure 5.5: Map showing the 1984 NDVI maps of the 61 km by 61 km square box together with ward boundaries and the extent of agricultural fields. Low NDVI values indicate low vegetation cover and high NDVI values indicate high vegetation cover within a 0 to 255 range.

sightings. We then normalised $\lambda(x)$ by dividing it by the expected number of events in R to produce a normalised or probability function $\lambda_n(x)$ (Fotheringham, *et al.* 2000):

$$\lambda_n(x) = \frac{\lambda(x)}{E(N(R, X))} \quad (5.2)$$

We used the $\lambda_n(x)$ to estimate the spatial distribution of elephants in the study area during the 1981-83 and 1993-95 periods. This spatial point pattern analysis was carried out in the S-PLUS software (Lam 2001). The

map was then exported to ILWIS GIS software (ITC 2002). This method was used because it is spatially explicit and gives weight to elephant location rather than absolute numbers: the aim was to determine whether spatial heterogeneity affects the preference of location by elephants. Finally, the mean probability of elephant presence in each of the sampling units was used as a measure of elephant distribution by crossing the probability of elephant distribution map (fig. 5.4) with the sampling unit map (i.e., intersection of wards and vegetation classes) and by calculating the mean probability of elephant presence in each sampling unit.

Remote sensing

Vegetation cover was estimated from NDVI derived from the readily available TM images of 19 October 1984:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \quad (5.3)$$

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 handling in image processing software. Fig. 5.5 shows the NDVI image of the 61 km x 61 km study area. NDVI was used because it is an established index for estimating vegetation quantity (Walsh, *et al.* 1997, Walsh, *et al.* 2001). NDVI has been shown to provide an effective measure of photosynthetically active biomass (Tucker and Sellers 1986, Los. 1998, Turner, *et al.* 1999, Birky 2001, Hill and Donald 2003) and it is an index of total vegetation biomass (Goward and Dye 1987). Also, NDVI is also strongly related to the extent of vegetation cover and therefore, can be used as an indicator of spatial heterogeneity in the landscape (Kerr and Ostrovsky 2003). In addition, since there is no water limitation in the study area (Cumming 1981) due to the fact that major rivers such as the Sengwa drain it, and since the African elephant is a habitat generalist (Kingdon 2001) it has a potential of being anywhere in the study area. Therefore, we can hypothesise that the levels of spatial heterogeneity in vegetation cover introduced by the human incursion in the Sebungwe may strongly influence the spatial distribution of the elephant.

In addition, dry season imagery was used in this study because the elephant counts by aerial surveys were conducted in the dry season. In

addition, it is easier to distinguish between fallow agricultural fields and natural vegetation from dry season NDVI than the wet season NDVI. This is because in the dry season high NDVI values are expected for natural vegetation and lower NDVI values are expected for fallow agricultural fields. In this regard, fig. 5.5 shows that low NDVI mainly coincided with agricultural fields in 1984. The 1984 agricultural field map was produced using a combination of aerial photographs and Landsat TM imagery.

Several advantages were envisaged in using Landsat TM imagery to characterise the spatial heterogeneity for the study of elephant distribution. Namely, the spatial resolution or grain of Landsat TM, i.e., 30 m was detailed enough to enable the quantification of spatial heterogeneity that is relevant for analysing elephant distribution. This is because generally, the grain should be several magnitudes smaller than the total range of the organism (Sparrow 1999). The grain of 30 m is about 300 times smaller than the estimated range of the elephant in Sebungwe.

Calculating the NDVI average and NDVI coefficient of variation

In this study the direct image approach involved the use of NDVI average and the NDVI coefficient of variation. Several steps were involved in calculating the NDVI average and NDVI coefficient of variation for each sampling unit. Firstly, we crossed the NDVI map (fig. 5.5) with the map of the sampling units in ILWIS GIS. Secondly, we summed the NDVI values of all the pixels within each sampling unit and divided the sum by the number of pixels in each sampling unit to obtain the NDVI average. Finally, we calculated the NDVI coefficient of variation within a sampling unit by dividing the NDVI standard deviation with the NDVI average and then multiplying the result by 100 %. The advantage of using the NDVI coefficient of variation over the NDVI standard deviation is that it is a measure not dependent on the magnitude of the mean in a sampling unit.

Characterising spatial heterogeneity using wavelets

Wavelet energy (Bruce and Hong-Ye. 1996) was used to quantify the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity in the NDVI image. The determination 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 an NDVI image $f(x,y)$ at successive bases, (2^j) , i.e., $j = 0,1,2,\dots,J$ in the vertical (north-south), diagonal (northeast- southwest and southeast-northwest) and horizontal (east-west) directions for the 2-dimensional data. A wavelet transform results in a set of coefficients and each coefficient is associated with a base level, i.e., $j = 0,1,2,\dots,J$, a direction and a particular location. The wavelet approximation $\hat{f}(x,y)$ of the original 2-dimensional function $f(x,y)$ is a sum of the smooths and the detail functions at different bases:

$$\hat{f}(x,y) = S_J(x,y) + \sum_{j=1}^J \sum_{dir} D_j^{dir}(x,y) \quad (5.4)$$

S_j represents the smooth coefficients and D_j^{dir} are the directional (i.e., vertical (north-south), horizontal (east-west) and diagonal (northeast-southwest and northwest-southeast)) detail coefficients. By convention, the smallest grain of $f(x,y)$ is equals to $j = 0$. Therefore, each level j corresponds to a grain equals $2^j * s$ where s is the size of the original grain at which $f(x,y)$ is mapped (in this case 30 m, the grain of Landsat TM). The decision on the magnitude of J (i.e., the broadest base or window of focus) is made in advance and depends on how much detail is required in the analysis and also on the extent of the image. In this study we selected J equals 7, an equivalent of a spatial dimension of 3840 m, larger than pixel size that we used to estimate the probability of elephant presence. Note that the theory and formal treatment of wavelets has been covered exhaustively elsewhere (Mallat 1989, Ogden 1997).

Wavelet coefficients can be positive or negative but the absolute coefficient value measures the magnitude of contrast in $f(x,y)$ at a specific location with a base of 2^j . Wavelet energy was calculated as a second moment of the wavelet transform defined as the sum of squares of the coefficients at base 2^j , divided by the sum of squares of all the coefficients in $\hat{f}(x,y)$:

$$E_j^d = \frac{1}{E} \sum_{k=1}^{n/2^j} d_{j,k}^2(x,y), j = 1,\dots,J \quad (5.5)$$

where $d_{j(x,y)}$ are the detail wavelet coefficients at j and position (x,y) , E is the total sum of squares of $\hat{f}(x,y)$ and $n/2^j$ is the number of coefficients at

level j . Then, wavelet energy values were plotted against scale and the highest local maxima in the wavelet energy function represented the intensity of spatial heterogeneity while the corresponding scale value represent the dominant scale of spatial heterogeneity (Murwira and Skidmore. 2003). The detail functions rather than the smooth approximations were used in the analysis because the former are scale specific. For example, details at $j = 1$ capture vegetation patches that have a size between 30 m and 60 m. In contrast, smooth coefficients can only capture scales that are equal or greater than 2^j , thus they are not scale specific.

The dominant scale and intensity in each of the sampling units was obtained through several steps. Firstly, we crossed the wavelet coefficient maps at each j with the ward and vegetation class maps in a Geographical Information system (GIS). Secondly, the wavelet functions of each unit were plotted. Thirdly, the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity were determined by considering the highest local maxima in wavelet energy and the scale margin that corresponds to the intensity values respectively. In other words, only the dominant scale and intensity defined by the highest maxima on the wavelet energy function was used in this analysis, i.e., the highest maximum on the wavelet energy function can be interpreted as the intensity that corresponds to the most dominant scale in the landscape. However, it is important to note that using a wavelet transform to estimate the first-order properties of NDVI enables us to deduce the dominant scale of spatial heterogeneity only in relation to the patch dimension at which the highest wavelet energy is recorded (Murwira and Skidmore. 2003).

Characterising spatial heterogeneity using a windowed variogram

In order to characterise the intensity of spatial heterogeneity plus the dominant scale of spatial heterogeneity using a variogram, we use the two main variogram structural parameters, the sill and the range (Curran 1988) respectively. The sill is the level at which the variogram becomes flat, and it exists if the process being analysed is stationary (Webster 2000). A spatial process is stationary when only the distance that separates points in space explains the difference in the values between them (Webster 2000). The range is normally used to measure the dominant scale of spatial correlation, which is the maximum distance at which spatial correlation is

present and beyond which spatial correlation is absent. The sill is normally used to measure the amount of variability or the average variance between points that are the distance of the range apart.

The following formula is used to calculate the variogram $\gamma(h)$:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \quad (5.6)$$

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 (Tretitz 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).

In this study a windowed variogram technique was used. But, in order to properly explain windowed variograms, first consider a global variogram based on NDVI image of our 61 km by 61 km study area D. The image provides information about a regionalized variable (amount of vegetation cover) being a function $z(x)$, within $x \in D$. In probabilistic terms, $z(x)$, is a realization of a random function $Z(x)$, an infinite family of random functions constructed at all points $x \in D$ (Wackernagel 1998). Therefore, for a global variogram, only a single dominant scale with a single intensity measure would characterize spatial heterogeneity in the NDVI image. The global variogram masks the spatial heterogeneity in individual sampling units (i.e., defined by each vegetation class and ward). Therefore, an alternative technique is needed to unravel the dominant scale and intensity of spatial heterogeneity in individual sampling units.

In order to be able to investigate variations in dominant scale and intensity of spatial heterogeneity in the individual sampling units, D was first decomposed into congruent windows w_k , $k=1,2,3,\dots,m$ with size $|w_k|$ equals 3840 m by 3840 m in ILWIS GIS software (ITC 2002) to obtain localised sub-samples of $Z(x)$. In other words, we are subdividing the extent of the study area into sub areas in order to calculate localised variograms (Myers 1997). This window size was selected so that it is larger than the distance of 3000 m used to model the probability of elephant presence. In addition, the window size was determined to contain sufficient sample pairs for estimating a variogram based on an exploratory

analysis. For each w_k , an empirical variogram $\lambda_k(h)$, the windowed variogram was calculated in ILWIS GIS. The empirical variograms were exported to S-PLUS where for each $\lambda_k(h)$, parameters were estimated by automatically fitting an appropriate theoretical variogram model using a non-linear least squares method (all the empirical variograms resembled a spherical model upon visual inspection and therefore, it was the appropriate theoretical model used in this study). Thus, the variogram range and the sill obtained for each $\lambda_k(h)$, were used to quantify dominant scale of spatial heterogeneity and intensity of spatial heterogeneity of NDVI respectively. All in all, 256 windowed variograms were estimated.

The dominant scale and intensity in each of the sampling units was obtained by first crossing the variogram range and variogram sill maps with the sampling unit map within a GIS and then calculating the mean variogram range and mean variogram sill in each sampling unit (there was more than one variogram range and variogram sill in each unit). The variogram sills were normalised to 0 – 1 by dividing each variogram sill value by the respective sum of all 256 variogram. This was done to facilitate interpretation across different sampling units.

The advantages that we envisaged in using a windowed variogram to estimate the dominant scale and intensity of spatial heterogeneity are based on the stationarity assumption (Webster 2000) and the ability to capture variations in spatial heterogeneity among sampling units in the landscape. Specifically, the intrinsic assumption upon which the variogram is 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 inter-predominant patch distance in the landscape. Therefore, by analysing the probability of elephant presence in relation to the dominant scale of spatial heterogeneity, we are not only testing the hypothesis about the effect of patch dimension on the spatial distribution of elephants but we are also testing the hypothesis about the effect of inter-patch distance on the spatial distribution of elephants. This is especially important for analysing elephant distribution in the agricultural landscapes where the distance that separates patches of suitable habitat is just as important as the size of patches of suitable habitat.

Osborn and Parker (2003) reported that habitat connectivity is important for elephants, based on a study in the Zambezi valley in Zimbabwe. In addition, the ability to capture variations in spatial heterogeneity among sampling units enables the relationship between the probability of elephant presence and spatial heterogeneity to be tested.

Predicting the probability of elephant distribution

As mentioned earlier, the analysis of the relationship between the probability of elephant presence and: (1) NDVI average and NDVI coefficient of variation, as well as (2) intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity derived from both windowed variograms and wavelets was conducted based on the 61 km x 61 km study area, i.e., in the communal lands of the Sebungwe and the individual units of analysis were defined by an intersection of each ward and a vegetation class in a GIS, thereby incorporating variation due to management and ecological factors respectively. The number of sampling units used in the analysis varied: 20 units were used for analysis involving spatial heterogeneity measured from windowed variogram whereas 22 units were used in the rest of the analysis. The basis of selecting the 20 units was that each unit had to have to contain at least two windowed variograms (i.e., at least two estimates of the variogram range and sill parameters) that can be used to calculate a mean.

Therefore, based on the defined units of analysis, regression was used to relate the probability of elephant presence to: (1) NDVI average and NDVI coefficient of variation, (2) the wavelet-based intensity and dominant of spatial heterogeneity and (3) the variogram-based intensity and dominant of spatial heterogeneity. To aid the explanation of the probability of elephant presence-intensity of spatial heterogeneity relationship, we conducted a confirmatory analysis to check whether the intensity of spatial heterogeneity (measured with both wavelets and variograms) was significantly correlated to the NDVI average (i.e., average estimate of vegetation cover) and NDVI coefficient of variation (i.e.,

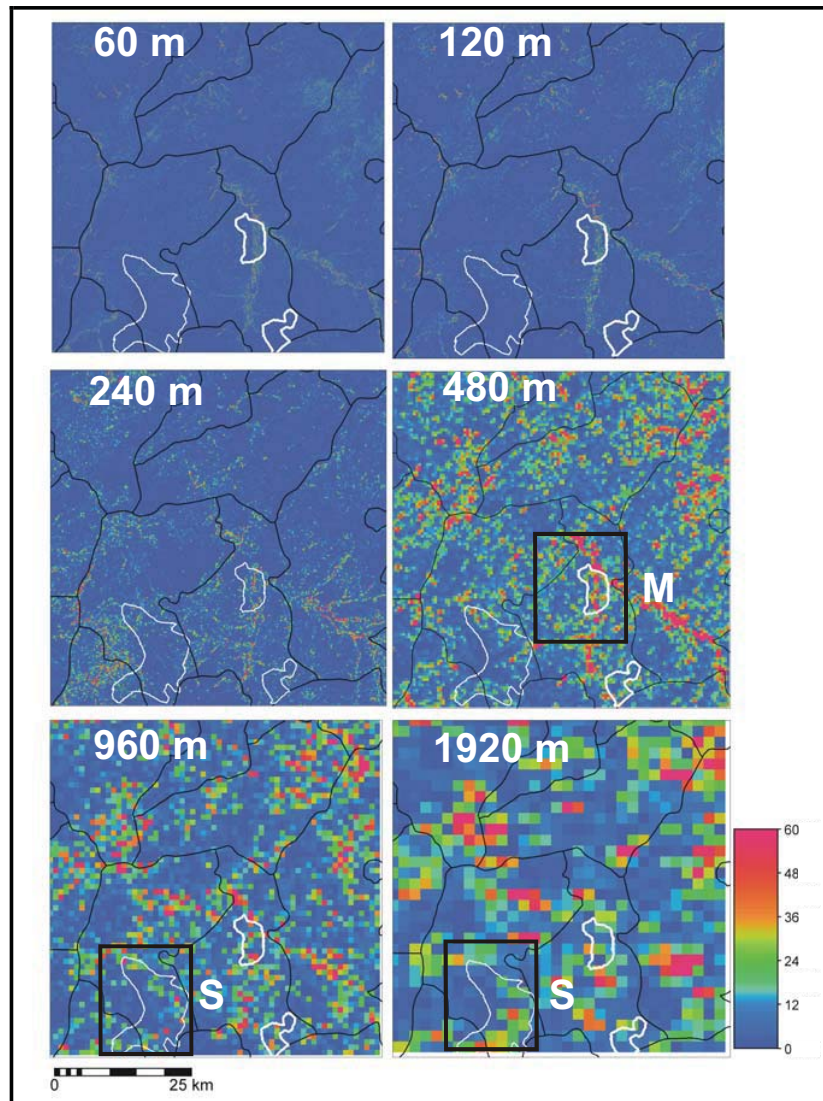


Figure 5.6a: The spatial distribution of total wavelet energy per pixel at different scales (wavelet spans) across different wards, as well as in selected vegetation class polygons (The total wavelet energy that we used as a denominator for calculating energy was divided by 1000000 and then stretched between 0 and 60 to enhance the wavelet energy for visual presentation). The polygon in box (S) depicts Setaria predominantly in Nenyunka ward while the polygon contained in the smaller box (M) is Miombo-Mopane vegetation class in Madzivazvido ward.

estimate of vegetation cover variability). This was because we hypothesise that the intensity of spatial heterogeneity estimates both the amount and variability of vegetation cover (NDVI).

5.3 Results

The spatial heterogeneity in the study area from wavelets and variograms

Fig. 5.6a reveals the spatial variation of wavelet energy in the study area based on each location at different wavelet spans or scales. In addition, fig. 5.6b shows 15 wavelet energy functions that reveal the variations in the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity among 5 selected wards and four different vegetation classes. The polygon within boxes (S) (fig. 5.6a) is the *Setaria* vegetation class that occurs in both Nenyunka and Madzivazvido wards. It can be observed that in Nenyunka ward, the intensity of spatial heterogeneity of this vegetation class equal to 0.0007 and it occurs at the dominant scale of spatial heterogeneity that is equal to 1920 m (fig. 5.6b). Furthermore, in Madzivazvido ward the *Setaria* vegetation class has an intensity of spatial heterogeneity of 0.0005 that occurs at a dominant scale of spatial heterogeneity of 960 m (fig. 5.6b). *Setaria* is mainly dominated by monotonously varying grassland. In contrast, the polygon within the box (M) (fig. 5.6a) is the Miombo-Mopane vegetation class in Madzivazvido ward. We can observe that the intensity of spatial heterogeneity of this Miombo-Mopane vegetation class in Madzivazvido is relatively higher than *Setaria* (i.e., 0.0016), occurring at a relatively smaller dominant scale of spatial heterogeneity that is equal to 480 m (fig. 5.6b).

Fig. 5.7 reveals that there were spatial variations in the variogram-derived intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity (i.e., represented by the variogram range and variogram sill respectively). Fig. 5.7a shows the variogram parameters (i.e., the range and the sill) in the original way they were estimated using

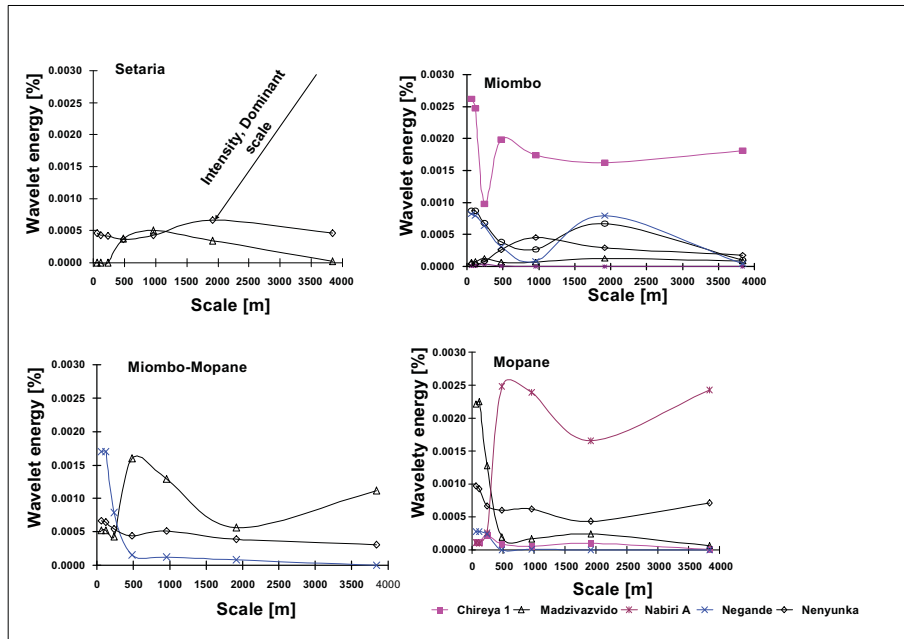


Figure 5.6b: Selected wavelet energy functions revealing the variations in intensity and dominant scale in different wards and vegetation classes. The arrow shows an example of the determination of the intensity and dominant scale of spatial heterogeneity from a wavelet energy function.

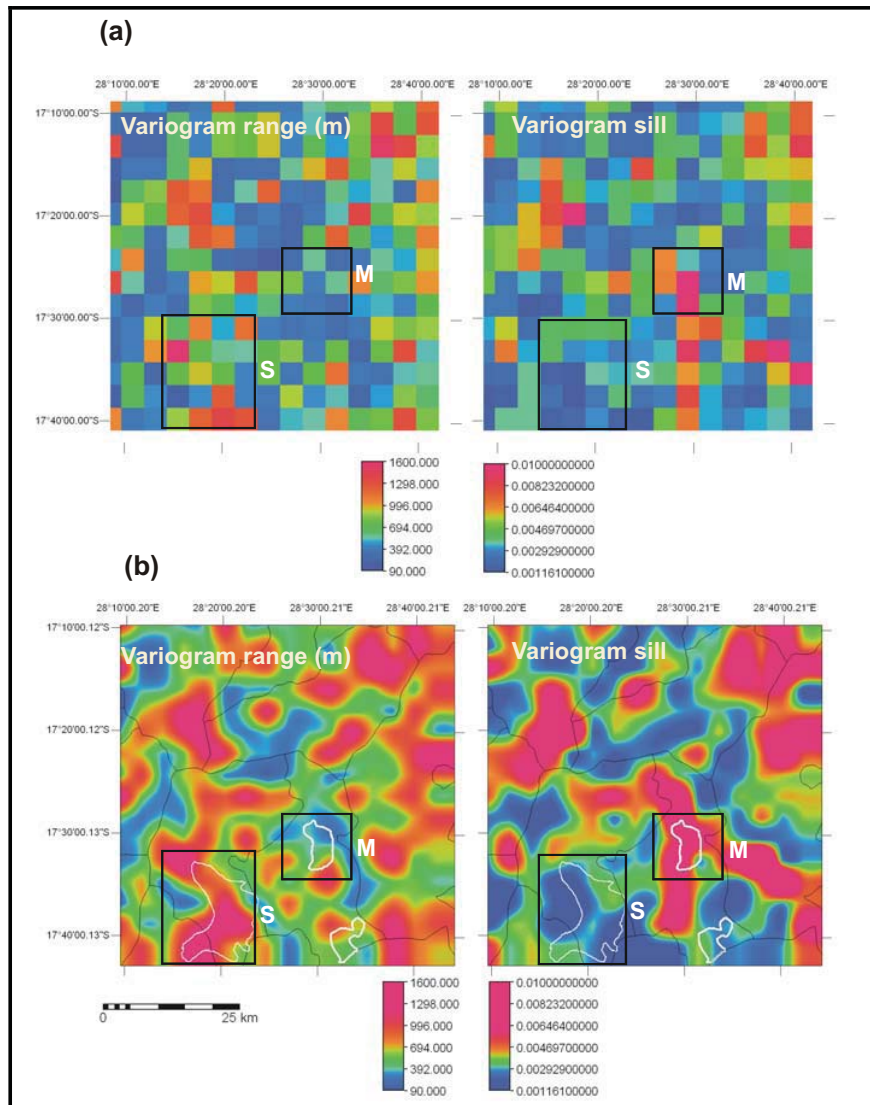


Figure 5.7: Maps showing (a) the distribution of the dominant scale of spatial heterogeneity (i.e., range) and the intensity of spatial heterogeneity (i.e., sill), as well as their (b) bicubic spline versions that clearly reveal the spatial trends in spatial heterogeneity. The polygon in box (S) depicts *Setaria* predominantly in Nenyunka ward while the polygon contained in the smaller box (M) is Miombo-Mopane vegetation class in Madzivazvido ward.

the windowed variogram method while fig. 5.7b shows the same variogram parameters that have been smoothed using a bicubic spline method in order to clearly reveal the spatial trends in spatial heterogeneity. We can observe clear differences in the levels of spatial heterogeneity between vegetation classes and different wards. For example, the intensity of spatial heterogeneity in *Setaria* vegetation class in Nenyunka, which is equal to 0.04, occurs at an estimated dominant scale of spatial heterogeneity equal to 900 m (fig. 5.7b) whereas, the Miombo-Mopane vegetation class in Madzivazvido is characterised by a relatively higher intensity of spatial heterogeneity (i.e., 0.05) that occur at a comparatively smaller dominant scale of spatial heterogeneity equal to 528 m.

Overall, it can be observed that the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity detected using the variogram and wavelet transform are similar. Even though, the absolute estimates of the intensity and the dominant scale of spatial heterogeneity in both *Setaria* and Miombo-Mopane are different between the methods, the relative differences in spatial heterogeneity between the two vegetation classes are revealed by both methods.

The probability of elephant presence, NDVI average and NDVI coefficient of variation

Fig. 5.8 reveals significant ($p < 0.05$) relationships between the probability of elephant presence and the NDVI average as well as the NDVI coefficient of variation. Both relationships are best described by a second order polynomial or a quadratic function. From fig. 5.8, it can be observed that the probability of elephant presence initially increases with increasing NDVI average and NDVI coefficient of variation up to a certain level and then it levels off or even decrease. The NDVI average explained 60 % of the variance in the probability of elephant presence while the NDVI coefficient of variation explained 48 % of the variance in the probability of elephant presence. It can also be observed that this relationship is not a result of differences in vegetation class because, even in a single class such as Miombo, a quadratic relationship is clear.

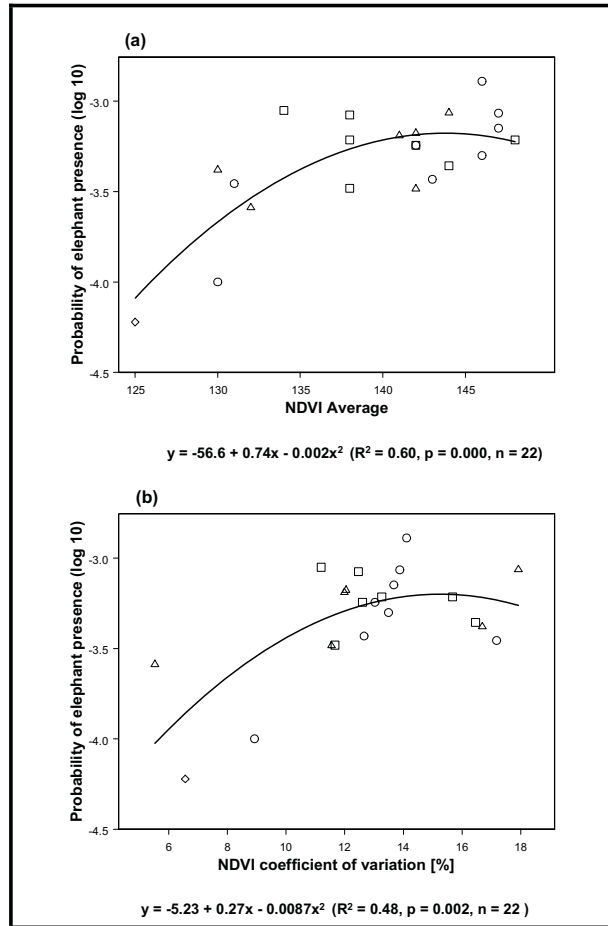


Figure 5.8: Significant ($p < 0.05$) relationships between the probability of elephant presence and the (a) NDVI average and (b) NDVI coefficient of variation in (O) Miombo, (□) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane floristic-physiognomic vegetation classes.

The probability of elephant presence and wavelet-derived spatial heterogeneity

Although in reality the dominant scale and intensity of spatial heterogeneity are inseparable, we first related them individually to the probability of elephant presence before proceeding before proceeding to

use them in combination to explain the probability of elephant presence. Fig. 5.9 shows significant ($p < 0.05$) relationships between the probability of elephant presence and the individual properties of spatial heterogeneity (i.e., dominant scale of spatial heterogeneity and intensity of spatial heterogeneity) (fig. 5.9a and fig. 5.9b), as well as the relationship between the probability of elephant presence and the intensity of spatial heterogeneity plus the dominant scale of spatial heterogeneity (fig. 5.9c). The relationship between the probability of elephant presence and dominant scale of spatial heterogeneity was best described by a second order polynomial (fig. 5.9a). From this relationship, it can be observed that the probability of elephant presence decreases with an increase in the dominant scale of spatial heterogeneity (fig. 5.9a). Fig. 5.9b also shows that the relationship between the probability of elephant presence and the intensity of spatial heterogeneity is also best described by a second order polynomial. However, unlike its relationship with the dominant scale of spatial heterogeneity, the probability of elephant presence initially increases with increasing intensity of spatial heterogeneity until up to a certain level and then it levels off. The dominant scale of spatial heterogeneity explained 65 % of the variance in the probability of elephant presence whereas the intensity of spatial heterogeneity explained 61 % of the probability of elephant presence in the study area. Again, it can be observed that this relationship is not a result of differences in vegetation class because in a single class, e.g., in Miombo; the relationship is consistent with the overall relationship.

The intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity are inseparable properties of spatial heterogeneity. Therefore, we also investigated the relationship between the probability of elephant presence and both the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. Fig. 5.9c reveals that there was a significant ($p < 0.05$) near hump-shaped relationship between the probability of elephant presence and the combined effect of the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. We can observe that at the intermediate to the high intensity of spatial heterogeneity, the probability of elephant presence increases with the increasing dominant scale at small dominant scales of spatial heterogeneity

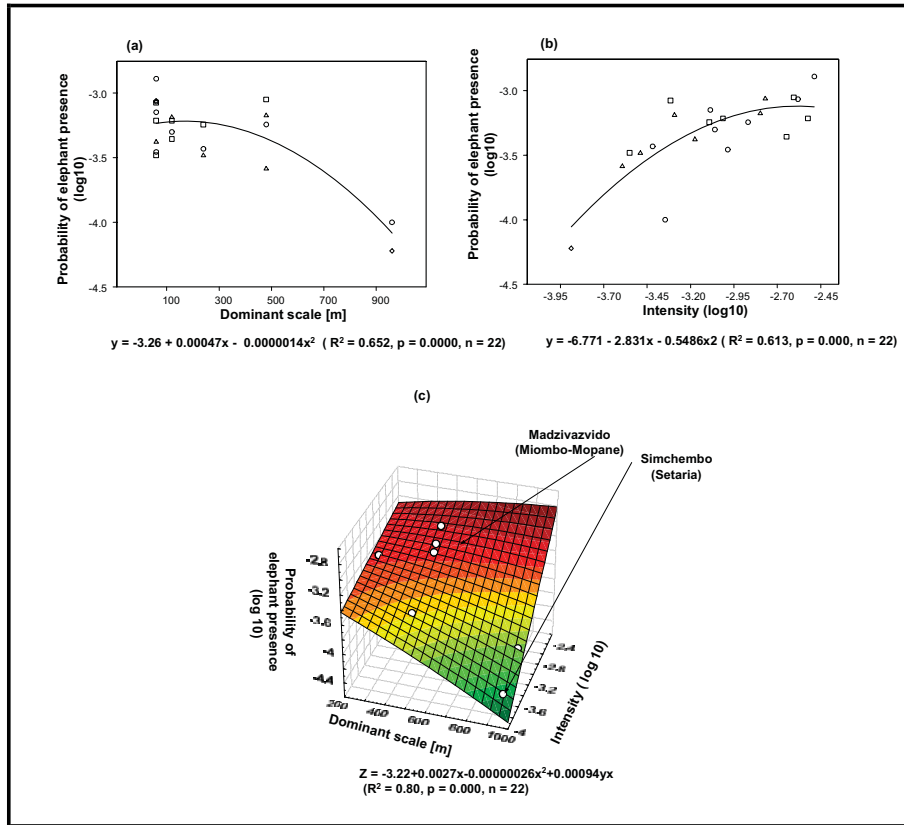


Figure 5.9: Significant ($p < 0.05$) relationships between the probability of elephant presence and wavelet-derived: (a) dominant scale of spatial heterogeneity, (b) intensity of spatial heterogeneity and (c) both the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. The floristic-physiognomic vegetation classes: (○) Miombo, (□) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane are shown in the bivariate relationships. The graph surface represents increasing probability of elephant presence from green (lowest probability) to deep red (the highest probability of elephant presence).

while at large dominant scales of spatial heterogeneity the probability of elephant presence decreases with the increasing dominant scale. In this situation, the peak probability of elephant presence is associated with the intermediate to the high intensity of spatial heterogeneity that occurs at intermediate dominant scales of spatial heterogeneity (i.e., around 480 m).

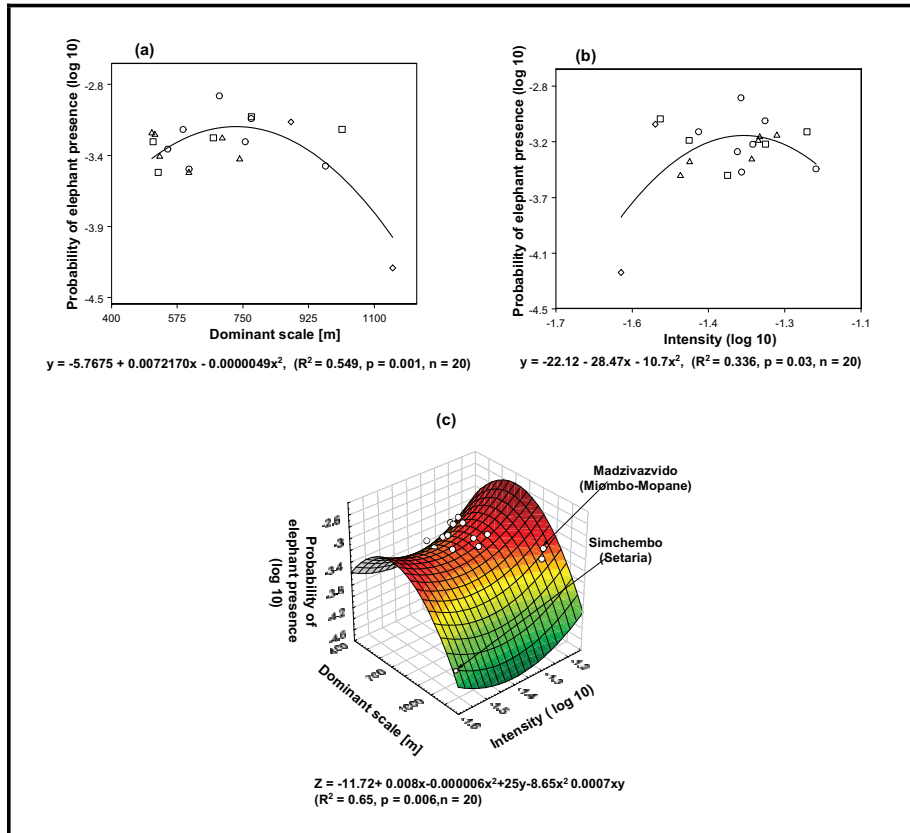


Figure 5.10: Significant ($p < 0.05$) relationships between the probability of elephant presence and variogram-derived: (a) the dominant scale of spatial heterogeneity, (b) the intensity of spatial heterogeneity and (c) both the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. The floristic-physiognomic vegetation classes: (○) Miombo, (□) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane are shown in the bivariate relationships. The graph surface represents increasing probability of elephant presence from green (lowest probability) to deep red (the highest probability of elephant presence).

For example, the high probability of elephant presence in the Miombo-Mopane vegetation class in Madzivazvido is associated with a high intensity of spatial heterogeneity that occurs at the intermediate dominant scale of spatial heterogeneity. In contrast, the low probabilities of elephant presence in the Setaria vegetation class in Simchembo ward are associated

with the low intensity of spatial heterogeneity that occur at large dominant scales of spatial heterogeneity. The intensity of spatial heterogeneity plus the dominant scale of spatial heterogeneity explained 80 % of the variance in the probability of elephant presence.

The probability of elephant presence and variogram-derived spatial heterogeneity

Finally, we analysed the relationship between the probability of elephant presence and the variogram-derived spatial heterogeneity measures. Like in the wavelet case, we first related the probability of elephant presence to the intensity of spatial heterogeneity and to the dominant scale of spatial heterogeneity respectively (fig. 5.10a and fig. 5.10b) before proceeding to relate the probability of elephant presence to the combination of the two properties of spatial heterogeneity (fig. 5.10c). There were significant ($p < 0.05$) relationships in all the three cases (fig. 5.10). The relationship between the probability of elephant presence and the dominant scale of spatial heterogeneity is best described a second order polynomial that has a clear hump-shape. The dominant scale of spatial heterogeneity explained 55 % of the variance in the probability of elephant presence. It can also be observed that a second order polynomial also best describes the relationship between the probability of elephant presence and the intensity of spatial heterogeneity. However, the intensity of spatial heterogeneity in this case explained only 34 % of the variance in the probability of elephant presence. The earlier observation that the nature of the relationships is not a result of differences in vegetation class still holds.

Fig. 5.10c depicts the relationship between the probability of elephant presence and the combined effect of the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. Again, we can observe that at the intermediate to the high intensity of spatial heterogeneity, the probability of elephant presence increases with the increasing dominant scale at small dominant scales of spatial heterogeneity while at large dominant scales of spatial heterogeneity the probability of elephant presence decreases with the increasing dominant scale, thereby leaving high probabilities of elephant presence at intermediate dominant scales of spatial heterogeneity. We can also observe that it is the descending limb of the hump that is pronounced. For example, it can be observed that high probabilities of elephant presence in the Miombo-

Mopane vegetation class in Madzivazvido is associated with a high intensity of spatial heterogeneity that occurs at intermediate dominant scales (i.e., around 734 m) of spatial heterogeneity around the peak of the hump. In contrast, the low probabilities of elephant presence in the Setaria vegetation class in Simchembo ward are associated with low intensity of spatial heterogeneity that occur at large dominant scales of spatial heterogeneity. The combined function of the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity explained 65 % of the variance in the probability of elephant presence.

The correlation of intensity to NDVI average and NDVI coefficient of variation

Fig. 5.11 illustrates that the intensity of spatial heterogeneity is positively correlated to the NDVI average and the NDVI coefficient of variation. It can be observed that the wavelet-derived intensity of spatial heterogeneity is significantly ($p < 0.05$) correlated to both the NDVI average and the NDVI coefficient of variation (fig. 5.11a). In contrast, the variogram-derived intensity of spatial heterogeneity is only correlated significantly ($p < 0.05$) to the NDVI average but not significantly ($p > 0.05$) to the NDVI coefficient of variation (fig.5.11b).

5.4 Discussion

Our results indicated that the intensity and the dominant scale of spatial heterogeneity (i.e., derived from both wavelets and variograms) predicted the probability of elephant presence better than the usual NDVI average and NDVI coefficient of variation (figs. 5.8, 5.9, 5.10, table 5.1). This result is consistent with the hypothesis that by using the intensity and the dominant scale as inseparable properties of spatial heterogeneity, we are not only characterising the variability of vegetation cover that is emphasized by the NDVI coefficient of variation using the intensity (fig. 5.11), but, in addition, we are able to allocate this variability to the patch dimension using the dominant scale (see introduction). Classical statistics such as the NDVI average and the NDVI coefficient of variation have been successfully used to characterise certain aspects of wildlife species distribution (Oindo and Skidmore 2001). However, our new

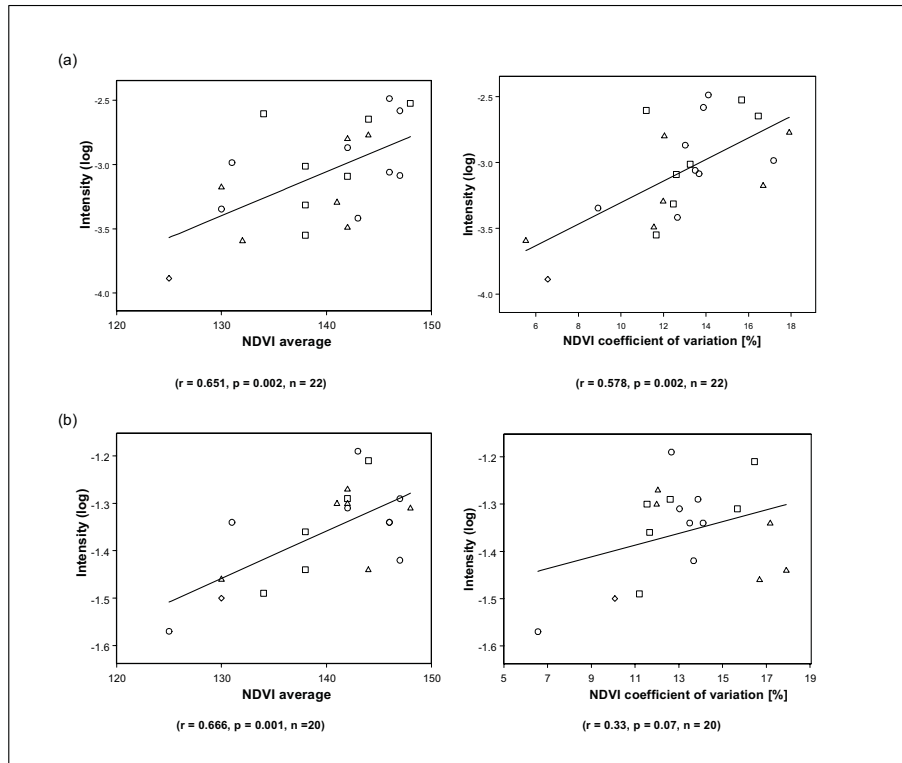


Figure 5.11: Positive correlation of (a) wavelet-derived intensity of spatial heterogeneity, as well as, variogram-derived intensity of spatial heterogeneity to NDVI average and NDVI coefficient of variation. All the correlation coefficients are significant ($p < 0.05$) except the one between the variogram-derived intensity of spatial heterogeneity and NDVI coefficient of variation. The floristic-physiognomic vegetation classes: (○) Miombo, (□) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane are shown in the bivariate correlations.

approach improves upon this by considering the effect of spatial structure (i.e., dominant scale) in the distribution of ecological phenomena such as the spatial distribution of wildlife species (Legendre and Fortin 1989). In other words, the results are consistent with the hypothesis that the effect of spatial heterogeneity on ecological pattern can be reliably assessed when the effects of scale are accounted for (Ettema and Wardle 2002). Thus, we assert that the intensity and dominant scale approach to spatial heterogeneity, specifically the one using wavelets improves upon the direct

image approach for predicting ecological patterns like elephant distribution.

Although we observed that the behaviour of the relationship between the probability of elephant presence and the wavelet and variogram-derived spatial heterogeneity was similar (i.e., both were best described by a second order (parabolic) function), the wavelet-derived spatial heterogeneity yielded a better prediction (fig. 5.9 and fig. 5.10). This confirms that wavelets quantify spatial heterogeneity better owing to their localised nature compared with variograms that are global functions (Dale and Mah. 1998). Nevertheless, the fact that the nature of the relationship was similar (fig. 5.9 and fig. 5.10) is evidence of the ecological validity of our intensity and dominant scale perspective to spatial heterogeneity. In other words, it confirms that elephants also respond to patch dimension rather than just the variability in vegetation cover (i.e. as characterised by the NDVI coefficient of variation and NDVI average).

Table. 5.1. A summary comparison of the predictive power of the NDVI average and NDVI coefficient of variation (NDVIcv) and the wavelet and variogram based spatial heterogeneity. All relationships were statistically significant ($p < 0.05$).

	Overall (R^2)	Intensity (R^2)	Dominant scale (R^2)
Wavelets	80 %	61 %	65 %
Variogram	65 %	34 %	55 %
NDVI average	60 %		
NDVIcv	48 %		

Furthermore, there is evidence that the intensity and the dominant scale of spatial heterogeneity gave a greater insight into spatial heterogeneity as a limiting factor to elephant distribution in the study area compared with the usual NDVI average and NDVI coefficient of variation. Specifically, we see that when intensity is high, the probability of elephant presence increases with increasing dominant scale, until a certain threshold, and then decreases with increasing dominant scales of spatial heterogeneity (fig. 5.9 and fig. 5.10). From this unimodal relationship, we deduce that, intensity being high, high probabilities of elephant presence

are associated with environments with intermediate dominant scales of spatial heterogeneity, (i.e., around 480 m in the wavelet case, and at 734 m in the variogram case), suggesting an optimal level of spatial heterogeneity that encourage elephant persistence in the agricultural landscape. In contrast, we deduce that since the small dominant scales of spatial heterogeneity reflect the predominance of small patch dimensions, and elephants tend to avoid them. This may be because small patch dimensions may not provide enough buffers from human contact in this agricultural landscape. On the other hand, elephants avoid environments with low intensity and large dominant scales of spatial heterogeneity because these are environments dominated by either agricultural fields or grassland such as the *Setaria* vegetation class in Simchembo (fig. 5.5, 5.9 and 5.10). In these environments, elephants have neither enough high vegetation cover to keep them away from human contact nor high enough vegetation cover for thermoregulation (Guy 1976b, Guy 1976a). However, because intermediate and large dominant scales of spatial heterogeneity dominate the study area, the descending limb of this unimodal relationship is more pronounced than the ascending limb.

Because the new approach (intensity and dominant scale) to spatial heterogeneity characterises the landscape comprehensively by giving an indication of both variability and patch dimension respectively (fig. 5.1), the method could help in conservation planning for the elephant much more than the usual approach based on the NDVI average and NDVI coefficient of variation. For example, we showed in fig. 5.1 that two land units with different dominant scales of spatial heterogeneity can have the same maximum variability (intensity) in canopy cover and also that two land units can have different intensity of canopy cover but have the same dominant scale of spatial heterogeneity. Therefore, since the NDVI average and NDVI coefficient of variation cannot capture a variation in the dominant scale of spatial heterogeneity, their use in aiding conservation planning is insufficient.

5.5 Conclusions

The successful understanding of ecological patterns from spatial heterogeneity depends on the objective characterisation of spatial heterogeneity. The results of this study suggest that the characterisation of

spatial heterogeneity of NDVI from an intensity and dominant scale perspective predicts ecological patterns such as the spatial distribution of elephant better than the usual NDVI average and NDVI coefficient of variation that assume a uniform scale in the landscape. Furthermore, wavelet-derived spatial heterogeneity predicted the probability of elephant presence better than variogram-derived spatial heterogeneity. Therefore, the intensity and the dominant scale approach to characterise spatial heterogeneity is an invaluable preamble to predicting the spatial distribution of wildlife species in the landscape. In the case of the Sebungwe, this study provides the basis upon which elephant presence in the landscape can be monitored in relation to changes in spatial heterogeneity over time. All in all, because the new approach (intensity and dominant scale) to spatial heterogeneity characterises the landscape comprehensively by giving an indication of both variability and patch dimension respectively, the method could help in conservation planning for the elephant much more than the usual approach based on the NDVI average and NDVI coefficient of variation.