Scale matters!

A new approach to quantify spatial heterogeneity for predicting the distribution of wildlife

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THESIS

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Abstract

It is hypothesised that the spatial distribution of organisms in landscapes is largely a response to spatial heterogeneity that reflect, for instance, varying levels of resource availability or varying levels of human disturbance. In this regard, the ecologically meaningful characterisation of spatial heterogeneity is critical. It is for this purpose that remote sensing provides an important source of spatial data. However, current approaches and techniques to quantify spatial heterogeneity from remote sensing imagery as a precursor to predicting different ecological patterns such as wildlife distribution largely remain underdeveloped.

In this thesis, a new approach is developed to quantify spatial heterogeneity from remote sensing imagery, based on 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 (i.e., the window size or scale at which the intensity is displayed). This is followed by investigating whether this new approach can be used to reliably predict the probability of elephant (*Loxodonta africana*) presence in the landscape, as well as changes in the probability of elephant presence over time. The investigation was conducted in the communally managed agricultural areas of the Sebungwe in northwestern Zimbabwe. Overall, the thesis contributes to a wider scientific debate about the role of scale in understanding ecological patterns, as well as to a wider societal debate, that aims to attain a mutually beneficial human-wildlife co-existence in increasingly agricultural landscapes.

In this thesis, it is demonstrated that variograms and wavelets can be used to quantify spatial heterogeneity from remote sensing imagery based on intensity and dominant scale. Wavelets are found to be particularly invaluable for this purpose compared with variograms. Furthermore, using the new approach, the probability of elephant presence, as well as changes in the probability of elephant presence over time in the Sebungwe is reliably predicted.

Samenvatting

Aangenomen wordt dat de ruimtelijke verdeling van organismen in landschappen grotendeels afhangt van de ruimtelijke heterogeniteit die een afspiegeling is van, bijvoorbeeld, sterk uiteenlopende beschikbaarheid van middelen of verschillende niveaus van verstoring door de mens. In dit opzicht is het op ecologische wijze kenschetsen van de ruimtelijke heterogeniteit cruciaal. Voor dit doel vormen aardobservatiebeelden een belangrijke bron van ruimtelijke gegevens. Echter, de huidige benadering en het gebruik van technieken voor het bepalen van de ruimtelijke heterogeniteit uit aardobservatiebeelden als tussenstap voor het voorspellen van verschillende ecologische patronen, zoals de verspreiding dieren, is nog onvoldoende ontwikkeld.

In dit proefschrift wordt een nieuwe manier beschreven voor het bepalen van ruimtelijke heterogeniteit uit aardobservatiebeelden die gebaseerd is op de intensiteit (d.w.z., de maximale variantie die wordt gemeten wanneer een eigenschap van de ruimtelijke verdeling van het landschap, zoals bedekking door plantengroei, verandert met een successievelijk toenemende schaal) en de overheersende schaal (d.w.z., de schaal waarop die intensiteit zich voordoet). Vervolgens wordt onderzocht of deze nieuwe benadering gebruikt kan worden voor het betrouwbaar voorspellen van de kans op aanwezigheid van olifanten (*Loxodonta africana*), alsmede veranderingen in de kans op aanwezigheid van olifanten. Het onderzoek richtte zich op de gemeenschappelijk beheerde landbouwgebieden in Sebungwe in het noordwesten van Zimbabwe. Daarenboven draagt het proefschrift bij aan een bredere wetenschappelijke discussie aangaande de rol van de schaal in het begrijpen van ecologische patronen, alsmede aan een bredere maatschappelijke discussie die zich richt op het bereiken van een wederzijds voordeel in het samenleven van mens en dier in landschappen die meer en meer worden gebruikt voor landbouw.

In dit proefschrift wordt aangetoond dat variogrammen en wavelets kunnen worden gebruikt voor het bepalen van ruimtelijke heterogeniteit uit aardobservatiebeelden, gebaseerd op de intensiteit en de overheersende schaal. Wavelets worden bijzonder waardevol bevonden voor dit doel, vergeleken met variogrammen. Gebruikmakend van de nieuwe benadering, wordt de kans op aanwezigheid van olifanten, alsmede veranderingen in de kans op aanwezigheid van olifanten, in Sebungwe betrouwbaar voorspeld.

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Chapter 1
General introduction

1.1 Sustainable utilization as a conservation paradigm

Sustainable utilization of wildlife is the current conservation paradigm in the Southern African wildlife management strategies. This paradigm promotes the coexistence of wildlife and humans in landscapes outside of the national parks, particularly in communally managed areas such as the communal agricultural landscapes or in landscapes that are used for other purposes such as for pastoralism, timber extraction or mining, through non-exhaustive utilization of wildlife (Hoare and Du Toit 1999, Hulme and Murphree 2001). This sustainable utilization is a relatively new conservation paradigm in communally managed areas and it advocates for the wise use of natural resources while not compromising the future availability of the natural resource. The inception of this paradigm in the communal areas followed a realization in the early 1980s that the wildlife preservation strategy had failed as poaching in wildlife reserves and particularly, expanding agricultural activities, e.g., arable agricultural field expansion in wildlife habitats continued to cause wildlife species loss (Hulme and Murphree 2001). Thus, the sustainable utilization marks a departure from the preservation paradigm that advocates for the total exclusion of wildlife in landscapes outside of the national parks (Prins*, et al.* 2000). However, the success of the sustainable utilization paradigm in conserving wildlife species hinges upon the persistence of wildlife species in the landscapes outside of the national parks, especially in communal lands. In other words, only when wildlife species are present outside the national parks in preferred numbers the sustainable utilization paradigm succeeds.

In order to sustainably utilize wildlife, there is a need to understand and promote landscape conditions that enable the persistence of wildlife, particularly in unfenced communally managed agricultural landscapes. This focus on sustainability may take the form of understanding the habitat conditions under which wildlife species of interest can persist, in the face of pressure from expanding agricultural activity. The term habitat is generally defined as the place where an animal lives and this takes into consideration that all animals, excluding humans, can live in an area with sufficient basic resources such as food, water and cover (Morrison, *et al.* 1992). In this regard, the need for researchers to devote attention to the habitat of wildlife species they are studying has been emphasized (Yapp 1922, Southwood 1977) and not so much their coexistence with humans. However, agricultural landscapes provide unique environments where agricultural fields and human settlements subdivide a continuous habitat into discontinuous habitat patches of different quality and spatial arrangements. In other words, agricultural activity results in a landscape that is uniquely spatially heterogeneous (patchy). In this situation, not only the amount of natural habitat is important, but the spatial arrangement and the amount of natural vegetation cover in the habitat patches also become particularly critical. Therefore, all being the same, whether wildlife species populations can persist in an unfenced agricultural landscape could be a function of how suitable the spatial arrangement of natural habitat patches is for the particular wildlife species. In other words, the persistence of a wildlife species population in an agricultural landscape that is not bound by a wildlife fence could be a function of the optimal levels of spatial heterogeneity that results from the imposition of agricultural activity (e.g., arable fields and logging) and human settlements on the natural habitat template. These optimal levels of spatial heterogeneity then define habitat permitting the coexistence of both wildlife and humans in a sustainable way.

As a preamble, the terms landscape and spatial heterogeneity need to be properly defined to avoid unnecessary confusion. A landscape is defined as an area that is spatially heterogeneous (Pickett and Rogers. 1997) and ranges in size from a few square metres to tens of square kilometres. Spatial heterogeneity is defined as the patchiness of a landscape property in space, e.g., vegetation cover (Legendre and Fortin 1989, Pickett and Rogers. 1997, Gustafson 1998). A patch is defined as an internally homogenous entity in the landscape (Kotliar and Wiens 1990).

In other words, a patch is a definable area on the Earth's surface whose structure differs from adjacent areas (Pickett and Rogers. 1997). However, the perception of the internal homogeneity of the patch may vary between wildlife species (Hostetler 1999).

To the best of our knowledge, not much is currently known about the response of wildlife species to spatial heterogeneity. Although, empirical and theoretical literature indicates the importance of spatial heterogeneity to wildlife species distribution (Turner 1989, Johnson, *et al.* 1992, Kareiva and Wennergren 1995, Turner, *et al.* 1997, Lynam and Billick 1999, Adler, *et al.* 2001), an understanding of the optimal levels of spatial heterogeneity at which specific wildlife species can persist in agricultural landscapes is still rudimentary. This has been attributed to the lack of clarity in the definition and therefore, quantification of spatial heterogeneity (Sparrow 1999).

1.2 Quantifying spatial heterogeneity

In this thesis, special focus is put on the quantification of spatial heterogeneity as a forerunner (Perry, *et al.* 2002) to testing hypotheses about ecological patterns such as wildlife species distribution. Traditionally, researchers have quantified spatial heterogeneity from remote sensing images using two basic approaches: (a) the direct image approach, where variance measures derived from 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 its choice of scale is arbitrary, thus it is subjective. 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 categorical maps upon which the patch mosaic model depends facilitate the contextual interpretation of spatial heterogeneity. Furthermore, 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, categorical representation of spatial heterogeneity may not be valid in most landscapes where gradients exist and therefore boundaries between patches are not clearly defined (Pearson 2002).

Therefore, by using either of the abovementioned approaches to predict ecological patterns, only the influence of measured spatial heterogeneity is considered, which either reflects the arbitrary scale at which the observer collected the data (i.e., the grain) or the scale at which the observer delimited patches. This is in contrast to functional spatial heterogeneity (Legendre 1998), which reflects the dominant scale of natural variability (see next paragraph) that influences the response of specific organisms in the landscape (Western and Bloschl 1999). Furthermore, this single scale approach is inconsistent with the hypothesis that the scale at which humans perceive spatial heterogeneity may have little connection to the scale at which wildlife species perceive spatial heterogeneity (Turner 1989). Thus, in view of these limitations, it can be argued that further advances in understanding ecological patterns may be constrained by the underdevelopment of approaches and analytical tools for characterising spatial heterogeneity.

In this thesis, a new approach to characterise spatial heterogeneity from remote sensing imagery is developed, based on the intensity, as well as the dominant scale. 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

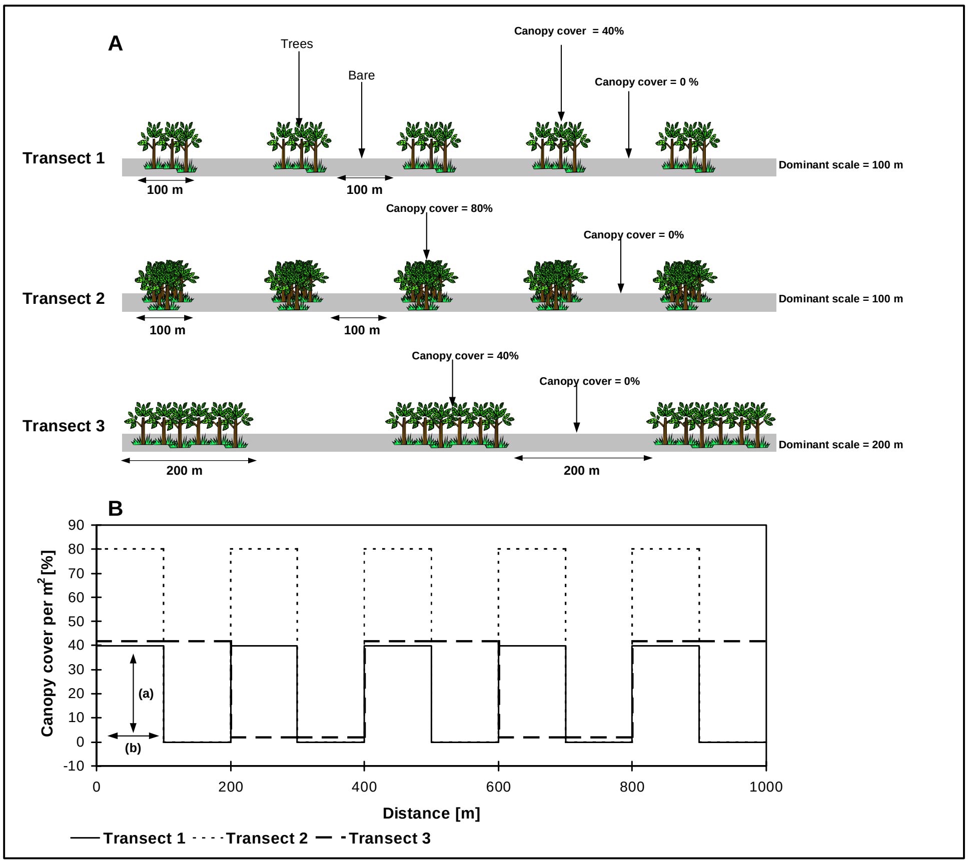

Figure 1.1: Part (A) are transects with alternating spaces of trees and bare ground and part (B) shows the simulation tree canopy cover along each transect assuming that the cover measurements are made after every 1 m (i.e., grain = 1 m) and an extent of 1000 m. For example, the (a) intensity (maximum variance) of transect 1 occurs at (b) a dominant scale of 100 m.

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 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) whereby scale refers to 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. Hereinafter, we treat scale as a linear dimension, e.g., m, km. Note that the definition of scale used in this thesis is the opposite of the cartographic definition (Foody and Curran 1994). We therefore propose that spatial heterogeneity be defined and quantified using both intensity and the dominant scale. However, 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).

Furthermore, in order to elucidate the centrality of the intensity and the 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. 1.1). 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 (initial observation scale) while 1000 m defines the extent (overall 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. Therefore, both intensity and dominant scale of spatial heterogeneity cannot be separated and must be quantified prior to analysing ecological patterns.

1.3 Thesis objectives

In this thesis, the objectives were: (1) to develop a new approach to quantify spatial heterogeneity from remote sensing imagery, based on the intensity and the dominant scale, and (2) to investigate whether the new approach can be used to reliably predict the probability of wildlife species presence, particularly that of the elephant (*Loxodonta africana*) in the communal lands (i.e., agricultural landscape) of the Sebungwe (fig. 1.2) between 1983 and 1995.

Fig. 1.3 is a graphic illustration of the hypothesised relationship between elephant and the dominant scale and intensity of spatial heterogeneity. Specifically, we hypothesise that the probability of elephant presence yields a unimodal and a positive asymptotic response to the dominant scale and the intensity of spatial heterogeneity respectively (fig.1.3c). The unimodal component of the model with regards to the dominant scale of spatial heterogeneity (fig. 1.3a) is a result of small patch sizes "repelling" elephants due to inadequate cover against human disturbance (e.g., by simple human contact or hunting) while at larger dominant scales, the enlarged hostile patches "repel" elephants. The latter patches can be, for instance, agricultural fields or bare ground. In addition, the hypothesised positive asymptotic response of elephant presence to the intensity of spatial heterogeneity is because at high variability of vegetation cover, the chances of the elephant to find food and shelter increase, but as the variability becomes increasingly higher, it tends to have no effect on the elephant presence (fig. 1.3b).

Moreover, in this thesis, focus was on a single species, i.e., the African elephant. This single species approach was adopted because different wildlife species interact with spatial heterogeneity differently (Wiens 1989, Van Langevelde 1999, Bailey, *et al.* 2002). For example, larger animal or bird species are likely to perceive spatial heterogeneity at a larger dominant scale than smaller animal or bird species (Hostetler 1999) based on their mobility and size. This thesis focused on the African elephant and several reasons justified the choice its choice. Firstly, the Africa elephant is a keystone species of the African savanna (Hoare and Du Toit 1999) that needs to be conserved. Secondly, the African elephant is on the list of the world's endangered species (IUCN 2002) and is considered a conservation priority (Burton 1999). Thirdly, the study area has been the only agricultural landscape in Zimbabwe outside the protected areas with a healthy expanding elephant population (Cumming 1981) that may now be threatened by agriculture. Fourthly, there is no water limitation in the study area (Cumming 1981), and since the African elephant is a habitat generalist (Kingdon 2001) it has a potential of being anywhere in the study area and only the level of agricultural field driven spatial heterogeneity can affect its distribution. Fifthly, good survey data exists on the spatial distribution of the African elephant in the study area.

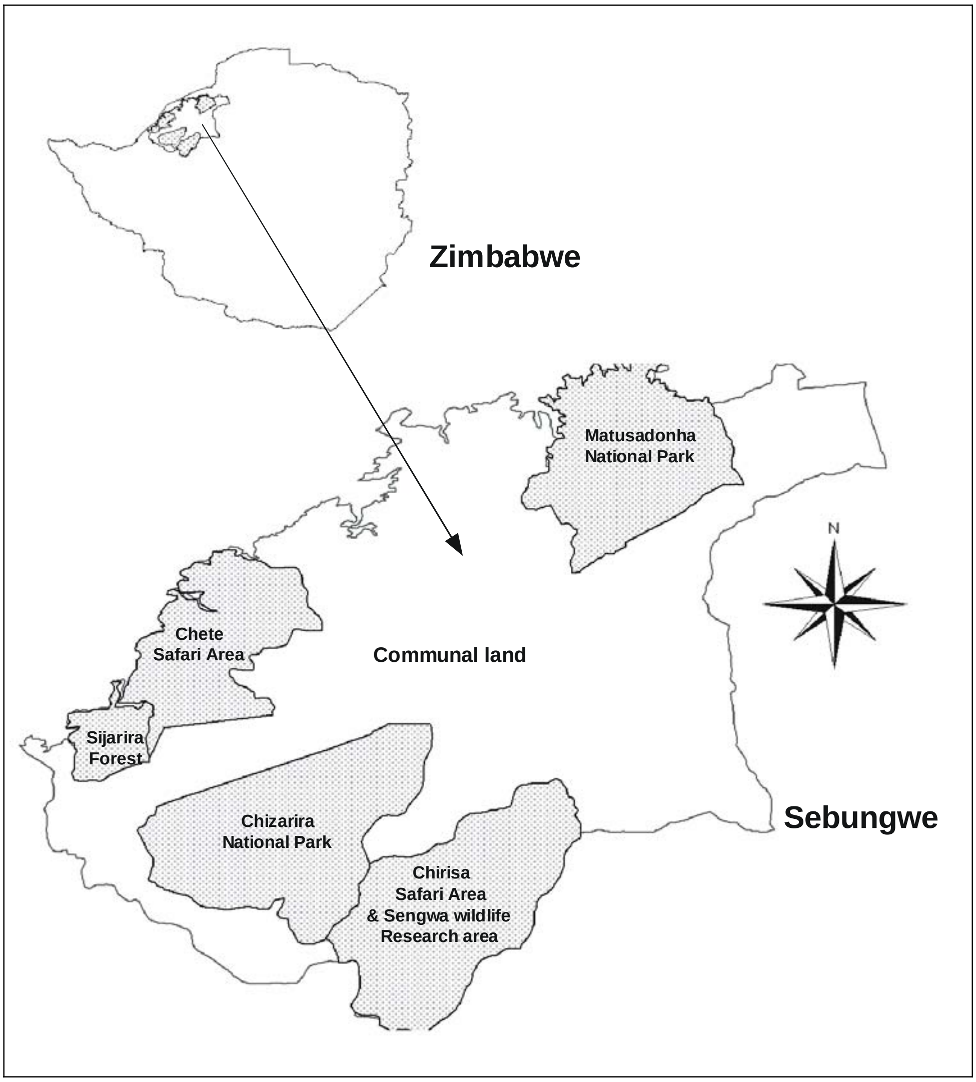

Figure 1.2: Map showing the location of the Sebungwe region in Zimbabwe.

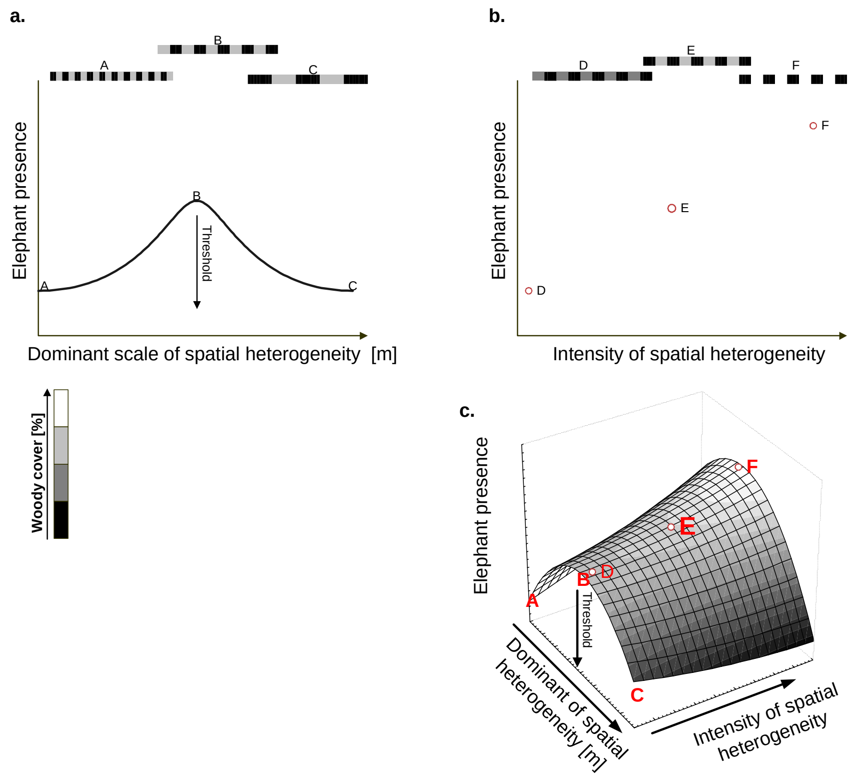

Figure 1.3: Hypothetical relationship: between elephant presence and: (a) the dominant scale of spatial heterogeneity, (b) the intensity of spatial heterogeneity, plus (c) both the dominant scale and intensity of spatial heterogeneity. The bars in (a) with gray levels representing woody cover in indicate variations in the dominant scale of spatial heterogeneity in different parts of the landscape, i.e., from (A) small a dominant scale of spatial heterogeneity, (B) medium dominant scale of spatial heterogeneity, to a large dominant scale of spatial heterogeneity (C). The bars in (b) represent the same dominant scale of spatial heterogeneity with increasing levels of intensity, from (D) low, (E) medium to (F) high.

Furthermore, Landsat TM imagery was selected as the appropriate source of remote sensing imagery to characterise the spatial heterogeneity of vegetation amounts, estimated using the normalised difference vegetation index (NDVI). This is because the spatial resolution or grain of Landsat TM, i.e., 30 m by 30 m was detailed enough to enable the quantification of spatial heterogeneity that is relevant for analysing elephant distribution. Generally, the grain should be several magnitudes smaller than the total range of the organism (Sparrow 1999). In this case, elephants in the Sebungwe region have an estimated range of between 83 km^2 to 263 km^2, approximating a horizontal length scale (horizontal dimension) of 9.1 km and 16.2 km, respectively (Guy 1976a, Dunham 1986) thus, making the grain of 30 m at least 300 times smaller than the dimension of the elephant range. In addition, the extent of the study area, i.e., 3721 km^2, which is at least 14 times the range of the elephant in the Sebungwe, is large enough for this study.

1.4 Thesis Outline

This thesis is based on a series of papers; each chapter can be read as a stand-alone unit. As a result, some degree of repetition of terms and definitions is inevitable among the chapters; however, they are considered important in each case.

Chapter 1 provides a brief background of approaches to quantify spatial heterogeneity of landscapes as well as, introducing our new approach to quantifying spatial heterogeneity, objectives and outline of the thesis.

In Chapter 2, wavelets and variograms are explored as methods to quantify the dominant scale and intensity of spatial heterogeneity of a landscape, using artificial transect data with known characteristics, as well as remotely sensed NDVI imagery of actual landscapes. In addition, Chapter 3 demonstrates the use of wavelets to detect change in spatial heterogeneity of NDVI over time from the intensity and the dominant scale perspective.

Chapter 4 puts the thesis into context by presenting the dynamics of agricultural fields in the Sebungwe landscape following tsetse eradication, as well as, making an initial test of whether the expanding agricultural fields had a significant effect on the probability of elephant presence in different wards and vegetation classes of the study area. This chapter provides a necessary preamble to the investigation of whether and how the probability of elephant presence in different parts of the study area was as a function of spatial heterogeneity.

In chapter 5, the results of whether the new intensity and dominant scale approach to quantify spatial heterogeneity (implemented using variograms and wavelets) can predict the probability of elephant presence better than the usual NDVI average and the NDVI coefficient of variation that assume a uniform scale are presented.

Chapter 6 and Chapter 7 further present results on an investigation of whether the spatial distribution of the elephant in the Sebungwe agricultural landscape (1) consistently responded to spatial heterogeneity of NDVI irrespective of time and also (2) whether the spatial distribution of the elephant respond to changes in the spatial heterogeneity of NDVI. In Chapter 6, the variogram-derived intensity and dominant scale of spatial heterogeneity of NDVI were used while in Chapter 7, wavelet transform-derived intensity and dominant scale of spatial heterogeneity of NDVI were used.

Finally, Chapter 8 synthesizes the findings of the thesis and discusses the implications of these to the modelling of ecological patterns, as well as the future management of wildlife species in the increasingly human dominated landscapes such as the Sebungwe region.

Chapter 2

Characterising the spatial heterogeneity of a landscape[1]

Amon Murwira and Andrew K. Skidmore

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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[1] In review: International Journal of Geographical Information Science

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

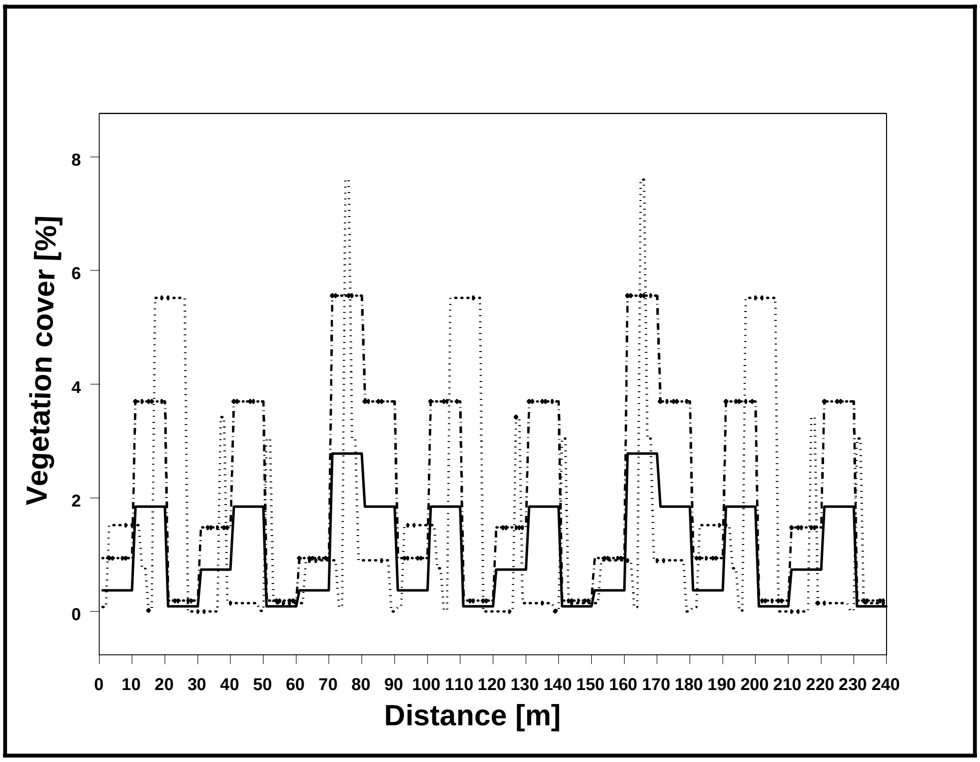

Figure 2.1: Artificial transects simulating vegetation cover with different dominant scales or intensity of spatial heterogeneity. Transects A (-) and B (-·-) have the same dominant scale of spatial heterogeneity (10 m), but transect B has a higher intensity than transect A. Transect C (······) has two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

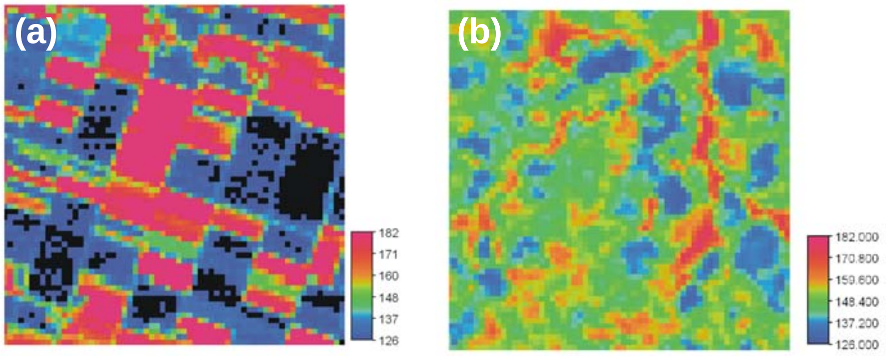

Figure 2.2: The NDVI images derived from Landsat TM imagery (same pixel size or grain of 30 m) of the northern Netherlands (a) and northwestern Zimbabwe (b) study sites. Low NDVI values indicate low vegetation cover while high NDVI values indicate high vegetation cover.

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.

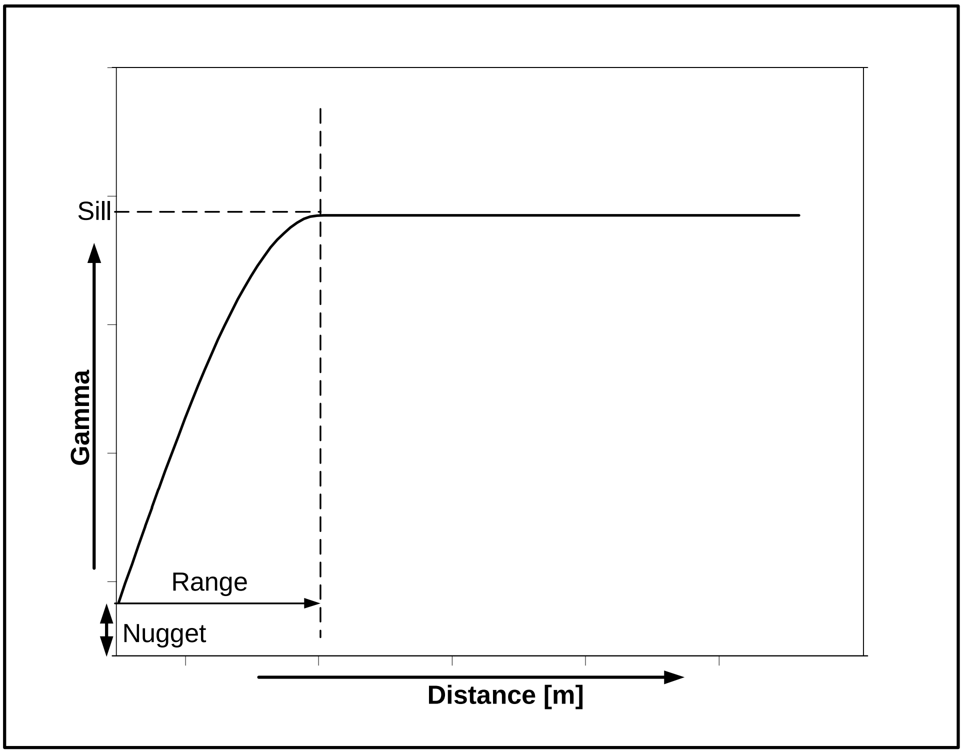

Figure 2.3: The three parameters (i.e., nugget, the range and sill) of the variogram used to measure dominant scale and intensity.

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

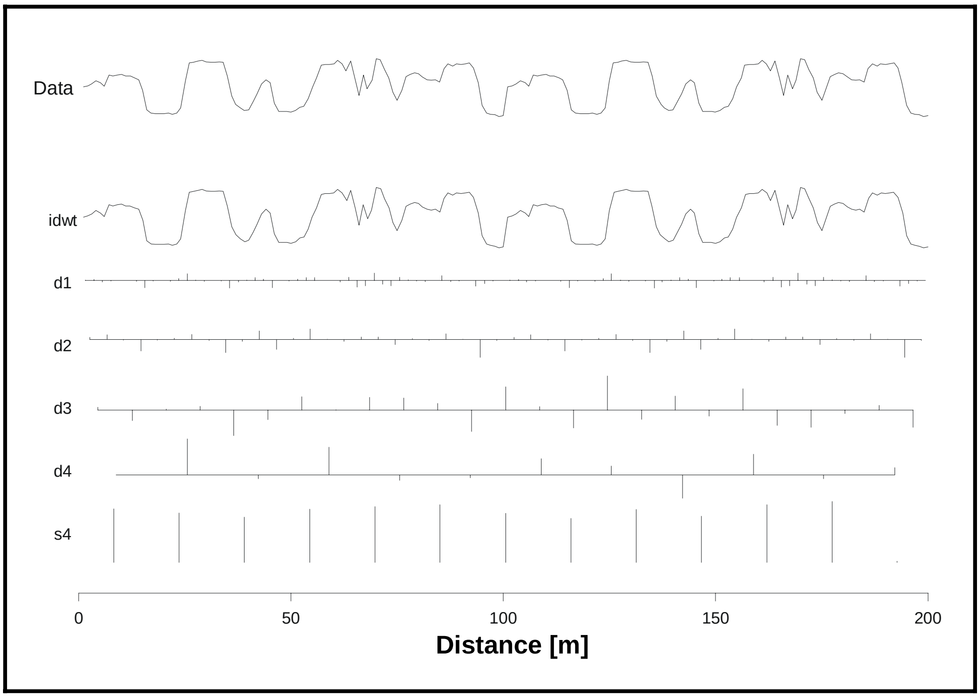

Figure 2.4: The Haar wavelet transform showing wavelet coefficients of four scale levels. Idwt is the data function reconstructed using inverse discrete wavelet transform. The d1…d4 are detail wavelet coefficients at levels *j* = 1…*j* = 4, and S4 are the smooth wavelet coefficients at level *j* = 4. 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.

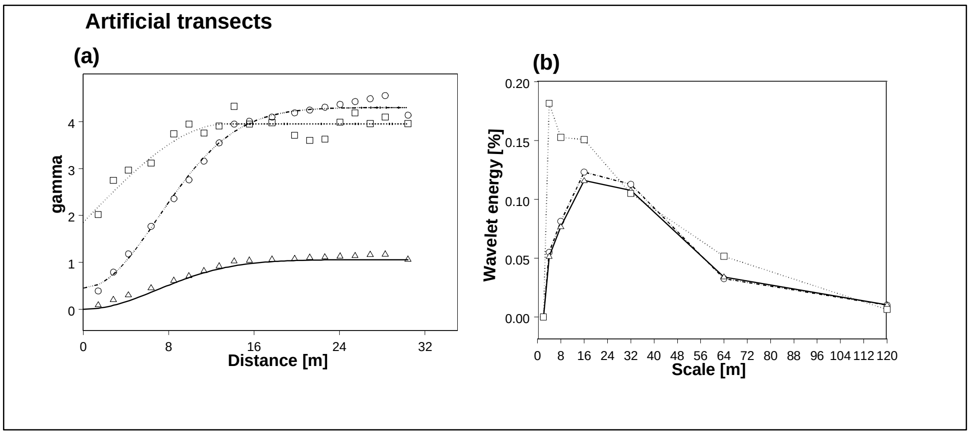

Figure 2.5: The variogram (a) and wavelet energy (b) functions describing spatial heterogeneity in artificial transects A (△), B (○) and C (□).

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.

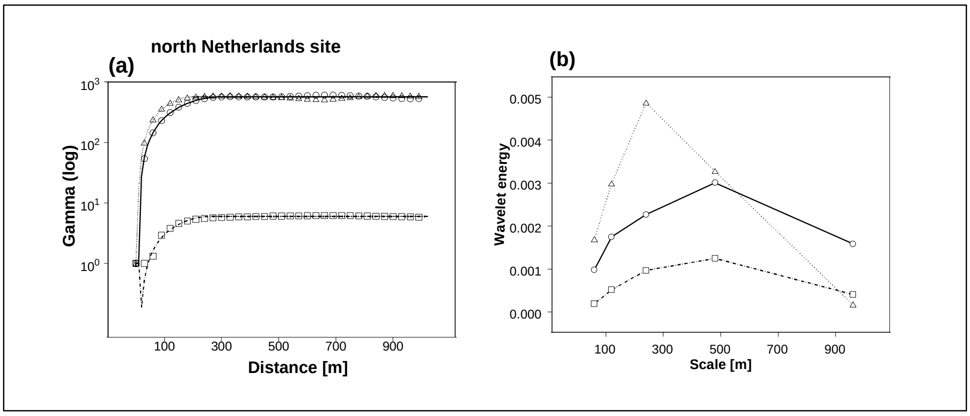

Figure 2.6: The variogram (a) and wavelet (b) functions describing the spatial heterogeneity of the north Netherlands NDVI image in the horizontal (east-west) (○), and diagonal (northeast-southwest and northwest-southeast) (□) and vertical (north-south) (△) orientations.

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.

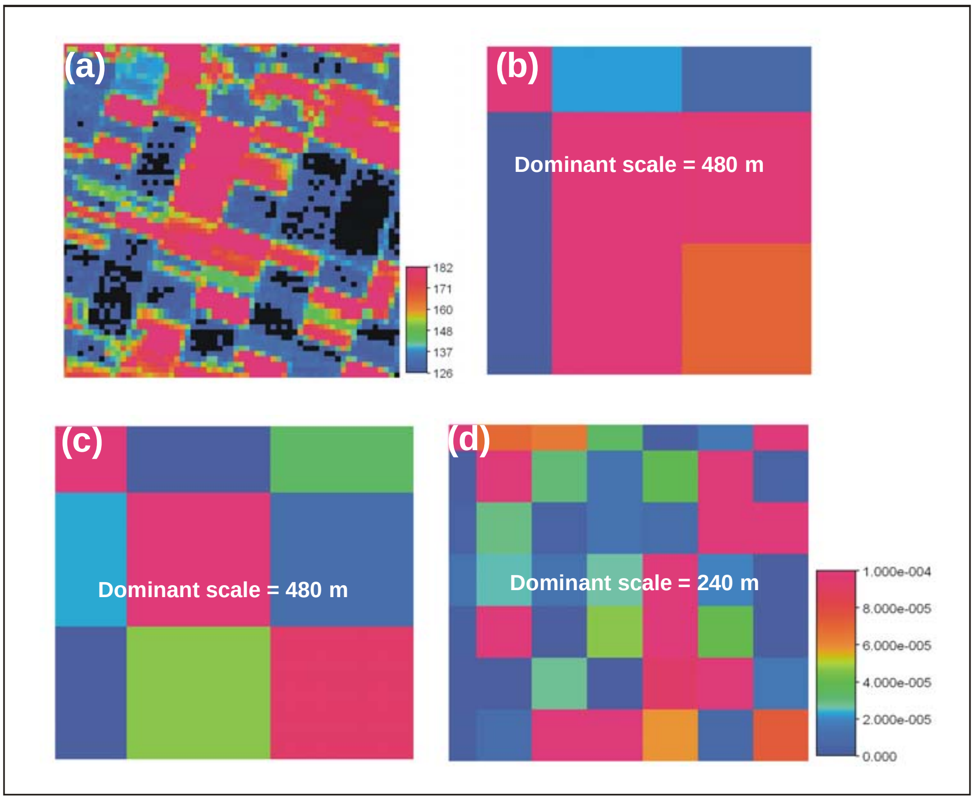

Figure 2.7: The north Netherlands site showing the (a) original NDVI image and the wavelet energy images that make up the most dominant scales of spatial heterogeneity in the (b) horizontal (east-west), (c) diagonal (northeast-southwest and northwest-southeast) and (d) vertical (north-south) orientations.

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.

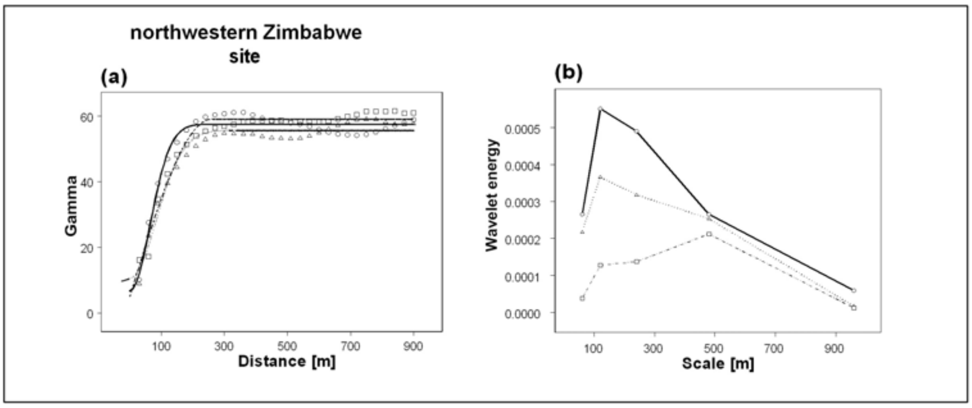

Figure 2.8: The variogram (a) and wavelet (b) functions describing the spatial heterogeneity of the northwestern Zimbabwe NDVI image in the horizontal (east-west) (○), and diagonal (northeast-southwest and northwest-southeast) (□) and vertical (north-south) (△) orientations.

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.

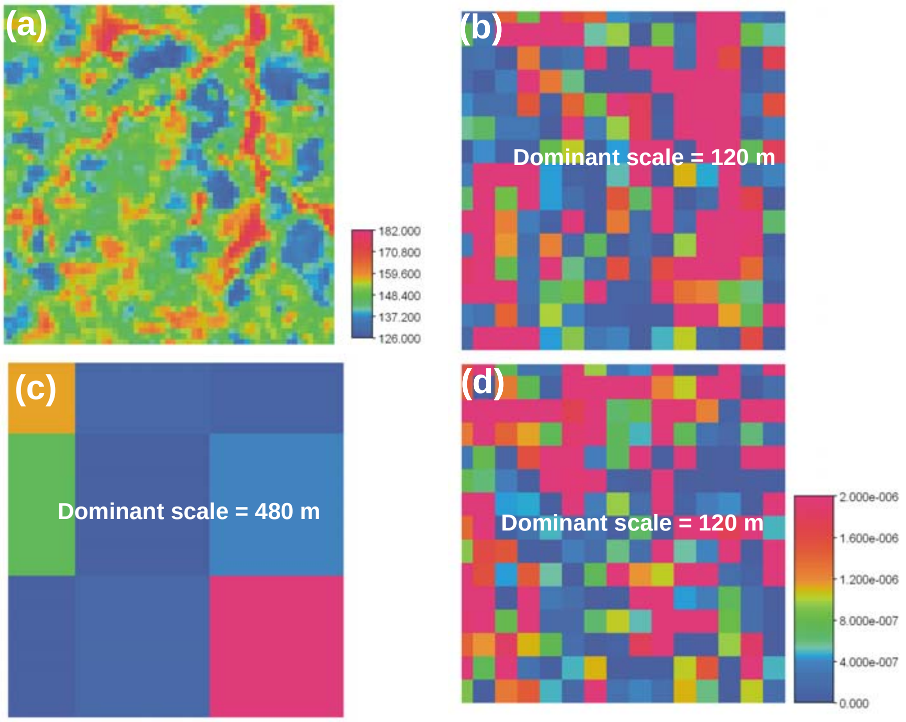

Figure 2.9: The Zimbabwe site showing the (a) original NDVI image and the wavelet energy images that make up the most dominant scale of spatial heterogeneity in the (b) horizontal (east-west), (c) diagonal (northeast-southwest and northwest-southeast) and (d) vertical (north-south) orientations.

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.

Chapter 3

Detecting changes in the spatial heterogeneity of NDVI using a wavelet transform[2]

Amon Murwira and Andrew K. Skidmore

Abstract

We investigate the use of a wavelet transform to detect changes in the intensity of spatial heterogeneity (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 of spatial heterogeneity (i.e., the scale or window size at which the intensity is recorded) based on a normalised difference vegetation index (NDVI) of 1984 and 1999 in northwestern Zimbabwe. The results demonstrated that a wavelet transform implemented within the innovative framework of the intensity and dominant scale of spatial heterogeneity could be an invaluable tool to analyse scale explicit changes in the landscape. We concluded that this approach positively capitalises on the strengths of both the pixel-based or post-classification-based change detection methods. In addition, we concluded that this innovative approach could improve the understanding of ecological patterns and their dynamics in the landscape. In other words, it has a potential to radically improve studies that aim at predicting the spatial distribution and redistribution of organisms in the landscape in a scale explicit fashion.

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[2] In review: International Journal of Remote sensing

3.1 Introduction

In a landscape, land cover is spatially heterogeneous (i.e., patchy), as well as temporally dynamic (Turner 1989). In addition, spatial heterogeneity of land cover is hypothesised to regulate biosphere dynamics such as the hydrological cycle and the variability in the spatial distribution of terrestrial wildlife species (Morrison, *et al.* 1992, Mac Nally and Bennet 1997). In this regard, the monitoring of changes in the spatial heterogeneity of land cover is critical for understanding global change, as well as changes in wildlife habitat.

The advent of satellite remotely sensed data and the concurrent development of digital change detection have improved the capacity to monitor changes in the spatial heterogeneity of land cover over time in large areas (Almeida-Filho and Shimabukuro. 2002, Rogan, *et al.* 2002). Thus, traditionally, remote sensing has used change detection techniques to monitor the spatial heterogeneity of land cover over time, largely at the grain (i.e., spatial resolution) of the satellite sensor. However, the limitation of this approach is that its choice of scale is arbitrary, thus it is subjective. This is because by assuming a constant and arbitrary pixel size or scale across the image, this approach ignores the scale dimension of spatial heterogeneity (Legendre and Fortin 1989, Legendre 1998, Ettema and Wardle 2002). In other words, it is difficult to neglect the fact spatial heterogeneity occurs at a diversity of scales and that, often some scales are relatively more important than others (Wiens 1989, Hall and Hay 2003). Alternatively, remote sensing has used post classification techniques to detecting change in spatial heterogeneity (Trani and Giles 1999). However, the major weakness of this approach is that characterisation of spatial heterogeneity is highly dependent on the initial definition of mapping units by the researcher (Turner 1989). In fact, using this approach, the variation within the patches is suppressed and assumed to be irrelevant (McGrigal and Cushman 2002).

Moreover, despite a recent interest in scale explicit analyses of remotely sensed imagery (Qi and Wu. 1996, Friedl 1997, Goodchild and Quattrochi. 1997, Walsh, *et al.* 1997, Hay, *et al.* 2001), approaches and methods to achieve this goal remain largely underdeveloped. Therefore, in this study we develop a new approach to monitor spatial heterogeneity of land cover from remote sensing imagery, based on intensity and dominant scale. 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 maximum degree of contrast in vegetation cover between the bare ground and the tree stands. Therefore, we can argue that the dominant scale is the relatively most important scale of spatial heterogeneity in the landscape. The definition of scale used in this study follows that of (Levin 1992, 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 this study, scale is treated as a linear dimension, e.g., m, km etc. 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). We propose that spatial heterogeneity be quantified and monitored using both the intensity and the dominant scale. Therefore, the need to use methods that implement this approach is critical.

A wavelet transform can be used to analyse satellite remotely sensed data to detect changes in the dominant scale and intensity of spatial heterogeneity of land cover over time. This is because wavelets partition the variance of a data function such as a satellite image on a scale-by-scale basis (Lindsay, *et al.* 1996). Wavelet transform was initially developed in the 1980s for signal analysis, but has also enjoyed increased attention in landscape studies (Bradshaw and Spies. 1992, Dale and Mah. 1998, de Carvalho 2001, Epinat, *et al.* 2001). However, to the best of our knowledge the application of wavelets to analyse changes in the spatial heterogeneity of land cover from a dominant scale and intensity perspective has not been done.

In this study, the objective was to test whether a wavelet transform can be used to analyse change in the dominant scale and intensity of spatial heterogeneity of land cover estimated from a normalised difference vegetation index (NDVI) images. To accomplish our objective, we selected of a part of northwestern Zimbabwe. This particular site was selected because there were very visible changes that occurred between 1984 and 1999, thus making the site suitable for testing whether a wavelet transform can be used to analyse change in the dominant scale and intensity of spatial heterogeneity of land cover.

3.2 Materials and methods

Remote sensing

Two Landsat TM images acquired on the 19th of October 1984 and 6th of November 1999 were used in this study. The images were subset to extract a farming area of a size 6 km x 6 km. The farming area is situated in the northern part of Zimbabwe. This particular site was selected because there are obvious changes that occurred between 1984 and 1999, particularly the presence of dammed water bodies in 1999 that were absent in 1984 with the corresponding presence of irrigated fields (see fig. 3.2 below). Firstly, the images were geometrically matched. Secondly, a relative atmospheric correction using the a regression method was applied on each band to correct for any radiometric differences that may have arisen due to atmospheric differences between the two dates (Song, *et al.* 2001). The pseudo variant objects that were used for the regression analysis were deep-water bodies and airstrips present in both images (fig. 3.1).

Next, we estimated land cover heterogeneity for each date using *NDVI*, derived from the TM image:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{3.1}$$

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 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

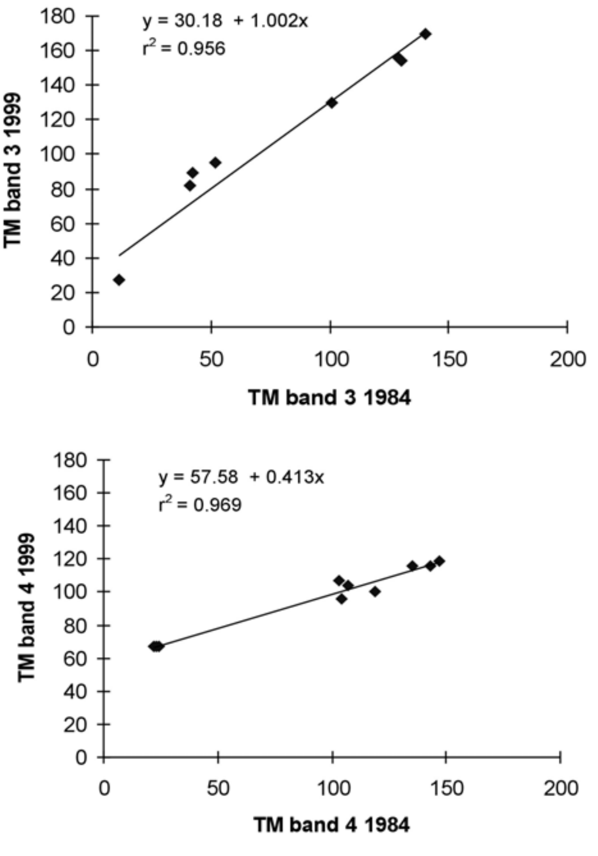

Figure 3.1: Relationship between the DN values of sampled pseudo variant objects between the Landsat TM images of 19 October 1984 and 6 November 1999.

cover and therefore, can be used as an indicator of spatial heterogeneity in the landscape (Kerr and Ostrovysky 2003). Fig. 3.2 shows the NDVI images of the study site for 1984 and 1999.

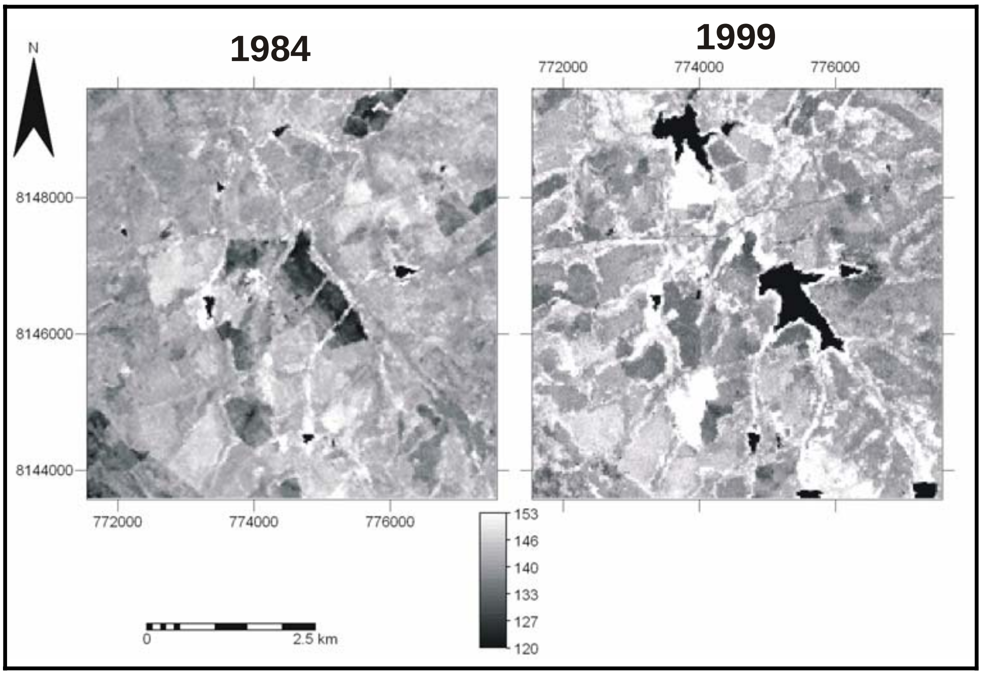

Figure 3.2: The 1984 and 1999 NDVI images of the study site. Low NDVI values indicate low vegetation cover and high NDVI values indicate high vegetation cover within a 0 (no vegetation) to 255 (high vegetation cover) range. The coordinates in metres (Universal Transverse Mercator (UTM) projection Zone 35 South).

Detecting change in spatial heterogeneity using a wavelet transform

A wavelet transform (Bruce and Hong-Ye 1996) was used to characterise the changes in the intensity of spatial heterogeneity, as well as the dominant scale of spatial heterogeneity in the NDVI images of 1984 and 1999. As a preamble, we denoted the 1984 image by $F(x,y)$ and the 1999 image by $Z(x,y)$. It is important to note that both images have the same spatial resolution s in both directions (i.e., s = 30 m). The analysis of the change in spatial heterogeneity started with a wavelet transform (a Haar wavelet was used), which is defined as the convolution of two wavelet functions, i.e., the *smooth function* $\phi(x,y)$ and *detail function* $\varphi(x,y)$, and a function $f(x,y)$ at successive bases, (2^j), i.e., $j = 0,1,2 \ldots J$ in the vertical (north-south), diagonal (northeast-southwest and southeast-northwest) and horizontal (east-west) directions. A wavelet transform results in a set of coefficients where each coefficient is associated with a base level (i.e., $j = 0,1,2 \ldots J$), a direction and a particular location.

Thus, the wavelet approximations, $\hat{F}(x,y)$ and $\hat{Z}(x,y)$, of the original NDVI images $F(x,y)$ and $Z(x,y)$ respectively are each a is a sum of the smooth and the detail functions at different bases:

$$\hat{F}(x,y) = S_J(x,y) + \sum_{j=1}^{J} \sum_{dir} D_j^{dir}(x,y) \tag{3.2}$$

$$\hat{Z}(x,y) = S_J(x,y) + \sum_{j=1}^{J} \sum_{dir} D_j^{dir}(x,y) \tag{3.3}$$

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 $j = 0$. Therefore, each scale level j corresponds to a grain equals $2^j * s$ where s is the size of the original grain at which the NDVI 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 5, an equivalent of a spatial dimension of 960 m. Note that the theory and formal treatment of wavelets has been covered exhaustively elsewhere (Mallat 1989, Ogden 1997)

In a wavelet transform, wavelet coefficients can either be positive or negative. However, the absolute coefficient value measures the magnitude of contrast in a function (in the case, $F(x,y)$ and $Z(x,y)$ at a specific location with a base of 2^j. Therefore, we calculated wavelet energy 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 $\hat{F}(x,y)$ and $\hat{Z}(x,y)$:

$$E_j^d = \frac{1}{E}\sum_{k=1}^{n/2^j} d^2 j(x,y),\ j = 1,2,3\ldots J \tag{3.4}$$

where $d_{j(x,y)}$ are the detail wavelet coefficients at j and position (x,y), E is the total sum of squares of either $\hat{F}(x,y)$ or $\hat{Z}(x,y)$, and $n/2^j$ is the number of coefficients at level *j*. We used wavelet energy to determine the intensity and the dominant scale of spatial heterogeneity.

In order to analyse the changes in spatial heterogeneity between 1984 and 1999, we began by plotting the wavelet energy functions for 1984 and 1999 using only the significant wavelet coefficients obtained after applying a universal filter (Bruce and Hong-Ye. 1996) to all the wavelet coefficients (i.e., in the horizontal (east-west), vertical (north-south), and diagonal (northeast-southwest and northwest-southeast) orientations). Specifically, the wavelet energy values obtained for 1984 and 1999 were plotted separately against scale (i.e., from 60 m to 960 m). Next, to see whether there was a change in spatial heterogeneity, the highest local maxima representing the intensity, as well as the corresponding dominant scale of spatial heterogeneity in 1984 and 1999 were determined and compared. It is important to note that this was implemented using only the detail functions rather than the smooth approximations. This is because detail functions 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. Finally, we plotted the maps of the wavelet coefficients that correspond to the intensity and the dominant scales of spatial heterogeneity at which the intensity occurred in both 1984 and 1999.

3.3 Results

Fig. 3.3 shows the wavelet energy functions that resulted from the wavelet transform of the 1984 and 1999 NDVI images. It can be observed that in the horizontal (east-west) orientation, the intensity of spatial heterogeneity occurred at a dominant scale 120 m in 1984 whereas in 1999 it occurred at a dominant scale of 480 m, an increase of 360 m.

In addition, it can be observed that in the vertical (north-south) orientation the intensity of spatial heterogeneity occurred at the dominant scale of 240 m in 1984 whereas in 1999 it occurred at a dominant scale of 480 m, an increase of 240 m. Also, in the diagonal (northeast-southwest and northwest-southeast) orientation, the intensity of spatial heterogeneity occurred at a dominant scale of 240 m in 1984 whereas in 1999 it occurred at a dominant scale of 480 m. Furthermore, it can be generally observed that the intensity of spatial heterogeneity was higher in 1999 compared with 1984.

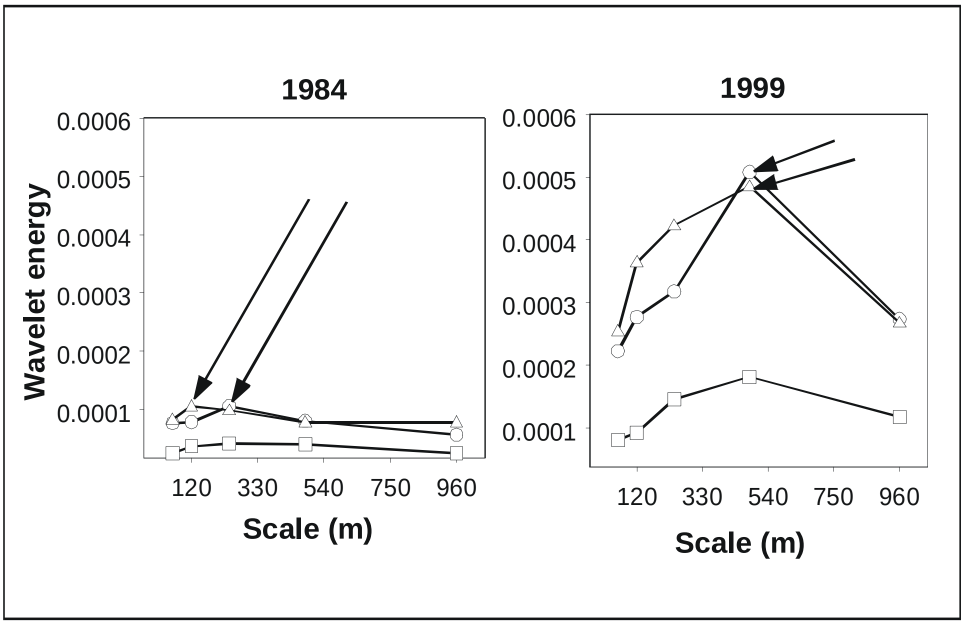

Figure 3.3: Directional wavelet energy functions for study site in the (△) horizontal (east-west), (○) vertical (north-south) and (□) diagonal (northeast-southwest and northwest-southeast) orientation in 1984 and 1999. The arrows indicate the intensity, as well as the dominant scale of spatial heterogeneity in the horizontal (east-west) and vertical (north-south) orientations in 1984 and 1999.

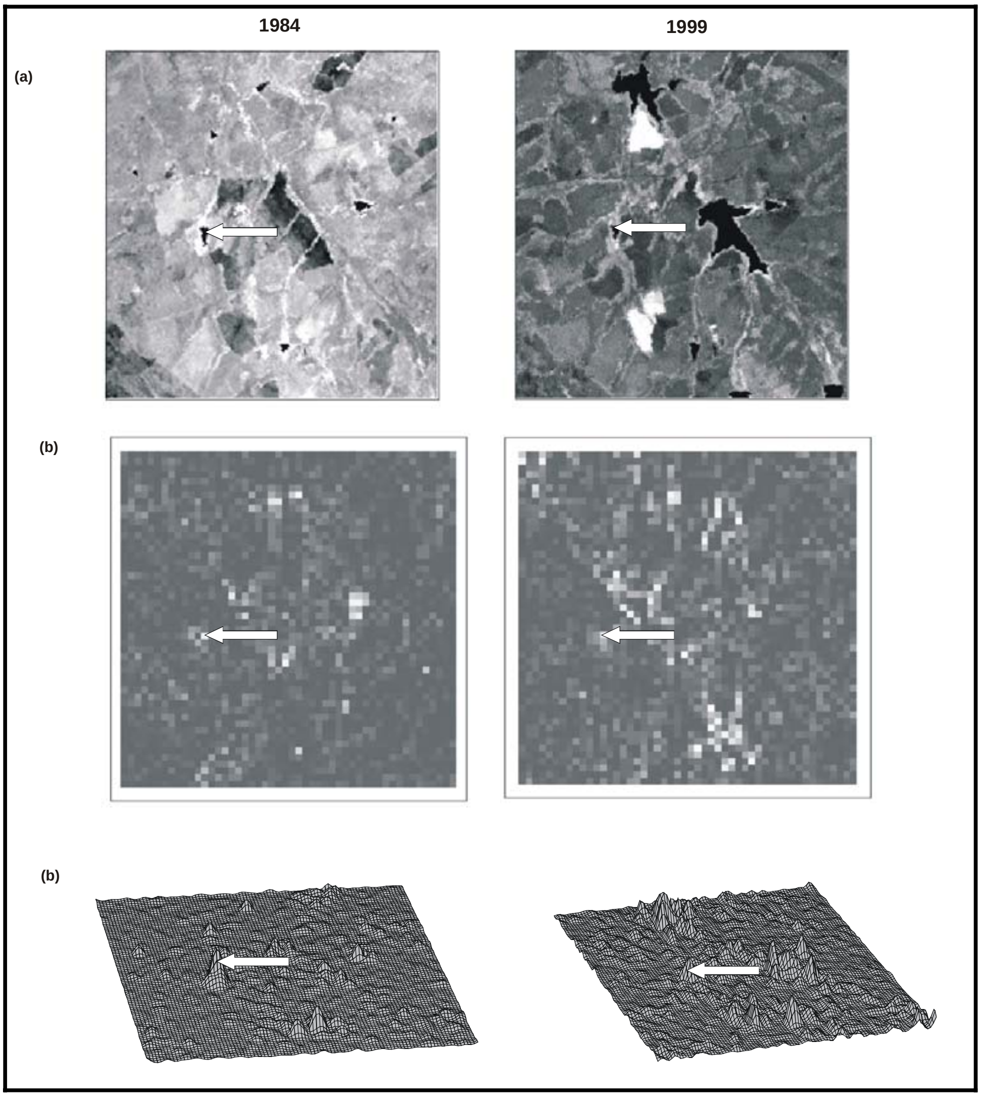

Figure 3.4: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the horizontal (east-west) orientation in 1984 shown in fig. 3.3 (i.e., dominant scale = 120 m). The arrows indicate a high wavelet coefficient that coincides with the small water body in 1984 and in 1999.

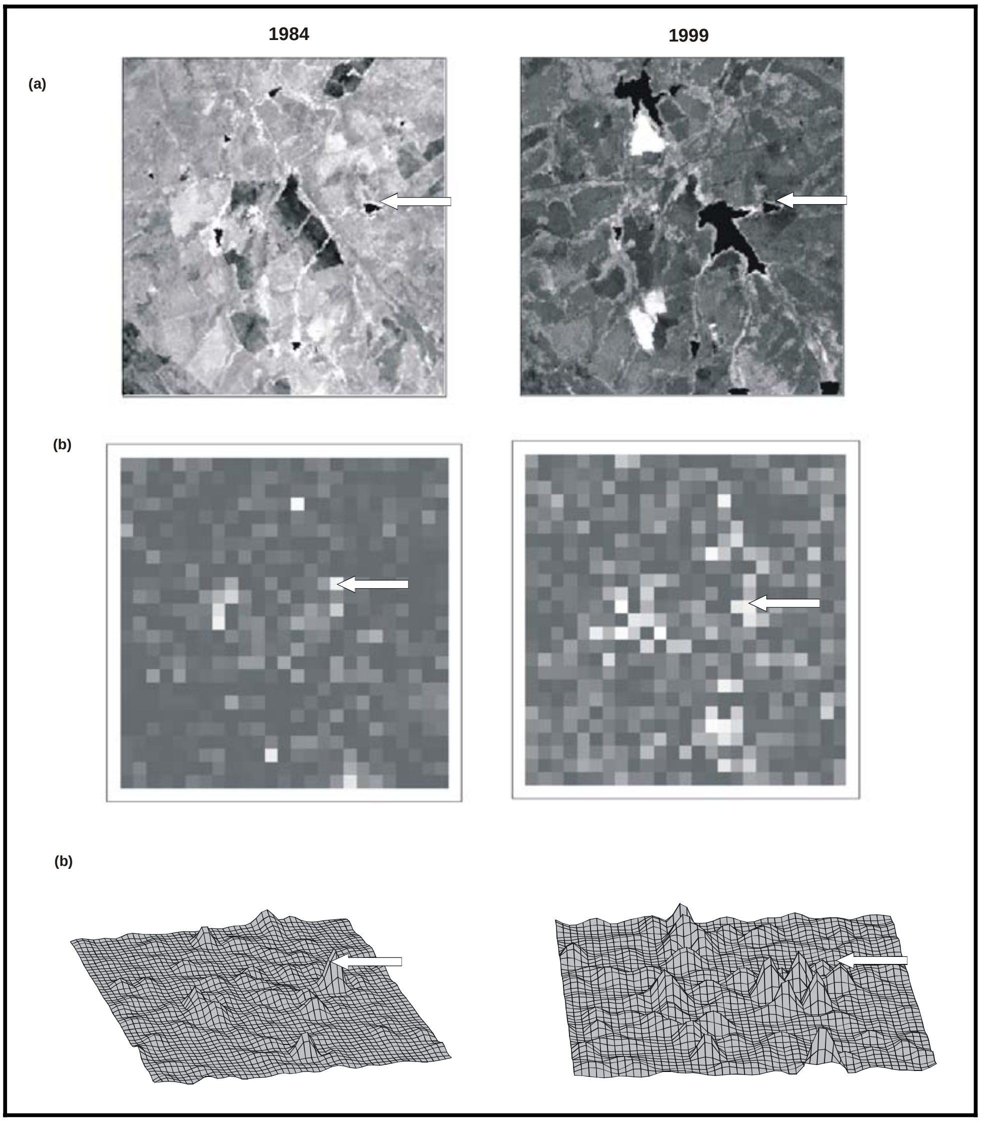

Figure 3.5: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the vertical (north-south) orientation in 1984 shown in fig. 3.3 (i.e., dominant scale = 240 m). The arrows indicate a high wavelet coefficient that coincides with the small water body in 1984 and in 1999.

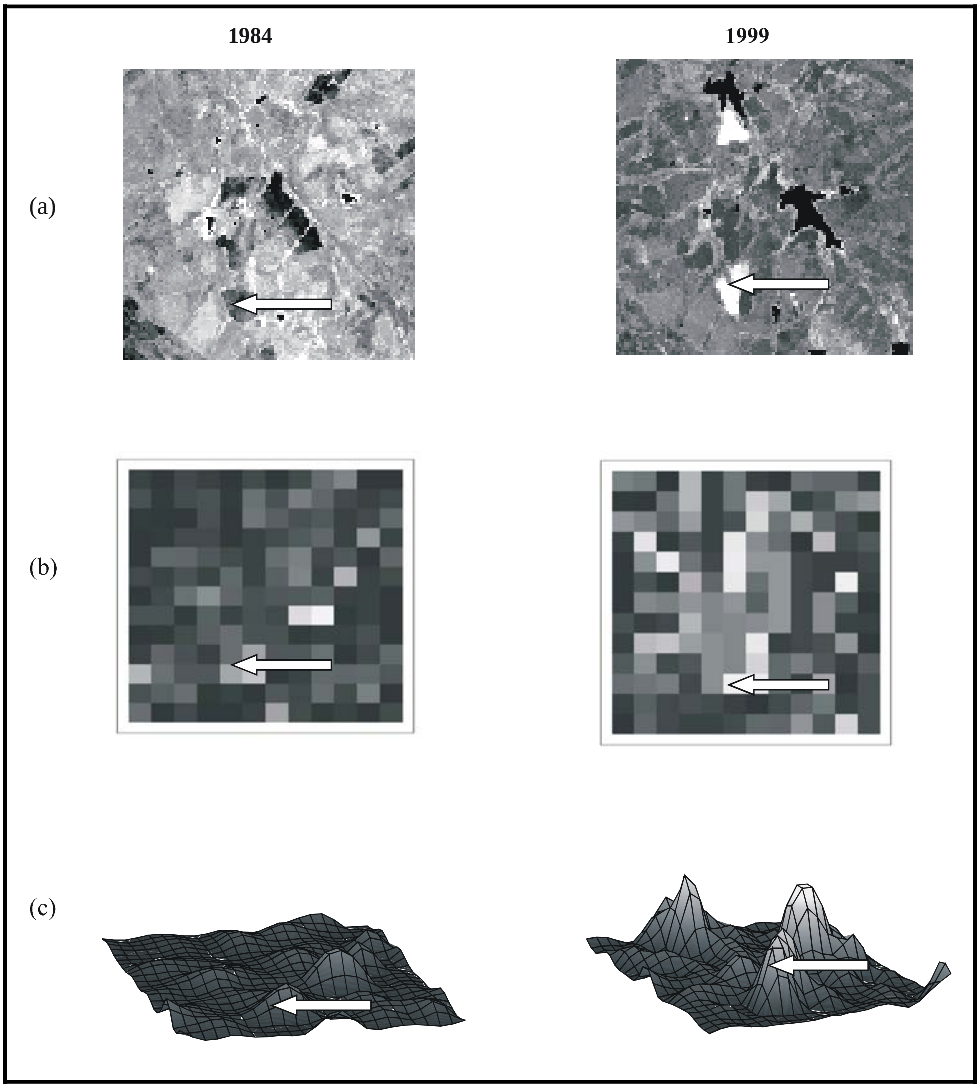

Figure 3.6: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the horizontal (east-west) orientation in 1999 shown in fig. 3.3 (i.e., dominant scale = 480 m). The arrows indicate a high wavelet coefficient that coincides with the large water body in 1999.

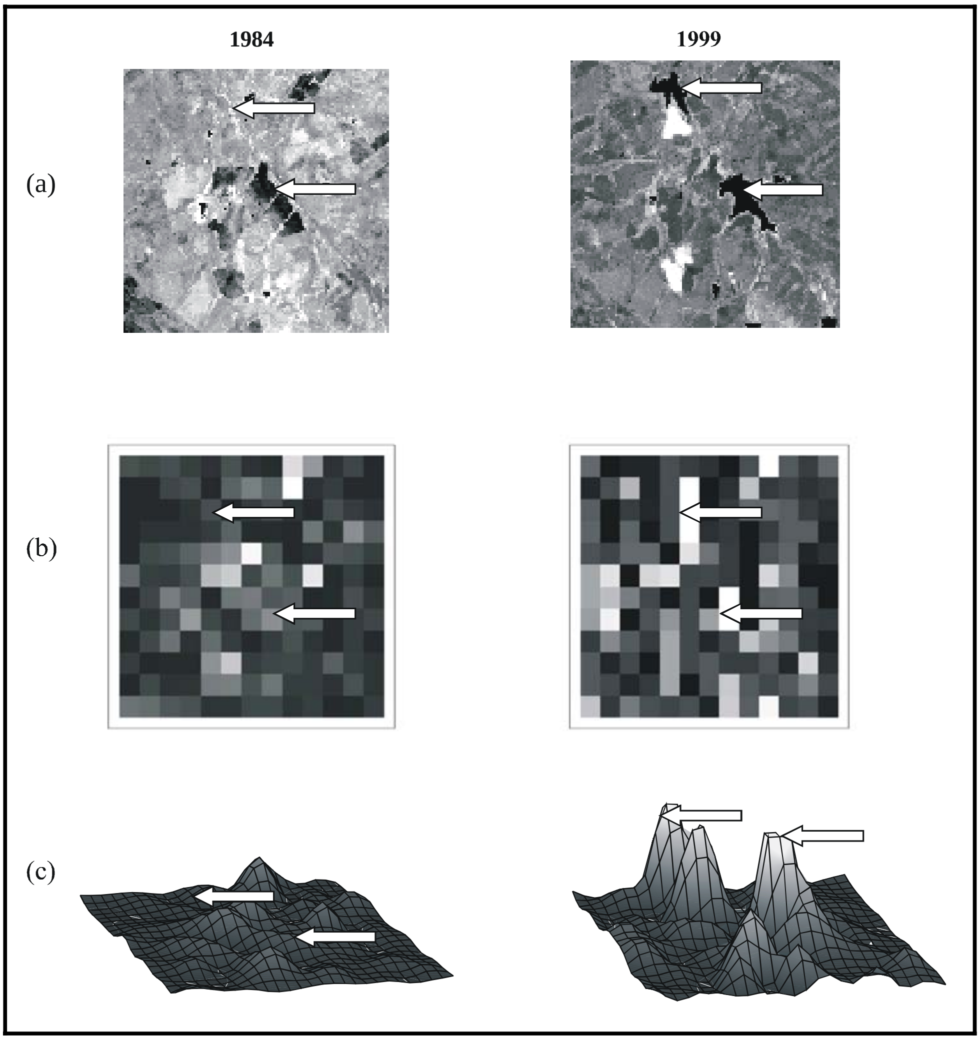

Figure 3.7: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the vertical (north-south) orientation in 1999 shown in fig. 3.3 (i.e., dominant scale = 480 m). The arrows indicate a high wavelet coefficient that coincides with the large water body in 1999.

Figs. 3.4 and 3.5 illustrate the spatial distribution of wavelet coefficients that constituted the intensity of spatial heterogeneity that occurred at the dominant scale of 120 m and 240 m in 1984 in the horizontal (east-west) and vertical (north-south) orientations respectively, as well as the corresponding wavelet coefficients in 1999 for comparison purposes. It can be observed that the highest coefficients in 1984 represented small water bodies, as well as agricultural fields of sizes between 120 m and 240 m. In addition, it can be observed that despite the fact that the intensity of spatial heterogeneity occurred at these dominant scales (i.e., 120 m and 240 m) in 1984, the wavelet coefficients and hence the wavelet energy was relatively higher at the same scales in 1999. In other words, in the year 1999 the 120 m and 240 m no longer constituted the dominant scales of spatial heterogeneity.

Furthermore, figs. 3.6 and 3.7 show the spatial distribution of wavelet coefficients that constituted the intensity of spatial heterogeneity that occurs at the dominant scale of 480 m in 1999, in the horizontal (east-west) and vertical (north-south) orientations respectively, as well as the corresponding or constituent wavelet coefficients in 1984. It can be observed that the largest increase in the magnitude of the wavelet coefficients was associated with the emergence of two large water bodies in 1999. In addition, it can be observed that in 1984 agricultural fields occupied the spots now occupied by water bodies in 1999. Furthermore, it can be observed that the horizontal (east-west) wavelet coefficients (fig. 3.6) reflect that change in the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity is not only an effect of the introduction of water bodies onto the farm but also a contribution of irrigated fields reflected in the high NDVI values of 1999.

3.4 Discussion

In this study, we have demonstrated that a wavelet transform can be applied on multi-temporal remote sensing imagery to detect changes in both the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. For example, the dominant scale of spatial heterogeneity increased from between 120 m and 240 m in 1984 to 480 m in 1999, suggesting that the dominant patches size at which NDVI (vegetation cover) varied maximally had increased (fig. 3.3). This is mainly due to the large water bodies that were introduced between 1984 and 1999. In addition, the intensity of spatial heterogeneity was higher in 1999 than in 1984, suggesting that the maximum variance in vegetation cover increased dramatically between the years (fig. 3.3). The increase in the amount of vegetation cover (NDVI) in places and also the decrease in vegetation cover due to the introduction of large water bodies explains the increase in intensity. Therefore, we can deduce that by using a wavelet transform, we are not only able to detect the differences in the maximum variance of vegetation cover, but we are also able to detect any the changes in the constituent patch dimensions at which the maximum variance occurs. This supports the main hypothesis in landscape ecology that changes in the spatial heterogeneity of a landscape are scale dependent (Turner 1989).

Moreover, the results in this study demonstrated that a wavelet transform uses the strengths of both the pixel-based or post-classification-based change detection methods by being able to detect changes in both the maximum variability (intensity) and in the size (dominant scale) of recognisable features in the landscape. In other words, while the pixel-based method makes it difficult to know the size of the patches that dominate the landscape without further analysis, it can capture variability in the landscape. In contrast, the post-classification-based change detection can give an idea about the size of the constituent patches in the landscape but it leads to the loss of quantitative information on variability in the landscape. Consequently, we can conclude that the wavelet transform based change detection within the framework of the intensity and dominant scale of spatial heterogeneity is a novel improvement over the abovementioned methods because we can detect both the change in variance and the size of the constituent patches that contribute to that change.

3.5 Conclusion

Landscapes are spatially heterogeneous and temporally dynamic at different scales (Turner 1989). In addition, landscapes are composed of scale domains that represent the relative importance of a landscape property at different scales (Wiens 1989). In this regard, any methodological framework that analyse change in the landscape must have the capacity to handle scale explicitly (Hall and Hay 2003).

The findings in this study demonstrated that a wavelet transform implemented within the framework the intensity and dominant scale of spatial heterogeneity could be used to analyse scale explicit changes in the landscape. We conclude that the approach used in this study uses the strengths of both the pixel-based or post-classification-based change detection methods. In addition, we conclude that the approach used in this study is innovative and could improve the understanding of ecological patterns and their dynamics in the landscape. In other words, it could radically improve studies that aim at predicting the spatial distribution and redistribution of organisms in the landscape in a scale explicit fashion.

Chapter 4

Tsetse eradication, arable fields and the elephant (*Loxodonta africana*) distribution in Zimbabwe: How strong is the link?[3]

A Murwira, A. K. Skidmore, H. G. J. Huizing and H.H.T Prins

Abstract

We investigated whether the proportion of arable fields increased in relation to the tsetse eradication regime in the Sebungwe region. We also investigated whether and to what extent this increase in arable fields may have affected the distribution of the African elephant (*Loxodonta africana*) between the 1980s and 1990s. Results showed a relatively higher increase in the proportion of the habitat under arable fields in the zone cleared of tsetse by 1986 compared to the zone that was still tsetse infested by the same date. Results also showed a change in the relationship between the proportion of the habitat under arable fields and elephant distribution between the two periods. In the 1980s, when arable field cover was between 0 % and 11 %, there was a weak positive relationship between elephant presence and the proportion of the habitat under arable fields. In contrast, a negative relationship emerged in the 1990s, when arable field cover ranged between 0 % and 88 %. Furthermore, the results demonstrated that the change in the probability of elephant presence between the early 1980s and the early 1990s was significantly related to the change in the proportion arable fields. In conclusion, this study demonstrated that the expansion of arable fields in the Sebungwe was greater in areas where tsetse had been eradicated compared with areas that were still tsetse infested. Overall, the results suggest that tsetse eradication led to new ecological patterns, manifested in the redistribution of elephants in response to arable field expansion.

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[3] In review: African Journal of Ecology

4.1 Introduction

The shortage of land that resulted from population pressure in parts of the country, forced the authorities in Zimbabwe to initiate a programme to eradicate tsetse fly *(Glossina* spp.) in the Zambezi valley since the 1960s, particularly in the Sebungwe region (Lovemore 1994, Cumming and Lynam 1997, Nobanda, *et al.* 1998). However, this action would unleash new landscape conditions for wildlife species. The tsetse fly transmits sleeping sickness to humans and Trypanosomiasis to livestock. Hence, areas that are tsetse-infested are normally not supporting a large agricultural population and livestock but instead support thriving wildlife populations that are not affected by tsetse (du Toit 1985, du Toit 1995). As a consequence of tsetse eradication, farmers began to increasingly occupy the valley since the 1960s (Cumming and Lynam 1997). By the mid-1980s agricultural expansion accelerated thereby threatening the persistence of wildlife in the area (Cumming and Lynam 1997).

Despite efforts to preserve wildlife species through a network of national parks in the 1960s, poaching in wildlife reserves, as well as expanding agriculture in wildlife habitats continued to negatively affect wildlife species persistence in the Sebungwe (Hulme and Murphree 2001). Therefore, from the early 1980s, the approach to wildlife management shifted to encompass conservation in agricultural areas, this time by involving local communities (Cumming 1981). This approach was formalized through the communal areas management programme for indigenous resources (CAMPFIRE) in 1989. In this programme, local communities would treat wildlife as an economic asset rather than an impediment to agricultural production (Logan and Moseley 2002). In other words, the programme envisions the of agriculture-wildlife coexistence outside the protected wildlife reserves. Naturally, the success of CAMPFIRE can only be ensured by the persistence of wildlife in these agricultural landscapes. Consequently, the need to understand the spread of arable agriculture following tsetse eradication as well as how this may have affected wildlife distribution is critical.

The first critical question is whether, in the first place, we can quantitatively attribute the increase in arable fields to the tsetse eradication regime. In addition, if there was an increase in arable fields, how did the proportion of the habitat under arable fields impact on the spatial distribution of wildlife species in the area? To date, only a few attempts have been made to quantitatively investigate a link between the expansion of arable fields and the tsetse eradication process (Pender and Rosenburg 1995). Furthermore, few attempts have also been made to quantitatively establish how and to what extent the proportion of the habitat under arable fields in areas where tsetse had been eradicated may have affected the spatial distribution of wildlife (Cumming and Lynam 1997). Existing work has mainly focused on how human population density and settlement in the Sebungwe is related to the distribution of wildlife, particularly that of the elephant (Hoare and Du Toit 1999) without a temporal investigation in the context of the tsetse eradication regime. Therefore, it is important to understand how wildlife responded to varying amounts of agricultural incursions in their habitat over time as this may lead to solutions that lead to the possibility of wildlife-human coexistence.

In the Sebungwe, understanding the extent to which arable fields expanded following tsetse eradication, as well as understanding the extent to which this has affected the spatial distribution of wildlife is critical for aiding CAMPFIRE. Previous studies have suggested a negative relationship between agriculture and wildlife distribution (Ottichilo 2000). However, for the management of programmes such as CAMPFIRE, it is not only important to know that there may be a negative relationship between wildlife presence and agriculture but it is also important to know the conditions under which this negative relationship might set in as this may lead to the establishment of possible thresholds favourable for wildlife-human coexistence. Therefore, analysing the expansion of arable fields and their possible effect on wildlife in a spatial and temporal context is critical.

In this study, we investigated whether the proportion of the habitat under arable fields increased in the Sebungwe region in Zimbabwe in relation to the tsetse eradication process. We also investigated whether and to what extent arable fields could have affected the distribution of the African elephant (*Loxodonta africana*), i.e., a keystone species (Hoare and Du Toit 1999), between the early 1980s and the early 1990s. Therefore, based on the Sebungwe region, we specifically made three predictions. Firstly, we predicted a statistically significant difference in the proportion of the habitat under arable fields between the zones in which tsetse had been eradicated by 1986 and the ones still tsetse infested by the same date. Secondly, we predicted a statistically significant relationship between the proportion of the habitat under arable fields and the probability of elephant presence in sampling units defined by an intersection of administrative ward and vegetation class boundaries in 1983 and 1995. Finally, we predicted a statistically significant relationship between changes in the probability of elephant presence and the changes proportion of arable fields in sampling units defined by an intersection of administrative ward and vegetation class boundaries between the early 1980s and the early 1990s

4.2 Material and methods

Study area

The study was based on the Sebungwe region in Zimbabwe (fig. 4.1). The Sebungwe has undulating topography with the average elevation of 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 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. 4.1b). The floristic-physiognomic vegetation units are constant 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. 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

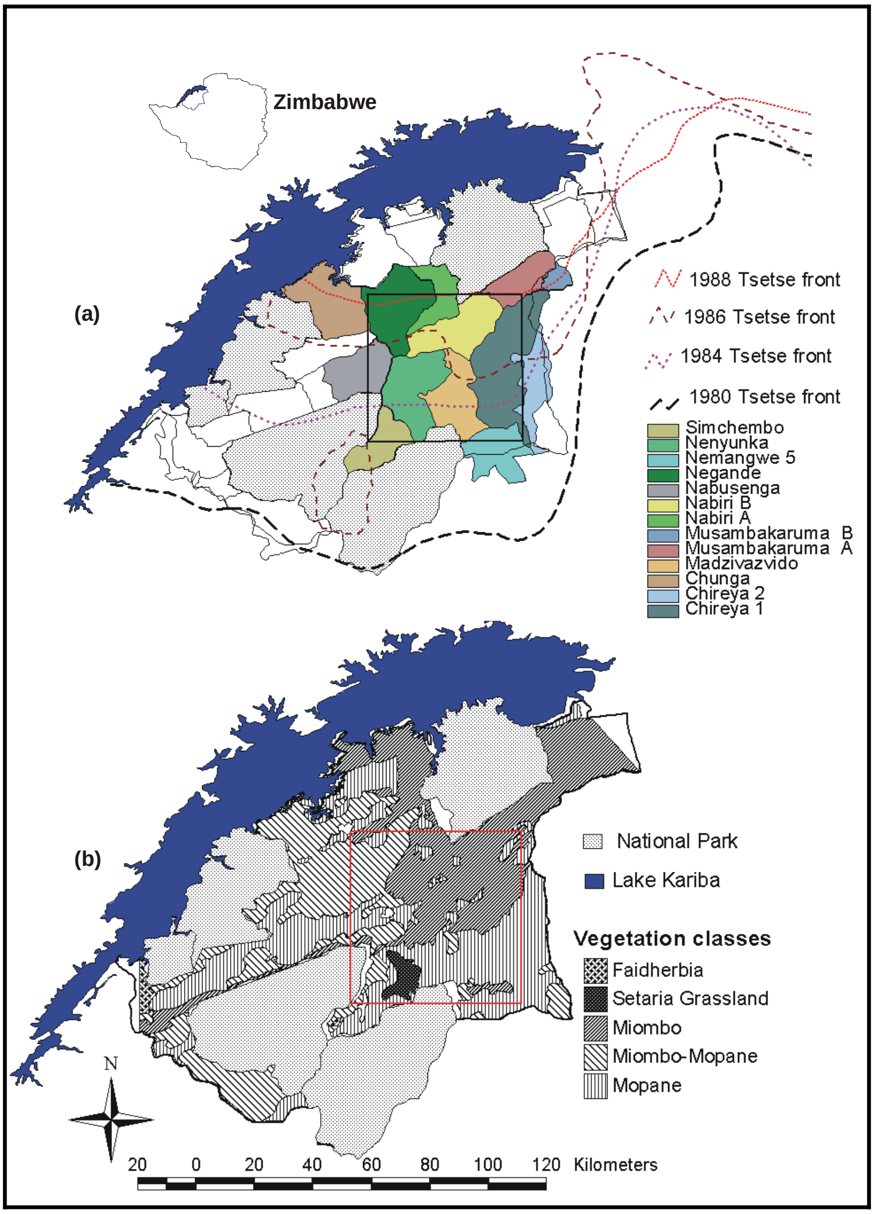


Figure 4.1: The location of the Sebungwe region in Zimbabwe and (a) the wards, national parks and the history of the progression of tsetse eradication (source: Tsetse and Trypanosomiasis control branch, Harare) and (b) the physiognomic-floristic vegetation classes in the communal lands based on Timberlake and Nobanda (1993). The square box is a 61 km x 61 km area selected for this study.

characterised by collective or community land ownership and they are subdivided into administrative or management units called wards (fig. 4.1a). 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, i.e., in communal lands elephants are present provided there are necessities such as enough cover and water available for both elephants and humans. Elephants have to cross the communal lands when moving between the wildlife reserves, thereby making communal lands an important wildlife corridor that links the national parks.

The Sebungwe landscape evolved from a complex of different historical forces linked to the eradication of tsetse fly (*Glossina* sp.) (fig. 4.1a). 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.

Agricultural fields from remote sensing

In order to fulfil the objectives of the study, agricultural field distribution was extracted from land cover for 1984 and 1992 and the land cover maps were derived from an image classification of Landsat Thematic Mapper (TM). In this case, the 1984 map was produced from a supervised image classification of a 19th October image performed by the authors while the 1992 map was sourced from the Forestry Commission of Zimbabwe based on a 16th April image. Dry season imagery was used because 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 imagery. Aerial photographs were used for both image classification and accuracy assessment of the 1984 image and for accuracy assessment of the 1992 map. Overall accuracies of 90% and 80% were obtained for the 1984 and 1992 maps respectively.

Elephant distribution data

The data on the spatial distribution of elephants in the 1980s and 1990s were determined using respectively a GIS based combination of 1981-1983 point data sets, and 1993-1995 point data sets. These data were obtained from point location data from the analyses of Sebungwe aerial surveys by Cumming and Lynam (1997) and made available by the World Wildlife Fund (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.

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 λ(*x*) for the elephant point map to give an expected number of events per unit area (Fotheringham, *et al.* 2000):

$$\lambda(x) = \lim_{r=0} \frac{E(N(C(x,r),X))}{\pi r^2} \tag{4.1}$$

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

$$\lambda n(x) = \frac{\lambda(x)}{E(N(R,X))} \qquad (4.2)$$

We used the λn(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) and the map data were transferred to ILWIS GIS software (ITC 2002) where it was converted to a raster map format. 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 presence of at least a single elephant and since the elephant survey data sets were combined, adding the total number of observed elephants of the years would give a false impression.

Analysis of agricultural field expansion

We started the analysis by using GIS overlay to explore changes in the spatial patterns of arable fields (fields) between 1984 and 1992 relative to the tsetse status in 1986, i.e., by subdividing the study area into two zones (with tsetse and where tsetse had been eradicated) while specifically focussing on the communal lands. The operation produced a map of fields in each tsetse status zone in 1984 and 1992. Consequently, we calculated the proportion of fields in 1984 and 1992 in the two zones. Finally, we statistically compared the amount of arable fields in each zone at different times (1984 and 1992), as well as between the two zones at each time based on proportions.

Analysis of agricultural fields and the probability of elephant presence

We investigated whether there was a significant relationship between the proportion of fields and the probability of elephant presence by focusing on a 61 km by 61 km subset of the study area, specifically covering communal lands in the zone that had become largely free of tsetse by 1988 (fig. 4.1a). This was to facilitate the study of the effects of tsetse eradication on wildlife distribution. This study area was considered large enough for studying the spatial distribution of elephants. Specifically, elephants in the Sebungwe region have an estimated range of between 83 km^2 to 263 km^2, approximating a horizontal (east-west) length scale (horizontal (east-west) 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 km^2, which is at least 14 times the estimated range of the elephant in the Sebungwe large enough to study elephant distribution.

We based our analysis on 22 different land units (sampling units) that were defined by an intersection of ward and the physiognomic-floristic vegetation class boundaries. The intersection was accomplished in a GIS. The sampling units were appropriate from a management and ecological point of view, i.e., the ward boundaries cater for the fact that arable and wildlife management decisions are made at ward level whereas the vegetation classes cater for ecological differences between sampling units. Fig. 4.2 illustrates the sampling units used in this study.

Next, the probability of elephant presence in each of the sampling units, which was used to measure elephant distribution, was obtained by crossing the probability of elephant distribution map with the sampling unit map (i.e., intersection of wards and vegetation classes) in a GIS and then calculating the mean probability of elephant presence in each sampling unit. Also, the proportion of arable fields in each sampling unit was obtained by crossing a map of arable fields with the sampling unit map in a GIS and then calculating the proportion of arable fields by dividing the amount of arable fields with the total area of the sampling unit.

The next procedure involved using the 1980s and 1990s data to analyse the relationship between the proportion of fields and the mean probability of elephant presence, through regression. The differences in date between the elephant data and arable field data was expected to have negligible effects on the results because the dates were close enough. In a situation whereby a sampling unit is close to a National park, there is likely to be a high level of elephant persistence despite the amount of arable fields. Therefore, the distance from National Parks was calculated in a GIS for use in aiding the proportion of the habitat under arable fields to explain elephant distribution. Finally, we used regression to investigate whether changes in the proportion of arable fields (plus distance from the National parks) in each sampling unit significantly explained changes in the probability of elephant presence in the study area. In order to accomplish this, the proportion of arable fields in the 1980s was subtracted from the proportion of arable fields in the 1990s for each sampling unit. In this way, positive values would represent an increase while negative values

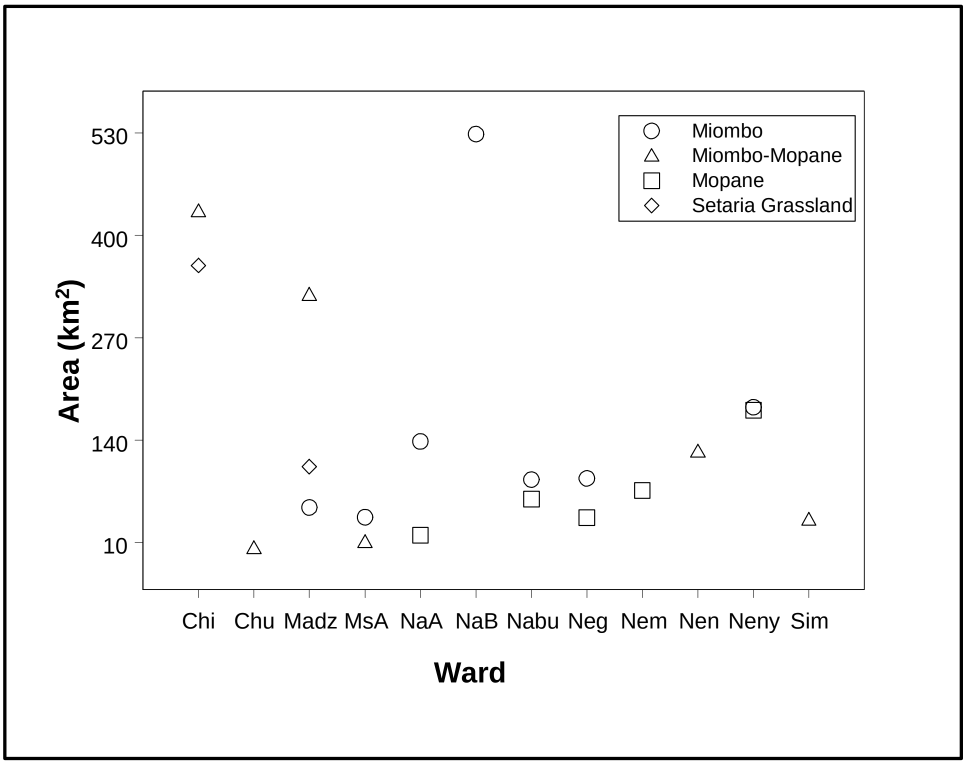


Figure 4.2: Sampling units (intersection of wards and vegetation classes) used in the regression of the probability of elephant presence on the dominant scale and intensity of spatial heterogeneity based on the early 1980s and the early 1990s data (Chi = Chireya 1, Chu = Chunga, Madz = Madzivazvido, MsA = Musambakaruma A, NaA = Nabiri A, NaB = Nabiri B, Nabu = Nabusenga, Nem = Nemangwe 5, Neg = Negande, Neny = Nenyunka and Sim = Simchembo).

would represent a decrease in each factor between the two dates. The same was done to obtain changes in the probability of elephant presence between the early 1980s and the early 1990s.

4.3 Results

Fig. 4.3 shows the distribution of arable fields in 1984 and 1992. It can be observed that the amount of arable fields increased in the study area

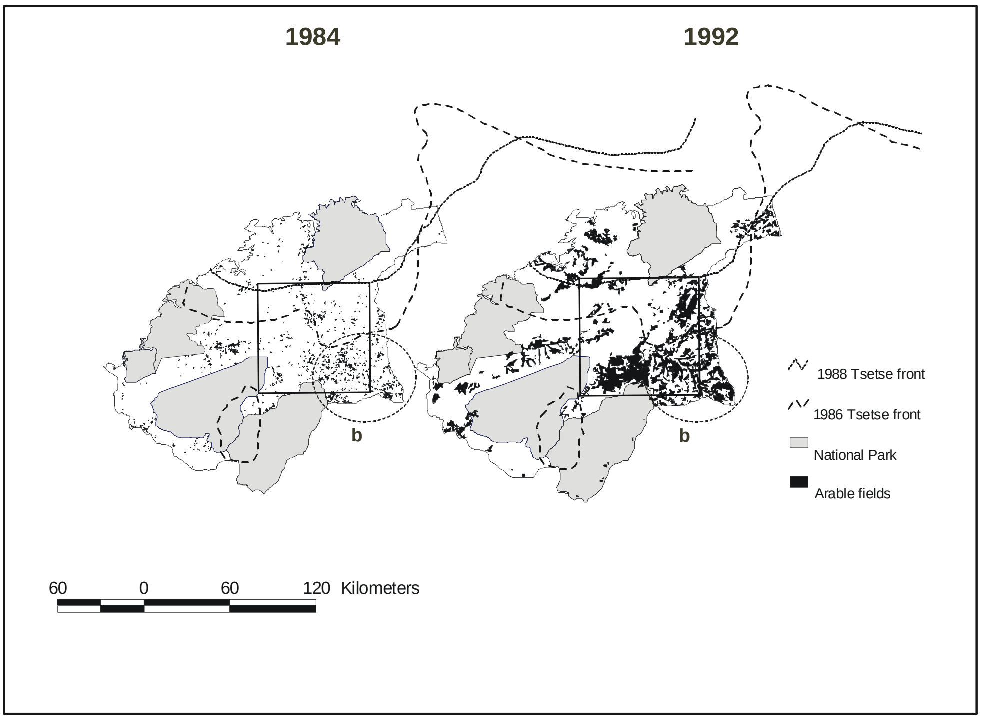


Figure 4.3: Maps showing the distribution of fields in relation to tsetse eradication status in 1984 and 1992 and the 61 km by 61 km square box selected for detailed spatial analysis. The total area of the tsetse zone by 1986 equals to 482 100 hectares while the total area of the eradicated zone is equals to 514 825 hectares (these figures exclude the nature parks). The ellipse (b) illustrates an area where there was a high increase in arable fields between 1984 and 1992**.**

between 1984 and 1992. The highest increase in the area under arable fields between 1984 and 1992 can be observed in the southeastern corner of the study area marked by an ellipse (b).

In addition, fig. 4.4 shows the proportions of arable fields in both tsetse-eradicated and tsetse zones in 1984 and 1992. It can be observed that the proportion of the habitat under arable fields in the tsetse-eradicated zone was higher than the proportion of the habitat under arable fields the tsetse zone in both 1984 and 1992. There were more new fields in the tsetse-eradicated zone than in the tsetse zone. A comparison of the proportions of arable fields within each zone between 1984 and 1992, as well as between the zones in both 1984 and 1992, showed that the proportions were significantly different ($p < 0.05$)

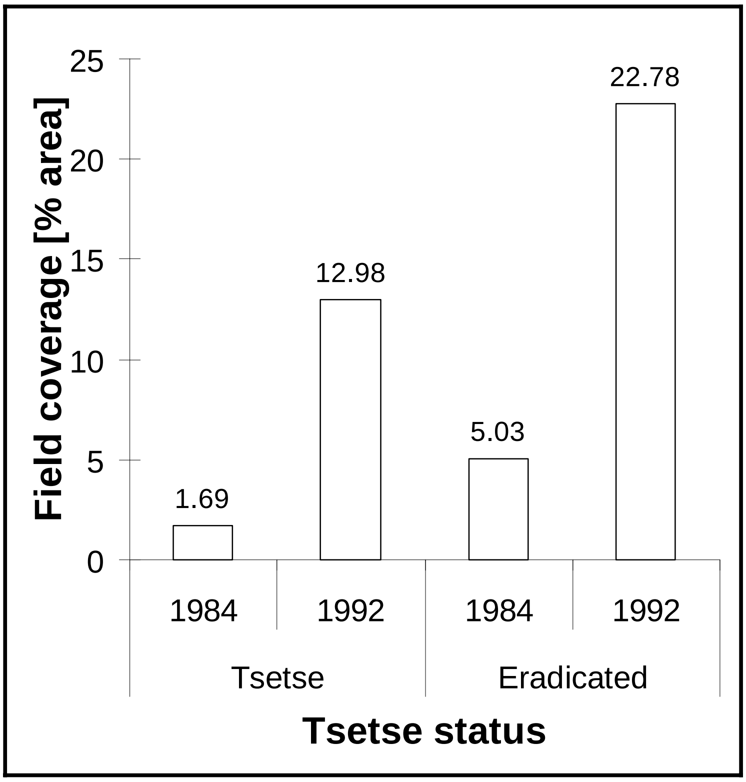


Figure 4.4: The proportion of the habitat under arable fields in the tsetse and tsetse-eradicated zones in 1984 and 1992.

Fig. 4.5 shows the probability of elephant presence between 1981-83 and 1993-95. It can be observed that the probability of elephant presence decreased noticeably between 1981-83 and 1993-95 in areas that had a higher increase in the amount of arable fields (fig. 4.3), particularly in the southeastern corner of the study area marked by the ellipse (b). It can also be observed that areas close to the National parks can have relatively high probabilities of elephant presence despite high proportions of arable fields (fig. 4.3).

Fig. 4.6 shows that the relationship between the probability of elephant presence and the proportion of arable fields in 1984 and in 1992 revealed contrasting patterns. In the 1980s, a non-significant ($p > 0.05$)

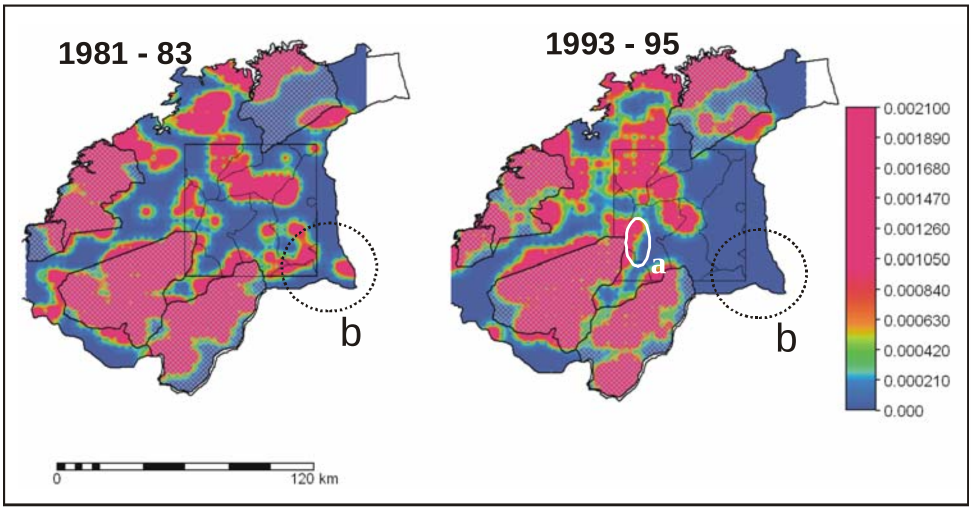


Figure 4.5: Maps probability of elephant presence within a 3 km radius in the study area in 1981-83 and 1993-95 and the 61 km by 61 km square box selected for detailed spatial analysis. The ellipse (b) illustrates an area where there was a major noticeable decrease in the probability of elephant presence between 1981-83 and 1993-95 and ellipse (a) shows an area close to the park where the probability of elephant presence is high.

and weak positive relationship appeared between elephant presence and the proportion of fields in different sampling units. It can be observed that in 1984 all sampling units had less than 11 % of their area covered by arable fields. In contrast, there was a significant ($p < 0.05$) quadratic relationship between the probability of elephant presence and the proportion of the habitat under arable fields in the 1990s. The relationship is largely negative. It can also be observed that during this period the proportions of arable fields in different land units ranged between 0 % and 88 %.

Fig. 4.7 shows the results of the investigation on whether the probability of elephant presence could be significantly explained by the interaction between the proportion of the habitat under arable fields and the distance to the national parks in both the 1980s and the 1990s, as well as whether the changes in the probability of elephant presence were also explained by changes in the proportion of arable fields modified by the distance from the national parks (fig. 4.7). Fig. 4.7a shows that there was a non-significant ($p > 0.05$) relationship between the probability of elephant

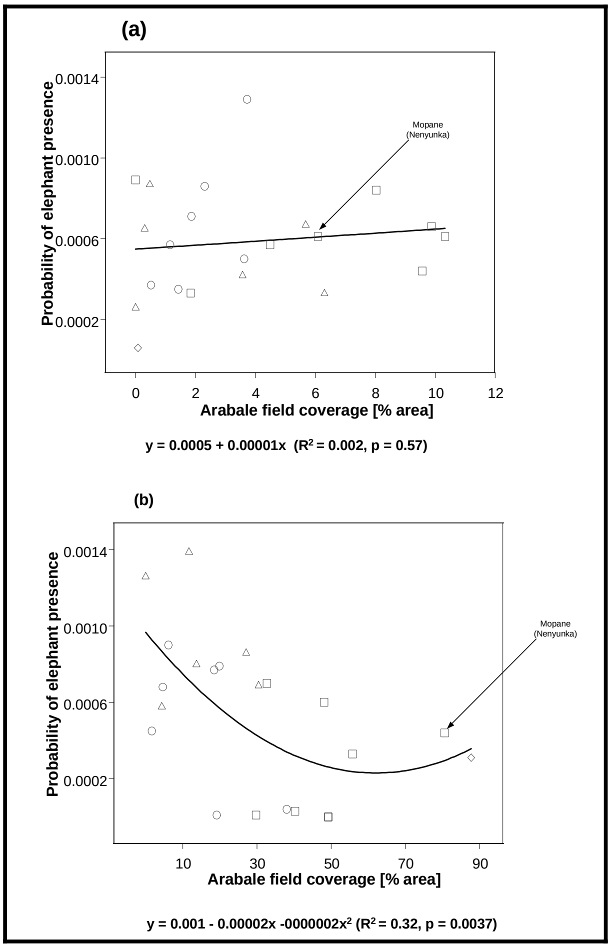


Figure 4.6: Non-significant ($p > 0.05$) relationship between probability of elephant presence on the proportion of the habitat under arable fields in the (a) 1980s and significant ($p < 0.05$) relationship in the (b) 1990s in (○) Miombo, (☐) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane floristic-physiognomic vegetation classes. The marked point is close to National parks.

presence in the 1980s and the interaction between the proportion of the habitat under arable fields and the distance to the national parks while fig. 4.7b shows a significant ($p < 0.05$) largely negative relationship in the 1990s.

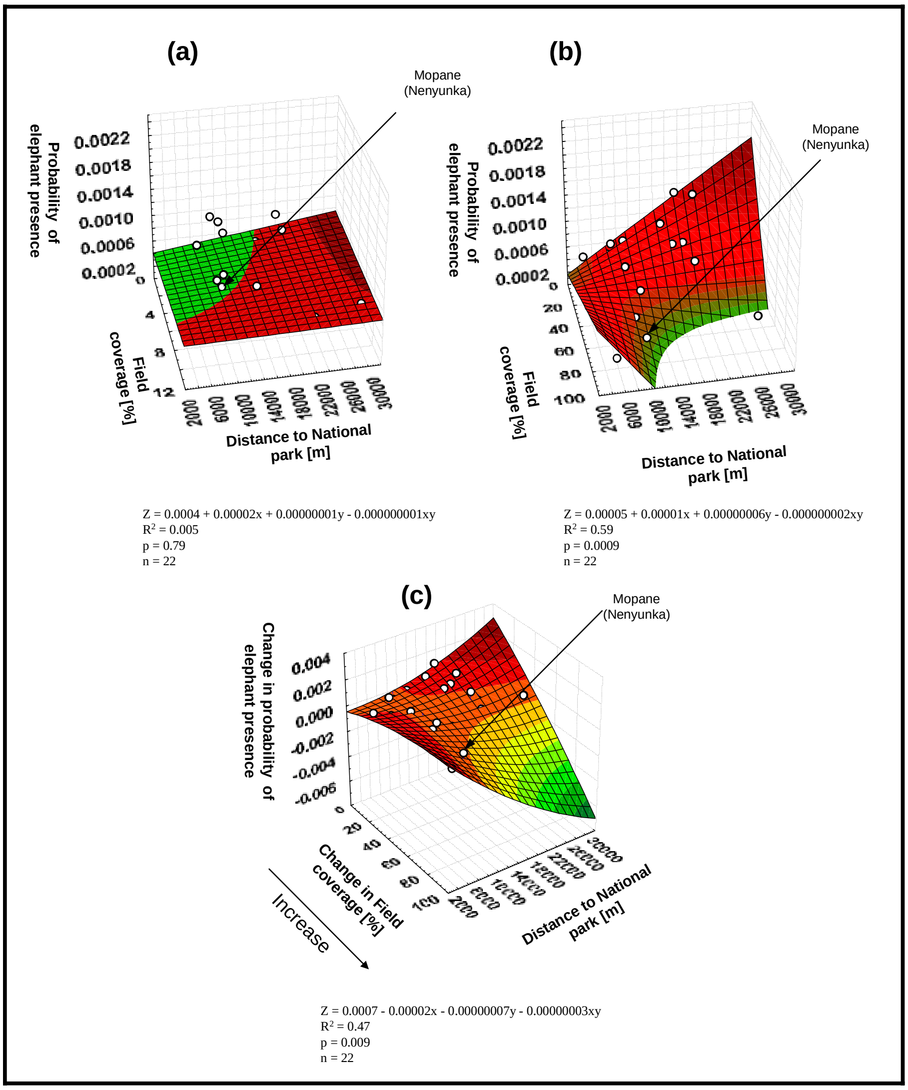
During both periods, the proportion of arable fields, modified by the influence of the distance to the national park explained < 1 % and 59 %

of the variance in the probability of elephant presence respectively. Fig. 4.7c shows that the changes in the probability of elephant presence between the early 1980s and the early 1990s were significantly ($p < 0.05$) explained by the increase in the proportion of arable fields between the two dates. In fact, elephants decreased most where arable fields increased most. This model predicted 47 % of the variance of the change in the probability of elephant presence. For example, the Mopane vegetation class in Nenyunka clearly illustrates that increases in the levels of arable fields negatively affected the probability of elephant presence (fig. 4.6 and fig. 4.7). In addition, the same sampling unit illustrates the positive influence of shorter distance to the national park to the probability of elephant presence.

4.4 Discussion

This study revealed a link between tsetse eradication and the expansion of arable fields in the Sebungwe, between 1984 and 1992. This confirms reports from related work, suggesting an increasing number of farmers settling in the area as tsetse was being progressively eradicated in the Sebungwe (Cumming and Lynam 1997). The results also support the widely held hypothesis that tsetse eradication drives changes in land use and therefore, land cover patterns (De Vos 1978, Rogers and Randolph 1988, Jordan 1992, Reid, *et al.* 1997).

An interesting finding of this study was that elephants showed a variation in their reaction to the transformation of habitat by arable agriculture in the Sebungwe following tsetse eradication (fig. 4.6 and fig. 4.7). The results suggested that in the early 1980s when the proportion of arable fields was between 0 % and 11 % there was no significant relationship between elephants and the proportion of the habitat under arable fields. In contrast, the results indicated that in the early 1990s when the proportion of the habitat under arable fields rose up beyond 11 %, the relationship between elephant presence and the proportion of the habitat under arable fields became significantly negative. Since the elephant data were collected in the dry season when arable fields are fallow, the



(a)
$Z = 0.0004 + 0.00002x + 0.00000001y - 0.000000001xy$
$R^2 = 0.005$
$p = 0.79$
$n = 22$

(b)
$Z = 0.00005 + 0.00001x + 0.0000006y - 0.000000002xy$
$R^2 = 0.59$
$p = 0.0009$
$n = 22$

(c)
$Z = 0.0007 - 0.00002x - 0.00000007y - 0.00000003xy$
$R^2 = 0.47$
$p = 0.009$
$n = 22$

Figure 4.7: A non-significant ($p > 0.05$) relationship between probability of elephant presence on the proportion arable fields plus distance to National parks in the (a) 1980s, a significant ($p < 0.05$) relationship in the (b) 1990s, as well as a significant ($p < 0.05$) relationship between the change in the probability of elephant presence between the 1980s and the 1990s and the increase in arable fields plus a modification by the distance to the National the park during the same period. The labelled sampling unit illustrates the decrease in the probability of elephant presence with the increase in the proportion of arable fields. The graph surfaces represent relatively low probability of elephant presence in green and the highest probability of elephant presence in deep red.

relationship between elephant presence and the proportion of the habitat under arable fields can be explained from a cover (or shelter) perspective. In this regard, at low proportions of arable fields within a land unit, elephants still have sufficient cover to hide from humans. However, when the proportion of the habitat under arable fields increases, the landscape is opened up and there are less hiding opportunities for the elephants. These observations are supported by the findings of (Hoare and Du Toit 1999) that elephants are expected to persist in areas where human settlement occurs within a matrix of untransformed habitat. From the results, we can deduce that the relationship between agricultural encroachment and elephant presence is not necessarily a negative one, but instead, it depends on the proportion the habitat transformed into arable fields. The distance from the national park modifies the relationship, as places that are close to national parks tend to have high levels of elephant presence, even though the proportion of habitat under arable fields is high (figs. 4.6 and 4.7).

We also observed that elephants decreased most where arable fields increased most, suggesting that the increase in the proportion of habitat under arable fields had a negative impact on elephant persistence in the Sebungwe. This result confirms the findings of Cumming and Lynam (1997) who reported that although there was an increase in the Sebungwe elephant population between the 1980s and 1990s, the dry season range shrunk by 15 %. The decline in the elephant range has negative implications for CAMPFIRE, since the survival of this programme hinges upon wildlife species persistence in the agricultural areas. However, the increase in the proportion of arable fields explained only less that half of the variance of the decrease in the probability of elephant presence, suggesting the influence of other factors that need to be investigated in future studies.

4.5 Conclusions

Three main conclusions could be drawn from this study. Firstly, the expansion of arable fields was greater in areas where tsetse had been eradicated earlier compared with areas that were still tsetse infested in the Sebungwe, suggesting that tsetse eradication gave way to accelerated arable field expansion. Secondly, the increase in the proportion of the habitat under arable fields was negatively related to elephant presence in the Sebungwe but only when the proportion of the habitat under arable fields ranged beyond 11 % among the sampling units. Finally, the results suggest that tsetse eradication lead to new ecological patterns, manifested in the redistribution of elephants in response to arable field expansion.

Chapter 5

Evaluating a new approach to predict the spatial distribution of elephants from NDVI[4]

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.

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[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 Ostrovysky 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

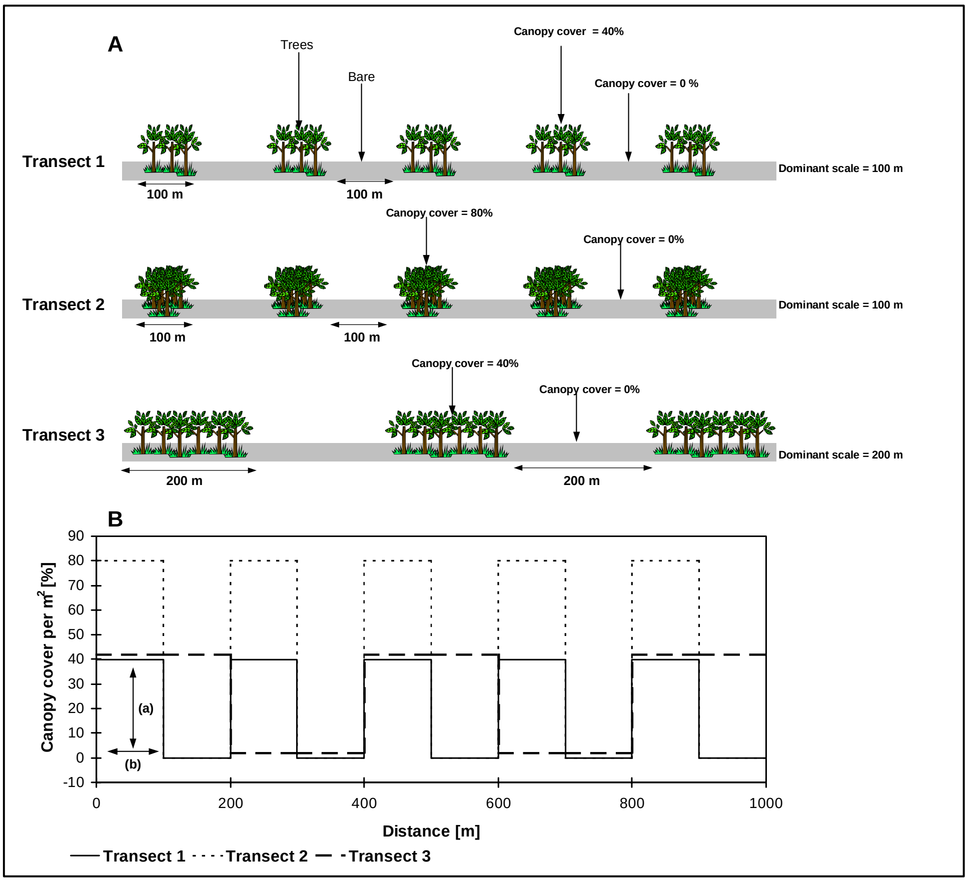

Figure 5.1: Part (A) are transects with alternating spaces of trees and bare ground and part (B) shows the simulation tree canopy cover along each transect assuming that the cover measurements are made after every 1 m (i.e., grain = 1 m) and an extent of 1000 m. For example, the (a) intensity (maximum 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, m^2, km^2) 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

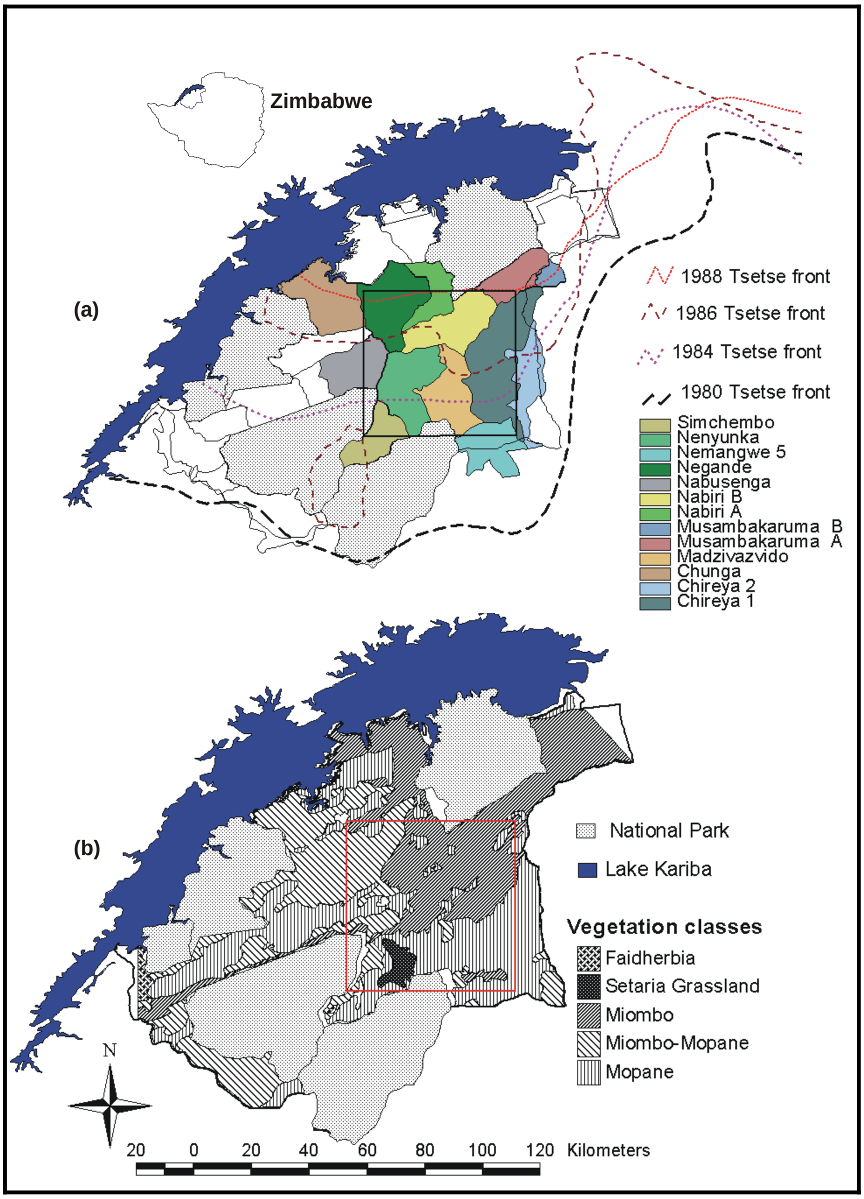

Figure 5.2: The location of the Sebungwe region in Zimbabwe and (a) the wards, national parks and the history of the progression of tsetse eradication (source: Tsetse and Trypanosomiasis control branch, Harare) and (b) the physiognomic-floristic vegetation classes in the communal lands based on (Timberlake 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 km^2 to 263 km^2, 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 km^2, 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.

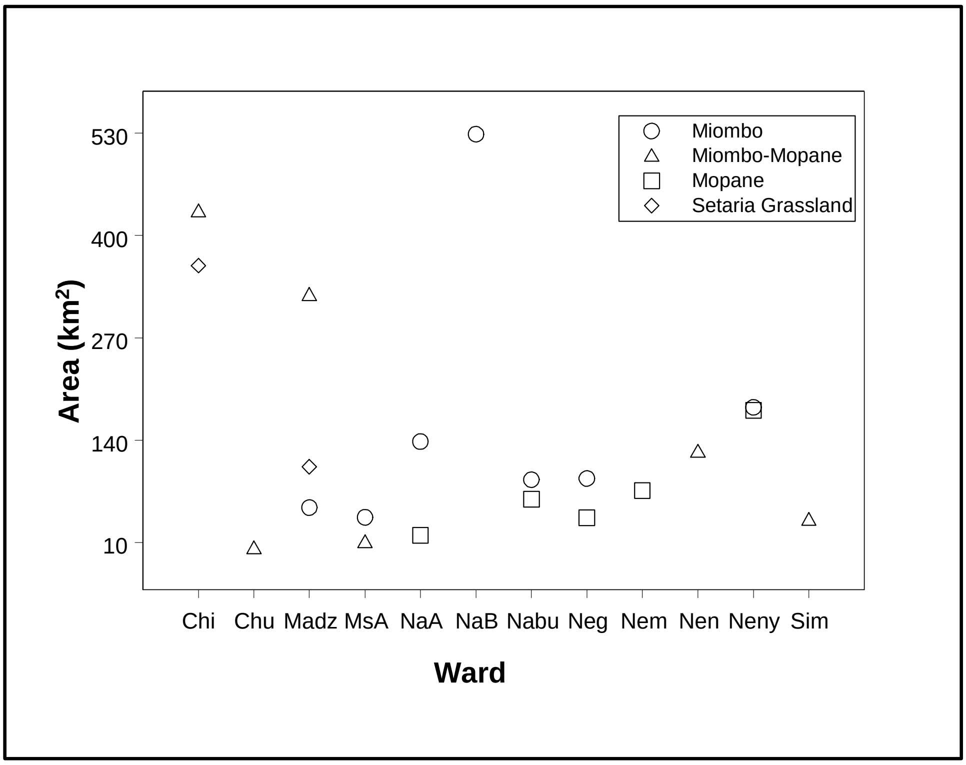

Figure 5.3: Sampling units (intersection of wards and vegetation classes) used in the regression of the probability of elephant presence on the dominant scale and intensity of spatial heterogeneity based on the early 1980s and the early 1990s data (Chi = Chireya 1, Chu = Chunga, Madz = Madzivazvido,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

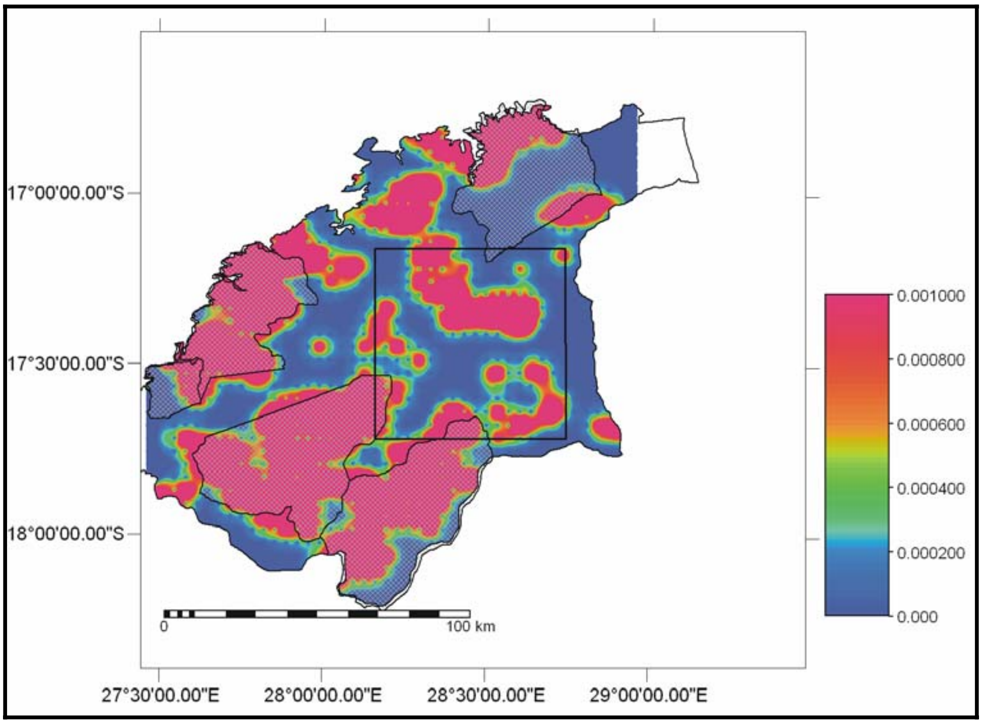

Figure 5.4: Map showing the probability of elephant presence within a 3 km radius in the Sebungwe in 1981-83 and the 61 km by 61 km square box shows the area used in this study.

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 λ(x) for the elephant point map to give an expected number of events per unit area(Fotheringham, *et al.* 2000):

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

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

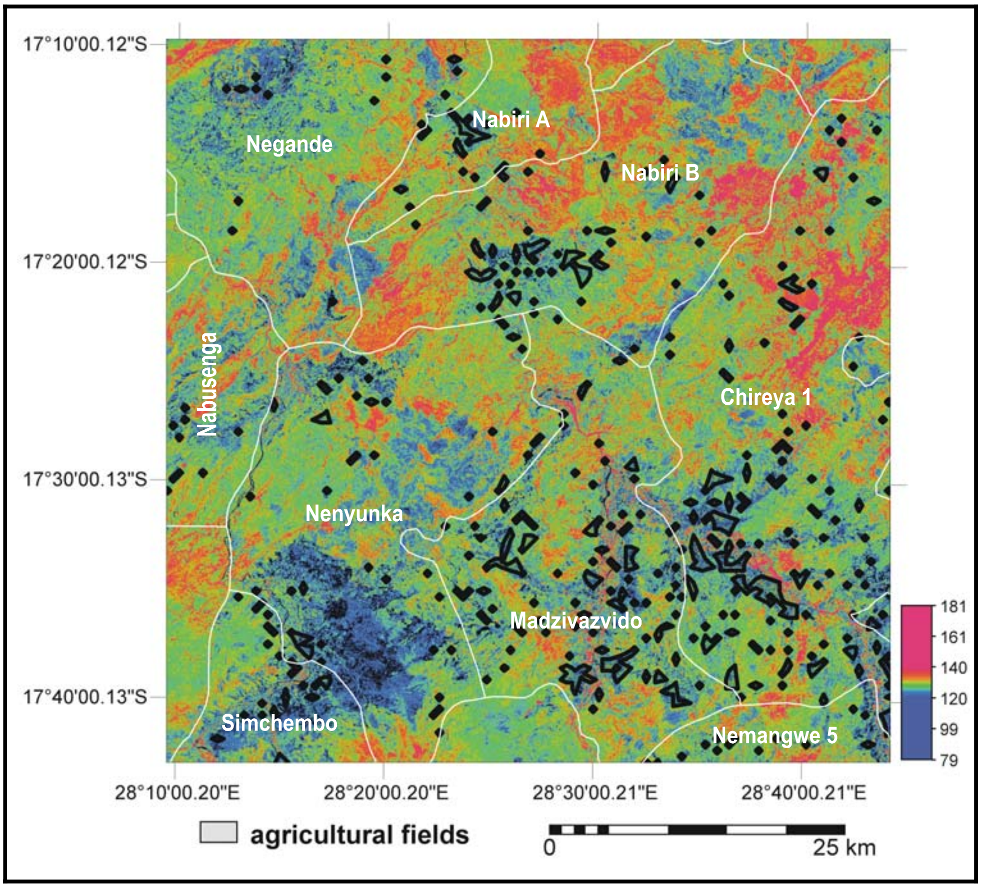

Figure 5.5: Map showing the 1984 NDVI maps of the 61 km by 61 km square box together with ward boundaries and the extent of agricultural fields. Low NDVI values indicate low vegetation cover and high NDVI values indicate high vegetation cover within a 0 to 255 range.

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

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

We used the λ*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:

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

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 handing 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 Ostrovysky 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., $j = 0,1,2\ldots J$ 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., $j = 0,1,2\ldots J$, 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:

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

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 $\hat{f}(x,y)$:

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

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 $\gamma(h)$:

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

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 (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).

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,…,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 was (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.,

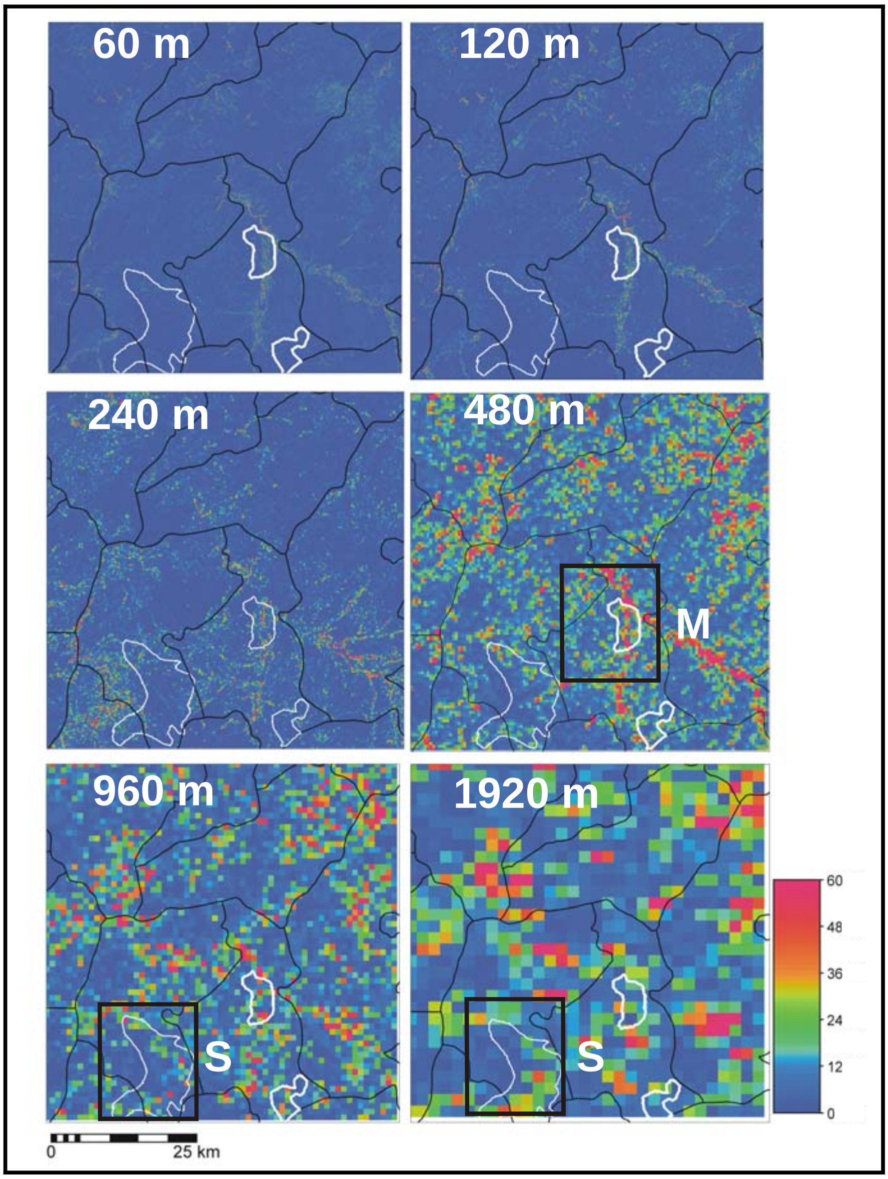

Figure 5.6a: The spatial distribution of total wavelet energy per pixel at different scales (wavelet spans) across different wards, as well as in selected vegetation class polygons (The total wavelet energy that we used as a denominator for calculating energy was divided by 1000000 and then stretched 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

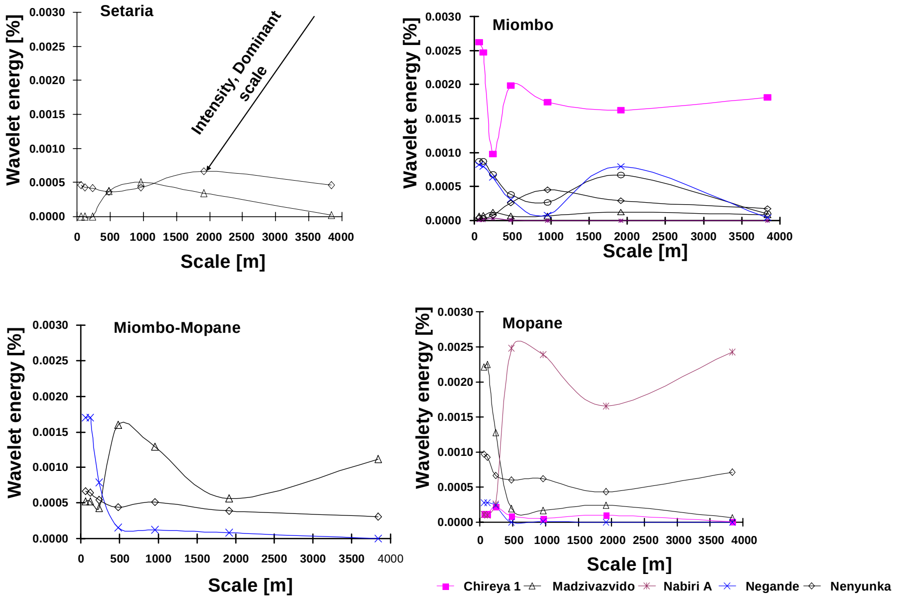

Figure 5.6b: Selected wavelet energy functions revealing the variations in intensity and dominant scale in different wards and vegetation classes. The arrow shows an example of the determination of the intensity and dominant scale of spatial heterogeneity from a wavelet energy function.

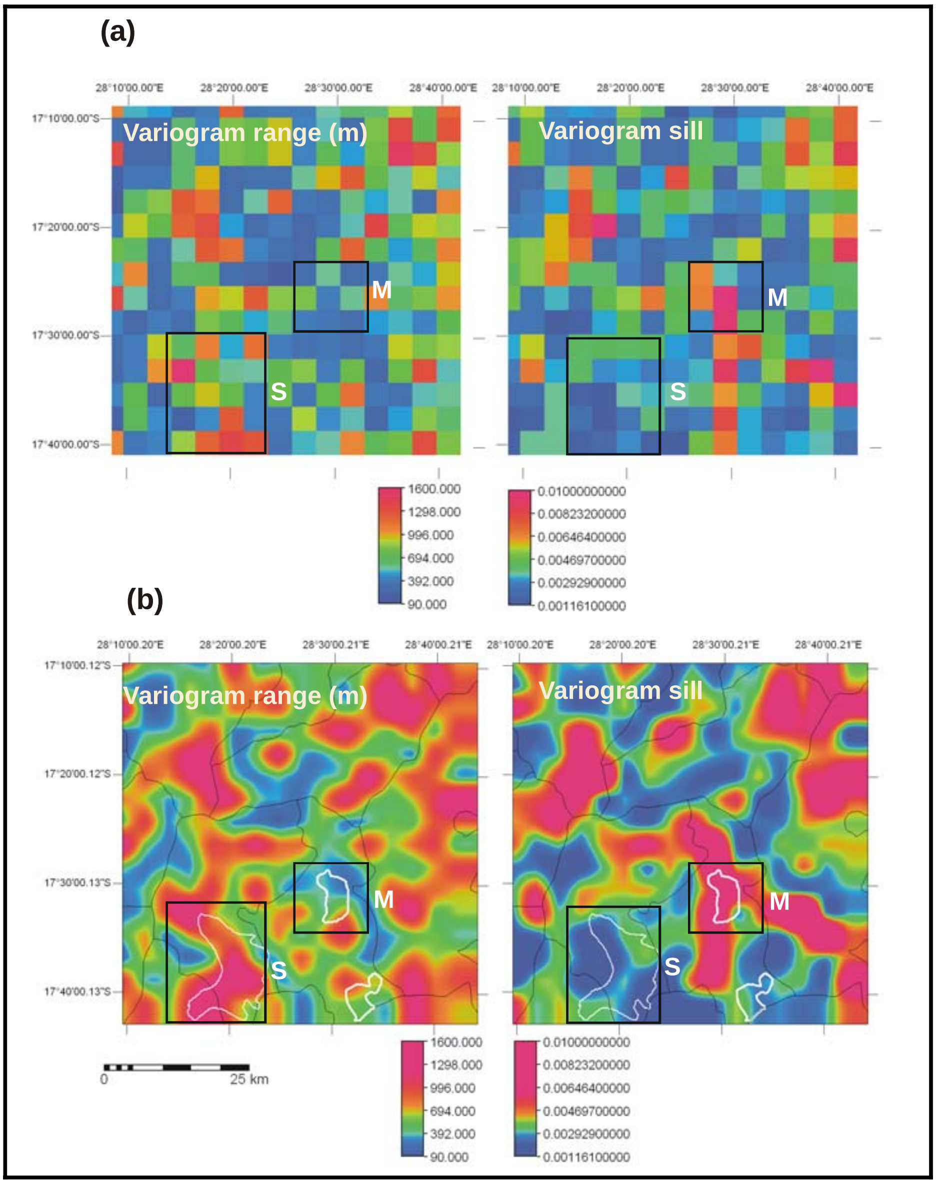

Figure 5.7: Maps showing (a) the distribution of the dominant scale of spatial heterogeneity (i.e., range) and the intensity of spatial heterogeneity (i.e., sill), as well as their (b) bicubic spline versions that clearly reveal the spatial trends in spatial heterogeneity. The polygon in box (S) depicts 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.

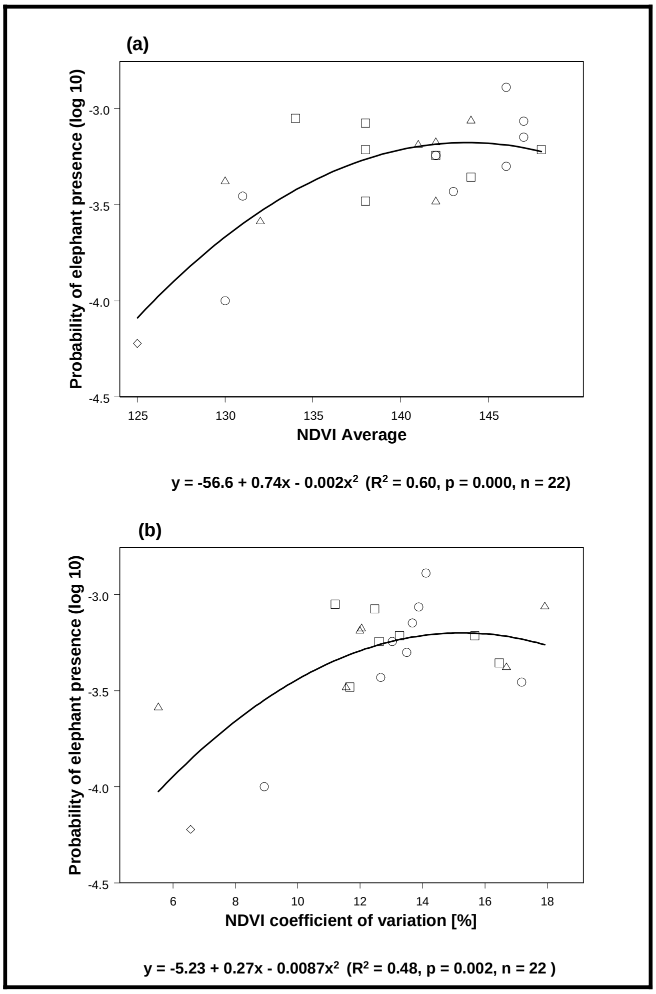

Figure 5.8: Significant ($p < 0.05$) relationships between the probability of elephant presence and the (a) NDVI average and (b) NDVI coefficient of variation in (○) Miombo, (☐) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane floristic-physiognomic vegetation classes.

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

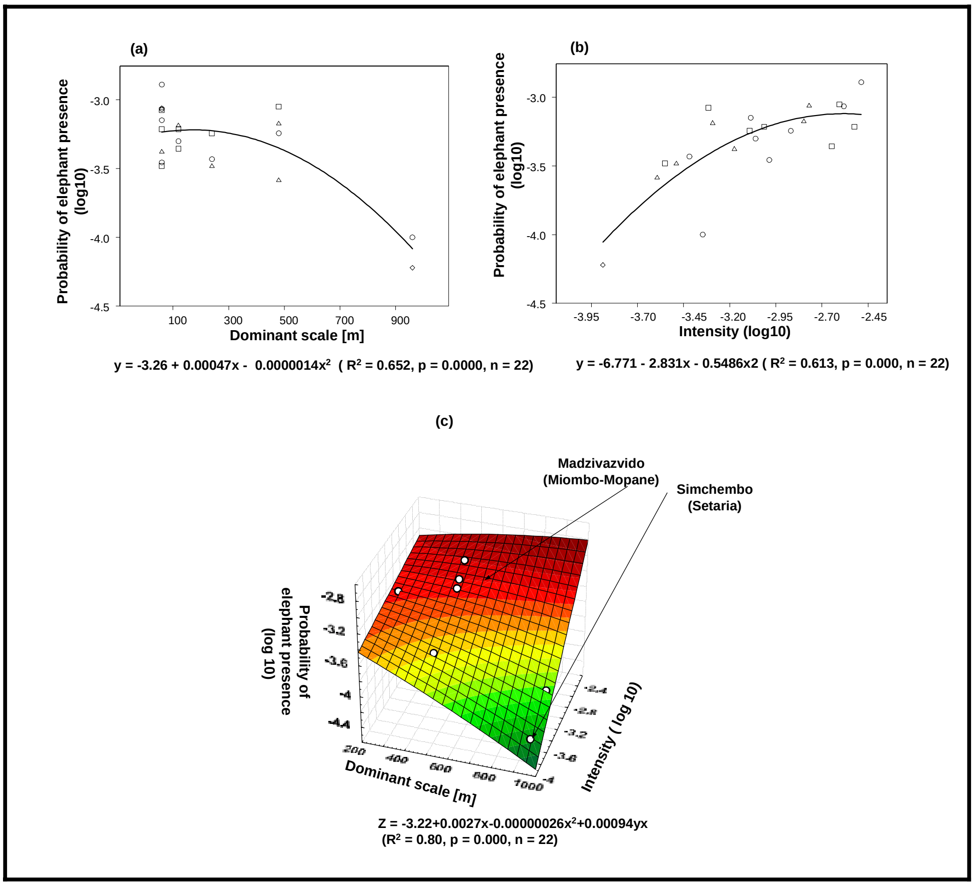

Figure 5.9: Significant ($p < 0.05$) relationships between the probability of elephant presence and wavelet-derived: (a) dominant scale of spatial heterogeneity, (b) intensity of spatial heterogeneity and (c) both the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. 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).

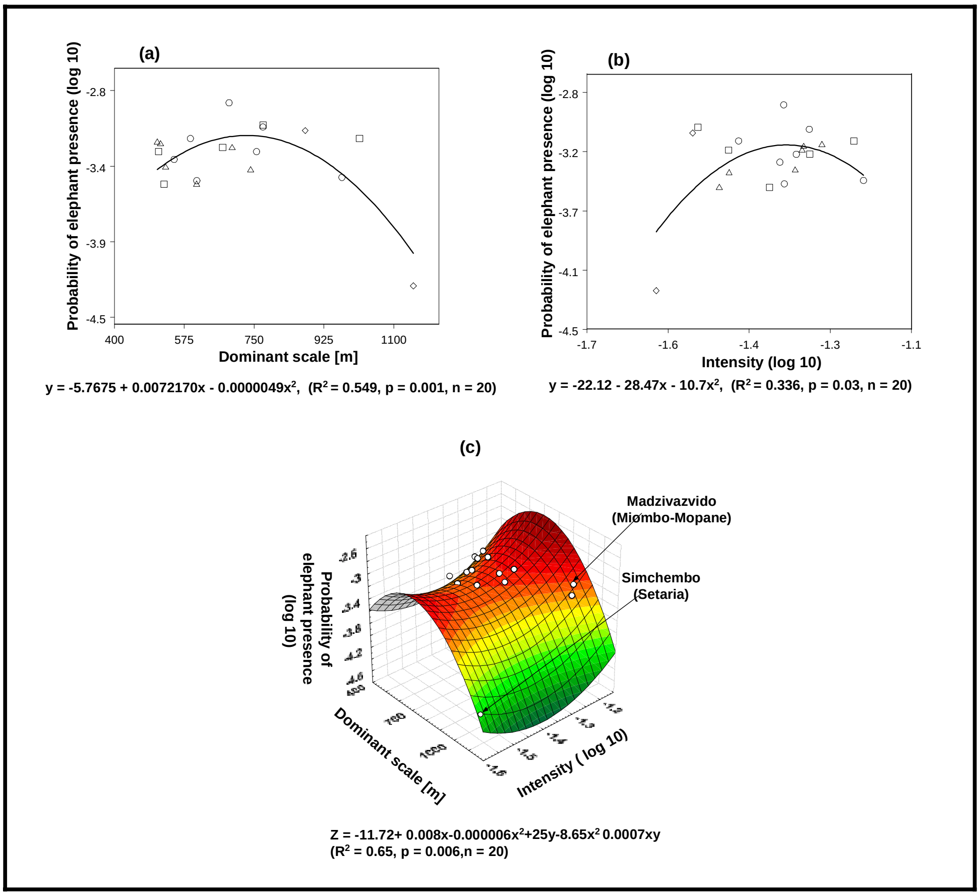

Figure 5.10: Significant ($p < 0.05$) relationships between the probability of elephant presence and variogram-derived: (a) the dominant scale of spatial heterogeneity, (b) the intensity of spatial heterogeneity and (c) both the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity. 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 dominate 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

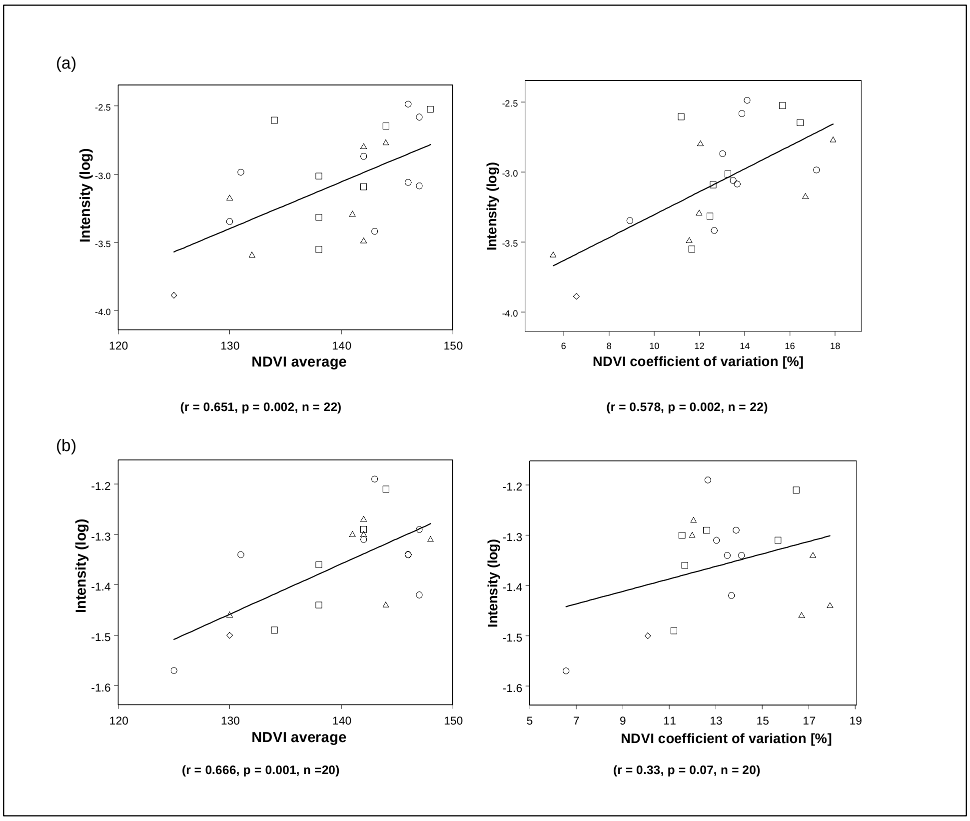

Figure 5.11: Positive correlation of (a) wavelet-derived intensity of spatial heterogeneity, as well as, variogram-derived intensity of spatial heterogeneity to NDVI average and NDVI coefficient of variation. All the correlation coefficients are significant ($p < 0.05$) except the one between the variogram-derived 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.

Chapter 6

The response of elephants to the spatial heterogeneity of vegetation in a Southern African agricultural landscape[5]

Amon Murwira and Andrew K. Skidmore

Abstract

Based on the agricultural landscape of the Sebungwe in Zimbabwe, we investigated whether and how the spatial distribution of the African elephant (*Loxodonta africana*) responded to spatial heterogeneity of vegetation cover based on data of the early 1980s and early 1990s. We also investigated whether and how elephant distribution responded to changes in spatial heterogeneity between the early 1980s and early 1990s. Vegetation cover was estimated from a normalised difference vegetation index (NDVI). Spatial heterogeneity was estimated from a new approach based on 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 dominant scale (i.e., the scale or window size at which the intensity is displayed). We used a variogram to quantify the dominant scale (i.e., range) and intensity (i.e., sill) of NDVI based congruent windows (i.e., 3.84 km x 3.84 km in a 61 km x 61 km landscape). The results indicated that elephants consistently responded to the dominant scale of spatial heterogeneity in a unimodal fashion with the peak elephant presence occurring in environments with dominant scales of spatial heterogeneity of around 457 m to 734 m. Both the intensity and dominant scale of spatial heterogeneity predicted 65 % and 68 % of the variance in elephant presence in the early 1980s and in the early 1990s respectively. Also, changes in the intensity and dominant scale of spatial heterogeneity predicted 61 % of the variance in the change in elephant distribution. The results imply that management decisions must take into consideration the influence of the levels of spatial heterogeneity on elephants in order to ensure elephant persistence in agricultural landscapes.

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[5] In review: Landscape Ecology

6.1 Introduction

Since the 1980s Zimbabwe's wildlife management approach to elephants (*Loxodonta africana*), among other wildlife species, has shifted from a strategy based solely on protected areas to one involving local communities and encompassing conservation in agricultural landscapes (Cumming 1981). This approach was formalized in 1989 through the government's Communal Areas Management Programme For Indigenous Resources (CAMPFIRE). Under this programme, local communities would treat wildlife as an economic asset rather than an impediment to agricultural production (Logan and Moseley 2002). In other words, the programme envisions the coexistence of arable cultivation and wildlife management outside the protected areas. In this study we focus on the elephant because: (1) it is a keystone species of the African savanna (Hoare and Du Toit 1999) and, (2) the African elephant is on the list of the world's threatened species (IUCN 2002) and is considered a conservation priority (Burton 1999).

The success of CAMPFIRE in conserving the elephant can only be measured by the sustained presence or persistence of elephants in agricultural landscapes. However, elephant persistence in Zimbabwe's agricultural landscapes is increasingly being threatened by agricultural field expansion into its natural habitat (Cumming and Lynam 1997). We use the term habitat in its general form, whereby it is defined as the place where an animal lives and this takes into consideration that all animals, except humans, can live in an area with basic resources such as food, water and cover (Yapp 1922, Southwood 1977, Morrison, *et al.* 1992). An agricultural landscape is herein defined as a landscape where agriculture is the primary land use. The critical question for wildlife managers and ecologists is: how can elephant persistence in agricultural landscapes be ensured in the face of expanding agriculture? The answer may lie in understanding the kind of habitat conditions that can make elephants thrive within the unique context of agricultural landscapes, i.e., agricultural landscapes provide a unique environment in which agricultural fields divide natural habitats into discontinuous patches of different spatial arrangements. As a result, not only the amount of natural habitat is important for wildlife species persistence, but also the spatial arrangement (patch dimension and inter-patch distance) of habitat patches is particularly critical (Fahrig 2001). Thus, to ensure elephant persistence in agricultural landscapes it is critical to understand how elephants respond to spatial heterogeneity, i.e., the patterning or patchiness in vital landscape properties such as vegetation cover (Legendre and Fortin 1989, Pickett and Rogers. 1997, Gustafson 1998) that results from the imposition of agricultural fields onto the natural vegetation template.

Although the importance of spatial heterogeneity as a determinant of wildlife species distribution has been widely hypothesised in empirical and theoretical literature (Turner 1989, Johnson, *et al.* 1992, Kareiva and Wennergren 1995, Turner, *et al.* 1997, Lynam and Billick 1999, Adler, *et al.* 2001) an understanding of the levels of spatial heterogeneity at which specific wildlife species such as the African elephant can persist in agricultural landscapes remains rudimentary. This may stem from the ambiguity surrounding the characterisation of spatial heterogeneity (Sparrow 1999). Thus, the unanswered question is: at what level of spatial heterogeneity do wildlife species such as the African elephant thrive in agricultural landscapes? However, in order to properly investigate this question, an objective characterisation of spatial heterogeneity is critical, even before the wildlife response to spatial heterogeneity can be understood.

Remote sensing provides an invaluable source of spatial data that is useful for the quantification of spatial heterogeneity in the landscape. Traditionally, ecologists have quantified spatial heterogeneity from remote sensing images using two basic approaches: (a) the direct image approach, where straight reflectance or reflectance indices of remote sensing images 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 its choice of scale is arbitrary, thus it is subjective. 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. As a result of using the two abovementioned approaches to characterise spatial heterogeneity, ecological patterns such as the spatial distribution of wildlife species have typically been related to measured spatial heterogeneity at a single scale, which either reflects the scale at which the observer collected the data or the scale at which the observer delimited patches, unlike functional spatial heterogeneity (Legendre 1998), which reflects the dominant scale that influences the response of specific organisms in the landscape. Therefore, the need for alternative approaches to characterising spatial heterogeneity is critical.

In view of the limitations of the abovementioned approaches, we develop a new approach to characterising spatial heterogeneity from remote sensing imagery, based on the intensity, as well as the dominant scale as a forerunner to predicting the spatial distribution of elephants in agricultural landscapes. 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

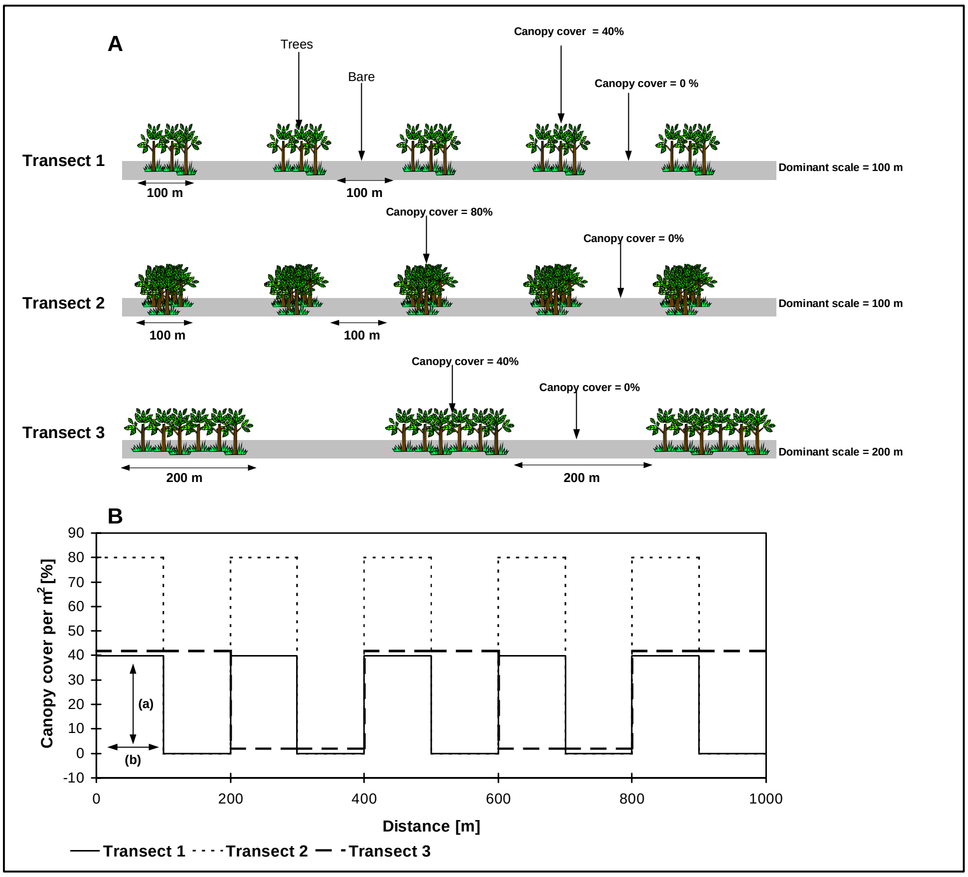


Figure 6.1: Part (A) are transects with alternating spaces of trees and bare ground and part (B) shows the simulation tree canopy cover along each transect assuming that the cover measurements are made after every 1 m (i.e., grain = 1 m) and an extent of 1000 m. For example, the (a) intensity (maximum variance) of transect 1 occurs at (b) a dominant scale of 100 m.

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 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 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 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. 6.1). 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 spatial heterogeneity of a normalised difference vegetation index (NDVI) (a measure of vegetation cover and biomass) was related to the probability of African elephant (*Loxodonta africana*) presence in different parts of the agricultural landscape in northwestern Zimbabwe based on data from the early 1980s and early 1990s. We intended to answer three questions. Firstly, in what kind of agricultural landscape do elephants thrive? Secondly, what kind of agricultural landscape do elephants avoid? Finally, how do elephants respond to changes in the spatial heterogeneity over time? Therefore, we specifically tested whether and how the probability of African elephant presence was related the dominant scale and intensity of spatial heterogeneity of NDVI based on different sampling units defined by an intersection of ward and vegetation class boundaries in the agricultural areas of the Sebungwe. Based on the same sampling units, we also tested whether and how changes in the spatial distribution of the African elephant between the early 1980s and early 1990s were related to changes in the dominant scale and intensity of spatial heterogeneity. As a preamble to testing the above hypotheses, we used a novel windowed variogram technique to characterise spatial heterogeneity from a dominant scale and intensity perspective.

6.2 Materials and methods

Study area

The study was based on the Sebungwe region in Zimbabwe (fig. 6.2). 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 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. 6.2b). 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).

The Sebungwe consists of five wildlife reserves, interspersed with communal lands (fig. 6.2a). The communal lands have varying degrees of agriculture within the natural vegetation units and varying

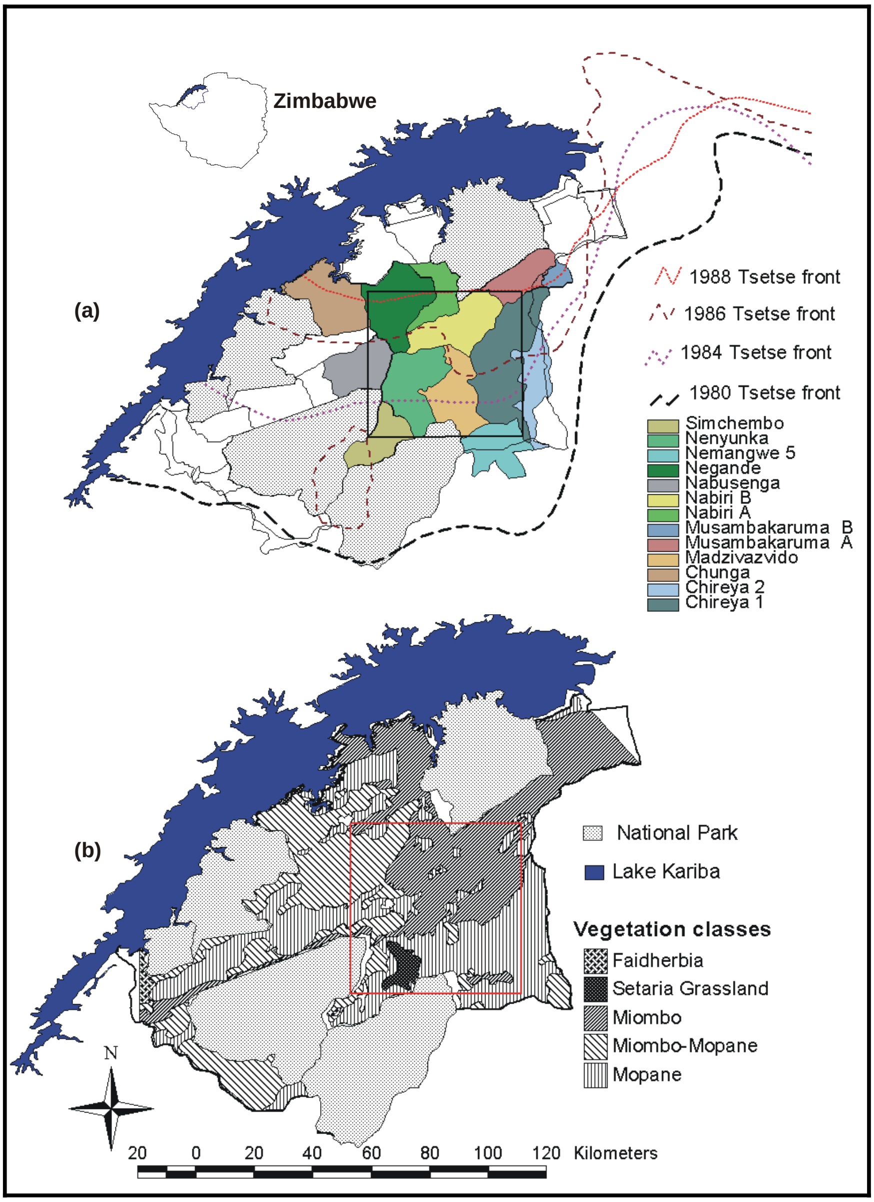


Figure 6.2: The location of the Sebungwe region in Zimbabwe and (a) the wards, national parks and the history of the progression of tsetse eradication (source: Tsetse and Trypanosomiasis control branch, Harare) and (b) the physiognomic-floristic vegetation classes in the communal lands based on (Timberlake and Nobanda 1993). The square box is a 61 km x 61 km area selected for this study.

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. 6.2a). In the communal lands elephant presence is affected rather than by conservation measures or laws like those enforced in wildlife reserves, i.e., in communal lands elephants are present provided there are necessities such as enough cover and water available for both elephants and humans. Elephants have to cross the communal lands when moving between the wildlife reserves.

The Sebungwe landscape evolved from a complex of different historical forces linked to the eradication of tsetse fly (*Glossina* sp.) and the related land use (fig. 6.2a). 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 area mainly covering the communal lands (fig. 6.2). 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 km^2 to 263 km^2, 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 km^2, which is at least 14 times the estimated range of the elephant in the Sebungwe large enough to study elephant distribution. The individual units of analysis in this study were defined by an intersection of ward boundaries and floristic-physiognomic vegetation class boundaries (fig. 6.2b). The floristic-physiognomic vegetation class map (fig. 6.2b) describes the potential vegetation classes, and is therefore constituted by floristic units that do not change over time (Timberlake, *et al.* 1993). By using units that incorporate both floristic-physiognomic vegetation classes and wards, the aim was to incorporate variation due to management and ecological factors respectively. For example, a ward with 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).

Remote sensing

Vegetation cover was estimated from NDVI derived from the readily available TM images of 19 October 1984 and the one of 16 April 1992:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{6.1}$$

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. Relative radiometric correction of the two images was done using the regression method based on pseudo invariant objects such as water bodies, airstrips and roads identifiable in both images (fig. 6.3). This method minimises differences between the two images that result from atmospheric differences between the two dates of image acquisition (Song, *et al.* 2001). Fig. 6.4 shows the NDVI images 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). We used NDVI to study elephant distribution because NDVI have 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 to detect land cover changes (e.g., woodland replacement with agriculture) and can also be used as an indicator of spatial heterogeneity in the landscape (Kerr and Ostrovysky 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 safely 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.

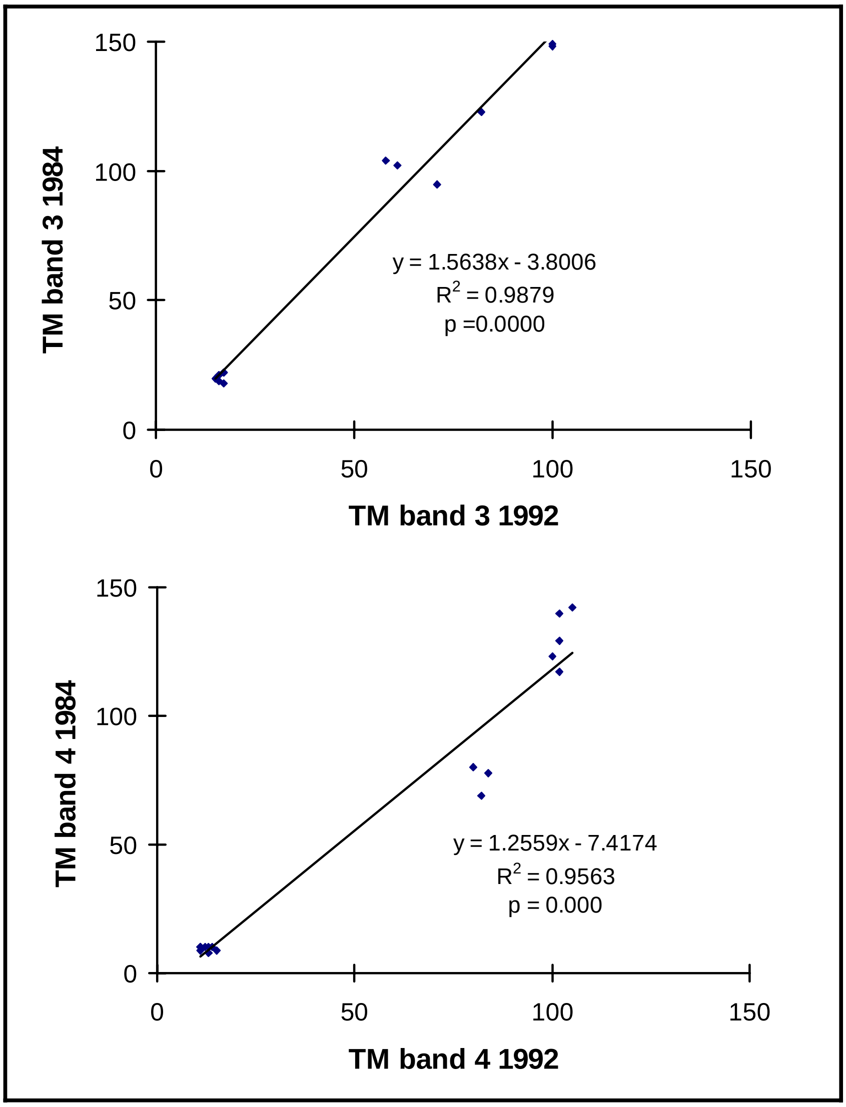


Figure 6.3: Relationship between the DN values of sampled pseudo variant objects (deep water body, airstrips and roads) between the Landsat TM images of 19 October 1984 and 16 April 1992.

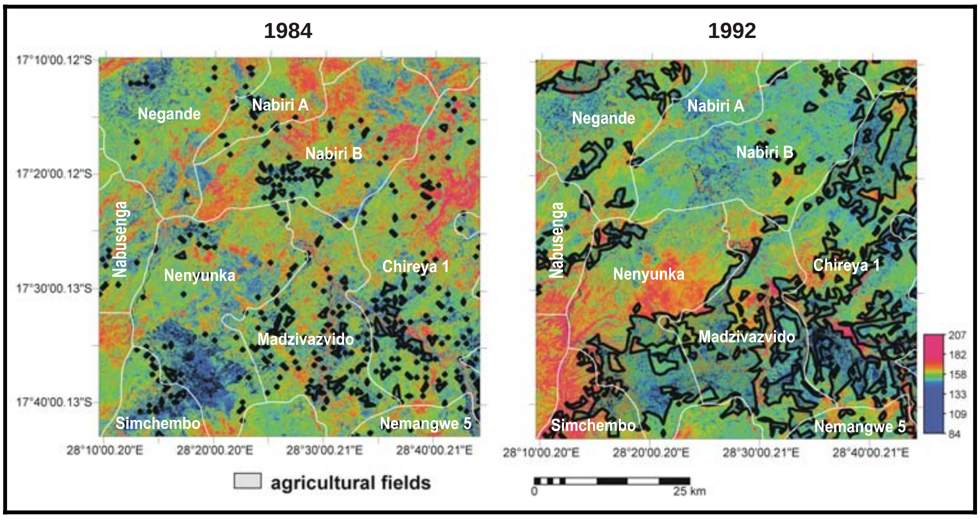


Figure 6.4: Map showing the 1984 and 1992 NDVI maps of the 61 km by 61 km square box overlaid with layers of ward boundaries and agricultural fields. Low NDVI values indicate low vegetation cover and high NDVI values indicate high vegetation cover within a 0 to 255 range.

In this study dry season imagery was used because 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. 6.4 shows that low NDVI mainly coincided with agricultural fields in 1984 and 1992. The 1984 and 1992 agricultural field maps were 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. Besides, being one of the oldest sensors (launched in the early 1980s) that provide a good historical record, 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.

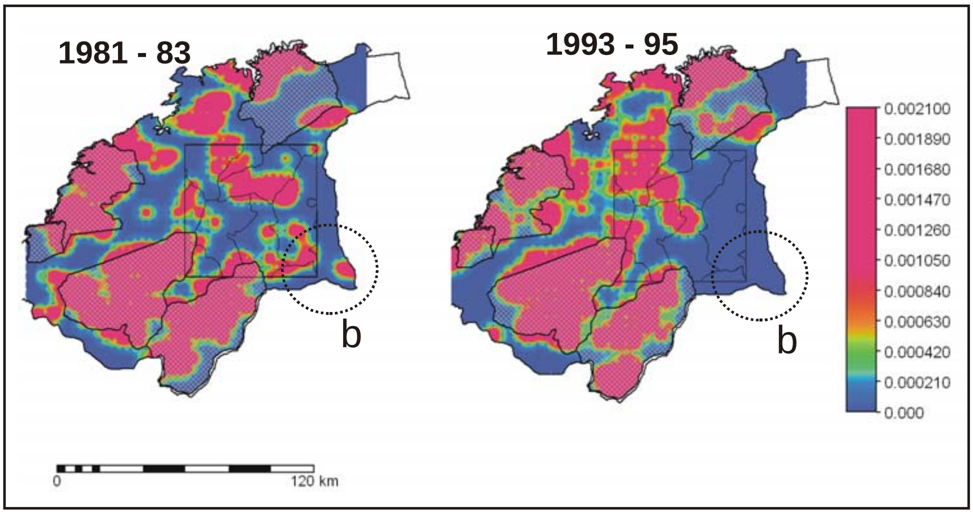


Figure 6.5: Maps showing the probability of elephant presence within a 3 km radius in the study area in 1981-83 and 1993-95. The ellipse (b) illustrates an area where there was a major noticeable decrease in the probability of elephant presence between 1981-83 and 1993-95.

Elephant data

The data on the spatial distribution of elephants in the 1980s and 1990s were determined using respectively a GIS based combination of 1981-1983 point data sets, and 1993-1995 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.

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 λ (*x*) for the elephant point map to give an expected number of events per unit area(Fotheringham, *et al.* 2000):

$$\lambda(x) = \lim_{r=0} \frac{E(N(C(x,r),X))}{\pi r^2} \tag{6.2}$$

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 *r* equal to 3000 m based on a visual exploratory analysis in S-PLUS software (Lam 2001). This kernel radius was also large enough to overcome any locational errors in elephant sightings. We then normalised λ(*x*) by dividing it by the expected number of events in R to produce a normalised or probability function λ*n*(*x*) (Fotheringham, *et al.* 2000):

$$\lambda n(x) = \frac{\lambda(x)}{E(N(R,X))} \tag{6.3}$$

We used the λ*n*(*x*) to estimate the spatial distribution of elephants in the study area during the 1981-83 and 1993-95 periods (fig. 6.5). This spatial point pattern analysis was carried out in the S-PLUS software (Lam 2001) and the map data were transferred to ILWIS GIS software (ITC 2002) where it was converted to a raster map format. 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 presence of at least a single elephant and since the elephant survey data sets were combined, adding the total number of observed elephants of the years would give a false impression. 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. 6.5) 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.

Characterising spatial heterogeneity using a windowed variogram

In this study, the dominant scale and intensity of spatial heterogeneity in NDVI were quantified using a windowed variogram and its main structural parameters, the sill and the range (Curran 1988). 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 (Webster 2000). The range is 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 measures intensity because it is the maximum variance between points that are the distance of the range apart.

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

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x_i) - z(x_i) + h \right]^2 \qquad (6.4)$$

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).

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, $k=1,2,3...,m$ 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 for both the 1984 and 1992 NDVI images (fig. 6.6).

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). This was done for both the 1984 and 1992 NDVI images. The variogram sills in 1984 and 1992 were normalised to 0 – 1 by dividing each variogram sill value by the respective sum of all 256 variogram sills in 1984 and 1992 (fig. 6.6). This was to ensure the comparability and the easy interpretability of intensity of spatial heterogeneity between the dates.

The advantages that we envisaged in using a windowed variogram to estimate the dominant scale and intensity of spatial

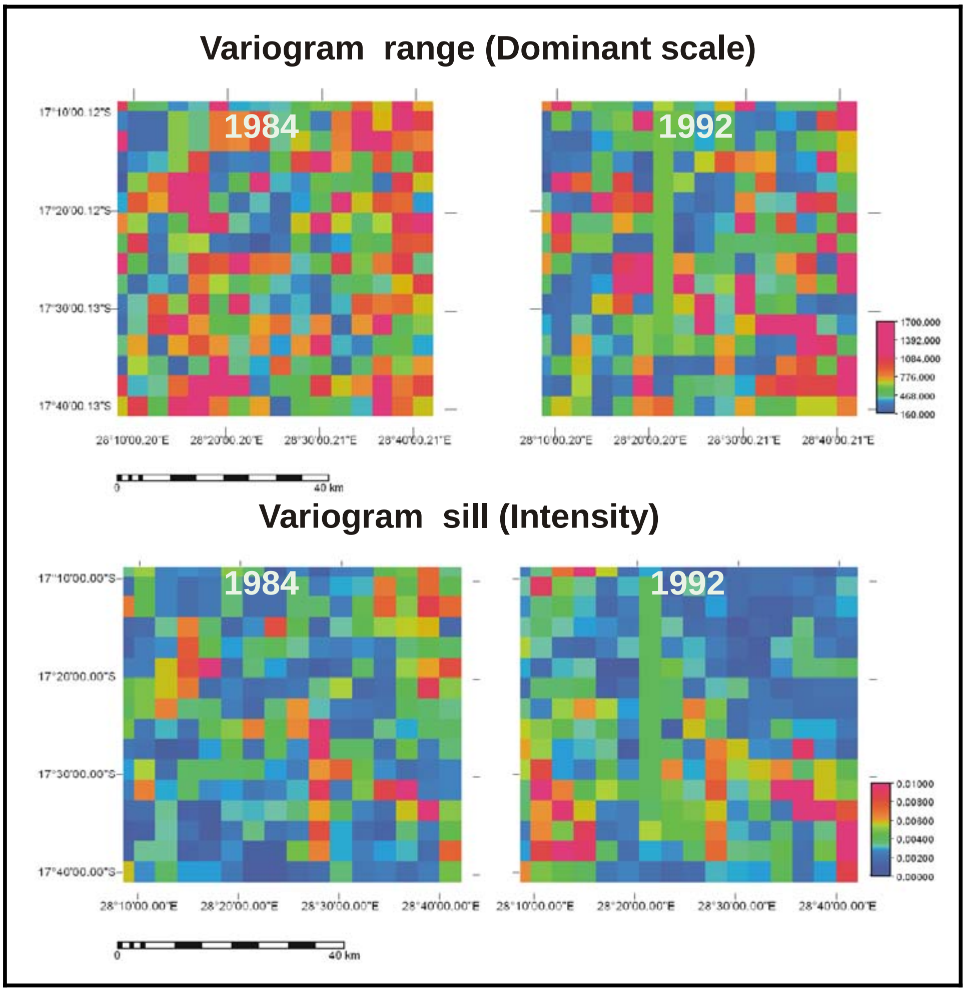


Figure 6.6: Maps showing variations in the variogram range (m) (dominant scale of spatial heterogeneity) and the variogram sill (intensity of spatial heterogeneity) in the 61 km by 61 km square box in 1984 and 1992.

heterogeneity are in the assumption of stationarity (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-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.

Relating the probability of elephant presence to spatial heterogeneity

As mentioned earlier, the analysis of the relationship between the probability of elephant presence and the dominant scale and intensity of spatial heterogeneity 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. A total of 20 units were used in the regression 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). It was assumed that the time differences between the dates of the wildlife surveys and the satellite images was close enough and therefore, had negligible negative effects on the analysis. Fig. 6.7 shows the 20 units that were used in this analysis and their respective area in square kilometres.

Next, regression analysis was used to relate the probability of elephant presence to the dominant scale and intensity of spatial heterogeneity respectively, firstly based on the 1981-1983 elephant data and the 1984 NDVI (early 1980s data), and secondly based on the

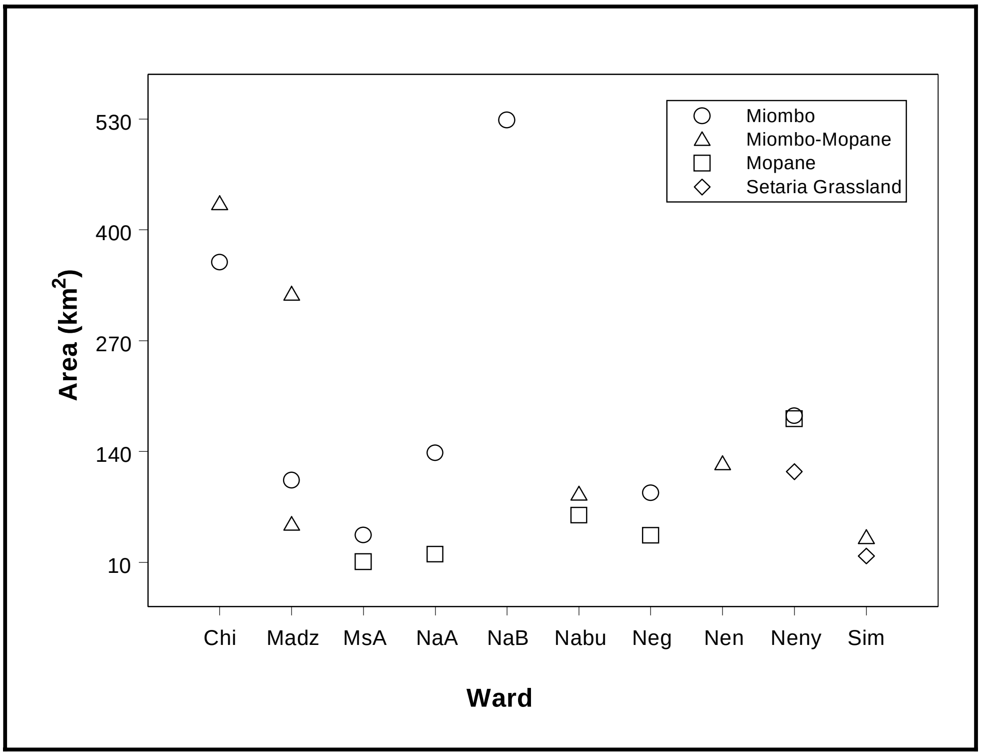


Figure 6.7: Sampling units (intersection of wards and vegetation classes) used in the regression of the probability of elephant presence on the dominant scale and intensity of spatial heterogeneity based on the early 1980s and the early 1990s data (Chi = Chireya 1, Madz = Madzivazvido, MsA = Musambakaruma A, NaA = Nabiri A, NaB = Nabiri B, Nabu = Nabusenga, Neg = Negande, Neny = Nenyunka and Sim = Simchembo).

1993-1995 elephant data with the 1992 NDVI (early 1990s data). In addition, the probability of elephant presence was modelled as a function of both the dominant scale and intensity of spatial heterogeneity plus the interaction between the dominant scale of spatial heterogeneity and the intensity of spatial heterogeneity. Use of data from two dates enabled us to check whether elephant presence was consistently related with the dominant scale and intensity of spatial heterogeneity.

Finally, regression analysis was used to test whether there was a relationship between the changes in both dominant scale and intensity of spatial heterogeneity between the early 1980s and the early 1990s and the concurrent changes in the probability of elephant presence. To accomplish this, the intensity and dominant scale values of 1980s were subtracted from the values of 1990s for each sampling unit, and in this way, positive values would represent an increase while negative values would represent a decrease in each factors between the two dates. Then, the change in the probability of elephant presence was regressed on both the changes in the dominant scale and intensity of spatial heterogeneity plus the interaction between the changes in the dominant scale and intensity of spatial heterogeneity.

6.3 Results

Elephant presence and spatial heterogeneity in space

Fig. 6.8a shows that there were significant ($p < 0.05$) quadratic relationships between the probability of elephant presence and the dominant scale of spatial heterogeneity both in 1980s and 1990s. It can be observed that as the dominant scale of spatial heterogeneity increases, there is a concomitant increase in the probability of elephant presence until it reaches a peak, which is equal to 734 m in the early 1980s and equal to 457 m in the early 1990s, and then the probability of elephant presence begins to decrease. The regression functions for 1980s and 1990s explain 55 % and 57 % of the variance in the probability of elephant presence respectively. In addition, Fig. 6.8b shows that there were also significant ($p < 0.05$) quadratic relationships between the probability of elephant presence and the intensity of spatial heterogeneity both in 1980s and 1990s. It can be observed that as the intensity of spatial heterogeneity increases, there is an associated increase in the probability of elephant presence until a certain level and then the probability of elephant presence begins to either saturate (1990s) or even decrease (1980s). The regression functions for 1980s and 1990s explain 34 % and 39 % of the variance in the probability of elephant presence respectively.

The encircled point (Mopane vegetation class in Chireya 1) is an outlier in the intensity of spatial heterogeneity and the probability of elephant presence regression function of the 1990s, but it is not an outlier in the dominant scale of spatial heterogeneity and the probability of elephant presence function of the 1990s. This, it is observed, is the effect

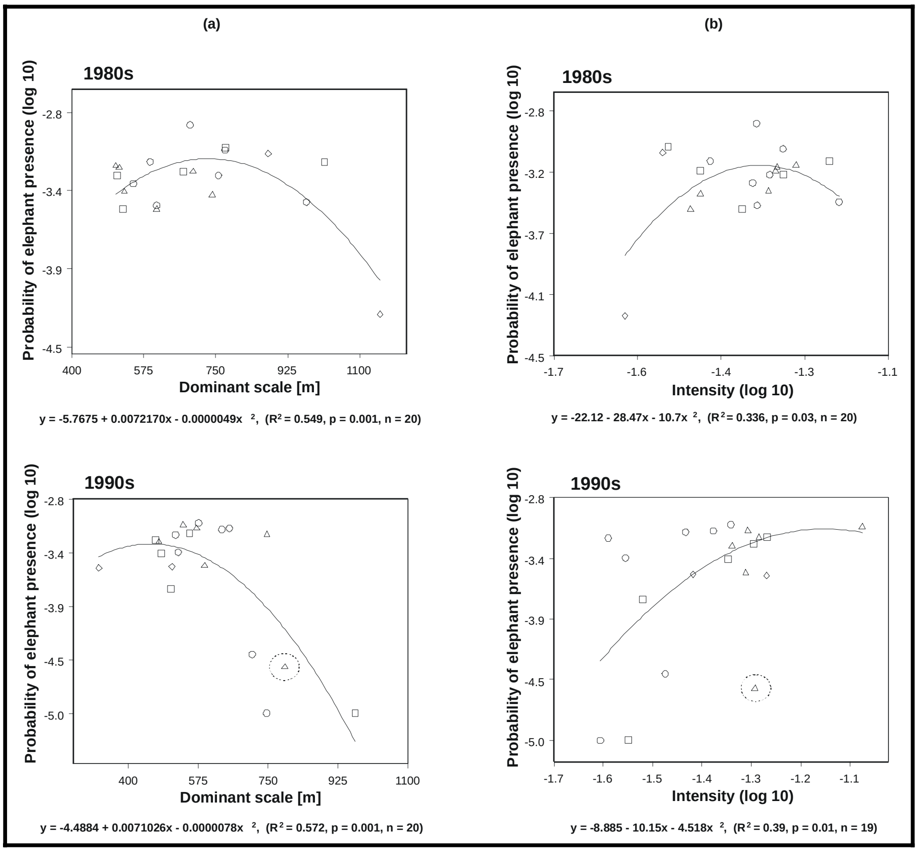


Figure 6.8: Significant ($p < 0.05$) relationships between the probability of elephant presence and the (A) dominant scale of spatial heterogeneity and (B) intensity of spatial heterogeneity (intensity) in the study area in the 1980s and 1990s in (○) Miombo, (☐) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane floristic-physiognomic vegetation classes. The encircled point is an outlier in the probability of elephant presence-Intensity function but it is not an outlier in the elephant presence-dominant scale function, thus illustrating the interactive effect of dominant scale and intensity of spatial heterogeneity on the probability of elephant presence.

of the interaction between intensity of spatial heterogeneity and dominant scale of spatial heterogeneity on the probability of elephant presence (see fig. 6.8 below). It can also be observed that the curvilinear nature of the relationship between the probability of elephant presence and intensity and dominant scale of spatial heterogeneity is not a result of difference in vegetation class. For example, it is apparent in fig. 6.8 that the probability of elephant presence responds in a curvilinear nature, to the variation in dominant scale in individual vegetation classes such as Mopane and Miombo. In other words, the points belonging to different vegetation classes are not clumped into specific areas of the graph.

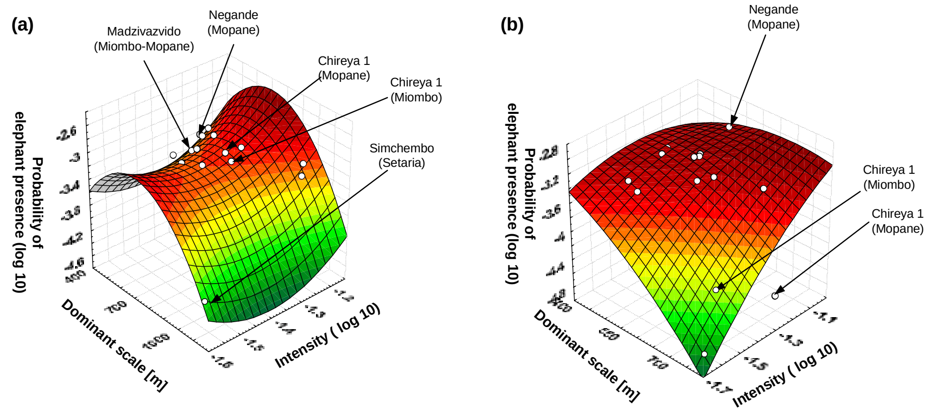
Fig. 6.8 shows the probability of elephant presence as a significant function ($p < 0.05$) of dominant scale and intensity of spatial heterogeneity plus their interaction in 1980s and 1990s. The regression functions for 1980s and 1990s explain 65 % and 68 % of the variance in the probability of elephant presence respectively. Several observations can be made from fig. 6.8. From fig. 6.8a it can be observed that a low probability of elephant presence is associated with a combination of: (1) low or high intensity of spatial heterogeneity and small dominant scales of spatial heterogeneity (less than 734 m), as well as, (2) low intensity of spatial heterogeneity occurring at large dominant scales of spatial heterogeneity. For example, the low probability of elephant presence in the Mopane vegetation class in Negande is associated with high intensity of spatial heterogeneity and small dominant scales of spatial heterogeneity, and the low probability of elephant presence in the Miombo-Mopane vegetation class in Madzivazvido is associated with a combination of a high intensity and small dominant scale of spatial heterogeneity (fig. 6.8a). In addition, the low probability of elephant presence in the Setaria vegetation class in Simchembo is associated with low intensity of spatial heterogeneity and large dominant scales of spatial heterogeneity (greater than 734 m) (fig. 6.8a). In contrast, a combination of high intensity of spatial heterogeneity and medium dominant scales of spatial heterogeneity (around 734 m) are associated with a high probability of elephant presence. For example, the Miombo and Mopane woodland classes in Chireya 1 that have a combination of high intensity of spatial heterogeneity and dominant scales of spatial heterogeneity that are around 734 m are associated with a high probability of elephant presence (fig. 6.8a). In addition, it can be observed that there were a few agricultural fields in Chireya 1 in the early 1980s (fig. 6.4).

Fig. 6.9b shows new landscape conditions of the early 1990s where mostly the left part of fig. 6.9a (i.e., the 1980s landscape condition) is represented. It can be observed that a combination of low intensity and large dominant scales of spatial heterogeneity is associated with a low probability of elephant presence. For example, in the Miombo and Mopane vegetation classes in Chireya 1, the low intensity of spatial heterogeneity occurring at large dominant scales of spatial heterogeneity is associated with a low probability of elephant presence in the 1990s (fig. 6.9b). In addition, there was an increase amount of agricultural fields (fig. 6.4). On the other hand, in the Mopane vegetation class in Negande, a combination of the high intensity of spatial heterogeneity occurring at dominant scales of spatial heterogeneity around 457 m are associated with a high probability of elephant presence (fig. 6.9b). It can also be observed that the upper left corner of Negande has small patches of low NDVI, as well as small agricultural fields (fig. 6.4).

Change in elephant presence and change in spatial heterogeneity over time

The changes in the probability of elephant presence between 1980s and 1990s were related with changes in dominant scale and intensity of spatial heterogeneity during the same period. Fig. 6.10 shows a statistically significant ($p < 0.05$) relationship between changes in the probability of elephant presence and changes in the intensity of spatial heterogeneity, as well as changes in the dominant scale of spatial heterogeneity. It can generally be observed that a combination of an increase in intensity of spatial heterogeneity and a decrease in the dominant scale of spatial heterogeneity relative to no change were generally associated with a decrease in the probability of elephant presence in the study area. In addition, combined decreases in the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity were associated with a decrease in the probability of elephant presence between the 1980s and 1990s. For example, in the Miombo vegetation classes in Chireya 1 there was a decrease in both intensity and dominant scale of spatial heterogeneity that was associated with a decrease in the probability of elephant presence between the 1980s and the 1990s. In addition, fig. 6.4 shows a related increase in the amount of agricultural fields in Chireya 1 between the 1980s and 1990s.

In contrast, it can be generally observed that a combined increase in both the intensity of spatial heterogeneity and dominant scale of spatial heterogeneity was associated with an increase in the probability of elephant presence in the study area between the 1980s and 1990s. In addition,



$Z = -11.72 + 0.008x - 0.000006x^2 + 25y - 8.65x^2\ 0.0007xy$

$R^2 = 0.65$
$p = 0.006$
$n = 20$

$Z = -10.62 + 0.013x - 0.000004x^2 - 7.19y + -1.68y^2\ 0.067xy$

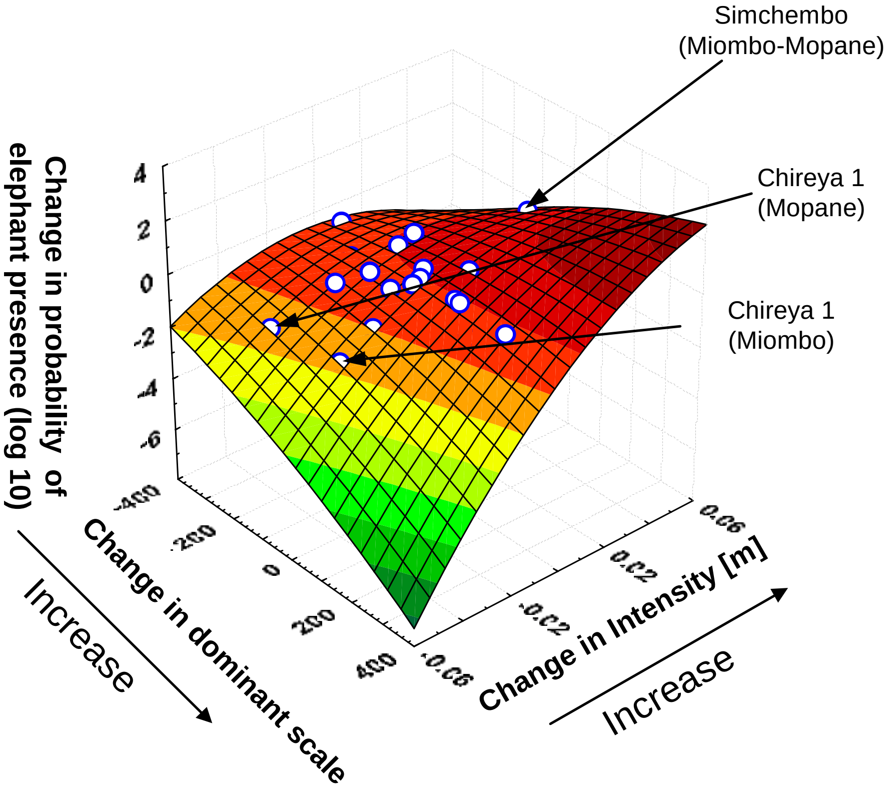
$R^2 = 0.\ 68$
$p = 0.003$
$n = 20$

Figure 6.9: A significant ($p < 0.05$) relationship between the probability of elephant presence and the intensity and dominant scale of spatial heterogeneity plus their interaction in the study area in the (a) 1980s and (b) 1990s. The graph surface represents increasing probability of elephant presence from green (lowest probability) to deep red (the highest probability of elephant presence).

relative stability in the dominant scale of spatial heterogeneity and an increase in the intensity of spatial heterogeneity were associated with an increase in the probability of elephant presence. For example, the Miombo-Mopane vegetation class in Simchembo had an increase in intensity and a constant dominant scale of spatial heterogeneity between 1980s and 1990s and this was associated with an increase in the probability of elephant presence between the two periods. Fig. 6.4 shows a related increase in the NDVI in Simchembo between the 1980s and 1990s.

6.4 Discussion

So, in what kind of agricultural landscape do elephants thrive? Our results indicated that elephants do not mind an environment where there are scattered agricultural fields within a largely natural area. In our analysis, the preferred environments, i.e., environments with the peak probabilities of elephant presence are associated with high intensity of spatial



$Z = -0.008-0.00012x-0.000003x^2+38.93y-487.25y^2+0.108xy$

$\mathbf{R^2 = 0.61}$

$\mathbf{p = 0.02}$

$\mathbf{n = 20}$

Figure 6.10: A significant ($p < 0.05$) relationship between change in the probability of elephant presence and changes in the intensity and dominant scale of spatial heterogeneity between the 1980s and 1990s. On all axes, positive values indicate an increase, negative (-) indicate a decrease and zero (0) indicates no change. The green on the graph surface represents a greater decrease in the probability of elephant presence and deep red represents an increase in the probability of elephant presence.

heterogeneity (i.e., high variability in vegetation cover) that occurs at intermediate dominant scales of spatial heterogeneity with peaks at 734 m (early 1980s) and 457 m (early 1990s) (fig. 6.9). We can deduce that the existence of high amounts of vegetation cover at patch dimensions, as well as inter-patch distances of 457 m to 734 m encourage elephant persistence in the agricultural landscape. For example, there was a peak probability of elephant presence in the Mopane and Miombo vegetation classes in Chireya 1 during the 1980s that was associated with a high intensity occurring at the dominant scales of spatial heterogeneity of 734 m and (fig. 6.8a) and during this time, there were little agricultural fields in these units. The dominant scales of spatial heterogeneity at which the peak probability of elephant presence was found are close to the findings reported by (Guy 1976b, Guy 1976a) that the Sebungwe elephant prefers an environment with high variability of vegetation species cover and that the elephant can stay for more than 5 hours in natural vegetation patches of about 0.25 km^2 or alternatively patches with a linear dimension of 0.5 km (500 m). Therefore, given a high intensity of spatial heterogeneity, the 457 m to 734 m dominant scales of spatial heterogeneity may define "the optimal range of spatial heterogeneity " at which elephant persistence can be ensured in the agricultural landscape and below and above which elephant persistence in the Sebungwe agricultural landscapes can be threatened (fig. 6.11).

Moreover, the shift in the dominant scale of spatial heterogeneity at which the peak probability of elephant presence occurred (fig. 6.11) represents a phenomenon that reflects the changes in landscape conditions, particularly increased agricultural activity that occurred between the early 1980s and the early 1990s. Specifically, we deduce that in the 1980s, when there was quasi-intensive agricultural activity; elephants could roam "freely" across the hostile patches, e.g., agricultural fields, but with intensive agricultural activity in the 1990s, the peak of the probability of elephant presence shifted downwards to 457 m, suggesting that elephants could only "tolerate" relatively smaller dimensions of hostile patches. From this perspective, we can deduce that the 457 m to 734 m range constitute the "optimal range" of the dominant scale of spatial heterogeneity, where the lower limit (457 m) of the "optimal range" represents the level of spatial heterogeneity that elephants "do not mind" in agriculture-dominated environmental conditions while the upper limit of the range (734 m) represents the level of spatial heterogeneity at which elephants "thrive" in natural vegetation-dominated environmental

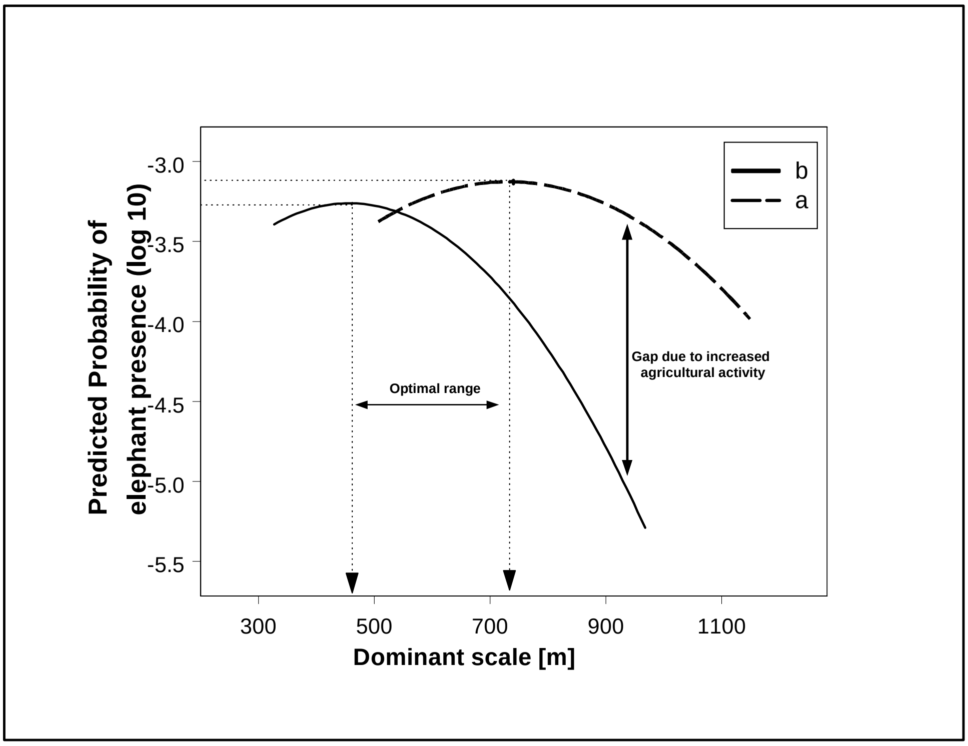


Figure 6.11: The regression models of the relationship between the probability of elephant presence and dominant scale of spatial heterogeneity in the (a) early 1980s and the (b) early 1990s extracted from fig. 6.8 to illustrate the effect of changes in the dominant scale of spatial heterogeneity on the probability of elephant presence (i.e., illustrated by the gap) due to increased agricultural activity between the two periods. Also illustrated is the upper limit (734 m) and lower limit (457 m) of that may define the "optimal range" of spatial heterogeneity determined from the distance between the peaks of elephant presence in the 1980s and 1990s models.

conditions. In addition to the shift in the dominant scale of spatial heterogeneity at which the peak probability of elephant presence occurred between the 1980s and the 1990s, we see that the probability of elephant presence dropped more sharply with increasing dominant scales of spatial heterogeneity in the 1990s compared with the 1980s, resulting in a gap between the models of the two dates (fig. 6.11). The increased levels of agricultural activity in the 1990s also explain this "gap" phenomenon. In other words, as stated earlier, the quasi-intensive nature of agricultural activity in the 1980s supported a "free movement" of elephants in the landscape, whereas in the 1990s elephant movement got more “restricted” due to the intensified agricultural activities. Therefore, we could hypothesise that if dominant scale of spatial heterogeneity continues to drop below the lower limit (i.e., 457 m), regardless of the level of intensity, elephants could increasingly disappear from the agricultural landscape of the Sebungwe. In addition, we could hypothesise that if agricultural activity increases unchecked beyond the 1990s levels, the “gap” will become increasingly larger as the elephants increasingly disappear from those parts of the agricultural landscape where agricultural activity is increasing.

Apart from suggesting the preferable environments for elephants, our results also showed that elephants avoid certain environments. Specifically, elephants appear to avoid environments that have either low intensity of spatial heterogeneity that occurs at relatively large dominant scales of spatial heterogeneity or environments where low or high intensity of spatial heterogeneity occurs at small dominant scales of spatial heterogeneity. In order to properly explain this, we must first understand the important context of the study area, i.e., it is an agricultural area situated in a savanna landscape where there will never arise a situation where a complete tree cover results in low intensity of spatial heterogeneity at a large dominant scale because savannas are constituted by a discontinuous tree cover that occurs in relatively small patches interspersed with patches of grassland or agriculture (Scholes 1997). In other words, low intensity of spatial heterogeneity at large dominant scales is always associated with grassland or agriculture (fig. 6.4 and fig. 6.9). Thus, it is apparent that the low probability of elephant presence that is associated with a combination of low intensity and large dominant scale of spatial heterogeneity occurred within grassland areas such as Setaria (fig. 6.4 and fig. 6.9a) in the 1980s and areas with a relatively continuous coverage of agricultural fields (fig. 6.9b and fig. 6.4) in the 1990s. Such environments have only scattered remnants of woodland that remain within a largely agricultural landscape and this repulses elephants in the Sebungwe. In addition, there is evidence that elephants also avoid high intensity that occurs at small dominant scales of spatial heterogeneity that indicate high variability in vegetation cover that occurs in small patch dimensions in the Sebungwe landscape. In this regard, we can deduce that a landscape dominated by small patches of both high vegetation cover (e.g., remnants of woodland) and low vegetation cover, (e.g., patches of bare ground, grassland or agricultural fields) is not preferred by elephants. For example, the sample unit of Mopane vegetation class in the upper left corner of the study area in Negande had small patches of high vegetation cover that were interrupted with agricultural fields and patches of low vegetation cover in the 1980s and, it was associated with a low probability of elephant presence (fig. 6.4 and fig. 6.9a).

Having investigated how elephants respond to spatial heterogeneity in space, we next investigated whether elephants also respond to changes in the intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity over time. Our findings showed that elephants do respond to changes in spatial heterogeneity over time. Agricultural field expansion following the accelerated tsetse eradication since the early 1980s is the main driving agent for changes in the levels of spatial heterogeneity of vegetation in the Sebungwe (Cumming 1981, du Toit 1985, du Toit 1995, Cumming and Lynam 1997). For example, a decrease in the probability of elephant presence was associated with: (1) a decrease in the intensity of spatial heterogeneity that occurred together with an increase in dominant scale of spatial heterogeneity in those wards where agricultural fields expanded as tsetse was eradicated, suggested that elephants were repelled when patch dimensions of low vegetation, e.g., agricultural fields in the landscape became larger and (2) a decrease in both the intensity of spatial heterogeneity and dominant scale of spatial heterogeneity suggested that elephants moved away when small vegetation cover patches constituted the agricultural landscape. In contrast, elephant presence persisted and even increased in land units where there was no change in terms of spatial heterogeneity and increased in situations when there was an increase in both the intensity and the dominant scale of spatial heterogeneity (fig. 6.10). In other words, elephants persisted in non-changed environments (i.e., environments with constant levels of spatial heterogeneity). Therefore, from our findings, we proved that elephants are sensitive to changes in the levels spatial heterogeneity in agricultural landscapes such as the Sebungwe over time.

Furthermore, we proved that the different vegetation classes do not influence the temporally consistent hump-shaped relationship between the probability of elephant presence and the level of spatial heterogeneity, thereby confirming the existing knowledge that the African elephant is a habitat generalist (Kingdon 2001). The hump-shaped relationship also confirms the existing observation that spatial fragments of resources (spatial heterogeneity) can produce abrupt ecological responses (With and Crist 1995). However, as Jansson (2002) noted, when ecologists succeed in defining measures of e.g., measures of spatial heterogeneity, the next question is over what areas are the measures applicable or biologically relevant? We feel that our method can be relevant for an area with similar ecological conditions and for different wildlife species. We also feel that if these findings can be replicated elsewhere, this may go a long way in improving the understanding of the habitat space requirements of different wildlife species in agricultural environments, such as the Sebungwe, that may allow for human-wildlife coexistence.

Finally, where our study differs significantly from those studies that view spatial heterogeneity from the direct image (Oindo and Skidmore 2001) and patch mosaic approaches (Griffith, *et al.* 2000, Li, *et al.* 2001), is in our intensity and dominant scale perspective to spatial heterogeneity, i.e., by using the intensity and the dominant scale as inseparable properties of spatial heterogeneity, we were able to incorporate both the variability of vegetation cover that is emphasized by variance measure of the direct image approach, as well as the patch dimension that the patch mosaic approach emphasizes. Also, using the windowed variogram, we measured the variation in a landscape property (NDVI), as well as incorporated the gradient that characterises patch boundaries in the savanna landscape, thereby avoiding the crisp boundary approach of the patch mosaic model, which was criticized as inappropriate for modelling ecological patterns like wildlife distribution (Legendre and Fortin 1989, Legendre 1998). Thus, we argue that our approach is more valid for understanding an ecological pattern like elephant distribution since it incorporates some characteristics of both the direct image approach and the patch mosaic approach, in addition to capturing the gradient component that is missed by the latter. However, we have to caution that the variogram method can only work in situations where there is stationarity, i.e., where a range and sill, that are the basis upon which the dominant scale and intensity of spatial heterogeneity is quantified, can be defined. But other methods, such as wavelets can also be applied (Murwira and Skidmore. 2003).

6.5 Conclusions

We investigated (1) whether and how the spatial distribution of the African elephant was related the dominant scale and intensity of spatial heterogeneity in the agricultural landscape of Sebungwe, and (2) whether and how changes in the spatial distribution of elephants between the early 1980s and early 1990s were related concurrent changes in the dominant scale and intensity of spatial heterogeneity. Consequently, some conclusions and management recommendations can be drawn from the results. Firstly, we concluded that the intensity and dominant scale of spatial heterogeneity could consistently (i.e. in the 1980s and 1990s) predict the spatial distribution of elephants in the agricultural landscapes, such as the Sebungwe. Consequently, changes in the intensity and dominant scale of spatial heterogeneity can also predict changes in the probability of elephant presence. Secondly, we concluded that given high intensity, the 457 m to 734 m dominant scale of spatial heterogeneity could be the “optimal landscape environment” at which elephant persistence can be ensured in the agricultural landscape and below and above which elephant persistence in the Sebungwe agricultural landscapes can be threatened. Thirdly, we also concluded that although the relationship between the probability of elephant presence and the dominant scale of spatial heterogeneity in the Sebungwe was stable over time (i.e., in the 1980s and the 1990s), the level of agricultural activity determined the rate of decrease in the probability of elephant presence with the increasing dominant scale of spatial heterogeneity. Finally, we observed that, in managing the Sebungwe landscape to enhance wildlife species presence for the benefit of community based wildlife management programmes such as CAMPFIRE, management decisions must take into consideration the appropriate levels of spatial heterogeneity to ensure wildlife species persistence in the agricultural landscapes.

Chapter 7

Predicting elephant (*Loxodonta africana*) presence in a Southern African agricultural landscape from the spatial heterogeneity of NDVI [6]

Amon Murwira and Andrew K. Skidmore

Abstract

We investigated whether and how the probability of African elephant (*Loxodonta africana*) presence was related to spatial heterogeneity of vegetation cover (estimated from a remotely sensed normalised difference vegetation index (NDVI) from Landsat TM) in space and over time in the agricultural landscape in northwestern Zimbabwe between the early 1980s and early 1990s. A new approach was used to characterise spatial heterogeneity based on 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 dominant scale (i.e., the scale or window size at which the intensity is measured). This approach was implemented using a wavelet transform. The results showed that spatial heterogeneity could explain 80 % and 93 % of the variance of the probability of elephant presence in the early 1980s and early 1990s respectively. The changes in spatial heterogeneity predicted 89 % of the variance of the change in elephant presence between the 1980s and 1990s. These results imply that if elephants are to be conserved in agricultural landscapes, it is important that wildlife management strategies aimed at sustaining wildlife species in agricultural landscapes take into account the level of spatial heterogeneity of natural vegetation. In addition, the results imply the wavelet transform-derived spatial heterogeneity could improve the prediction of ecological patterns.

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[6] Based on: The spatial distribution of elephants (*loxodonta africana*) in relation to the spatial heterogeneity of vegetation cover in a Southern African agricultural landscape, paper presented to the conference on Scales and Dynamics in Observing the Environment, 10-12, September 2003, Nottingham, UK. Also submitted to: Remote Sensing of Environment

7.1 Introduction

Community based natural resource management (CBNRM) programmes in the agricultural landscapes of Southern Africa such as the Communal Areas Management Programme For Indigenous Resources (CAMPFIRE) in Zimbabwe (Hoare and Du Toit 1999, Hulme and Murphree 2001, Logan and Moseley 2002) owe their existence to the persistence of wildlife species throughout these landscapes. However, wildlife species persistence in agricultural landscapes of Southern Africa, particularly in Zimbabwe, is increasingly being threatened by agricultural field expansion into the natural habitats (Cumming 1982, Cumming and Lynam 1997, Hoare 1999, Hoare and Du Toit 1999). The critical question for wildlife managers and ecologists is: how can wildlife persistence outside the wildlife reserves be ensured in the face of expanding agriculture? In other words, in what kind of agricultural landscape can wildlife species thrive? The answer is in understanding the kind of habitat conditions that can make elephants persist within the unique context of agricultural landscapes where arable fields cut up natural habitats into discontinuous patches of different spatial arrangements. In such a landscape, it is not only the amount of natural habitat that is important for wildlife species persistence, but the spatial arrangement of habitat patches also becomes particularly critical. Thus, to ensure wildlife species persistence in agricultural landscapes it is critical to understand how they respond to spatial heterogeneity (i.e., the patchiness in vital landscape properties such as vegetation cover (Legendre and Fortin 1989, Pickett and Rogers. 1997, Gustafson 1998) that is imposed by the agricultural fields onto the natural habitat. Consequently, the need for research to characterise wildlife species response to spatial heterogeneity in agricultural landscapes is critical.

Although empirical and theoretical literature recognises the importance of spatial heterogeneity to wildlife distribution (Turner 1989, Johnson, *et al.* 1992, Kareiva and Wennergren 1995, Turner, *et al.* 1997, Lynam and Billick 1999, Adler, *et al.* 2001), an understanding of the levels of spatial heterogeneity at which specific wildlife species can persist in agricultural landscapes is still rudimentary. This may stem from the lack of clarity in the characterisation of spatial heterogeneity (Sparrow 1999).

In other words, this suggests that spatial heterogeneity needs to be properly characterised even before the wildlife response to spatial heterogeneity can be understood.

The quantification of spatial heterogeneity is an empirical approach based on observed data, thus it is a forerunner to testing specific hypotheses about ecological patterns (Perry, *et al.* 2002). In this regard, ecologists have traditionally quantified spatial heterogeneity from remote sensing imagery by using two basic approaches: (a) the direct image approach, where straight reflectance or reflectance indices of remote sensing images 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 at the pixel size of the image and, in this case, it is only the reflectance values that are important. The limitation of this approach is that its choice of scale (i.e., window size) is arbitrary, thus it is subjective. 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 to characterise spatial heterogeneity remain underdeveloped.

In view of the limitations in the approaches mentioned above, we develop a new approach to characterising spatial heterogeneity, based on intensity, as well as the dominant scale and apply it to predict wildlife species distribution, particularly that of the African elephant (*Loxodonta africana*) in an agricultural 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 equal 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) in the landscape. 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 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 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).

Furthermore, in order to properly elucidate the centrality of the intensity and the dominant scale in the characterisation of spatial heterogeneity, we present a simulation of tree canopy cover along three artificial transects (fig. 7.1). The tree canopy cover along by the three artificial transects that stretch over 1000 m is sampled at an interval of 1 m. Thus, the interval of 1 m defines the grain (observation scale) while the 1000 m defines the extent (overall transect length). The transects 1 and 2 have a dominant scale of spatial heterogeneity of 100 m, i.e., maximum variance is recorded at the window size of 100 m whereas transect 3 has a dominant scale of 200 m. The dominant scale of spatial heterogeneity in transects 1 and 2 is equal but the intensity of spatial heterogeneity is

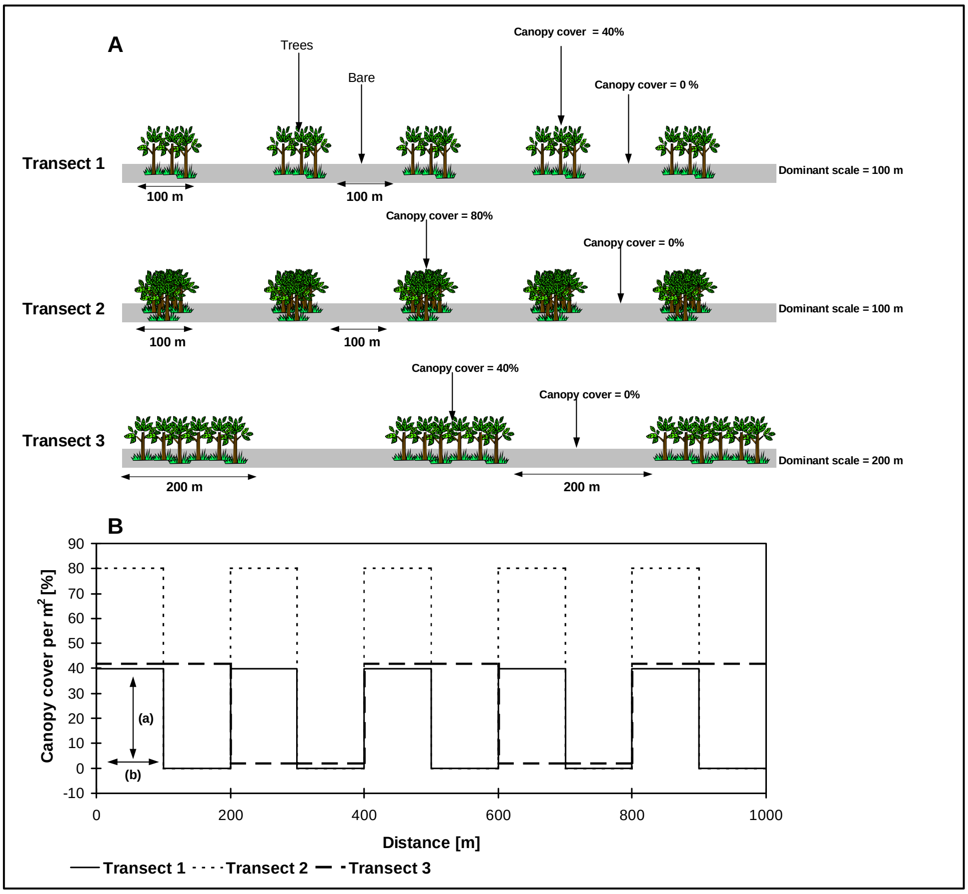


Figure 7.1: Part (A) are transects with alternating spaces of trees and bare ground and part (B) shows the simulation tree canopy cover along each transect assuming that the cover measurements are made after every 1 m (i.e., grain = 1 m) and an extent of 1000 m. For example, the (a) intensity (maximum variance) of transect 1 occurs at (b) a dominant scale of 100 m.

different. Next, a look at transects 1 and 3 shows that they have equal intensity of spatial heterogeneity but have different dominant scales of spatial heterogeneity. Therefore, characterizing spatial heterogeneity in this example is incomplete if only the intensity or the dominant scale of spatial heterogeneity is considered. Thus, we propose that both the intensity and dominant scale describe the spatial heterogeneity of a landscape. This method of characterising spatial heterogeneity in the landscape was developed and tested by Murwira and Skidmore (2003)

In this study, the objective was to use a wavelet transform to quantify the spatial heterogeneity of a normalised difference vegetation index (NDVI) and then test whether the wavelet-quantified spatial heterogeneity consistently explain wildlife species distribution in a landscape, particularly that of the African elephant (*Loxodonta africana*) in northwestern Zimbabwe between the early 1980s and early 1990s. Specifically we tested: (1) whether the probability of African elephant presence in different parts of the landscape was consistently and significantly related the dominant scale and intensity of spatial heterogeneity during the two dates and, (2) whether changes in the probability of elephant presence in different parts of the landscape, between the early 1980s and early 1990s, were related with changes in the dominant scale and intensity of spatial heterogeneity. Murwira and Skidmore (2003) demonstrated the utility of wavelets in characterising spatial heterogeneity from a dominant scale and intensity perspective.

The African elephant was selected for several reasons. Firstly, the Africa elephant is a keystone species of the African savanna (Hoare and Du Toit 1999) that need to be conserved. Secondly, the African elephant is on the list of the world's threatened species (IUCN 2002) and is considered a conservation priority. Thirdly, the study area has been the only agricultural landscape in Zimbabwe outside the protected wildlife reserves with a healthy expanding elephant population (Cumming 1981). Nevertheless, this situation is increasingly being threatened by agricultural field expansion following the continual eradication of tsetse (Glossina sp.) since the 1960s. Thus, there is need of interventionist strategies to conserve the elephant. Fourthly, water is not a limiting factor in the study area (Cumming 1981), and since the African elephant is a habitat generalist (Kingdon 2001) it has a potential of being anywhere in the study area and it can be hypothesised that the level of spatial heterogeneity mainly affect its distribution. Also, good survey data exists on the spatial distribution of the African elephant in the study area.

7.2 Materials and Methods

Study area

This study is based on the Sebungwe region in the northwestern part of Zimbabwe (fig. 7.2). The Sebungwe region is composed of 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, i.e., 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 dominated by *Setaria incrassata, Ischaemum afrum* and *Dicathium papillosum* (Timberlake, *et al.* 1993) (fig. 7.2b). 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 contains of five wildlife reserves, interspersed with communal lands (fig. 7.2a) with varying degrees of agriculture and varying degrees of wildlife presence. Communal lands are a land category characterised by collective or community land ownership and they are subdivided into administrative or management units called wards (fig. 7.2a). In the communal lands wildlife presence is affected by the ecological conditions such as the availability of vegetation cover, and also poaching and human disturbance, and also poaching and human disturbance rather than by conservation measures or laws like in the wildlife reserves, i.e., wildlife species are present provided there are necessities such as enough cover and water. Wildlife has to cross the communal lands when moving between the wildlife reserves. Thus, the communal lands also provide wildlife corridors that link the wildlife reserves (Cumming and Lynam 1997).

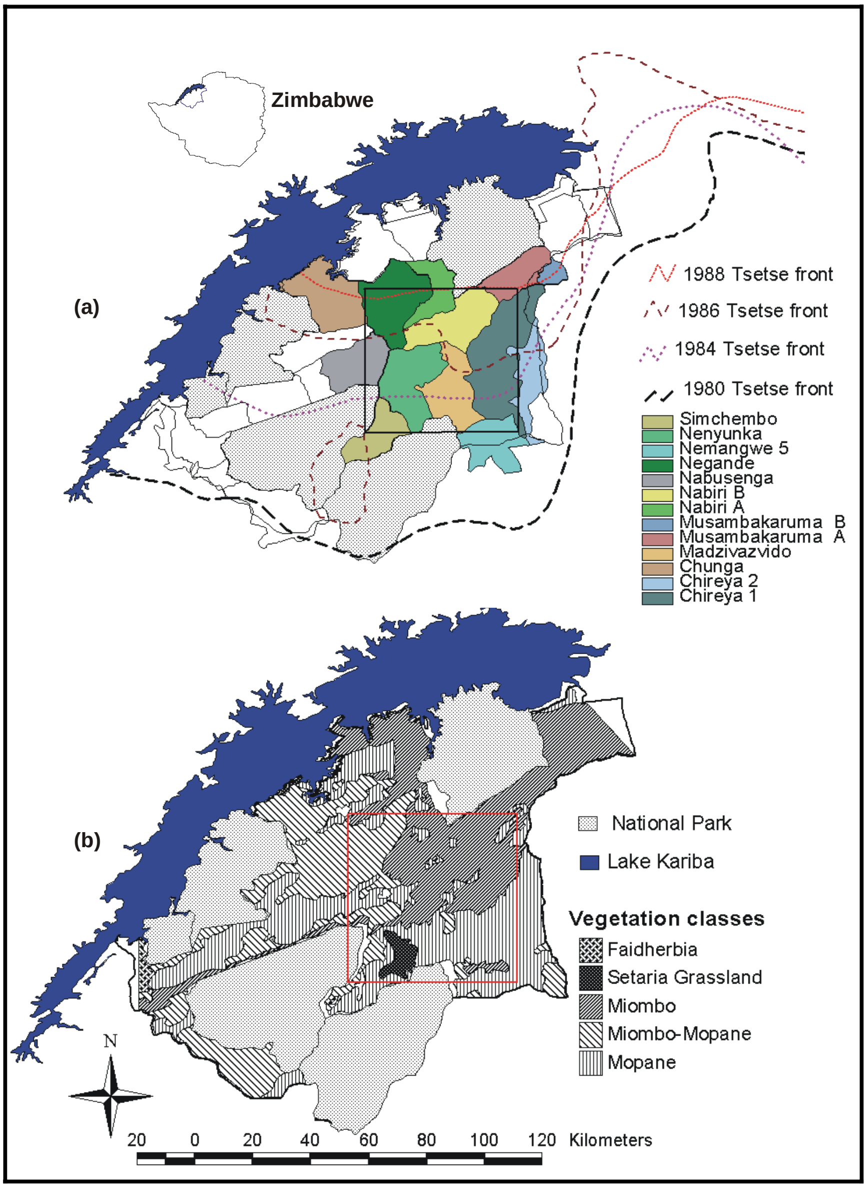


Figure 7.2: The location of the Sebungwe region in Zimbabwe and (a) the wards, national parks and the history of the progression of tsetse eradication (source: Tsetse and Trypanosomiasis control branch, Harare) and (b) the physiognomic-floristic vegetation classes in the communal lands based on (Timberlake and Nobanda 1993). The square box is a 61 km x 61 km area selected for this study.

Moreover, the Sebungwe landscape evolved from a complex of different historical forces linked to the eradication of tsetse fly (*Glossina* sp.) and the related land use (fig. 7.2)a. 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). The results were the varying degrees wildlife presence as a function of varying levels of arable agriculture (Hoare and Du Toit 1999).

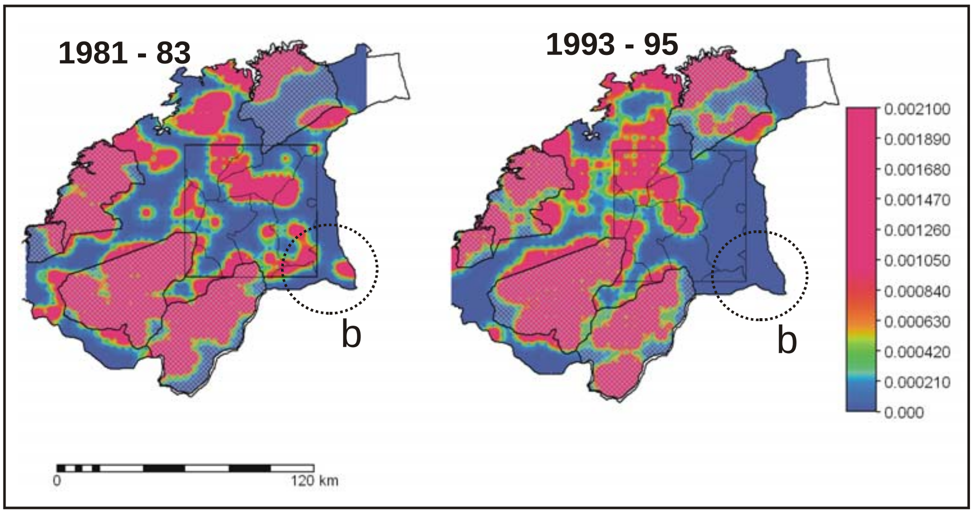


Figure 7.3: The probability of elephant presence within a 3 km radius in the study area in 1981-83 and 1993-95 and the 61 km by 61 km square box selected for this study. The ellipse (b) illustrates an area where there was a major noticeable decrease in the probability of elephant presence between 1981-83 and 1993-95.

This study is based on a 61 km x 61 km area (square box in fig. 7.2), mainly covering the communal lands. This study area was considered large enough for studying elephant distribution in the

Sebungwe. Specifically, elephants in the Sebungwe region have an estimated range of between 83 km^2 to 263 km^2, 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 km^2, which is at least 14 times the estimated range of the elephant in the Sebungwe large enough to study elephant distribution.

Elephant data

The data on the spatial distribution of elephants in the 1980s and 1990s were determined using respectively a combined 1981-1983 data set, and 1993-1995 data set. 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 locational error of the elephant sightings was within 500 m, i.e. 250 m on the side of the aircraft and 1000 m along the flight path (Cumming and Lynam 1997). 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 this time. Crop fields tend to attract the elephants outside their normal natural range, thus making wet season (October to March) data much 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. The data were in digital point map format. 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 λ(x) for the elephant point map to give an expected number of events per unit area(Fotheringham, *et al.* 2000):

$$\lambda(x) = \lim_{r=0} \frac{E(N(C(x,r),X))}{\pi r^2} \tag{7.1}$$

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

$$\lambda n(x) = \frac{\lambda(x)}{E(N(R,X))} \tag{7.2}$$

Next, λ*n*(*x*) was used to estimate the spatial distribution of elephants in the study area during the 1980s and 1990s. The point pattern analysis 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 presence of at least a single elephant and since the elephant survey data sets were combined, adding the total number of observed elephants of the years would give a false impression about absolute elephant abundance. Fig. 7.3 shows the maps of the probability of elephant presence in the early 1980s and the early 1990s.

Remote sensing data

The amount of vegetation cover or biomass was estimated from NDVI derived from the readily available TM images of 19 October 1984 and the one of 16 April 1992:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{7.3}$$

where *NIR* and *R* are respective 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. Relative radiometric correction of the two images was done using the regression method based on pseudo variant objects such as water bodies, airstrips and roads (fig. 7.4). This was done to minimise atmospheric effects in the analysis of spatial heterogeneity from the NDVI images of the two different dates. Fig. 7.5 shows the NDVI images of the 61 km x 61 km study area. As mentioned earlier, NDVI was used because it is an

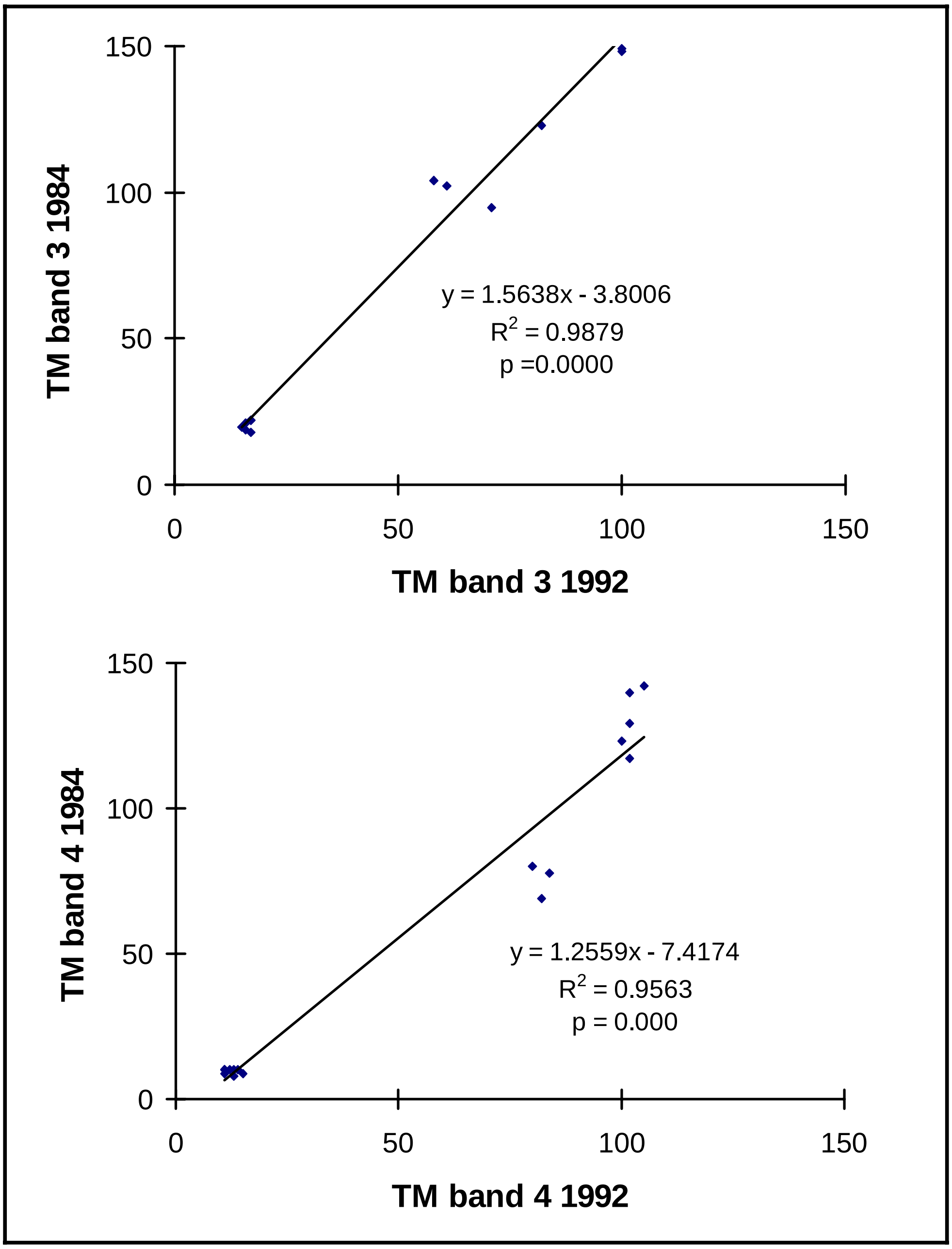


Figure 7.4: Relationship between the DN values of sampled pseudo variant objects between the Landsat TM images of 19 October 1984 and 16 April 1992.

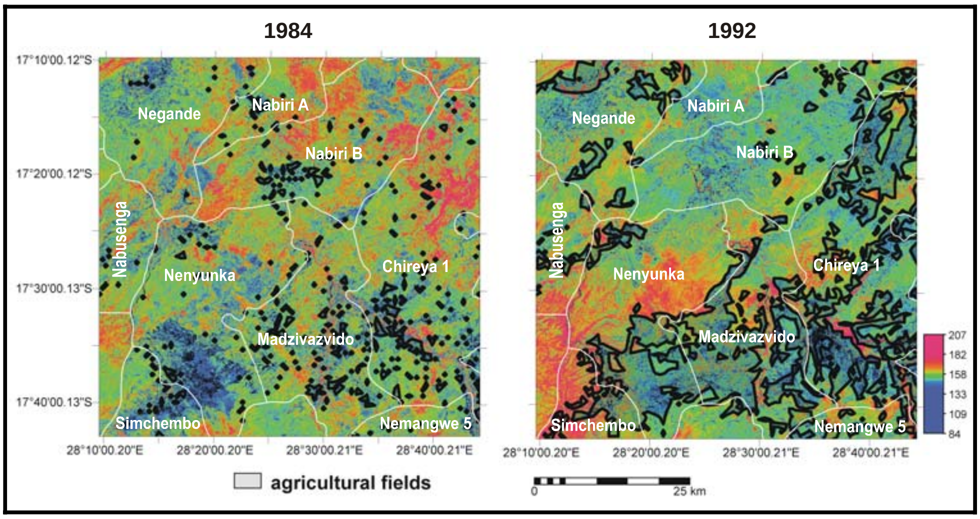


Figure 7.5: Map showing the 1984 and 1992 NDVI maps of the 61 km by 61 km square box overlaid with layers of ward boundaries and agricultural fields. Low NDVI values indicate low vegetation cover and high NDVI values indicate high vegetation cover within a 0 to 255 range. The NDVI values were stretched the same way for display to make them comparable but the NDVI ranges were different for 1984 and 1992.

established index for estimating vegetation quantity (Walsh, *et al.* 1997, Walsh, *et al.* 2001). Also, NDVI have 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 to detect land cover changes (e.g., woodland replacement with agriculture) and can also be used as an indicator of spatial heterogeneity in the landscape (Kerr and Ostrovysky 2003). Dry season imagery was used in this study because elephant data was collected in the dry season. In addition, it is easier to distinguish between fallow agricultural fields and natural vegetation using NDVI in the dry season than in the wet season, i.e., high NDVI values are expected for natural vegetation and lower NDVI values are expected for fallow agricultural fields (fig. 7.5). Thus, it is apparent in fig. 7.5 that areas with low NDVI mainly coincide with agricultural fields. It was assumed that the time differences between the dates of the wildlife surveys and the satellite images was close enough and therefore, had negligible negative effects on the analysis.

Several advantages were envisaged in using Landsat TM imagery to characterise the spatial heterogeneity for the study of elephant distribution. Most importantly, the spatial resolution or grain of Landsat TM, i.e., 30 m by 30 m was detailed enough to enable the quantification of spatial heterogeneity that is relevant for analysing elephant distribution; generally, the grain should be several magnitudes smaller than the total range of the organism (Sparrow 1999). Since elephants in the Sebungwe region have an estimated range of 83 km^2 to 263 km^2, approximating a horizontal length scale (horizontal dimension) of 9.1 km and 16.2 km, respectively (Guy 1976a, Dunham 1986), the grain of 30 m makes it 300 times smaller than the minimum range of the elephant.

Characterising spatial heterogeneity using wavelets

Wavelet energy (Bruce and Hong-Ye. 1996) was used to quantify the intensity and the dominant scale of spatial heterogeneity in the NDVI images of 1984 and 1992. 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., $j = 0,1,2\ldots J$ in the vertical (north-south), diagonal (northeast-southwest and northwest-southeast) and horizontal (east-west) directions for the 2-dimensional data. A wavelet transform results in a set of coefficients where each coefficient is associated with a base level, $j = 0,1,2\ldots J$, 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:

$$\hat{f}(x,y) = S_J(x,y) + \sum_{j=1}^{J} \sum_{dir} D_j^{dir}(x,y) \qquad (7.4)$$

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 grain of $f(x,y)$ is equals to $j = 0$. Therefore, each scale level j corresponds to a window size or scale 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 spatial resolution 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 size of the image. In this study we selected J equals 7, an equivalent of a spatial dimension of 3840 m. Note that the theory and formal treatment of wavelets has been covered exhaustively elsewhere (Mallat 1989, Ogden 1997) and is beyond the scope of this study.

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 $\hat{f}(x,y)$:

$$E_j^d = \frac{1}{E}\sum_{k=1}^{n/2^j} d^2 j(x,y),\ j = 1,2,3 \ldots J \qquad (7.5)$$

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 they 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.

Relating the probability of elephant presence to spatial heterogeneity

The relationship between the probability of elephant presence and the dominant scale and intensity of spatial heterogeneity was tested on the 61 km x 61 km study area, i.e., in the communal lands of the Sebungwe. The individual units of analysis (sampling units) were defined to be the intersection of the ward boundaries and vegetation class boundaries, thereby incorporating variation due to management and ecological factors respectively. These sampling units were obtained by crossing the ward and vegetation class maps in a Geographical Information system (GIS). The floristic-physiognomic vegetation class map (fig. 7.2) describes the potential vegetation classes, and is therefore constituted by floristic units that are constant over time (Timberlake, *et al.* 1993). All in all, 22 units of analysis were used in this study.

Before the probability of elephant presence was related to the dominant scale and intensity of spatial heterogeneity, the wavelet functions for separate wards, as well as physiognomic-floristic vegetation classes (Miombo, Mopane, Miombo-Mopane and Setaria) were plotted and the dominant scale and intensity information was determined for each unit of analysis. The Faidherbia vegetation class was excluded in the analysis because it covers a very small part of the study area such that not enough coefficients are included in the Faidherbia unit. Then, the probability of elephant presence in each sampling unit was determined by crossing the map of the probability of elephant presence (fig. 7.3) and the map of sampling units defined by wards and vegetation classes and calculating the average probability of elephant presence. The mean probability of elephant presence for each sampling unit of analysis was used as a measure of elephant presence in regression analysis.

Next, regression analysis was used to relate the probability of elephant presence to the dominant scale and intensity of spatial heterogeneity respectively using both the 1980s and 1990s data. In addition, the probability of elephant presence was analysed as a function of the dominant scale and intensity of spatial heterogeneity plus the interaction between the two. Use of data from two dates gave us a possibility to check whether elephant presence was consistently related with the dominant scale and intensity of spatial heterogeneity irrespective of time. The final regression analysis attempted to determine whether there was a relationship between the spatial changes in both dominant scale and intensity of spatial heterogeneity between 1984 and 1992 and the spatial changes in the probability of elephant presence between 1981-83 and 1993-95. To accomplish this, the intensity and dominant scale values of 1984 were subtracted from the respective values of 1992 so that positive values would represent an increase in each respective factor while negative values would represent a decrease in each respective factor between the two periods.

7.3 Results

Spatial heterogeneity in Sebungwe in 1984 and 1992

Fig. 7.6 shows selected wavelet energy functions that illustrate changes in the dominant scale and the intensity of spatial heterogeneity in the study area between 1984 and 1992. Generally, the wavelet energy functions in 1992 had higher values than in 1984. For example, the Setaria typifies changes in both the dominant scale of spatial heterogeneity and intensity of spatial heterogeneity between the two dates. In 1984 the Setaria had larger dominant scales of spatial heterogeneity than in 1992, whereas the intensity of spatial heterogeneity in 1984 was less than in 1992.

Fig. 7.7 shows a multiscale wavelet energy representation of NDVI in the study area in 1984 and 1992. It can be observed that there was a decrease in the dominant scales of spatial heterogeneity in the selected Setaria analysis units from 1920 m and 960 m in 1984 to 240 m and 480 m in 1992 respectively in Nenyunka and Madzivazvido. In contrast, it can be observed that there was no change in the dominant scale of spatial heterogeneity for the selected Miombo-Mopane analysis unit in Madzivazvido between 1984 and 1992.

Relationship between elephant presence and spatial heterogeneity in space

Fig. 7.8 shows that there were significant ($p < 0.05$) quadratic relationships between the probability of elephant presence and the dominant of spatial heterogeneity, as well as between the probability of elephant presence and the intensity of spatial heterogeneity both in 1980s and 1990s. The relationship between the dominant scale of spatial heterogeneity and the probability of elephant presence is such that there is an initial increase in the probability of elephant presence with increasing dominant scale until a certain level after which the probability of elephant presence declines with increasing dominant scale (fig. 7.8a). The probability of elephant presence-dominant scale regression functions for 1980s and 1990s explain 65 % and 68 % of the variance in the probability of elephant presence respectively. Furthermore, it can also be observed that as the intensity of spatial heterogeneity increases, there is a concomitant increase in the probability of elephant presence until a certain level and then the probability of elephant presence begins to saturate or even decrease

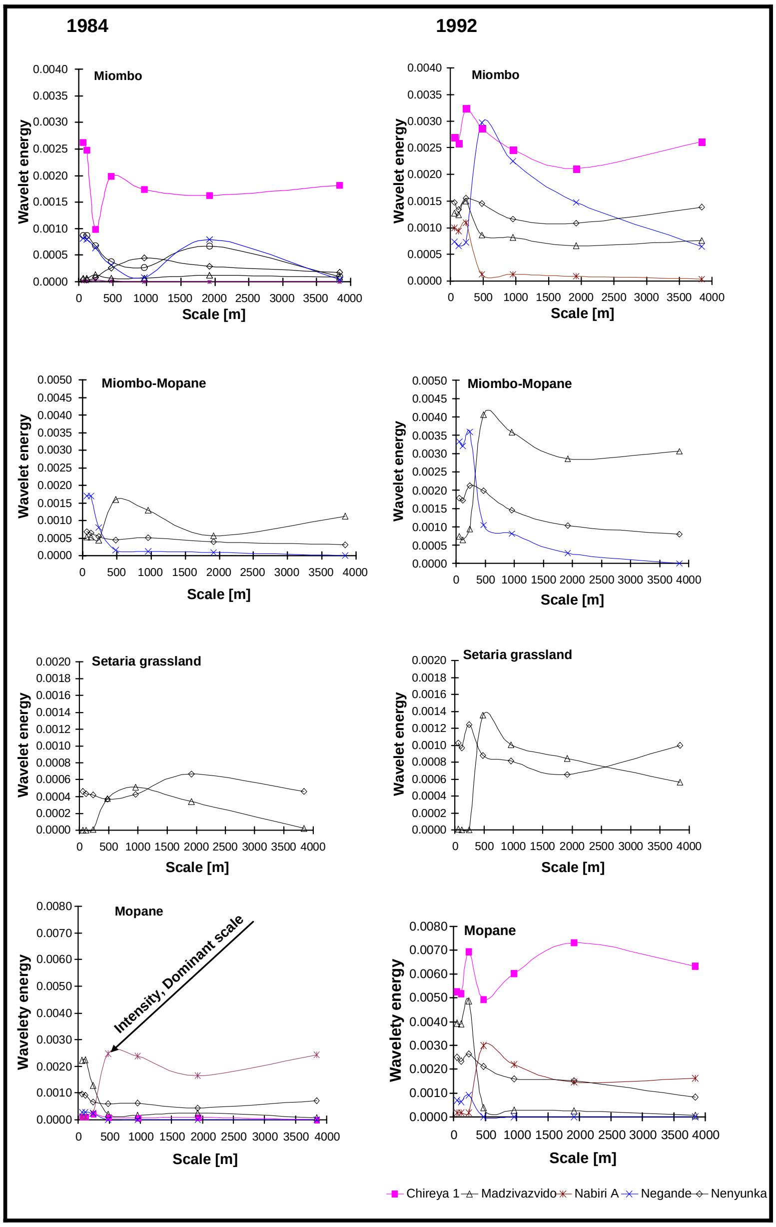


Figure 7.6: Selected wavelet energy functions illustrating variations in intensity and dominant scale in different wards and vegetation classes in 1984 and 1992. The arrow shows an example of the determination of the intensity and dominant scale of spatial heterogeneity from a wavelet energy function.

Figure 7.7: The spatial distribution of total wavelet energy per pixel at different scales (wavelet spans) across different wards in 1984 and 1992, as well as in selected vegetation class polygons (the total wavelet energy for the image was divided by 1000000 and then stretched between 0 and 20 to enhance the wavelet energy for visual presentation). The polygon contained in a larger box depicts Setaria predominantly in Nenyunka ward while the polygon contained in the smaller box is Miombo-Mopane vegetation class in Madzivazvido ward.

(fig. 7.8b). The regression functions for 1980s and 1990s explain 61 % and 71 % of the variance in the probability of elephant presence respectively.

Fig. 7.9 shows the probability of elephant presence as a significant ($p < 0.05$) function of both the dominant scale and the intensity of spatial heterogeneity in 1980s and 1990s. It can be observed that a combination of low intensity of spatial heterogeneity and large dominant scales of spatial heterogeneity is associated with a low probability of elephant presence. For example, it can be observed the Setaria vegetation class in Simchembo ward, had a combined low intensity and large dominant scale in the 1980s and it was associated with a low probability of elephant presence (fig. 7.9a). In addition, it can be observed that the

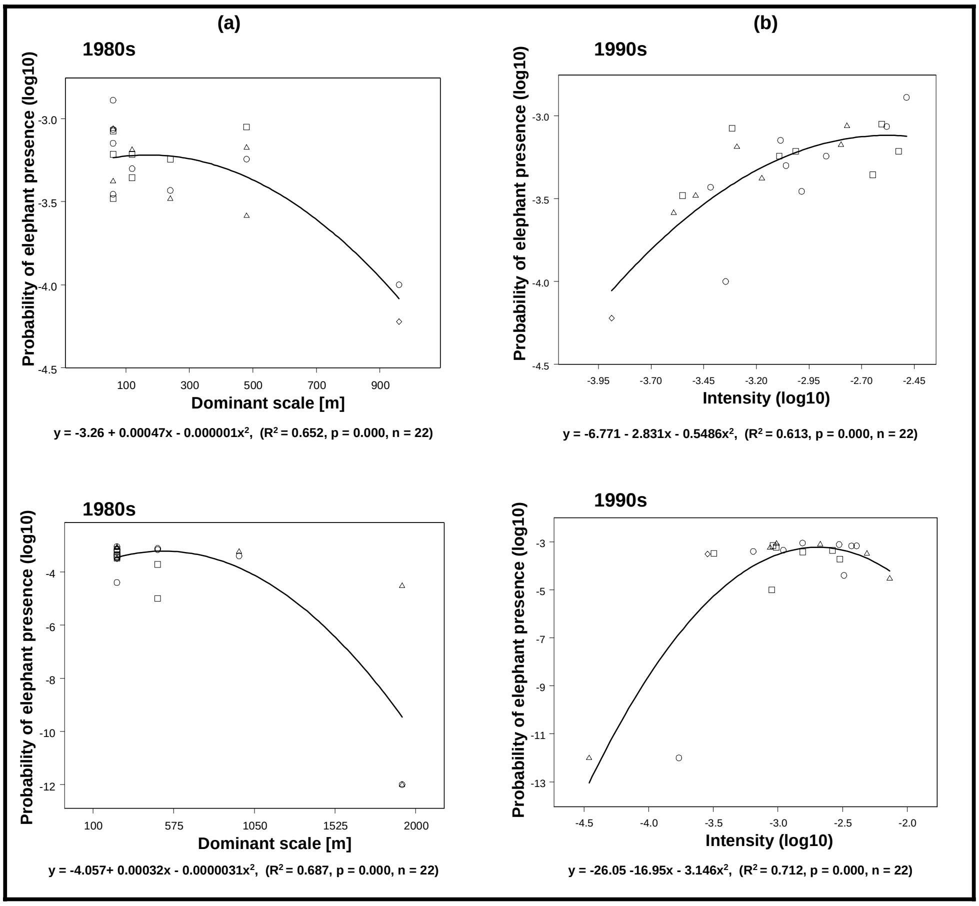


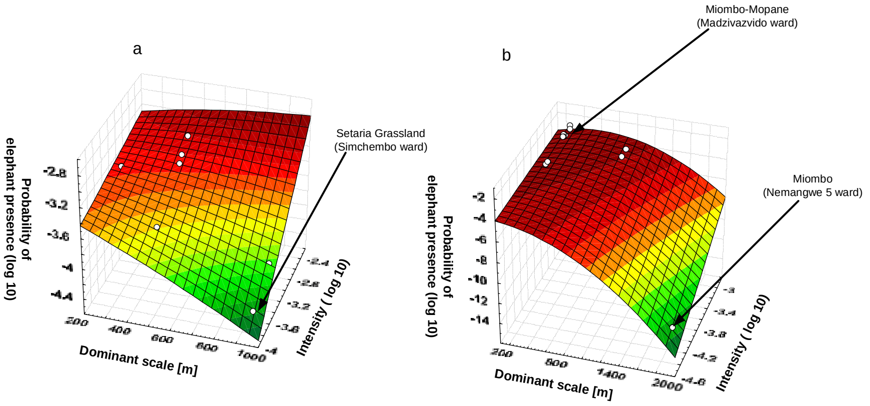
Figure 7.8: Significant ($p < 0.05$) relationships between the probability of elephant presence and the (A) dominant scale of spatial heterogeneity and (B) intensity of spatial heterogeneity (intensity) in the study area in the 1980s and 1990s in (❍) Miombo, (☐) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane floristic-physiognomic vegetation classes.

Miombo vegetation class in Nemangwe 5 ward had a combined low intensity and large dominant scale in the 1990s that was associated with a low probability of elephant presence (fig. 7.9b). It can also be observed that agricultural fields covered most of Nemangwe 5 in 1992 (fig. 7.5). Next, it can be observed that the probability of elephant presence is high in environments where the intensity of spatial heterogeneity is high at intermediate dominant scales of spatial heterogeneity, namely around

480 m. For example, it can be observed that the Miombo-Mopane vegetation class in Madzivazvido has an intermediate dominant scale of spatial heterogeneity and a high intensity of spatial heterogeneity that are associated with a high probability of elephant presence (fig. 7.9). All in all, the regression functions of the 1980s and the 1990s explain 80 % and 93 % of the variance in the probability of elephant presence respectively.

Relationship between elephant presence and changes in spatial heterogeneity

After, analysing how spatial heterogeneity is related to the probability of elephant presence from sampling unit to sampling unit, we also analysed whether changes in spatial heterogeneity in the sampling units over time explained the changes in the probability of elephant presence between the early 1980s and the early 1990s. Fig. 7.10 shows that spatial changes in the probability of elephant presence between the early 1980s and the early 1990s were significantly ($p < 0.05$) related with changes in dominant scale and intensity of spatial heterogeneity in the sampling units between the same periods. It can be observed that a combination of an increase in intensity of spatial heterogeneity and a decrease in the dominant scale of spatial heterogeneity were associated with a decrease in the probability of elephant presence in the study area. On the other hand, a decrease in the intensity of spatial heterogeneity in combination with an increase in the dominant scale of spatial heterogeneity is also associated with the decrease in the probability of elephant presence. For example, a combination of the decrease in the dominant scale of spatial heterogeneity and the increase in intensity of spatial heterogeneity in Setaria in Nenyunka ward were associated with a decrease in the probability of elephant presence (fig. 7.6, fig. 7.7 and fig. 7.10). Concurrently, an increase in agricultural fields in the same land unit between 1984 and 1992 can be observed (fig. 7.5). In addition, a combination of the increase in dominant scale of spatial heterogeneity and the decrease in intensity of spatial heterogeneity in the Mopane vegetation class in Nemangwe 5 ward was associated with a decrease in the probability of elephant presence (fig. 7.6, fig. 7.7 and fig. 7.10). Also, a concurrent increase in agricultural fields in the same land unit between 1984 and 1992 (fig. 7.5) can be observed. In contrast, it is apparent (fig. 7.10) that a combined increase in the intensity of spatial heterogeneity and dominant scale of spatial heterogeneity was associated with an increase in the probability of elephant presence up to a certain level and then it decreases. For example an increase in the intensity and dominant scale of spatial heterogeneity in the Miombo vegetation class in Nabusenga was associated with an increase in the probability of elephant presence (fig. 7.10) The regression function explained 89 % of the variance of the change in probability of elephant presence between the 1980s and 1990s.



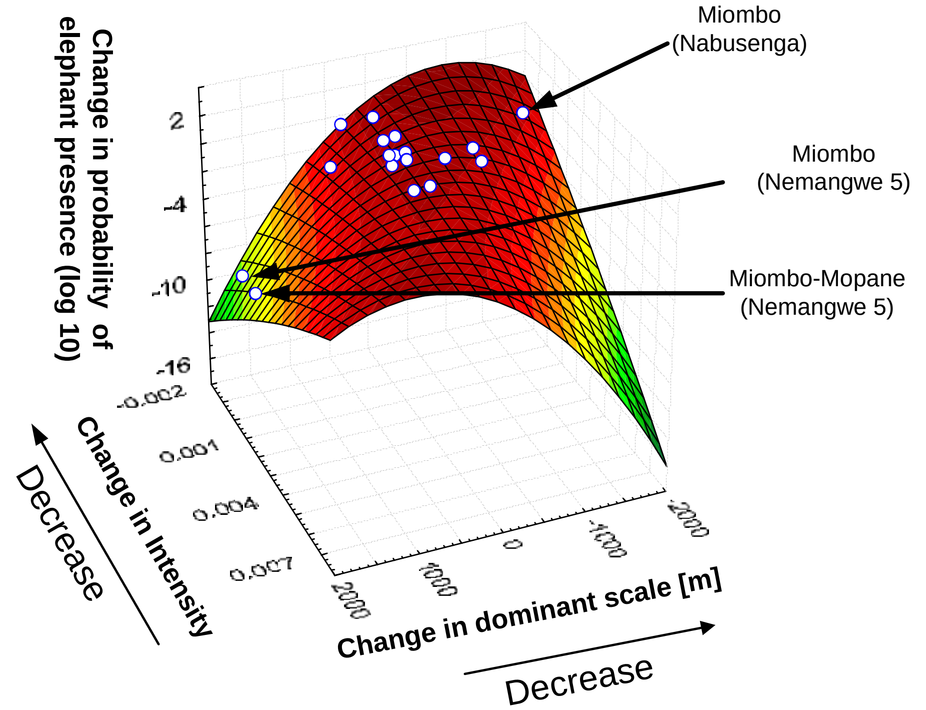
$Z = -3.22+0.0027x-0.00000026x2+0.00094yx$

R^2 = 0.80
p = 0.0000
n = 22

$Z = -3.998 + 0.00772x-0.000002x^2+0.00176xy$

R^2 = 0.93
p = 0.0000
n = 22

Figure 7.9: A significant ($p < 0.05$) relationship between the probability of elephant presence and the intensity and dominant scale of spatial heterogeneity plus their interaction in the early (a) 1980s and (b) 1990s. The graph surface represents increasing probability of elephant presence from green (lowest probability) to deep red (the highest probability of elephant presence).



$Z = 0.567 - 0.0019x - 0.0000018x^2 - 59.69y + 25374.9y^2 + 0.707xy$
$R^2 = 0.89$
$p = 0.000$
$n = 22$

Figure 7.10: A significant ($p < 0.05$) relationship between change in the probability of elephant presence and changes in the intensity and dominant scale of spatial heterogeneity between the 1980s and 1990s. On all axes, positive values indicate an increase, negative (-) indicate a decrease and zero (0) indicates no change. The green on the graph surface represents a greater decrease in the probability of elephant presence and deep red represents an increase in the probability of elephant presence.

7.4 Discussion

Spatial heterogeneity and the probability of elephant presence in space

Murwira and Skidmore (2003) demonstrated the utility of wavelets in characterising spatial heterogeneity from the dominant scale and intensity perspective. Using wavelets to analyse spatial heterogeneity from this perspective, the findings in this study have demonstrated a temporally consistent (i.e., in the 1980s and the 1990s) near unimodal (i.e., the relationship describes mainly the descending part of a unimodal model) elephant presence-spatial heterogeneity relationship along the dominant scale and the intensity gradients across 22 land units (fig. 7.8 and fig. 7.9). This result is consistent with the unimodal species distribution or limiting factor models, such as the species-productivity (Wang, *et al.* 1999, Wang, *et al.* 2001) and the species-altitude (Wang, *et al.* 2002) models, except that in this case, it is spatial heterogeneity that is limiting to the distribution of elephants. However, the fact that only the descending part (i.e., from intermediate dominant scale to large dominant scale) of the unimodal relationship is pronounced is because the study area is largely constituted by intermediate to large dominant scales of spatial heterogeneity but not a full range of dominant scales of spatial heterogeneity that include small dominant scales. This finding (i.e., unimodal relationship) is invaluable for landscape planning that takes elephant conservation into consideration because spatial heterogeneity could be manipulated to suit a threshold favourable for both elephants and humans.

Moreover, results on the bivariate elephant presence-intensity and the elephant presence-dominant scale relationships shade the first light on how elephants interact with spatial heterogeneity. For example, the elephant presence-intensity relationship, demonstrates that elephants tend to prefer environments with high intensity of spatial heterogeneity (i.e., with high variability) in vegetation cover compared with areas with low variability (fig. 7.5, fig. 7.8b) (see Chapter 1). An investigation by Murwira, *et al.* (2003) demonstrated that intensity of spatial heterogeneity correlates strongly with the NDVI average and the NDVI coefficient of variation that estimate the amount of cover and its variability respectively. Therefore, since high intensity or variability represents a spatially complex vegetation cover pattern, this confirms the observation that elephants in the Sebungwe associate with areas of high vegetation density and variability to maximise their chances of finding food and shelter (Guy 1976b). However, the fact that this relationship either saturates or even decrease at high intensity values imply that as the variability in vegetation cover increases beyond a certain level, it either no longer has an effect on elephant presence or it even results in a negative trend (fig. 7. 8b) just like in the species richness-productivity relationship (Said 2003). But it may as well be partly due to the related influence of the dominant scale of spatial heterogeneity, i.e., the patch dimension at which the intensity is manifested because the quadratic elephant presence-dominant scale relationship indicated that elephants prefer intermediate dominant scales of spatial heterogeneity but avoid relatively small and relatively large dominant scales of spatial heterogeneity (fig. 7.8a).

Furthermore, this study demonstrated that a comprehensive understanding of the elephant presence-spatial heterogeneity relationship could only be satisfactorily enhanced if both intensity and dominant scale are used in the analysis (see Chapter 1). In this regard, the results showed that the peak probability of elephant presence is defined by high intensity (high variability in vegetation cover) that occur at intermediate dominant scales of spatial heterogeneity (i.e., around 480 m) that reflect environments characterised by intermediate patch dimensions of natural vegetation and fewer agricultural fields (fig. 7.5 and 7.10). In contrast, lower probabilities of elephant presence are associated with: (1) environments with low intensity (low variability in vegetation cover) that occur at large dominant scales of spatial heterogeneity (descending limb of the unimodal curve), and (2) environments that have small dominant scales of spatial heterogeneity (ascending limb of the unimodal curve) (fig. 7.9). The former coincides with environments that are dominated by grasslands and agricultural fields (fig. 7.5 and fig. 7.9) while the latter coincides with environments dominated by small patches, suggesting (as mentioned earlier) that elephants avoid environments that are largely open (grasslands and agricultural fields) and environments that are dominated by small vegetation patches respectively.

The determination of wildlife species-specific thresholds of the spatial distribution of habitats is critical for the effective management of wildlife species but the perpetual and troubling question has always been whether these thresholds can be ecologically relevant (Jansson 2002). Given the prominence of the community based wildlife management programmes, such as CAMPFIRE, whose existence is rooted in the sustainable utilisation paradigm (Hulme and Murphree 2001), we feel that our findings are ecologically relevant by giving an indication of the kind of optimum or threshold environment that may encourage human-elephant coexistence, namely high intensity (i.e., high variability) in vegetation cover at intermediate dominant scales of spatial heterogeneity (i.e., around 480 m), as well as environments that elephants tend to avoid (fig.7.9).

Changes in spatial heterogeneity and the probability of elephant presence

Our findings demonstrated that the changes in elephant presence between the early 1980s and the early 1990s were unimodally related to changes in spatial heterogeneity, suggesting that elephants are repulsed by extreme changes of spatial heterogeneity while intermediate changes of spatial heterogeneity may encourage elephant persistence in the landscape. In fact, the results demonstrated that elephants relocate when an increase or decrease in the intensity of spatial heterogeneity occurs together with a decrease in dominant scale of spatial heterogeneity, or a decrease in intensity occurs together with an increase in the dominant scale of spatial heterogeneity. This suggests that elephants avoid areas that are increasingly being dominated by either: (1) small patches irrespective of the level of the intensity or maximum variability in vegetation cover or (2) large patches with a predominantly low intensity or maximum variability in vegetation cover, e.g., grasslands or agricultural fields. In contrast, elephant presence increased or remained constant with intermediate increases or no change in both intensity and the dominant scale of spatial heterogeneity, suggesting that elephants prefer environments that remain unchanged in terms of the levels of spatial heterogeneity. Consequently, we deduce that a combined change in the intensity and dominant scale of spatial heterogeneity had a significant effect on the probability of elephant presence in the communal lands of the Sebungwe region between the 1980s and 1990s.

7.5 Conclusions

We tested whether and how elephants were related to the wavelet transform derived-intensity and dominant scale of spatial heterogeneity. We also tested whether and how changes in elephant presence were related to changes in the intensity and the dominant scale of spatial heterogeneity across different sampling units in the study area between the early 1980s and the early 1990s. Therefore, some conclusions and management recommendations were drawn from the results. Firstly, we concluded that the wavelet transform-based intensity and dominant scale of spatial heterogeneity could reliably and consistently predict elephant distribution in an agricultural landscape. Secondly, we concluded that changes in the intensity and dominant scale of spatial heterogeneity could also reliably predict changes in elephant distribution. Furthermore, we could recommend from the results that management decisions must take into consideration the factor of spatial heterogeneity when planning the amount and spatial arrangements of agricultural fields that could enhance wildlife species persistence for the benefit of CAMPFIRE. Finally, we assert that considering the dominant scale and intensity factors improves the characterisation of spatial heterogeneity from remote sensing that can be useful in predicting other ecological patterns such as the distribution of different wildlife species.

Chapter 8

A synthesis: Spatial heterogeneity and the persistence of wildlife in an agricultural landscape

8.1 Introduction

The sustenance of the community based natural resource management (CBNRM) programmes such as the Communal Areas Management Programme For Indigenous Resources (CAMPFIRE) in Zimbabwe (Hoare and Du Toit 1999, Hulme and Murphree 2001, Logan and Moseley 2002) will depend on the understanding of factors that promote the persistence of wildlife species outside of the national parks, i.e. in communally managed agricultural landscapes, or in landscapes that are used for other purposes such as pastoralism, timber production or mining. This is in the light of the assertion that wildlife conservation is best served by converting wildlife into an economic asset (Child 2000). However, agricultural landscapes provide unique environments where agricultural fields subdivide a continuous habitat into discontinuous habitat patches of different quality and spatial arrangements. In other words, agricultural activity results in a landscape that is uniquely spatially heterogeneous (patchy). In this situation, the critical question for ecologists and wildlife managers responsible for the CAMPFIRE will always be: in what kind of non-protected agricultural landscapes can wildlife species persist or thrive? This question can only be satisfactorily answered on the premise that the spatial distribution of organisms is a response to the spatial heterogeneity that reflect, for instance, varying levels of resource availability or varying levels of human disturbance (Johnson, *et al.* 1992). To this end, spatial heterogeneity needs to be characterised in a way that is ecologically relevant to the species under consideration (Gustafson 1998) and in this regard, remote sensing provides an important source of spatial data. However, approaches and associated techniques to quantify spatial heterogeneity for predicting different ecological patterns remain rudimentary (Ettema and Wardle 2002).

In this thesis, the objectives were: (1) to develop a new approach to quantify spatial heterogeneity from remote sensing imagery, based on the intensity and the dominant scale approach, and (2) to investigate whether this new approach can be used to reliably predict the probability of elephant (*Loxodonta africana*) presence in the agricultural areas of the Sebungwe between 1983 and 1995. The general motivation of this thesis was that: the maintenance of wildlife species in agricultural landscapes could depend on an understanding of the levels of spatial heterogeneity at which specific wildlife species can persist. Also, the scientific community has realised that current approaches used to characterise spatial heterogeneity for the purposes of predicting ecological patterns such as wildlife distribution largely remain underdeveloped. This thesis fits within the context of a wider scientific debate about the role of scale in understanding ecological patterns (Turner 1989, Wiens 1989, Levin 1992), as well as falling within the context of a wider societal debate, especially in Southern Africa that aims to attain a mutually beneficial human-wildlife co-existence in increasingly agricultural landscapes such as the Sebungwe.

8.2 Spatial heterogeneity from the intensity and dominant scale perspective

The objective and ecologically relevant quantification of spatial heterogeneity is a critical forerunner to testing spatial heterogeneity-related hypotheses (Perry, *et al.* 2002). In this regard, the principal assertion in this thesis was that the success in understanding how spatial heterogeneity explains other ecological patterns relies on its objective characterisation (McGrigal and Cushman 2002).

The development of remote sensing has provided an invaluable source of spatial data to quantify spatial heterogeneity through the unparalleled capacity of remote sensing to provide spatial data at scales beyond our innate capacities or experience (Hay, *et al.* 2002). However, the interpretation of spatial heterogeneity from remote sensing imagery for ecological applications has largely remained within the constraints of our anthropocentric focus (Burnett and Blaschke, 2003). Specifically, researchers have traditionally quantified spatial heterogeneity from remote sensing images using two basic approaches: (a) the direct image approach, where straight reflectance or reflectance indices of remote sensing images are used to quantify spatial heterogeneity (e.g., based on the variance measure), using the original pixel size or grain 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 prior to determining the spatial heterogeneity (Gustafson 1998). The limitation of the former is that its choice of scale (window size) is arbitrary while the latter is based on arbitrary criteria for the delineation of patches, forcing boundaries where they do not always exist. In addition, the direct image approach emphasises variability at the expense of patch size in the image while the patch mosaic model (Pearson 2002) emphasises the patch size at the expense of variability within and between the patches. However, in reality, both variability and patch size characterise the landscape inseparably. Therefore, the way traditional approaches characterise spatial heterogeneity may have limited relevance in analysing other ecological patterns such as the distribution of organisms in the landscape because they either predefine the scale of observation or the range of intensity within patch classes, often using subjective rules. In addition, the scale of any (semi-) natural environment varies in space and the variance of an environmental variable also changes in space. Furthermore, it is important to note that different organisms may perceive spatial heterogeneity differently (Hostetler 1999). Therefore, the need for a measure of spatial heterogeneity that is objective, spatially adaptive and incorporates both scale and local variance is critical.

In this thesis, we developed a new approach to quantify spatial heterogeneity based on 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 (i.e., the scale or window size at which the intensity is displayed). The core of this new approach is that when the landscape is observed (using either remote sensing or biological vision) the dominant scale(s) of spatial heterogeneity that correspond to significant landscape features (e.g., patches of different tree canopy cover) in the landscape lie somewhere between the grain (initial observation scale) and the extent (the range over which observations at a particular grain are made) (Chapter 1, Chapter 2 and Chapter 3). Conceptually, this means that patches in the landscape that are expressed through the dominant scale of spatial heterogeneity are independent objects (not necessarily having sharp boundaries) that can be resolved only when the grain is smaller and the extent is larger than them. The consequence of this assertion is that we can conceptualise spatial heterogeneity as a natural expression of the landscape, i.e., it is expressed through ecologically meaningful features (see fig.1.1 in Chapter 1). By applying this new measure of spatial heterogeneity that uses the intensity and the dominant scale as inseparable properties of spatial heterogeneity, we are able to incorporate both the variability of vegetation cover that is emphasized by variance measure of the direct image approach, as well as the patch size that the patch mosaic approach emphasizes. Thus, we deduced that quantifying spatial heterogeneity using the intensity and dominant scale is invaluable since it incorporates characteristics of both the direct image approach and the patch mosaic approach.

A key finding in this thesis is that we can use variograms and wavelets to quantify spatial heterogeneity based on the intensity and dominant scale, in a way that excludes the a priori determination of the scale at which spatial heterogeneity is analysed such as being done when analysing spatial heterogeneity at a fixed grain in the direct image approach (Chapter 2). However, unlike variograms that can only characterise the largest dominant scale of spatial heterogeneity, we see that the localised nature of wavelets enable them to characterise more than a single intensity and dominant scale of spatial heterogeneity (Chapter 2). Furthermore, we could use wavelets to extract the features at different scales (Chapter 2 and Chapter 3). To this end, we also found that we can characterise temporal changes in spatial heterogeneity within the framework the intensity and dominant scale approach (Chapter 3).

8.3 Elephant presence relates well with spatial heterogeneity

In this thesis, we found that the results (Chapter 5, Chapter 6 and Chapter 7) largely confirmed the hypothesis, as stated in Chapter 1 (fig. 8.1c), that the probability of elephant presence yields a unimodal and a positive asymptotic response to the dominant scale and the intensity of spatial heterogeneity respectively, plus their interaction. The unimodal component of the model with regards to the dominant scale of spatial heterogeneity (fig. 8.1a) is a result of small patch sizes “repelling” elephants due to inadequate cover against human disturbance while at larger dominant scales, the enlarged hostile patches “repel” elephants. The latter patches can be, for instance, agricultural fields. In addition, the hypothesised positive asymptotic response of elephant presence to the intensity of spatial heterogeneity is because at high variability of vegetation cover, the chances of the elephant to find food and shelter increase, but as the variability becomes increasingly higher, it tends to have no effect on the elephant presence (fig. 8.3b).

It is apparent that the hypothesised relationship between the probability of elephant presence and spatial heterogeneity was largely confirmed; independent of whether variograms (Chapter 6) and wavelets (Chapter 7) were used to quantify spatial heterogeneity. Nevertheless, wavelets yielded better predictions (fig. 8.2), confirming that wavelets quantify spatial heterogeneity better owing to their localised nature compared with variograms that are global functions (Dale and Mah. 1998). However, the descending limb of the hump-shaped relationship with respect to the dominant scale is pronounced, suggesting the domination of the landscape by intermediate to large dominant scales of spatial heterogeneity.

We also see that the parts of the empirical model in fig. 8.2 correspond to the hypothetical parts in the model in fig. 8.1. For example, part E has a peak probability of elephant presence that corresponds to an environment with an intermediate dominant scale of spatial heterogeneity and a high intensity of spatial heterogeneity (i.e., an optimal environment for elephants). In contrast, part C has the lowest probability of elephant presence that corresponds to an environment with a large dominant scale of spatial heterogeneity and low intensity of spatial heterogeneity (i.e., a sub-optimal environment for elephants). It is however, important to note that the explanation given above about the pronounced descending limb phenomenon of the empirical model has to be treated with caution since the absence of the full range model in this case could also be a result of the dyadic nature of wavelets that lumps dominant scales of spatial heterogeneity into a range rather than a precise value, as is the case with variograms (Chapter 2), especially in 1980s (see Chapter 6 for the 1980s relationship when spatial heterogeneity was quantified using variograms).

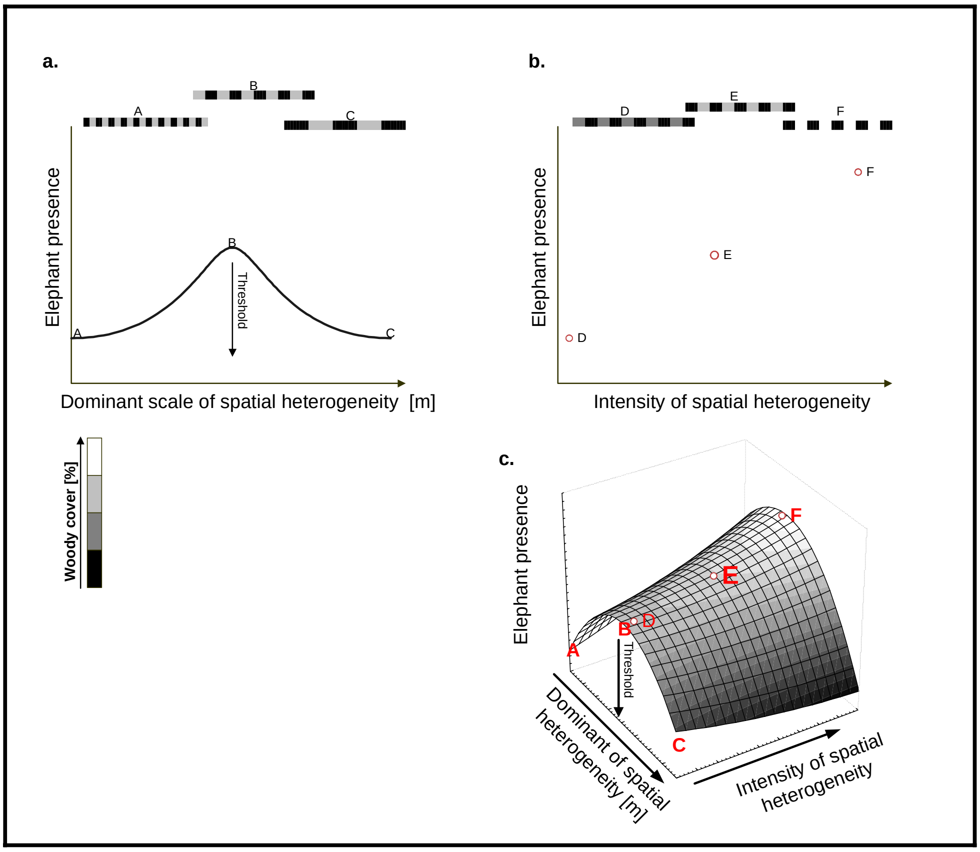
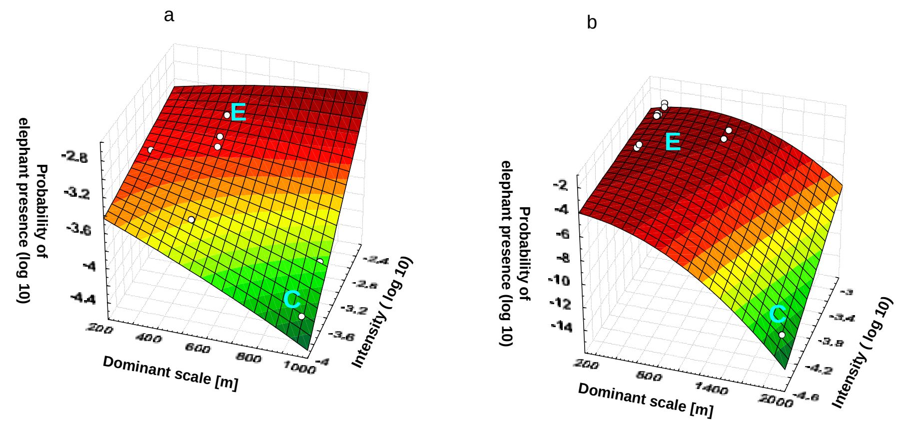


Figure 8.1: Hypothetical relationship: between elephant presence and: (a) the dominant scale of spatial heterogeneity, (b) the intensity of spatial heterogeneity, plus (c) both the dominant scale and intensity of spatial heterogeneity. The bars in (a) with gray levels representing woody cover in indicate variations in the dominant scale of spatial heterogeneity in different parts of the landscape, i.e., from (A) small a dominant scale of spatial heterogeneity, (B) medium dominant scale of spatial heterogeneity, to a large dominant scale of spatial heterogeneity (C). The bars in (b) represent the same dominant scale of spatial heterogeneity with increasing levels of intensity, from (D) low, (E) medium to (F) high.

Moreover, in this thesis we demonstrated that spatial heterogeneity quantified using the intensity and dominant scale approach explained more variance in the probability of elephant presence than the proportion of agricultural fields following the eradication of tsetse (Chapter 4). The effect of arable field cover on the probability of elephant presence was not consistent over time. For example, when the field cover was low in the early 1980s, i.e., 0 % - 11 %, we found no significant effect of arable fields on elephant presence (Chapter 4). A negative relationship only emerged when the amount of arable fields increased beyond this range (i.e., when it became 0 % - 88%) during the 1990s (Chapter 4). In contrast, the intensity and dominant scale of spatial heterogeneity consistently explained the probability of elephant presence between the early 1980s and the early 1990s, suggesting that, with this approach, we can improve the understanding of ecological patterns such as the spatial distribution of elephants.



Z = -3.22+0.0027x-0.00000026x2+0.00094yx

R^2 = 0.80

p = 0.0000

n = 22

$Z = -3.998 + 0.00772x-0.000002x^2+0.00176xy$

R^2 = 0.93

p = 0.0000

n = 22

Figure 8.2: Significant ($p < 0.05$) relationships between the probability of elephant presence and (a) wavelet transform quantified spatial heterogeneity in the Sebungwe during the 1980s and 1990s. The labels C and E, are an example showing the parts of the model that correspond to the hypothetical case in fig. 8.1. The graph surface represents relatively increasing probability of elephant presence from green (lowest probability) to deep red (the highest probability of elephant presence).

In this thesis, we also found that the intensity and dominant scale approach to quantify spatial heterogeneity improves upon the usual direct image approaches in predicting ecological patterns (Chapter 5). The results of an investigation on whether spatial heterogeneity quantified from the intensity and dominant scale approach using both variograms and wavelets 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 (Chapter 5), strongly indicated that the new approach predicted the probability of elephant presence better than the usual NDVI average and the NDVI coefficient of variation. Specifically, the 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. This meant that the new approach improves the understanding of the spatial distribution of wildlife species.

8.4 Elephant redistribution relates to changes in spatial heterogeneity

We found that changes in the probability of elephant presence between 1980s and 1990s could be reliably explained by the changes in the intensity and dominant scale of spatial heterogeneity in the agricultural areas (Chapter 6 and Chapter 7). For example, we found that although the nature of the relationship between the probability of elephant presence and spatial heterogeneity was consistent between the 1980s and the 1990s, there was a shift in the dominant scale of spatial heterogeneity at which the peak probability of elephant presence occurred between the two periods (fig. 8.3). For instance, in the 1980s, the peak probability of elephant presence in the landscape occurred at the dominant scale of spatial heterogeneity equal to 734 m, whereas in the 1990s, the peak had shifted down to 457 m. We attributed this phenomenon to the increasing levels of agricultural activity, whereby during the 1980s when there was quasi-

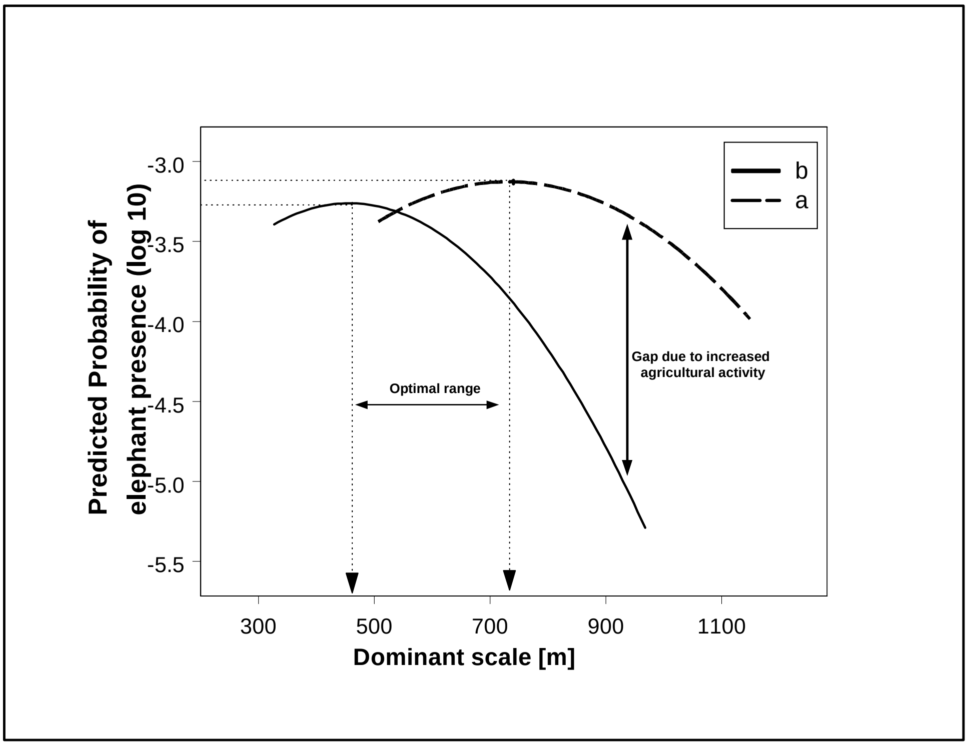
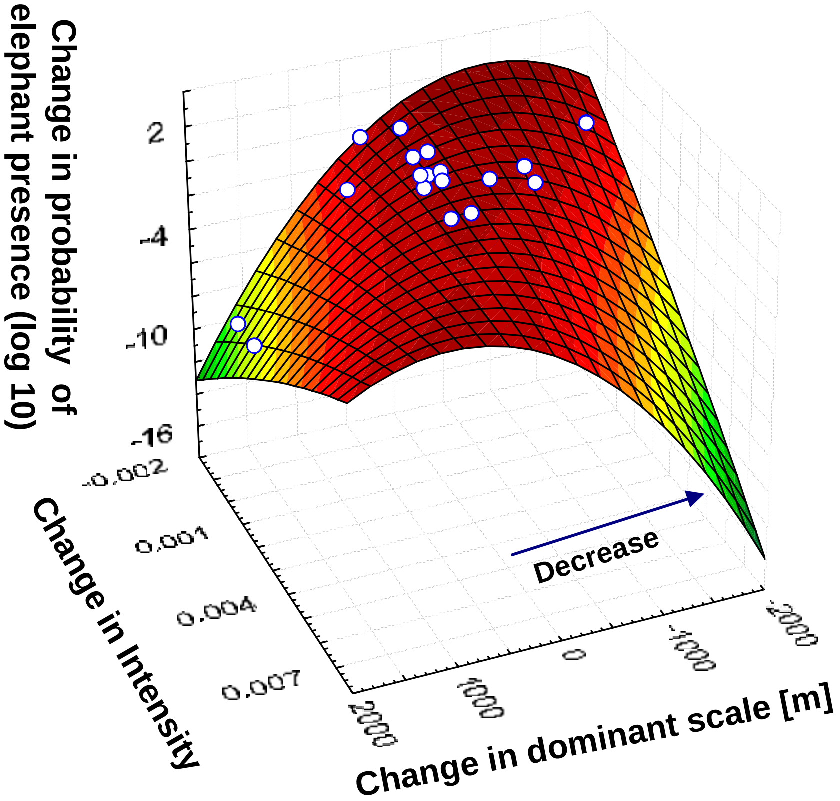


Figure 8.3: The regression models of the relationship between the probability of elephant presence and dominant scale of spatial heterogeneity in the (a) early 1980s and the (b) early 1990s extracted from fig. 6.8 (Chapter 6) to illustrate the effect of changes in the dominant scale of spatial heterogeneity on the probability of elephant presence (i.e., illustrated by the gap) due to increased agricultural activity between the two periods. Also illustrated is the upper limit (734 m) and lower limit (457 m) of that may define the "optimal range" of spatial heterogeneity determined from the distance between the peaks of elephant presence in the 1980s and 1990s models.

intensive agricultural activity; elephants could roam "freely" across the hostile patches, e.g., agricultural fields, but given the intensive agricultural activity in the 1990s, the peak probability of elephant presence shifted downwards to 457 m, suggesting that elephants could only "tolerate" relatively smaller dimensions of hostile patches. Thus, we deduced that the 457 m - 734 m range could constitute the "optimal range" of the dominant scale of spatial heterogeneity, whereby the lower limit (457 m) of the "optimal range" represents the level of spatial heterogeneity that elephants "do not mind" in agriculture-dominated environmental conditions while the upper limit of the range (734 m) represents the level of spatial heterogeneity at which elephants "thrive" in natural vegetation-dominated environmental conditions. Therefore, we could hypothesise that if dominant scale of spatial heterogeneity continues to drop below the lower limit (i.e., 457 m), regardless of the level of intensity, elephants could increasingly disappear from the agricultural landscape of the Sebungwe.

Moreover, we found that the probability of elephant presence dropped more sharply with increasing dominant scales of spatial heterogeneity in the 1990s compared with the 1980s (fig. 8.3), thereby further confirming the initial hypothesis that changes in the levels of spatial heterogeneity resulting from increased agricultural activity, had a strong bearing on the redistribution of elephants. Specifically, the quasi-intensive nature of agricultural activity in the 1980s supported a freer movement of elephants in the landscape. In contrast, in the 1990s elephants could not roam as freely compared with the 1980s due to the intensified agricultural activities. Therefore, although the unimodal nature of the relationship between the probability of elephant presence and the dominant scale of spatial heterogeneity did not change over time (i.e., in the 1980s and the 1990s), the increased levels of agricultural activity accelerated the rate of decrease in the probability of elephant presence with the increasing dominant scale of spatial heterogeneity in the 1990s. Therefore, we can hypothesise that if agricultural activity increases unchecked beyond the 1990s levels, the "gap" will become larger as the elephants increasingly disappear from those parts of the agricultural landscape where agricultural activity is increasing.

We further showed in this thesis that absolute changes in the in the probability of elephant presence between the early 1980s and the early 1990s were significantly explained by the absolute changes in the levels of spatial heterogeneity (fig. 8.4). Specifically, the hump-shape of the relationship between the absolute changes in the probability of elephant presence and the absolute changes in the intensity and dominant scale of spatial heterogeneity suggest that elephants relocate from environments that are increasingly being dominated by either: (1) relatively small dominant scales of spatial heterogeneity, or (2) or relatively very large



$Z = 0.567 - 0.0019x - 0.0000018x^2 - 59.69y + 25374.9y^2 + 0.707xy$

$R^2 = 0.89$

$p = 0.000$

$n = 22$

Figure 8.4: Significant ($p < 0.05$) relationships between change in the probability of elephant presence and changes in the wavelet transform-quantified spatial heterogeneity between the 1980s and 1990s. On all axes, positive values indicate an increase, negative (-) indicate a decrease and zero (0) indicates no change. The green on the graph surface represents a greater decrease in the probability of elephant presence and deep red represents an increase in the probability of elephant presence.

dominant scales of spatial heterogeneity that are associated with a low intensity of spatial heterogeneity. In contrast, the probability of elephant presence increased or remained constant in environments where both intensity of spatial heterogeneity and the dominant scale of spatial heterogeneity remained the same. Therefore, it could be concluded that dynamics in the intensity and dominant scale of spatial heterogeneity over time have a significant effect on the persistence of elephants in the agricultural landscape. This further confirms the relevance of the dominant scale and intensity of spatial heterogeneity in predicting the probability of elephant presence.

8.5 A summary of the findings

In this thesis, we developed a new approach to the definition and quantification of spatial heterogeneity based on dominant scale and intensity. We proposed two techniques to quantify spatial heterogeneity based on dominant scale and intensity, i.e. the windowed variogram and a wavelet transform. Finally, we established through statistical tests that the probability of elephant presence in the landscape is a function of dominant scale and intensity of spatial heterogeneity. A number of conclusions were drawn. Firstly, we observed that variograms, and particularly wavelets proved to be invaluable tools for quantifying spatial heterogeneity from a dominant scale and intensity perspective, thus making hypothesis regarding the effect of dominant scale and intensity of spatial heterogeneity on ecological patterns (in this case elephant distribution) testable. Secondly, we concluded that, intensity being high, the intermediate dominant scales of spatial heterogeneity may be the "optimal or threshold landscape environment" at which elephant persistence can be ensured in the agricultural landscape and below and above which elephant persistence in the Sebungwe agricultural landscapes may be threatened. Thirdly, we recommend that in order to be able to conserve wildlife outside the national parks, land use planning should take into consideration optimum levels of spatial heterogeneity, i.e. dominant scale and intensity that are optimal for specific wildlife species. We also recommend that further research should concentrate on testing whether dominant scale thresholds of spatial heterogeneity can be detected for elephants in agricultural landscapes elsewhere, as well as for different wildlife species for the purpose of promoting CBNRM programmes such as the CAMPFIRE.

8.6 Spatial heterogeneity and wildlife-human coexistence

What emanates from this thesis is the notion that spatial theories and models in ecology need to include realistic assumptions about the spatial heterogeneity of ecological phenomena in order to improve an understanding of the determinants of species distribution and species persistence in human dominated landscapes (Legendre 1998, Sparrow 1999). The ultimate goal is to enhance the chances of human-wildlife coexistence. The hypothesis on which this has to be based is that each wildlife species has a specific range of optimal dominant scales of spatial heterogeneity, at which it can persist in the landscape, and that human decisions that impact the landscape at different dominant scales would affect different wildlife species (Hostetler and Knowles-Yanez 2003). This could be an appropriate area for future research.

References

ADLER, P. B., D. A. RAFF and W. K. LAUENROTH. 2001. The effect of grazing on the spatial heterogeneity of vegetation. *Oecologia* **128**:465-474.

ALMEIDA-FILHO, R. and Y. E. SHIMABUKURO. 2002. Digital processing of Landsat-TM time series for mapping and monitoring degraded areas caused by independent gold miners, Roraima State, Brazilian Amazon. *Remote Sensing of Environment* **79**:42-50.

BAILEY, S. A., R. H. HAINES-YOUNG and C. WATKINS. 2002. Species presence in fragmented landscapes: modelling of species requirements at the national levels. *Biological Conservation* **108**:307-316.

BIRKY, A. K. 2001. NDVI and a simple model of deciduous forest seasonal dynamics. *Ecological Modelling* **143**:43-58.

BRADSHAW, G. A. and T. A. SPIES. 1992. Characterizing canopy gap structure in forests using wavelet analysis. *Journal of Ecology* **80**:205-215.

BRUCE, A. and G. HONG-YE. 1996. Applied Wavelet Analysis with S-PLUS. Springer, New York.

BURNETT, C. and T. BLASCHKE. 2003. A multi-scale segmentation/object relationship modelling methodology for landscape analysis. *Ecological Modelling* **In Press, Corrected Proof**.

BURTON, M. 1999. An assessment of alternative methods of estimating the effect of the ivory trade ban on poaching effort. *Ecological Economics* **30**:93-106.

CHILD, B. 2000. Making Wildlife pay: conserving wildlife's comparative advantage into real incentives for having wildlife in African savannas, case studies from Zimbabwe and Zambia. Pages 335-387 *in* H. H. T. Prins, J. G. Grootenhuis and T. T. Dolan, editors. Wildlife Conservation by sustainable use. Kluwer Academic Publishers, Boston, Dordrecht, London.

COHEN, W. B., T. A. SPIES and G. A. BRADSHAW. 1990. Semivariograms of digital imagery for analysis of conifer canopy structure. *Remote Sensing Of The Environment* **34**:167-178.

CUMMING, D. H. M. 1981. The management of elephant and other large mammals in Zimbabwe. Pages 91-118 *in* P. A. Jewel, S. Holt and D. Hart, editors. Problems in Management of Locally Abundant Wild Animals. Academic Press Inc., New York.

CUMMING, D. H. M. 1982. The influence of Large Herbivores on Savanna Structure in Africa. Pages 217-245 *in* B. J. Huntley, and Walker, B.H., editor. Ecology of Tropical Savannas. Springer-Verlag, New York.

CUMMING, D. H. M. and T. P. J. LYNAM. 1997. Land use changes, Wildlife Conservation and Utilisation and the Sustainability of Agro-ecosystems in the Zambezi Valley, Final Technical Report, Vols. 1-7. European Union Contract B7-50440/93/06. WWF Project ZW0024, WWF, Harare.

CURRAN, P. J. 1988. The Semivariogram in Remote Sensing: An Introduction. *Remote Sensing Of The Environment* **24**:493-507.

DALE, M. R. T. and M. MAH. 1998. The use of wavelets for pattern analysis in ecology. *Journal of Vegetation Science* **9**:805-814.

DE CARVALHO, L. M. T. 2001. Mapping and Monitoring forest remnants: A multiscale analysis of spatio-temporal data. PhD. Wageningen Universiteit, Wageningen.

DE VOS, A. 1978. Must Africa suffer the environmental consequences of tsetse-fly control. *Unasylva* **30**:19-24.

DIGGLE, P. J. 1983. Statistical analysis of spatial point patterns. Academic press, London.

DU TOIT, J. T. 1995. Determinants of the Composition and Distribution of Wildlife Communities in Southern Africa. *Ambio* **24**:2-6.

DU TOIT, R. 1985. A middle way for wildlife parks. *New Scientist* **105**:33-36.

DUNHAM, K. M. 1986. Movements of elephant cows in the unflooded Middle Zambezi Valley, Zimbabwe. *African Journal of Ecology* **24**:287-291.

EPINAT, V., A. STEIN, S. M. DE JONG and J. BOUMA. 2001. A wavelet characterization of high-resolution NDVI patterns for precision agriculture. *International Journal of Applied Earth Observation and Geoinformation* **3**:121-132.

ETTEMA, C. H. and D. A. WARDLE. 2002. Spatial soil ecology. *Trends in Ecology & Evolution* **17**:177-183.

FAHRIG, L. 2001. How much habitat is enough? *Biological Conservation*:65-74.

FOODY, G. M. and P. J. CURRAN. 1994. Scale and environmental remote sensing. Pages 223-232 *in* G. M. Foody and P. J. Curran, editors. Environmental remote sensing from regional to global scales. John Wiley & Sons, Chichester.

FOTHERINGHAM, A. S., C. BRUNDSON and M. CHARLTON. 2000. Quantitative Geography: Perspectives on spatial data analysis. SAGE publications Ltd, London.

FRIEDL, M. A. 1997. Examining the effects of sensor resolution and sub-pixel heterogeneity on spectral vegetation indices: Implications for

Biophysical Modelling. Pages 113-139 *in* D. A. Quattrochi and M. F. Goodchild, editors. Scale in Remote Sensing and GIS. Lewis Publishers, New York.

GOODCHILD, M. F. and D. A. QUATTROCHI. 1997. Scale, Multiscaling, Remote Sensing and GIS. Pages 1-11 *in* D. A. Quattrochi and M. F. Goodchild, editors. Scale in Remote Sensing and GIS. Lewis Publishers, New York.

GOWARD, S. N. and D. G. DYE. 1987. Evaluating North American net primary productivity with satellite observations. *Advances in Space Research* **7**:165-174.

GRAPS, A. 1995. An Introduction to Wavelets. *IEEE Computational Science and Engineering* **2**:50-61.

GRIFFITH, J. A., E. A. MARTINKO and K. P. PRICE. 2000. Landscape structure analysis of Kansas at three scales. *Landscape and Urban Planning* **52**:45-61.

GUSTAFSON, E. J. 1998. Quantifying landscape spatial pattern: What is the state of the art? *Ecosystems* **1**:143-156.

GUY, P. R. 1976a. Diurnal activity patterns of elephant in the Sengwa Area, Rhodesia. *East African Wildlife Journal* **14**:285-295.

GUY, P. R. 1976b. The feeding behaviour of elephant (*Loxodonta africana*) in the Sengwa Area, Rhodesia. *South African Journal of Wildlife Research* **6**:55-63.

HALL, O. and G. J. HAY. 2003. A Multiscale Object-Specific Approach to Digital Change Detection. *International Journal of Applied Earth Observation and Geoinformation* **In Press, Corrected Proof**.

HAY, G. J., P. DUBE, A. BOUCHARD and D. J. MARCEAU. 2002. A scale-space primer for exploring and quantifying complex landscapes. *Ecological Modelling* **153**:27-49.

HAY, G. J., D. J. MARCEAU, P. DUBE and A. BOUCHARD. 2001. A multiscale framework for landscape analysis: object-specific analysis and upscaling. *Landscape Ecology* **16**:471-490.

HILL, M. J. and G. E. DONALD. 2003. Estimating spatio-temporal patterns of agricultural productivity in fragmented landscapes using AVHRR NDVI time series. *Remote Sensing of Environment* **84**:367-384.

HOARE, R. E. 1999. Determinants of human-elephant conflict in a land-use mosaic. *Journal of Applied Ecology* **36**:689-700.

HOARE, R. E. and J. T. DU TOIT. 1999. Co-existence between people and elephants in African Savannas. *Conservation Biology* **13**:633-639.

HOSTETLER, M. 1999. Scale, birds, and human decisions: a potential for integrative research in urban ecosystems. *Landscape and Urban Planning* **45**:15-19.

HOSTETLER, M. and K. KNOWLES-YANEZ. 2003. Land use, scale, and bird distributions in the Phoenix metropolitan area. *Landscape and Urban Planning* **62**:55-68.

HULME, D. and M. MURPHREE. 2001. Community Conservation in Africa. Pages 1-8 *in* D. Hulme and M. Murphree, editors. African Wildlife and Livelihoods: The promise and performance of community conservation. Weaver, Harare.

ITC, R. G. 2002. Integrated Land and Water Information System (ILWIS). *in*. ITC, The Netherlands, Enschede.

IUCN. 2002. IUCN Red List of Threatened Species. *in*. www.redlist.org.

JANSSON, G. 2002. Scaling and habitat proportions in relation to bird diversity in managed boreal forests. *Forest Ecology and Management* **157**:77-86.

JOHNSON, A. R., J. A. WIENS, B. T. MILNE and T. O. CRIST. 1992. Animal movements and population dynamics in heterogeneous landscapes. *Landscape Ecology* **7**:63-75.

JORDAN, A. M. 1992. Degradation of Environment: an inevitable consequence of Trypanosomiasis control? *World Animal Review* **1-2**:2-7.

KAREIVA, P. and U. WENNERGREN. 1995. Connecting landscape patterns to ecosystem and population processes. *Nature* **373**:299-302.

KERR, J. T. and M. OSTROVYSKY. 2003. From space to species: ecological applications for remote sensing. *Trends in Ecology & Evolution* **In press**.

KINGDON, J. 2001. The Kingdon field guide to African mammals. Academic Press, London.

KOTLIAR, N. B. and J. A. WIENS. 1990. Multiple scales of patchiness and patch structure: a hierarchical framework for the study of heterogeneity. *OIKOS* **59**:253-260.

LAM, L. 2001. An introduction of S-PLUS. CANdiensten, Amsterdam.

LEGENDRE, P. 1998. Numerical Ecology. Elsevier, Amsterdam.

LEGENDRE, P. and M. FORTIN. 1989. Spatial pattern and ecological analysis. *Vegetatio* **80**:107-138.

LEVIN, S. A. 1992. The problem of pattern and scale in ecology. *Ecology* **73**:1943-1967.

LI, X., L. LU, G. CHENG and H. XIAO. 2001. Quantifying landscape structure of the Heihe River Basin, north-west China using FRAGSTATS. *Journal of Arid Environments* **48**:521-535.

LINDSAY, R. W., D. B. PERCIVAL and D. A. ROTHROCK. 1996. The Discrete Wavelet Transform and the scale Analysis of Surface Properties of Sea Ice. *IEEE Transactions on Geoscience and Remote Sensing* **34**:771-787.

LOGAN, B. I. and W. G. MOSELEY. 2002. The political ecology of poverty alleviation in Zimbabwe's Communal Areas Management Programme for Indigenous Resources (CAMPFIRE). *Geoforum* **33**:1-14.

LOS., S. O. 1998. Linkages between global vegetation and climate: An analysis based on NOAA Advanced Very High Resolution Radiometer Data. PhD. Vrije Universiteit te Amsterdam, Amsterdam.

LOVEMORE, D. F. 1994. Overview of past and present tsetse distributions and control in Zimbabwe. Pages 5-25 *in* Workshop to coordinate studies of land use change in the Zambezi valley of Zimbabwe, Harare, Zimbabwe.

LYNAM, A. J. and I. BILLICK. 1999. Differential responses of small mammals to fragmentation in a Thailand tropical forest. *Biological Conservation* **91**:191-200.

MAC NALLY, R. and A. F. BENNET. 1997. Species-specific predictions of the impact of habitat fragmentation: local extinction of birds in the Box-Ironbark forests of Central Victoria, Australia. *Biological Conservation* **82**:147-155.

MALLAT, S. G. 1989. A theory for multiresolution Signal Decomposition: The wavelet Representation. *IEEE Transactions on Pattern analysis and Machine Intelligence* **11**:674-693.

MCGRIGAL, K. and S. A. CUSHMAN. 2002. The gradient concept of landscape structure. *in*. http://www.umass.edu/landeco/pubs/Gradients~_short.pdf.

MORRISON, M. L., B. G. MARCOT and R. W. MANNAN. 1992. Wildlife-Habitat Relationships: Concepts and Applications. The University of Wisconsin Press, Wisconsin.

MURWIRA, A., A. K. SKIDMORE and J. DE LEEUW. 2003. Evaluating a new approach to predict the spatial distribution of elephants from NDVI. *In review*.

MURWIRA, A. and A. K. SKIDMORE. 2003. Characterising the spatial heterogeneity of a landscape. *In review*.

MYERS, D. E. 1997. Statistical models for multiple-scaled analysis. Pages 273-307 *in* D. A. Quattrochi and M. F. Goodchild, editors. Scale in Remote Sensing and GIS. Lewis Publishers, New York.

NOBANDA, N., M. MOYO and A. MURWIRA. 1998. Ecoregions: A first approximation. Pages 406-432 *in* M. Chenje, L. Sola and D. Placezny, editors. The state of Zimbabwe's environment. Government of Zimbabwe, Harare.

OGDEN, R. T. 1997. Essential Wavelets for Statistical Applications and Data Analysis. Birtkhauser, Boston.

OINDO, B. O. 2001. Spatial patterns of species diversity in Kenya. PhD. Wageningen University, Wageningen.

OINDO, B. O. and A. K. SKIDMORE. 2001. Interannual variability of NDVI and species richness in Kenya. *International Journal Of Remote Sensing* **23**:285-298.

OSBORN, F. V. and G. E. PARKER. 2003. Linking two elephant refuges with a corridor in the communal lands of Zimbabwe. *African Journal of Ecology* **41**:68 -74.

OTTICHILO, W. K. 2000. Wildlife dynamics: An analysis of change in the Masai Mara Ecosystem of Kenya. PhD. Wageningen Universiteit, Wageningen.

PEARSON, D. M. 2002. The application of local measures of spatial autocorrelation for describing pattern in north Australian landscapes. *Journal of Environmental Management* **64**:85-95.

PENDER, J. and J. ROSENBURG. 1995. Impact of tsetse control on land use in the semi-arid zone of Zimbabwe. Natural Resources Institute, United Kingdom.

PERRY, J. N., A. M. LIEBHOLD, M. S. ROSENBURG, J. DUNGAN, M. MIRITI, A. JAKOMULSKA and S. CITRON-POUSTY. 2002. Illustrations and guidelines for selecting statistical methods for quantifying spatial pattern in ecological data. *Ecography* **25**:578-600.

PICKETT, S. T. A. and K. H. ROGERS. 1997. Patch dynamics: the transformation of landscape structure and function. Pages 101-127 *in* J. A. Bissonette, editor. Wildlife and Landscape ecology: Effects of pattern and scale. Springer, New York.

PRINS, H. H. T., J. G. GROOTENHUIS and T. T. DOLAN. 2000. Wildlife Conservation by Sustainable use. Kluwer Academic Publishers, Boston, Dordrecht, London.

QI, Y. and J. WU. 1996. Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. *Landscape Ecology* **11**:39-49.

REID, R. S., C. J. KRUSKA and W. MULATU. 1997. Impact of tsetse control and land-use on vegetative structure and tree species composition in south-western Ethiopia. *Journal of Applied Ecology*.

RIETKERK, M., P. KETNER, J. BURGER, B. HOORENS and H. OLFF. 2000. Multiscale soil and vegetation patchiness along a gradient of herbivore impact in a semi-arid grazing system in West Africa. *Plant ecology* **148**:207-224.

RIETKERK, M., J. VAN DE KOPPEL, L. KUMAR, F. VAN LANGEVELDE and H. H. T. PRINS. 2002. The ecology of scale: Editorial. *Ecological Modelling* **149**:1-4.

RITCHIE, M. E. 1997. Populations in a Landscape Context: Sources, Sinks, and Metapopulations. Pages 160-183 *in* J. A. Bissonette, editor. Wildlife and Landscape Ecology: Effects of Pattern and Scale. Springer, New York.

ROGAN, J., J. FRANKLIN and D. A. ROBERTS. 2002. A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. *Remote Sensing of Environment* **80**:143-156.

ROGERS, D. J. and S. E. RANDOLPH. 1988. Tsetse flies in Africa: Bane or Boon? *Conservation Biology* **2**:59-65.

SAID, M. Y. 2003. Multiscale perspectives of species richness in East Africa. PhD. ITC and Wageningen, Enschede, The Netherlands.

SCHOLES, R. J. 1997. Savanna. Pages 258-277 *in* R. M. Cowling, D. M. Richardson and S. M. Pierce, editors. Vegetation of Southern Africa. Cambridge University Press, Cambridge.

SONG, C., C. E. WOODCOCK, S. K., M. P. LENNEY and S. A. MACOMBER. 2001. Classification and Change Detection Using Landsat TM data: When and How to Correct Atmospheric Effects? *Remote Sensing of Environment* **75**:230-244.

SOUTHWOOD, T. R. E. 1977. Habitat, the template for ecological strategies? presidential address to the British ecological society 5 January 1977. *Journal of Animal ecology* **4**:337-365.

SPARROW, A. D. 1999. A heterogeneity of heterogeneities. *Trends in Ecology & Evolution* **14**:422-423.

TANSER, F. C. and A. R. PALMER. 1999. The application of remotely-sensed diversity index to monitor degradation patterns in semi-arid, heterogeneous, South African landscape. *Journal of Arid Environments* **43**:477-484.

TIMBERLAKE, J. and N. NOBANDA. 1993. Vegetation survey in Zimbabwe. *The Zimbabwe Journal of Botany* **14**:24-48.

TIMBERLAKE, J. R., N. NOBANDA and I. MAPAURE. 1993. Vegetation survey of the communal lands-north and west Zimbabwe. *Kirkia: The Zimbabwe Journal of Botany* **14**:171-271.

TRANI, M. K. and J. GILES, ROBERT H. 1999. An analysis of deforestation: Metrics used to describe pattern change. *Forest Ecology and Management* **114**:459-470.

TREITZ, P. and P. HOWARTH. 2000. High Spatial Resolution Remote Sensing Data for Forest Ecosystem Classification: An Examination of Spatial Scale. *Remote Sensing of Environment* **72**:268-289.

TUCKER, C. J. and P. J. SELLERS. 1986. Satellite remote sensing and primary production. *International Journal of Remote Sensing* **7**:1395-1416.

TURNER, D. P., W. B. COHEN, R. E. KENNEDY, K. S. FASSNACHT and J. M. BRIGGS. 1999. Relationships between Leaf Area Index and Landsat TM Spectral Vegetation Indices across Three Temperate Zone Sites. *Remote Sensing of Environment* **70**:52-68.

TURNER, M. G. 1989. Landscape ecology: The effect of pattern on process. *Annual Review of Ecological Systems* **20**:171-197.

TURNER, M. G., S. M. PEARSON, W. H. ROMME and L. L. WALLACE. 1997. Landscape heterogeneity and ungulate dynamics: What spatial scale are important. Pages 331-348 *in* J. A. Bissonette, editor. Wildlife and landscape ecology: Effects of pattern and scale. Springer, New York.

VAN LANGEVELDE, F. 1999. Habitat connectivity and fragmented nuthatch populations in agricultural landscapes. Wageningen Universiteit, Wageningen.

WACKERNAGEL, H. 1998. Multivariate Geostatistics. Springer, Berlin.

WALSH, J. S., A. MOODY, T. R. ALLEN and D. G. BROWN. 1997. Scale dependence of NDVI and its Relationship to Mountainous Terrain. Pages 27-55 *in* D. A. Quattrochi and M. F. Goodchild, editors. Scale in Remote Sensing and GIS. Lewis Publishers, New York.

WALSH, S. J., T. W. CRAWFORD, W. F. WELSH and K. A. CREWS-MEYER. 2001. A multiscale analysis of LULC and NDVI variation in Nang Rong district, northeast Thailand. *Agriculture, Ecosystems & Environment* **85**:47-64.

WANG, G., Z. WANG, Q. ZHOU and W. ZHONG. 1999. Relationship between species richness of small mammals and primary productivity of arid and semi-arid grasslands in north China. *Journal of Arid Environments* **43**:467-475.

WANG, G., G. ZHOU, L. YANG and Z. LI. 2002. Distribution, species diversity and life-form spectra of plant communities along an altitudinal gradient in the northern slopes of Qilianshan Mountains, Gansu, China. *Plant Ecology* **165**:169-181.

WANG, G., Q. ZHOU, W. ZHONG, C. SUN and Z. CHEN. 2001. Species richness -- primary productivity relationship of plants and small mammals in the Inner Mongolian steppes, China. *Journal of Arid Environments* **49**:477-484.

WEBSTER, R. 2000. Is soil variation random? *Geoderma* **97**:149-163.

WESTERN, A. W. and G. BLOSCHL. 1999. On the spatial scaling of soil moisture. *Journal of Hydrology* **217**:203-224.

WIENS, J. A. 1989. Spatial scaling in ecology. *Functional Ecology* **3**:385-397.

WITH, K. A. and T. O. CRIST. 1995. Critical thresholds in species responses to landscape structure. *Ecology* **76**:2446-2459.

YAPP, R. H. 1922. The concept of habitat. *Journal of Ecology* **10**:1-17.

Curriculum vitae

Amon Murwira was born on the 20th of December 1969 in the Gutu district, Masvingo province in Zimbabwe. He completed his primary education at Shumbairerwa primary school in 1984 in Gutu. He then proceeded to Rafomoyo secondary school in Gutu and successfully completed his University of Cambridge Ordinary level certificate in 1988. In 1989, he proceeded to Gutu High School for his University of Cambridge Advanced level and completed it in 1990.

In 1991, he registered at the University of Zimbabwe to study Geography, and graduated in 1993 with an Honours degree in Geography. In 1994, he joined the Zimbabwean Ministry of Education where he taught Geography at two secondary schools in Masvingo province in Southern Zimbabwe: at Nemamwa secondary school from January to February 1994 and at Victoria High school from March to November 1994.

In December 1995, he joined the Zimbabwean Ministry of Environment and Tourism, as an Ecologist with a specific responsibility to do environmental research, as well as make natural resources inventories using Remote Sensing and Geographic Information Systems in the Department of Natural Resources. While in the Department of Natural Resources he was attached to the Ontario Ministry of Natural Resources in Canada, at several intervals from 1995 to 1998. He also represented the Department of Natural Resources at different research workshops in several Southern African countries.

In August 1998, he joined the University of Zimbabwe as a staff development fellow in the Department of Geography and Environmental Science under a scholarship to do an MSc in Environmental Systems Analysis and Monitoring, as well as a PhD at ITC in The Netherlands. He successfully completed his Msc in 2000 and immediately commenced his PhD research with ITC and Wageningen University that resulted in this thesis.

Appendix 1: ITC PhD Dissertation List

Akinyede, 1990, Highway cost modelling and route selection using a geotechnical information system
Pan He Ping, 1990, 90-9003757-8, Spatial structure theory in machine vision and applications to structural and textural analysis of remotely sensed images
Bocco Verdinelli, G., 1990, Gully erosion analysis using remote sensing and geographic information systems: a case study in Central Mexico
Sharif, M, 1991, Composite sampling optimization for DTM in the context of GIS
Drummond, J., 1991, Determining and processing quality parameters in geographic information systems
Groten, S., 1991, Satellite monitoring of agro-ecosystems in the Sahel
Sharifi, A., 1991, 90-6164-074-1, Development of an appropriate resource information system to support agricultural management at farm enterprise level
Zee, D. van der, 1991, 90-6164-075-X, Recreation studied from above: Air photo interpretation as input into land evaluation for recreation
Mannaerts, C., 1991, 90-6164-085-7, Assessment of the transferability of laboratory rainfall-runoff and rainfall - soil loss relationships to field and catchment scales: a study in the Cape Verde Islands
Ze Shen Wang, 1991: 90-393-0333-9, An expert system for cartographic symbol design
Zhou Yunxian, 1991, 90-6164-081-4, Application of Radon transforms to the processing of airborne geophysical data
Zuviria, M. de, 1992, 90-6164-077-6, Mapping agro-topoclimates by integrating topographic, meteorological and land ecological data in a geographic information system: a case study of the Lom Sak area, North Central Thailand
Westen, C. van, 1993, 90-6164-078-4, Application of Geographic Information Systems to landslide hazard zonation
Shi Wenzhong, 1994, 90-6164-099-7, Modelling positional and thematic uncertainties in integration of remote sensing and geographic information systems
Javelosa, R., 1994, 90-6164-086-5, Active Quaternary environments in the Philippine mobile belt
Lo King-Chang, 1994, 90-9006526-1, High Quality Automatic DEM, Digital Elevation Model Generation from Multiple Imagery
Wokabi, S., 1994, 90-6164-102-0, Quantified land evaluation for maize yield gap analysis at three sites on the eastern slope of Mt. Kenya
Rodriguez, O., 1995, Land Use conflicts and planning strategies in urban fringes: a case study of Western Caracas, Venezuela
Meer, F. van der, 1995, 90-5485-385-9, Imaging spectrometry & the Ronda peridotites
Kufoniyi, O., 1995, 90-6164-105-5, Spatial coincidence: automated database updating and data consistency in vector GIS

Zambezi, P., 1995, Geochemistry of the Nkombwa Hill carbonatite complex of Isoka District, north-east Zambia, with special emphasis on economic minerals

Woldai, T., 1995, The application of remote sensing to the study of the geology and structure of the Carboniferous in the Calañas area, pyrite belt, SW Spain

Verweij, P., 1995, 90-6164-109-8, Spatial and temporal modelling of vegetation patterns: burning and grazing in the Paramo of Los Nevados National Park, Colombia

Pohl, C., 1996, 90-6164-121-7, Geometric Aspects of Multisensor Image Fusion for Topographic Map Updating in the Humid Tropics

Jiang Bin, 1996, 90-6266-128-9, Fuzzy overlay analysis and visualization in GIS

Metternicht, G., 1996, 90-6164-118-7, Detecting and monitoring land degradation features and processes in the Cochabamba Valleys, Bolivia. A synergistic approach

Hoanh Chu Thai, 1996, 90-6164-120-9, Development of a Computerized Aid to Integrated Land Use Planning (CAILUP) at regional level in irrigated areas: a case study for the Quan Lo Phung Hiep region in the Mekong Delta, Vietnam

Roshannejad, A., 1996, 90-9009284-6, The management of spatio-temporal data in a national geographic information system

Terlien, M., 1996, 90-6164-115-2, Modelling Spatial and Temporal Variations in Rainfall-Triggered Landslides: the integration of hydrologic models, slope stability models and GIS for the hazard zonation of rainfall-triggered landslides with examples from Manizales, Colombia

Mahavir, J., 1996, 90-6164-117-9, Modelling settlement patterns for metropolitan regions: inputs from remote sensing

Al-Amir, S., 1996, 90-6164-116-0, Modern spatial planning practice as supported by the multi-applicable tools of remote sensing and GIS: the Syrian case

Pilouk, M., 1996, 90-6164-122-5, Integrated modelling for 3D GIS

Duan Zengshan, 1996, 90-6164-123-3, Optimization modelling of a river-aquifer system with technical interventions: a case study for the Huangshui river and the coastal aquifer, Shandong, China

Man, W.H. de, 1996, 90-9009-775-9, Surveys: informatie als norm: een verkenning van de institutionalisering van dorp - surveys in Thailand en op de Filippijnen

Vekerdy, Z., 1996, 90-6164-119-5, GIS-based hydrological modelling of alluvial regions: using the example of the Kisaföld, Hungary

Pereira, Luisa, 1996, 90-407-1385-5, A Robust and Adaptive Matching Procedure for Automatic Modelling of Terrain Relief

Fandino Lozano, M., 1996, 90-6164-129-2, A Framework of Ecological Evaluation oriented at the Establishment and Management of Protected Areas: a case study of the Santuario de Iguaque, Colombia

Toxopeus, B., 1996, 90-6164-126-8, ISM: an Interactive Spatial and temporal Modelling system as a tool in ecosystem management: with two case studies: Cibodas biosphere reserve, West Java Indonesia: Amboseli biosphere reserve, Kajiado district, Central Southern Kenya

Wang Yiman, 1997, 90-6164-131-4, Satellite SAR imagery for topographic mapping of tidal flat areas in the Dutch Wadden Sea

Saldana-Lopez, Asunción, 1997, 90-6164-133-0, Complexity of soils and Soilscape patterns on the southern slopes of the Ayllon Range, central Spain: a GIS assisted modelling approach

Ceccarelli, T., 1997, 90-6164-135-7, Towards a planning support system for communal areas in the Zambezi valley, Zimbabwe; a multi-criteria evaluation linking farm household analysis, land evaluation and geographic information systems

Peng Wanning, 1997, 90-6164-134-9, Automated generalization in GIS

Lawas, C., 1997, 90-6164-137-3, The Resource Users' Knowledge, the neglected input in Land resource management: the case of the Kankanaey farmers in Benguet, Philippines

Bijker, W., 1997, 90-6164-139-X, Radar for rain forest: A monitoring system for land cover Change in the Colombian Amazon

Farshad, A., 1997, 90-6164-142-X, Analysis of integrated land and water management practices within different agricultural systems under semi-arid conditions of Iran and evaluation of their sustainability

Orlic, B., 1997, 90-6164-140-3, Predicting subsurface conditions for geotechnical modelling

Bishr, Y., 1997, 90-6164-141-1, Semantic Aspects of Interoperable GIS

Zhang Xiangmin, 1998, 90-6164-144-6, Coal fires in Northwest China: detection, monitoring and prediction using remote sensing data

Gens, R., 1998, 90-6164-155-1, Quality assessment of SAR interferometric data

Turkstra, J., 1998, 90-6164-147-0, Urban development and geographical information: spatial and temporal patterns of urban development and land values using integrated geo-data, Villaviciencia, Colombia

Cassells, C., 1998, Thermal modelling of underground coal fires in northern China

Naseri, M., 1998, 90-6164-195-0, Characterization of Salt-affected Soils for Modelling Sustainable Land Management in Semi-arid Environment: a case study in the Gorgan Region, Northeast, Iran

Gorte B.G.H., 1998, 90-6164-157-8, Probabilistic Segmentation of Remotely Sensed Images

Tenalem Ayenew, 1998, 90-6164-158-6, The hydrological system of the lake district basin, central main Ethiopian rift

Wang Donggen, 1998, 90-6864-551-7, Conjoint approaches to developing activity-based models

Bastidas de Calderon, M., 1998, 90-6164-193-4, Environmental fragility and vulnerability of Amazonian landscapes and ecosystems in the middle Orinoco river basin, Venezuela

Moameni, A., 1999, Soil quality changes under long-term wheat cultivation in the Marvdasht plain, South-Central Iran

Groenigen, J.W. van, 1999, 90-6164-156-X, Constrained optimisation of spatial sampling: a geostatistical approach

Cheng Tao, 1999, 90-6164-164-0, A process-oriented data model for fuzzy spatial objects

Wolski, Piotr, 1999, 90-6164-165-9, Application of reservoir modelling to hydrotopes identified by remote sensing

Acharya, B., 1999, 90-6164-168-3, Forest biodiversity assessment: A spatial analysis of tree species diversity in Nepal

Akbar Abkar, Ali, 1999, 90-6164-169-1, Likelihood-based segmentation and classification of remotely sensed images

Yanuariadi, T., 1999, 90-5808-082-X, Sustainable Land Allocation: GIS-based decision support for industrial forest plantation development in Indonesia

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