Chapter 3
Detecting changes in the spatial heterogeneity of NDVI using a wavelet transform[2]

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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.

[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

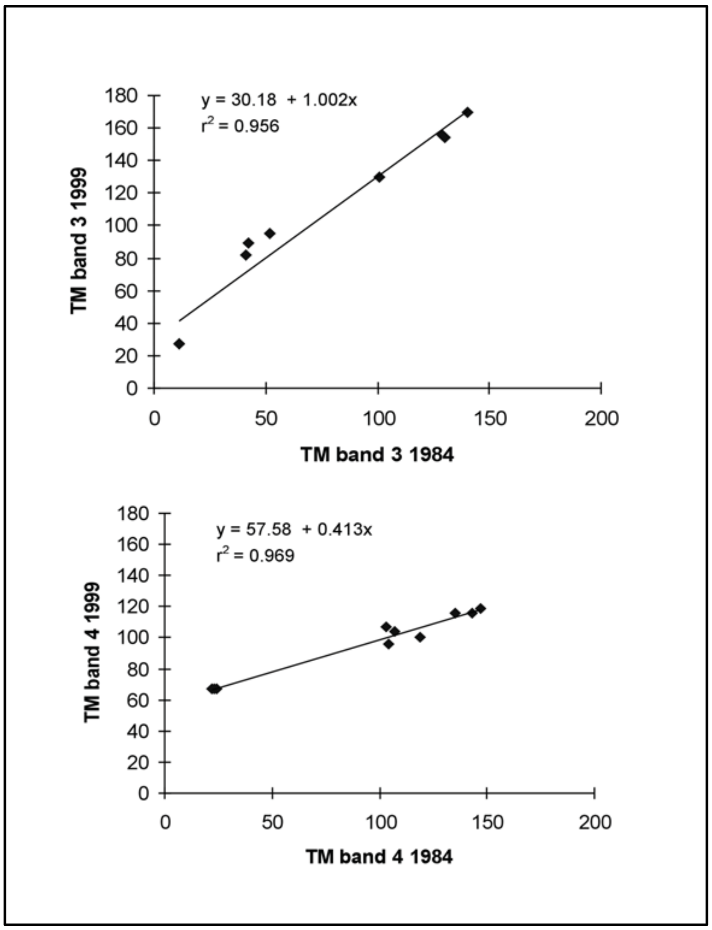

Figure 3.1: Relationship between the DN values of sampled pseudo variant objects between the Landsat TM images of 19 October 1984 and 6 November 1999.

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.

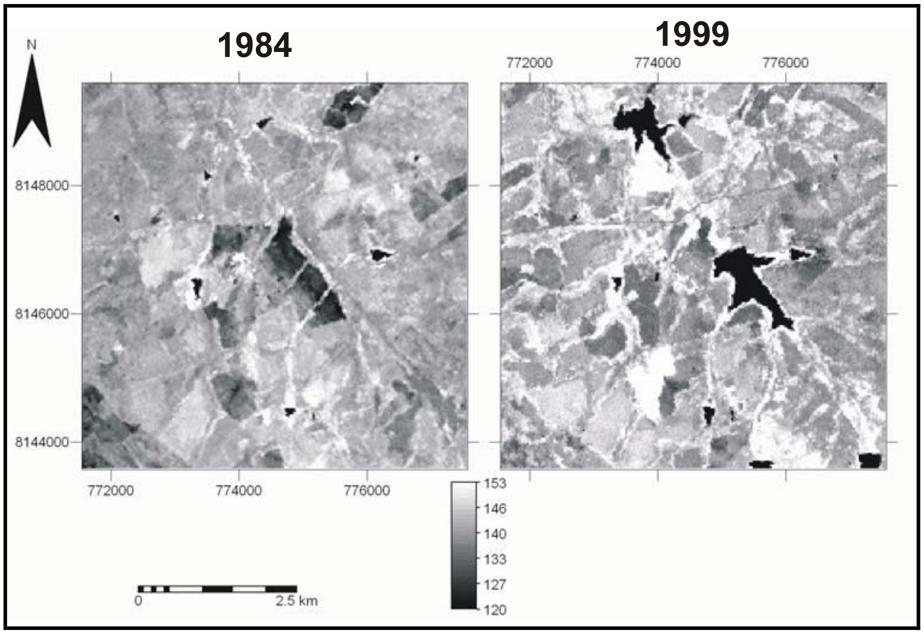

Figure 3.2: The 1984 and 1999 NDVI images of the study site. Low NDVI values indicate low vegetation cover and high NDVI values indicate high vegetation cover within a 0 (no vegetation) to 255 (high vegetation cover) range. The coordinates in metres (Universal Transverse Mercator (UTM) projection Zone 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…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… 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 $\hat{Z}(x,y)$:

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

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.

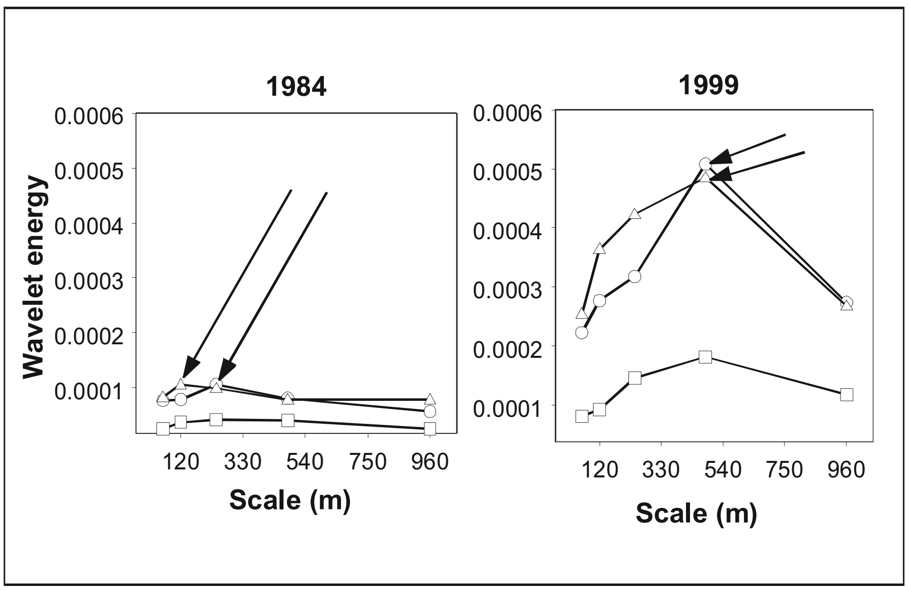

Figure 3.3: Directional wavelet energy functions for study site in the (△) horizontal (east-west), (○) vertical (north-south) and (□) diagonal (northeast-southwest and northwest-southeast) orientation in 1984 and 1999. The arrows indicate the intensity, as well as the dominant scale of spatial heterogeneity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

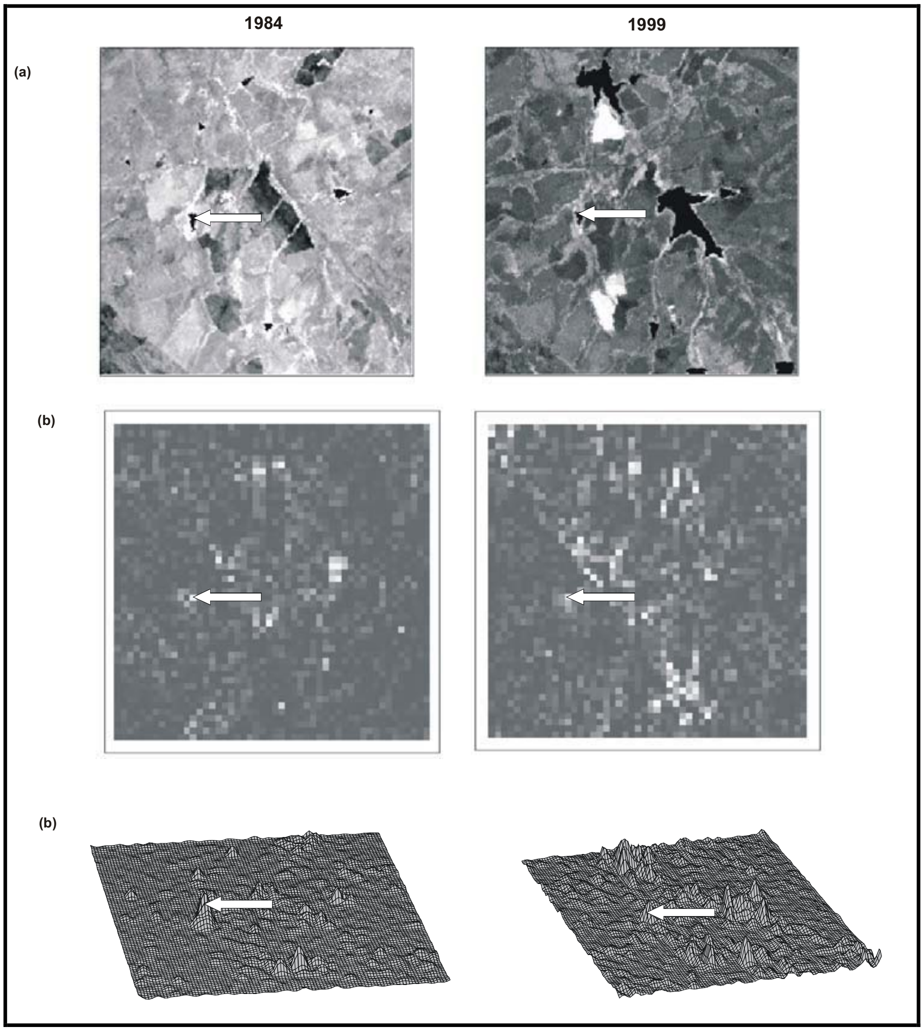

Figure 3.4: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the horizontal (east-west) orientation in 1984 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.

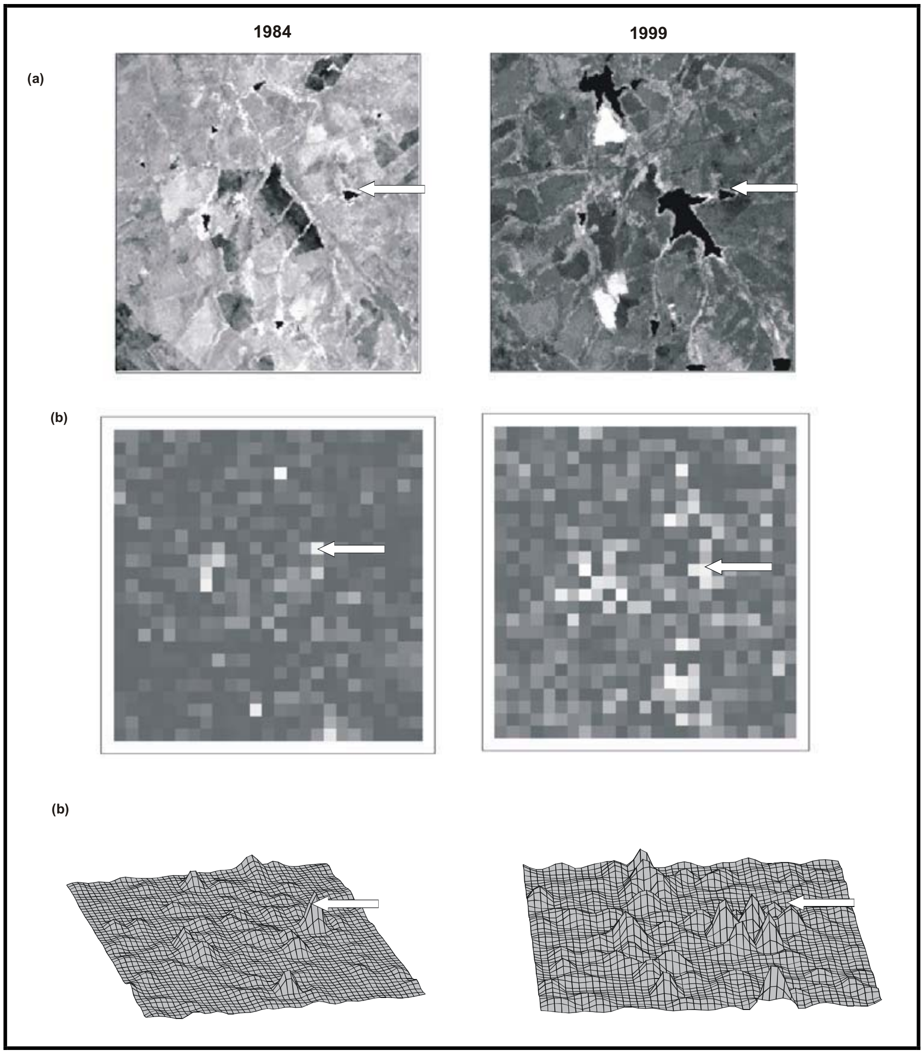

Figure 3.5: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the vertical (north-south) orientation in 1984 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.

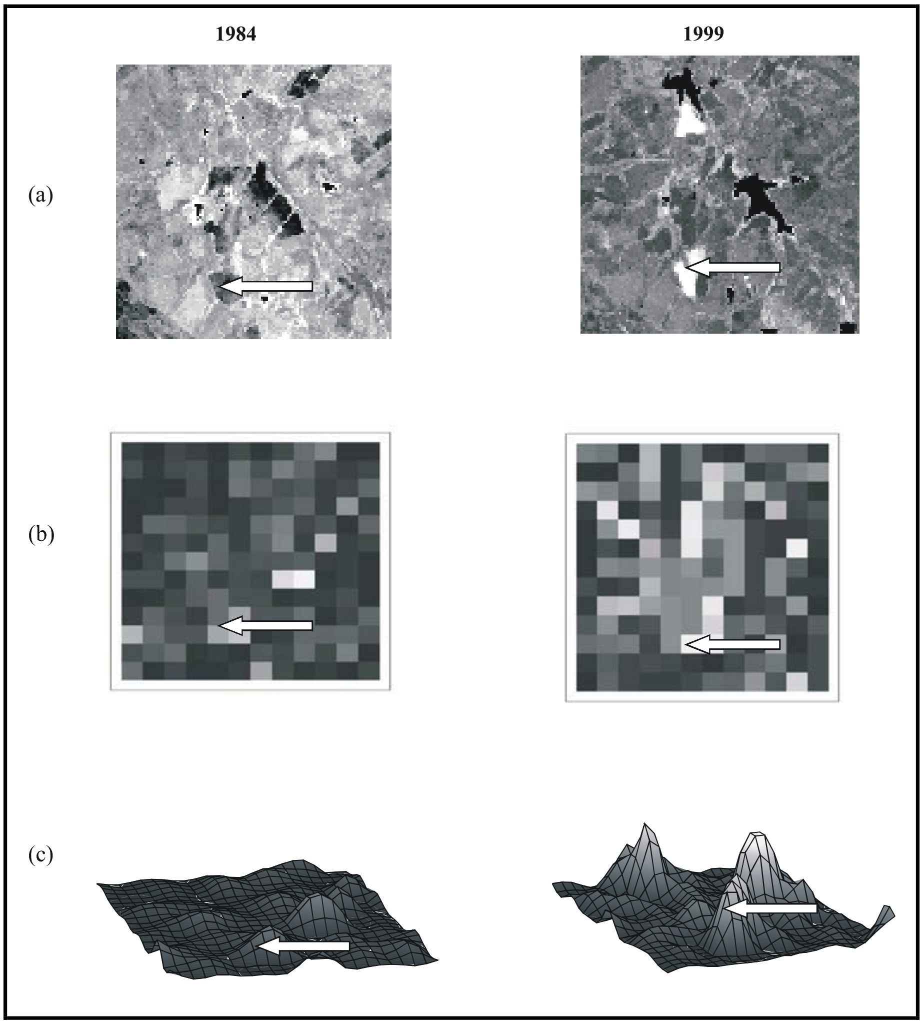

Figure 3.6: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the horizontal (east-west) orientation in 1999 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.

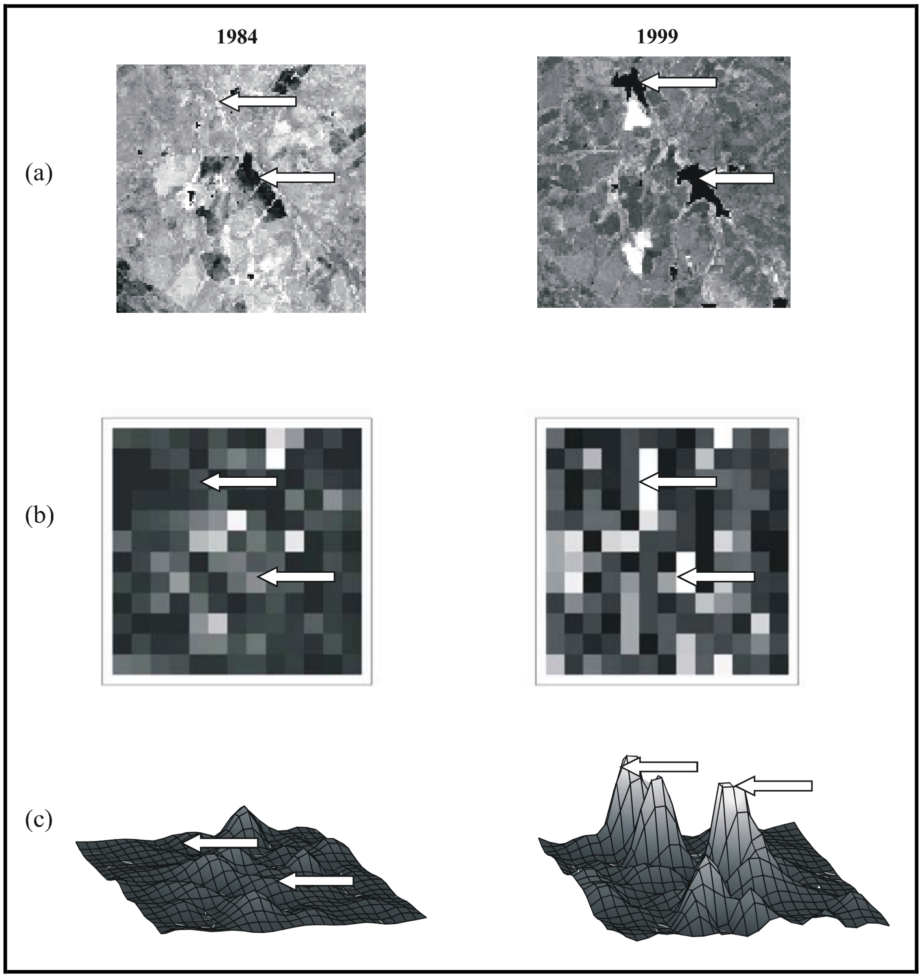

Figure 3.7: The (a) NDVI images of the study site in 1984 and 1999 and the (b) two dimensional and (c) 3-dimensional images showing the magnitude of the wavelet coefficients that constitute the intensity and the dominant scale of spatial heterogeneity in the vertical (north-south) orientation in 1999 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.