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Optimal Spatial Scale for Land Use Change Modelling : A Case Study in a Savanna Landscape in Northern Ghana

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지표피복변화 연구에서 최적의 공간스케일의 문제 : 가나 북부지역의 사바나 지역을 사례로

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Abstract : Land Use and Land Cover Changes (LUCC) occur over a wide range of space and time scales, and involve complex natural, socio-economic, and institutional processes. Therefore, modelling and predicting LUCC demands an understanding of how various measured properties behave when considered at different scales. Understanding spatial and temporal variability of driving forces and constraints on LUCC is central to understanding the scaling issues. This paper aims to 1) assess the heterogeneity of land cover change processes over the landscape in northern Ghana, where intensification of agricultural activities has been the dominant land cover change process during the past 15 years, 2) characterise dominant land cover change mechanisms for various spatial scales, and 3) identify the optimal spatial scale for LUCC modelling in a savanna landscape. A multivariate statistical method was first applied to identify land cover change intensity (LCCI), using four time-sequenced NDVI images derived from LANDSAT scenes. Three proxy land use change predictors: distance from roads, distance from surface water bodies, and a terrain characterisation index, were regressed against the LCCI using a multi-scale hierarchical adaptive model to identify scale dependency and spatial heterogeneity of LUCC processes. High spatial associations between the LCCI and land use change predictors were mostly limited to moving windows smaller than 10×10km. With increasing window size, LUCC processes within the window tend to be too diverse to establish clear trends, because changes in one part of the window are compensated elsewhere. This results in a reduced correlation between LCCI and land use change predictors at a coarser spatial extent. The spatial coverage of 5-10km is incidentally equivalent to a village or community area in the study region. In order to reduce spatial variability of land use change processes for regional or national level LUCC modelling, we suggest that the village level is the optimal spatial investigation unit in this savanna landscape.

Key Words : LUCC, scale, multi-scale adaptive model, Ghana

요약 : 토지이용 및 지표피복변화 (Land Use and Land Cover Changes, LUCC)는 지구환경변화의 원인으로 중요한 연구대상이 되고 있다. LUCC는 복잡한 사회적, 경제적, 정치적 상호작용속에서 다양한 시 · 공간적 스케일에서 발생하게 된다. 따라서 LUCC를 모

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델화하기 위해서는 LUCC를 야기시키는 원인(driving forces)과 제한요인(constraints)들의 시 · 공간적인 다양성을 이해하는 작업이 선행되어야 한다. 특히, 특정 지역에서 나타나는 LUCC의 동인을 파악하기 위해서는 스케일에 따른 그 특성의 변화를 이해하는 것이 급선무이다. 이 연구는 가나(Ghana) 북부지역의 사바나 지역을 대상으로 지난 15년간 나타난 지표피복변화의 공간적인 다양성을 파악한 뒤, 공간적 스케일을 달리하면서 나타나는 LUCC의 원인을 분석하였다. 이 과정을 통해 사바나 지역에서 LUCC 과정을 모형화하기 위한 최적의 공간적인 스케일을 규명하고자 하였다. 연구지역은 지난 15년간 인구증가의 결과로 농업생산활동이 급격하게 증가한 지역이다. 연구지역에서 나타나는 지표피복변화의 정도는 LANDSAT 위성영상에서 추출한 NDVI들을 다변량 통계분석기법을 이용하여 정량화하였다. 그리고 지표피복변화의 원인을 스케일별로 파악하기 위한 도구로 다축척 계층분석기법(multi-scale hierarchical adaptive model)을 개발 · 제안하였다. 개발된 기법은 지표피복의 변화정도와 원인이 될 수 있는 공간변수들간의 상관성을 공간적인 스케일을 달리하면서 순차적으로 계산해낼 수 있는 기법이다. 이 연구에서 지표피복변화의 원인으로는 '도로에서부터의 거리', '하천으로부터의 거리', '지형특성' 의 세가지 변수를 사용하였다. 지표피복 변화정도와 위의 세가지 변수들간의 상관관계는 공간적인 범위가 10×10km 이하인 경우에 높게 나타났다. 하지만 공간범위가 그 이상이 될 경우에는 그 내부에서 나타나는 다양성으로 인해 통계적인 상관성이 현격하게 낮아지는 것을 관찰할 수 있었다. 이러한 결과는 지역 및 국가 단위의 환경변화모델에서 모델의 공간적인 구성범위가 일정한 수준을 넘으면, 그 내부에서 발생하고 있는 다양성이 급격하게 증가하여 지표피복변화의 원인과 결과를 정확하게 파악하기 힘들게 된다는 것을 의미한다. 10×10km의 공간적인 범위는 농업생산이 위주가 되는 사바나 지역에서는 주로 개별 마을이 차지하고 있는 공간적인 범위와 대체적으로 일치한다. 따라서 사바나 지역에서 나타나는 지표피복변화의 다양성을 고려하면서 보다 정확하게 모형화하기 위해서는 마을단위에서 나타나는 지표피복변화과정이 최소의 모델단위가 되어야 함을 시사한다.

주요어 : 지표피복변화, 스케일, 다축척계층 분석기법, 가나

1. Introduction

The impact of Land Use and land Cover Change (LUCC) on the sustainability of ecosystems becomes an increasingly important issue in global-change research. Alterations of the earth's surface conditions result in changes in energy, water, and geochemical fluxes at the local, regional, and global scale. These changes will inevitably influence the sustainability of natural resources and the socio-economic activities of many people living in ecologically sensitive areas (Turner II *et al.*, 1995; Lambin *et al.*, 1999).

In recent years, human-induced LUCC is being considered one of the main causes for climate change, in addition to anthropogenic green house gas emission (NASA, 2002). Modelling LUCC processes is necessary to predict the influence of LUCC on other global and local environmental issues, and to formulate effective environmental policies and management strategies (Lambin *et al.*, 1999). Reflecting the overall importance and also the extreme complexity of LUCC processes, many different models have been developed. Comprehensive reviews on the existing land use change models are available in the literature (see Lambin *et al.*, 2001; Irwin and Geoghegan, 2001; Veldkamp and Lambin, 2001; Agarwal *et al.*, 2002; Verburg *et al.*, 2002; Parker *et al.*, 2002).

One of the major problems in modelling LUCC, especially at regional and global scales, is the diversity of both drivers and constraints of LUCC at the local scale (Turner II *et al.*, 199 Lambin *et al.*, 1999, p.75). LUCC is the result of complex interactions between socio-economic conditions, the natural environment and the historical heritage of individuals and communities. The quality and quantity of natural resources are highly variable in both time and space. Furthermore, individual land use activities vary greatly, depending on environmental opportunities and constraints, educational background, and cultural-social structures. In a comprehensive review of 152 case studies on tropical deforestation, Geist and Lambin (2002) showed that tropical forest decline is determined by different combinations of various factors in varying geographical and historical context. They concluded that there is no universal policy for controlling tropical deforestation, and argued that a detailed understanding of the complex set of causes and driving forces is required prior to any policy intervention.

Adequate understanding on the spatial (and also temporal) heterogeneity of LUCC processes is often hampered by the problem of scale. The identification of patterns and processes of LUCC processes is strongly determined by the spatial, temporal, and measurement scales chosen to investigate heterogeneous landscapes (Kirkby *et al.*, 1996 Gibson *et al.*, 1998). In addition, a change in the scale of observation is directly linked with changes in dominant system components and interactions. Therefore, the factors explaining LUCC will likewise change with changing scale, making it difficult to combine and transfer findings across different scales (Gibson *et al.*, 1998; Verburg *et al.*, 2002). Despite the overall importance on model construction and results, only few land use change studies have investigated the influence of spatial scale (e.g. Walsh *et al.*, 1999; Veldkamp *et al.*, 2001). Recently, Verburg *et al.* (2002) reviewed land use models to identify priority research areas, and concluded that multi-scale characteristics of the land use system is one of the most poorly understood components of LUCC modelling.

The main objective of this research is to understand how spatial heterogeneity of LUCC processes determines to what extent land use change at the different spatial scales. The specific setting is the sub-humid to semi-arid savanna landscape in Ghana, West Africa. The high seasonal and yearly variability of rainfall, in combination with the low soil nutrient status of the soils in the savanna landscape, render this ecosystem very sensitive to global change. A detailed understanding of the land use change processes is the first step towards the subsequent development of a general framework to ensure the livelihood of people in the study area under certain scenarios of global change and policy interventions (Vlek *et al.*, 2003).

The specific research questions are: 1) How does the local heterogeneity of LUCC drivers and constraints influence regional LUCC model outputs ?, 2) Are there any changes in functional relationships between land use change patterns and drivers with changes in spatial scale?, and 3) What is the optimal scale to include the necessary detail of diversity and complexity of LUCC processes at regional level? The last of these three questions, the existence of an optimum scale for LUCC modelling, is controversial. It is widely acknowledged that ecosystem functions vary continuously with scale. It is rare that a single scale can be regarded as correct or optimal for measurement and prediction (Gibson *et al.*, 1998; Schulze, 2000). At the same time, however, the identification of the optimal spatial scale (or sampling units) to capture the social and ecological patterns and processes of LUCC is considered necessary, and is seen as one of the first technical challenges to construct model components and their interactions (Lambin *et al.* 1999; Redman *et al.*, 2000). In this paper, the optimum spatial scale is defined as the spatial extent (or unit) that is large enough to include local heterogeneity, but small enough to reduce the extreme complexity of overall LUCC processes at the regional scale. The identification of such an optimal spatial scale may encourage the set up of a common framework among modellers to collect and analyse data for a broader spatial coverage.

2. Study Area

The study area is a 100km by 100km area in the Northern Region of Ghana, with Tamale as the regional capital in the center (Figure 1). The area is bounded by latitudes 8° and 10° 50°'N and longitudes 3° 40° and 1° 40°'E. The climate is tropical continental with one rainy season (May to October) and a prolonged dry season (November to April). Annual precipitation is about 1,100mm. The vegetation type is a Guinea savanna comprising of tall grasses with interspersed trees or shrubs. The soils are Luvisols, but Gleysols and Vertisols occur in lowlands and valley bottoms. These soils developed over sandstones, shales, quartz, and mudstones.

The main economic activity is agricultural food production (Clottery and Kombiok, 2000). The most common crops in this area are maize, yam, sorghum, millet, cowpea, rice, cassava, and groundnut as food crops, and cotton, kenaf, sheanut, and soybean as industrial crops. Estimated population growth during the last 15 years (from 1984 to 2000) was 2.7% in the Northern Region. Especially the Tamale District has experienced rapid population growth. Abudulai (1996) reports a 136% increase in

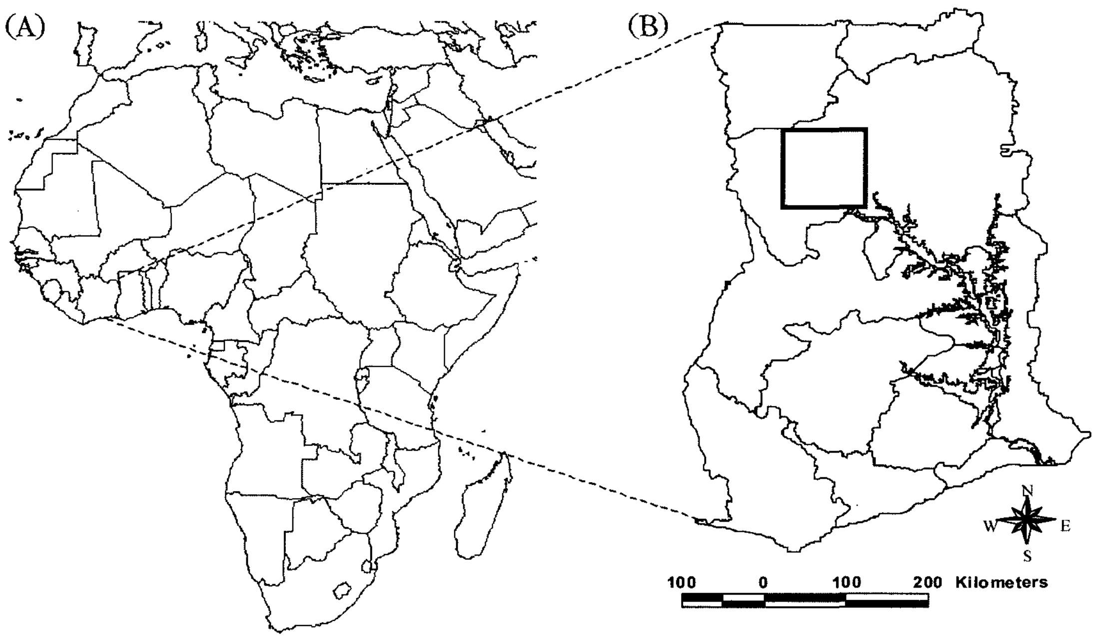


Figure 1. The location of the study area in this research. The square presented in Figure 1 (B) is approximately 100km by 100km located at the Guinea savanna

population from 1984 to 1995. The main land use changes are the intensification of agriculture and expansion of agricultural land into previously forested areas. However, population growth in the region can not be considered the sole and major cause of LUCC (Clottery and Kombiok, 2000 Braihmoh, 2003). The economic and structural adjustment programs of the late 1980s and early 1990s led to rapid land use changes and displacement of many farmers into formerly forested areas. The rice and cotton production introduced in the early 1980s was greatly reduced in the 1990s due to low market prices and expensive fertiliser (Clottery and Kombiok, 2000).

Using multi-temporal remotely sensed imagery of the study area (Vescovi *et al.*, 2002), two kinds of land use change can be distinguished: 1) short-term change due to seasonal effects, and 2) long-term or permanent change due to human actions such as construction of new infrastructure, deforestation, and farming. Short-term change is simply due to the effect of the seasonal climate on vegetation. Long-term change includes two kinds of change: conversion from one land cover category to another (e.g. from forest to grassland) and modification within one category (e.g. from closed forest to open forest).

3. Human-Induced Land Cover Change

1) Change Detection: Multivariate Variance Component Analysis

Prior to the investigation of the scale dependency of LUCC processes, the spatial extent and intensity of land use change was determined. Due to the lack of historical and socio-economic data, change detection was solely based on the interpretation of remote sensing (RS) imagery. Many RS-based change detection methods are available, and the success and efficiency of individual methods depend on the characteristics of the landscape and the type of land cover change (see Singh, 1989; Civco *et al.*, 2002). Traditional change detection methods based on land-use classes have severe limitations for the study area. In a typical savanna landscape, settlements are widely scattered and individual agricultural fields are small and frequently mixed with other natural and secondary vegetation. Furthermore, seasonal phenological vegetation changes are too pronounced to confidently separate agricultural land from natural savanna vegetation using RS imagery alone. Land use classification was also strongly affected by wide-spread bush-fire scars in some remote sending images.

A new, multi-variate statistical approach was developed to quantify human-induced land cover change, utilizing the variance characteristics of time-sequenced NDVIs (Normalized Difference Vegetation Index) derived from LANDSAT images. The NDVI, the normalized difference of brightness values from the near infrared and visible red bands, has been found to be highly correlated with crown closure, leaf area index, and other vegetation parameters (Singh, 1989). We made the explicit assumption that NDVI reflects the land use condition on the ground. The proposed method does not differentiate between detailed types of land use and trajectories of change, but offers the relative intensity of land cover changes over the study period. We define this index as the Land Cover Change Intensity (LCCI) over a certain time period, which provides information on the possible location and intensity of human-induced land use and cover changes. This single-continuous indicator is particularly useful to investigate the subsequent scale dependency of LUCC processes in this study.

The following is a brief summary of the algorithm developed to detect human-induced land use changes. Park and Vlek (2005) will provide a more detailed account of the methodology itself. Four NDVI (NDVI=*(infrared-red)/(infrared+red)*) images were derived from 30m resolution LANDSAT TM and ETM scenes after atmospheric correction and ground truthing (Vescovi et al, 2002). These include two LANDSAT-TM scenes from 14 November 1984 and January 1991, and two LANDSAT-ETM+ scenes from 7 November 1999 and 14 March 2000. The two images from November 1984 and November 1999, display the area at the end of the rainy season, when vegetation is still well developed and NDVIs are high. The two images from January 1991 and March 2000 were acquired in the dry season and the vegetation was wilted. The average coregistration error was less than 1.5 pixel for the four NDVI images. The original 30m grid NDVIs were re-sampled to a 90m grid using binary interpolation.

The total variance in spatio-temporal environmental data (∂_t^2) consists of three variance components (Park and Vlek, 2005):

$$\partial_t^2=\partial_d^2+\partial_s^2+\varepsilon$$

where ∂_d^2 is caused by any directional or human-induced change, ∂_s^2 is due to seasonal and cyclic changes, and ε is the remainder or error term. The error term includes noise caused by measurements and instrumentation. Remote sensing images taken from the same spatial extent are often subject to high variation due to atmospheric conditions, receiving angles, and the calibration of receivers. The error associated with such instrumentation is difficult to separate from spatio-temporal data sets, and can only be considered as random error.

The separation of seasonality and error components from total variance, may yield human-induced changes. The cyclic variance component is the result of climatic seasonality, vegetation growth, and land management activities. In our example, it is clear that the NDVI in the savanna landscape is always subject to cyclic climatic conditions. Various attempts have been made to develop mathematical expressions that fit vegetation development curves for remotely sensed data (e.g. Badhwar and Henderson, 1985; Lambin and Strahler, 1994). Such detailed mathematical modelling requires an extensive time-sequence data set, which is not available for the study area.

In order to separate the variance component caused by seasonal phenological changes and the random error components from the total variance of the NDVIs, it is assumed that the variance of the NDVIs is linearly correlated with the mean of the NDVIs. From the phenological point of view, this implies that a more dense vegetation shows higher seasonable variations over a certain time period. Park and Vlek (2005) observed that spatio-temporal data, including groundwater salinity, remote sensing signals, and soil moisture content, show a clear relationship between the mean (z) and total variance (∂^2). This assumption was further supported by a linear relationship between the mean and the variance of the NDVIs of the study area, as

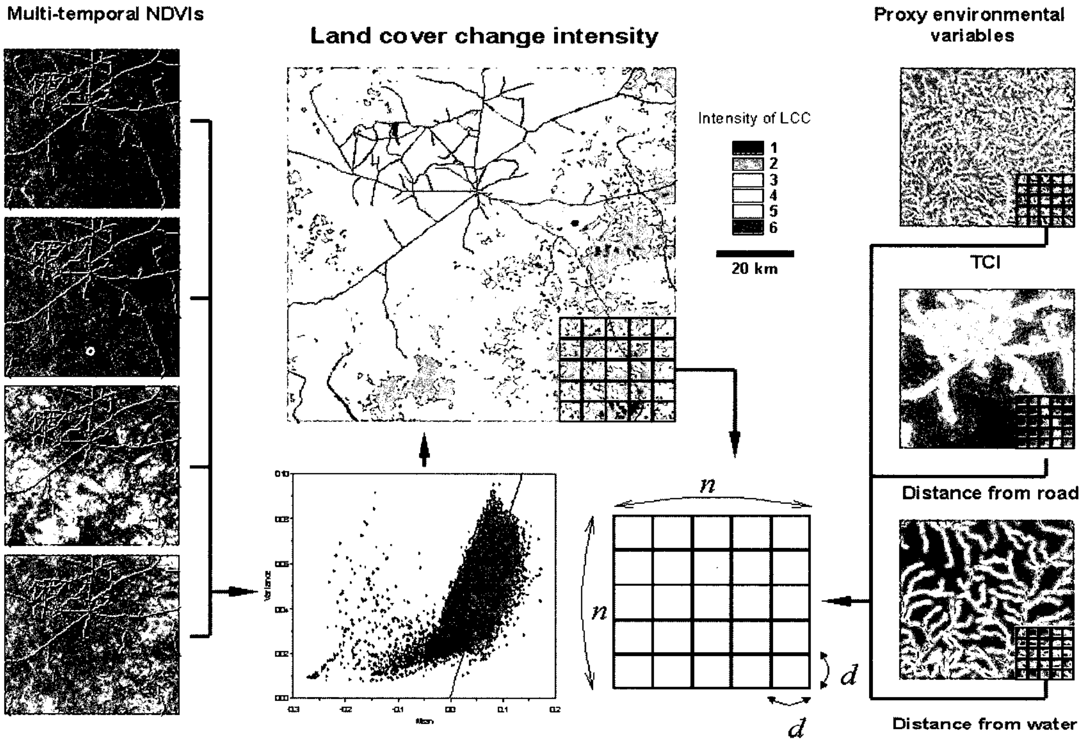


Figure 2. The overall procedure for the change detection methods and the multiscale adaptive model to investigate the spatial heterogeneity and scale dependency in northern Ghana.

shown in the scatter plot in Figure 2. The variance of the NDVIs is a linear function of the mean of the NDVI with a high coefficient of determination (∂^2=1.405 z, R^2=0.56).

While the majority of the points are scattered within ± 1 ∂^2 of the regression coefficient in Figure 2, some points significantly deviate from the regression line both in the positive and negative directions. We hypothesized that those areas that show significant deviation from the regression line reflect human-induced land cover changes, which have been caused by other than seasonal phenological changes. The variance component caused by seasonal phenological changes of the vegetation was removed from the total variance using residual analysis. In Figure 2, the residual is presented on a standard deviation scale, indicating the relative intensity of land cover change over the last 15 years.

2) Spatial Distribution of Land Cover Change

Figure 3 shows the distribution of land cover change at the study site and the comparison of remote sensing images at three locations where significant changes were evident for two time periods (November 1984 and November 1999). This map shows that intensive land cover change is concentrated along the major road network, even though there are several 'hotspots' that are not linked with roads. High intensity of land cover change along the roads is to be expected, as the majority of settlements are located along

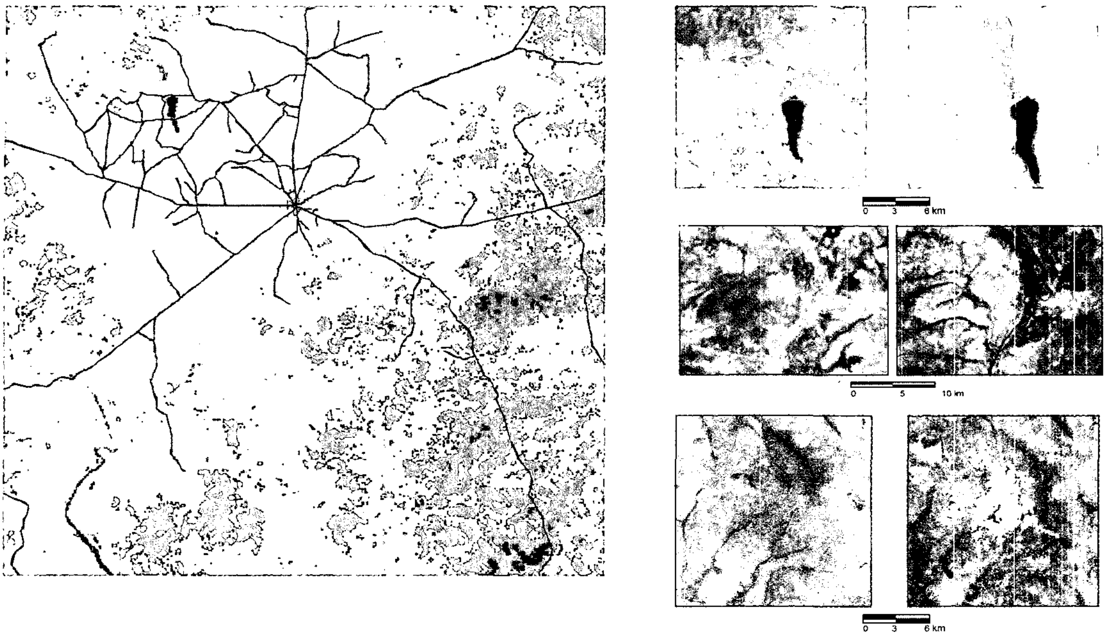


Figure 3. Intensity of land cover changes in northern Ghana as well as three hotspots. (A) Increase of bush farms in an area in the neighbourhood of Fufulsu, North Region, Ghana. (B) Construction of an irrigation system in Daboya. During the dry season the effect of the irrigation on the landscape is very evident. (C) Deforestation and farming activities in Wuripe village (remote sensing images from Vescovi et al., 2002).

the roads, and major towns are at the junction of main roads. The rapid increase of population demands more agricultural land around the settlement, which results in the intensification and conversion of land use patterns. The change detection method was also useful to identify 'hotspots' where rapid land use changes occurred during the study period. The area A, shown in Figure 3 (A) yields very high LCCI values due to the new irrigation scheme below the newly constructed Daboya dam in the late 80s. The water body behind the dam shows a low intensity of change. Figure 3(B) is typical for the encroachment of agricultural land on the river riparian zones in Fufulsu. Before the 80s, it was not possible for the local people to settle close to the river because of the risk of onchocerciasis (river blindness). Increasing population pressure and eradication of river-blindness in West African countries, encourage farmers to explore riverine areas and wetlands for farming activities. Local people prefer the riparian zones for their high soil nutrient status and water security. Another example shows farming activities in the newly settled village of Wuripe (Figure 3 (C)). Intensive socio-economic surveys in this area show that most people in this village come to this site for farming while their permanent residences are elsewhere (Braihmoh, 2003).

We can distinguish two forms of land use change from the spatial distribution of LCCI: the first is diffusive agricultural intensification at or near existing human settlements, and the second is rapid alteration of land cover from natural vegetated areas to agricultural land-settlements ('hotspots'). Detailed RS image interpretation suggests that such rapid alterations have been caused by the rise of new environmental and economic opportunities, such as the construction of an irrigation scheme, new road, or the eradication of river blindness. While most of the land surface shows a gradual transition from one state to the other, accelerated changes occur in some hotspots where dynamic socio-economical and natural processes occur. The relative contribution of these two land use change modes to the rate of total land cover change is currently under investigation, but it is important to note that there are distinctively different drivers and constraints between the diffusive and 'sporadic' or hotspot type land use changes (Lambin and Ehrlich, 1997).

4. Multi-Scale Environmental Correlation

1) Proxy Land Use Change Predictors

Detailed understanding of the LUCC processes requires a large amount of empirical socio-economic, natural, and institutional information. The main drivers are often regional specific, rather than universal links between cause and effect (Geist and Lambin, 2002). Among many possible land use change drivers, three environmental variables distance to roads (ROAD), distance to permanent water bodies (HYDRO), and the Terrain Characterisation Index (TCI), were used as proxy predictors to investigate the relationship between LCCI and environmental conditions (Figure 2). In the study area, human settlement and markets are located along road networks, and LUCC has also been closely linked with road networks. As shown in Figure 2, strong LCCI occurs at, or around, the junctions of roads. In a savanna landscape, water availability is one of main constraints for agricultural activities (see Figure 3 (B) for rapid LUCC near the river). A distance matrix to surface water was used to represent the accessibility to fresh water. In addition, topographical shape, as expressed by TCI, was also included as one of the variables to explain LUCC. According to communication with local agricultural experts (Clottery and Kombiok, 2000), the increase of agricultural land forces farmers to encroach upon previously unfavourable landscape positions (shoulder and steep slope).

The readers should be warned that the selected proxy environmental variables are not sufficient to fully explain the causal relationship with the observed land use changes. The choice of these variables was made based not only on their relative importance as land use change drivers, but also on the availability of fine-scale spatial information that is necessary to examine the influence of scale. In a recent empirical study to analyse land use change processes at the same study area (Braihmoh, 2003), topographical parameters, land suitability index, distance from roads and markets, and population increase were selected as significant environmental variables in a logistic regression to explain land use change. The selected variables for this study are similar with those used in the empirical study. However, some other variables, such as population density and land suitability index, were not considered. Considering the large spatial extent of the study area (10,000km^2), it is difficult to generate continues fine resolution information to assess their influence on the spatial correlation described below.

Distance from roads and surface water were calculated for a 90m grid, based on GIS layers that were digitised from 1:50,000 topographical maps. In order to include topography in land use change processes, the TCI was calculated from the digital elevation model according to the following equation;

$$TCI = Log\,(As) \cdot Cs$$

where *As* is the upslope contributing area, and *Cs* is surface curvature. *As* is an approximation of the water flow potential over the landscape, and *Cs* is a combined terrain index representing slope angle and slope curvature (Park *et al.*, 2001). A higher, positive TCI indicates a more erosive environment, often low in soil nutrients, while a lower, negative TCI is found in predominantly depositional environments with high soil quality and water accessibility (Park *et al.*, 2001). The original 200 ft digital elevation model digitised from the topographical maps was re-sampled to a 90m grid before calculation of the TCI.

2) Multi-Scale Hierarchical Adaptive Model

In order to identify associations between LCCI and the proxy land use change predictors at different spatial scales, a multi-scale hierarchical adaptive model was developed. This method places a square moving window with a grid size (*d*) and the size of window (*n*) on the maps of both the dependent and independent variables, and calculates either the Pearson correlation coefficient (*r*) or the coefficient of determination (R^2) within the moving window (Figure 2). When the size of a cell (*d*) is defined, a moving window with a given number of cells (*n*) was placed at the upper left-hand corner, and the spatial association between LCCI and proxy environmental variable(*s*) is calculated between the cells within the window. This calculation is repeated from the upper left-hand corner to the lower-right corner of the raster image. When the calculation at one size of window (*n*) is finished, the size of the moving window is increased and the same calculation is repeated.

The method developed is a modification of the widely(Nelson, 2001) known kernel filtering or convolution filtering. Nelson (2001) demonstrated a similar technique to calculate Pearson's *r* between two variables and visualise the spatial distribution of this correlation. In this research, however, the Pearson *r* is calculated when one independent variable is used, while R^2 can be calculated when two or more independent variables are used. To calculate R^2, a step-forward least square regression method is used within each moving window. Since a large number of regression equations are involved for the whole area, it is difficult to assess whether each regression meets the basic assumptions of multiple regression analysis. Furthermore, direct interpretation of the relative contribution of the individual indepen-dent variables to the total regression model is difficult to assess. A hierarchical approach in which the three environmental parameters were successively included in the analysis, was applied in order to estimate the importance of individual variables following the method used in Park and Vlek (2002). In total, six different combinations of proxy variables were included and their model performance was compared. The multi-scale adaptive model was programmed in S language and run in S-Plus 6.0. ArcView with the spatial extension was used for visualisation and spatial analysis.

We expect that the method developed is able to explore two different aspects of scale issues by changing either d or n. Spatial scale is frequently referred to in terms of either spatial resolution or spatial extent (Gibson *et al.*, 1998). The resolution refers to the minimum observation unit, such as cell size in the raster image, the size of a quadrat for ecological investigation, and measurement interval for certain hydrological processes. On the other hand, the extent indicates the spatial coverage or boundary for an investigation. For this research, the size of each cell (d) of a moving window may be defined as the resolution of the calculation, while the size of moving window (n) is the extent of the calculation. When the mean and standard deviation of r and R^2 are plotted against window size (n) or cell size (d), we may characterise the scale-dependent relationships of associations between LCCI and proxy variables.

Interpretation of the results requires special attention. Both Pearson's r and R^2 are Euclidian distance based statistics, which are subject to various statistical assumptions: the deviations (errors) are random, the random deviations are independent, normally distributed, and have a constant variance. In addition, spatial variables normally exhibit spatial dependence (autocorrelation). Sample points that are close to each other may contain similar information, which results in duplication of the same information in calculating the correlation between two variables. In the current literature, few techniques are available to estimate a localised version of the 'global' regression model that takes account of the influence of spatial autocorrelation. They include geographically weighted regression (Brunsdon *et al.*, 1986; Fortheringham *et al.*, 1997), spatial adaptive filtering (Foster and Gorr, 1986), and random coefficient modelling (Aitkin, 1996). In ecological studies, also the Mantel correlogram is used to identify associations between two spatial variables in series of discrete distance classes (Urban *et al.*, 2002).

The existing methods to remove spatial autocorrelation mainly prefer to point measurements. The raster images used in this research contain a large number of cells for each variable (90m grid size over 100×100km). Identifying and removing spatial autocorrelation would be well beyond the computing capacity of a desk-top computer. Furthermore, the separation of the partial influence of spatial autocorrelation from the 'real' correlation between variables may be difficult in many cases. Since the main research interest in this paper was to identify the influence of scale, we accept the possible existence of spatial autocorrelation in model outputs and the derived statistical parameters will be only used for descriptive purposes(Nelson, 2001).

5. Results

1) 'Global' Regression vs. 'Local' Regression

A stepwise regression between LCCI and the three proxy variables for the whole study area explained about 5% of the total variance of LCCI (LCCI = 0.0003 + 0.0099TCI + 0.0043HYDRO, R^2= 0.054). Despite some clear spatial associations between LCCI and these variables seen in Figure 3 (e.g., the association between road network and intensity of land cover changes), the 'global' regression model yields virtually no correlation between LCCI and proxy variables. Such low 'goodness-of-fit' is partly due to the limited

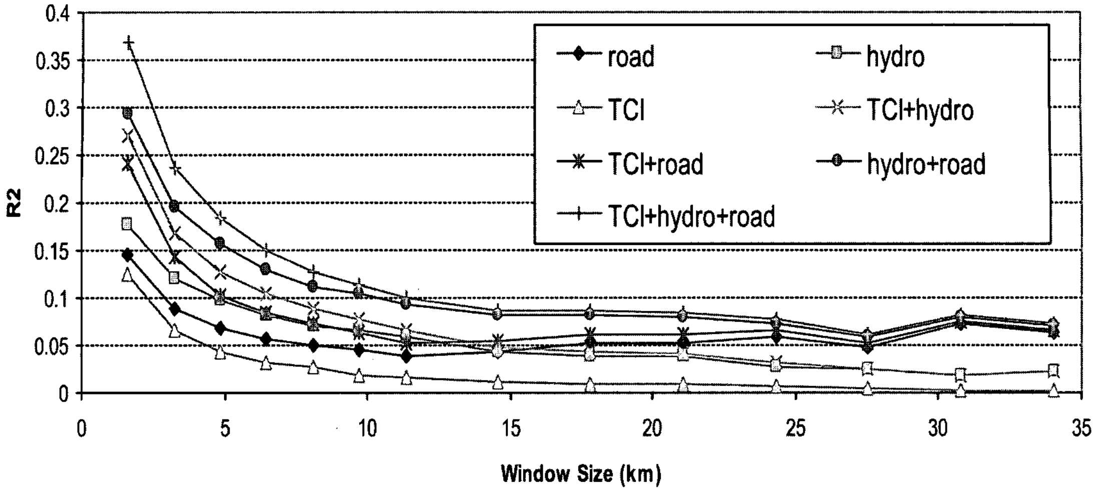


Figure 4. R^2 changes in regression analyses between land cover change intensity and environmental factors with the size of the moving window. Please note that the values given in this figure are averaged values from many repeated calculations. During the regression analyses for each size of the moving window, only one third of the windows were overlapped with the adjacent window.

information contained in the proxy land use change predictors used in the model (see section 4.1). More importantly, however, we believe that strong non-stationarity of LUCC in the study area caused the low R^2 value. The interpretation of the spatial distribution of LCCI has already shown that there are significant differences in relationships and processes of LCCI within the study area (Figure 3). As an example, the strong association of LUCC with the road network at the upper parts of the images might be compensated by weak association in the lower left corner.

The application of the multi-scale hierarchical adaptive model produced relatively high R^2 values at a finer spatial scale (Figure 4). The influence of spatial extent on the localised regression model was explored, by changing the size of the moving window (n) from 9 (approximately 1km) to 303 (approximately 28 km) of the 90m grid resolution (d). In Figure 4, the three proxy predictors jointly explain on average 37% of LCCI within a 2km moving window, whereas the actual R^2 on this scale varies from 0.0 to 0.91. As the size of the moving window is increased, the average R^2 rapidly decreases until a window size of 10km is reached. An increase in window size is associated with a further decrease of R^2 for > 10km windows, eventually approaching the global R^2 value of 0.05. Even though detailed interpretation of actual LUCC processes is difficult using the currently available proxy variables, it is clear that when the study area is considered as a whole in the regression model, LUCC processes tend to be too diverse to be modelled.

2) Variance Characteristics of Environ-mental Correlation

When each proxy variable is regressed separately against LCCI, the average Pearson's r slightly increases with the increase in spatial extent for all three environmental factors (Figure 5 (A), (B), (C)). Since correlation coefficients

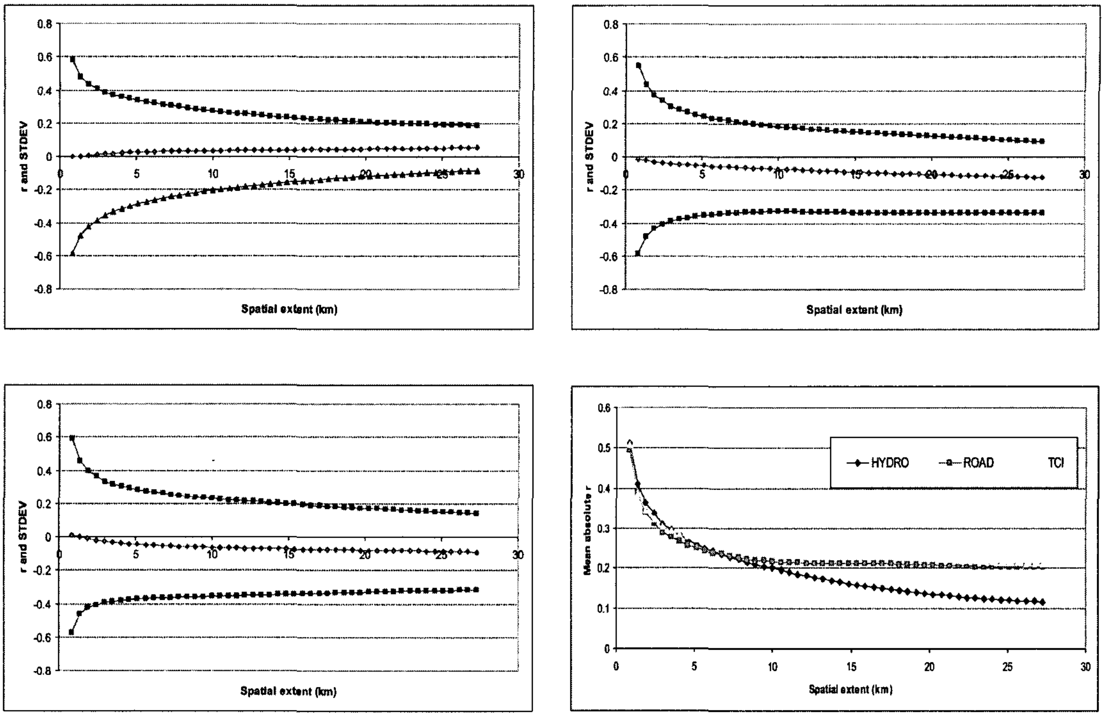
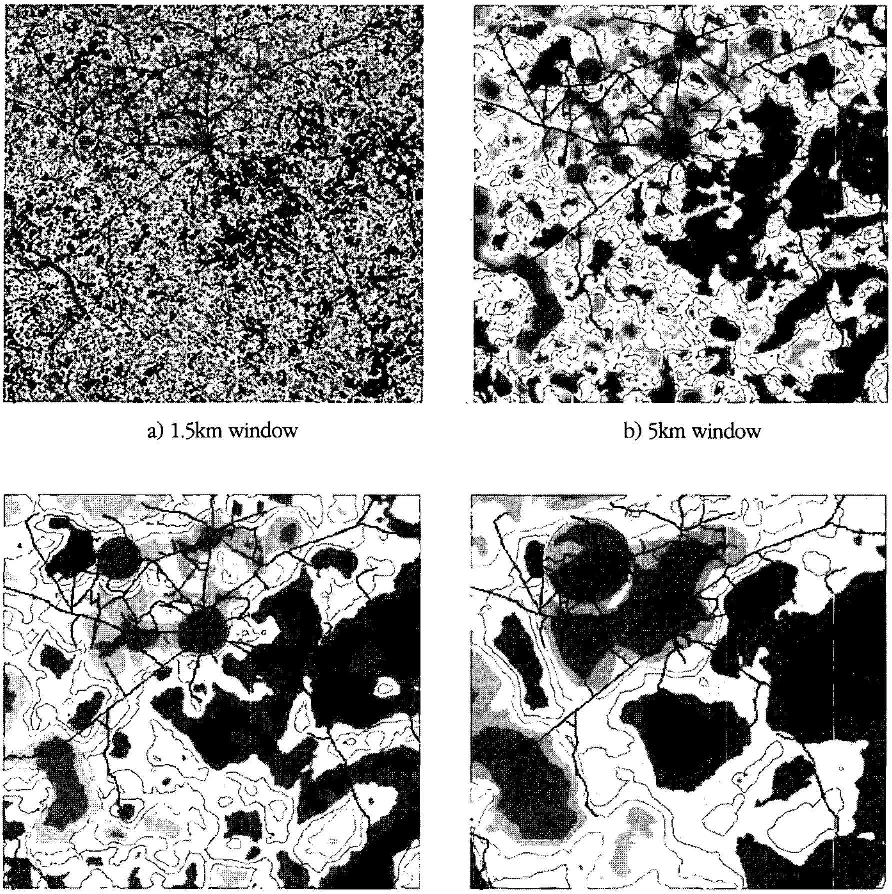


Figure 5. The change of Pearson's r between LCCI and three proxy land use change drivers as the spatial extent of the multi-scale adaptive model was increased. (A) distance from hydrological network (HYDRO), (B) distance from road network (ROAD), (C) Terrain characterisation index (TCI), and (D) absolute r for three proxy land use predictors.

range from -1 to 1, it is necessary to take absolute values to investigate the magnitude of the spatial association. The absolute mean r decreases exponentially with an increase in window size for all three variables (Figure 5 (D)). The average correlation coefficient and the variation, presented as standard deviation of total r, gradually decrease with an increase in spatial extent. This pattern suggests that the association between LCCI and environmental proxy variables is stronger at the finer spatial scale.

There is, however, also a marked difference in the intensity of association over space (ranging from high negative to positive r). Figure 6 presents the spatial distribution of correlation coefficients between LCCI and TCI for four different sizes of the moving window. In a 1.5 km moving window, the spatial distribution of Pearson's r shows highly scattered patterns, but strong positive r along the riparian zone and at the highly populated upper western part of the study area. It is expected that the high positive association of LCCI and TCI indicates that the farmers take terrain shape more actively into account in the river riparian zone and highly populated area. With the increase in size of the moving window, there are clear spatial divisions between positively and negatively correlated areas. With increasing window size, such heterogeneities and diversities of LUCC processes eventually become smoothened as changes in one part of the window are compensated



a) 1.5km window

b) 5km window

c) 10km window

d) 20km window

Figure 6. The influence of different moving window size on the correlation coefficient between LCCI and TCI. The LCCI intensity is rescaled in a standard deviation (see Figure 1 for the legend).

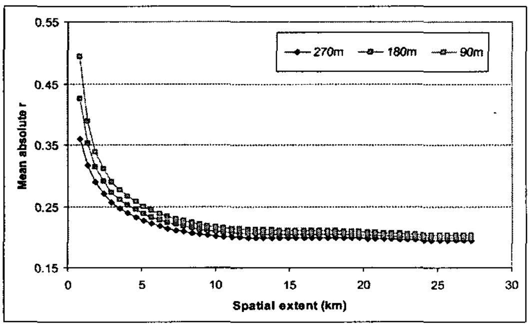


Figure 7. The change of of Persons's r between LCCI and the distance from roads with changes of grid resolution (d in Figure 1).

elsewhere.

The effect of grid size (*d*) on the correlation between LCCI and environmental factors was explored using the LCCI and the distance from the road (Figure 7). The 90m grid data were aggregated into 180m and 270m grids using binary interpolation. Correlation coefficients show similar patterns as before, decreasing with an increase in the size of the moving window. However, the average r from a coarser grid is lower than that of a finer grid, e.g., 0.52 for the 90 m grid, 0.46 for the 180 m grid, and 0.38 for

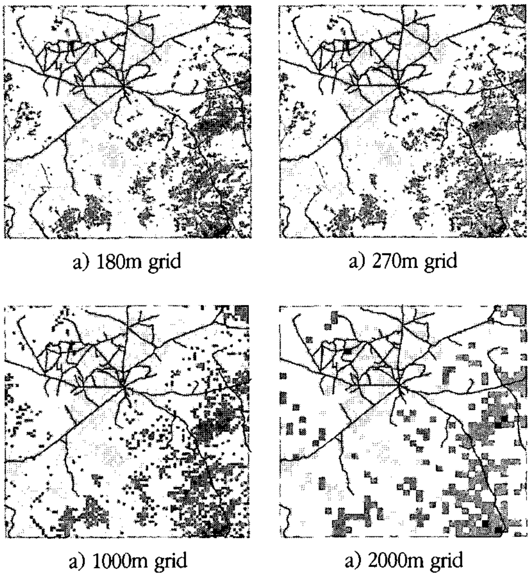


Figure 8. The influence of spatial resolution on the identification of land use change intensity in northern Ghana

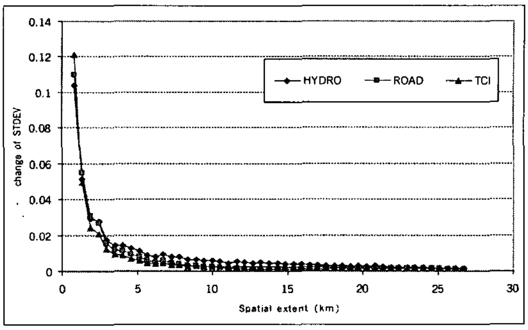


Figure 9. The change of standard deviation (STDEV) of Persons' r between LCCI and proxy land use change drivers.

270 m grid for the 1km window. Similar shifts were also observed for the standard deviations. The low average r at the coarser resolution is probably caused by the aggregation effect for both the LCCI and the proxy variables. The increase in grid resolution is related to reduction in variance was found in several ecological and hydrological studies (Gibson *et al.*, 1998; Blöschl and Sivapalan, 1995). One pattern that should be noted in Figure 8 is the loss of spatial 'hotspot' beyond the 1000 m grid resolution. The mean of certain spatial information may be maintained at coarser grids, but the reduced variation results in the spatial homogenization of forms and processes.

When comparing the relative influence of spatial resolution and spatial extent on the overall spatial correlation, spatial extent has more significant influence than spatial resolution. There is a relatively large difference in r at the smaller spatial extent (less than 10km), but at the larger extent the differences become much smaller, and eventually no difference remains. The difference in average r between 90 m and 270 m grids is about 22 % for the 2km window, but this decreases to less than 4% with the 10km spatial extent, and continues to decline with an increase in the spatial extent. The change of r due to increased spatial extents between 2km to 10km is over 50% for all environmental variables (see also Figure. 5(D)), a far greater effect than was observed for spatial resolution. In their investigation of the influence of spatial extent and grid resolution on the land use change processes in various regions, Kok and Veldkamp (2001) also found that the effect of spatial resolution, by aggregating a basic grid to larger units, is small in comparison to the effect of increased spatial extent.

Different scale dependencies were observed for the three environmental variables used (Figure 4 (D)). Whereas the correlation with TCI and road network shows a rather stable r for windows 〉 5km, the correlation with the surface-water body continuously decreases with increasing window size. Further studies are necessary to connect these patterns with actual land cover change processes. However, we hypothesize that there is a spatial 'threshold' between land use change and environmental conditions. For example, areas beyond 5km from major roads change less due to the low accessibility to markets and high transportation cost. A similar critical window size might emerge for TCI. Considering the fact that the size of first- or second-order catchments in Ghana ranges between 5 and 10km, this window size might best reflect changes of land use patterns from catchment to catchment. On the other hand, the scale dependency in the case of surface-water bodies continuously decreases with the size of the moving window, which might reflect the overriding importance of water availability in the semi-arid landscape.

The spatial dependency in the relation between LCCI and the proxy variables within the 5-10km spatial extent is further related to the reduction in the variation of *r*. Figure 9 shows the difference in standard deviation as a function of spatial extent. When the moving window is made smaller than 5km, there is a rapid change in the standard deviation, whereas it is low but stable at extended values of over 5km. Spatial extents of less than 5-10km are characterised by intensive spatial heterogeneity of LUCC processes. For larger spatial extents, there are few additional changes in correlation values (Figure 9). The spatial scale of 5-10km can be considered as the 'threshold scale' in terms of correlation intensity and also in terms of variance.

6. Discussion

The results presented in this paper confirm that spatial heterogeneity deserves careful consideration when modelling land use change processes at a regional scale. The global regression model yields virtually no linear relationship between land cover change index and proxy drivers, but the multi-scale adaptive model shows that this was solely caused by the diversity of land use change processes and scaling effects. High positive correlations at one site may be compensated by high negative correlations at other sites. Furthermore, global regression models have clear limitations with respect to the 'hotspot' type of land use change. The occurrence of this land use change is locally specific and is considered 'noise' in the regression models.

In recent years, interest in more spatially and also temporally disaggregated process models has grown (reviewed by Agarwal *et al.*, 2001; Parker *et al.*, 2002). Process models may be able to cope with the spatial heterogeneity of LUCC model components and interactions of system components in their modelling framework, by taking account of spatially disaggregated information based on prior understanding of LUCC processes. Unlike traditional statistical models, however, process based models require predefined system boundaries and components that often need intensive data collection and programming. One immediate question is what would be the optimal spatial scale (for both spatial extent and boundary) and the system components, when someone want to model LUCC processes at a regional scale.

The most detailed spatial resolution (e.g., household level for decision making processes) is probably best when one is interested in the characterisation of the land use change processes in a predominantly agricultural society. Different households may apply totally different land use strategies based on their individual economic situation, technological adaptations, and customary social regulations. However, the greatest constraint for such land use change modelling is the lack of appropriate data on such a fine spatial scale. As shown in this research, there is a trade-off between scale and information. A high level of aggregation of data reduces the causal relationships of LUCC. On the other hand, fine scale information provides details, but their use is limited due to difficulties to extend the spatial boundary to a large area (Mertens and Lambin, 1997).

One of the main challenges for future LUCC modelling is how the detailed decision making processes at the fine resolution (household) are included in a model for a large study area, which cause apparent sampling and upscaling problems. If we are searching for an optimal spatial scale for a spatially disaggregate land use change model, this scale should match a model element (spatial unit) that is sufficiently large to average out all the small-scale variability but will explicitly represent spatial differences in land use drivers and constraints. One possible way to incorporate spatial heterogeneity across scales is to divide the spatial and temporal extents into smaller units in which patterns and processes are relatively similar. There are parallel concepts available in hydrology (Wood *et al.*, 1988; Blöschl and Sivapalan, 1995; Flügel, 1995). This approach is based on findings that the variances and covariances of key variables are invariant in landscapeunits above a certain threshold size. Studying rainfall and runoff, Wood *et al.* (1988) observed that the variability of rainfall and runoff appears to be controlled by variabilities in soils and topography whose correlation length scales are on the order of 10^2-10^3 m typical hilllsope scales. At increased spatial scale, the increased sampling of hillslopes leads to a decrease in the difference between sub-catchment responses. At a particular scale, the variance between hydrological responses for catchments of the same scale should reach a minimum. Wood *et al.* (1988) suggest that this threshold scale reflects a representative element area (REA), which they propose as a fundamental building block for hydrologic modelling and scaling. Therefore, the variability must be explicitly presented at scales larger than the element size, while variability at the sub-element scale can be presented in a lumped way. Others have shown that the size of REA depends on various factors, including the nature of the climate, terrain and vegetation in the areas for which the model is applied and the nature of variability (Blöschl *et al.*, 1995). In a similar way, our method identifies the size of representative LUCC areas.

The multi-scale adaptive model in this research showed that the correlation between LCCI and proxy environmental factors rapidly declines at a finer scale (5-10km), but the difference becomes small at spatial scales coarser than 10km (Figures 7 and 9). The high correlation at less than the 5 km window is also characterised by high variance of environmental correlation within the study area. Therefore, the spatial scale of 5-10km may be considered as the 'threshold scale' for a spatially explicit modeling of LUCC processes in the study region. The spatial variability at this threshold scale should be explicitly modeled in order to consider the spatial heterogeneity of LUCC processes.

The spatial extent of 5 to 10km more or less coincides with the spatial boundary of most villages or farming communities in the West African savanna. We also observed that the occurrence of many land use change hotspots correspond to this spatial extent of 5 to 10km. We anticipate several advantages of the inclusion of village-level investigations into a LUCC model. In the savanna landscape, the village boundary often coincides with natural boundaries such as catchments or hillslopes, which provides a good opportunity to merge socio-economic and natural processes in a unified LUCC model. Land-tenure and land-use related decisions are often determined at the village level which induces different types of land use change trajectories between villages. Furthermore, government policies are often targeted to be disseminated at village or community level (Hoddinott *et al.*, 2001). In terms of practical data collection, spatially disaggregated information is often available at the village level from national census data. Considering data availability and the potential to reduce spatial heterogeneity of landscape processes at the regional or national level, the village level (5-10km) may be the optimal spatial unit suitable for both process-based and regression-based LUCC models.

7. Conclusions

There is a strong spatial heterogeneity in land use change and its environmental correlations with proxy variables in the savanna in Northern Ghana. Strong correlations between the LCCI and the chosen environmental variables are mostly limited to spatial scales of less than 5-10km. With increasing spatial extent, LUCC processes within the area tend to be too diverse to establish clear change trends, because changes in one part of the window are compensated elsewhere. Spatial extent turned out to be more important than spatial resolution in land use change modelling, due to the spatial heterogeneity of LUCC processes. Given the spatial heterogeneity of LUCC processes and the paucity of data availability, we contend that the village level (5-10km) might be the optimal spatial unit for both process-based and regression-based land use change models. Village level modelling might also be more effective for upscaling of land use change models toward a larger spatial extent.

References

Abudulai, S., 1996, Perceptions of land rights, rural-urban land use dynamics and policy development, in: *Managing land tenure and resource access in west Africa.* Proceedings of a regional workshop held at Goree Senegal. Nov. 18-22 1996, 107-127

Agarwal, C., Green, G.M., Grove, J.M., Evans, T.P. and Schweik, C.M., 2002, *A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice*, CIPEC Collaborative Report No. 1.

Aitkin, M., 1996, A general maximum likelihood analysis of over dispersion in generalised linear models, *Statistics and Computing*, 6, 251-261.

Badhwar, G. D. and Henderson, H.K., 1985, Application of thematic mapper data to corn and soy-bean development stage estimation, *Remote Sensing and Environments*, 17, 197-201.

Beven, K., 1995, Linking parameters across scales: subgrid parameterizations and scale dependent hydrological models, in Kalma, J.D. and Sivapalan, M. (eds), *Scale Issues in Hydrological Modelling*. John Wiley & Sons, Chichester, 263-282.

Blöschl, G. and Sivapalan, M., 1995, Scale issues in hydrological modeling: a review, in: Kalma, J.D. and Sivapalan, M. (eds), *Scale Issues in Hydrological Modelling*, John Wiley & Sons, Chichester, 9-48.

Blöschl, G., Grayson, R.B., and Sivapalan, M., 1995, On the representative elementary area (REA) concept and its utility for distributed rainfall-runoff modelling, in Kalma, J.D. and Sivapalan, M. (eds), *Scale Issues in Hydrological Modelling*, John Wiley & Sons, Chichester, 71-88.

Braihmoh, A.K., 2003, *Modelling of land use change in the Volta basin of Ghana using GIS, Remote Sensing and Geostatistical techniques*, Unpublished Ph.D. thesis, University of Bonn

Brunsdon, C., Fotheringham, A.S. and Charlton, M.E., 1996, Geographically weighted regression: A method for exploring spatial nonstationarity, *Geographical Analysis*, 28, 281-298.

Civco D.L., Huff, J.D., Wilson, E.H., Song, M. and Zhang, Z., 2002, A comparison of land use and land over change detection methods. Proceedings of 2002 ASPRS-ACSM *Annulal Conference and FIG XXII Congress.*

Clottery, V. and Kombiok, J.M., 2000, Land use types in Northern Region of Ghana, in *The report on 'Workshop on Land use types in the Volta Basin', Tamale. November* 2000. ZEF, Bonn. 13-15.

Flügel, W.A., 1995, Delineating hydrological response units by geographical information system analyses for regional hydrological modelling using PRMS/MMS in the drainage basin of the river Brl, Germany, in Kalma, J.D. and Sivapalan, M. (eds),. *Scale Issues in Hydrological Modelling*, John Wiley & Sons, Chichester, 181-194.

Fortheringham, A.S., 1997, Trends in quantitative methods I: stressing the local, *Progresses in Human Geography*, 21, 88-96.

Foster S.A. and Gorr, W.L., 1986, Adaptive filter for estimating spatially varying parameters: application to modelling police hours spent in response to calls for service, *Management Science*, 32, 878-889.

Geist, H.J. and Lambin, E.F., 2002, Proximate causes and underlying driving forces of tropical deforestration, *Bioscience*, 52, 143-150.

Gibson, C., Ostrom, E. and Ahn, T.-K., 1998, *Scaling Issues in the Social Sciences*, A Report for the International Human Dimensions Programme on Global Environmental Change, IHDP Working Paper No. 1. IHDP, Bonn.

Hoddinott, J., Adato, M., Besley T. and Haddad, L., 2001, *Participation and poverty reduction: Issues, theory, and new evidence from South Africa*, FCND Discussion Paper No. 98. International Food Policy Research Institute, Washington D.C.

Irwin, E.G. and Geoghegan, J., 2001, Theory, data, methods: developing spatially explicit economic models of land use change, *Agriculture Ecosystems and Environment*, 85, 7-23.

Kirkby, M.J., Imeson, A.C., Bergkamp, G. and Cammeraat, L.H., 1996, Scaling up process and models, *Journal of Soil and Water Conservation*, 15, 391-396.

Kok, K. and Veldkamp, A., 2001, Evaluating impact of spatial scales on land use pattern analysis in Central America, *Agriculture, Ecosystems and Environment*, 85, 205-221.

Lambin, E.F., Baulies, X., Bockstael, N., Fischer, G., Krug, T., Leemans, R., Moran, E.F., Rindfuss, R. R., Sato, Y., Skole, D., Turner II, B.L. and Vogel, C., 1999, *Land-Use and Land-Cover Change Implementation Strategy*, IGBP Report No. 48 and IHDP Report No. 10. Bonn.

Lambin, E.F, Turner II, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., Folke, C., George, P.S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E.F., Mortimore, M., Ramakrishnan, P.S., Richards, J.F., Skanes, H., Steffen, W., Stone, G.D., Svedin, U., Veldkamp, T.A., Vogel, C. and Xu, J., 2001, The Causes of Land-Use and Land-Cover Change: Moving Beyond the Myths, *Global Environmental Change*, 11, 261-269.

Lambin, E.F. and Strahler, A.H., 1994, Change vector analysis in multitemporal space: a tool to detect and categorise land-cover change processes using high temporal resolution satellite data, *Remote Sensing of Environment*, 48, 231-244.

Lambin, E.F. and Ehrlich, D., 1997, Land-cover changes in Sub-saharian Africa (1982-1991): Application of a change index based on remotely sensed surface temperature and vegetation indices at a continental scale, *Remote Sensing of Environment*, 61, 181-200.

Mertens, B. and Lambin, E.F., 1977, Spatial modelling of deforestation in southern Cameroon, *Applied Geography*, 12, 143-162.

NASA. 2002. land cover changes may rival greenhous gases as cuase of climate change. in Top story. http://www.gsfc.nasa.gov/topstory/20020926landcover.html.

Nelson, A., 2001, Analysing data across geographic scales: Detecting levels of organisation within systems, *Agriculture, Ecosystems and Environment*, 85, 107-131.

Park, S.J. and Vlek, P.L.G., 2002, Environmental correlation of three-dimensional spatial soil variability: A comparison of three adaptive techniques, *Geoderma*, 109, 117-140.

Park, S.J. and Vlek, P.L.G., 2005, Detection of land use and cover using multi-temporal spatial information, *Remote Sensing of Environment* (in review),.

Park, S.J., McSweeney K. and Lowery B., 2001, Prediction of soils using a process based terrain characterisation, *Geoderma*, 103, 249-272.

Parker, D.C., Berger, T. and Manson, S. M., 2002, *Agent-Based Models of Land-Use and Land-Cover Change*, Report and Review of an International Workshop October 47, 2001, Irvine, California, USA. LUCC report series No.6., Bonn.

Redman, C., Grove, J.M. and Kuby, L., 2000, *Toward a Unified Understanding of Human Ecosystems: Integrating Social Sciences into Long-Term Ecological Research,* White Paper of the Social Science Committee of the LTER Network. Accessible at http://www.lternet.edu/research/pubs/informal/socsciwhtppr.htm.

Schulze, R., 2000, Transcending scales of space and time in impact studies of climate and climate change on agrohydrological responses, *Agriculture, Ecosystems and Environment*, 82, 185-212.

Singh, A., 1989, Digital change detection techniques using remotely sensed data, *International Journal of Remote Sensing*, 10, 989-1003.

Turner II, B.L., Skole, D., Sanderson, S., Fischer, G., Fresco L. and Leemans, R., 1995, *Land-Use and Land-Cover Change Science/Research Plan*, IGBP Report No. 35/HDP Report No. 7, Bonn.

Urban, D.S., Pierce G.K. and Lookingbill, T., 2002, Extending community ecology to landscapes. *Ecoscience*, 9, 200-202.

Veldkamp, A. and Lambin, E.F., 2001, Predicting land-use change: Editorial, *Agriculture, Ecosystems and Environment*, 85, 1-6.

Verburg, P.H., Schot, P., Dijst, M. and Veldkamp, A., 2002, Land-Use Change Modeling: Current Practice and Research Priorities, *GeoJournal* (in press).

Vescovi, F.D., Park, S.J. and Vlek, P.L.G., 2002, Detection of human-induced land cover changes in a savannahsavanna landscape in Ghana: I. Change detection and quantification, *Proceedings of the EARSeL workshop "Remote sensing for developing countries"* 18-20 Sept. 2002., Bonn.

Vlek P.L.G., Berger, T., Iskandarani, M., Park, S.J. and van de Giesen, N., 2003, Integrative water research project: GLOWA-Volta. in Ehlers, E. (ed.) *Earth System Science in the Antropcene: Emerging Issues and Problems*, Springer Verlag

Walsh, S.J., Evans, T.P., Welsh, W.F., Entwisle B. and Rindfuss, R.R., 1999, Scale dependent relationships between population and environment in Northeastern Thailand, *Photogrammetric Engineering and Remote Sensing*, 65, 97-105.

Wood, E.F., Sivapalan, M. Beven, K.J. and Band, L., 1988, Effects of spatial variability and scale with implications to hydrologic modelling, *Journal of Hydrology*, 102, 29-47.

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