Ecology and Development Series

No. 14, 2004

Ademola K. Braimoh

Modeling land-use change in the Volta Basin of Ghana

Zentrum für Entwicklungsforschung
Center for Development Research
University of Bonn

ZEF Bonn

Ecology and Development Series No. 14, 2004

Ademola K. Braimoh

Modeling land-use change in the Volta Basin of Ghana

Cuvillier Verlag Göttingen

Bibliografische Information Der Deutschen Bibliothek
Die Deutsche Bibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über http://dnb.ddb.de abrufbar.
1. Aufl. - Göttingen : Cuvillier, 2004
Zugl.: Bonn, Univ., Diss., 2004
ISBN 3-86537-044-6

1. Referent : Prof. Dr. Paul L.G. Vlek

2. Referent : Prof. Dr. Gunter Menz

Tag der Promotion: 22. Januar 2004

Angefertigt mit Genehmigung der Mathematisch-Naturwissenschaftlichen Fakultät der Rheinischen Friedrich-Wilhelms-Universität Bonn

Gedruckt mit Unterstützung des Deutschen Akademischen Austauschdienstes

Nonnenstieg 8, 37075 Göttingen
Telefon: 0551-54724-0
Telefax: 0551-54724-21
www.cuvillier.de

1. Auflage, 2004
Gedruckt auf säurefreiem Papier

ISBN 3-86537-044-6

ABSTRACT

The Volta Basin in West Africa drains about 400,000km^2 area of land, including 70% of mainland Ghana. Low rainfall reliability, high population growth rate and macroeconomic transformations in the last few decades have had a profound influence on the livelihood strategies of the largely rural populace. Therefore, many parts of the basin are *hotspots* of land-use / land-cover change (LUCC). The determinants of LUCC in a 5,400km^2 area within the Volta Basin of Ghana were identified using multiscale, spatial statistical analyses and household surveys. Land-cover change trajectories were defined using multitemporal Landsat TM images acquired in 1984, 1992 and 1999. Training signatures for land-cover classification using maximum likelihood algorithm were developed based on PCA, tasseled cap and NDVI transforms, whereas ground truth data were obtained from aerial photo interpretation and field surveys. Change detection was based on synergy between image-differencing and post classification comparison techniques. Statistical relationships between land-cover and selected proxy driving factors of change were determined using two modeling techniques. The first technique answered the question: *what are the factors that determine the conversion of a location to cropland?* It involved the use of logistic regression to determine the relationships between cropland change and selected variables at different cell resolutions ranging from 30m (household level) to 5100m (village level). The second technique using linear multiple regression was used to answer the question: *given the socioeconomic characteristics of households within a locality, how much land will be cleared for agriculture for domestic and commercial purposes?*

The results of the study show that the dominant land-cover change process was conversion of natural vegetation to cropland, which occurred at an annual rate of 5% between 1984 and 1999. A higher increase in woody biomass in 10% and a simultaneous decrease in 9% of the landscape indicates a certain level of rainfall-induced resilience in the savannah ecosystem. A study of the association between land-cover change and soil properties indicated that correlation between organic C, an index of agricultural sustainability and selected soil fertility indices - ECEC, N and P - declined as cultivation persisted. There is evidence of nutrient mining in about 12% of the land area continuously cultivated between 1984 and 1999.

Logistic regression results show the time and scale-dependency of LUCC patterns in the study area. Between 1984 and 1992, the main drivers of change were altitude, distance from roads, distance from the main market and localities, initial population density and change in population density. In the second period (1992-1999), land suitability index, distance from villages and localities, change in population density, and rainfall zone were the main drivers of cropland change. Linear multiple regression identified increase in household size, frequency of tractor use, proportion of rice marketed, child dependency ratio, labor availability, and distance from localities to the main market as the major factors determining the amount of land a household cleared for agriculture. This suggests the coexistent processes of agricultural intensification and extensification in the land-use strategies of the populace.

The choice of an appropriate scale for LUCC models to support land-use planning requires a trade-off between spatial detail and extent. At the scale of individuals, households and commercial farmers (30m-1050m), land-use change processes are highly heterogeneous, requiring a large amount of data for characterization. The variograms of standardized logit residuals suggest that the size of land change processes at the village ranged from 3km to 7km. Future land change models should therefore be based on these spatial scales.

Policy suggestions for sustainable land management include coercive environmental protection, integration of livestock and crops in the production systems, research to improve the quality of soil organic matter, and institutional arrangement to promote agricultural commercialization.

Modellierung von Landnutzungsänderungen im ghanaischen Teil des Volta Beckens

KURZFASSUNG

Das Volta Becken ist ein Einzugsgebiet in Westafrika mit einer Größe von ca. 400.000 km^2, und umfasst damit 70% der Fläche von Ghana. Hohe Niederschlagsvariabilität, hohe Bevölkerungswachstumsraten und makro-ökonomischer Wandel in den letzten Jahrzehnten haben sich tiefgreifend auf die Lebensunterhaltsstrategien der überwiegend ländlichen Bevölkerung ausgewirkt. Viele Bereiche des Beckens sind daher Schwerpunkte (‚*hotspots*') von Landnutzungs-/Landbedeckungsänderungen (LUCC). Die bestimmenden Faktoren von LUCC in einer 5.400km^2 großen Fläche innerhalb des Volta Beckens in Ghana wurden durch räumlich-statistische Analysen auf verschiedenen Maßstäben und durch Haushaltsbefragungen ermittelt. Die Tendenzen der Landbedeckungsänderungen wurden mithilfe multitemporaler Landsat TM Satellitenbilder aus den Jahren 1984, 1992 und 1999 ermittelt. Trainingssignaturen für die Landbedeckungsklassifizierung mit dem „größte Wahrscheinlichkeit"-Algorithmus wurden auf der Grundlage von PCA, ‚tasseled cap' und NDVI Transformationen entwickelt, während Bodenverifikationsdaten aus Luftbildern und Felduntersuchungen ermittelt wurden. Die Veränderungen wurden auf der Grundlage der Synergie zwischen den Methoden der Bilddifferenzierung und des nachträglichen Klassifizierungsvergleichs bestimmt. Statistische Beziehungen zwischen Landbedeckung und ausgewählten Veränderungsfaktoren wurden durch zwei Modellierungsmethoden ermittelt. Die erste gab Antwort auf die Frage: *welche Faktoren bestimmen die Umwandlung eines Standortes in eine landwirtschaftliche Anbaufläche?* Hier wurde die logistische Regression zur Bestimmung der Beziehungen zwischen dieser Umwandlung und ausgewählten Variablen bei unterschiedlichen Zellenauflösungen von 30m (Haushaltsebene) bis 5100m (Dorfebene) eingesetzt. Die zweite Methode verwendete die lineare multiple Regression zur Beantwortung der Frage: *bei gegebenen sozioökonomischen Merkmalen der Haushalte innerhalb eines Bereiches, wie viel Land wird für die landwirtschaftliche Nutzung für private und wirtschaftliche Zwecke gerodet?*

Die Ergebnisse der Studie zeigen, dass Landbedeckungsänderungen hauptsächlich aus der Umwandlung von natürlicher Vegetation hin zu Anbauflächen bestanden, mit einer jährlichen Rate von 5% zwischen 1984 und 1999. Eine höhere Zunahme der Holzbiomasse in 10% und einer gleichzeitigen Abnahme in 9% der Landschaft weist auf eine gewisse durch Niederschlag verursachte Widerstandsfähigkeit des Savannenökosystems hin. Die Untersuchung der Beziehung zwischen Landbedeckungsveränderungen und Bodenmerkmale zeigt, dass die Korrelation zwischen organischem C, ein Index der landwirtschaftlichen Nachhaltigkeit und ausgewählten Bodenfruchtbarkeitsindices - ECEC, N und P bei andauernder Bewirtschaftung abnahm. Es gibt Hinweise auf den Abbau von Nährstoffen in ca. 12% des zwischen 1984 und 1999 ständig bewirtschafteten Landes.

Die Ergebnisse der logistischen Regression zeigen eine Zeit- und Maßstabsabhängigkeit der LUCC-Muster im Untersuchungsgebiet. Zwischen 1984 und 1992 waren die wichtigsten Faktoren Höhe, Entfernung von Straßen, Entfernung von den wichtigsten Märkten und Orten, und ursprüngliche Bevölkerungsdichte sowie Veränderungen dieser. Im zweiten Zeitraum (1992-1999) waren diese Merkmale Landeignungsindex, Entfernung von Dörfern und Orten, Veränderung in der Bevölkerungsdichte, und Niederschlagszone. Die lineare multiple Regression ergab eine Zunahme der Haushaltsgröße, der Häufigkeit der Nutzung von Traktoren, des Anteils des vermarkten Reises, des Kindabhängigkeitsverhältnisses, der Verfügbarkeit von Arbeitskräften sowie die Entfernung zum wichtigsten Markt als die Hauptfaktoren, die die Größe der Fläche bestimmten, die ein Haushalt für die landwirtschaftliche Nutzung rodete. Dies deutet auf die gleichzeitigen Prozesse der landwirtschaftlichen Intensivierung und räumlichen Ausdehnung in den Landnutzungsstrategien der örtlichen Bevölkerung hin.

Die Auswahl eines geeigneten Maßstabs für LUCC-Modelle zur Unterstützung von Landnutzungsplanung erfordert einen Kompromiss zwischen räumlicher Genauigkeit und Ausdehnung. Im Maßstab von Einzelpersonen, Haushalten und gewerblichen Farmern (30m-1050m) sind die Landnutzungsveränderungsprozesse sehr heterogen und erfordern zur Charakterisierung große Datenmengen. Die Variogramme der standardisierten Logit-Restgrößen deuten darauf hin, dass der Umfang der Veränderungen der Landnutzungsprozesse auf der Dorfebene zwischen 3km bis 7km lag. Zukünftige Modelle zu Ermittlung von Landnutzungsveränderungen sollten daher auf diesen räumlichen Maßstäben aufgebaut sein.
Empfehlungen für nachhaltige Landbewirtschaftung umfassen zwingenden Umweltschutz, Integration von Tierhaltung und Kulturpflanzen in die Produktionssysteme, Forschung zur Verbesserung der Qualität von organischem Material, sowie institutionelle Regelungen zur Förderung der landwirtschaftlichen Kommerzialisierung.

TABLE OF CONTENTS

1 INTRODUCTION

The Volta Lake in Ghana occupying a surface area of about 8,500 km^2 is the largest man-made lake on earth. It has a catchment area of 400,000 km^2 covering six West African countries, including 70% of mainland Ghana (Figure 1.1).

The Volta Lake is one of Ghana's most important physiographic features. It is the major source of hydroelectric power for the country. Formation of the Volta Lake also led to a great potential for fisheries development, water transport, tourism, and irrigation of vast hectrage of agricultural land (Gordon and Amatekpor, 1999). An estimate of about 60% of the over 18 million population of Ghana lives within the largely rural Volta Basin. There is a high incidence of poverty in the area, with population growth rate above 2.5%. Livelihood of the inhabitants of the Volta Basin is closely linked to agriculture and natural resources exploitation. Most of the food crops of the country, namely cereals and tubers, are produced in the Volta Basin.

The Volta Basin of Ghana has undergone tremendous environmental changes since the formation of the lake more than 30 years ago. Major problems affecting agricultural production relate to poor land and water management. Intensive exploitation for crop and livestock production has led to profound degradation of native vegetation. Land degradation manifests in declining soil fertility and accelerated soil erosion (Gordon and Amatekpor, 1999). Bush burning is an important source of carbon in the atmosphere, whereas loss of soil organic matter (SOM) destroys soil structure and accelerates desertification.

Land-use and land-cover change (LUCC) are sources and sinks for most of the material and energy flow processes that are of importance to the biosphere and geosphere. Land uses account for about 40% of net primary productivity of the earth (Vitousek et al., 1997), whereas land-cover change has a significant impact on structure and functioning of ecosystems. Hopkinson and Vallino (1995) also note that land-cover is the most important variable affecting water quality and run-off in watersheds.

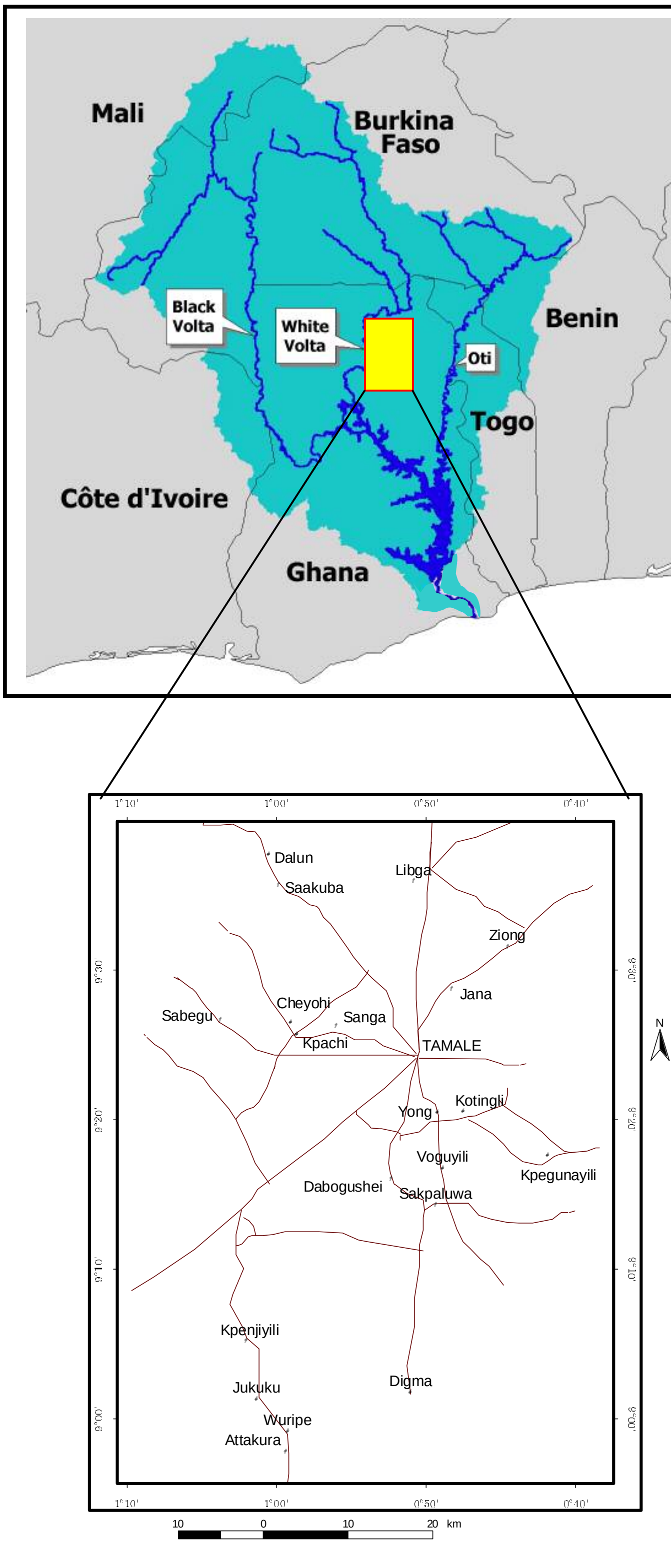


Figure 1.1: Extent of the Volta Basin in West Africa and tributaries of the Volta Lake are shown on top. The study area of about 5,400 km^2 is below.

Changes in patterns of land-use have the potential to influence weather patterns. Andreini et al. (2000) already observed that precipitation in the Volta Basin is characterized by wide variability. High rainfall variability has an adverse effect on agriculture, as the soils become droughty in the absence of adequate moisture for a long time. The resulting climate change may in turn force changes in land-use, which may result in desertification and land abandonment (Meyer and Turner, 1994). The overall implication is that sustainable livelihood depends on effective management of land and water resources in the Volta Basin.

The GLOWA-Volta project (http://www.glowa-volta.de) was set up to develop a decision support system for water management in the Volta Basin. The overall goal of this research is to provide land-use and land-cover information for the decision support system. The specific objectives of the research are:

1. To quantify changes in land cover;
2. To determine the factors responsible for land-cover change processes; and
3. To highlight the impacts of land-cover change on soils of the area.

This thesis is divided into six chapters. Chapter 2 reviews the state-of-the-art in LUCC modeling, pertinent issues in land-use research, and LUCC modeling techniques. Chapter 3 describes the study area in terms of biophysical and socioeconomic characteristics. In Chapter 4, remote sensing analysis procedures are first discussed, as well as change-detection techniques for creating dependent variables for LUCC modeling. Thereafter, methods for producing other datasets (independent variables) are presented. The chapter concludes with specific modeling techniques used in the study and model validation methods. Results of the research are presented in Chapter 5, while Chapter 6 is a summary of the major findings and policy implications of the research.

2 STATE OF THE ART

2.1 Concepts and definitions

This section describes some of the basic terminologies used in LUCC research. The definitions facilitate information exchange amongst LUCC researchers, and also improve the understanding of LUCC research by a broad readership. They are based largely on Turner et al (1993b), and Turner et al (1995).

Land-cover refers to the biophysical state of the earth's surface and immediate subsurface. It includes biota, surface water, ground water, soil, topography and human-made structures.

Land-use is the intent underlying human exploitation of land-cover. For instance, forest (a type of land-cover) may be exploited for timber production, whereas grassland may be devoted to pasture. Thus, land-use is a main cause of land-cover change.

Land-cover change can be classified into *land-cover conversion* and *land-cover modification*. Land-cover conversion is the complete replacement of one cover type by another, whereas land-cover modification refers to subtle changes that affect the character of the land-cover, but does not necessarily change its overall classification.

Agricultural intensification involves production of higher crop yields without increasing the cultivated land area. A distinction can be made between *input intensification* and *output intensification*. Input intensification measures increases in input such as pesticides and fertilizers, whereas output intensification measures increases in production versus constant unit of land area and time.

Agricultural extensification is the opposite of agricultural intensification. It involves expansion of production to previously uncultivated areas. A low level of input per hectare is used in the agricultural production process. Agricultural extensification is common in areas where population density is low.

Driving forces are factors responsible for LUCC. They are subdivided into biophysical drivers, socioeconomic drivers and proximate causes. Biophysical and socioeconomic drivers are the underlying or fundamental forces underpinning the proximate causes of LUCC. The socioeconomic drivers can be further subdivided into demographic, institutional, economic and technological factors (Table 2.1).

Table 2.1: Driving forces of land-cover change and associated factors (adapted from Geist and Lambin, 2001).

Demographic factors	Population density	
	Population growth	
	Spatial population distribution	
	Migration	
Economic factors	Economic structure	Poverty and related factors
		Economic crises
	Market growth	Growth of demand for consumer goods (e.g., agriculture-related products)
		Growth of sectoral industries (e.g., wood, agriculture-related)
		Increased market accessibility
Biophysical drivers	Soil quality	
	Soil fertility decline	
	Fragmentation, diversity of land-cover	
	Slope/topography	
	Aridity, flooding, etc.	
Institutional factors	Formal policies	On taxation, prices, etc.
		On credits, subsidies
		On population (e.g., migration)
		On land
	Informal policies	Development of cooperatives and other work coalitions
	Property rights regime	Insecure ownership
		Customary rights
		Open access conditions
Technological factors	Agro-technological change	Land-use intensification
		Land-use extensification

While biophysical variables do not directly drive LUCC, they can influence land-use decisions, e.g., decline in soil fertility might cause farmers to migrate to previously uncultivated areas. *Proximate causes* of LUCC are the obvious near final or final human activities that directly affect the environment. Three broad categories of proximate causes are presented in Table 2.2.

Table 2.2: Proximate causes of land-cover change and associated factors (adapted from Geist and Lambin, 2001

Agricultural expansion	Shifting Cultivation	Traditional shifting cultivation
		Colonist shifting cultivation
	Permanent cultivation	Subsistence (small holder) agriculture
		Commercial agriculture
		Integrated rural development project
	Cattle rearing	Smallholder ranching (pasture creation)
		Large scale ranching (pasture creation)
	Colonization/resettlement	Spontaneous/local transmigration (resettlement)
Wood extraction	Commercial wood extraction	State-run logging
		Private company logging
		Illegal logging
	Fuelwood extraction	Domestic/Industrial uses
	Charcoal production	Domestic/Industrial uses
Infrastructure extension	Transport infrastructure	Roads (public or logging roods)
	Market infrastructure	Food markets, storage facilities
	Settlement expansion	Urban/semi-urban settlement
		Rural settlements

2.2 Paradigms of Land-use Change

To date, there is no single unifying theory of land-use change. This results from the difficulty in linking the complex social and environmental dimensions of LUCC. The absence of formal process theories of land-use change implies that theories developed in social and natural sciences are adapted for case studies of LUCC (Veldkamp et al 2001). Such theories include the Malthusian, Boserupian and Chayanovian paradigms that relate land-use to population growth; the Ricardian paradigm that links land-use to intrinsic land quality; the von Thünen paradigm that associates land-use to location of land parcels; and Landscape, Human and Political Ecology paradigms that examine interrelationships of scales, patterns and processes and emphasize the role of people and exogenous variables in shaping the environment.

Malthus (1967) originally argued that food production could only grow at a linear rate compared to population that grows geometrically. Thus, population growth would ultimately outstrip the capability of the economy to meet the demand for food, owing to the ecological limits imposed by natural resources. The most important parameter that relates to LUCC in the Malthusian paradigm is population density (Mortimore, 1993). The increase in population density results in a corresponding increase in the frequency of cultivation and the shortening of fallow periods needed to rejuvenate soil fertility. As fallow length is reduced, soil fertility declines, and this leads to declining yields. Falling output is experienced which eventually culminates in food scarcity. The problem of food scarcity leads to further increases in cultivation. As arable land decreases, farmers move to marginal lands where cultivation accelerates land degradation, soil erosion and subsequently environmental degradation. So far, results of the application of the Malthusian paradigm of land-use change cannot be generalized. Contrary to Malthus' earlier proposition, advancements in science in the last 50 years have played a major role in meeting the challenge to produce enough food to feed the global population. Evidence of a Malthusian response to LUCC has been found in several regional case studies. An example is the case of Honduras (Kok, 2001). Population growth was observed to lead to deforestation, while crop yields stagnated for a period of twenty years. However, land degradation may not always be associated with high population pressure, as land productivity does not only depend on its intrinsic properties, but also on management practices adopted for farming (Tiffen et al, 1994).

The Boserupian paradigm is the antithesis of the Malthusian paradigm of land-use change. Boserup (1965) emphasizes two factors: accumulation of human and physical capital, as well as substitution of abundant factors for scarce ones. Thus, population growth is regarded as an impetus for agricultural intensification. An increase in population density leads to an increase in demand for food. Thus, labor input per unit of land is increased to meet the demand for more frequent cultivation as well as intensive farm management. Thereafter, land conserving techniques and high yielding species are adopted to maintain soil fertility and increase yield. Empirical tests of the Boserupian paradigm include studies by Guyer and Lambin (1993) and Turner et al (1993a). The paradigm is ideally suited to perfect market conditions. However, inefficient markets, characteristic of the African economy, do not lead to a Boserupian response in many situations. Lele (1989) observes that artificially low producer prices for agricultural products and lack of property rights in many countries in Africa act as disincentives for land resources conservation.

The Chayanovian land-use theory applies to peasant (smallholder) economies. It relates agricultural practices to age structure of households. It is similar to the Boserupian paradigm in the sense that both treat agricultural intensification as population-induced. Chayanov (1966) argues that the amount of land cultivated by households is a function of the consumer: labor ratio of the household, and additional inputs to production are dependent on changes in this ratio. In the early stage of a household's life cycle, a relatively small hectrage is cultivated due to the presence of small children. As time passes, the average age of the household increases and children become economically active, leading to expansion of cultivated land. The theory further argues that farm households do not necessarily seek production or profit maximization by producing as much as possible. Owing to the drudgery of labor, they rather seek to maximize utility with a trade-off between household consumption and leisure (Turner and Ali, 1996). Perz (2002) recently studied the effects of household demography on land-use allocation in Brazil using the Chayanovian paradigm. Empirical analysis confirmed that household duration of land ownership, age structures, and generational transitions influence land-use allocation among peasants. However, Perz (2002) noted the limitation of the paradigm in addressing household migration. He also noted the unrealistic assumption that input markets are limited, and the assumption that family labor is neither shared nor hired, which is the rule rather than the exception in most peasant households.

The land rent theory is attributable to Ricardo and von Thünen. Land rent refers to the excess of total revenue over total variable cost of production on a parcel of land. A distinction can be made between *natural* rent and *location* rent. Natural rent applies to the value intrinsic to a given location, whereas location rent is the value that applies to a location owing to the presence of the surrounding neighborhood. The initial formulation of the land rent theory is attributable to Ricardo. He introduced the notion that land rent is a function of land quality, i.e, soil fertility and/or climate. Later, von Thünen extended Ricardo's theory by adding location and transport costs to the model. Modern land-use theory based on the land rent paradigm states that any parcel of land given its attributes and location is assumed to be allocated to the use that earns the highest rent (Chomitz and Gray, 1996). Higher soil fertility and nearness to market (implying lower transportation cost) confer a high rent to a parcel of land. Thus, models based on land rent theory incorporate agricultural suitability and distance to market as explanatory variables. A major limitation of land rent theory is that it treats space as a featureless entity, reducing it to a mere measure of distance from the urban center. This limitation can be overcome by adding some elements of costs, e.g., using travel time rather than distance in the land-use model. Another limitation is that the land rent theory is a static equilibrium representation of the spatial distribution of land-use. It only considers land-use at a point in time, and assumes that current land-use is independent of past use(s). This limitation can, however, be overcome by adding a temporal dimension to the model through, for example, time series of dependent variables from remotely sensed data.

The Landscape and Human Ecology paradigms draw upon ecology and systems theories to describe the complex interactions between people and their environment. The land-use system is *functionally* complex in the sense that it is influenced by a large number of actors with differing goals and objectives. Secondly, land-use systems are *structurally* complex in the sense that patterns and processes are scale-dependent. Specific environmental and social processes function at different scales. This causes certain spatial patterns to be discernible at given scales, whereas they are obscure at other scales. Thus, the Landscape and Human Ecology paradigms posit that populated landscapes are a composite of complex social and biophysical phenomena that are manifested on the landscape through composition and spatial organization of different land-cover types. The Political Ecology paradigm states that exogenous variables (e.g., macroeconomic changes), though beyond the control of land users, can drastically affect their decisions (Walsh et al, 2001). The paradigms attempt to quantify relationships between land-cover change and associated driving forces at different spatial scales. The scales of analyses often correspond to the level of activities of land users or managers. According to Merchant (1990), the major limitation of the ecosystem approach is that it does not adequately specify the processes of social change that lead to environmental impacts.

Given the fact that a single theory may not adequately explain land-use dynamics in a case study, it is important to adopt modeling techniques that allow different paradigms to be tested simultaneously. This may lead to a better understanding of LUCC, and the formulation of appropriate policies for sustainable land management.

2.3 Priority issues in LUCC Research

This section reviews four issues considered to be crucial to LUCC modeling (Verburg et al, 2003). A discussion of each issue is made, as well as of the challenges they pose to LUCC modeling. A discussion is also made on how the issues have been addressed in the past, and how they are dealt with in this research. The issues are spatial scale, selection of driving forces, spatial interaction and correlation, and land-cover change trajectory.

2.3.1 Spatial scale

Scale refers to the spatial dimension used to study a phenomenon (Gibson et al, 1998). Scale, defined in terms of extent (size) or resolution (grain), helps in the analysis of patterns at a given level of investigation. Relationships between LUCC and the associated driving forces are usually scale-dependent (Kok, 2001). This scale dependency is related to the levels of organization e.g., individual, household, village, regional or national level within a hierarchically organized system. Coarse scales usually obscure local patterns/variability. Conversely, patterns invisible at detailed scales may be revealed at coarser scales. Hierarchy theory and recent studies (O'Neill 1988; Walsh et al 1999; Walsh et al 2001) suggest that relationships between phenomena are not generalizable across spatial scales. Thus, to be of value for land-use planning, multi-scale LUCC modeling is essential. Major issues in terms of matching scales are upscaling and downscaling. Upscaling involves aggregation of information from a fine scale to a coarser scale, whereas downscaling involves detailing information collected at a scale towards a finer scale (Stein et al, 2001).

Aggregation of data does not often lead to a proper depiction of higher-level processes (Verburg et al, 2003). A first cause is non-linearity of many ecological variables. Non-linear relationship leads to a form of aggregation error (ecological fallacy) when such data are averaged. Secondly, interactions at the micro scale often lead to the phenomenon of *emergence* at higher scales. An emergent property is a macroscopic outcome resulting from interrelationships between lower-level dynamics (Parker et al, 2002). Lastly, people within a social system have varying goals that are difficult to aggregate.

There are three methods of studying scale-dependency of LUCC (Verburg et al, 2003). The first is the use of multilevel statistics (Hoshino, 2001), in which data are hierarchically structured and different driving forces are analyzed at different levels. The second method involves changing the spatial units of analyses in a scale sensitive way for specific purposes. Geographically weighted regression is then used to examine relationships between LUCC and driving forces (Nelson, 2001). The last method involves upscaling of data and determination of relationships between LUCC and driving forces at multiple resolutions (Walsh et al, 1999). The last technique was used in this study, as a major interest of this research is to determine the relative importance of driving forces to LUCC at different spatial resolutions.

2.3.2 Selection of driving forces

Land-use change is often modeled as a function of selected biophysical and socioeconomic variables. To facilitate modeling, driving forces are usually considered exogenous to the land-use system (Verburg et al, 2003). However, a variable that is exogenous in a given context may be endogenous in another. For instance, if construction of roads and logging activities were jointly determined, it would be inappropriate to consider road as an exogenous variable in a deforestation model (Pfaff, 1999). Similarly, population may be endogenous to deforestation if government policies encourage development of (i.e., migration to) forested areas. Treating population as an exogenous factor in such a situation would yield biased estimates and hence lead to wrong policy conclusions. The effect of an endogenous variable can be reduced by explicitly introducing another variable that influences land-use in the model. For instance, a variable measuring agricultural land suitability may be included where road is considered endogenous to agricultural land-use. Similarly, the existence of collinearity among driving forces would yield unbiased but inefficient estimates that misrepresent the significance of driving forces in the model.

The selection of variables is usually based on the theoretical assumptions underlying the model. For instance, a model based on the land rent theory makes use of utility functions, and might include transportation cost and climatic suitability as explanatory variables. However, as rational behavioral assumption of conventional economic theory is not always valid (Janssen and Jager, 2000), flexibility in behavioral assumptions in LUCC modeling is required. This is achieved through the use of discrete choice probability models such as logistic and probit regressions.

Relationships between driving force and LUCC could be addressed qualitatively or quantitatively. The use of qualitative methods (qualitative differential equations) stems from non-availability of quantitative data (Petschel-Held et al, 1999). A quantitative approach on the other hand makes use of economic theories and physical laws, empirical statistical methods or expert knowledge to derive relationships between land-use and its driving forces (Verburg et al, 2003).

2.3.3 Spatial correlation and interaction effects

Spatial correlation is the tendency of land-covers near in space to be similar than those further apart. Such spatial correlation results from the spatial distribution of landscape features that determine land-use on the one hand, and the interaction between land-cover types on the other. Spatial correlation is often perceived as a nuisance in conventional regression analysis. In land-use studies however, spatial correlation is what provides information on spatial pattern and processes (Overmars et al, 2003). Spatial correlation of land-use/cover can be either positive or negative. Positive spatial correlation implies that a given land-cover type is clustered in space, whereas negative spatial correlation implies that the presence of a given land-cover type inhibits the presence of the same cover type in its neighborhood. Appropriate statistical methods are required to deal with spatial correlation. Neglecting spatial correlation in LUCC modeling would yield model parameters, and estimates with higher variances (Griffith and Layne 1999). Spatial correlation in land-use patterns is scale-dependent (Geoghegan, 2001). It is thus important to quantify spatial dependencies in land-use at varying spatial scales. Spatial interaction can be incorporated in LUCC modeling by including landscape indices (pattern metrics) as explanatory variables (Geoghegan et al, 1997). Landscape indices help to identify and quantify patterns in the spatial heterogeneity of the landscape. Furthermore, spatial correlation can be investigated using autoregressive or geostatistical techniques (Griffith and Layne 1999). While autoregressive techniques are primarily concerned with enhancing statistical description, geostatistical techniques are mainly concerned with prediction. Overmars et al (2003) recently used autoregressive techniques to detect and model spatial dependency of land-use in Ecuador.

While there is potential to apply geostatistical methods for incorporating spatial correlation in LUCC modeling, not much has been done in this regard. Central to geostatistical techniques is the use of the variogram, which is a quantitative statistics that describes the spatial structure of a dataset. The variogram (also called semi-variance) is a function of distance (lag) separating data points. Given a set of n observations, there are $\frac{n(n-1)}{2}$ unique pairs of data. The empirical variogram is computed as half the average squared difference between the components of all data pairs (Isaaks and Srivastava, 1989). Experimentally derived variograms are used to fit an approved variogram model (e.g., linear, exponential or spherical model), which is subsequently used for interpolation (kriging). The parameters of a typical variogram (Figure 2.1) include a nugget, sill and range. The nugget is an indication of spatially uncorrelated variation in the data. It reveals information on the variability of adjacent pixels. The partial sill is the proportion of variation that is spatially dependent. The sill provides information on the total variability of the area studied. The range is the distance beyond which there is no spatial correlation. It is related to sizes of objects in the terrain (e.g., patches of savannah or built-up area), whereas the shape of the variogram is related to variability in size of the objects in the terrain (de Jong and Burrough, 1995; Goovaerts 2002).

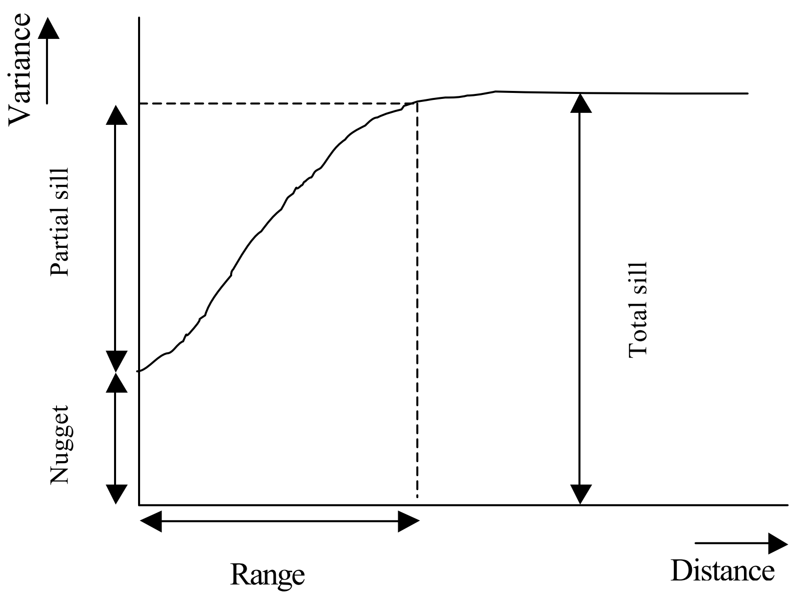


Figure 2.1: Components of a typical variogram

The major advantage of geostatistical over autoregressive techniques is that kriging provides the best linear unbiased predictor (BLUP). Geostatistical techniques were applied to LUCC modeling in this study.

2.3.4 Land-cover change trajectories/temporal dynamics

Land-cover change trajectory refers to the succession of land-cover types for a given sampling unit over more than two observation years (Lambin, 1997). Land-cover changes are seldom continuous in space, sometimes reversible and usually follow time sequences of successive cover types (Mertens and Lambin, 2000). The sequence could be linear (e.g., conversion of woodland to agriculture, and then to abandoned / degraded land) or cyclical (e.g., long crop-fallow cycle). Temporal dynamics could result from several factors including climate variability, government policies (e.g., infrastructure development may lead to changes in market structure), or as a long-term consequence of demography-induced agricultural intensification. Inclusion of such complexity in LUCC analysis leads to a better understanding of the causes of change as well as a better prediction of possible evolutions of land-cover types. This is particularly relevant for semi-arid areas that are noted for some resilience (Tucker et al, 1991). Temporal dynamics in land-cover calls for repetitive observation for more than two observation periods. It also calls for modeling for more than one time period to capture the relative importance of variables that determine LUCC over time. Another implication of temporal dynamics is the need to validate LUCC models using data different from those used for calibration. This helps to assess the predictive ability of the model. Model performance should be validated on the basis of the ability to correctly specify quantity of change on the one hand, and the location of change on the other (Pontius, 2000). Such validation is of value to policy makers, as it shows the level of uncertainty in model outcomes. It also helps the researcher to assess areas where the model could be improved for a given application. Appropriate methods that take account of these factors were used in this study.

2.4 LUCC modeling approaches

Land-use change models can be either prescriptive or descriptive in scope. Prescriptive models (Van Ittersum et al, 1998) aim at determination of the optimum land-use patterns that satisfy a set of goals and objectives. Descriptive models (Lambin et al, 2000) on the other hand aim at simulating current and near future land-use patterns. The overall utility of any land-use change model is to guide land-use planning and policy formulation. In line with the objectives of this study, attention focuses on descriptive models of LUCC.

Descriptive models of LUCC consist of three components: multitemporal land-cover maps, a change function that modifies the values and spatial arrangement of the initial land-cover map, and the resulting prediction map of land-cover change (Lambin, 1994). The land-cover maps are usually derived from remote sensing at spatial resolutions comparable with the study objectives, whereas change functions can be created by mathematical functions that describe processes of change (Lambin, 1997). Descriptive models help to answer the following important questions (Lambin, 1997):

- What biophysical and socioeconomic variables explain land-cover changes?
- At what rate do land-cover changes progress?
- What are the pathways of land-cover change? and
- Where are the locations (likely to be) affected by change?

There are six types of such models used in LUCC research. These are Optimization, Dynamic (process-based) simulation, Agent-based, Hybrid/Integrated, Stochastic (Markov Chain) and Empirical-statistical models. Examples of each are given in table 2.3 as well as references that discuss their features and applications.

In this study empirical statistical models using linear multiple regression and logistic regressions to identify the driving forces associated with LUCC. Empirical statistical models attempt to capture the driving forces of land-use change in an integrated manner (Veldkamp et al, 2001). A wider range of biophysical and socio-economic factors presumed to influence land-use is used. It is therefore interdisciplinary and applicable to multiple scales. Unlike process-based models, upscaling problems are minimized as both dependent and independent variables are equally scaled for compatibility, leading to derivation of relationships at the same scale.

Table 2.3. Description of model types

Model Type	References	Description	Application area
Empirical-statistical (Linear Multiple Regression)	Veldkamp and Fresco (1996)	Multi-scale derivation of relationships between land-use (change) and driving factors using cross-sectional data. It is also used to project future land-use patterns under certain assumptions of possible future developments (i.e., "what if" scenarios).	Central America, China
Empirical-statistical (Logistic Regression)	Geoghegan et al (2001)	Discrete choice logit model used to estimate the probability that sites will be deforested as a function of hypothesized variables affecting deforestation in study area.	Yucatan Peninsular Region, South America
Agent-based	Rouchier et al (2001)	Heuristic decision rules are used to simulate human interaction with others, and with biophysical resources.	North Cameroon
Optimization	Fischer and Sun (2001)	Applied general equilibrium modeling techniques (input-output accounting tables) are used to represent the economy. Detailed agroecological characterization of region within the study area is also carried out. Used to analyze multiple land-use types.	China
Stochastic (Markov Chain)	Thornton and Jones (1998)	Conceptual model of agricultural land change in a simulated landscape. It investigates the possibility of constructing top-down land-use models based on few processes that drive land-use change.	-
Dynamic Simulation	Stéphenne and Lambin (2001)	The model projects land-cover change at a national scale for Sudano-Sahelian countries. It represents in a dynamic way current understanding of processes of LUCC in the region. Extensification and intensification were simulated using farming system research principles.	Sudano-Sahelian countries of Africa
Integrated	Alcamo (1994)	Explores the long-term dynamics of global change and evaluates the environmental consequences of human activities. Various sub-models such as general equilibrium economy model, population model, land-cover and energy demand models are basic inputs in modeling future scenarios.	Global

3 THE STUDY AREA

3.1 Location and climate

The study area of about 5, 400 km^2 is located in the Savannah agroecological zone of Northern Ghana. It lies between latitude 8° 50' and 10° N and stretches between longitudes 0^o 30' to 1^o 30'W (Figure 1.1). The natural vegetation is characterized by short grasses with scattered shrubs and trees that are drought- and fire-resistant. Trees of economic importance found in the study area include *Butyrospermum pakii* (Shea butter tree), *Parkia biglobosa* (locally referred to as Dawadawa), *Andasonia digitata* (Baobab), *Ceiba pentandra* (Kapok) and *Mangifera indica* (Mango) (Kipo, 1993).

The North East Trade Winds (NETW) and the South West Monsoon Winds (SWMW) govern climatic patterns in the study area. The NETW, also called harmattan winds, blowing from the Sahara desert bring the dry season, while the SWMW bring moisture. The convergence of the two air masses, referred to as the inter-tropical convergence zone (ITCZ), is closely connected to weather variability (Walker, 1962). The onset of rains is usually not predictable but falls somewhere between April and June. The first rains are usually torrential with only a small amount percolating into the soils. A large fraction is lost due to run-off. Rainfall patterns are usually uncertain, while unexpected droughts lead to crop failure.

Rainfall data collected in Tamale over a 30-year period from 1970-1999 is plotted as bar lines in Figure 3.1a. The mean annual rainfall for the period was 1083 mm. A 3-year moving range was also constructed over the 30-year period to show the variability in rainfall pattern. The moving range curve shows wide variability in annual rainfall. In figure 3.1, the first point on the curve is 226 mm, indicating that the annual rainfall in 1972 was higher by 226 mm than that of 1970. The lowest moving range of -579 mm was recorded between 1991 and 1993, followed by a range of –430 mm between 1990 and 1992. The drought of 1992, i.e, the lowest annual rainfall of 695 mm is the reason for this difference. The highest moving range of 470 mm was recorded between 1987 and 1989, few years after another drought in 1984 (annual rainfall in 1984 was 926 mm). Thirteen out of the 28 moving ranges computed between 1970 and 1999 are negative. Therefore, the probability that annual rainfall was lower every third year between 1970 and 1999 was $\frac{13}{28} = 0.46$. That is, between 1970 and 1999, the chances were 1:1 that rainfall was lower every third year.

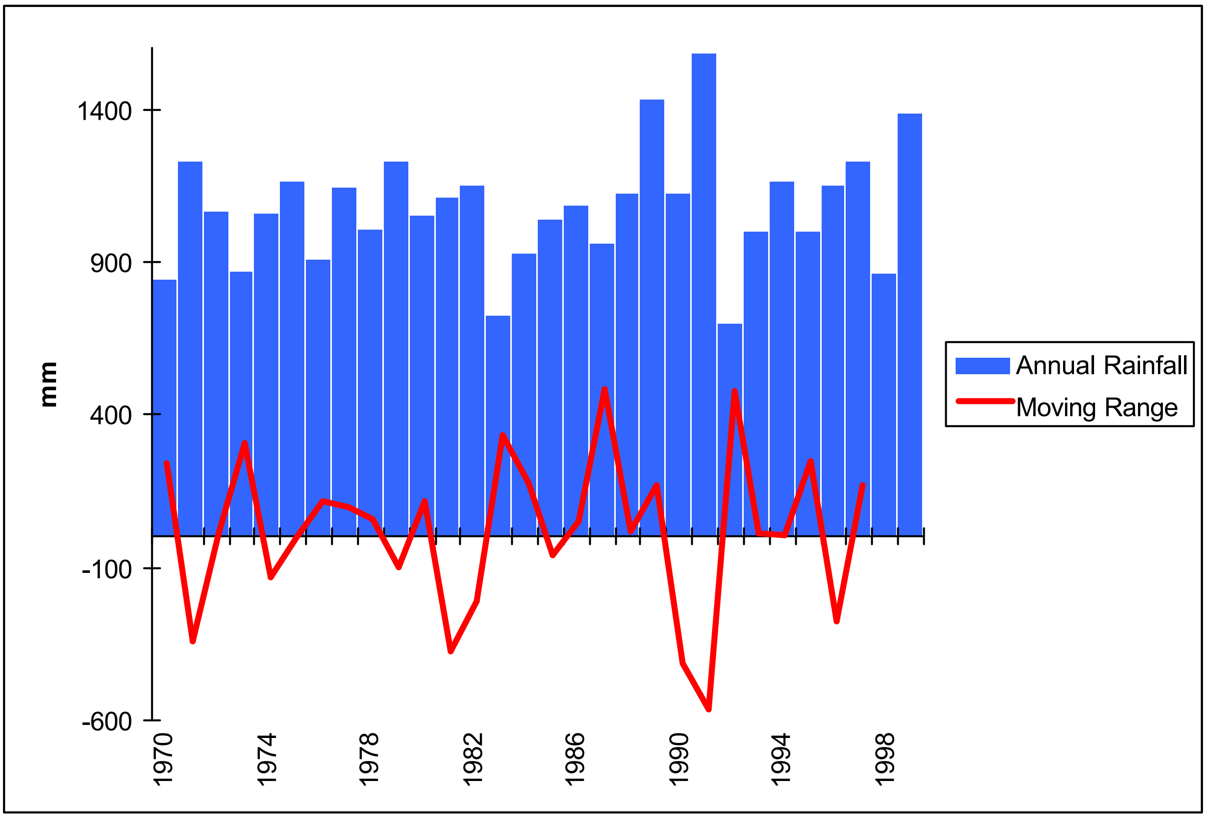


Figure 3.1a: Annual rainfall for Tamale and 3-year moving range between 1970 and 1999 (Data Source: *Ghana Meteorological Services*)

A 3-year moving coefficient of variation was further used to characterize the level of uncertainty in annual rainfall over the 30-year period (Figure 3.1b). The moving coefficient of variation ranged from 5% between 1980 and 1982 to 41% between 1991 and 1993, indicating a high level of uncertainty in rainfall patterns in the study area. The two peaks in Figure 3.1b coincide with the two lowest moving ranges in figure 3.1a. This suggests that unusually low rainfall (between 600-930 mm) was the major cause of the high uncertainty in rainfall.

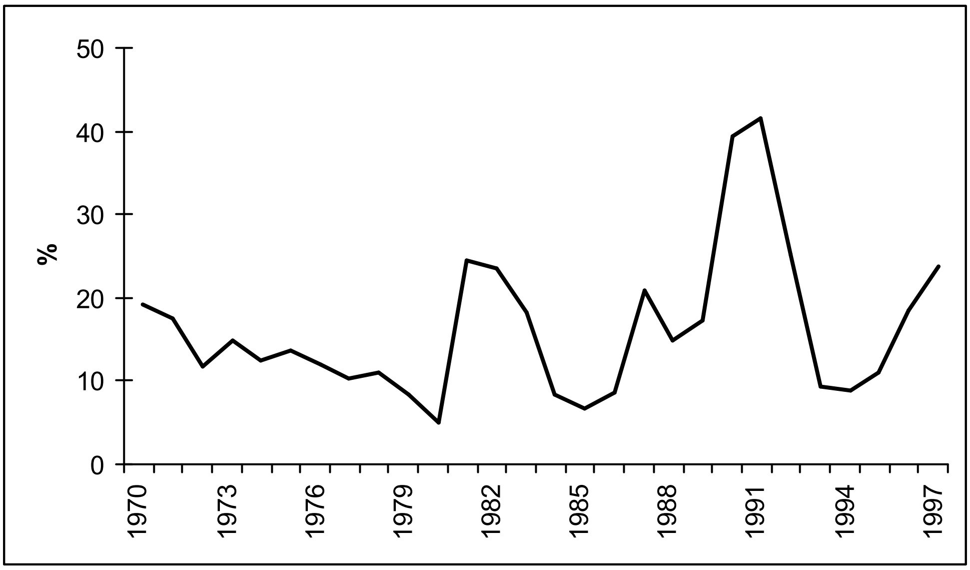


Fig 3.1b: 3-year moving coefficient of variation of annual rainfall between 1970 and 1999 (Data Source: *Ghana Meteorological Services*)

Temperature is generally high (mean temperature above 27°C) all the year round. The mean annual temperature increases from south to north (Overseas Development Institute, 1999), probably due to the effect of increasing distance from the Atlantic Ocean that modifies temperature. Between November and February, maximum day temperatures are usually between 33° C and 37° C, whereas minimum night temperatures vary between 20° C and 22° C. The hottest month is usually March before the onset of rains, while the coolest period of the year is usually August (Overseas Development Institute, 1999). Wide diurnal fluctuations in temperature occur during the dry season. Mean diurnal range of temperatures in January and December could be as much as 14–20°C (Overseas Development Institute, 1999).

Relative humidity is highest in the night (about 95%) between April to October, falling to about 70% in the afternoons (Overseas Development Institute, 1999). During the remaining part of the year, relative humidity at night is below 80% and falls to as low as 25% in January due to extreme dryness of wind, laden with dust particles.

Despite high variability and uncertainty reflected in the moving range and moving coefficient of variation curves (Figure 3.1), the rainfall exceeds potential evapotranspiration between July and September (Figure 3.2). The peak period of rain is September, with moisture deficits occurring in the months November to May. The relatively high rainfall variability and seasonal moisture deficits are a major problem to rural livelihood.

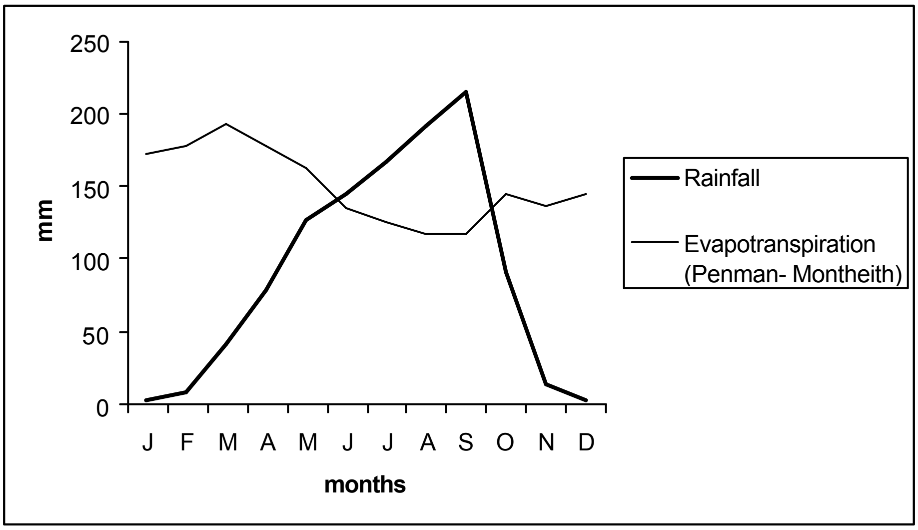


Figure 3.2: Monthly water balance 1970-1999 (Data Source: *Ghana Meteorological Services)*

3.2 Geology and soils

The main geological formation is the Voltaian, comprising sandstone, shale and mudstone with a characteristic layer of ironstone at shallow depths (Bates, 1962). Shale and mudstone beds underlie over 80% of the study area, whereas the remaining portion is mainly sandstone (Figure 3.3). The rocks are thought to be of the Lower Paleozoic age, probably ranging from the Cambrian upwards. The major mineral component of the rocks is alumino-silicates. Weathered products of the rocks constitute the parent materials from which the soils have formed (Bates, 1962).

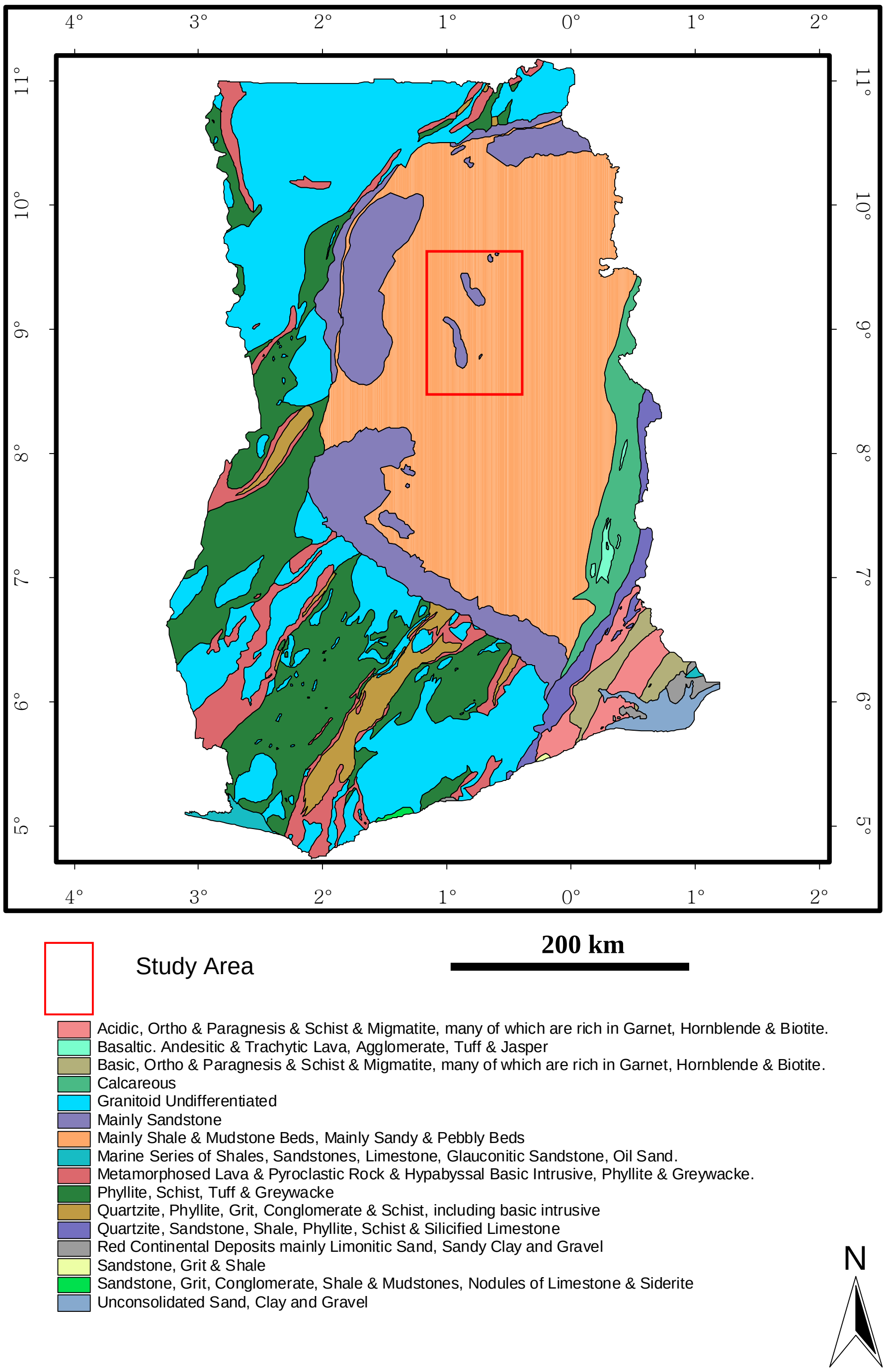


Figure 3.3: Geological Map of Ghana (Data source: Environmental Protection Agency, 1999).

Depending on precipitation, the soils are temporarily flooded during the rainy season. Soil fertility tends to increase with the amount of clay. Soil fertility is also influenced by the amount of plinthite, which impedes root growth. According to

Asiamah (2002), one major form of soil degradation in Ghana is the formation of plinthite, which hardens irreversibly to petroplinthite in upland agriculture soils. Plinthite and petroplinthite occur in all agroecological zones of Ghana, with 54% of total land area of Ghana threatened by plinthization (Asiamah, 2002). Formation of plinthite is facilitated by the removal of vegetation cover, leading to erosion of topsoil and subsequent enrichment of iron oxide, the main constituent of plinthite.

Three broad groups of soils can be distinguished in the 5,400km^2 study area. These include the reddish well-drained upland sandy loams on the Upper Voltaian sandstones where agricultural activity is mainly concentrated; the yellowish imperfectly drained sandy loams on slopes close to the valley bottoms; and in-situ alluvial soils of the valley floors (Overseas Development Institute, 1999). The soils are classified as *Rhodic Paleustalf, Typic Plinthaqualf* and *Typic Plinthaquept* (Soil Survey Staff, 1994). The upland soils are generally shallow and gravely with plinthite and ironstone. They are light textured at the surface and as a result they dry up quickly after rainfall.

Nye and Stephens (1962) provide an account of some of the results of pioneering research on soil fertility in Ghana. The remaining part of this subsection is therefore based largely on their findings. With the exception of valley bottom soils, most Ghanaian soils are old and have been intensely leached for a long time. This implies that the soils have lost most of the native nutrients from the parent materials. Furthermore, given the humid and tropical conditions in which the rocks were weathered, the predominant clay minerals is kaolinite with low cation exchange capacity (CEC). Organic carbon content in the soils is very low (0.3%-0.5%) particularly in savannah soils. Organic matter is closely associated with nutrients in the soil for two reasons (Nye and Stephens, 1962). Firstly, it has a high CEC (150-200 cmolkg^{-1}) compared to 9 cmolkg^{-1} of the clay. Secondly, the whole of the soil's nitrogen (N) reserve and an important part of its phosphorus (P) is associated with organic matter. Thus, soil fertility is synonymous to soil organic matter (SOM) in Northern Ghana. Though decomposition rate is relatively lower in the savannah compared to the forest agroecological zone, supply of fresh materials is markedly reduced by annual bush burning (Greenland and Nye, 1959).

Organic N is not available to plants, but is slowly mineralized by soil bacteria to NH_4^+ and NO_3^- utilized by plants. Nitrogen dynamics in the soil are closely associated with rainfall pattern (Figure 3.4). During the dry season there is a gradual increase in the amount of NO_3^-. The increase becomes more rapid as the rains begin until a peak is reached in the dry season. The increase in NO_3^- level in the dry season may be attributed to slow mineralization and no loss by leaching, whereas the rapid rise at the beginning of rains may be explained by stimulation of mineralizing bacteria and conversion of the nitrogen to a form that is mineralizable (Nye and Stephens, 1962). The rapid fall in NO_3^- may be due to leaching as the soil becomes saturated with water during rains. NH_4^+ is not of much importance compared to NO_3^-, as it is usually converted to NO_3^- in aerobic soils.

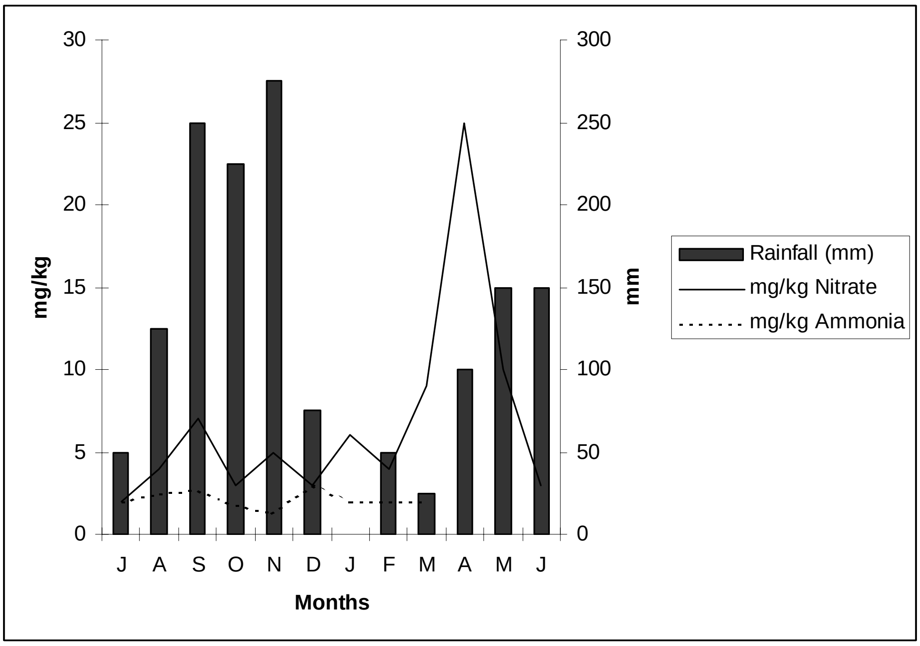


Figure 3.4: Nitrogen dynamics in savannah soils of Ghana, July to June. (Redrawn from Nye and Stephens, 1962).

The mineral apatite found in rocks is the source of P in soils. During weathering, P is released from apatite and combines with Fe, Al and Ca to form complexes that are sparingly soluble. Plants and soil fauna take up inorganic P and convert it to organic forms such as phytin, making SOM another source of P in the soils. The proportion of inorganic P in the sparingly soluble complexes, known as exchangeable P, maintains the soil P potential. Soil nutrient potential refers to the ability of the soil to supply crops with the required nutrients. Nye and Stephens (1962) observe that the soil P potential is not uniform throughout the soils, but that plants take up the nutrient in areas with relatively high potential. The remaining part of inorganic P complexes is not usually in direct contact with soil solution. Organic P does not form part of the pool, but any phosphate released by it through mineralization contributes to the pool. The rate of loss of organic C in the first 0-30cm is about 4% per annum (Nye and Stephens, 1962). The deficiency of P is therefore common in the soils, making P fertilizers an essential requirement especially in areas where continuous cropping is carried out.

Available nutrient cations (K, Ca, and Mg) are held in the cation exchange complex. The potential of each of them is closely associated with its proportion in the exchange complex. Though their content is usually low, their proportion, and therefore their potential, is usually high enough for plant growth (Nye and Stephens, 1962). Deposition and replenishment of bases with ash from bush burning and from harmattan dust inputs also contribute to high base status in the soils (Abekoe and Tiessen, 1998).

Recent characterization of the soils shows that soils of the Northern Region of Ghana have pH values of 4.5 - 6.7, organic matter content of 0.6%-2.0%, total nitrogen ranging from 0.02% to 0.05%, available phosphorus varying from 2.5 to 10.0 mg P/kg of soil, and available calcium ranging from 45 to 90 mg/kg of soil (Soil Research Institute, 2001). Low organic matter level and phosphorus reserve, occurrence of plinthite and erodible sandy topsoils make the soils inherently infertile. Soil fertility in northern Ghana has been on the decline in the last two decades (Abatania and Albert 1993; Gordon and Amatekpor 1999). The causes are mainly attributed to bush burning, continuous cropping, monocropping and overgrazing. This has resulted in low crop yields: 0.5-1.0 tha^{-1} for maize, 0.75-1.0 tha^{-1} for sorghum and 0.2-0.5 tha^{-1} for groundnut (Abatania and Albert 1993).

3.1 Demography

The population of the Northern Region of Ghana in 2000 was more than 1.8 million (Ghana Statistical Service, 2002). This is about 10% of the entire country's over 18 million population. Three quarters of this population live in the rural areas (Ministry of Food and Agriculture, 1997). Population growth rate is more than 2.5%, whereas average population density is about 26 persons/km^2 (Ghana Statistical Service, 2002). However, population density varies widely from 10 persons/km^2 to more than 150 persons/km^2 across the entire Northern Region (Ghana Statistical Service, 2002). The highest population densities (100 to more than 150 persons/km^2) are found in Tamale and other main localities: Dalun, Savelugu, Tolon, Kumbungu and Nyankpala (Ghana Statistical Service, 2002). The settlement pattern is in form of nucleated villages with houses clustered around markets or the chief's house. There are over 3000 of such nucleated villages in the Northern Region (Overseas Development Institute, 1999). The population of smaller villages is generally below 500.

Population movement within Northern Ghana has been rampant in the last few years. One main cause is low rainfall reliability and the problem of water insecurity, which has reinforced migration as an alternative livelihood strategy (Overseas Development Institute, 1999). Another factor contributing to widespread internal migration is the macroeconomic reform in Ghana in the last two decades. Four macroeconomic epochs in Ghana can be identified since independence:

a) Between 1957-1982, the government of Ghana consistently intervened in both input and output markets of the agricultural sector. Stiff restrictions were imposed on food imports to encourage domestic production. For instance, the overvaluation of Ghanaian currency contributed to an increase in protection of the rice sector in the mid 1970s to early 1980s (Abdulai and Huffman, 2000).
b) In the Stabilization/Economic Recovery Program Phase I (1983-1986), protection of the food sector decreased substantially as a result of changes in the fiscal environment. The currency was progressively devalued in nominal terms from 2.75 to 90 Ghanaian cedis per US dollar (Tshikata, 1999).
c) In the Structural Adjustment/Economic Recovery Program Phase II (1987-1991), liberalization of food trade and import of fertilizers and other agricultural inputs continued. Removal of subsidies on fertilizers and other inputs substantially increased the prices of these inputs to farmers due to devaluation of exchange rates. While trade liberalization exposed the food sector to stiff competition with imported food items, currency devaluation

made imported food relatively more expensive than domestic food, giving domestic agricultural producers a competitive edge (Abdulai and Huffman, 2000). By the end of the economic recovery programs, inflation had reduced from 142% in 1983 to 10% in 1991.

d) The post-structural adjustment period (1992 to present) has been characterized by recurrent fiscal imbalances. The period has witnessed large wage increases in the public sector and overspending in capital budgets, particularly roads. The government has also pursued initiatives to enhance the efficiency of the tax system.

The response of the agricultural sector to these policy changes has received attention in the literature (e.g., Abdulai and Hazell, 1995). Pearce (1992) and Horton et al. (1994) indicate that there was substantial migration of labour back into agriculture in Ghana during the structural adjustment period. This was because structural adjustment policies led to a reduction in the gap between rural and urban wages (Ahmed and Lipton, 1997), making urban wages less attractive than before structural adjustment. Furthermore, empirical analyses by Abdulai and Huffman (2000) show that farmers in Northern Ghana are highly responsive to changes in product and input markets associated with structural adjustment. This suggests that structural adjustment policies have made profit maximisation an appealing economic objective for farmers.

The strategic importance of Tamale as an administrative and commercial center also explains migration patterns in Northern Ghana. Abudulai (1996) reports that Tamale District’s population witnessed a phenomenal increase of about 136% from 98,560 in 1984 to 232,243 inhabitants in 1995. Thus, there was pressure on available land in municipal and peri-urban Tamale, leading to the displacement of many farmers and conversion of farmlands to residential uses. Besides, most farmland has been over-cropped due to reduction in fallow length, resulting in a decline in soil fertility (Abatania and Albert 1993; Abdulai 1996).

3.2 Land tenure

Land ownership and tenure are entrenched in a traditional common property system with land administration vested in the village chief. Allocation (lease) to households is done according to family needs without prejudice to the principle of common ownership. Usufructary right, i.e., right of usage of land is heritable patrilinealy (Overseas Development Institute, 1999). Households present gifts, including a fraction of the harvest, to the village chief in recognition of his authority. Tenure is generally secure so long as the land is actually cropped. As soon as land is fallowed, there is a possibility that it will be redistributed especially in light of the scarcity occasioned by the high population density. Land policies of the colonial era affected traditional customary land tenure (Kassim-Kasanga, 1992). In the colonial era, the administration of land was placed under the control of the Governor, and no valid title to land could occur without the Governor's consent. To date, some tracts of land are still regarded as *Stateland* in Northern Ghana. Furthermore, customary land tenure has undergone changes in the form of land sales. The major cause is the increasing population density as well as urbanization. The effect of urbanization has markedly reduced access to farmland around Tamale, the capital of the Northern Region (Abudulai, 1996).

3.3 Agricultural land-use

Agriculture accounts for 45% of the GDP of Ghana. It contributes about 60% of the export earnings, employs 70% of the rural labor force and supplies about 90% of the food needs of the people (Ofori, 1998). Agriculture is not merely an occupation in Northern Ghana. Farming is also regarded as part of the custom or way of life (Kipo, 1993). Farming systems in Northern Ghana are characterized by low external input. Agricultural land is of three main types, namely compound farms near the farmers' homes, bush farms located at distances of up to 10 km from the villages and irrigated farmland (Runge-Metzger and Diehl 1993; Clottey and Kombiok, 2000). Compound farms are prominent in areas where the population density is up to 100 persons/km^2. Household wastes are the primary means of maintaining soil fertility. Crops grown in the compound farms include maize, which is cultivated annually, tobacco, vegetables and occasionally yam. Crop rotation is not usually practiced in compound farms (Tsigbey and Clottey, 2003). The objectives of compound farming include the need to reduce overall crop losses from bushfire and livestock, to provide an immediate source of food for families and the need to give close attention to crops (Kipo, 1993).

The bush farms are normally found in the uplands, hydromorphic zones and lowlands (Figure 3.5) with each type of land having a characteristic cropping pattern. Sole cropping is relatively unimportant, covering about 7% of cultivated land, compared to cereals/legume mixture, which covers 61% (Diehl, 1986). The hydromorphic zones are transitional between the upland and the valley bottom. They do not get completely flooded but can sometimes be waterlogged (Tsigbey and Clottey, 2003). The distance from bush farms to homes has implications for farming activities in Northern Ghana. Fertility of the bush farms depends on either crop rotation or the application of inorganic fertilizers (Tsigbey and Clottey, 2003).

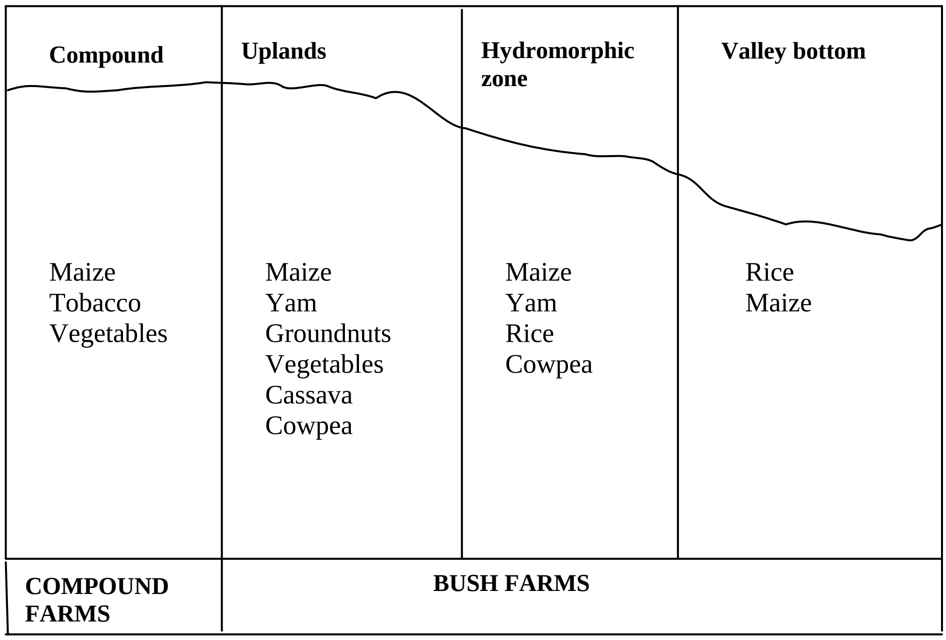


Figure 3.5: Schematic representation of different types of land-use in the Tolon-Kumbungu district of Northern Region of Ghana (source: Tsigbey and Clottey, 2003)

Crops cultivated in the bush farms include maize, groundnuts, sorghum, millet, cowpea, yam, rice and cassava. In the valley bottom, rice is grown yearly, but similar to compound farms no crop rotation is carried out. Tsigbey and Clottey (2003) observe that crop rotation varying between 2 to 9 years in upland farms is influenced by land ownership and size of holding. The more secured the tenure and the larger the size of holding (> 2 ha), the more diverse the cropping pattern, and the more likely it is for a farmer to practice crop rotation. Furthermore, Tsigbey and Clottey (2003) observe that younger farmers are more cash crop-oriented than the older ones, and grow mainly vegetables or peanuts. Crop mix and sequence in a typical 4-year crop rotation cycle is given in Table 3.1

Table 3.1: Cropping sequence in a typical 4-year crop rotation cycle in Northern Ghana (source: Kipo, 1993)

Year	Crop mix
1	Yam intercropped with millet and vegetables
2	Maize and sorghum/maize; sorghum and groundnut
3	Sorghum and groundnut or cowpea
4	Millet and groundnuts
5	Fallow period begins

Cropping and fallow are alternated in bush farms. The fallow objective is to restore soil fertility after 4-6 successive years of farming. In the traditional system, fallows of about 10-15 years alternated with 4-6 years of cultivation (Hesse, 1997). Due to increasing land pressure, fallow length has reduced to 2 years in Northern Ghana in the last few years, or has virtually been eliminated in some places (Kranz et al 1998). The fallow vegetation (predominantly grasses) and length are considered inadequate to rejuvenate fertility (Clottey and Kombiok, 2000). Thus, most of the increase in crop production has been through agricultural extensification (IFDC, 1994).

Irrigation farming to support year-round production was introduced in Ghana in the 1950s. According to FAO (2001), Ghana has a potential 500,000 ha of irrigable land but only 10,000 ha are developed. The establishment of the Bontanga irrigation project (about 610 ha) Northwest of Tamale has led to a reduction in the pressure on land. About 3000 ha of land is under irrigation in Northern Ghana (Mercer-Quarshie, 2000). According to Dekuku (1993), the northern parts of Ghana comprising Northern, Upper East and Upper West regions account for 60-70% of Ghana’s rice cultivation and production. Similarly, most of the rice consumed locally in the Northern Region is from the Bontanga irrigation scheme. Most rice farmers in Northern Ghana plant local varieties, which mature in 5 to 6 months (Al-Hassan and Jatoe, 2002). Rice yields in the savannah areas of Ghana are estimated at 1.2 tha^{-1}, 1.8 tha^{-1}, and 4.5 to 7 tha^{-1} for rain-fed upland, rain-fed lowland, and irrigated systems, respectively (Al-Hassan and Jatoe, 2002). Other crops produced with irrigation include maize, groundnuts and vegetables.

The most important input in the agricultural production process is labor. About 89% of farming activities in the Northern Region is carried out by the farmer and his family members (Kipo, 1993). Other sources of labor available to the farmer include exchange labor, hired labor and communal labor. Exchange labor is an arrangement between farmers to work on each other's farm for the same amount of time. For hired labor, payment for work done is either in cash or kind, whereas communal labor is a form of cooperation in which farmers come together to perform specific operations for one another in turn (Kipo, 1993). In most cases no cash payments are made for communal labor, but the beneficiary may present food and kolanut as a token for payment.

Most farmers generate their funds through the sale of farm produce and livestock. Bicycles play a prominent role as a productive capital resource, with about 10% of the farming community owning a bicycle (Kipo, 1993). The percentage may have increased as population pressures have caused farmers to move farther from their homes to establish new farms. Livestock is not considered as part of agriculture in Northern Ghana. According to Kipo (1993), the major integration of livestock in the crop production involves the use of bullocks to pull farm implements. Rather, livestock is considered as a capital resource. It is a source of cash in times of urgent family needs. Animals kept include poultry, goats, sheep, pigs and cattle.

4 RESEARCH METHODS

4.1 Land-cover mapping

A time series of Landsat Thematic Mapper (TM) images was acquired for the years 1984, 1992, and 1999 (table 4.1). Each image was geometrically registered to the UTM projection system. A first order affine transformation and nearest neighbor resampling was applied, resulting in a root mean square error below 0.35 for each image.

Table 4.1: Identification marks for the Landsat TM scenes used in the study

Scene ID	Date of acquisition
LT5194053054084310	5 November 1984
LT4194053054092356	21 December 1992
LT7194053009931150	7 November 1999
LT7194054009931150	7 November 1999

To compensate for the transient effects of differences in atmospheric optical properties and solar illumination between image dates, radiance values of 1984 and 1992 images were normalized to those of the 1999 images (Hall et al, 1991). The procedure involved selection of bright targets (urban features) and dark targets (water), respectively, from the images, and using a linear regression (equation 1) to correct the radiance values:

$$y_i = mx_i + c \tag{1}$$

In equation (1) y_i is the corrected digital number for $band_i$ for the subject image, x_i is the original digital number, c the intercept of the regression line and m, the slope. The parameters of the linear regression were determined as follows:

$$c = \frac{W_r U_s - W_s U_r}{U_s - W_s} \tag{2}$$

$$m = \frac{U_r - W_r}{U_s - W_s} \tag{3}$$

where U_r is the mean digital number for urban areas for the reference image; U_s, the mean digital number for urban targets for the subject image; W_s, the mean digital number for water for the subject image and W_r the mean digital number for water for the reference image.

Different land-cover types in the study area display marked similarity in the spectral space, typical of savannah environments. It was thus necessary to determine an appropriate band set as input for land-cover classification. Several transformations were carried out on the original bands of the Landsat images to achieve this. Firstly, normalized difference vegetation index (NDVI) maps were produced as a measure of biomass distribution over the landscape. Secondly, a tasseled cap orthogonal transformation of the original six bands in the image was computed (Kauth and Thomas, 1976). The first three bands are the conventional indices used for land applications. They correspond to soil, green vegetation and moisture indices, respectively. Thirdly, principal components analysis was carried out on the original six bands of each image to reduce data redundancy. The first two principal components accounted for over 90% of the variability in the data. Thus, higher order components (3-6) were dropped from further analyses, as they correlate with noise in the data set. The first two principal components were combined with the NDVI and tasseled cap bands to generate a 6-band image for signature development and classification. Land-cover classification was carried out using the maximum likelihood algorithm. Ground-truth data were obtained from two sources: available panchromatic aerial photos for 1992 at a scale of 1:10,000 and a GPS-assisted field campaign carried out between July and December 2001. The aerial photographs were interpreted and digitized to assist image classification. The separability of the training samples was evaluated using the Transformed Divergence (TD) index (Swain and Davis, 1978):

$$TD_{ij} = 2\left(1 - \exp\left(\frac{-D_{ij}}{8}\right)\right) \tag{4}$$

where D_{ij} is the divergence between signatures *i* and *j* being compared, given as

$$D_{ij} = \frac{1}{2}tr\left((C_i - C_j)(C_i^{-1} - C_j^{-1})\right) + \frac{1}{2}tr\left((C_i^{-1} - C_j^{-1})(m_i - m_j)(m_i - m_j)^T\right) \tag{5}$$

where C_i = the covariance matrix of signature *i*

μ_i = the mean vector of the signature *i*

tr = the trace function (matrix algebra)

T = the transpose function

Values of TD are in the interval [0,2] with 0 indicating perfect similarity and 2, total separability of the signatures. The classification scheme in table 4.2 was used to assign pixels to land-cover classes. Accuracy assessment was based on 312 independent samples from field studies and aerial photos.

Table 4.2: Land-cover classification scheme

Land-cover class	Description
Closed woodland	Mainly trees over 5m high, riparian vegetation (>150 trees/ha)
Open woodland	Mainly trees (75-150 trees/ha) with shrub undergrowth
Grassland	Mainly mixture of grasses and shrubs without or with scattered trees (<10 trees/ha)
Cropland	Agricultural land with crops, harvested agricultural land
Built-up area	Settlement, airports, and roads
Water	Rivers, inland waters, reservoirs

Samples of the different land-cover types are shown in Figure 4.1. The photos were taken during field surveys in 2001.

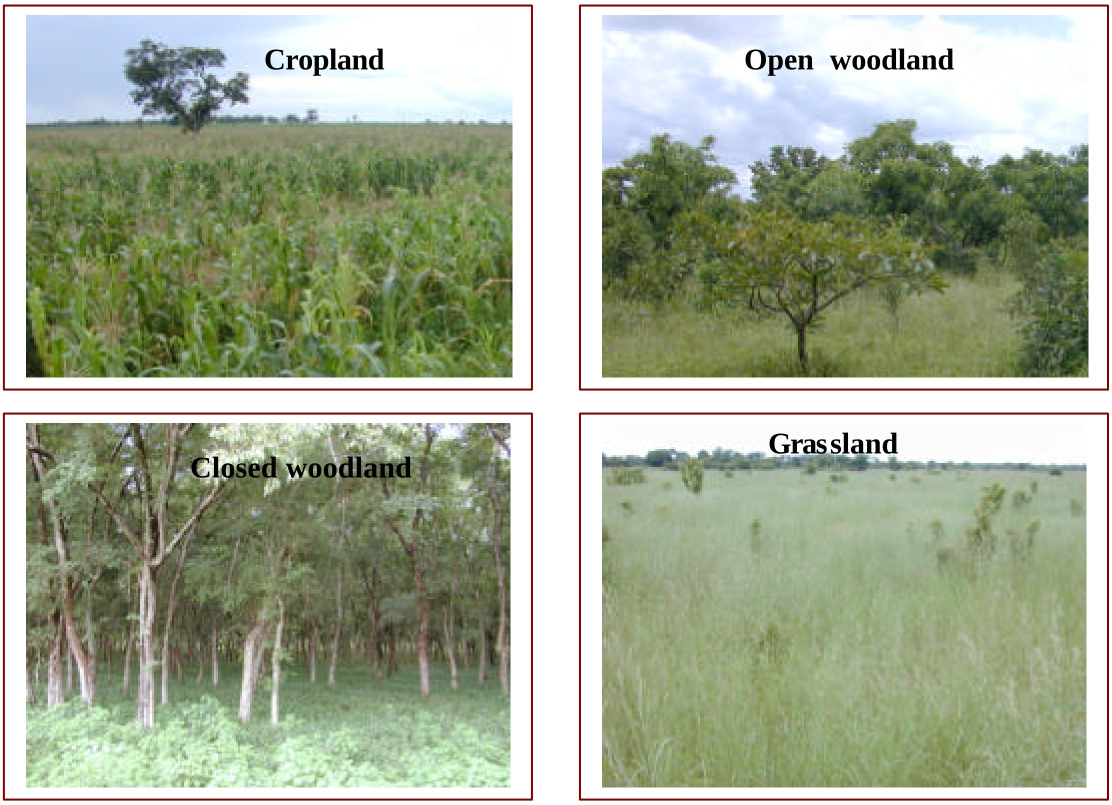


Figure 4.1: Visualization of samples of the six land-cover types

4.2 Change detection

Change detection was used to derive the dependent variable for the LUCC models. It was based on synergy between post-classification and image differencing (Figure 4.2). Image differencing involved subtraction of Band 4 (infra-red) at time t_1 from corresponding Band 4 at time t_2. Different thresholds were tested based on field observations to determine the most appropriate value to consider a pixel as *change*.

Asymmetric thresholds of –1.5 or 1.0 standard deviations from the mean were eventually chosen to reflect a decrease or increase in vegetation, respectively. The result of the image differencing was a binary change/no-change map. The output of supervised maximum likelihood classification was used to label the change product from image differencing with the appropriate ‘from’ and ‘to’ identifiers (Macleod and Congalton, 1998). The mask of no-change pixels from image differencing was applied to the land-cover map at time t_1, whereas the mask of change pixels was applied to the land-cover map at time t_2. The masked classifications were thereafter combined to obtain an improved land-cover map for time t_2 (Pilon et al. 1988, Petit et al, 2001). Finally, combining the land-cover map at time t_1 with the improved land-cover map at time t_2 resulted in a land-cover change map with ‘from’ and ‘to’ identifiers.

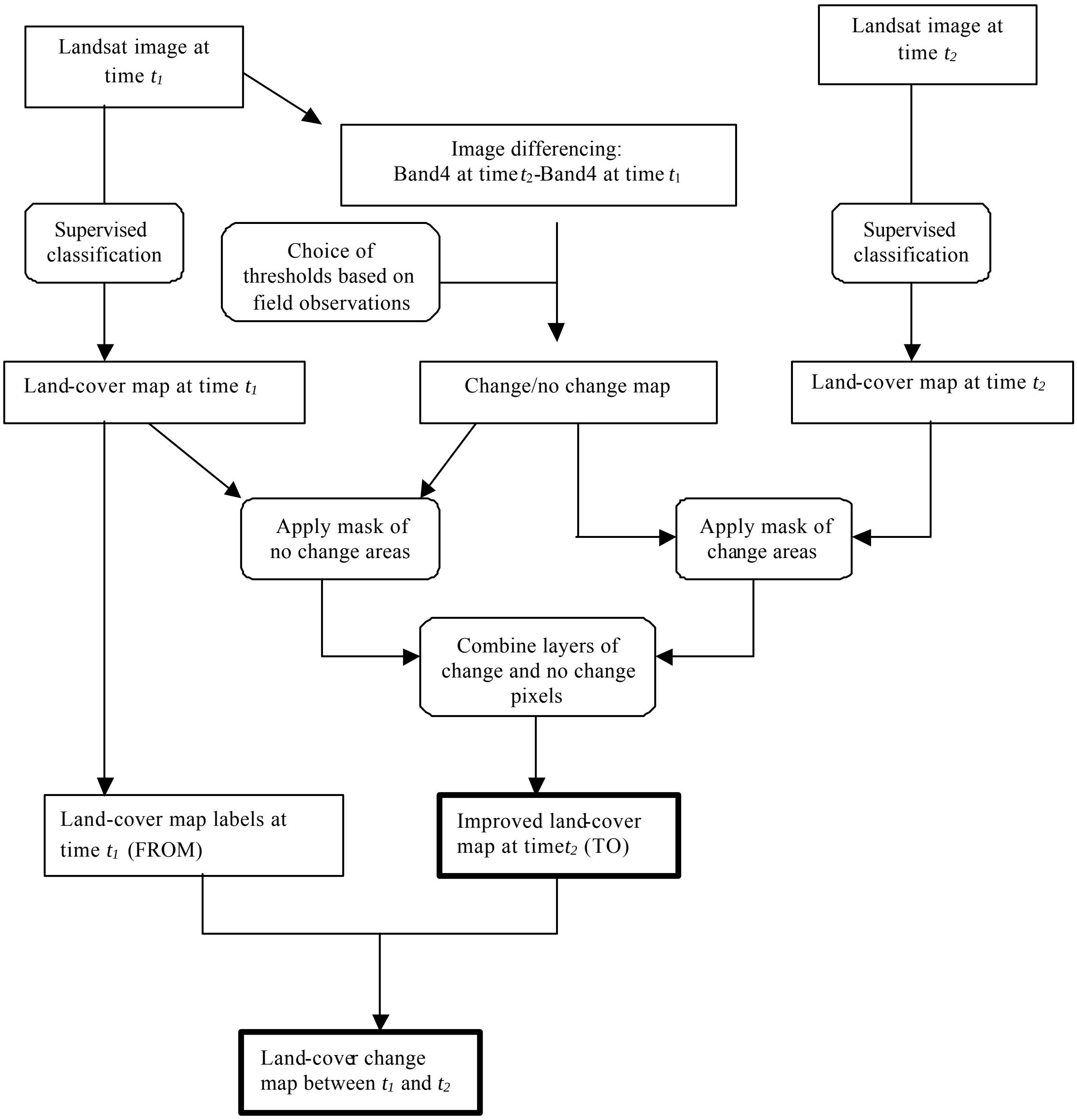


Figure 4.2: Change detection procedure (adapted from Petit et al, 2001)

4.3 Land suitability assessment

The soil study was primarily oriented towards the relationship between land suitability and LUCC (Figure 4.3). A total of 120 soil samples were collected along transects following the major road network of the study area (figure 4.3). Sampling sites were located in woodland, grassland and cropland.

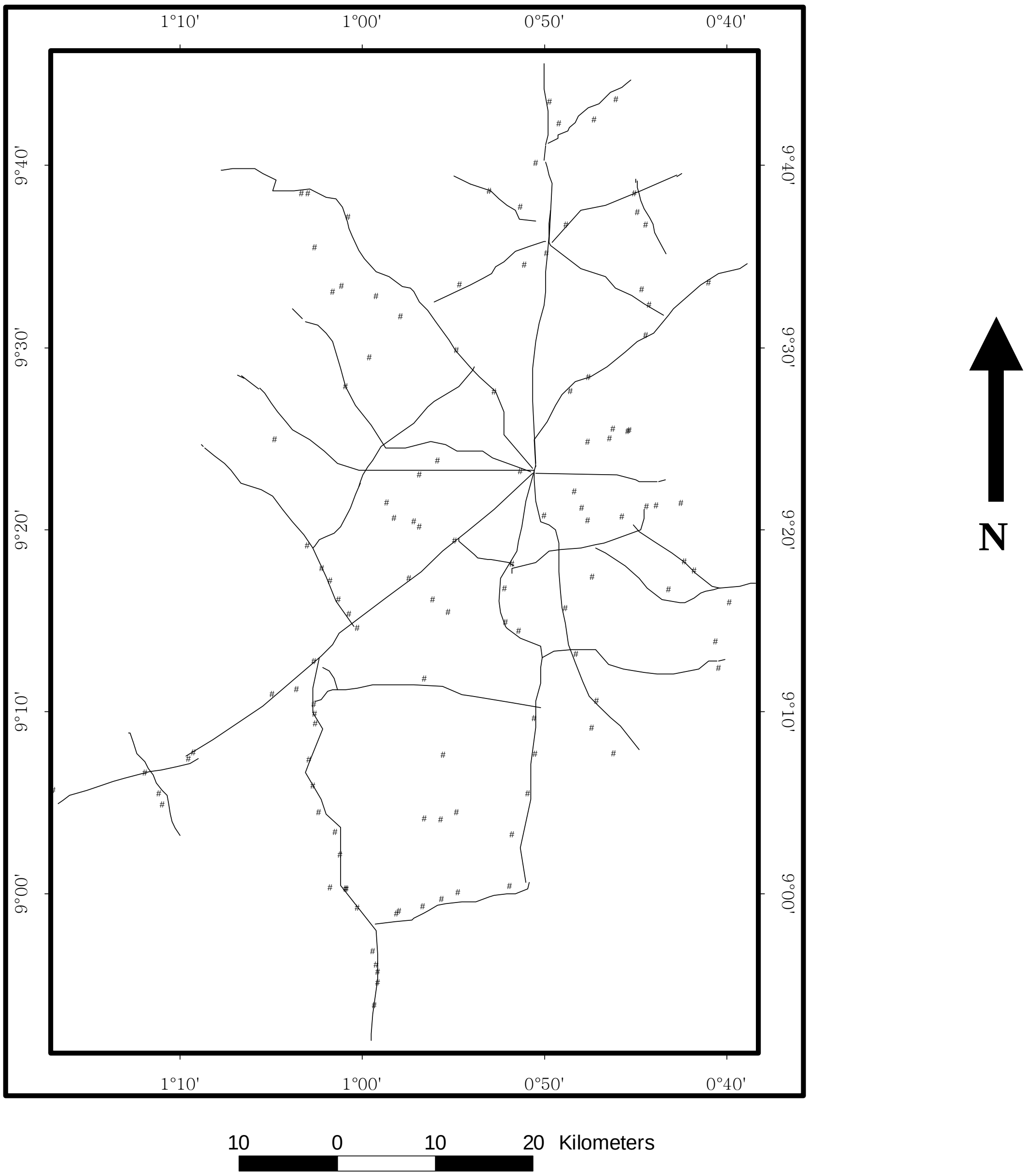


Figure 4.3: Soil sampling locations.

Samples collected from 0-20cm depths were air-dried and passed through a 2 mm sieve, and subsequently analyzed in the Savannah Agriculture Research Institute (SARI) Nyankpala laboratory for pH, determined with a potentiometer in 0.01 $CaCl_2$ solution using a soil to solution ratio of 1:2.5. Organic C was determined using the modified Walkley-Black method (Nelson and Sommers, 1982), available P by Bray-P1 method (Bray and Kutz, 1945), total N by Kjeldahl method (Black, 1965), exchangeable acidity by 1N KCl extraction (Thomas, 1982), extractable bases by 1N ammonium-acetate extraction at pH 7 with the cations in the leachate measured by atomic adsorption spectrophotometer, and particle size by hydrometer method (Bouyoucos, 1926). Effective cation exchange capacity (ECEC) was calculated by summing up extractable cations and exchangeable acidity.

Association between soil properties and land-cover change was determined by overlaying land-cover maps for 1984, 1992 and 1999 on the map of soil sampling points. This resulted in the definition of three land-cover change categories (Table 4.3). An analysis of variance (ANOVA) was performed for soil properties of the three land-cover change categories to identify properties influencing land-cover change. The selected soil properties were used to compute an agricultural land suitability index (LI) using fuzzy set techniques (Figure 4.4).

Table 4.3: Land-cover change categories to determine association between land-cover change and soil properties

Category	Land-cover in			Description
	1984	1992	1999	
1	Natural vegetation [a]	Natural vegetation	Natural vegetation	Non-cultivated land
2	Natural vegetation	Cultivated land	Cultivated land	Recent conversion to agriculture
3	Cultivated land	Cultivated land	Cultivated land	Permanent agriculture

[a] This refers to woodland and grassland

A fuzzy set may be used for classification of objects where classes do not have rigidly defined boundaries (Zadeh, 1965). If Z represents a space of objects or phenomena, then the fuzzy set A is the set of ordered pairs

$$A = \{z, m_A(z)\} \qquad \forall \qquad z \in Z \tag{6}$$

where m_A is the membership function. It indicates the degree of membership of z in A by taking values within the interval [0,1], with 0 representing non-membership, and 1 full membership of the set (Burrough and McDonnell, 2000). Intermediate values $(0 < m_A < 1)$ reflect the degree of closeness of an entity to the defined class. The Boolean logic on the other hand has two crisp possibilities of membership: none ($m_A = 0$) and full ($m_A = 1$). Examples of its application in land evaluation include Burrough et al (1992), Tang and Van Ranst (1992), Davidson et al (1994) and Groenemans et al (1997).

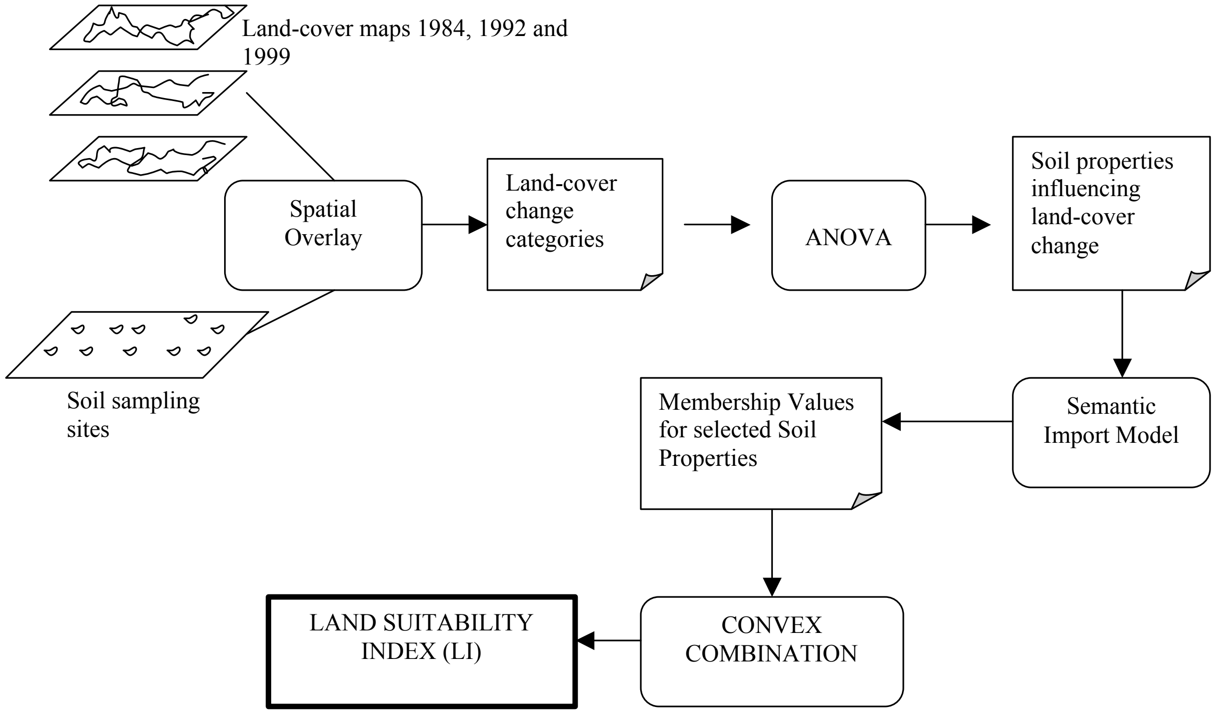


Figure 4.4: Steps leading to the computation of Land Suitability Index (LI)

Fuzzy logic is preferred to Boolean logic for land evaluation as the former estimates land-use suitability on a continuous scale, and may therefore be more informative than the Boolean (crisp) technique. Secondly, the fuzzy technique captures the continuous spatial variation of soil properties, which is the *raison d'etre* of land suitability evaluation. Lastly, fuzzy-based evaluation helps to deal with vagueness or imprecision characterizing natural resource data (Burrough, 1989).

Land suitability evaluation using the fuzzy set technique consists of three steps: generation of membership values for the land characteristics, determination of weights for the membership values, and combination of weighted membership values to produce a joint membership value or land suitability index, *LI*. Membership values were generated for six land characteristics considered to be important to agricultural land-use in the study area using the Semantic Import (SI) model (Figure 4.5). The basic symmetric SI model is of the form

$$m_A(z) = \frac{1}{(1 + a(z - c)^2)} \quad \text{for } 0 \le z \le a \tag{7}$$

where A is the land characteristic set, a is the parameter that determines the shape of the function and c (also called the *ideal point or standard index*) is the value of the property z at the center of the set, and a is the maximum value that z can take. The lower crossover point (LCP) and the upper crossover point (UCP), corresponding to c_1 and c_2, respectively, in Figure 4.5(a) represent situations where the value of the land characteristics is marginal for a specified purpose. At these points, $m_A(z) = 0.5$. The choice of crossover points specified for fuzzy membership computation could be based on data, expert knowledge or conventionally imposed criteria (McBratney and Odeh, 1997). If only the lower or upper limits of a class are of practical relevance to the envisaged land utilization type, asymmetric variants of the SI model are used. For instance, for the land characteristic "organic C" in which higher values contribute positively to crop yield, a suitable model is

$$m_A(z) = \frac{1}{(1 + \{(z - c \;\; - t_1)/t_1\}^2)} \quad \text{for } 0 < z < c + t_1 \tag{8}$$

where t_1 is the width of the transition zone [Figure 4.5(b)]. The transition zone for an asymmetric model refers to the absolute difference between the value of the property at the ideal and cross over points. A similar model [equation (9)] applies to a land characteristic for which lower values contribute positively to crop yield:

$$m_A(z) = \frac{1}{(1 + \{(z - c \;\; + t_2)/t_2\}^2)} \quad \text{for } 0 < z < c - t_2 \tag{9}$$

where t_2 is the width of the transition zone [Figure 4.5 (c)]

An overall land suitability index *(LI)* at each sampling point was computed using the convex combination rule, which is a linear weighted combination of membership values of each characteristic A_i:

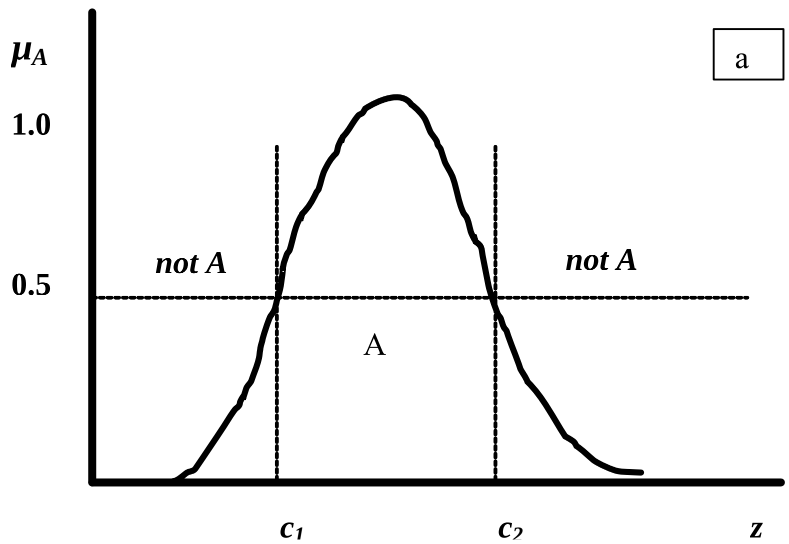
$$LI = \sum_{i=1}^{n} w_i m_{A_i} \tag{10}$$

where $\sum_{i=1}^{n} w_i = 1$, $\quad w_i > 0$

Equation (10) shows that the choice of weights (w_i) is crucial in the determination of the overall land suitability index. Davidson et al. (1994) suggest that this choice should be based on data and knowledge of the relative importance of differentiating land characteristics to crop growth. In this study, simple ranking was used to rate land characteristics from 1 (least important) to 6 (most important). This ranking was based on the relative importance of the land characteristics to agricultural land-use in the study area, as suggested in the analysis of variance. To ensure that weights sum up to unity, the rank r_i of a land characteristic A_i was converted to weight w_i using the formula

$$w_i = \frac{r_i}{\sum_{i=1}^{n} r_i} \tag{11}$$

A spatial interpolation of land suitability indices was carried out by kriging (Chilès and Delfiner, 1999). Ordinary point kriging provides the best linear unbiased predictor at point locations under the assumption that the mean of the quantity being predicted is constant.



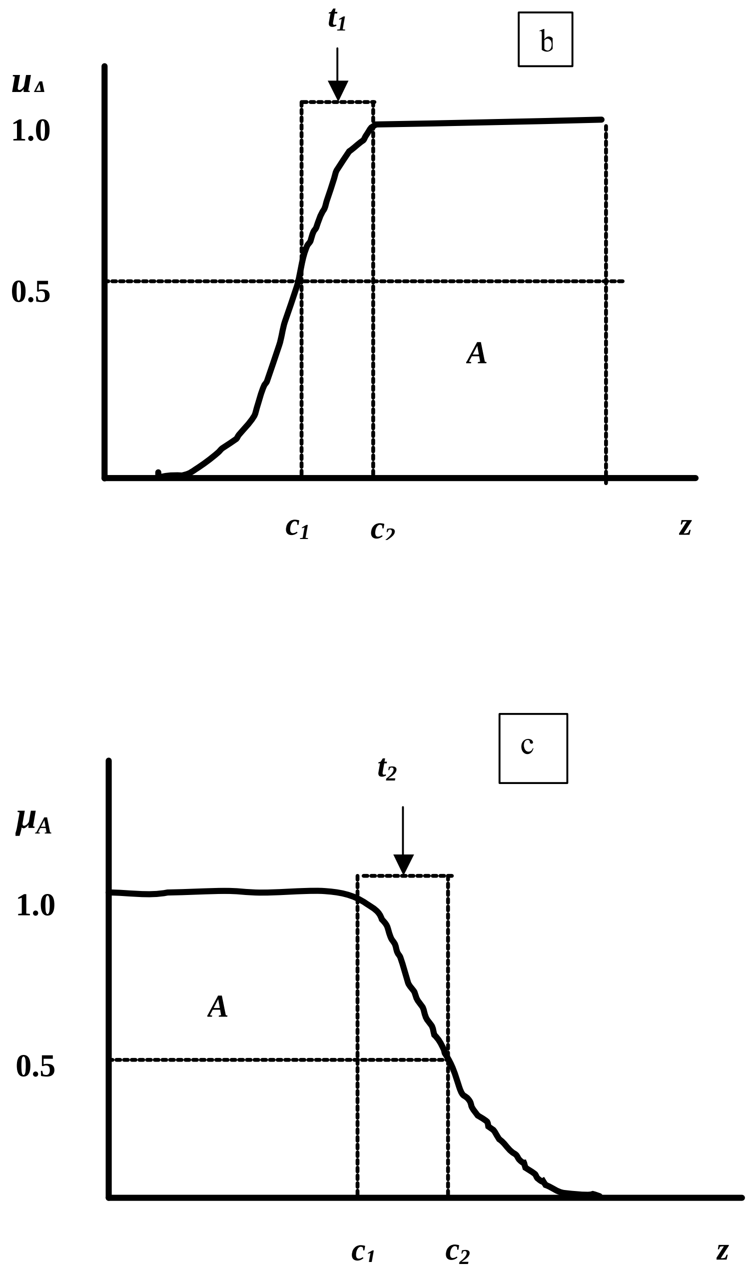


Figure 4.5: Different membership functions and parameters used to determine membership values of land characteristics (source: Burrough and McDonnell, 2000)

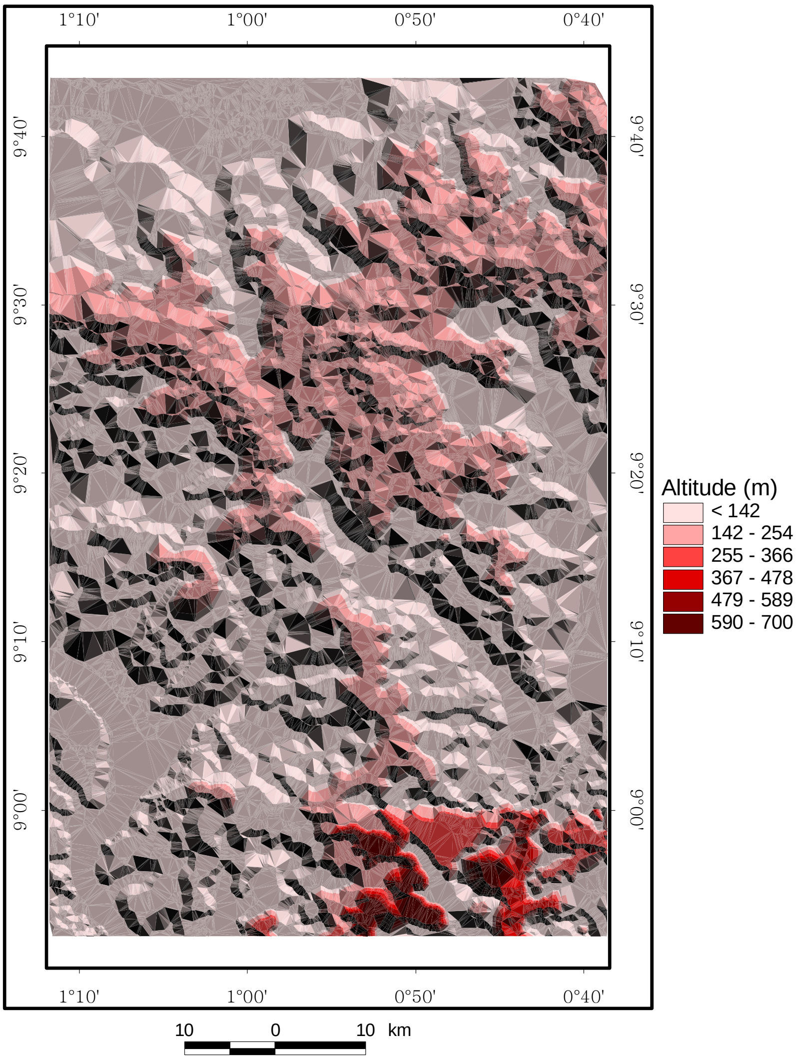
4.1 Creation of other datasets

Topographical variables

A digital elevation model (DEM) was constructed from 50 ft vertical interval contour lines digitized from a 1: 50,000 topographic map of the 5,400 km^2 study area using the triangulated irregular network (TIN) procedure (Figure 4.6). The resulting map was reclassified in units of 30m intervals. Elevation (ALTITUDE), Slope gradient in % (SLOPE) and Aspect (ASPECT) was derived from the DEM. Aspect was transformed into a linear variable using

$$ASPECT = 0.5[1 - \cos(r - 30)] \qquad (12)$$

where r is Aspect in degrees.



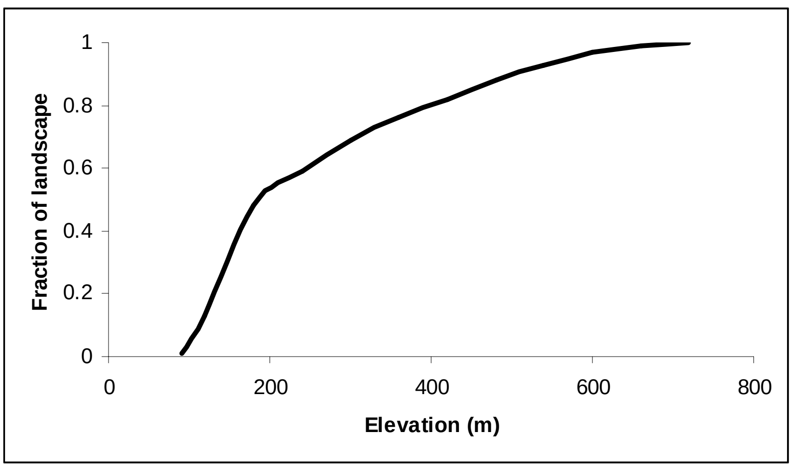


Figure 4.6: Digital terrain model of study area with cumulative density function of elevation

Distance to Tamale

Tamale is the most important commercial center in the Northern Region of Ghana. It has the largest market for agricultural produce, and is also the main link to neighboring Burkina Faso. Thus, distance to Tamale was considered as an important variable in the model. Distance to Tamale (TAMALE) was calculated as a series of 1-km buffers expanding from the center of the city (Figure 4.7).

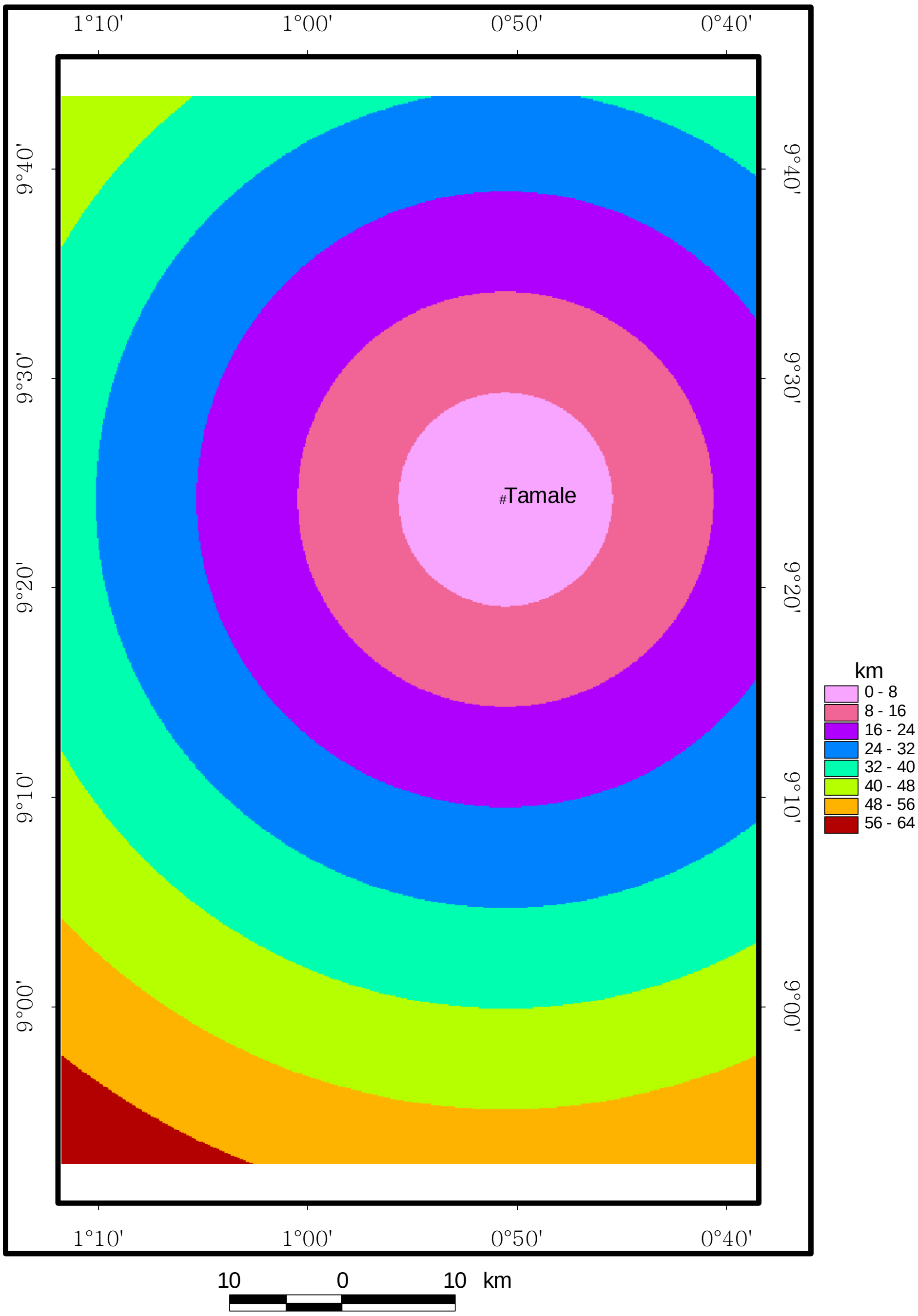


Figure 4.7: Distance from Tamale

Distance to roads

The variable (ROADS) was calculated as a series of buffers of 30 m expanding from each arc of the road coverage (figure 4.8).

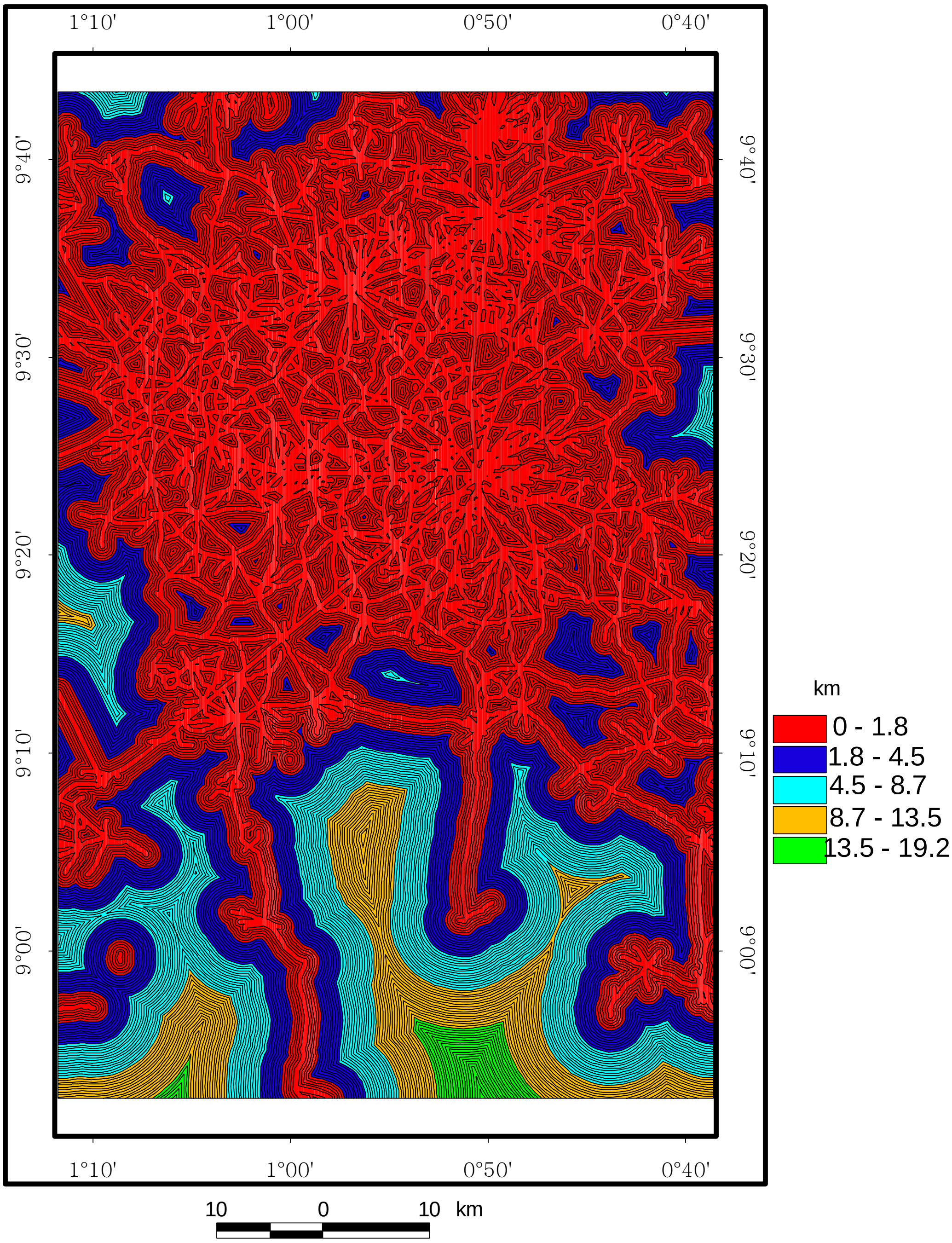


Figure 4.8: Distance from roads

Distance to water

Permanent water bodies (rivers and lakes) from existing maps were updated by digitizing from current satellite images. Distance to water (WATER) was thence calculated as a series of buffers of 30 m expanding from each arc.

Climatic variables

The study area falls into two categories in the existing mean annual temperature map (EPA, 1999). The upper portion has a mean annual temperature of above 28°C, while the lower portion has a temperature range of 27°C - 28°C. Temperature (TEMP) was represented as a binary layer with TEMP=1 if mean annual temperature is greater than 28°C, and TEMP=0 otherwise. Annual rainfall (RAIN) was similarly represented as a binary layer with RAIN=1 if mean annual rainfall is greater than 1100mm, and RAIN=0 otherwise.

Population density

Population census data exists for 1984 and 2000 (Ghana Statistical Service, 1989, 2002). Intercensal growth rate, *r* between the periods was calculated as

$$r = \frac{In\left[\frac{P_2}{P_1}\right]}{t} \tag{13}$$

where P_1 is the population in the year 1984, P_2 the population in the year 2000 and t the time interval. Population estimates for 1992 were then derived using

$$P_{1992} = P_{1984} \cdot e^{8r} \tag{14}$$

Population density surfaces for the study area were mapped for 1984, 1992 and 2000. Population density surfaces were constructed such that values of all points (village centers) within a search radius are summed, and distributed outward from each point. A search radius of 5 km corresponding to average distance traveled by villagers to farm plots was used.

Land ownership

Land ownership (TENURE) within the study area was mapped as a binary variable with 1 representing Stateland and 0 otherwise.

Landscape indices

Three landscape indices calculated in 3 x 3 pixels kernel were also included as independent variables. Formulas for calculating the indices are presented below:

Shannon-Weaver Diversity (DIVERSITY) is an index that incorporates measures of the relative abundance of different cover types on a landscape.

$$DIVERSITY = -\sum_{i=1}^{n} p_i \cdot In(p_i) \tag{15}$$

where p_i is the proportion of each class *i* in the kernel and *n* is the number of classes present.

Dominance (DOMINANCE) is a measure of the degree to which a landscape departs from maximum possible diversity. It is given by

$$DOMINANCE = In(n) - DIVERSITY \tag{16}$$

Fragmentation (FRAGMENTATION) characterizes the length of the perimeter line of pixels of a given cover that is exposed to other cover types. It is a measure of accessibility of the land-cover. It is given by:

$$FRAGMENTATION = \frac{n-1}{c-1} \tag{17}$$

where *c* is the number of cells considered.

Collinearity in independent variables was tested by regressing one continuous independent variable against the others. A threshold R^2 value of 0.8 was used to eliminate strongly multicollinear variables from further analysis (Menard, 1995).

4.1 Socioeconomic surveys

A socioeconomic survey was carried out to determine the driving forces of land-use change at household and village levels. Structured questionnaires were administered to 237 households in 20 villages (Figure 4.8).

Wuripe was purposely selected as one of the surveyed villages owing to its peculiar nature. It was established about 15 years ago as a result of in-migration from Tamale and its environs. Four households settled temporarily in the village in the year 1989, but by 2001, a total of 201 households consisting of 1361 individuals had migrated into the village. One striking feature of Wuripe is that the inhabitants do not live there all year round. Every year, they come to Wuripe at the onset of the farming season (typically June), and carry out intense farming and other natural resource-based activities, until the beginning of the dry season when lack of water for domestic and other uses forces them back to their permanent places of abode. This phenomenon is referred to as *seasonal migration*. A special questionnaire was designed to highlight the causes of such seasonal migration, and factors that determine the amount of land that households in Wuripe clear for food and commercial crops over the period spent at Wuripe.

A general village-level questionnaire was designed to elucidate the factors associated with the increase/decrease in plots cultivated by the household over the period covered by the Landsat images. The survey focused on household composition, increase/decrease of agricultural plots, technology (fallow length, labor, tools), and production by crop types. A major interest of this part of the study is the integration of remote sensing and socio-economic (household) data. The boundaries of the agricultural area of each village were defined from the center of the village by a circle whose radius is the maximum distance traveled to farm plots.

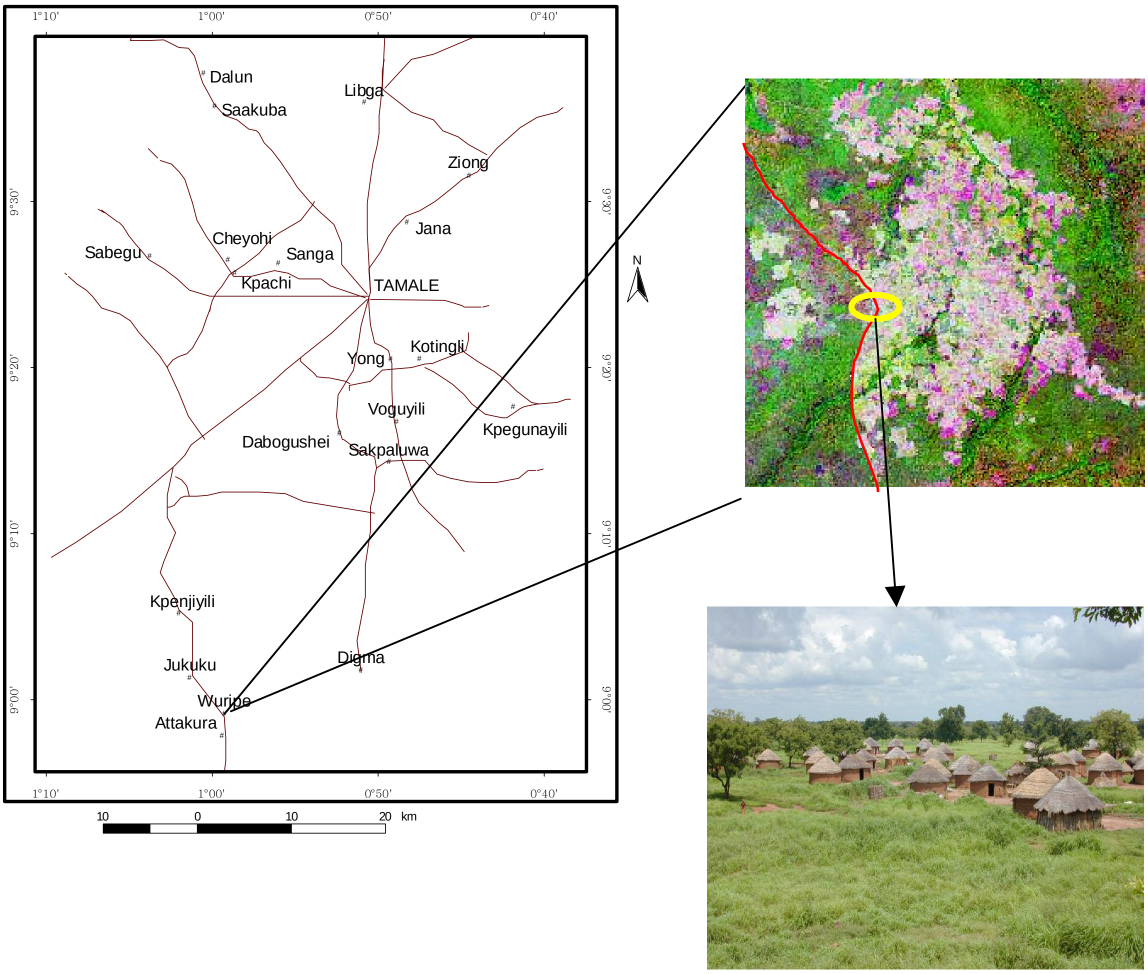


Figure 4.8: Map showing locations of surveyed villages. The satellite image on the right is Wuripe area on 7 November 1999. Notice the large expanse of agricultural land (light purple), as well as distinct shapes of farm plots. Part of the settlement is shown below.

4.1 Modeling

Two modeling techniques addressing different questions were used in the study. The first model uses logistic regression to determine the probability that a piece of land will be converted to agriculture given the biophysical and socioeconomic characteristics of that location. The modeling was carried out at six spatial scales corresponding to levels of activities of different land-users. The second model involves the use of linear multiple regression. It answers the following question: Given the socioeconomic characteristics of households within a village, how much land will be cleared for agriculture? As stated in section 4.5, the second model was implemented at household and village levels.

4.6.1 Modeling location of conversion to Cropland

Logistic regression was used to model the probability of a pixel being converted to cropland (between 1984 and 1992, and between 1992 and 1999) as a function of the explanatory variables summarized in Table 4.4. Modeling was performed at six spatial resolutions, which are spatially aggregated multiples of the 30 m basic resolution of Landsat TM.

The major interest was to ascertain the relative importance of the variables in explaining the conversion to cropland at different scales. Cells at aggregated scales (dependent and categorical independent variables) were coded with the value of the geometrically nearest/closest pixel in the *n x n* subpixels. Spatial mean was used to aggregate continuous independent variables. The spatial scales in increasing order of coarseness were 1 (30 m), 5 (150 m), 10 (300 m), 35 (1050 m), 100 (3000 m) and 170 (5100 m). The "small" scales (1 and 5) correspond to sizes of individual and household agricultural plots, "medium" (10 and 35) to sizes of commercial farms, and large (100 and 170) to sizes of agricultural area for localities.

Table 4.4: Summary of independent variables

Variables	Description
ALTITUDE	DEM was derived from 50 ft vertical interval contour lines using triangulated irregular network
ASPECT	Derived from same source as above. Transformation into linear variable was carried out using $ASPECT = 0.5[1 - \cos(x - 30)]$ where *x* is aspect in degrees
SLOPE	Derived from same source as above, calculated in %
RAIN	Rainfall zones mapped as binary layer with RAIN=1 if rainfall$\geq$1100mm and 0 otherwise.
TEMP	Temperature zone mapped as binary layer with TEMP=1 if temperature$\geq$28°C and 0 otherwise
LSI	Agricultural land suitability index derived from fuzzy set and interpolation techniques. Fuzzy membership values for Sand, Clay, Drainage, Organic C, pH, and effective Cation Exchange Capacity were calculated for point observations, while overall joint suitability index was computed using convex combination rule. Spatial interpolation was carried out using ordinary kriging.
WATER	Distance from permanent water bodies
DOMINANCE	Landscape index calculated for 3x3 kernel size of land-cover map as $DOMINANCE = In(n) - \left(- \sum_{i=1}^{n} p_i \cdot In(p_i) \right)$ where p_i is the proportion of each class *i* in the kernel and *n* is the number of classes present
ROADS	Distance from roads
TAMALE	Distance from Tamale, the major market center
VILLAGES	Distance from villages
POPD84	Population density in 1984
POPD92-84	Difference in population density 1984-1992
POPD92	Population density in 1992
POPD2000-92	Difference in population density 1992-2000
TENURE	Land tenure, mapped as binary layer with TENURE=1 if stateland, and 0 otherwise

Logistic regression belongs to the class of Generalized Linear Models (GLM). It can be used to model categorical data with non-normal distribution (McCullagh and Nelder, 1989). A GLM relaxes the independent and identically distributed (*iid*) assumption commonly used for (Gaussian) normal data (Griffith and Layne, 1999). The GLM has three distinct parts: a random component which is the qualitative variable being modeled; a systematic component which refers to the explanatory or independent variables that could be either categorical or continuous, and a link function which is used to relate the random and systematic components of the model (McCullagh and Nelder 1989). Logistic regression modeling involves fitting of a linear model to a function of the mean, also called the link function (Gotway and Stroup, 1997). The logistic regression model is of the form:

$$\ln\left[\frac{p(y=1|\boldsymbol{x})}{1-p(y=1|\boldsymbol{x})}\right]=\beta_0+\beta_1x_1+\beta_2x_2+.....+\beta_nx_n+e(s) \tag{18}$$

where $p(y=1|\boldsymbol{x})$ is the probability that y takes the value 1 (conversion to cropland) given the explanatory variables; $\boldsymbol{x}$ the vector of explanatory variables, βs the model parameters to be estimated and $e(s)$ a Gaussian random field with the spatial dependency structure to be determined. It is assumed to be a second-order stationary process with a mean of zero and variance-covariance matrix $\Sigma(\boldsymbol{\theta})$. The notation $\Sigma(\boldsymbol{\theta})$ means that the structure of $e(s)$ depends on parameter vector $\boldsymbol{\theta}$ whose elements need to be estimated. Parameters of $\boldsymbol{\theta}$ are usually estimated using isotropic semivariogram models (Schabenberger and Pierce, 2002). The quantity $\frac{p(y=1|\boldsymbol{x})}{1-p(y=1|\boldsymbol{x})}$ is referred to as the odds-ratio, whereas $\ln\left[\frac{p(y=1|\boldsymbol{x})}{1-p(y=1|\boldsymbol{x})}\right]$ is called the logit. The odds ratio is a measure of association between independent and dependent variables. It indicates how likely or unlikely the outcome is, given a set of values of the independent variables. After back transformation, the result of the regression may be expressed in terms of conditional probability as:

$$\widehat{p}(y=1|x)=\frac{e^{\beta_0+\beta_1x_1+\beta_2x_2+.....+\beta_nx_n+e(s)}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2+.....+\beta_nx_n+e(s)}} \tag{19}$$

where the hat-notation is used to indicate estimated values. Equation (19) shows logistic regression results in the form of continuous predicted values in the interval [0,1], although the dependent variable is categorical. Logistic regression was implemented in the study using the maximized log-likelihood algorithm.

A spatial prediction (interpolation) was carried out by kriging (Chiles and Delfiner, 1999). Ordinary point kriging provides the best linear unbiased predictor at point locations, under the assumption that the mean of the quantity being predicted is constant. The predicted probability is a non-linear and also non-stationary variable. Therefore it cannot be used directly for kriging. The logits, however, are linear and the standardized logit residuals have a constant mean of zero. Thus, spatial prediction is proceeded by first modeling spatial dependence of logit residuals [*e(s)*] using weighted least squares (Heuvelink 1992). Subsequently, the variogram model parameters *(θ)* were used in kriging to predict logit residuals. Finally, estimated logits were added to predicted logit residuals, and subsequently transformed into probability using

$$p(s_o) = \frac{e^{\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + .. + \hat{\beta}_n x_n \hat{e}_{p(s_o)}}}{1 + e^{\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + .. + \hat{\beta}_n x_n + \hat{e}_{p(s_o)}}} \qquad (20)$$

where $p(s_o)$ is the probability of conversion to cropland in an unobserved location s_o, $\hat{\beta}'s$ the estimated logistic regression parameters, and $\hat{e}_{p(s_o)}$ the predicted residual.

Validation of probability models

The logistic regression model only estimates the probability that a pixel will be converted to cropland given its location characteristics. There is a need to further estimate the quantity of pixels to convert to cropland. Given the proportion of cropland in 1984 and 1992, linear extrapolation was used to estimate the quantity of cells to convert to cropland in 1999. This assumes that annual conversion to cropland from 1984 to 1992 stays constant through 1992 to 1999. Cropland was allocated sequentially to pixels with the largest probability values after masking pixels that were cropland already in 1992.

The accuracy of the models was evaluated on the basis of the ability to correctly specify location and quantity. Quantification error occurs when a model assigns a given point in the landscape to a category different from its real category, whereas location error occurs when a point of a given category is assigned to a location different from its actual location in the landscape (Pontius, 2000). The first validation procedure involved the use of relative operating characteristics (ROC). The ROC technique compares observed values, i.e., binary data of change/no change over the whole range of predicted probabilities. It aggregates into a single index of agreement, the ability of the model to predict the probability of conversion to cropland at various locations in the landscape. ROC is both a measure of goodness-of-fit and ability to correctly specify location. If the model assigns the probability of change at random across the landscape, the ROC will be equal to 0.5. More generally, ROC increases as the model assigns higher probabilities to sites that are changed than sites that are not. Lastly, two variants of the Kappa index of agreement were used to partition the effects of quantity and location errors in the model at each scale (Pontius 2000). These are Kappa for location (κ_{loc}) and Kappa for quantity (κ_q). κ_{loc} is the success due to the model's ability to specify location divided by the maximum possible success due to a model's ability to specify location perfectly. It ranges from 0 for a model that assigns location at random to 1 for a model that specifies location perfectly. κ_q is the success due to the model's ability to specify quantity divided by the maximum possible success due to a model's ability to specify quantity perfectly. κ_q can be negative in the presence of large quantification error, but its value approaches 1 with increasing ability of the model to correctly specify quantity.

4.6.2 Modeling amount of land converted to Cropland

Linear multiple regression (LMR) was used to identify the variables driving land-use change for two periods (1984-1992 and 1992-1999). The model estimates the amount of land within a village that is converted to cropland, given the aggregated household characteristics in the village. Land-use change (dependent variable) was defined as increase/decrease in a village's cropland area over two time periods as measured from land-cover maps. The LMR model is of the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \qquad (21)$$

where y is the change in cropland measured from land-cover maps, β_0 is the intercept $\beta_1,......,\beta_n$ is the estimated regression parameters for each of *n* independent variables (driving forces), and $x_1......x_n$ the driving forces derived from socio-economic surveys. As all migrants did not arrive in Wuripe at the same time, driving forces in the household-level model were developed to reflect the number of years spent in the village. Validation of the village level model was carried out by computing predicted cropland change (1992-1999) based on the land-use change model for 1984-1992. Predicted cropland change was then compared to observed change (measured from remote sensing) using the Pearson correlation coefficient.

5 RESULTS AND DISCUSSION

5.1 Land-cover maps

The results of the transformation methods are illustrated using the1999 image in Figures 5.1 and 5.2. In Figure 5.1, soil, vegetation and water indices are displayed in red, green and blue guns, respectively. Cropland (magenta) and built-up area (yellow) were well discriminated. Other vegetation types appear as different shades of green.

Figure 5.2 shows principal component 1, principal component 2 and NDVI displayed in red, green and blue guns, respectively. It is clear that these transformations discriminated cropland less than the tasseled cap transform. Water bodies (rivers and dams) appear as blue, whereas grassland is represented as light blue. Light green on the image corresponds to Closed woodland, whereas greener objects are Open woodland.

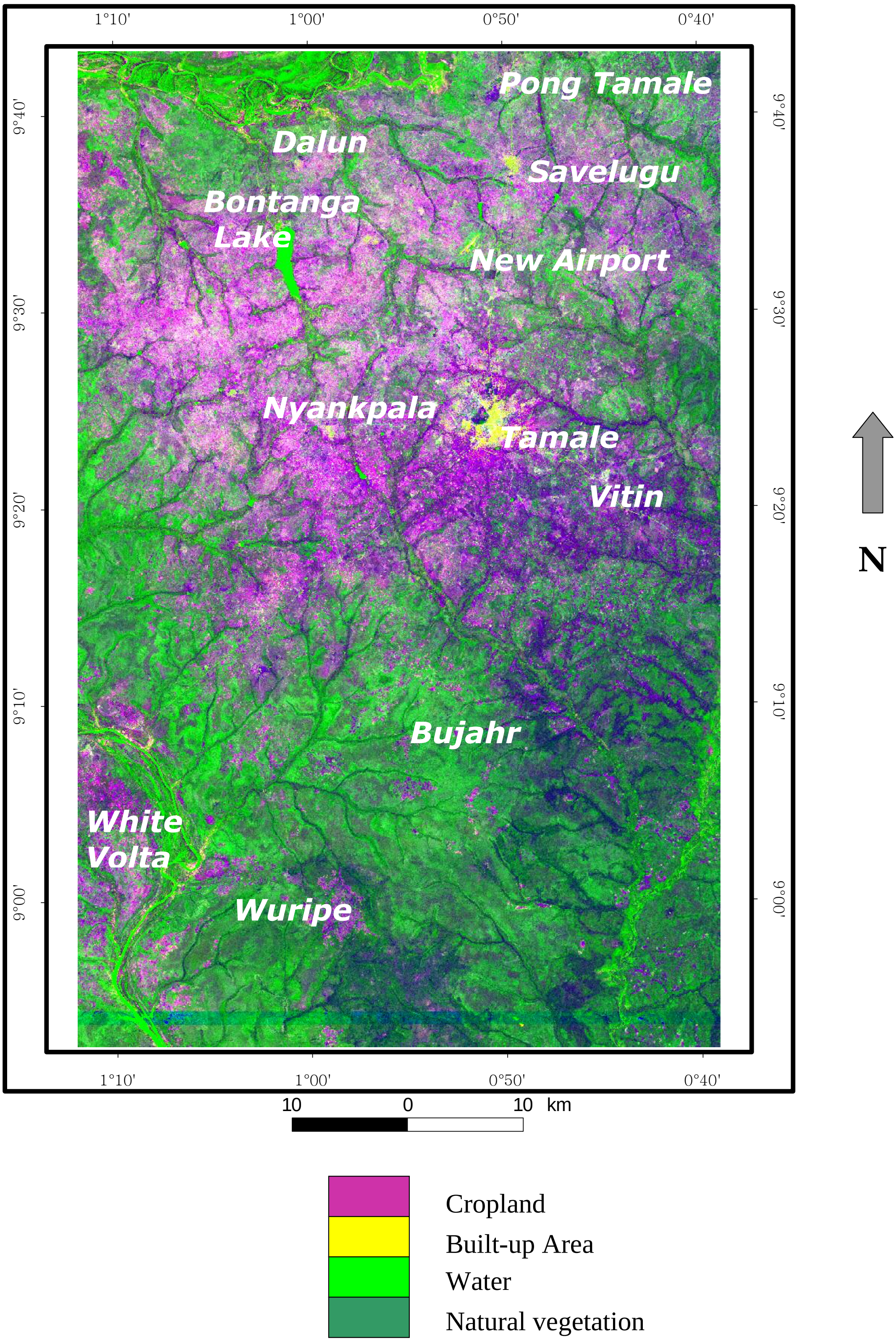


Figure 5.1: Tasseled cap orthogonal transform of the 1999 image.

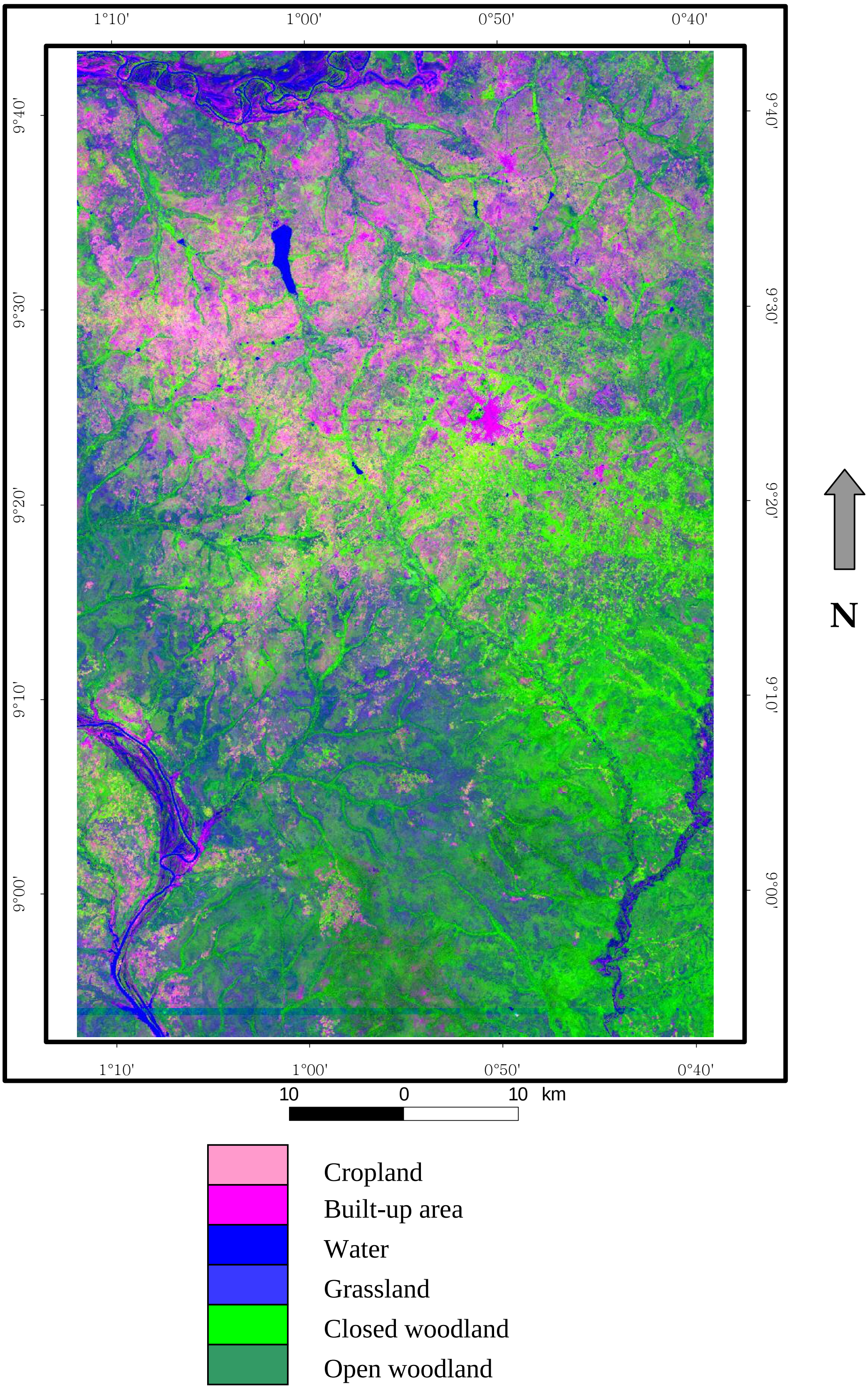


Figure 5.2: Display of PC1, PC2 and NDVI

Transformed Divergence indices for pairs of land-covers that theoretically range from 0 to 2 are given in Table 5.1. The separability of the covers is rather uniform and fairly high. Cropland and Built-up area is the least separable pair, as shanty settlements are scattered all over the landscape and are usually found in association with agricultural fields.

Table 5.1: Transformed Divergence of land-cover types

	Closed woodland	Open woodland	Grassland	Cropland	Built-up area	Water
Closed woodland		1.99	1.99	1.99	1.99	2.00
Open woodland			1.82	1.99	1.99	2.00
Grassland				1.99	1.99	2.00
Cropland					1.75	2.00
Built-up area						2.00

Land-cover maps for 1984, 1992 and 1999 are presented in Figure 5.3.

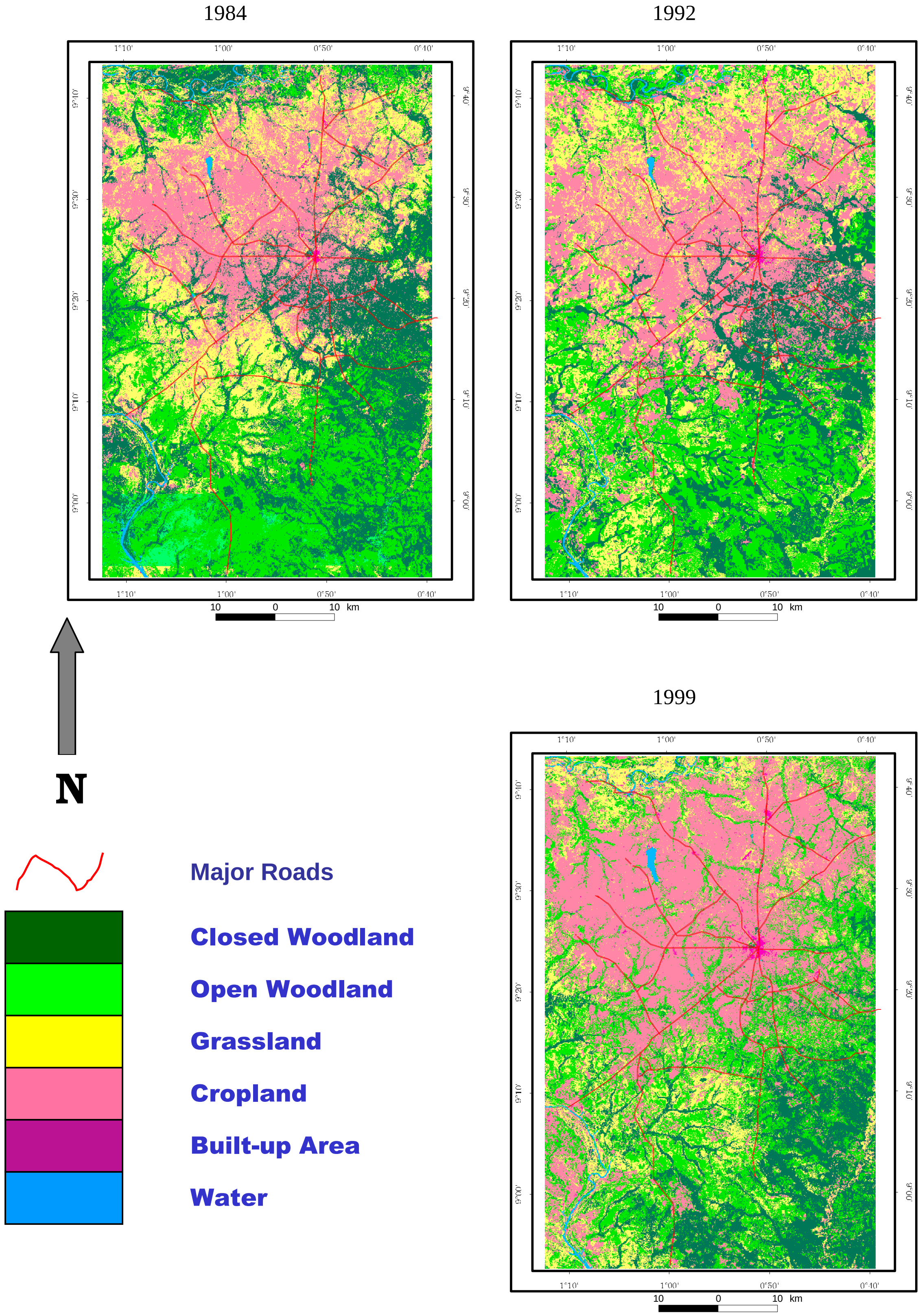


Figure 5.3: Land-cover maps of the study area

The contingency matrix (Table 5.2a-c) shows the accuracy of the classification results. It is derived by comparing the location and class of each ground truth pixel (columns) with the corresponding location and class in the classified image (rows). Each column of the contingency matrix represents a ground truth class, which defines the true class of the pixels. The values in the column correspond to the amount of pixels of that class which the maximum likelihood algorithm classifies to various classes. For instance, in Table 5.2a, out of the 58 Closed woodland pixels, 42 were correctly classified, whereas the remaining 16 were misclassified as Open woodland. The main diagonal elements in Table 5.2 represent correct classifications, whereas the off-diagonal elements represent misclassifications or errors. Overall classification accuracies (sum of diagonal elements divided by grand total, expressed as percent) were 85%, 81% and 88%, respectively for 1984, 1992 and 1999.

Table 5.2: Contingency matrices for supervised maximum likelihood classifications

a) 1984

		Ground truth						
		Closed woodland	Open woodland	Grassland	Cropland	Built-up area	Water	**Total**
Classification	Closed woodland	42	8	2				**52**
	Open woodland	16	75	10	2			**103**
	Grassland			57	13			**70**
	Cropland				36	2		**38**
	Built-up area				2	35		**37**
	Water						12	**12**
Total		**58**	**83**	**69**	**53**	**37**	**12**	**312**

Overall classification accuracy 85%

b) 1992

		Ground truth						
		Closed woodland	Open woodland	Grassland	Cropland	Built-up area	Water	**Total**
Classification	Closed woodland	43	10					**53**
	Open woodland	7	67	12				**86**
	Grassland	8	6	51	3			**68**
	Cropland			6	46	3		**55**
	Built-up area				4	34		**38**
	Water						12	**12**
	Total	**58**	**83**	**69**	**53**	**37**	**12**	**312**

Overall classification accuracy 81%

c) 1999

		Ground truth						
		Closed woodland	Open woodland	Grassland	Cropland	Built-up area	Water	**Total**
Classification	Closed woodland	51	9	1				**61**
	Open woodland	7	67	7				**81**
	Grassland		7	60				**67**
	Cropland			1	51	5		**57**
	Built-up area				2	32		**34**
	Water						12	**12**
	Total	**58**	**83**	**69**	**53**	**37**	**12**	**312**

Overall classification accuracy 88%

Apart from overall classification accuracy, which indicates the probability that a given pixel was correctly classified, other measures that indicate the level of accuracy of individual land-cover classes exist (Jensen 1986; Story and Congalton, 1986). The producer accuracy, P_a (Table 5.2 d) is obtained by dividing the number of correctly classified pixels by its column total. It is important for producers of spatial data, as it measures the probability that a reference sample (ground truth data) was correctly classified. That is, it indicates how accurate a given area in the landscape can be mapped. The lowest value of 68% was obtained for cropland in 1984. Such a low level of correspondence between mapped and reference data may be due to the time difference between data acquisition and reference data. This is confirmed by higher values of producer accuracy for more recent data for cropland in 1992 (87%) and 1999 (96%). P_a is also related to the error of omission, E_o (i.e., percent of pixels left out of class) as $E_o = 100 - P_a$. The error of omission was highest for Cropland in 1984 (32%), Closed woodland and Grassland in 1992 (26%) and Open woodland in 1999 (19%).

Table 5.2d: Producer's accuracy (%)

	1984	1992	1999
Closed woodland	72	74	88
Open woodland	90	81	81
Grassland	83	74	87
Cropland	68	87	96
Built-up Area	95	92	86
Water	100	100	100

The user's accuracy, U_a (Table 5.2 e) is obtained by dividing the number of correctly classified pixels by its row total. It indicates the probability that a pixel from the land-cover map actually matches what it is from the ground truth data. It therefore represents the level of confidence that map users can place on the map. The values of U_a are fairly high (73-100%), indicating that users can place a reasonably high confidence in the maps. The relationship between U_a and error of commission, E_c (the percent of extra pixels in a class) is given as $E_c = 100 - U_a$. Highest E_c was obtained for open woodland in 1984 (27%), grassland in 1992 (25%) and open woodland in 1999 (17%). This may be due to the similarity of open woodland and grassland in the spectral space as reflected by a transformed divergence vale of 1.82 (Table 5.1).

Table 5.2e: User's accuracy (%)

	1984	1992	1999
Closed woodland	81	81	84
Open woodland	73	78	83
Grassland	81	75	90
Cropland	95	84	89
Built-up Area	95	89	94
Water	100	100	100

5.1 Changes in land-cover

Land-cover statistics (Figure 5.4) show that the landscape was predominantly natural vegetation (Woodland and Grassland) in 1984. After 15 years in 1999, these land covers decreased from 76% to 59%. The proportion of cropland increased from 23% in 1984 to nearly 40% in 1999. Closed woodland declined progressively from 28% in 1984 to 18% in 1999. Figure 5.5 shows that the annual rate of decrease was higher (more than 3%) in the first period (1984-1992) compared to 2%, in 1992-1999. Open woodland increased slightly from 25% in 1984 to 27% in 1999. The rate of increase was fairly constant during the two periods (<1%), and is associated with natural/secondary regrowth. Grassland experienced the highest absolute annual change (decrease of about 5%) in the second period, whereas cropland had the highest annual absolute change in the first period (more than 4% increase).

Built-up area increased gradually from 0.5% in 1984 to 0.6% 1999. The increase was most likely due to population growth. Built-up area consistently had the lowest land-cover proportion over the 15 years covered by the images. Water decreased by 0.2% in 1984-1992 but increased by about 1% in 1992-1999. Field visits revealed that erosion from catchment areas caused siltation of the Bontanga reservoir, resulting in loss of depth of Bontanga dam. This probably led to increase in water submergence surface area of the reservoir, explaining the 1% increase.

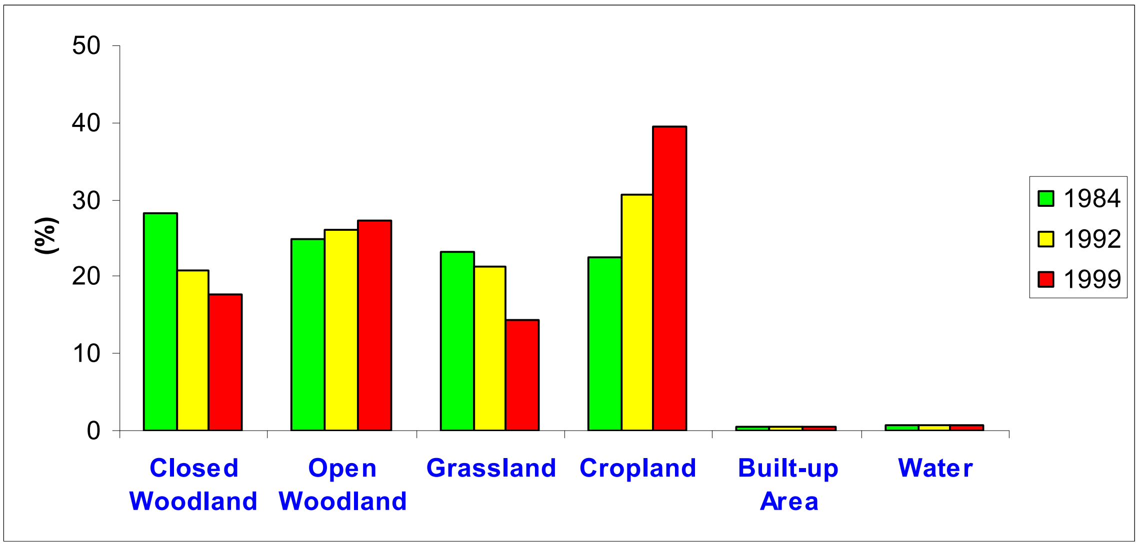


Figure 5.4: Land-cover proportions for 1984, 1992 and 1999

Changes in land-cover proportions were unidirectional for all land-covers except water (Figure 5.5). With the exception of closed woodland and cropland, the absolute annual rates of change were lower during the first period for the other land-covers. Thus, most of the land-cover change processes occurred in the second period. The overall annual rate of change in land-cover (1984-1999) was highest for cultivated land (5%) and lowest for water (0.3%).

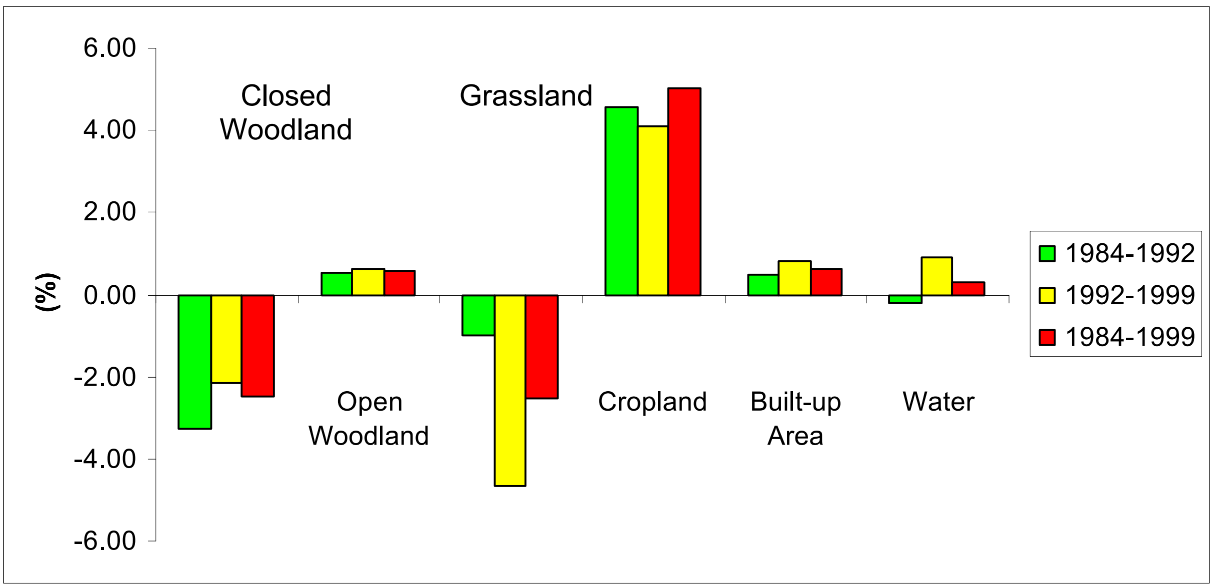


Figure 5.5: Annual rates of land-cover change

Land-cover change matrices are given in Table 5.3. About 45% of the land did not experience a change between 1984 and 1992, whereas between 1992 and 1999, the proportion was about 42% (sum of diagonal elements in Tables 5.3a and 5.3b respectively). For the two periods, the proportion of unchanged cropland was the highest (14% between 1984 and 1992, and 22% between 1992 and 1999). This suggests that some farmland areas had been continuously cultivated for between 7 to 8 years.

A transition of about 8% from Closed woodland to Open woodland occurred during the two periods, whereas transition from closed woodland to grassland was 4% and 2%, respectively, in both periods. Charcoal burning and firewood collection for domestic and commercial purposes are the processes commonly associated with these changes. Between 1984 and 1992, the transition of natural vegetation to cropland was in the order grassland (9%) > closed woodland (5%) > open woodland (3%). Between 1992 and 1999, the transition of natural vegetation to cropland was in the order grassland (10%) > open woodland (4.2%) > closed woodland (4%). These processes are related to increases in demand for food, while the preference for converting grassland to agriculture may reflect the relative ease of clearing grassland compared to woodland. The transition from cropland to natural vegetation was in the order grassland (6%) > closed woodland (2%) > open woodland (1%) in the first period, whereas in the second period the transition was in the order open woodland (6%) > grassland (3%) > closed woodland (1%). These processes are related to fallow and land abandonment. Table 5.3c shows that between 1984 and 1999, the proportion of unchanged land was about 39%. The overall transition of open woodland to closed woodland was about 8%, whereas the overall transition of grassland to cropland was about 12%.

Table 5.3: Land-cover change matrix (%)

a) 1984-1992

		From 1984					
		Closed woodland	Open woodland	Grassland	Cropland	Built-up area	Water
To 1992	Closed woodland	11.28	5.53	2.12	1.73	0.04	0.13
	Open woodland	7.49	12.22	4.79	1.36	0.05	0.11
	Grassland	3.75	4.50	7.12	5.69	0.13	0.09
	Cropland	5.45	2.68	8.85	13.51	0.17	0.07
	Built-up area	0.04	0.04	0.16	0.16	0.13	0.00
	Water	0.18	0.04	0.12	0.05	0.00	0.22

b) 1992-1999

		From 1992					
		Closed woodland	Open woodland	Grassland	Cropland	Built-up area	Water
To 1999	Closed woodland	7.25	7.68	1.85	0.86	0.02	0.03
	Open woodland	7.56	8.48	5.33	5.70	0.06	0.07
	Grassland	1.86	5.54	4.18	2.64	0.05	0.11
	Cropland	4.01	4.21	9.71	21.25	0.28	0.05
	Built-up area	0.05	0.04	0.13	0.21	0.13	0.01
	Water	0.09	0.06	0.08	0.07	0.00	0.35

c) 1984-1999

		From 1984					
		Closed woodland	Open woodland	Grassland	Cropland	Built-up area	Water
To 1999	Closed woodland	8.10	8.38	0.86	0.29	0.02	0.04
	Open woodland	10.60	7.54	5.98	2.93	0.07	0.08
	Grassland	3.05	5.50	4.52	1.10	0.06	0.14
	Cropland	6.21	3.52	11.54	17.90	0.26	0.08
	Built-up area	0.07	0.03	0.17	0.19	0.11	0.01
	Water	0.17	0.04	0.09	0.08	0.00	0.28

Table 5.4a shows that the transition to less vegetation was higher (16%) than the transition to more vegetation (12%) in the first period. However, in the second period (Table 5.4b), both transitions balanced each other (15%). Overall transition to more vegetation was 4% lower than overall transition to more vegetation (Table 5.4c). For each period, the increase in proportion of cropland (8% for the first period and 9% for the second period; Figure 5.4) was lower than the respective transition to more vegetation. This suggests that even though population density increased, farmers tended to create a bush fallow system to maintain a certain level of soil fertility. Overall increase in Cropland of 17% between 1984 and 1999 clearly indicates that pressure on land increased, as this was 2% higher than overall transition to more vegetation.

Table 5.4: Analyses of transitions among natural vegetation

a) 1984-1992

Transition to less vegetation (%)		**Transition to more vegetation (%)**	
Closed woodland to Open woodland	7.49	Open woodland to Closed woodland	5.53
Closed woodland to grassland	3.75	Grassland to Closed woodland	2.12
Open woodland to grassland	4.50	Grassland to Open woodland	4.79
Total	**15.74**	**Total**	**12.44**

b) 1992-1999

Transition to less vegetation (%)		**Transition to more vegetation (%)**	
Closed woodland to Open woodland	7.56	Open woodland to Closed woodland	7.68
Closed woodland to grassland	1.86	Grassland to Closed woodland	1.85
Open woodland to grassland	5.54	Grassland to Open woodland	5.33
Total	**14.96**	**Total**	**14.86**

c) 1984-1999

Transition to less vegetation (%)		**Transition to more vegetation (%)**	
Closed woodland to Open woodland	10.60	Open woodland to Closed woodland	8.38
Closed woodland to grassland	3.05	Grassland to Closed woodland	0.86
Open woodland to grassland	5.50	Grassland to Open woodland	5.98
Total	**19.15**	**Total**	**15.22**

Figure 5.6a reveals marked spatio-temporal patterns in land-cover change. Between 1984 and 1992, change to Closed and Open woodlands occurred mostly in the southern part, where population density was lowest. Patches of conversion to cropland are widespread around Tamale. From 1992-1999, there was a spatial development of cropland patches around the Bontanga irrigation project. Large tracts of land were also converted to cropland around the White Volta River in the southwest of the image, and Wuripe (bottom center). Most of the change to open woodland occurred to the east of Tamale. In the first period, most of the area experienced conversion to cropland.

Most of the unchanged areas around Tamale in both periods correspond to areas where continuous cultivation was carried out, whereas most of the unchanged areas in the southern part of the images correspond to natural vegetation. Expansion of built-up area shows a pattern of diffusion mostly from the center of Tamale, and to a lesser extent from the center of Savelugu. The land-cover change map for 1984-1999 gives an overall picture of the patterns of change. Unchanged areas corresponding to permanent cropland are found around Bontanga and Tamale. Change to natural vegetation occurred in association with conversion to cropland in many parts of the landscape.

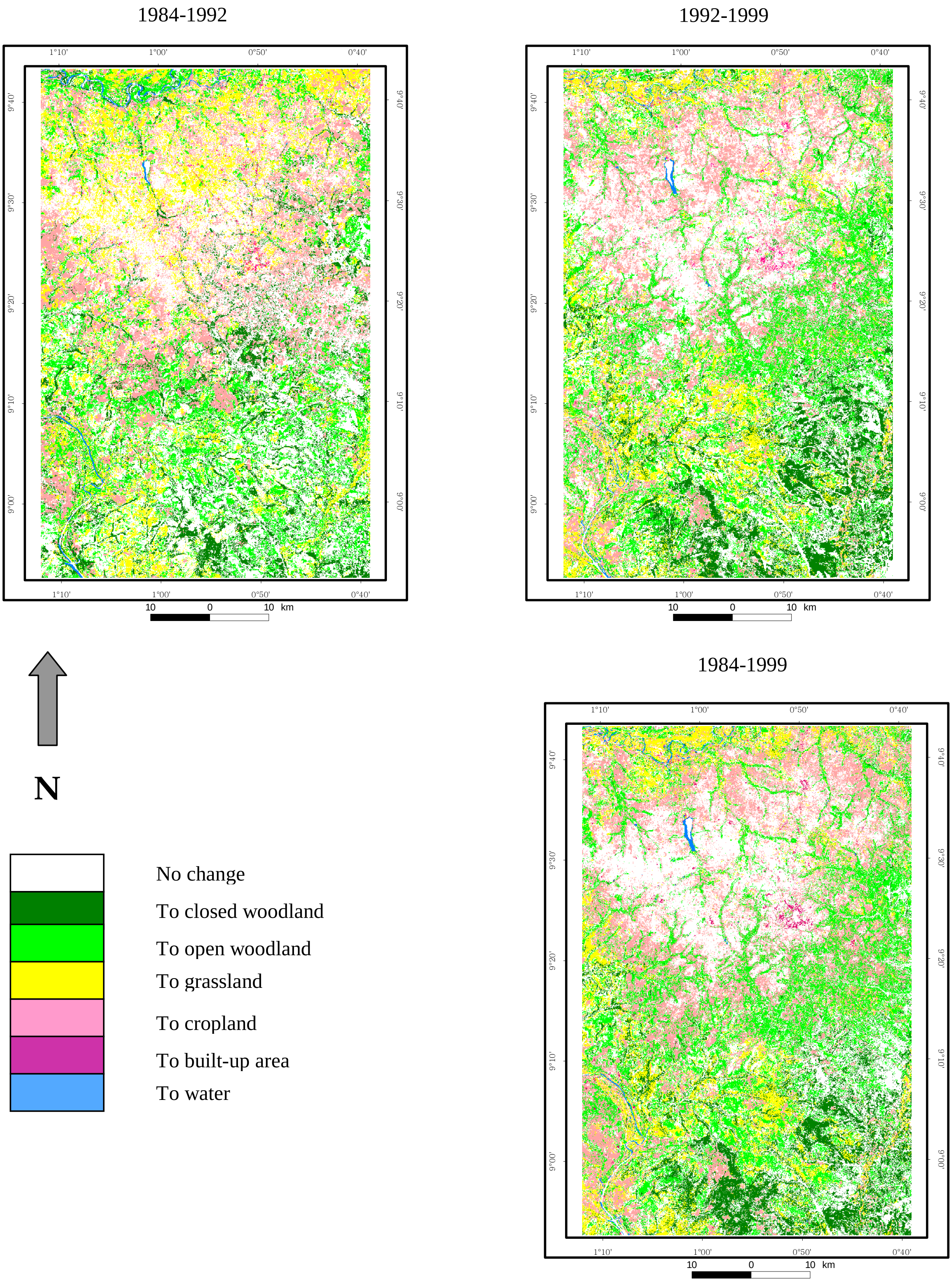


Figure 5.6a: Land-cover change maps with “to” identifiers

Land-cover change trajectories

Sequential changes in land-cover from 1984-1999 are in Table 5.5 and Figure 5.6b. Given the fact that 6 land-cover classes were discriminated in the 3 observation years, potential number of trajectories is $6^3 = 108$. Merging woodland and grassland into a single class (natural vegetation) markedly reduced the number of trajectories. This is quite reasonable, as most of the transitions concerned conversion of natural vegetation to cropland. However, the description of the trajectories in table 5.5 only has meaning with respect to the timing of observation by the satellite. For instance transition from natural vegetation to cropland (sequence 2) could have occurred anytime between 1992 and 1999.

Between 1984 and 1992, more than 9% of the natural vegetation was permanently transformed to cropland (sequence 4) compared to about 12% of the natural vegetation having been converted to cropland between 1992 and 1999. The same amount of land was permanently occupied by cropland between 1984 and 1999. Three sequences (3, 5 and 7) associated with fallow agriculture occupy over 15% of the study area. About 3% of the landscape that was cropland in 1984 was abandoned. This may be due to loss in soil fertility.

Table 5.5: Trajectories of land-cover change

Sequence	Land-cover in 1984	1992	1999	Description	Proportion of land (%)
1	Natural vegetation	Natural vegetation	Natural vegetation	Non-cultivated	46.91 [a]
2	Natural vegetation	Natural vegetation	Cropland	Recent cropland	11.65
3	Natural vegetation	Cropland	Natural vegetation	Recent crop-fallow cycle	7.38
4	Natural vegetation	Cropland	Cropland	Old cropland	9.47
5	Cropland	Natural vegetation	Cropland	Crop-fallow cycle	6.13
6	Cropland	Natural vegetation	Natural vegetation	Abandoned cropland	2.54
7	Cropland	Cropland	Natural vegetation	Recent fallow	1.74
8	Cropland	Cropland	Cropland	Permanently cultivated land	11.65
9		Others [b]			2.53

[a] See table 5.6; [b] This refers to all trajectories involving water and built-up areas

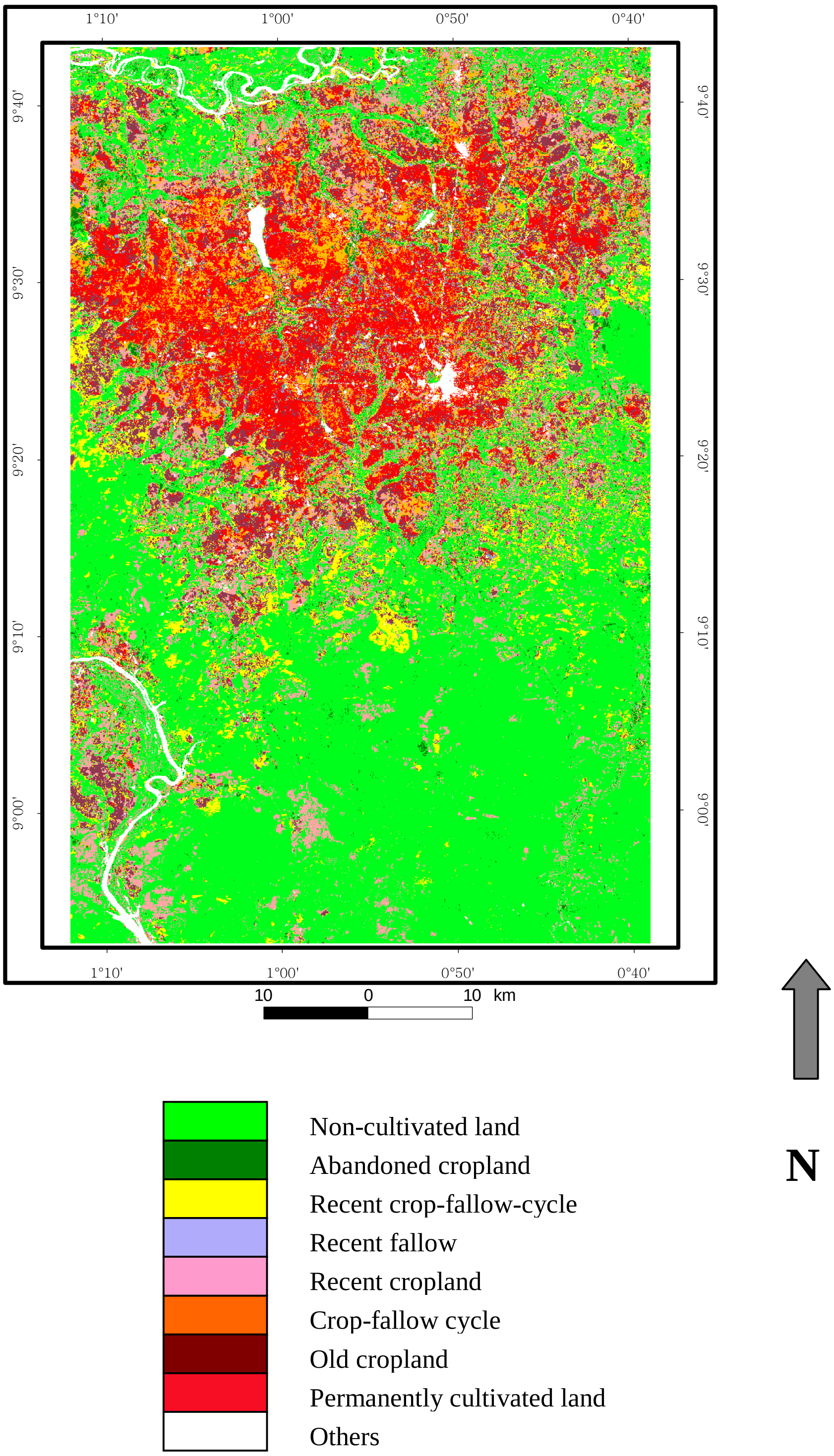


Figure 5.6b: Land-cover change trajectories 1984-1992-1999

Detailed trajectories for sequence 1 are shown in Table 5.6. Over 28% of the landscape occupied by woodland and grassland (sequences 1 and 8) did not experience change in land-cover class. An early accumulation of woody biomass occurred in more than 3% of the landscape (sequence 5) compared to an early decrease in woody biomass in 2% (sequence 4).

Table 5.6: Detailed trajectories showing modification of natural vegetation

Sequence	Land-cover in 1984	1992	1999	Description	Proportion of land area (%)
1	Woodland	Woodland	Woodland	Non-change woodland	26.65
2	Woodland	Woodland	Grassland	Recent conversion to grassland	5.23
3	Woodland	Grassland	Woodland	Reversible change in woodland	4.31
4	Woodland	Grassland	Grassland	Early conversion to grassland	2.19
5	Grassland	Woodland	Woodland	Early conversion to woodland	3.12
6	Grassland	Grassland	Woodland	Recent conversion to woodland	2.06
7	Grassland	Woodland	Grassland	Reversible change in grassland	1.78
8	Grassland	Grassland	Grassland	Non-change grassland	1.57

The recent increase in woody biomass on 2% of the land (sequence 6) is lower than the recent decrease in woody biomass over more than 5% (sequence 2). Reversible change in woodland (more than 4% of the landscape) as well as recent accumulation of woody biomass indicates the phenomenon of resilience. A resilient ecosystem is one that is able to resist external shock and reverse to its former state. Recovery of vegetation in drylands is usually associated with high precipitation in areas with relatively low population density. Between 1984 and 1999, the annual rainfall for 9 out of the 16 years was higher than the long-term (30-year) average of 1083mm (Figure 3.1a). This may have stimulated such a turnaround in vegetation growth. Reversible change in grassland (about 2% of the landscape; sequence 7) may be related to frequent woodcutting and charcoal burning as an alternative source of livelihood in the post-structural adjustment period. The overall decrease in woodland consisting of sequences 2, 4 and 7 (9%) was more than compensated by an overall gain of about 10% (sequences 3, 5 and 6). This is again a measure of resilience in the environment.

5.1 Soil characteristics

Table 5.7 shows that the soils are generally silty to sandy in texture, probably due to the effects of wind deposition in the study area (Abekoe and Tiessen, 1998). The low contents of organic matter and clay resulting in poor soil structure may explain why the soils are very prone to erosion. Table 5.7 also reveals that the soils are generally slightly acidic and highly deficient in C, N and P. The dominant exchangeable cation is Ca, with fairly high base saturation (60-99%). The effective CEC is quite low (mean = 4.42 cmol kg^{-1}), a phenomenon related to the clay mineralogy (i.e., kaolinitic 1:1 minerals) of the soils (Nye and Stephens, 1962). The coefficients of variation indicate that soil hue and elevation are the least variable physical properties (CV = 13%), whereas the highest variation in physical properties was recorded for slope (CV = 66%). Coefficients of variation among soil chemical properties range from 0% for base saturation to 112% for exchangeable acidity.

Table 5.7: Descriptive statistics for the soils (N=120)

	Minimum	Mean	Maximum	Std. Dev	cv (%)
pH	4.20	5.16	6.30	0.47	9
Organic Carbon (%)	0.50	1.22	2.38	0.39	32
Total N (%)	0.00	0.06	0.28	0.04	65
Available P (ppm)	1.50	7.68	34.06	4.64	60
K (cmol kg^{-1})	0.04	0.22	1.36	0.22	99
Ca (cmol kg^{-1})	0.21	3.05	14.45	2.18	72
Mg (cmol kg^{-1})	0.07	1.03	3.87	0.66	64
EA [a] (cmol kg^{-1})	0.01	0.11	0.71	0.12	112
ECEC [a] (cmol kg^{-1})	0.84	4.42	17.02	2.74	19
Base Saturation (%)	60	96	99	0.05	0
Hue [b]	2.00	3.89	5.00	0.50	13
Value	3.00	5.25	7.00	1.17	22
Chroma	1.00	3.41	6.00	1.24	36
Sand (%)	13.1	53.1	89.1	13.6	26
Silt (%)	8.8	39.8	83.8	12.5	31
Clay (%)	0.7	7.1	23.6	4.4	62
Slope (%)	2	7.0	20	4.7	66
Elevation (m)	119	164	234	21	13
Drainage [c]	1	1.62	3	0.68	42

[a] ECEC= Effective cation exchange capacity derived by summing exchangeable cations (K, Ca, Mg) and exchangeable acidity (EA)
[b] Soil color is often described by the hue, value and chroma components of Munsell color chart (Munsell Color Company, 2000). Many soil quality parameters can be inferred from soil colour. The hue notation is the dominant spectral color and is indicated by characters R, Y, G, B, P representing Red, Yellow, Green, Blue and Purple, respectively. Value represents the lightness of color, and is represented numerically from 0 to 10. Chroma represents the degree of purity of the color, and it takes value from 0 to 20. In this study, soil hues were coded as 2.5YR=1; 5YR=2; 7.5YR=3; 10YR=4 and 2.5Y=5.
[c] Drainage as an ordinal variable was coded as Well-drained = 1; Imperfectly drained = 2 and Poorly drained = 3

Table 5.8 shows that permanently cultivated soils have the reddest hue (mean = 3.95), the highest value (lightness of color) (mean = 5.59) and the highest chroma (strength of color) (mean = 4.05). Among these soil color variables, chroma is significantly different between non-cultivated and permanently cultivated soils ($p<0.01$) (table 6). They also significantly differ in terms of drainage. The fact that permanently cultivated soils are better drained than soils under natural vegetation reflects the preference of farmers for well-drained soils, as poorly drained areas have a history of high prevalence of Onchocerciasis (river blindness) disease.

Permanently cultivated soils are on the lowest slopes (mean slope = 6.9%), whereas soils recently converted to agriculture have a slightly higher slope (mean = 7.0%); the differences, however, are not significant. Elevation is significantly different

($p<0.05$) between recently cultivated and permanently cultivated soils (table 5.9). This can be explained by the settlement pattern and population dynamics (Abudulai, 1996). Population and therefore agriculture is largely concentrated around Tamale, which is at a relatively higher elevation (350 m) compared to other localities. Decline in soil fertility, however, has forced farmers to move to previously uncultivated areas.

Permanently cultivated soils have the highest sand content (mean = 59.5%), whereas non-cultivated soils have the highest silt (mean = 41.3%) and clay (mean = 7.8%) contents. The differences between sand, silt and clay contents of non-cultivated and permanently cultivated soils were significant ($p<0.05$; Table 5.9). Permanently cultivated soils had the lowest values of exchangeable bases K, Ca, Mg (Table 5.8). Mean exchangeable K was not significantly different among the land-cover categories (Table 5.9), but there were significant higher contents of Mg, Ca and effective CEC in non-cultivated compared to permanently cultivated soils on the one hand, and soils recently converted to agriculture compared to permanently cultivated soils on the other. This supports the work of Kosmas et al (2000) who noted a deterioration of soil fertility under continuous cropping as well as lower contents of exchangeable bases and CEC compared to soils under natural vegetation.

Table 5.8: Statistics for soils of the land-cover change categories

	Non-cultivated land n = 68		**Recent conversion to agriculture n = 30**		**Permanently cultivated n = 22**	
	Mean	**Sd**	**Mean**	**Sd**	**Mean**	**Sd**
Drainage	1.71	0.69	1.60	0.62	1.36	0.66
Slope (%)	7.0	4.6	7.1	4.4	6.9	5.5
Elevation (m)	164	20	158	22	171	22
Hue	3.87	0.54	3.90	0.31	3.95	0.58
Value	5.09	1.22	5.37	1.13	5.59	1.01
Chroma	3.15	1.18	3.53	1.22	4.05	1.25
Sand (%)	50.9	13.1	53.3	14.0	59.5	13.1
Silt (%)	41.3	12.2	39.9	13.4	35.1	11.6
Clay (%)	7.8	4.7	6.9	4.3	5.4	3.1
pH	5.19	0.51	5.21	0.38	5.01	0.47
Exchangeable acidity (cmol kg^{-1})	0.12	0.14	0.09	0.08	0.11	0.10
K (cmol kg^{-1})	0.22	0.18	0.25	0.29	0.19	0.24
Mg (cmol kg^{-1})	1.10	0.68	1.09	0.71	0.73	0.43
Ca (cmol kg^{-1})	3.23	2.28	3.33	2.43	2.14	1.11
ECEC (cmol kg^{-1})	4.67	2.79	4.76	3.08	3.17	1.57
Base saturation	96	6	98	1	96	4
N (%)	0.06	0.03	0.06	0.05	0.04	0.04
Available P (ppm)	8.42	5.52	7.18	3.45	6.06	1.89
Organic carbon (%)	1.27	0.39	1.28	0.44	1.00	0.23

Permanently cultivated soils are slightly more acidic (mean pH = 5.0) than other land-cover categories (Table 5.8), suggesting deterioration (decrease) in this soil quality parameter as cultivation persists. No significant differences were however observed in pH and exchangeable acidity among the land-cover categories (Table 5.9a).

The average total N of recently cultivated and non-cultivated soils was the same (mean =0.06%) and slightly higher than of soils under permanent cultivation (mean = 0.04%); ($p<0.05$). Organic C content for non-cultivated soils and soils recently converted to agriculture was also found to be similar and significantly higher than that of permanently cultivated soils ($p<0.01$).

Table 5.9a: LSD test for soil properties

Physical properties				**Chemical Properties**			
Soil Properties	Land-cover change categories [a]		Mean Difference [b]	Soil Properties	Land-cover change categories [a]		Mean Difference [b]
Hue							NS
	1	2	NS	pH	1	2	
	1	3	NS		1	3	NS
	2	3	NS		2	3	NS
Value							NS
	1	2	NS	Organic C	1	2	
	1	3	NS		1	3	**
	2	3	NS		2	3	**
Chroma							
	1	2	NS	N	1	2	NS
	1	3	**		1	3	*
	2	3	NS		2	3	*
Sand							
	1	2	NS	P	1	2	NS
	1	3	**		1	3	*
	2	3	NS		2	3	NS
Silt							NS
	1	2	NS	K	1	2	
	1	3	*		1	3	NS
	2	3	NS		2	3	NS
Clay							NS
	1	2	NS	Ca	1	2	
	1	3	*		1	3	*
	2	3	NS		2	3	*
Slope			NS				
	1	2		Mg	1	2	NS
	1	3	NS		1	3	*
	2	3	NS		2	3	*
Elevation			NS				NS
	1	2		EA	1	2	
	1	3	NS		1	3	NS
	2	3	*		2	3	NS
Drainage							NS
	1	2	NS	ECEC	1	2	
	1	3	*		1	3	*
	2	3	NS		2	3	*
				Base Saturation	1	2	NS
					1	3	NS
					2	3	NS

[a] 1=Non-cultivated soils, 2= Recently cultivated soils and 3= Permanently cultivated soils
b NS= Not significant; * Significant at $p<0.05$, ** Significant at $p<0.01$

Properties that were significantly different between land-cover categories are presented in Table 5.9b. There were no significant differences between properties of non-cultivated soils and soils put under cultivation after 1992. The soils recently opened up for cultivation were found to have significantly higher contents of organic C, N, Ca, Mg, and ECEC than those under permanent cultivation. There were, however, no significant differences in physical properties, suggesting that soil physical properties are more stable (i.e., less prone to changes due to changes in land-cover) than chemical properties. Furthermore, permanently cultivated soils were found to exhibit a significantly lower status in physical and chemical soil properties compared to non-cultivated soils. This suggests that continuous cropping is primarily responsible for deterioration in soil quality in the study area.

Table 5.9b: Soil properties that were statistically different between land-cover change categories

Non-cultivated (1) versus permanently cultivated (3)	**Recently cultivated (2) versus permanently cultivated (3)**
Drainage	Organic C
Sand	N
Silt	Ca
Clay	Mg
Chroma	ECEC
Organic C	Elevation
N	
P	
Ca	
Mg	
ECEC	

5.2 Land suitability indices

Based on the above ANOVA, the literature (Sys 1985, Fugger 1999) and opinion of researchers at the Savannah Agricultural Research Institutes (SARI) in Tamale, six properties (land characteristics) were selected for computing the agricultural land suitability index, *LI*. The land characteristics and their rankings in order of importance (1 = least important, 6 = most important) are shown in table 5.10a.

Table 5.10a: Ranking of land characteristics

Land characteristics	Rank	Justification
Organic C	6	Soil organic matter is crucial to the supply of N and cations. Soil organic C shows significant correlations with N, P, K, Ca, Mg, Clay, ECEC, Base Saturation and pH. Analysis of variance also shows that organic C contents of cultivated and virgin lands are highly significant at $p<0.01$(table 5.9a). Soil organic matter also helps to improve the water holding capacity of the soils. Fugger (1999) also showed that low SOM mineralization was the main cause of low maize yield, an important cereal in the study area.
ECEC	5	Cation exchange capacity determines the nutrient holding capacity of the soil. It was rated next to organic C, as most of the ECEC are contributed by organic colloids (Fugger, 1999).
Drainage	4	Drainage influences air and water regimes of the soil. Good drainage leads to deeper rooting of crops, whereas water logging may reduce the uptake of cations. Drainage problems are usually encountered in Northern Ghana due to excess water in the rainy season. Thus, drainage was rated higher than other physical land characteristics.
pH	3	Nutrient availability in the soils is strongly dependent on pH. For instance, an increase in pH through liming may lead to an increase in CEC. Only about 11% (13 out of 120 samples) of the soils have pH below 4.5, whereas the remaining 89% have pH ranging from 4.5 to 6.3. Thus, pH cannot be taken as a major constraint to crop production in the study area.
Clay	2	Owing to the sandy nature of the soils, clay content plays a crucial role in nutrient supply. Clay is significantly correlated ($p<0.05$) with organic C and N in the study area (section 5.8). This suggests that contents of organic C and N in the soils are clay-dependent. Clay is also important in moisture retention for crop growth.
Sand	1	Soils of the study area are coarse-textured soils with sand content > 80%, water-holding capacity and soil organic matter are usually low (Overseas Development Institute, 1999). Cultivation of such soils often leads to rapid soil degradation, as there is no sufficient organic matter to bind soil aggregates together.

Membership functions and parameters of the land characteristics are shown in table 5.10b. An asymmetric function I was used for pH, as the pH values range from 4.2-6.3 in the study area (table 5.7). Thus, the Lower Cross-over Point (LCP) was the most important in defining the membership function. Similarly, organic C and ECEC were fitted to the asymmetric function I model, as high amounts contribute positively to crop growth. The LCP was set at 0.8% and 2 cmol kg^{-1}, respectively (Sys, 1985). Asymmetric function II was applied to drainage, with the optimum drainage class set at

1. Thus, the Upper Cross-over Point (UCP) was the most crucial in fitting the membership function. The symmetric model was applied to Sand and Clay, as the optimum texture for maize ranges from clay loam to loam (Sys, 1985). Thus, both the UCP and LCP are crucial in fitting the membership functions. Other parameters for each function were derived using the respective models, whereas the weights are the normalized values of the rankings in table 5.10a.

Table 5.10b: Land characteristics and fuzzy membership model parameters.

Soil properties	**Model type**	**Membership function parameters**						**Weight**
		LCP	c	UCP	a	t_1	t_2	
PH	Asymmetric I (equation 8)	4.5	5.5	-	-	1.0	-	0.14
ECEC cmol kg^{-1}	Asymmetric I (equation 8)	2	16	-	-	14	-	0.23
Organic Carbon (%)	Asymmetric I (equation 8)	0.8	1.5	-	-	0.7	-	0.29
Sand (%)	Symmetric (equation 7)	20	40	60	0.0005	-	-	0.05
Clay (%)	Symmetric (equation 7)	15	25	35	0.01	-	-	0.10
Drainage	Asymmetric II (equation 9)	-	1	3	-	-	2	0.19

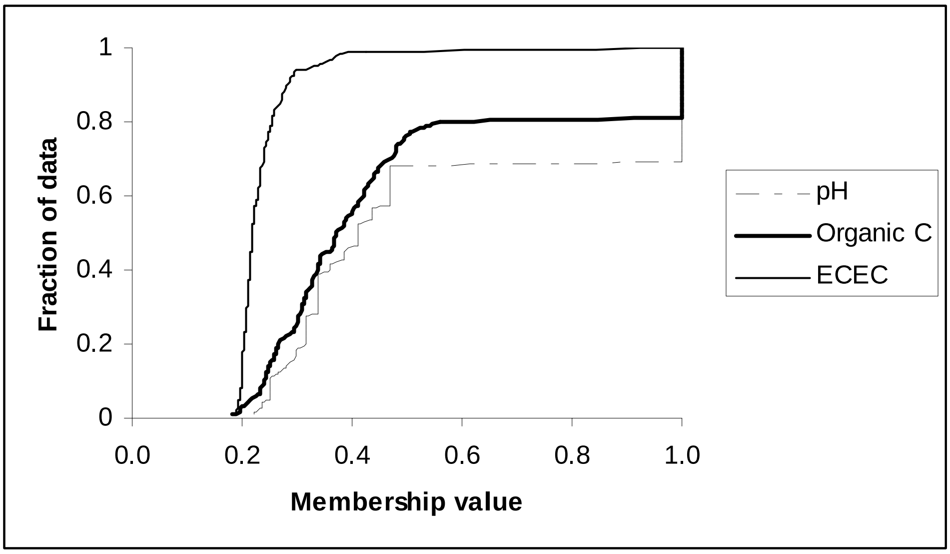
Statistics of membership values and land suitability index are presented in table 5.11. Membership value indicates degree of suitability at a given location with respect to a given land characteristic. For instance, a membership value of 0.4 for a land characteristic indicates that suitability of the location is 40% of the ideal requirement of the land characteristic. It also implies the location has a limitation of 60% with respect to the land characteristic. Average membership value for organic C was the lowest (0.24), while that of Sand was the highest (0.66). Membership value of organic C also has the lowest coefficient of variation (34%), whereas coefficients of variation of membership values for drainage and ECEC were the highest (57%).

Table 5.11: Statistics of membership values of land characteristics and *LI*

Statistics	μ_{pH}	μ_{ECEC}	$\mu_{OrganicC}$	μ_{Sand}	μ_{Clay}	$\mu_{Drainage}$	LI
Minimum	0.22	0.18	0.19	0.14	0.14	0.20	0.23
Mean	0.56	0.48	0.24	0.66	0.27	0.64	0.45
Maximum	1.00	1.00	1.00	1.00	1.00	1.00	0.89
Std. Dev	0.31	0.27	0.08	0.25	0.14	0.36	0.14
C.V. (%)	55	57	34	38	52	57	31

Cumulative distribution functions (cdfs) of membership values of land characteristics are shown in Figure 5.7.

a) Chemical properties



b) Physical properties

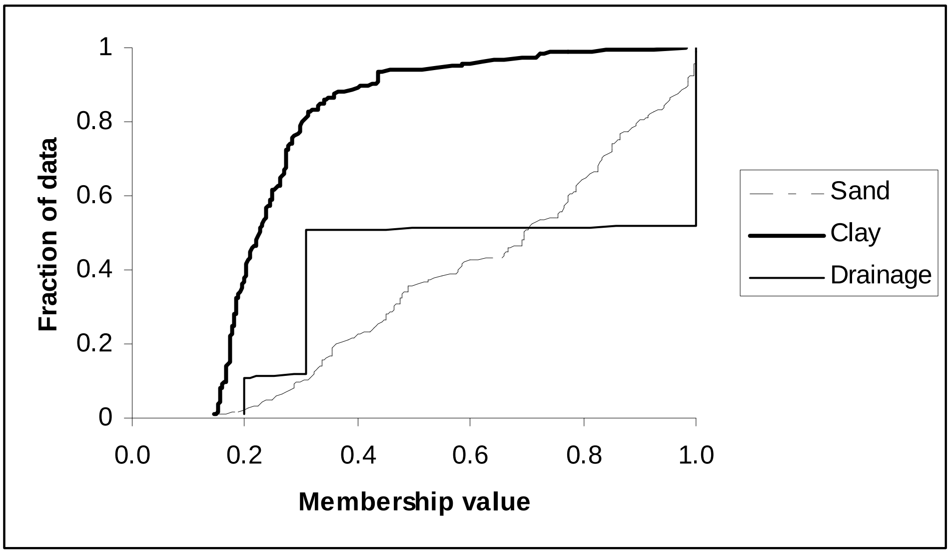


Figure 5.7: Cumulative distribution functions of membership values of land characteristics

The shapes and positions of the cdfs are different for the land characteristics. Sixty percent of the data had μ_{ECEC} < 0.23 (Figure 5.7a), indicating that ECEC limitation for agriculture was at most 77% for 60% of the data. Similarly, 60% of the data had μ_{pH} <

0.47 and $\mu_{OrganicC}$ < 0.42. Thus, for chemical properties, limitation for agriculture is in the order ECEC > Organic C > pH. For physical properties 60% of data had μ_{sand} < 0.78, μ_{clay} < 0.25 and $\mu_{drainage}$ < 1 (Figure 5.7b). Thus severity of limitation of physical properties for agriculture is in the order clay > sand > drainage. Table 5.11 indicates moderate variability in *LI* (CV=31%). Mean *LI* was 0.45, indicating that average land suitability for agriculture is 45% of ideal suitability. Figure 5.8 shows that 70% of the data is less than 50% of the ideal land suitability. Low values of *LI* reveal low intrinsic quality of the soil.

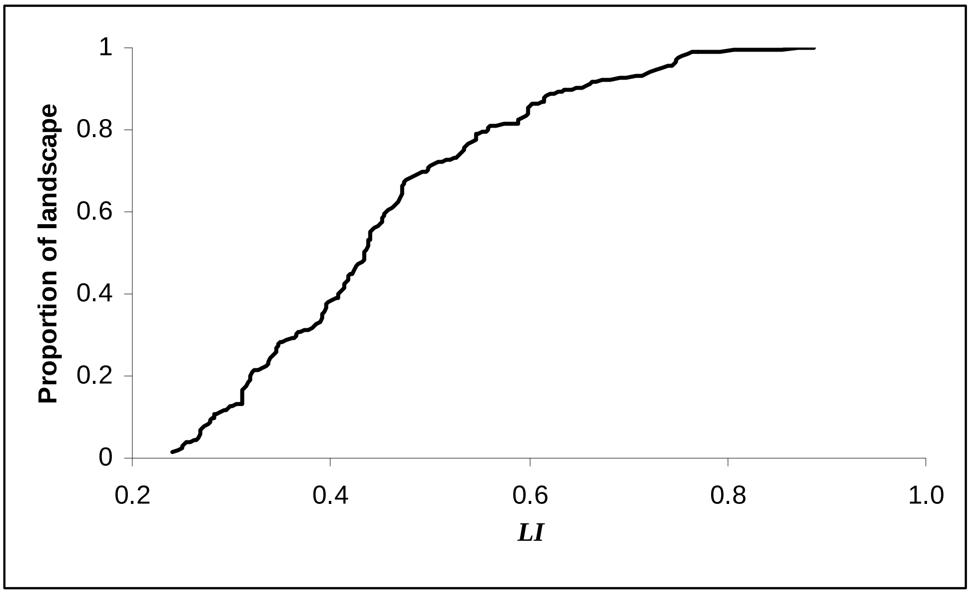


Figure 5.8: Cumulative density function of *LI*

The spatial variability in *LI* is indicated by a variogram (Figure 5.9). The fitted variogram is a linear model with a spatially uncorrelated variation (nugget variance) of 0.0137. The nugget variance accounts for about 64% of total variation. This suggests microvariability in *LI* that could not be detected at the scale of sampling. That is, there are large homogenous areas that are longer than the lags of the variogram. Future studies should consider reducing the sampling interval, as well as increasing the intensity of sampling to reduce random variation at small intervals and also account for short-scale variability in *LI*. The monotonically increasing section of the variogram represents the continuous (i.e., spatially dependent) component of the variation. The unbounded spatial dependence structure of *LI* suggests that the range (i.e., the distance beyond which there is no spatial correlation) is larger than the sampled area. This may be due to the fact that the area is predominantly characterized by a single geology (mainly sandstone).

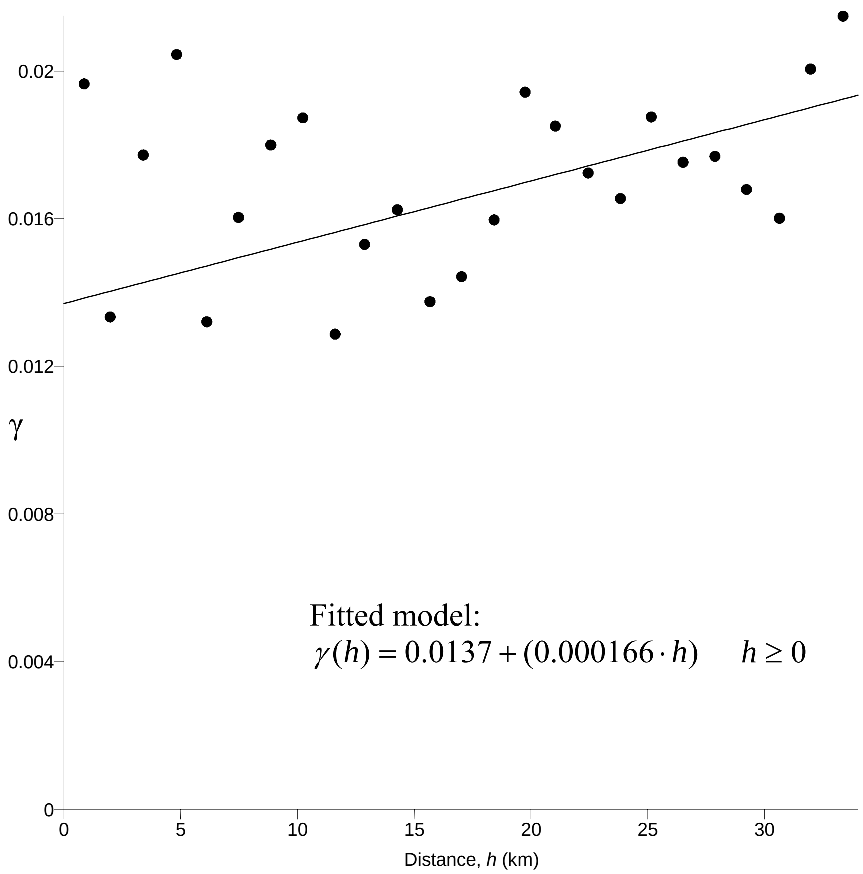


Figure 5.9: Variogram of *LI*

The spatial pattern of LI (Figure 5.10) shows that land suitability for agriculture generally increases from the north to the south of the landscape. It is apparent that this trend correlates with the amount of vegetation, as the spatial distribution of woodland is largest in the southern part of the study area. Land suitability is highest around Wuripe, an area recently opened up for agriculture by migrants. This suggests that soil quality is an important factor for migration.

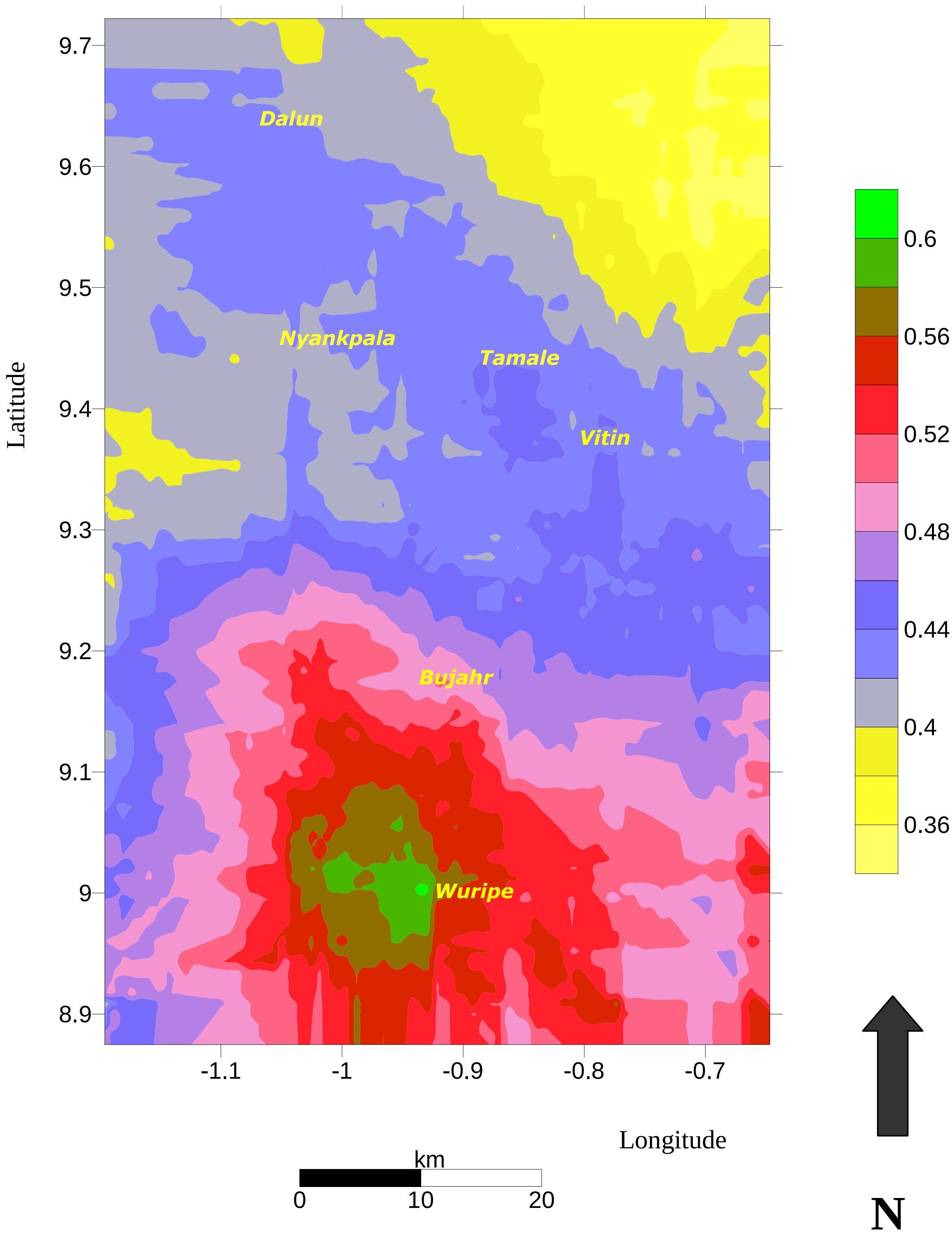


Figure 5.10: Land suitability index map using ordinary point kriging

5.5 Population density

Figure 5.11 shows that the population is largely concentrated around Tamale, the administrative capital of the Northern region. Tamale offers opportunities for domestic and international trade with neighboring West African countries in agricultural and non-agricultural products. It also offers non-farm employment opportunities for people from smaller villages. There has been a general increase in population density across the region. The least densely populated areas had up to 73, 88 and 107 persons/km^2, respectively, in 1984, 1992 and 2000. The most densely populated areas had 655, 794 and 963 persons/km^2, respectively, in the same periods. Changes in population density are presented in figure 5.12. There was an increase in density for places around Tamale, whereas most places further south experienced a decline in population density. This was primarily due to migration to Tamale for non-farm employment (Abudulai, 1996). However, places around Wuripe experienced an increase in density. Wuripe is characterized by migration from neighboring localities for farming.

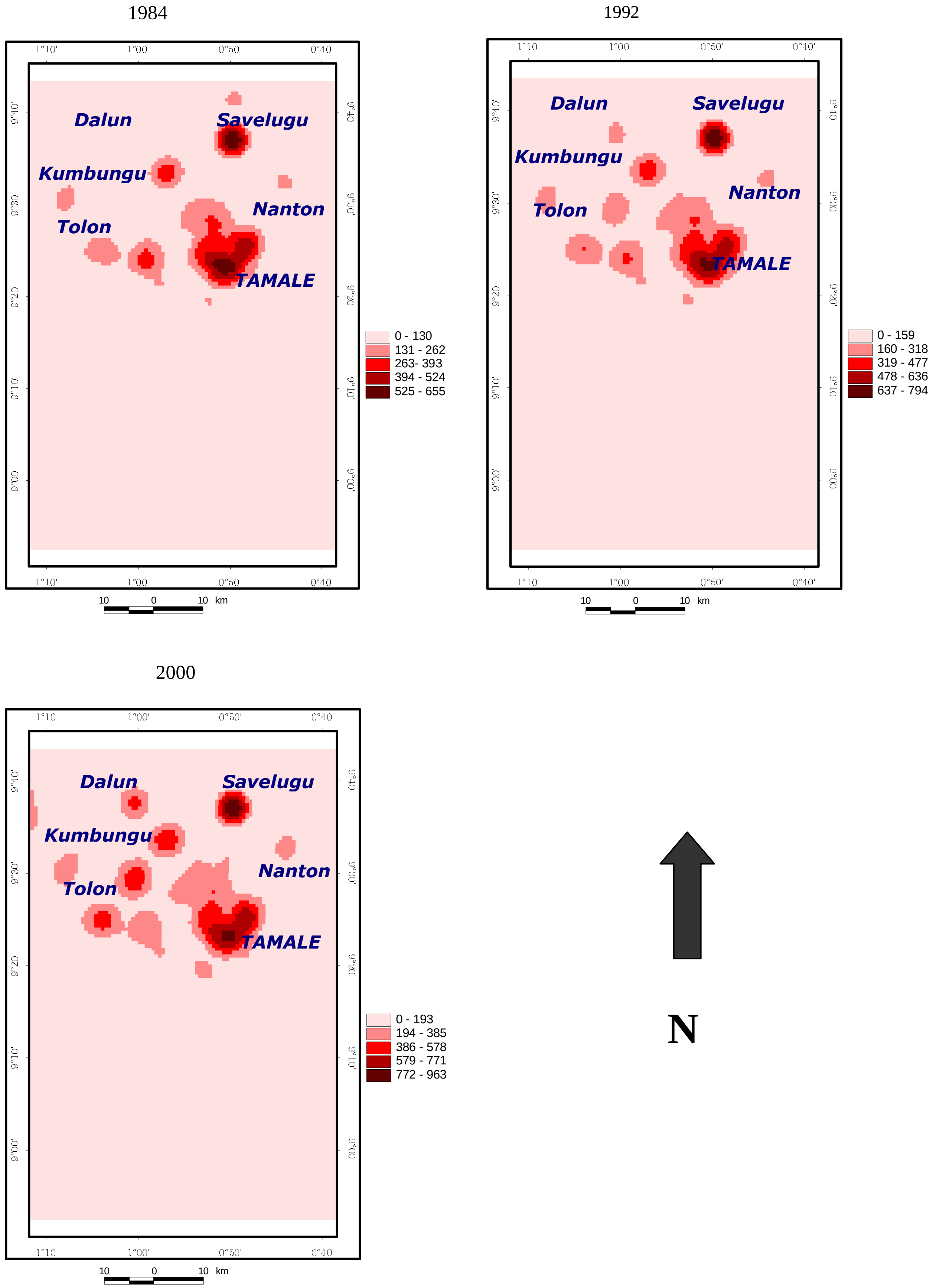


Figure 5.11: Population density maps (Data Source: Ghana Statistical Service 1989, 2002)

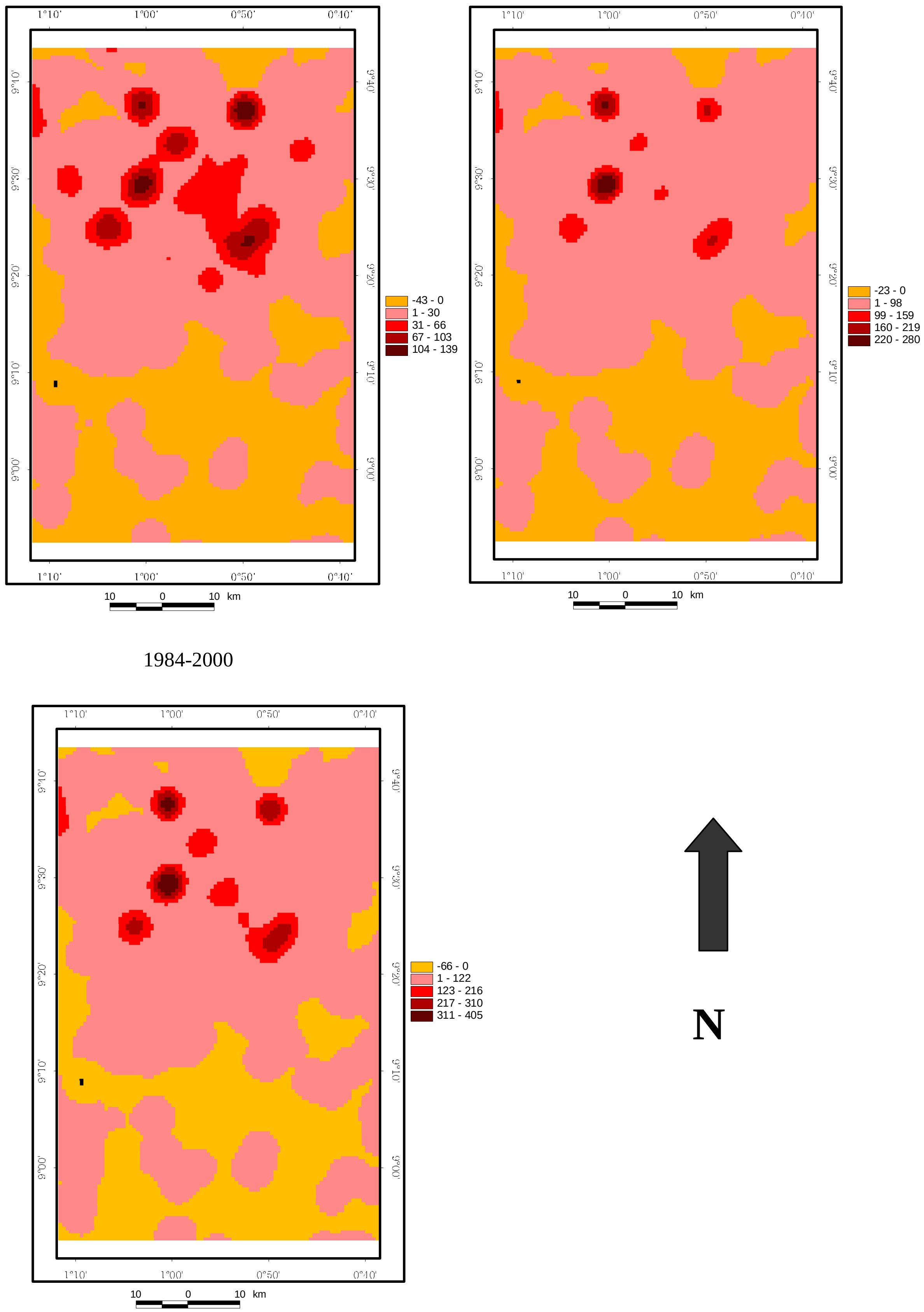


Figure 5.12: Changes in population density

5.5 Logistic regression results

The logistic regression results are presented in table 5.12. The results are discussed in terms of *essentiality* and *importance* of explanatory variables. Essentiality implies that a variable is required in the model at a given scale, whereas importance refers to the quantification of the relationship between the variable and Cropland change.

Table 5.12: Logistic regression results for the six spatial scales for the 1984-1992 and 1992-1999

a) Spatial scale 1: 30m (n = 10,000)

VARIABLES	β	S.E β	Prob.	e^{β}
1984-1992				
ALTITUDE	-0.394	0.110	0.000	0.674
ASPECT	-0.008	0.009	0.414	0.992
SLOPE	-0.058	0.760	0.939	0.944
RAIN	1.498	0.255	0.000	4.473
TEMP	0.109	0.107	0.310	1.115
LI	-0.090	0.040	0.025	0.914
WATER	0.013	0.004	0.000	1.013
DOMINANCE	0.732	0.206	0.000	2.079
ROADS	-0.051	0.007	0.000	0.950
TAMALE	-0.015	0.004	0.000	0.985
VILLAGES	-0.010	0.005	0.046	0.990
POPD84	0.016	0.043	0.703	1.016
POPD92-84	-0.174	0.044	0.000	0.840
TENURE	0.406	0.291	0.163	1.500
INTERCEPT	-1.163	0.935	0.214	-
1992-1999				
ALTITUDE	0.141	0.142	0.319	1.152
ASPECT	0.028	0.028	0.317	1.029
SLOPE	-0.149	0.431	0.730	0.862
RAIN	1.740	0.298	0.000	5.700
TEMP	0.123	0.233	0.598	1.131
LI	1.930	0.058	0.000	6.892
WATER	0.004	0.010	0.698	1.004
DOMINANCE	0.048	0.039	0.223	1.049
ROADS	0.001	0.027	0.957	1.001
TAMALE	-0.252	0.082	0.002	0.777
VILLAGE	-0.029	0.010	0.004	0.971
POPD92	-0.126	0.108	0.245	0.882
POPD2000-92	0.326	0.098	0.001	1.386
TENURE	0.673	0.680	0.322	1.959
INTERCEPT	-12.486	0.977	0.000	-

b) Spatial scale 5: 150m (n = 10,000)

VARIABLES	β	S.E β	Prob.	e^{β}
1984-1992				
ALTITUDE	-0.406	0.106	0.000	0.666
ASPECT	0.014	0.009	0.116	1.015
SLOPE	0.156	0.865	0.857	1.169
RAIN	1.198	0.241	0.000	3.314
TEMP	-0.069	0.104	0.507	0.933
LI	-0.117	0.040	0.003	0.889
WATER	0.103	0.025	0.000	1.109
DOMINANCE	0.186	0.019	0.000	1.205
ROADS	-0.319	0.052	0.000	0.727
TAMALE	-0.148	0.024	0.000	0.862
VILLAGES	-0.109	0.032	0.001	0.897
POPD84	-0.174	0.039	0.000	0.840
POPD92-84	-0.026	0.041	0.529	0.975
TENURE	0.230	0.288	0.425	1.258
INTERCEPT	-1.582	1.027	0.123	-
1992-1999				
ALTITUDE	0.080	0.141	0.570	1.083
ASPECT	-0.139	0.072	0.054	0.870
SLOPE	-1.303	0.951	0.171	0.272
RAIN	1.115	0.318	0.000	3.049
TEMP	-0.110	0.256	0.669	0.896
LI	1.833	0.056	0.000	6.250
WATER	-0.712	0.219	0.001	0.491
DOMINANCE	-0.037	0.066	0.572	0.964
ROADS	-0.020	0.026	0.441	0.980
TAMALE	0.205	0.072	0.004	1.227
VILLAGES	0.331	0.215	0.124	1.392
POPD92	-0.114	0.129	0.379	0.893
POPD2000-92	0.310	0.120	0.010	1.364
TENURE	0.627	0.571	0.272	1.871
INTERCEPT	-9.727	1.288	0.000	-

c) Spatial scale 10: 300m (n = 5,000)

VARIABLES	β	S.E β	Prob.	e^{β}
1984-1992				
ALTITUDE	-0.355	0.113	0.002	0.702
ASPECT	0.020	0.013	0.136	1.020
SLOPE	0.600	0.308	0.052	1.821
RAIN	2.138	0.328	0.000	8.484
TEMP	0.151	0.108	0.162	1.164
LI	-0.052	0.040	0.195	0.949
WATER	0.083	0.026	0.001	1.086
DOMINANCE	0.125	0.020	0.000	1.133
ROADS	-0.171	0.050	0.001	0.843
TAMALE	-0.191	0.026	0.000	0.826
VILLAGES	-0.212	0.033	0.000	0.809
POPD84	-0.194	0.042	0.000	0.824
POPD92-84	-0.043	0.034	0.209	0.958
TENURE	-0.029	0.276	0.917	0.972
INTERCEPT	-2.287	0.657	0.000	-
1992-1999				
ALTITUDE	-0.114	0.172	0.509	0.892
ASPECT	0.014	0.031	0.662	1.014
SLOPE	0.679	0.472	0.150	1.971
RAIN	1.457	0.414	0.000	4.293
TEMP	-2.352	0.321	0.000	0.095
LI	2.017	0.074	0.000	7.517
WATER	0.047	0.012	0.000	1.048
DOMINANCE	-0.118	0.193	0.542	0.889
ROADS	-0.074	0.019	0.000	0.929
TAMALE	0.000	0.012	0.985	1.000
VILLAGES	-0.065	0.017	0.000	0.937
POPD92	-0.440	0.191	0.021	0.644
POPD2000-92	0.569	0.197	0.004	1.766
TENURE	0.265	1.219	0.828	1.304
INTERCEPT	-11.209	1.632	0.000	-

d) Spatial scale 35: 1050m (n = 5,000)

VARIABLES	β	S.E β	Prob.	e^{β}
1984-1992				
ALTITUDE	-0.241	0.153	0.115	0.786
ASPECT	0.020	0.046	0.670	1.020
SLOPE	0.142	0.291	0.626	1.152
RAIN	1.780	0.355	0.000	5.927
TEMP	-0.139	0.163	0.391	0.870
LI	0.010	0.047	0.840	1.010
WATER	0.031	0.037	0.404	1.031
DOMINANCE	-0.038	0.025	0.137	0.963
ROADS	-0.098	0.069	0.153	0.907
TAMALE	-0.082	0.043	0.057	0.921
VILLAGES	-0.211	0.047	0.000	0.810
POPD84	0.001	0.047	0.984	1.001
POPD92-84	0.008	0.041	0.844	1.008
TENURE	0.975	0.307	0.002	2.651
INTERCEPT	-3.163	0.800	0.000	-
1992-1999				
ALTITUDE	-0.568	0.245	0.021	0.567
ASPECT	-0.020	0.026	0.435	0.980
SLOPE	0.257	2.086	0.902	1.293
RAIN	-0.531	0.560	0.343	0.588
TEMP	-0.785	0.278	0.005	0.456
LI	1.986	0.070	0.000	7.286
WATER	0.018	0.009	0.054	1.018
DOMINANCE	0.011	0.030	0.707	1.011
ROADS	-0.013	0.018	0.467	0.987
TAMALE	0.026	0.010	0.009	1.026
VILLAGES	-0.040	0.014	0.005	0.961
POPD92	0.030	0.038	0.426	1.031
POPD2000-92	1.481	0.195	0.000	4.395
TENURE	-0.039	0.540	0.942	0.961
INTERCEPT	-11.442	2.336	0.000	-

e) Spatial scale 100: 3000m (n = 2,500)

VARIABLES	β	S.E β	Prob.	e^{β}
1984-1992				
ALTITUDE	-0.249	0.336	0.460	0.780
ASPECT	0.016	0.036	0.656	1.016
SLOPE	-1.027	11.151	0.927	0.358
RAIN	0.212	0.717	0.767	1.237
TEMP	1.635	0.463	0.000	5.129
LI	-0.226	0.083	0.007	0.798
WATER	0.198	0.073	0.006	1.220
DOMINANCE	-0.018	0.042	0.671	0.982
ROADS	0.010	0.134	0.941	1.010
TAMALE	-0.330	0.096	0.001	0.719
VILLAGES	-0.146	0.108	0.177	0.864
POPD84	-0.112	0.181	0.535	0.894
POPD92-84	-0.266	0.174	0.127	0.767
TENURE	-2.247	1.096	0.040	0.106
INTERCEPT	5.130	11.218	0.647	-
1992-1999				
ALTITUDE	-1.250	0.298	0.000	0.287
ASPECT	0.020	0.024	0.406	1.020
SLOPE	-1.008	4.424	0.820	0.365
RAIN	-1.017	0.482	0.035	0.361
TEMP	0.005	0.288	0.986	1.005
LI	0.763	0.050	0.000	2.145
WATER	0.014	0.010	0.146	1.014
DOMINANCE	-0.032	0.034	0.358	0.969
ROADS	0.005	0.015	0.728	1.005
TAMALE	-0.015	0.009	0.096	0.985
VILLAGES	-0.032	0.012	0.008	0.968
POPD92	1.050	0.119	0.000	2.859
POPD2000-92	-0.322	0.104	0.002	0.724
TENURE	-1.328	0.683	0.052	0.265
INTERCEPT	-0.513	4.702	0.913	-

f) Spatial scale 170: 5100m (n = 2,500)

VARIABLES	β	S.E β	Prob.	e^{β}
1984-1992				
ALTITUDE	-0.049	0.419	0.908	0.953
ASPECT	0.036	0.044	0.414	1.036
SLOPE	-4.830	11.389	0.672	0.008
RAIN	0.558	0.700	0.425	1.748
TEMP	-1.869	0.725	0.010	0.154
LI	0.086	0.068	0.203	1.090
WATER	0.005	0.016	0.762	1.005
DOMINANCE	-0.020	0.056	0.714	0.980
ROADS	-0.005	0.040	0.899	0.995
TAMALE	-0.009	0.017	0.604	0.991
VILLAGES	-0.120	0.033	0.000	0.887
POPD84	-0.098	0.257	0.704	0.907
POPD92-84	-0.604	0.249	0.015	0.546
TENURE	0.097	0.838	0.908	1.101
INTERCEPT	6.071	11.562	0.600	-
1992-1999				
ALTITUDE	-0.393	0.159	0.014	0.675
ASPECT	0.015	0.022	0.491	1.016
SLOPE	-3.133	5.019	0.533	0.044
RAIN	0.579	0.358	0.105	1.785
TEMP	1.392	0.255	0.000	4.023
LI	0.016	0.054	0.770	1.016
WATER	-0.001	0.008	0.896	0.999
DOMINANCE	-0.053	0.026	0.043	0.948
ROADS	0.019	0.013	0.133	1.020
TAMALE	-0.026	0.009	0.004	0.975
VILLAGES	-0.045	0.011	0.000	0.956
POPD92	0.963	0.167	0.000	2.620
POPD2000-92	-0.692	0.160	0.000	0.501
TENURE	-0.851	0.498	0.087	0.427
INTERCEPT	1.376	5.059	0.786	-

Necessary variables for models

Regression modeling involves determining the relationship between variables. Modeling focuses on the dominant processes and ignores the less important ones. A distinction can be made between relationships that occur by chance and relationships that actually exist. The statistical significance (p-value) of a regression analysis is the probability that the observed relationships between variables in a sample occurred by pure chance. The smaller the p-value, the larger (stronger) the confidence we can attach to the relationship between two variables. The statistical significance (p-values in table 5.12) is used to identify the variables that are essential in explaining cropland change across scales. These are marked with 'x' in table 5.13.

Both biophysical and socioeconomic variables were significant at all scales ($p<0.05$), though to varying degrees. In the first period (1984-1992), ASPECT was not essential in explaining cropland change at any of the spatial scales, whereas it was essential at only scale 5 in the second period (1992-1999). Rainfall zone and proximity to water had the highest frequency of significance (4 out of 6 spatial scales), whereas DOMINANCE was only significant at detail to medium scale (1-10). Distance to MARKET and localities (VILLAGES) were the most frequent significant socio-economic variables (5 out of 6 spatial scales), while land tenure and population variables were the least (2 out of 6).

Table 5.13: Variables significant at p<0.05

a) 1984-1992

VARIABLES	SCALES					
	1	5	10	35	100	170
BIOPHYSICAL						
ALTITUDE	x	x	x			
ASPECT						
SLOPE						
RAIN	x	x	x	x		
TEMP					x	x
LI	x	x			x	
WATER	x	x	x		x	
DOMINANCE	x	x	x			
SOCIOECONOMIC						
ROADS	x	x	x			
TAMALE	x	x	x	x	x	
VILLAGES	x	x	x	x		x
POPD84		x	x			
POPD92-84	x					x
TENURE				x	x	

b) 1992-1999

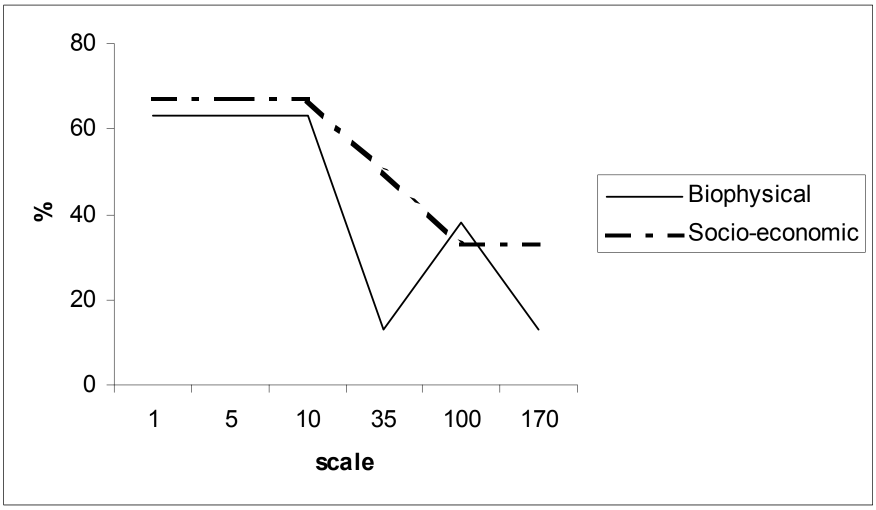
VARIABLES	SCALES					
	1	5	10	35	100	170
BIOPHYSICAL						
ALTITUDE				x	x	x
ASPECT		x				
SLOPE						
RAIN	x	x	x		x	
TEMP			x	x		x
LI	x	x	x	x	x	
WATER		x	x	x		
DOMINANCE						x
SOCIOECONOMIC						
ROADS			x			
TAMALE	x	x		x		x
VILLAGES	x		x	x	x	x
POPD92			x		x	x
POPD2000-92	x	x	x	x	x	x
TENURE						

In the second period (1992-1999), change in population density was significant at all spatial scales. Land suitability index (LI) and distance to villages (VILLAGES) were significant at 5 out of 6 spatial scales. ROADS, ASPECT and TENURE were significant at only one scale, whereas SLOPE was significant at none.

Figure 5.13 shows a clear difference in the statistical significance of the variables in time across scales. In the first period, the statistical significance of socio-economic variables generally decreased with increasing spatial extent (figure 5.13a). A similar trend is observed from scale 1 to 35 for biophysical variables. With the exception of scale 100, the proportion of significant socio-economic variables is higher for the investigated spatial scales. Thus, the number of variables essential in explaining cropland change generally decreased across scales. Benneh et al (1995) observed that in the predominantly agricultural society of Ghana, individuals and households make most land-use decisions. This group of people usually have differing goals and economic conditions that reflect in their land use decisions. This may therefore explain why more variables were essential in analyzing land use dynamics at small scales (1-5) in the first period.

In the second period (figure 2b), the proportion of significant socio-economic variables was higher at scales 10-170. This shows that generally, more socio-economic variables were required to explain cropland dynamics as spatial extent increases. This suggests increasing importance of social organizations (commercial farming and village level activities) in land-use decisions in the study area. It may also be due to interactions amongst lower levels (i.e., households and individuals) leading to the *emergence* of new patterns at higher levels. Emergent phenomena are aggregate results of dynamic processes involving the lower-level components of complex systems such as the land-use system (Manson, 2001). Complexity in land use systems results from heterogeneities, interdependencies and hierarchical relationships of anthropogenic and ecological processes (Parker et al, 2002), leading to macroscopic social patterns (Epstein and Axtell, 1996). For both periods, biophysical variables generally had the lower frequency of significance. This is largely due to the nature and effects of environmental variables that tend to occur at a slow pace (Glantz, 1998). Furthermore, Geist and Lambin (2001) noted that biophysical variables such as topography might not necessarily drive, but shape LUCC.

a) 1984-1992



b) 1992-1999

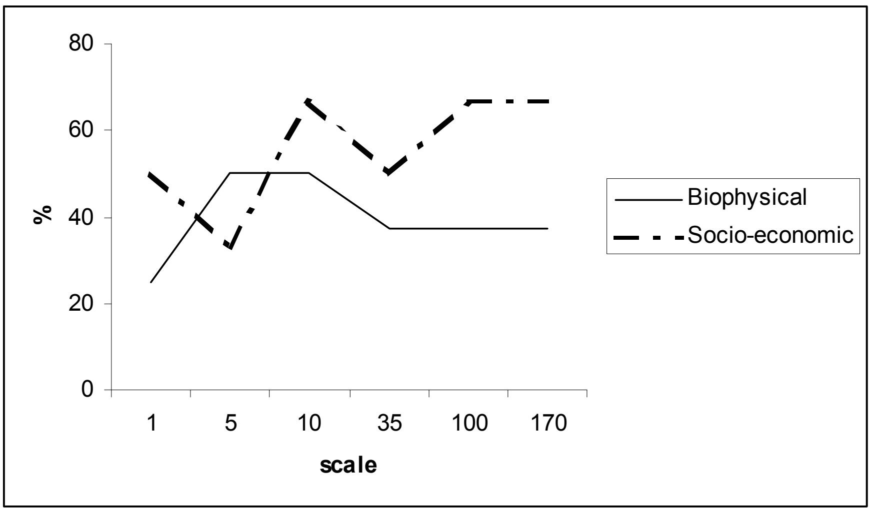


Figure 5.13: Proportions of significant variables ($p<0.05$) across spatial scales

Concepts of odds and odds ratio

To facilitate the interpretation of the results, basic concepts of odds and odds ratio are first discussed. If p is the probability that an event will occur, then the odds of the event is $\frac{p}{1-p}$. That is, the odds is the ratio of the probability that something will happen divided by the probability that it would not. Odds ratio is the ratio of two odds. It explains what happens to the dependent variable if the independent variable is increased by one unit. Mathematically, odds ratio *OR*, is defined as (Newton, 2000):

$$OR = \frac{P(event|x+1)/(1-P(event|x+1)}{P(event|x)/(1-P(event|x)}$$

where $P(event|x)$ is the probability of the event given x.

Odds ratio is a measure of relationship between the dependent and independent variables (Hosmer and Lemeshow, 2000). It does not require variables to be normally distributed as in the Ordinary Least Square (OLS) regression. Furthermore, it is able to handle categorical data (such as RAIN, TENURE, TEMP in this study). In the case of a binary variable, odds ratio measures the effect on the dependent variable if the independent variable belongs to a category rather than the reference category. Odds ratio has an asymmetric distribution (Hosmer and Lemeshow, 2000). In the case of a decrease given a unit increase in the independent variable, the odds ratio can vary from 0 to 0.99, whereas in the case of an increase given a unit increase in the independent variable, it can vary from 1.01 to infinity. Lastly, the odds ratio of an effect is constant regardless of the values of the independent variables (Newton, 2000). That is, incrementing an independent variable has the same multiplicative effect on the odds, regardless of values taken by the other independent variables.

In table 5.12, β is the logit or effect coefficient, and corresponds to the unstandardized β in the OLS regression. It is simply the natural log of odds ratio; thus odds ratio and logit measure the same thing, i.e., the strength of relationship between cropland change and independent variables (Hosmer and Lemeshow, 2000). Odds ratio is more intuitive than the logit coefficient, as we are rarely inclined to reason on the logit scale. Odds ratio is the exponentiated coefficient (i.e., e^{β}) in a logistic regression. When $\beta < 0$, $e^{\beta} < 1$, indicating that the odds (or likelihood) of the event is decreased. When $\beta > 0$, $e^{\beta} > 1$, implying that the likelihood of the event is increased. When $\beta = 0$, $e^{\beta} = 1$, showing that the likelihood of the event is unchanged.

For the basic 30m Landsat TM resolution (scale 1), the likelihood of conversion to cropland increases by more than 4 times in the zone with >1100mm rainfall in the first period (1984-1992), whereas it increases by about 6 times in the second period (1992-1999). According to the model, an increase in DOMINANCE (a measure of landscape heterogeneity) increased the likelihood of conversion to cropland by a factor of more than 2 in the first period, whereas it hardly increased this likelihood in the second period. The likelihood of conversion to cropland increased by 1% for every km increase in distance from water in the first period. This may be associated with avoidance of risk of flooding or river blindness disease. In the second period, an increase in distance from water did not affect the likelihood of conversion to cropland (*OR* = 1). An increase in distance of 30m from roads decreased the likelihood of conversion to cropland by a factor of 0.9 in the first period, whereas in the second period, increase in distance from roads did not affect the likelihood of conversion to cropland.

The likelihood of conversion to cropland decreased by a factor of between 0.7-0.9 for every km away from main market (TAMALE) and the villages for both periods. Initial population densities in 1984 and 1992 were not significant to the models, whereas change in population density between 1992 and 2000 increased the likelihood of conversion to cropland by 39%. In the first period, change in population density was in fact inversely related to cropland change. Several explanations could be offered to this observation. Firstly, it is likely that additions to population did not increase the proportion of the agricultural labor force, with the majority of the increase probably being children. This may also explain why the initial population density in the second period (POPD92) was inversely related to cropland change. Secondly, it may indicate availability of non-farm employment opportunities for the working population. Thirdly, the negative relationship suggests the substitution of labor for other inputs.

The model explains that agriculture more likely developed on less suitable soils in 1984-1992 (OR = 0.9), suggesting that sites for agriculture were not selected on the basis of suitability. Land-use may not always be positively correlated with land suitability due to socioeconomic reasons. Population distribution is largely concentrated around Tamale, which offers non-farm economic opportunities, but soils of lower fertility. In the second period, however, the land suitability index became the most important variable explaining conversion to cropland. The likelihood of conversion to cropland increased by a factor of about 7. In the first period, change to cropland was inversely related to elevation; an increase in elevation decreased the likelihood of conversion to cropland by a factor of about 0.7. That is, a location 50m higher up was 0.7 times less likely to be converted to agriculture. In the second period, agriculture seemed to have expanded to higher altitudes, as an increase in elevation by 50m increased the likelihood of conversion to cropland by 15%. This trend could exacerbate erosion in the study area.

Effects of spatial scales on variables influencing cropland change

The importance of specific variables in space and time are illustrated with changes in odds ratio (figure 5.14). The figures are based on the last columns of table 5.12. A description of the contribution of each variable to cropland change across scales follows.

ALTITUDE

In the first period, an increase in altitude by 50m decreased the likelihood of conversion to cropland by a factor ranging from 0.6 to 0.9. This indicates that agriculture was practiced mostly in lowlands. This may be as a result of more favorable agroclimatic condition such as higher water retention capacity of lowlands. In the second period odds ratio decreased with increasing aggregation from about 1.2 for scale 1 to 0.3 for scale 100. Odds ratio of altitude is greater than 1 for scales 1 and 5. This implies that an increase in elevation increased the likelihood of conversion to agriculture by 15% and 8% respectively, at scales 1 and 5. This suggests the tendency to expand agriculture to higher altitudes by individuals and households between 1992 and 1999. The low values of odds ratio (<1) at higher aggregation (i.e., for spatial scales 10-170) suggest that at these scales, an increase in altitude decreased the likelihood of cropland change.

Fig 5.14a: Changes in odds ratio of ALTITUDE

ASPECT

Aspect represents the direction of topographic gradients. It was not important in explaining cropland change in the first period, as odds ratio was constant at about 1 across scales. In the second period, ASPECT fluctuated below 1, indicating that an increase in ASPECT towards the east decreased the likelihood of cropland change by a factor of about 0.9 across scales (table 5.12).

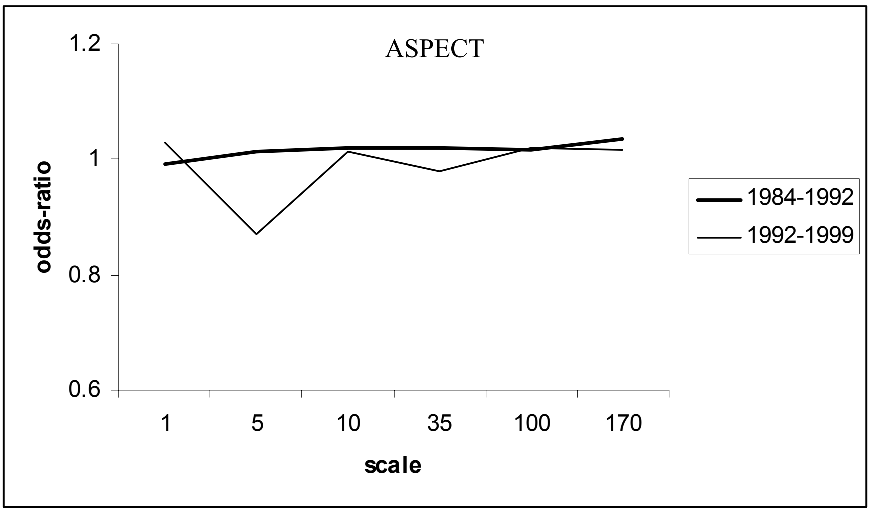


Figure 5.14b: Changes in odds ratio of ASPECT

SLOPE

At scales 5 –35, areas with slope gradients above 15% were 15% to 82% more likely to be converted to agriculture, whereas at other scales, a high slope gradient (> 15%) decreased the likelihood of conversion to cropland in the first period. This suggests expansion of farming to places with high slope gradients by households and commercial farmers. The trend continued for the case of commercial farming in the second period (scale 10) in which land areas with slope gradients above 15% were 2 times more likely to be cultivated. This could aggravate erosion in the area, as slope gradient reflects the gravity potential of water and soil.

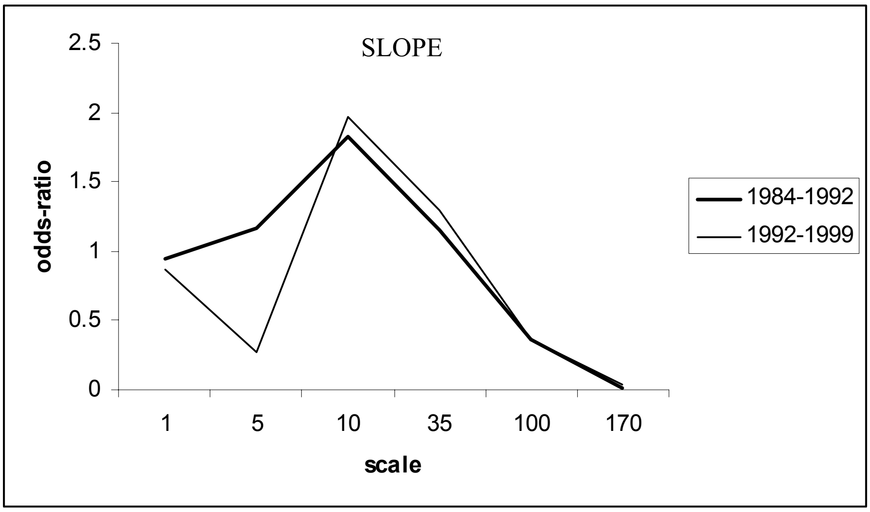


Figure 5.14c: Changes in odds ratio of SLOPE

RAIN

In the first period, odds ratio of RAIN was greater than 1 across spatial scales, ranging from more than 1.2 for scale 100 to about 8.5 for scale 10. Odds ratio was highest (about 6 to 8.5) at the scale of commercial farming (10-35). This suggests a preference of commercial farmers for the agroecological zone with rainfall >1100mm. In the second period, RAIN generally decreased in importance. Its odds ratio was highest for scale 1 (5.7), corresponding to the level of activity of individuals.

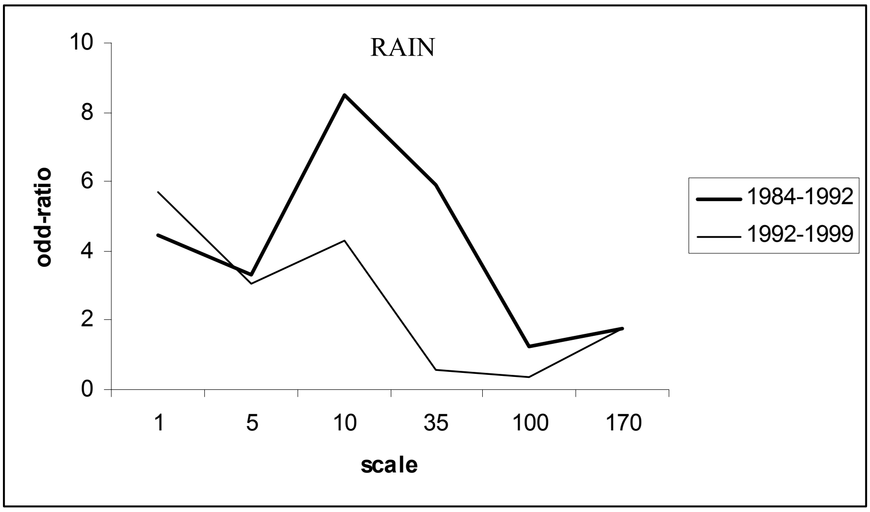


Figure 5.14d: Changes in odds ratio of RAIN

TEMP

In the first period, its temperature zone at scales 1-35 did not determine the likelihood that a site would be converted to agriculture, as odds ratio was fairly constant at 1. For small villages (about 3 km x 3 km), being in an area with temperature < 28°C increased the likelihood of conversion to agriculture by 5 times. In the second period, the likelihood of conversion to agriculture increased by more than 4 times for larger villages (about 5 km x 5 km). This suggests that the effect of temperature zone on land-use change is only discernible at large spatial extent (3 km to 5 km).

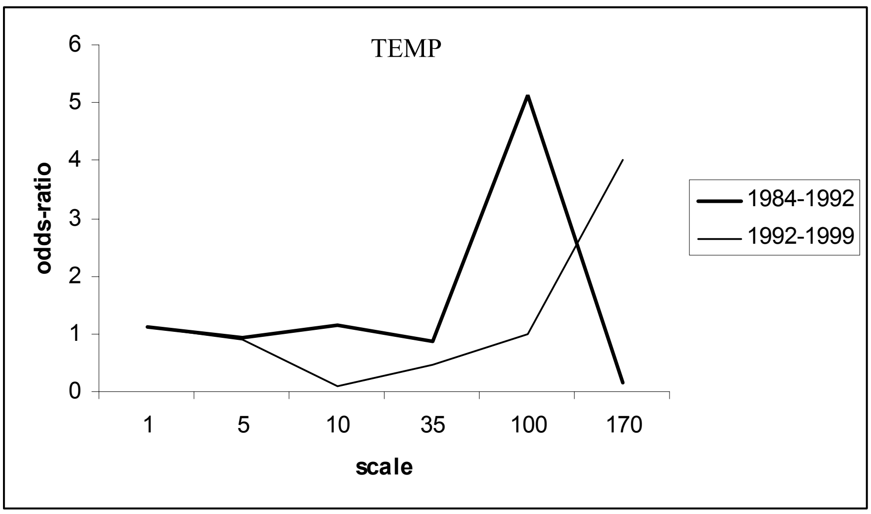


Figure 5.14d: Changes in odds ratio of TEMP

LI

In the first period, land suitability index ranged from 0.8 for scale 100 to 1.0 for scale 170, indicating that sites were not selected for agriculture on the basis of their suitability. In the second period, LI ranged from 1.0 for scale 170 to 7.5 for scale 10. The pattern is similar to RAIN in which the highest odd ratios (> 7) were observed for scales 10-35, corresponding to the level of activity of commercial farmers. This suggests the preference of commercial farmers for more suitable soils. The effect of aggregation is clear, as odds ratio generally decreased across spatial scales in the second period. Aggregation of data may have lowered the average land suitability index resulting in relatively lower level of association between *LI* and cropland change at scales 100-170 between 1992 and 1999.

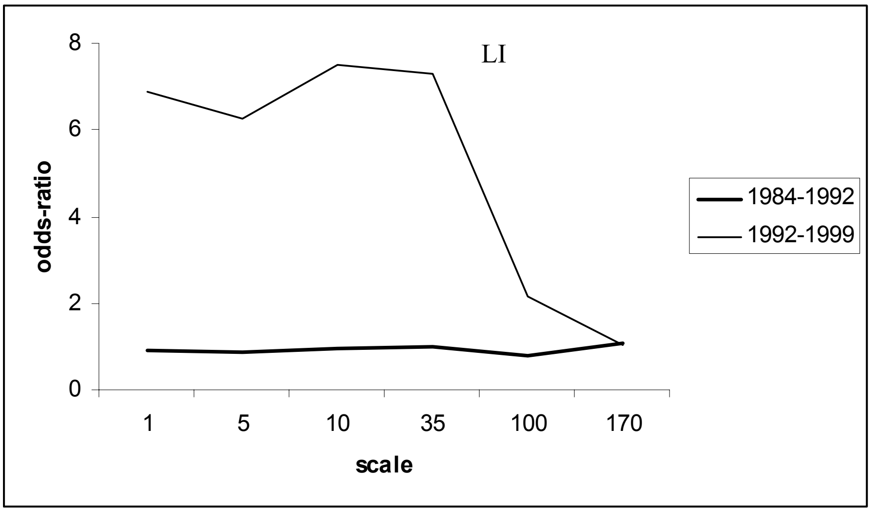


Figure 5.14e: Changes in odds ratio of Land suitability index (*LI*)

WATER

In the first period, an increase in distance from water did not increase the likelihood of conversion to cropland at scale 170, but increased the likelihood by between 1% for scale 1 and 22% for scale 100 (Table 5.12). Avoidance of the risk of flooding and river blindness disease were the likely factors for this observation. In the second period, an increase in distance to water reduced the likelihood of conversion to cropland for scale 5. This suggests that with the eradication of river blindness disease, households were sensitive to nearness to water in their choice of agricultural land in the second period.

The observation also underscores the increasing importance of valley bottoms and hydromorphic zones in the farming systems of households.

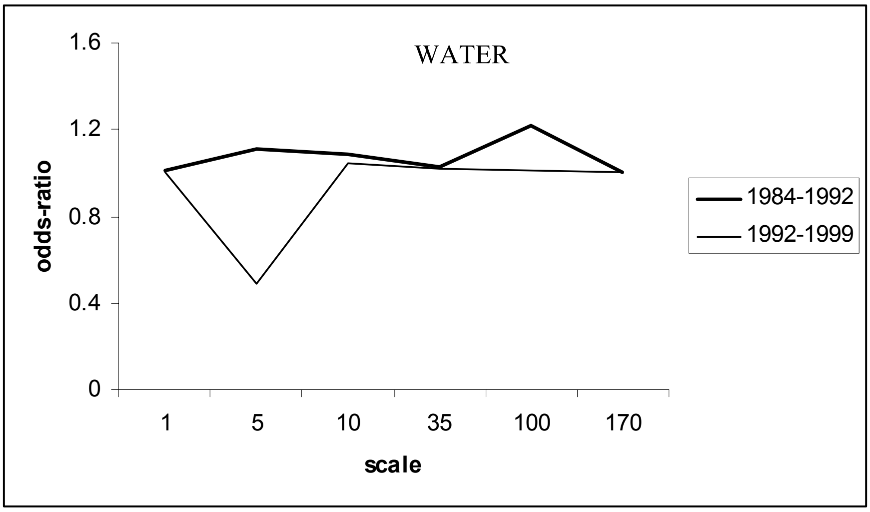


Figure 5.14f: Changes in odds ratio of WATER

DOMINANCE

Dominance is an index of landscape heterogeneity. Higher values indicate the presence of different cover types (woodland, grassland, cropland, etc.) in an area. In the first period, an increase in dominance increased the likelihood of conversion to cropland by individuals and households by a factor ranging from 1.2 to 2.1 (table 5.12). It can therefore be inferred that these categories of land users prefer heterogeneous areas. This may be due to the fact that such areas offer multipurpose uses - for instance woodland may be cut for firewood and charcoal production for domestic and commercial purposes before the land is prepared for crop production. At scale 10, the likelihood of conversion to cropland increased by 13% in the first period given an increase in dominance, whereas an increase in dominance hardly increased the likelihood of cropland change at scales 35-170.

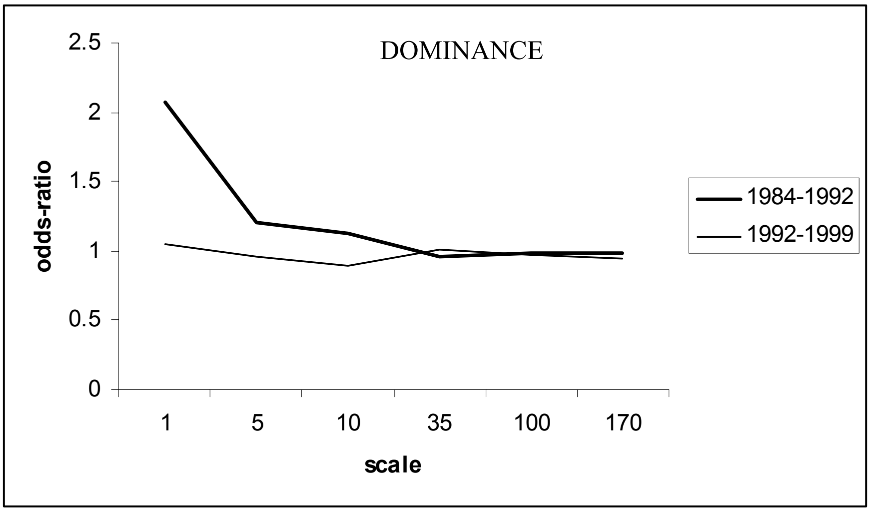


Figure 5.14g: Changes in odds ratio of DOMINANCE

In the second period, odds ratio for DOMINANCE was fairly constant at about 1.0 across the spatial scales. That is, an increase in landscape heterogeneity did not have any effect on likelihood of cropland change. This may as a result of a decrease in the proportion of natural vegetation in the second period.

ROADS

Figure 5.14h illustrates the relative importance of nearness to roads in predicting conversion to cropland. An increase in distance from roads reduced the likelihood of conversion to agriculture by a factor ranging from 0.7 to 0.9 for scales 1 and 5 in the first period. For scales 10-35, the decrease in the likelihood of conversion to agriculture ranged from a factor of 0.8 to 0.9. At higher spatial extent (scales 100-170), the likelihood of conversion to cropland is unchanged with an increase in distance from roads (odds ratio = 1). This reflects the importance of transportation costs in land-use in the study area, especially for households and commercial farmers.

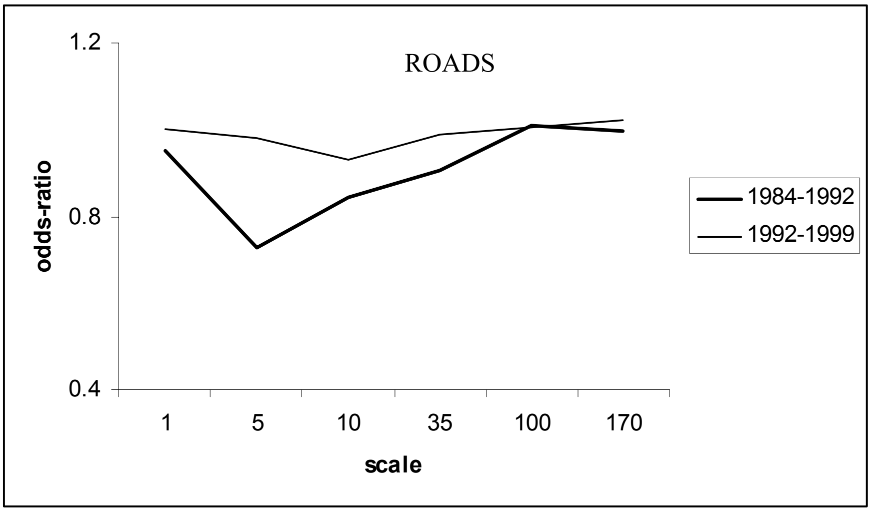


Figure 5.14h: Changes in odds ratio of ROADS

TAMALE

A unit increase in distance from main market decreased the likelihood of conversion to cropland by a factor ranging from 0.7 for scale 100 to 0.9 for scale 170 in the first period. This underscores the importance of distance to the main market for all categories of land users. With the exception of scale 5, a unit increase in distance to main market also decreased the likelihood of cropland change by a factor ranging from about 0.8 to 0.9 in the second period. This again reflects the importance of Tamale as the input and output market for agricultural produce.

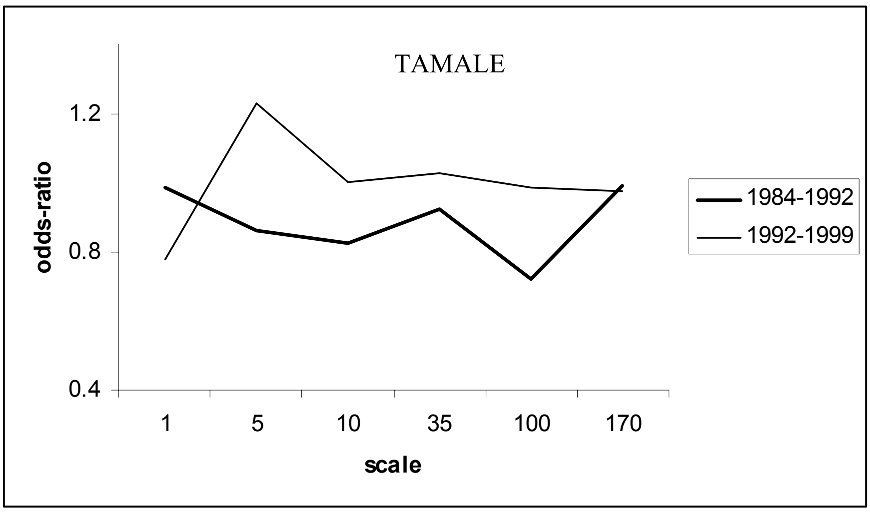


Figure 5.14i: Changes in odds ratio of TAMALE

VILLAGES

Distance to villages is similar to distance to roads and distance to main market, in that they all measure transportation cost. Between 1984 and 1992, odds ratio for VILLAGES generally ranged from 0.7 to 0.9 for scales 1 to 35, suggesting that individuals, households and commercial farmers were very sensitive to distance from villages. Figure 5.14j indicates that, with the exception of scale 5, a unit increase in distance from villages decreased the likelihood of conversion to agriculture by a factor of about 0.9 during 1992-1999. The influence of distance to roads, distance to Tamale and distance to villages on cropland change as analyzed above tends to support the vön Thunen paradigm that emphasizes the importance of transportation costs in land use decisions.

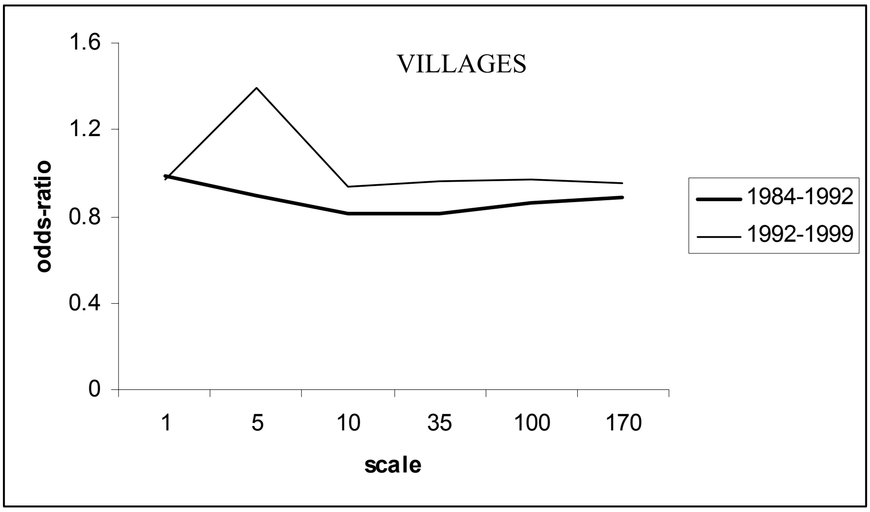


Figure 5.14j: Changes in odds ratio of VILLAGES

INITIAL POPULATION DENSITY

In the first period (1984-1992), the odds ratio for population density was fairly constant at 1 across scales, indicating that initial population density did not affect the likelihood of cropland change. In the second period (1992-1999), initial population density decreased the likelihood of cropland change by a factor ranging from 0.6 to 0.8 at scales 1-10. It increased the likelihood of cropland change by a factor ranging from 2.6 to 2.9 at the village level.

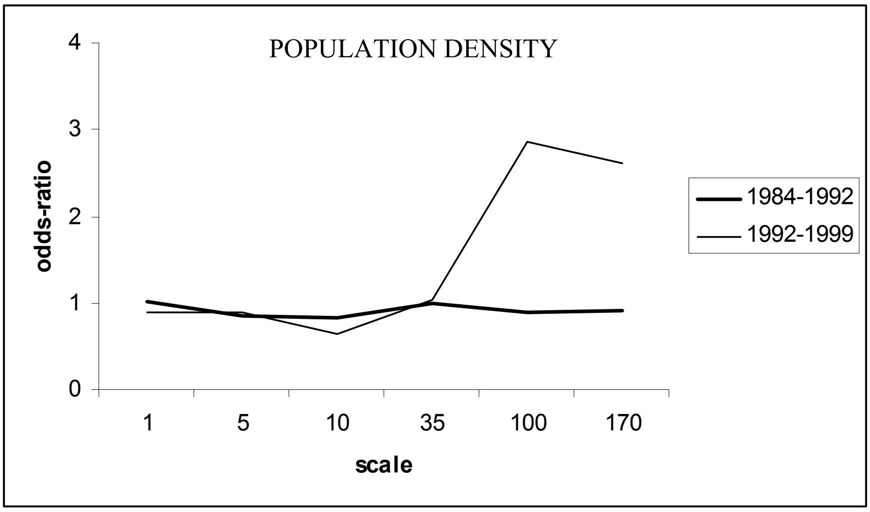


Figure 5.14k: Changes in odds ratio of INITIAL POPULATION DENSITY

CHANGE IN POPULATION DENSITY

In the first period, an increase in population density did not lead to an increase in the likelihood of cropland change. In the second period, however, an increase in population density increased the likelihood of cropland change by 1.4 to 1.8 for scales 1-10. The likelihood of cropland change was 4.4 at scale 35, suggesting that commercial farmers were the most sensitive to change in population density. At the village level (100-170), increase in population density decreased the likelihood of cropland change by a factor ranging from 0.5 to 0.7.

The following explanation may explain why change in population density had opposite effects, i.e., an increase in likelihood of change at small extent, and a decrease in likelihood of change at large extent. Levels in a hierarchical system such as the land-use system can influence one another through shared variables (Holling, 1995). Cross-level interaction may therefore have different effects on the functioning of the processes at different levels. Parker et al (2002) states that interactions of a household with other households within a village may lead to new constraints on resource use at the community level. Thus, a decrease in the likelihood of conversion to cropland at the village level suggests an overall effect in which households within a village experiencing a high population pressure probably migrated to other areas outside the village. This view is supported by the fact that initial population density was positively correlated with cropland change at the village level (odds ratio of 2.6 to 2.9; Figure

5.14k). It may also imply that the same farmland was farmed more intensely using external inputs such as fertilizer.

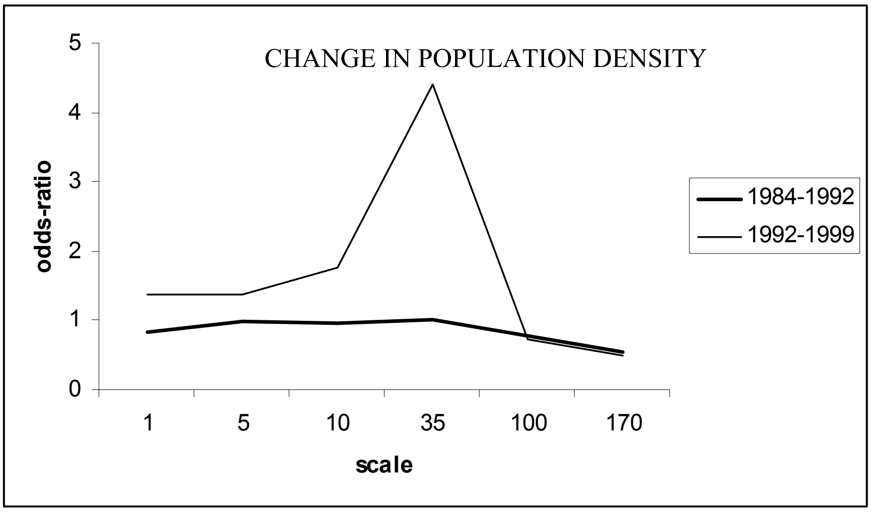


Figure 5.14l: Changes in odds ratio of ´CHANGE IN POPULATION DENSITY

TENURE

A non-Stateland location was 1.5 times more likely to be converted to cropland at scale 1 compared to a Stateland location in the first period. The odds ratio decreased to 1 at scale 10, indicating that tenure did not affect cropland conversion at this scale. At scale 35, non-Stateland was about 2.7 times more likely to be converted to cropland, indicating preference of commercial farmers to non-Stateland in the first period. In the second period, the likelihood of a non-Stateland being converted to agriculture ranged from 1.3 to 1.8 for scales 1-10. At scales 35-170, being a non-Stateland decreased the probability of conversion to cropland. This suggests pressure on non-Stateland, leading to reduced availability for farming. The preference for non-Stateland suggests that the prevailing traditional common property system acts as an incentive for farmers. Under the system, the village chief allocates land to farmers according to their needs; they only need to show appreciation to the chief by bringing parts of the produce at the end of the season. With increasing population however, profound changes in form of land sales are affecting access to land (Abudulai, 1996).

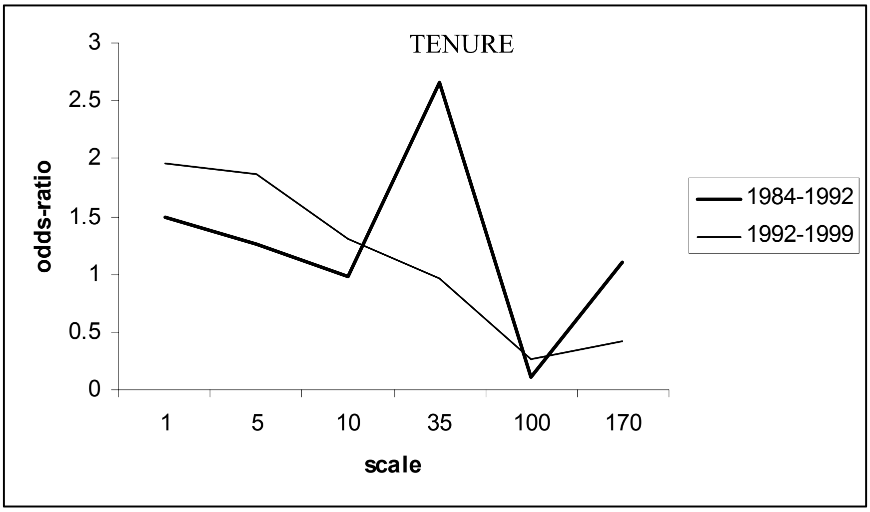


Figure 5.14m: Changes in odds ratio of TENURE

Relative importance of variables

The relative importance of significant variables was reclassified into low, medium and high following an equal interval classification technique. The equal interval classification requires the minimum ($OR_{\min}$) and maximum ($OR_{\max}$) odds ratio to determine the interval (C_{int}) of each class:

$$C_{\text{int}} = \frac{OR_{\max} - OR_{\min}}{n} \quad (22)$$

where *n* is the number of classes. The asymmetric property of odds ratio was taken into account so that intervals for decrease and increase in likelihood of cropland change given a change in the independent variables were separately determined.

Table 5.14a: Intervals for classification of odds ratio and interpretation of effects on likelihood of cropland change.

Class	Increase in likelihood of change		Decrease in likelihood of change	
	Odds ratio	Symbol	Odds ratio	Symbol
Low	< 2.49	⊕	< 0.33	Θ
Medium	2.49 - 4.98	⊕⊕	0.33 - 0.66	ΘΘ
High	> 4.98	⊕⊕⊕	> 0.66	ΘΘΘ

The resulting classification of degree of importance of significant variables to cropland change is shown in Tables 5.14b and 5.14c

Table 5.14b: Degree of importance of variables (1984-1992)

VARIABLES	SCALES					
	1	5	10	35	100	170
BIOPHYSICAL						
ALTITUDE	ΘΘΘ	ΘΘΘ	ΘΘΘ			
ASPECT						
SLOPE			⊕			
RAIN	⊕⊕	⊕⊕	⊕⊕	⊕⊕⊕		
TEMP					⊕⊕⊕	Θ
LI	ΘΘΘ	ΘΘΘ			ΘΘΘ	
WATER	⊕	⊕	⊕		⊕	
DOMINANCE	⊕	⊕	⊕			
SOCIOECONOMIC						
ROADS	ΘΘΘ	ΘΘΘ	ΘΘΘ			
TAMALE	ΘΘΘ	ΘΘΘ	ΘΘΘ	ΘΘΘ	ΘΘΘ	
VILLAGES	ΘΘΘ	ΘΘΘ	ΘΘΘ	ΘΘΘ		ΘΘΘ
POPD84		ΘΘΘ	ΘΘΘ			
POPD92-84	ΘΘΘ					ΘΘ
TENURE				⊕⊕	Θ	

Table 5.14c: Degree of importance of variables (1992-1999)

VARIABLES	SCALES					
	1	5	10	35	100	170
BIOPHYSICAL						
ALTITUDE				ΘΘ	Θ	ΘΘΘ
ASPECT		ΘΘΘ				
SLOPE						
RAIN	⊕⊕⊕	⊕⊕	⊕⊕		ΘΘ	
TEMP			Θ	ΘΘ		⊕⊕
LI	⊕⊕⊕	⊕⊕⊕	⊕⊕⊕	⊕⊕⊕	⊕	
WATER		ΘΘ	⊕	⊕		
DOMINANCE						ΘΘΘ
SOCIOECONOMIC						
ROADS			ΘΘΘ			
TAMALE	ΘΘΘ	⊕		⊕		ΘΘΘ
VILLAGES	ΘΘΘ		ΘΘΘ	ΘΘΘ	ΘΘΘ	ΘΘΘ
POPD92			ΘΘ		⊕⊕	⊕⊕
POPD2000-92	⊕	⊕	⊕	⊕⊕	ΘΘΘ	ΘΘ
TENURE						

Table 5.14b reveals that in the first period (1984-1992), the most important variables explaining cropland change were elevation (ALTITUDE), distance to roads (ROADS), distance to main market (TAMALE), distance to villages (VILLAGES) and change in population density (POPD92-84) at the basic Landsat TM resolution of 30m, i.e., scale 1. A unit increase in each of these variables decreased the likelihood of cropland change by a factor ranging from 0.7-0.9. Table 5.14b further reveals that

VILLAGES and TAMALE were the most important variables across scales, as a unit increase of the variables decreased the likelihood of cropland change by between 0.7-0.9. Cropland change is very sensitive to ROADS and ALTITUDE at scales 1-10, with a unit increase in the variables decreasing the likelihood of change by a factor ranging from 0.7-0.9.

In the second period (1992-1999), rainfall zone (RAIN), land suitability index (LI), distance to market (TAMALE) and distance to villages (VILLAGES) were the most important variables explaining the likelihood of cropland change at scale 1 (table 5.14c). A unit increase in distance to market and villages decreased the likelihood of conversion to cropland by a factor ranging from 0.7-0.9. A pixel located in the zone where annual rainfall exceeds 1100mm was at least 5 times more likely to be converted to cropland than one located in the zone where annual rainfall is less than 1100mm. Distance from villages was generally the most important socioeconomic variable across scales in the second period. A unit increase in the variable decreased the likelihood of conversion to cropland by 0.7-0.9. Land suitability index (LI) was the most important biophysical variable at scales 1-35 in the second period. An increase in the variable increased the likelihood of conversion to cropland by a factor of at least 5.

Paired-sample t-test was used to compare the mean odds ratio across scales for the two periods (table 5.15). Negative t-values indicate that on the average, the likelihood of change given a unit increase in the independent variable was higher in the second period. Table 5.14 shows that the likelihood of cropland change given a unit increase in 7 out of 14 of the variables was higher in the first period. They were predominantly biophysical variables (6 out of 8 of the biophysical variables). Thus, biophysical variables were generally more important in explaining cropland change in the first period. Socio-economic variables were generally more important across scales in the second period, as 5 out of 6 socio-economic variables has a negative t-value. Only three variables were found to be significantly more important across scales in the second period in predicting conversion to cropland ($p<0.1$). These were land suitability index (LI), ROADS and VILLAGES.

Table 5.15: Comparison of mean odds-ratio across scales for the two periods

Variables	t	Prob.
ALTITUDE	-0.10	0.93
ASPECT	1.11	0.32
SLOPE	0.66	0.54
RAIN	1.48	0.20
TEMP	0.28	0.79
LI	**-3.64**	**0.02**
WATER	1.50	0.19
DOMINANCE	1.54	0.18
ROADS	**-2.21**	**0.08**
TAMALE	-1.37	0.23
VILLAGES	**-2.14**	**0.09**
POPD	-1.43	0.21
CHANGE POPD	-1.59	0.17
TENURE	0.37	0.73

Three major inferences on behavior of land-use system can be drawn from the above analyses.

- Firstly, inclusion of potential biophysical and socio-economic driving forces in modeling is essential, as this leads to an improved understanding of relationships between land-use change and its determinants across scales.
- Secondly, the importance of most variables (as illustrated by odds-ratio) in explaining land-use change is scale-dependent. Thus, models describing the same process at different spatial scales are quite different in terms of significant variables and estimates of the regression coefficients. This may be due to the interactions between lower levels leading to the emergence of new relationships at the higher levels.
- Thirdly, the composition of variables explaining land-use change at a given scale is time-dependent. This may be due to modification (over time) of the processes leading to change. This makes predictive modeling uncertain.

Association between empirical data and regression models

The pseudo R^2 assesses the overall performance of the logistic regression model. Unlike the R^2 in Ordinary Least Square regression (OLS), pseudo R^2 is **not** a measure of the proportion of the overall variance explained. Rather, it measures the degree of association between empirical data and regression models, i.e., the overall fit. The pseudo R^2 in a logistic regression is usually much lower than the R^2 in OLS regression.

Changes in pseudo R^2 across scales are shown in figure 5.15. All pseudo R^2 are at least 0.2, which is the critical level above which the fit or a logistic regression is considered significant (Menard, 1995). Lower values were observed in the first period, indicating better model fit in the second period. Pseudo R^2 values indicated an increasing upward trend with spatial scale for both periods. This may be related to the smoothing effect associated with spatial aggregation.

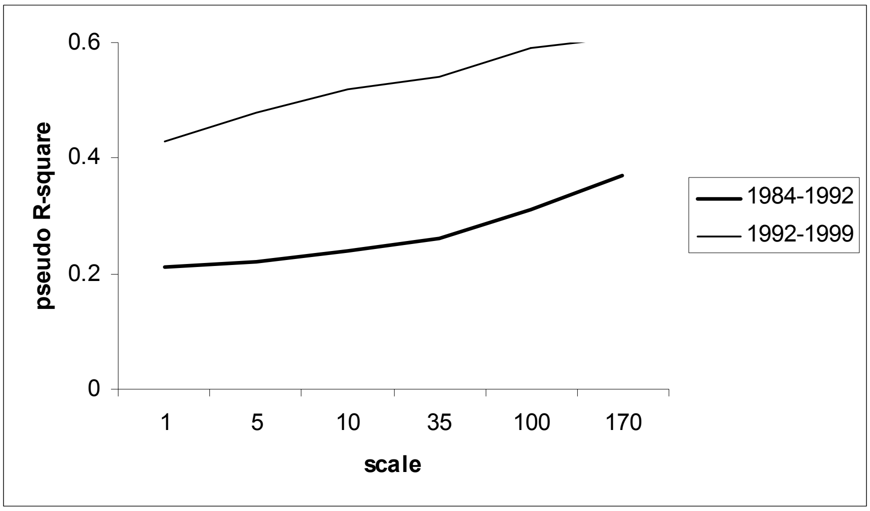


Figure 5.15: Changes in pseudo R^2 across spatial scales

Spatial correlation

Parameters of variograms of standardized logit residuals at different spatial scales are shown in table 5.16. Variograms for both periods generally showed similar patterns in terms of model type, except scale 35, which was fitted to a spherical model in the first period (1984-1992), but a linear model in the second period (1992-1999).

Table 5.16: Parameters of variograms of standardized logit residuals

a) 1984-1992

Scale	Nugget	Partial sill	Total variation	Slope	Range (km)	Model
1	0.91	-	0.98	0.34	-	Linear
5	1.03	-	1.10	0.32	-	Linear
10	0.93	-	1.02	0.30	-	Linear
35	0.78	0.23	1.01	-	3	Spherical
100	0.31	0.65	0.96	-	3	Spherical
170	0.12	0.64	0.76	-	7	Spherical

b) 1992-1999

Scale	Nugget	Partial sill	Total variation	Slope	Range (km)	Model
1	1.30	-	1.62	0.33	-	Linear
5	1.11	-	1.22	0.23	-	Linear
10	0.78	-	1.62	3	-	Linear
35	0.81	-	1.46	2.8	-	Linear
100	0.36	0.75	1.11	-	4	Spherical
170	0.21	0.77	0.98	-	6	Spherical

Figure 5.16a further shows the proportion of total variation that is accounted for by the nugget. The nugget indicates the level of spatially uncorrelated variation in the dataset. It is also referred to as the micro-spatial variability, i.e., variability between adjacent pixels or locations. The proportion of nugget relative to total variation generally decreased across scales (Figure 5.16). This pattern follows the trend in total variation, which also generally decreased across scales (Table 5.16). The nugget is at least 50% of total variation at scales 1-35 for both periods. This indicates that there is a high level of microvariation in the dataset. It reflects the complexity of the landscape, which in turn is related to the settlement pattern. In Northern Ghana, it is common to find a mixture of different vegetation types around cropland and the farmer's residence.

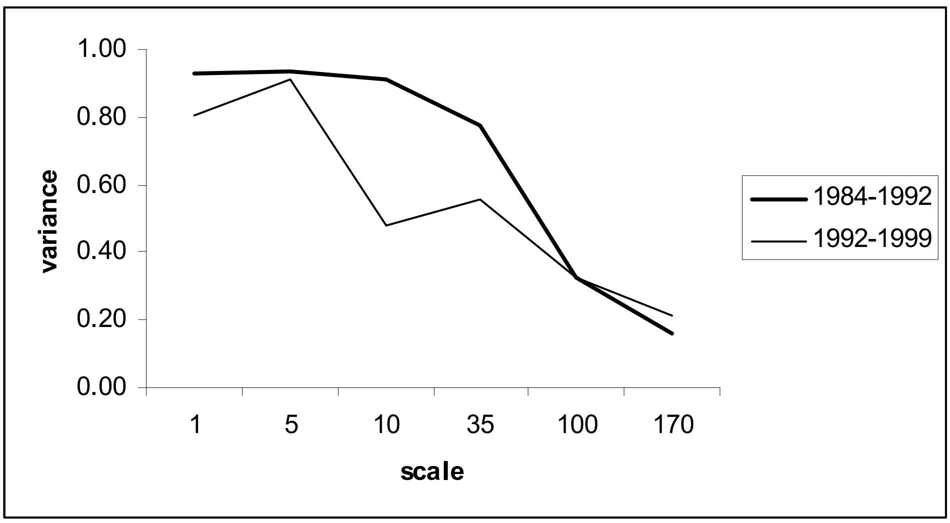


Figure 5.16a: Proportion of microvariation relative to total variation across scales

A general reduction in total variance across scales (Table 5.16a) shows that data aggregation reduces overall variance but blurs fine scale variation. Thus, there is a trade-off between spatial detail and variance as the spatial resolution is coarsened. This phenomenon has an implication for the characterization of cropland change at different scales. Modeling at detailed scale (1-5) captures systematic variation in the driving forces of land-cover change at individual and household levels. Land-use policy decisions such as land improvement and input distribution, however, require models at broader levels such as the village level. A major challenge is therefore to scale up land data to the level at which the policy makers require it for decision making (e.g., Dumanski et al, 1998). Scaling is a possible source of uncertainty in model estimates, and quantification of uncertainty in the estimates resulting from data aggregation would therefore be of benefit to planners, researchers and land users.

In the first period (1984-1992), moving from scale 1 (household level 1) to scale 170 (the village level), microspatial variability reduced from 93% to 16% (figure 5.16a). This is a measure of the amount of detail that is lost due to aggregation. In the second period (1992-1999), microvariability within the two scales reduced from 80% to 21% from scale 1 to 170. The proportion of spatially dependent components of variation is the complement of the proportion of microvariation. Figure 5.16b shows that aggregation led to an increase in spatial correlation in the dataset. The range of the spherical variograms in table 5 is 3 km to 7 km, which fairly corresponds to the boundary of agricultural areas for villages in the study area.

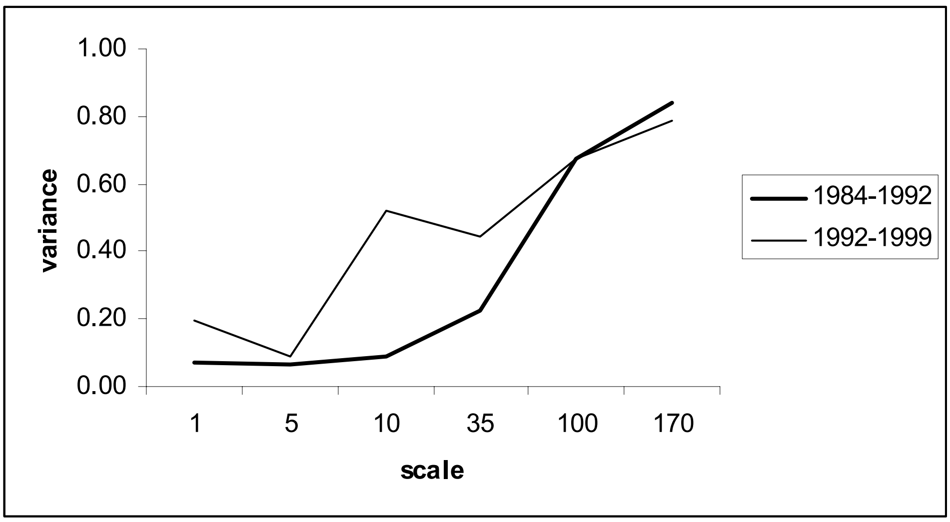
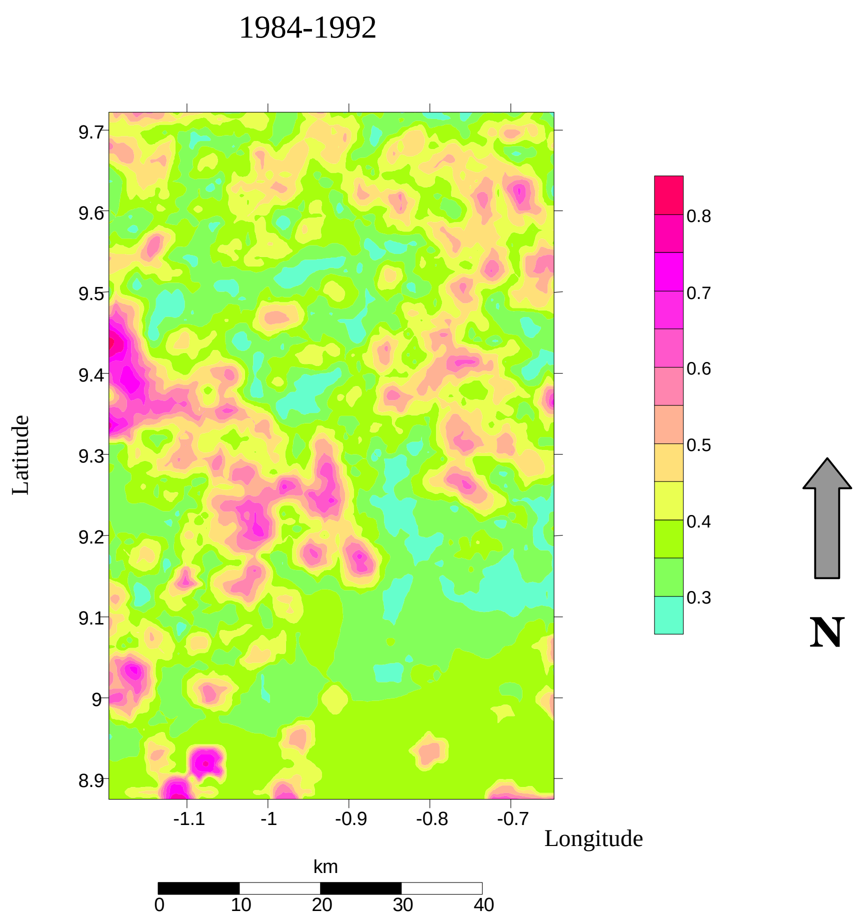


Figure 5.16b: Proportion of spatially dependent component of total variation across scales

Maps of probability of cropland change

Predicted probability maps of conversion to cropland based on the models at the basic 30 m scale for the two periods are shown in Figure 5.17. The maps fairly represent actual conversion to cropland in 1992 and 1999, respectively (Figure 5.6). Higher probabilities were generally assigned to areas that actually experienced change to cropland for the two periods indicating that variables in the models generally captured the driving factors of cropland change.



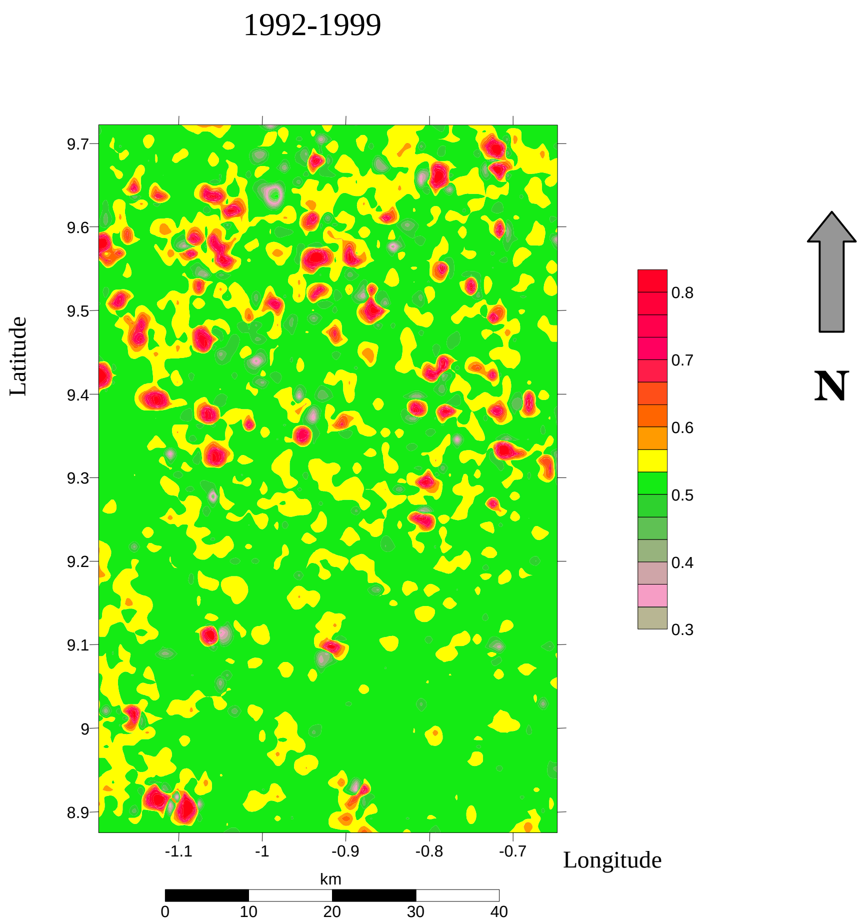


Figure 5.17: Predicted Probability of conversion to cropland

Validation of logistic regression models

Relative operating characteristics (ROC) is an index of agreement between observed and predicted data. It can be interpreted as the probability that a randomly selected changed pixel on the landscape is regarded with greater precision as being changed than a randomly selected non-changed pixel. It increased from 0.78 for scale 1 to 0.92 for scale 6 (figure 5.18). This shows better correspondence in observed and predicted conversion to cropland as spatial extent increases. This may also be due to the smoothing effect of averaging of data.

Different values of κloc and κq were observed across scales. Average values of κq were 0.75 (small scales), 0.98 (medium scales) and 0.64 (large scales). Thus, ability of the models to correctly specify quantity of pixels converted to cropland across scales is in the order medium>small>large. Average values of κloc were 0.82 (small scales), 0.94 (medium scales) and 0.99 (large scales), indicating that ability to correctly explain location is large>medium>small.

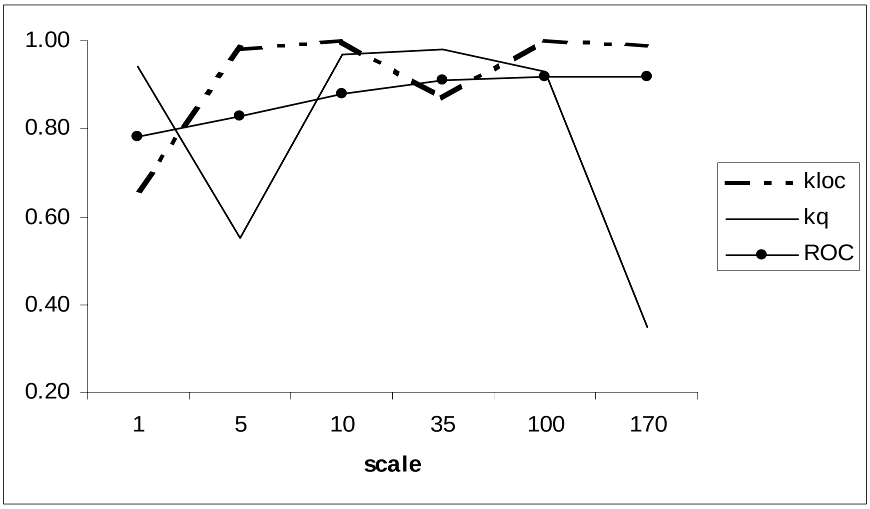


Figure 5.18: Changes in validation parameters across spatial scales

The validation parameters generally show that variables in the models were generally able to capture the determinants of cropland change in the study area. The models performed better in specifying location compared to specifying extent. This is due to the high explanatory power of the variables in the models. Lower values of κ_q may have resulted from

- Change in the variables that influenced land-cover change over time, and
- Change in the importance of the variables (i.e., estimated regression coefficients) that influenced cropland change over time.

Appropriate scale and drivers for LUCC modeling

The overall goal of LUCC modeling is to characterize land-use change processes to provide an effective guide for land-use planning decisions. To be of value for planning, LUCC models must be implemented at scales compatible with the level of activities of land users/managers. In this study, probability modeling was carried out at six different spatial scales ranging from the level of activity of individuals and households to that of villages. The resulting models are quite different in terms of explanatory variables and the importance of the variables in time and space. A vital question is the optimum scale for probability modeling in the study area.

The parameters of variograms of standardized residuals in Table 5.16 show that marked spatial heterogeneity in land-use change processes exist at distances up to 7km. At scales 30m-300m (1984-1992) and 30m-1050m (1992-1999), a range could not be determined for the variograms, indicating that the number of samples (5,000-10,000; Table 5.12) were inadequate for determining the range of spatial variation. The problem of large data requirement to effectively characterize the spatial pattern land-use change at small spatial extent (e.g., household level) is not limited to empirical statistical models used in the study. Process-based models also suffer the same problem (Veldkamp and Lambin, 2001). However, merely characterizing the behavior of the land-use system at the micro-scale would not lead to the derivation of the whole system function (Veldkamp et al, 1999). The overall implication is that the choice of an appropriate scale would involve a trade-off of spatial heterogeneity (detail) with spatial extent (size). In Table 5.16, the ranges of the spherical variograms vary from 3km to 7km. This fairly coincides with the boundary of agricultural areas for localities in the study area. Thus, the village level of 3km to 5km may be the most appropriate spatial unit for empirical statistical models in the study area. At these levels, the average values of validation parameters were relative operating characteristics (ROC) = 0.91, κ_{loc} = 0.99 and κ_q = 0.64 (Figure 5.18).

Another issue concerns the choice of explanatory variables to include in the models at these scales. Figure 5.15 and Table 5.14 help to answer this question. In Figure 5.15, better model fit was obtained for the 1992-1999 models across scales. Therefore, it is reasonably safe to assume that near-future land-use change pattern would depend on the most recent observed changes, and that spatial determinants of future land-use patterns would be similar to those of recent patterns. At the village level (i.e., scales 100-170 in Table 5.14c), the variables that explained cropland change between 1992 and 1999 were

- Altitude
- Rainfall zone
- Temperature zone
- Land suitability index

- Landscape heterogeneity (Dominance)
- Distance to main market
- Distance to villages
- Initial population density, and
- Change in population density

Future land-use change modeling should therefore incorporate these variables.

5.7 Socioeconomic analyses

Migration trend to Wuripe

Figure 5.19 is a representation of the trend in settlement at Wuripe from 1989 to 2001. The graph indicates that less than 20% of the households migrated before 1992, whereas the remaining 80% migrated into Wuripe from 1992 onwards. Thus, most of the population movements occurred in the post-structural adjustment era. This may be due to high macroeconomic instability resulting in higher inflation in the 1990s (Tshikata, 1999).

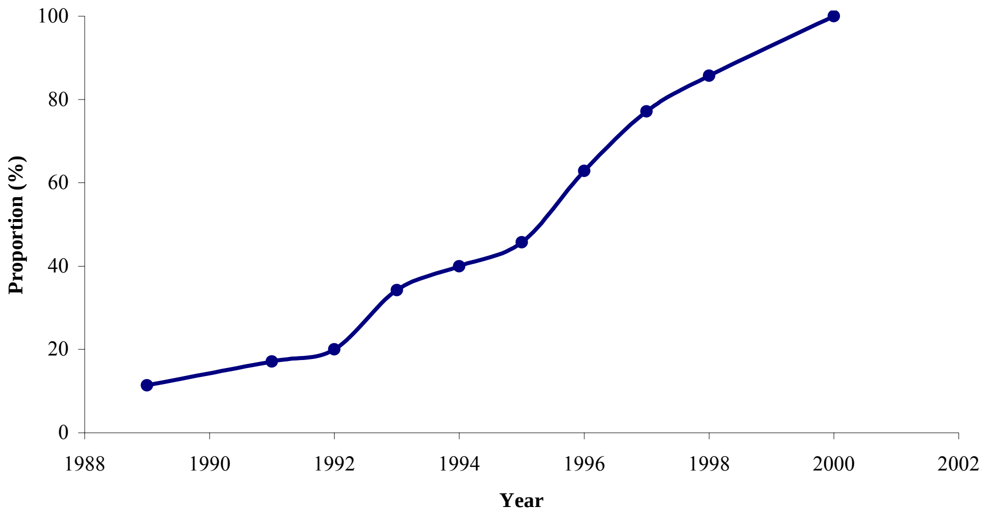


Figure 5.19: Cumulative distribution of household migration to Wuripe

The sampled households cited six reasons for migrating to Wuripe (table 5.17). It is apparent that soil quality deterioration at the source of migration and lack of access to land were the major migration push factors. The relatively more secure land tenure (an institutional factor) at Wuripe is obviously a pull factor. Smith (1991) already indicated that access to land in rural areas could reverse rural-urban migration. Institutions apparently are mediators of access to livelihood resources. Institutions determine, directly or indirectly, the outcomes of livelihood strategy embarked upon by the household (Scoones, 1998).

Table 5.17: Declared reasons for migrating to Wuripe [a]

Reason	Proportion (%)
Declining soil fertility	51
Scarcity of land at source of migration	37
To increase output/make more income	23
Changed employment to farming	17
Irregular/unreliable rainfall	6
Ethnic conflict	3

[a] Values do not add up to 100% because most households cited more than one cause of out-migration

Factors affecting land-use change at Wuripe

Table 5.18 indicates that, on the average, farm size increased yearly by about 0.3 ha. A typical household head is in the middle-age group. The average increase in household size was 3 persons per year, whereas the average increase in farm labour was about 2 persons per year. The average increase in child dependency ratio was about 0.5, suggesting an appreciable increase in the proportion of dependants. The average proportion of maize that was marketed (37%) was less than that of rice (46%). On the average about one-third of the period spent at Wuripe was allowed for fallow.

Table 5.18: Descriptive statistics of variables in the land-use change model for Wuripe

Variables	Definition	Minimum	Mean	Maximum	Std. Dev
DEPENDENT VARIABLE					
FARM SIZE	Change in total land area cultivated by household between year of inception at Wuripe and the year 2001 divided by length of time spent at Wuripe (ha/year)	-0.33	0.25	1.15	0.34
INDEPENDENT VARIABLES					
DISTANCE TO FARM	Maximum distance traveled by household to farm plots (km)	0.50	2.40	6.00	1.38
AGE	Age of household head (years)	27.00	45.03	70.00	12.07
CHILD DEPENDENCY RATIO	The difference between the ratio $\frac{No\ of\ people \leq 15\ years}{No\ of\ people > 15\ years\ and\ actively\ engaged\ in\ farming}$ at inception at Wuripe and 2001	-1.50	0.45	2.33	0.72
LABOR AVAILABILITY	Change in farm labor between inception at Wuripe and 2001 (persons)	0.00	1.69	7.00	1.51
MAIZE SALE	Mean proportion of harvested maize sold over the period (years) spent at Wuripe (%)	10	37	60	12
RICE SALE	Mean proportion of harvested rice sold over the period (years) spent at Wuripe (%)	10	46	80	18
FALLOW	Number of years allowed for fallow divided by length of time (years) spent at Wuripe	0.00	0.33	0.75	0.25
FERTILIZER	Number of years household has used fertilizer divided by length of time (years) spent at Wuripe	0.00	0.21	1.00	0.37
TRACTOR USE	Number of years household has used tractor divided by length of time (years) spent at Wuripe	0.00	0.36	1.00	0.42
HOUSEHOLD SIZE	Change in household size between inception at Wuripe and 2001 (persons)	1.00	3.06	12.00	2.25

The combined effects of the independent variables on the multiple regression model (table 5.19) are discussed as follows:

Demographic variables

Multiple regression analysis shows that there was a strong and positive relationship between land-use change (FARM SIZE) and change in household size ($p<0.01$). This confirms that land-use change is driven by an increase in the demand for food. A negative relationship between age of household head (main decision maker) and change in land-use shows that most of the increases in land-use change were associated with households with younger household heads. There was a negative and significant relationship between land-use change and change in age structure of household ($p=0.05$). This implies that increases in farm size were associated with households with a smaller number of children.

Table 5.17: Multiple regression model for Wuripe. Dependent variable is FARM SIZE

	Standardized β	Sig. Prob.
AGE	-0.14	0.13
HOUSEHOLD SIZE	0.38	<0.01
CHILD DEPEDENCY RATIO	-0.22	0.05
LABOUR AVAILABILITY	-0.08	0.41
TRACTOR USE	0.41	<0.01
FALLOW	-0.05	0.56
FERTILIZER USE	-0.40	0.01
RICE SALE	0.54	<0.01
MAIZE SALE	-0.07	0.43
DISTANCE TO FARM	0.11	0.26
R^2		0.84
Adjusted R^2		0.77
Sig. Prob.		<0.01

Technology

According to Mertens et al (2000), technological evolution can be evaluated by changes in fallow period and change in inputs (labour force, fertilizer, machinery, etc.) employed by the household. Fertilizer use and fallow were inversely related to land-use change. This suggests an increase in land-use intensity. A strong relationship between land-use change and fertilizer use was observed. An increase in fertilizer use tends to decrease the hectarage cultivated by a household, other factors remaining constant. Change in fallow length appears to be a weak predictor of land-use change at the household level. As fallow length generally tends to decrease due to population pressure, the inverse relationship also confirms the phenomenon of agricultural intensification at the household level. Change in labour availability was not significantly related to land-use change ($p>0.05$), whereas there was a strong and positive relationship between land-use change and use of tractors ($p<0.01$). This suggests the tendency to substitute farm labour with tractors for farming activities.

Market variables

There was a positive but non-significant relationship between DISTANCE TO FARM and land-use change. Households tend to create new farmlands at more distant places. Evolution of marketing of cereals measured as average proportion of maize and rice sold shows negative and positive relationships with land-use change; respectively. Marketing of rice was also significantly related with land-use change. There has been an increase in land area devoted to rice production to meet increasing local demand in Northern Ghana. The accessibility to market (Tamale) encourages the sale of agricultural produce.

Conclusions from the Wuripe study

Macroeconomic transformations in Ghana appeared to have played a major role in migration patterns and land-use change in Wuripe. Devaluation and other instruments of structural adjustment appear to have had a strong ecological impact by increasing pressure on land. Less favourable economic opportunities at sources of migration encouraged in-migration to Wuripe in the post-structural adjustment period. Resulting population increases led to expansion of cultivated areas to woodlands.

Land-use changes were a result of coexistent processes of extensification and intensification. The driving factors were household size, proportion of dependants, tractor use, fertilizer use, and marketing of rice. The increase in the use of fertilizer in spite of fiscal policies that reduced fertilizer subsidies could be interpreted in the light of farmers' response to marketing opportunities for sale of local rice. Increase in tractor use on the other hand may be explained by measures by the government to mitigate the effects of adjustments. For instance, Jebuni and Seini (1992) observe that while there was a tremendous increase in the nominal cost for tractor hire during the adjustment era, in real terms farmers paid 70% less for ploughing in 1990 than they did in 1980. Increased flow of spare parts was cited as a possible explanation for this.

Analyses of land-use and land-cover change as carried out for Wuripe could provide relevant information for policy makers who are responsible for land-use planning. While provision of basic infrastructure (e.g., potable water, health facility, schools, etc.) to facilitate permanent settlement of the people is required at Wuripe, there is also the need for environmental education and awareness programmes on the environmental consequences of woodcutting for firewood and charcoal. The development of alternative sources of energy could also minimize the overall impact of woodcutting.

Decline in closed woodland as a result of illegal woodcutting underscores the need for environmental protection policies. The large expansion of agricultural land at the expense of woodland also calls for agricultural intensification strategies to discourage expansion of cultivation on fragile lands. Such strategies should address sustainable soil management and farming techniques, and are discussed in detail in section 6.

Regional village level model

Descriptive statistics for variables in the village-level multiple regression models are given in Table 5.20. Owing to the high level of multicollinearity in the data, the variables for household (Wuripe) and village level models are not identical. The lowest amounts of land converted to agriculture for the two periods (631ha in 1984-1992 and 390 ha in 1992-1999) were recorded for Digma, whose population increased from 88 in 1984 to 187 in 2000. Dalun, whose population increased from 2116 in 1984 to 10636 in 2000 had the highest degree of land-use change for both periods (24115ha and 34030ha, respectively). Proximity to the Bontanga irrigation encouraged agricultural intensification and extensification in Dalun. The average annual rate of change in land-use was higher in the second period for the sampled villages ($\frac{7625}{7} = 1096 ha / year > \frac{7893}{8} = 987 ha / year$). Table 5.15 shows a clear decrease in fallow length over the entire period, as the minimum, mean and maximum fallow lengths were higher in the first period. This was likely a result of increasing population pressure. Average and maximum household size was higher in the second period. The age dependency ratio also showed an increase from the first to second period. The average proportion of households that declared an increase in the amount of fertilizer use also increased in the second period, suggesting an increasing trend in agricultural intensification. Table 5.18 also shows a remarkable increase in the amount of farm labor, as average farm labor increased more than 4 times in the second period.

Table 5.20: Descriptive statistics for variables in the multiple regression models for villages

a) 1984-1992 (N=18) [a]

Variables	Description	Min	Mean	Max	Std dev
LAND-USE (ha)	Difference between cropland extent in 1984 and 1992 (dependent variable)	631	7893.7	24115	7380.2
POP92-84 (persons)	Change in population between 1984 and 1992	-17	255.4	2628	607.3
FALLOW (years)	Average fallow length by households in a village	1.6	4.4	7.3	1.6
LAB92-84 (persons)	Change in farm labor between 1984 and 1992	7	46.1	235	56.8
FERTILIZER USE (%)	Proportion of households within a village that uses fertilizer	10	26.4	36	7.3
MARKET (km)	Distance from center of village to Tamale	8	22.4	52	12.9
HHSIZE (persons)	Average household size in a village	5	7.2	10	1.3
DEP-RATIO	Average of ratio $\frac{No\ of\ people \leq 15\ years}{No\ of\ people > 15\ years\ and\ actively\ engaged\ in\ farming}$ for households within a village between 1984 and 1992	0.23	0.36	0.55	0.09

b) 1992-1999 (N=20).

Variables	Description	Min	Mean	Max	Std dev
LAND-USE (ha)	Difference between cropland extent in 1992 and 1999 (dependent variable)	390	7675.3	34030	8418.5
POP2000-92 (persons)	Change in population between 1992 and 1999	-10	498.5	5892	1304
FALLOW (years)	Average fallow length by households in a village	0	1.8	3.8	1.3
LAB2000-92 (persons)	Change in farm labor between 1992 and 1999	12.00	180.8	987	221.2
FERTILIZER USE (%)	Proportion of households within a village that uses fertilizer	0	35.20	65	16.62
MARKET (km)	Distance from center of village to Tamale	8	26.10	60	16.61
HHSIZE (persons)	Average household size in a village	5	11.7	16	2.8
DEP-RATIO	Average of ratio $\frac{No\ of\ people \leq 15\ years}{No\ of\ people > 15\ years\ and\ actively\ engaged\ in\ farming}$ for households within a village between 1992 and 1999	0.56	0.77	1.07	0.15

[a] Analysis was limited to 18 villages in the first period, as two of the villages (Wuripe and Atta Kura were established after 1988).

Multiple regression results for the two periods are summarized in Table 5.21. In the first period, change in population was an important driving force of land-use change ($p<0.01$), whereas the variable was not significant in the second period. A similar trend was observed for child dependency ratio. Change in farm labor availability was an important driving force of land use change in both periods, whereas average fallow length was only significant between 1984-1992 ($p<0.1$). The sign of the coefficient of FALLOW in the first period was positive, indicating that low population density permitted fallow as a means of rejuvenating soil fertility. In the second period, however, the coefficient was negative due to increasing pressure on land. Distance to Tamale was significant and inversely related to land-use in the two periods ($p<0.1$). Fertilizer use was significantly related to land-use change in the second period ($p<0.1$).

Table 5.21: Estimated regression coefficients of village-level variables with LAND-USE (for description of variables, see Table 5.18)

a) 1984-1992

	β	Standard Error (*β*)	Standardized *β*	*t*	*t* prob.
INTERCEPT	3428.57	6375.52		0.54	0.60
POP92-84	6.60	1.06	0.54	6.23	<0.01
FALLOW	826.14	400.90	0.18	2.06	0.07
LAB92-84	93.24	11.93	0.72	7.81	<0.01
FERTILIZER USE	-14.78	92.48	-0.02	-0.16	0.88
MARKET	-88.72	48.49	-0.16	-1.83	0.10
HHSIZE	164.96	559.21	0.03	0.29	0.77
DEP-RATIO	-11124.42	6397.73	-0.14	-1.74	0.11
R^2					0.94
Adjusted R^2					0.89
F probability					<0.01

b) 1992-1999

	β	Standard Error (*β*)	Standardized *β*	*t*	*t* prob.
INTERCEPT	30267.55	8432.87		3.59	<0.01
POP2000-92	0.62	1.73	0.10	0.36	0.73
FALLOW	-135.16	748.64	-0.02	-0.18	0.86
LAB2000-92	27.83	10.26	0.73	2.71	0.02
FERTILZER USE	-108.47	57.68	-0.21	-1.88	0.08
MARKET	-222.85	70.85	-0.44	-3.15	0.01
HHSIZE	-54.06	409.65	-0.02	-0.13	0.90
DEP-RATIO	-22550.51	5955.49	-0.40	-3.79	<0.01
R^2					0.89
Adjusted R^2					0.84
F probability					<0.01

The relative importance of variables to land-use change over time is shown in figure 5.20. The standardized regression coefficient for labor was consistently the highest for the two periods. This is unexpected, as labor remains the most important factor of production in the land-use system. Distance to Tamale increased in importance, suggesting the commercialization of smallholder agriculture. The change in child-dependency ratio also became more important. Its inverse relationship with land-use change further reflects the importance of labor supply in the farming system of the localities. Total population reflects demand for food. Its decline in importance in the second period while distance to market increased in importance further confirms that the relative importance of market-oriented production in the farm-households increased. The proportion of households in the villages that declared an increase in land area devoted to rice increased from about 18% between 1984-1992 to 43% between 1992 and 1999. Furthermore, up to 76% of the surveyed households marketed rice at Tamale between 1992 and 1999 compared to only 41% between 1984 and1992.

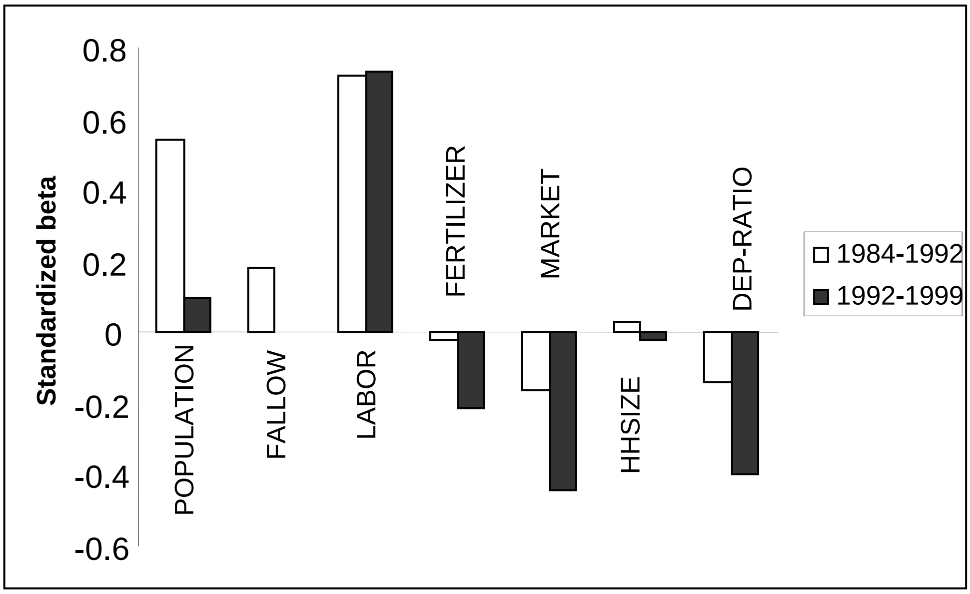


Figure 5.20: Standardized regression coefficients for village-level models for 1984-1992 and 1992-1999.

Validation of cropland change at village level

The relationship between observed and predicted cropland change is shown in figure 5.21. The correlation coefficient was significant at p=0.01. Over-prediction occurred in 60% of the villages. This was due to changes in significant variables affecting cropland change, as well as change in their importance over time. For instance, population change was not significant in the second period, whereas the model for the first period predicted an increase of 0.54 standard deviation units in cropland change if population increased by 1 standard deviation unit. Notice also that data for 18 villages were used in calibrating the model for the first period.

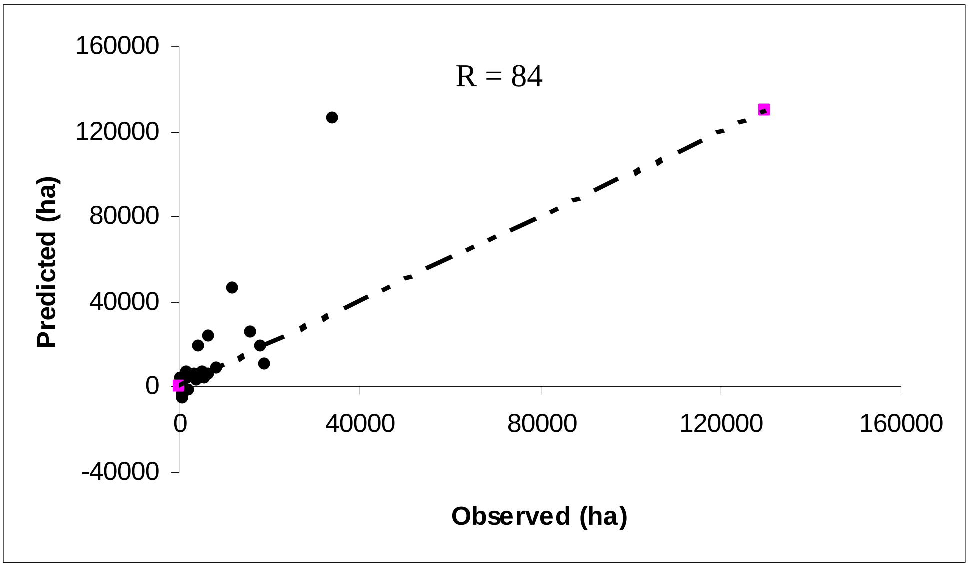


Figure 5.21: Association between observed and predicted cropland change 1992-1999. The hypothetical 1:1 association is shown as dashed line.

5.8 Effects of land-cover change on soil properties relationships

The section on soil characteristics (section 5.3) already touched on the effects of land-cover change on soil properties. The current section attempts to further evaluate the consequence of land-cover changes on relationships between soil properties, with a view to elaborating implications for agricultural sustainability.

Table 5.22 shows statistically significant correlations among many soil properties: pH with 11 other properties and organic C is with 10 properties. Nutrient availability is strongly pH-dependent and soil organic matter (SOM) is the storehouse of plant nutrients. Also, ECEC is significantly correlated with ten other properties, notably more with organic C ($r = 0.65$) than with clay ($r = 0.35$). This suggests that a decrease in organic matter will decrease ECEC, which may consequently lead to a reduction in the nutrient holding capacity of the soils. The significant correlations between organic C and clay ($r = 0.23$) and between N and clay ($r = 0.30$) suggest that the amounts of organic C and N in the soils are dependent on the amount of clay particles. Poorly drained soils are found in areas with low slope gradient, whereas high chroma is associated with well-drained soils.

Table 5.22: Intercorrelation of soil properties

	pH	Organic C	N	P	K	Ca	Mg	EA	Hue	Value	Chroma	Sand	Silt	Clay	ECEC	Base Saturation	Slope	Elevation
Organic C	**																	
N	**	**																
P	**	**	**															
K	**	**	**	**														
Ca	**	**	**	**	**													
Mg	**	**	**	*	**	**												
EA	**	NS	NS	NS	NS	NS	NS											
Hue	**	NS	*	*	NS	*	NS	**										
Value	**	**	**	**	**	**	**	*	**									
Chroma	NS	**	**	NS	NS	**	**	NS	NS	**								
Sand	NS	NS	NS	NS	NS	NS	*	NS	NS	NS	NS							
Silt	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	**						
Clay	NS	*	**	NS	NS	**	**	NS	NS	*	NS	**	NS					
ECEC	**	**	**	**	**	**	**	NS	NS	**	**	NS	NS	**				
Base Saturation	**	**	*	NS	*	**	**	**	**	**	NS	NS	NS	NS	**			
Slope	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS		
Elevation	NS	NS	NS	NS	NS	NS	NS	NS	*	NS	**	NS	NS	NS	NS	NS	**	
Drainage	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	*	NS	NS	NS	NS	NS	**	NS

* Significant at $p<0.05$, ** Significant at $p<0.01$, NS=Not significant

The correlation of organic C with many soil properties, its association with land-cover change, as well as its documented role in agricultural sustainability makes soil organic matter (SOM) the most important index of agricultural sustainability especially in tropical agriculture. A vital question, however, is whether organic matter management alone could replenish the fertility status of the soil to guarantee food security.

The relationship between organic C and three other soil quality parameters (ECEC, N and P) were evaluated and are presented in Figure 5.22. The figure shows that continuous cultivation degrades SOM. Between the non-cultivated and recently cultivated soils, there is decrease in SOM quality as cultivation persists, reflected in the lower slope and exponent of the models. With the apparent loss of organic matter (horizontal axis), the more recalcitrant materials are left in the soil. This fraction is of lower quality and contributes little to available P, ECEC and N in the soil. In the permanently cultivated soils, a decline in SOM does not lead to a change in N and P, suggesting that none is available to be set free. This phenomenon reflects the extent of nutrient mining in the study area. About 12% of the study area is thus affected (sequence 8 of land-cover change trajectory in Table 5.5)

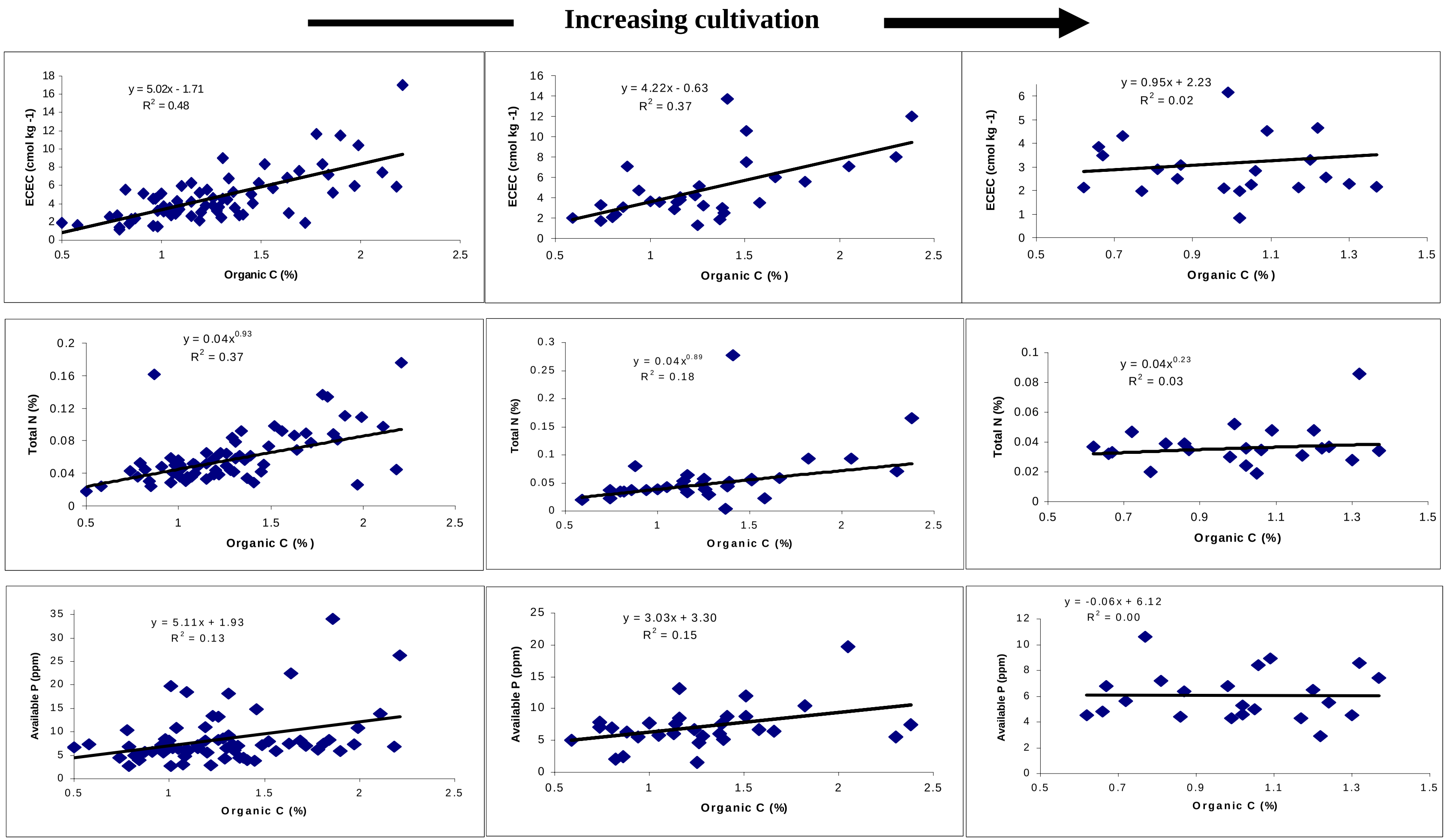


Figure 5.22: Functional relationships between organic C and selected soil properties

Based on the models in Figure 5.22, the minimum organic C levels to achieve critical levels for ECEC, N and P were estimated (Table 5.23). Minimum organic C requirements are higher for recently cultivated land. No calculations were made for the permanently cultivated land because a relationship between the parameters and organic C is virtually non-existent. For recently cultivated and non-cultivated soils, the minimum organic C requirements for the parameters are in the order P>N>ECEC. Table 5.20 further indicates the deficit in organic C needed to meet the critical level for each parameter. However, accumulation of organic matter in a savannah environment is very slow and it is difficult to make up for such deficits using organic inputs alone. It needs about 7 t ha^{-1} to replenish recently cultivated soils. Giller et al (1997) and Palm et al (1997) have discussed problems associated with addition of large amounts of organic manure. These include low quality of organic inputs generated by farmers, high labor and transportation costs and losses through leaching and denitrification. The low P content of organic inputs also makes them a poor supplier of P. The overall soil management implication is that considerable investment in inorganic fertilizers will also be required (Vlek et al, 1997), as removal of P from the soil is mainly by crop harvest and P is not compensated by nutrient recycling. Nitrogen on the contrary, is at least partially replenished by nitrogen fixation through Azotobacter and leguminous plants.

Table 5.23: Estimated minimum organic C content for selected soil quality parameters

		Non-cultivated soils n = 68			**Recently cultivated soils n = 30**		
Soil property	**Critical level**	**Minimum organic C (%)**	**Deficit organic C (%) [a]**	**Deficit organic C (t ha^{-1}) [b]**	**Minimum organic C (%)**	**Deficit organic C (%) [a]**	**Deficit organic C (t ha^{-1}) [b]**
ECEC	8 cmol/kg	1.93	0.66	1.79	2.04	0.76	2.13
Total N	0.1%	2.37	1.10	3.04	2.88	1.60	4.48
Available P	15ppm	2.56	1.29	3.61	3.86	2.58	7.22

[a] Obtained by subtracting mean organic C for the land-cover category from the estimated crucial organic C level
[b] Assumes bulk density of sampled layer is 1.40 g cm^{-3}

5.9 Implications for food security in Northern Ghana

Research on land-use and land-cover change in the largely rural Northern Ghana needs to be related to a reliable supply of food, as food insecurity manifesting in low consumption, high malnutrition and mortality rates is a widespread phenomenon in the area (Nyanteng and Asuming-Brempong, 2003). With erratic rainfall and only marginal soil fertility, feeding the growing population is a major challenge to rural development. Yields of major crops, particularly maize, have experienced a decline in the last few years in Northern Ghana (Figure 5.23).

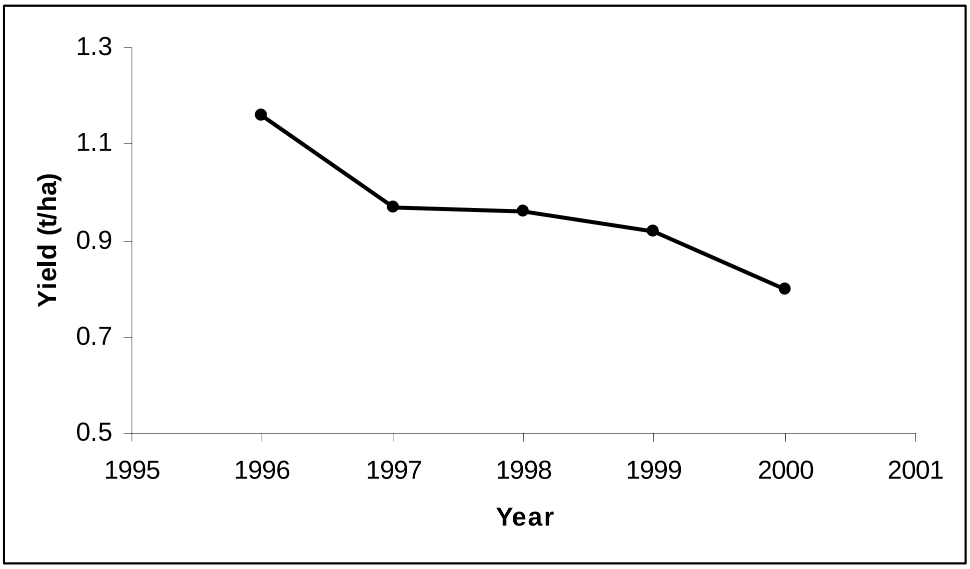


Figure 5.23: Average maize yield in Northern Ghana 1996-2000. (Data Source: Ministry of Food and Agriculture)

This calls for efforts to explain the downward trend and make recommendations for improvement. Yield information is of interest to users (farmers) and policy makers (government officials) who are responsible for rural development. Most often, climate is named as the major cause of declining productivity of cereals (e.g., CIMMYT, 1988). However, even with adequate rainfall, optimum yields cannot be attained without favorable soil conditions (Ogunkunle, 1993). The land suitability index (*LI*) was therefore related to observed maize yield in the surveyed villages between 1999 and 2001 (Table 5.24).

In examining the relationship between maize yield at the village level and the land suitability index, a spatial interpolation of computed land suitability was carried out using ordinary block kriging (Figure 5.24).

Table 5.24: Average maize yield and standard deviation (tha^{-1}) for villages (1999-2001)

No	Village	Yield
1	Kpenjiyili	1.07±0.15
2	Attakura	0.77±0.11
3	Jukuku	1.16±0.23
4	Wuripe	1.20±0.14
5	Kpegunayili	0.95±0.22
6	Digma	1.17±0.26
7	Sakpaluwa	0.77±0.15
8	Voguyili	0.64±0.13
9	Libga	0.61±0.09
10	Jana	0.72±0.10
11	Ziong	0.54±0.08
12	Dabogushei	0.67±0.22
13	Sanga	0.79±0.29
14	Kotingli	0.77±0.15
15	Yong	0.73±0.26
16	Sabegu	0.66±0.29
17	Saakuba	0.89±0.33
18	Dalun	0.71±0.28
19	Kpachi	0.68±0.20
20	Cheyohi	0.65±0.16

Ordinary point kriging provides the best linear unbiased predictor at point locations under the assumption that the mean of the quantity being predicted is constant, whereas ordinary block kriging provides average predictions of land suitability for areas of land. Land suitability indices were predicted for block sizes of 5 km x 5 km, being the average size of agricultural area of the villages.

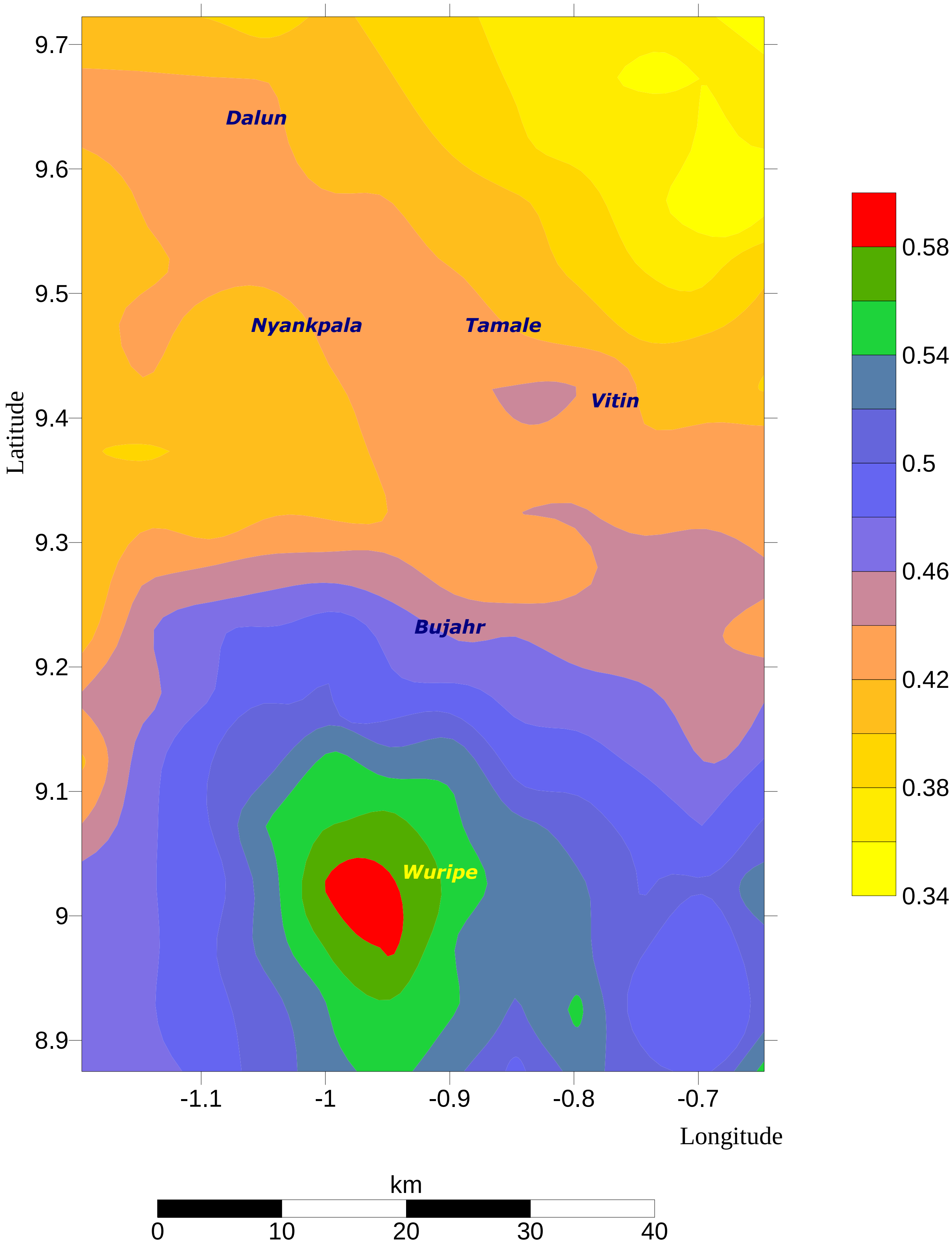


Fig 5.24: Land suitability index computed by kriging over 5 kmx5 km blocks

The relationship between the average village yields, and the interpolated *LI* by block kriging, is shown in figure 5.25.

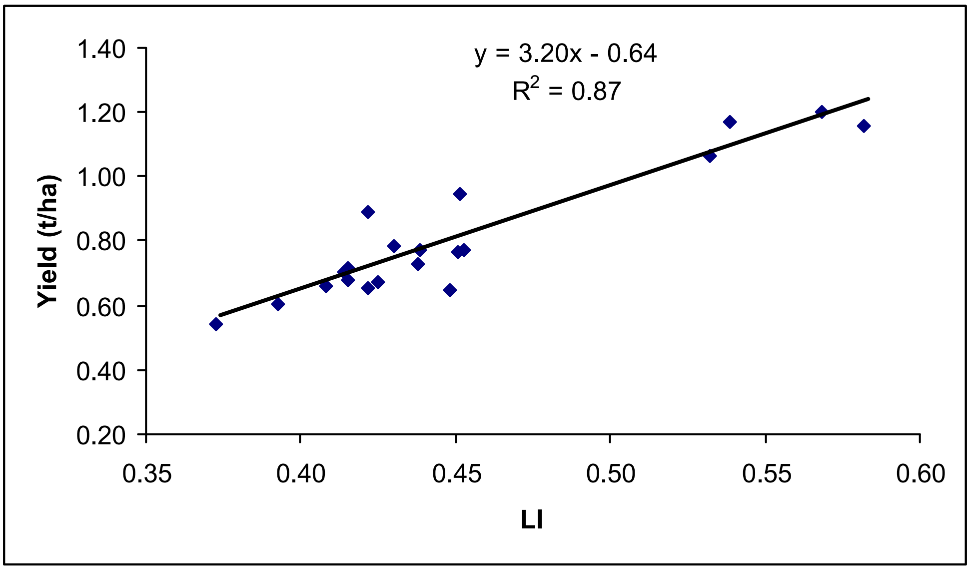


Figure 5.25: Relationship between maize yield and land suitability index at the village level

Both regression coefficients are significant (table 5.25), and the coefficient of determination is high (87%). This shows that land suitability is closely related to maize yield in the study area.

Table 5.25: Estimated regression coefficients b0 and b1 of maize yield and interpolated land suitability indices

b_0	Standard error (b_0)	b_1	Standard error (b_1)	*t* probability b_0	*t* probability b_1
-0.64	0.13	3.20	0.29	< 0.01	< 0.01

Land suitability indices are low, reflecting low inherent fertility of the soils. The low productivity potential of the soils is clearly a threat to food security given the increase in population and low external input such as fertilizer to support crop production. Continuous cultivation may make nutrient mining endemic in the study area, leading to lower incomes for farmers and deepening poverty for the populace at large. High correlation between maize yield and land suitability offers an explanation for the low maize yields observed in the study area. These results therefore support the work of Ruben et al (2003) who states that environmental degradation in developing countries is closely linked to low agricultural land productivity and food insecurity. The primary limitations of the soils for agriculture (section 5.4) are ECEC, organic C and Clay content. Emphasis should be placed on soil management techniques that conserve organic matter and enhance nutrient and water holding capacity of the soils. Detailed soil management strategies that are appropriate for the study area are suggested in the next chapter.

6 SUMMARY AND CONCLUSION

This section discusses concisely the major findings of this research vis-à-vis the study objectives. Research and policy implications are also highlighted.

6.1 What were the causes of land-cover change?

The proximate causes of LUCC were agricultural expansion and wood extraction for domestic and commercial purposes. The major underlying causes of change included population growth, spatial distribution of population and migration. Furthermore, changing macroeconomic conditions between 1984 and 1999 appeared to have affected the observed rates of land-cover change.

6.2 What were the rates of land-cover change?

About 55% of the landscape experienced a cover change in the period corresponding to the stabilization/structural adjustment era (1984-1992), whereas the proportion of changed land in the post-structural adjustment period (1992-1999) was 58%. Between 1984 and 1999, the proportion of changed landscape was about 62%. Thus, annual rates of land-cover change were 7% and 8% in the first and second periods, respectively, whereas the net rate (1984-1999) was over 4%. This suggests that changing economic opportunities and macroeconomic instability in the post-structural adjustment period probably affected land-cover change more than during stabilization/structural adjustment.

6.3 What were the rates of conversion amongst land-cover types?

The most dominant land-cover change was conversion of natural vegetation to cropland, which occurred at an annual rate of 5%. In the first period, about 17% of natural vegetation was converted to cropland, whereas a slightly higher fraction (18%) was converted to cropland in the second period. The net change from natural vegetation to cropland was 21%. The net transition to less vegetation was higher (19%) than overall transition to more vegetation (15%). These values indicate increasing human pressure on land.

6.4 What were the dominant change trajectories and what proportions of land-cover changes were reversible?

The most dominant trajectory was conversion to cropland in 1999 (i.e., *recent cropland,* 12%), followed by *old cropland* (i.e., natural vegetation converted to cropland from 1992 in over 9% of the landscape). Reversible change in woodland and grassland occurred in 4% and 2% of the landscape, respectively. A ligher proportion of reversible land-cover change is related to fallow agriculture (over 15% when aggregated). A higher overall increase in woody biomass (10%) and a simultaneous decrease of 9% indicate a certain level of resilience in the ecosystem.

6.5 What were the spatio-temporal patterns of land-cover change?

In the first period, there were patches of agricultural land that developed around Tamale, whereas transitions to natural vegetation occurred in the southern part of the study area with lower population densities. In the second period, spatial development of agriculture occurred near the Bontanga irrigation project and Wuripe. Unchanged agricultural land was widespread around Tamale and Bontanga, whereas change to natural vegetation occurred in association with conversion to cropland in many parts of the landscape. Such association reflects the probability of conversion of more natural vegetation to cropland in the future.

6.6 What were the major proxy variables driving land-cover change?

The factors explaining the probability that a piece of land will be converted to cropland given its location characteristics are both time and scale dependent, making generalizations difficult. In the first period, an increase in altitude, land suitability index, distance from roads, distance from main market, distance from villages and initial population density in 1984 and change in population density (1984 to 1992) decreased the likelihood of cropland change by 0.7-0.9, whereas being in the rainfall zone where annual rainfall is greater than 1100mm increased the likelihood of cropland change by a factor of about 2.5-5 at individual and household levels. With the exception of change in population density (1984 to 1992), the same variables had the same effect on cropland change at the level of commercial farming. At the village level, distance to villages, land suitability index and distance to main market reduced the likelihood of conversion to cropland by 0.7 to 0.9, whereas being in temperature zone < 28°C increased the probability of conversion to cropland by a factor above 5 at the village level.

In the second period (1992-1999), an increase in land suitability index and being in the rainfall zone with an annual rainfall > 1100mm increased the likelihood of conversion to cropland by a factor above 5, whereas an increase in distance from main market and villages decreased the likelihood by a factor ranging from 0.7 to 0.9 at the individual and household levels. These variables had the same effect at the level of commercial farming. Also, modeling indicated that commercial farmers were probably the most sensitive to distance from roads, as an increase in the variable reduced the likelihood of conversion to cropland by 0.9. The most important variables explaining the likelihood of conversion to cropland at the village level were distance to main market, distance to villages, change in population density (1992-2000), landscape heterogeneity (dominance) and altitude, which decreased the probability of cropland change by 0.7 to 0.9. Land suitability index and population density in 1992 also increased the probability of cropland change by a factor ranging from 2.5 to 5.

Multiple regression was used to investigate the factors that determined the amount of land that households converted to agriculture at the household (Wuripe) and village levels. At Wuripe, land-use change was primarily driven by change in household size (standardized b = 0.38; $p<0.01$), frequency of tractor use (standardized b = 0.41; $p<0.01$) proportion of rice marketed (standardized b = 0.54; $p<0.01$), and child-dependency ratio (standardized b = -0.22; $p<0.05$). This suggests that at the household level, land use strategies featured extensification and intensification processes. The negative relationship between land-use change and child-dependency ratio underscores the importance of labor in the land-use system.

At the village level, land use change was mainly driven by change in population between 1984 and 1992 (standardized b = 0.54; $p<0.01$), change in labor availability between 1984 and 1992 (standardized b = 0.72; $p<0.01$), average fallow length (standardized b = 0.18; $p<0.07$) and distance to main market (standardized b = -0.16; $p<0.10$) in the first period (1984-1992). In the second period (1992-1999), land-use change was mostly explained by change in labor availability between 1992 and 2000 (standardized b =0.73; $p<0.02$), distance to main market (standardized b =-0.44;

$p<0.01$), child-dependency ratio (standardized b =-0.40; $p<0.01$) and frequency of fertilizer use (standardized b =-0.21; $p<0.08$). This suggests that at the village level, the land-use system was predominantly labor-driven. Relatively lower population in the first period permitted fallow as a means of maintaining soil fertility. Distance from market increased in importance from the first to the second period, suggesting the commercialization of agriculture.

6.7 What is the appropriate spatial scale for LUCC modeling?

The choice of an appropriate scale for modeling to support land-use planning requires a trade-off between spatial detail (heterogeneity) and extent. At the scale of individuals, households and commercial farmers (30m –1050m), land-use change processes appear to be highly heterogeneous, requiring a large amount of data for characterization of the processes. The variograms of standardized residuals suggest that the size of agricultural areas for villages ranged from 3km to 7km. This fairly corresponds to the 3km-5km chosen for modeling cropland change at the village level. Future land models in the study area should therefore be implemented within 3km to 7km. Models implemented for the second period at these scales had a better fit (pseudo R^2 was between 0.42 and 0.59 between 1992-1999 compared to 0.20 to 0.37 from 1984-1992). Based on the assumption that future land change patterns would likely depend more on the most recent pattern, future LUCC models in the study area should incorporate variables that were important in explaining cropland change at the village level between 1992 and 1999. These were *Altitude, Rainfall zone, Temperature zone, Land suitability index, Landscape heterogeneity (Dominance), Distance to main market, Distance to villages, Initial population density* and *Change in population density*.

6.8 What were the effects of LUCC on soil properties?

Significant correlations between organic C and N, P, K, Ca, Mg, Clay, ECEC, Base Saturation and pH stress the role of soil organic matter (SOM) in fertility management of the soils. However, the correlations between organic C and selected soil fertility indices- ECEC, N and P declined as cultivation persisted. There is evidence of nutrient mining in soils continuously cultivated between 1984 and 1999 (about 12% of the landscape). Models relating organic C with ECEC, N and P showed that deficits in organic C levels for the critical levels of these parameters were in the order 7.2 tha^{-1} for P, 4.5 tha^{-1} for N and 2.1 tha^{-1} for ECEC. The difficulties in accumulating SOM in a savannah would make it difficult to replenish the soils with organic matter alone. Thus, investment in inorganic fertilizers is required.

6.9 What were the food security implications of the research?

Land suitability evaluation using fuzzy set and interpolation techniques capture the variation in soil properties. The techniques produce land suitability for agriculture on a continuous scale. The average land suitability index was 45% of the ideal suitability for agriculture, whereas 70% of data is less than 50% of the ideal suitability. These low values of land suitability indices reflect the low inherent capacity of the soils. Land suitability index explains 87% of the variation in maize yield at the village level, indicating that crop yield is closely related to soil quality in the study area. The major constraints to crop production were ECEC, organic C and Clay content. To guarantee a reliable food supply for the growing population, soil management strategies that conserve organic matter and enhance nutrient and water holding capacity of the soil are required.

6.10 What was the pathway of land-cover change?

The pathway of agricultural land change in the study area can be summarized with the acronym **REASONS**, **RESPONSE, and RESULTS**. These 3R's of change are portrayed in Figure 6.1.

Economic difficulties in the 1980's leading to the adoption of a structural adjustment program by the government of Ghana markedly affected consumption patterns and also led to a reduction in economic opportunities for households. On a positive note, structural adjustment policies encouraged production and marketing of domestic agricultural produce. Population growth on the other hand increased pressure on land, as well as demand for food. Continuous cultivation led to degradation of soil fertility. Soil fertility decline often occurs so creepingly to the extent that land managers fail to contemplate ameliorative measures. In response to these factors, households embarked on a number of livelihood strategies listed in Figure 6.1. In some cases, this included coexistent processes of agricultural intensification and extensification and other combinations of the listed strategies. It should be pointed out, however, that evidence of agricultural intensification in this study does not necessarily imply that farmers apply adequate amounts of fertilizer. Trade liberalization policies particularly appear to have led to an increase in hectrage of land for commercial rice production. The consequence of households' response to the combined influence of forces of change clearly manifests in replacement of woodland with agricultural land, as well as soil nutrient mining in several parts of the landscape. Soil quality appears both as a REASON and as a RESULT. This stresses the importance of the variable in land-use decisions. It also shows that in the absence of an effective land-use planning policy, LUCC in the study area is headed for a vicious degradational pathway.

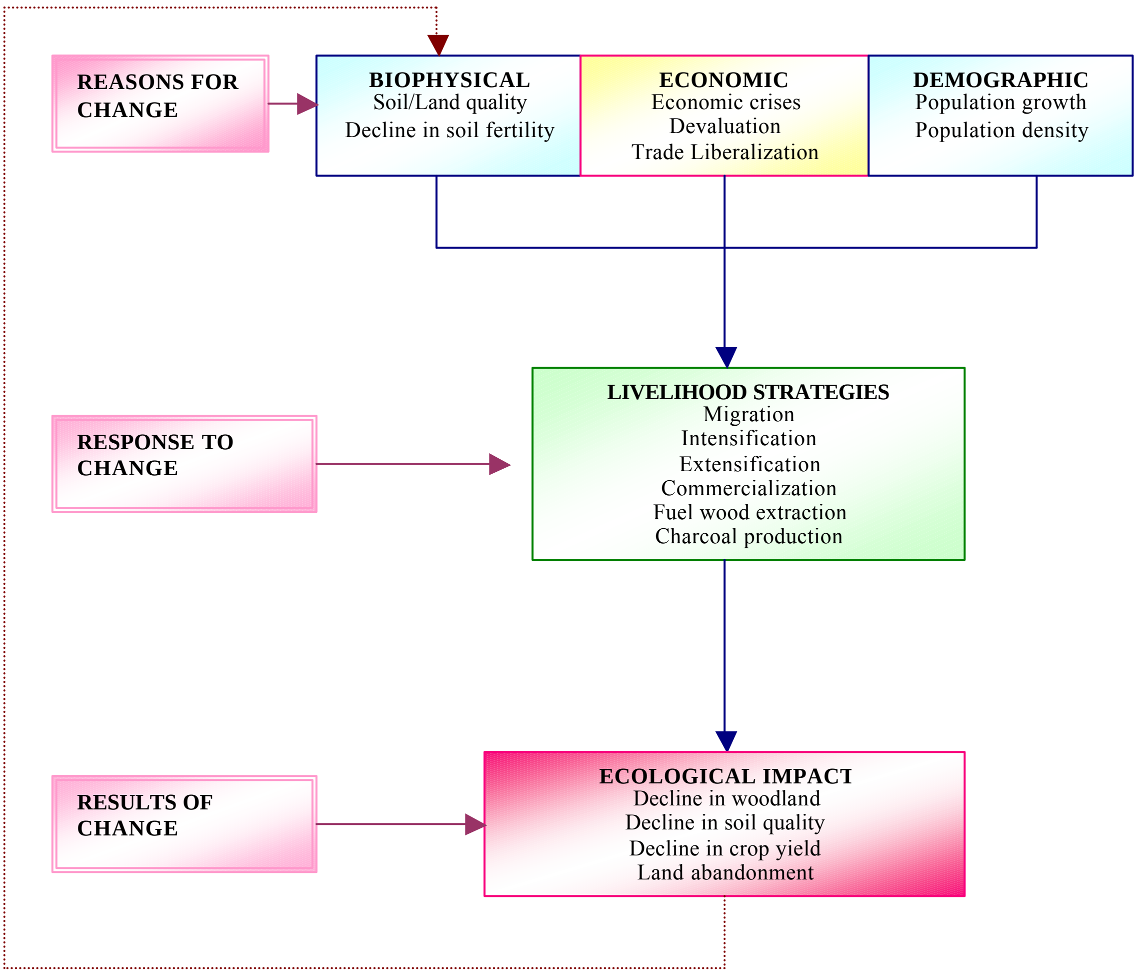


Figure 6.1: The 3R's of land-cover change

6.11 Research and policy implications

Analyses of local patterns of LUCC as carried out in this study could provide relevant information for policy makers who are responsible for land use planning and environmental protection. As land-cover change is multicausal, a set of policy prescriptions is required to address the adverse effects of the phenomenon.

- Decline in closed woodland as a result of woodcutting underscores the need for coercive environmental protection policies to relieve human pressure on vegetation resources.
- There is also the need for environmental education to create awareness on the environmental consequences of the phenomenon. Development of alternative sources of energy is also crucial.
- Phenomenal agricultural expansion at the expense of woodland leading to nutrient mining also calls for agricultural intensification-related policy initiatives to discourage expansion of cultivation on fragile lands. Such intensification strategies should address sustainable soil management and farming techniques that replenish phosphate, conserve SOM and minimize cultivation. Integrated nutrient management (Donovan and Casey, 1998), an approach that combines organic and mineral methods of soil fertilization with physical and biological measures for soil and water conservation, could be a promising soil management technique. Beneficial effects of inorganic fertilizer in dryland agriculture include an increase in SOM through an increase in biomass production in roots and above-ground parts. This may also lead to an increase in water use efficiency in crop production. Furthermore, inorganic fertilizers have an immediate effect on plant growth, as release of nutrients from inorganic fertilizers is often in harmony with plant growth (Sanchez et al, 1997). Lastly, uptake of nutrients is generally more efficient than from organic materials. An integration of inorganic and organic sources in the production systems would therefore create a synergistic effect on crop growth. Research needed to develop the intensification programmes needs to be site-specific and should involve local farmers in its implementation.

- Afforestation is needed to restore the degraded parts of the landscape. The establishment of vigorous vegetation will lead to an increase in both biomass C and soil organic C pools (Lal, 2003). Afforestation strategies in Northern Ghana should involve the choice of appropriate species (e.g. Acacia) that are well adapted to the environment.
- Erratic rainfall pattern calls for biotechnology research to develop drought, diseases and pest resistant crop and livestock varieties in dryland areas. The potentials for N-fixation in cereals using genetic modification technology could also be explored.
- There is the need for the development of production systems that integrate livestock production with cropping systems. Livestock integration should involve the production of leguminous fodder crops to enable proper nutrient cycling in the production systems.
- There is the need for research on quality of organic matter in drylands. Such research should improve our understanding of the determinants of SOM stability, mineralization and immobilization of nutrients from SOM, and also N and P transformation processes in such environments.
- Multiscale analyses of cropland change suggest the increasing importance of social organizations that is, higher level of decision makers such as large commercial farmers and village-based activities in land-use decisions. Future research in the study area should therefore aim at characterizing the emergent properties of the land-use systems and the ecological impact using for example landscape metrics.
- A high child-dependency ratio and its significant negative correlation with land-use change have important policy implications. First, an overwhelming proportion of young population (below 15 years) compared to the proportion of working age may create a financial burden on the ability of the government to provide basic social services such as education, healthcare and other infrastructure to the population. Second, as this young population matures, it may be difficult for them to find a profitable employment, as employment opportunities are few in Northern Ghana. Third, the implications of the lack of profitable employment may be quite severe if the young people do not acquire

the relevant marketable skills in the educational system. This may lead to more pressure on land, resulting in depletion of more woodland in Northern Ghana, or to migration to major cities such as Accra, the capital of Ghana. The capacity of Accra to support large population increases would therefore depend on the expansion of its infrastructure to prevent overcrowding, crime and other social problems. Thus, effective family planning policies are required to control fertility rates. There is also the need for rural infrastructure development to encourage the spread of economic activities. Provision of rural employment in the form of non-farm micro-enterprise programs may also be useful.

- An agricultural commercialization process cannot be successful if left to the forces of demand and supply. Policies relating to rural infrastructure development as well as institutional arrangement to encourage the process are required (von Braun and Kennedy, 1994). For example, access of farmers to small-scale irrigation facilities may further encourage commercialization. The integration of farmers with the marketing/processing firms would also make commercialization viable.

Land-use and land-cover change analyses are vital for effective land management planning. By integrating social and natural science data, this research provides relevant information towards the development of a decision support system that will make land resources management effective in the Volta Basin of Ghana.

7 REFERENCES

Abatania L and Albert H (1993) Potentials and constraints of legume production in the farming systems of Northern Ghana. In Proceedings of the Third Workshop on Improving Farming Systems in the Interior Savannah Zone of Ghana, Nyankapala Agricultural Experimental Station, NAES, Tamale, Ghana pp170-181

Abdulai A and Huffman W (2000) Structural Adjustment and Economic Efficiency of Rice Farmers in Northern Ghana *Iowa Agriculture and Home Economic Experiment Station, Journal Paper* J-18549, Iowa.

Abdulai A and Hazell P (1995) The role of Agriculture in sustainable Development in Africa. *Journal of Sustainable Agriculture* 7: 101-119

Abekoe MK and Tiessen H (1998). Fertilizer P transformation and P availability in hillslope soils of northern Ghana. *Nutrient. Cycling in Agroecosystems* 52: 45-54.

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 pp 107-127

Ahmed II and Lipton M (1997) Impact of Structural Adjustment on Sustainable Rural Livelihoods: A review of the literature. *IDS Working Paper* 62, University of Sussex, UK

Alcamo, J (ed) (1994) *IMAGE 2.0 Integrated Modeling of Global Climate Change*. Dordrecht: Kluwer Academic Publishers

Al-Hassan R and Jatoe JBD (2002) *Adoption and Impact of Improved Cereal Varieties in Ghana*. Paper prepared for the Workshop on the Green Revolution in Asia and its Transferability to Africa. Organized by Foundation for Advanced Studies in International Development (FASID), from 8th to10th December, 2002, in Tokyo, Japan.

Andreini M, van de Giesen N, van Edig A, Fosu M and Andah W (2000) Volta Basin Water Balance. *ZEF Discussion Papers on Development Policy No 21*. Center for Development Research, Bonn, Germany

Asiamah RD (2002) Plinthite Development in upland agriculture soils in Ghana. In *Proceedings World Congress of Soil Science Symposium* 22, paper no 1448:1-12

Bates DA (1962) Geology *in* Willis J.G. (ed) *Agriculture and Land-use in Ghana* pp 51-61 Oxford University Press, London

Benneh G, Kasanga K and Amoyaw D (1995) Land Tenure and Women's Access to Agricultural Land in the Household: A case study of three selected districts in Ghana. In: Ardayfio-Schandorf, E (ed) *The Changing Family in Ghana*. Proceedings of the National Research Conference, Accra Ghana. 25-27 January 1995.

Black CK (ed.) 1965. *Methods of soil analyses*. Part 2. Agron. Monogr. 9. ASA, Madison, WI.

Boserup E (1965) The Conditions of Agricultural Growth: The Economics of Agrarian Change under Population Pressure. New York: Aldine Publishing Company.

Bouyoucos GK (1926) Estimation of colloidal materials in soils. Science 64: 632
Bray RH and Kurtz LT (1945) Determination of total, organic and available forms of phosphorus in soils. Soil Sci 59: 39–45
Burrough PA (1989) Fuzzy mathematical methods for soil survey and land evaluation *Journal of Soil Science* 40: 477-492
Burrough PA and RA McDonnell (2000) Principles of Geographical Information Systems Oxford University Press, New York.
Burrough PA, McMillian RA and Van Deursen W (1992) Fuzzy Classification methods for determining land suitability from soil profile observation and topography. *Journal of Soil Science* 43: 193-210.
Chayanov AV (1966) *Theory of the Peasant Economy*. Madison: University of Wisconsin Press.
Chilès JP and Delfiner P (1999) *Geostatistics: Modeling Spatial Uncertainty*. Wiley Interscience
Chomitz KM and Gray DA (1996) Roads, Land Use, and Deforestation: A spatial model applied to Belize. *The World Bank Economic Review* 10, 487-512.
CIMMYT (1988) *Maize Production regions in the developing countries*. International Maize and Wheat Improvement Center (CIMMYT), EL. Batan Mexico.
Clottey V and Kombiok JM (2000) *Land Use types in Northern Region of Ghana*. Unpublished Report of a Workshop on Land Use types in the Volta Basin of Ghana held at GILLBT Tamale, November 13-15, 2000
Davidson DA, Theocharopoulos SP and Bloksma RJ (1994) A land evaluation project in Greece using GIS and based on Boolean and fuzzy set methodologies. *International Journal of Geographic Information Systems* 8(4): 369-384
de Jong, SM and Burrough PA (1995) A Fractal Approach to the Classification of Mediterranean Vegetation Types in Remotely Sensed Images. *Photogrammetric Engineering and Remote Sensing*. 61:1041-1053.
Dekuku RC (1993) Adapting rices to the northern savannahs of Ghana. In Proceedings of the Third Workshop on Improving Farming Systems in the Interior Savannah Zone of Ghana, Nyankapala Agricultural Experimental Station, NAES, Tamale, Ghana pp141-169
Diehl L (1986) *Small-holder farming systems in Northern Ghana* Paper presented at the first workshop on improving farming systems in the Savannah, 8-10th April 1986, Nyankapala, Ghana
Donovan G and Casey F (1998) Soil Fertility Management in Sub-Saharan Africa. *World Bank Technical Paper No 408* Washington DC, World Bank
Dumanski J, Pettapiece WW and McGregor RJ (1998) Relevance of scale dependent approaches for integrating biophysical and socio-economic information and development of agroecological indicators *Nutrient Cycling in Agroecosystems* 50**:** 13–22, 1998.
Environmental Protection Agency (1999) *Ghana –Country at a Glance*. Accra, Ghana
Epstein, J. M., Axtell, R., 1996. *Growing artificial societies: Social science from the ground up*. Brookings Institution Press, Washington, D.C.
FAO (2001) Proposal for an African Network on Integrated Irrigation and Aquaculture. Proceedings of a Workshop Held in Accra, Ghana, 20-21 September 1999

Fischer G and Sun L (2001) Model Based Analysis of Future Land Use Development in China. *Agriculture, Ecosystems and Environment* 85(1-3):163-176

Fugger W-D (1999) Evaluation of potential indicators for soil quality in Savanna soils in Northern Ghana. *PhD Thesis* Georg-August University, Göttingen, Germany

Geist HJ and Lambin EF (2001) What drives tropical deforestation? *LUCC Report Series No. 4.* Land Use and Land Cover Change (LUCC), International Geosphere-Biosphere Programme.

Geoghegan J, Villar SC, Klepeis P, Mendoza PM, Ogneva-Himmelberger Y, Chowdhury RR, Turner II BL, and Vance C (2001) Modeling tropical deforestation in the southern Yucatán peninsular region: comparing survey and satellite data. *Agriculture, Ecosystems and Environment* 85(2001) 1-3:25-46

Geoghegan J, Wainger LA and Bockstael NE (1997) Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. *Ecological Economics* 23: 251-264.

Ghana Statistical Service (1989) 1984 *Population Census of Ghana Special Report on localities by local authorities*. Ghana Statistical Service Accra, Ghana

Ghana Statistical Service (2002) 2000 *Population and Housing Census. Special Report on 20 Largest Localities.* Ghana Statistical Service, Accra, Ghana

Gibson C, Ostrom E and Ahn TK (1998) Scaling issues in the Social Sciences*, IHDP Working Paper no. 1*, Bonn.

Giller KE, Cadisch G, Ehaliotis C, Adams E, Sakala WD and Mafongoya PL (1997) Building Soil Nitogen Capital in Africa. In Buresh R.J., Sanchez P.A. and Calhoun F (eds) *Replenishing Soil Fertility in Africa* SSSA Special Publication No 51, Madison, Wisconsin USA pp 151-192.

Glantz MH (1998) The Aral Sea. In Kobori I and Glantz M.H. (eds) *Central Eurasian water crisis: Caspian, Aral and Dead Seas* pp 25-52. United Nations University Press, New York.

Goovaerts P (2002) Geostatistical incorporation of spatial coordinates into supervised classification of hyperspectral data *Journal of Geographical Systems* (2002) 4:99–111

Gordon C. and Amatekpor J.K (eds) (1999) *The Sustainable Integrated Development of the Volta Basin in Ghana*. Volta Basin Research Project, Accra, Ghana pp 159.

Gotway CA and Stroup WW (1997) A Generalized Linear Model Approach to Spatial Data Analysis and Prediction. *Journal of Agricultural, Biological and Environmental Statistics* 2(2): 157-197

Greenland DJ and Nye PH (1959) Increases in the carbon and nitrogen contents of tropical soils under natural fallows. Journal of Soil Science 9: 284-299

Griffith D and Layne L (1999) *A Casebook for Spatial Statistical Data Analysis: A Compilation of Analyses of Different Thematic Datasets*, NY: Oxford University Press.

Groenemans R, van Ranst E and Kerre E (1997) Fuzzy relational calculus in land evaluation. *Geoderma* 77: 283-298.

Guyer J, and Lambin EF (1993). Land use in an urban hinterland: ethnography and remote sensing in the study of African intensification. *American Ethnologist* 95: 836-59.

Hall FG, Strebel DE, Nickeson JE and Goetz SJ (1991) Radiometric rectification: Toward a common radiometric response among multidate, multisensor images. *Remote Sensing Environment*, 35, 11–27.

Hesse J (1997) Animal traction - a sustainable technology? A longitudinal case study on the dynamics of identical farm-households in Northern Ghana. Dissertation 1998. Institute of Rural Development, University of Goettingen, Germany

Heuvelink GBM (1992) *WLSFIT- a program for weighted least squares fitting of variogram models*. Internal Publication, Department of Physical Geography, University of Utrecht, the Netherlands

Holling CS, Schindler DW, Walker B, and Roughgarden J (1995) Biodiversity in the functioning of ecosystems: an ecological synthesis. *In*: Perrings, C., Maeler, K-G, Folke, C., Holling, C.S., Jansson, B-O. (Eds.), *Biodiversity loss: economic and ecological issues*. Cambridge University Press, Cambridge, pp. 44-83.

Hopkinson CS and Vallino JJ (1995) The relationship among man's activities in watershed and estuaries: A model of runoff effects on estuarine community metabolism. *Estuaries* 18: 598-621.

Horton S, Kanbur R and Mazumadar D (eds) (1994). *Labour markets in an era of adjustment* vol. I and II. Economic Development Institute of the World Bank, Washington DC

Hoshino S (2001) Multilevel modeling on farmland distribution in Japan. *Land Use Policy* 18, 75-90.

Hosmer DW and Lemeshow S (2000) *Applied Logistic Regression*. Wiley-Interscience, 2nd edition

International Fertilizer Development Center, IFDC (1994) Ghana policy environment and fertilizer sector development. *Technical Bulletin*; T 41

Isaaks EH and Srivastava RM (1989) *An Introduction to Applied Geostatistics*. Oxford University Press.

Janssen M. A. and Jager W. (2000) The Human Actor in Ecological-Economic Models: Preface. *Ecological Economics* 35: 307-310.

Jebuni C. and Seini W. (1992) Agricultural input policies under structural adjustment: their distributional implications. *Cornell Food and Nutrition Policy Program Working Paper No 31*. Ithaca, NY, USA, Cornell University.

Jensen JR (1986) *Introductory digital image processing*. Prentice-Hall, New Jersey.

Kassim-Kasanga R (1992) Agricultural Land Administration and Social Differentiation: A Case Study of the Tono, Vea and Fumbisi Belts of North-Eastern Ghana. *Joint Committee on African Studies, Working Paper 10*, New York, USA.

Kauth RJ and Thomas GS (1976) The Tasseled Cap - A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as seen by Landsat. *Proc. Symposium on Machine Processing of Remotely Sensed Data*. Purdue University. Indiana. 4B-41-50.

Kipo T (1993) Farmers' perception of the factors of production and agriculture in Northern Region. In *Proceedings of the Third Workshop on Improving Farming Systems in the Interior Savannah Zone of Ghana*, Nyankapala Agricultural Experimental Station, NAES, Tamale, Ghana pp189-197

Kok K (2001) Scaling the land use system: A modelling approach with case studies for Central America. *PhD Thesis*, Wageningen University, The Netherlands.

Kosmas C, Gerontidis S and Marathianou M (2000) The effect of land-use change on soils and vegetation over various lithological formations on Lesvos (Greece) *Catena* 40 (2000): 51-68.

Kranz B, Fugger W-D, Kroschel J, Sauerborn J (1998) The influence of organic manure on Striga hermonthica (Del.) Benth infestation in northern Ghana. In: HP Blume, H Egger, E. Fleischhauer, A Hebel, C Reij, K.G. Steiner (eds.) Towards Sustainable Land Use: furthering cooperation between people and institutions. *Advances in GeoEcology* 31 (I), 615 - 619.

Lal R (2003) Carbon sequestration in dryland ecosystems. *Environmental Management* in press

Lambin EF (1994) Modelling deforestation processes: a review. *TREES Publications Series B: Research Report 1*. Office of Official Publications of European Community, Luxembourg, 113pp.

Lambin EF, Rounsevell M and Geist HJ. (2000) Are agricultural land-use models able to predict changes in land use intensity? *Agriculture, Ecosystems and Environment* 82 (2000): 321-331

Lambin E (1997) Modelling and monitoring land-cover change processes in tropical regions, *Progress in Physical Geography* 21(3): 375-393.

Lele UJ (1989) Sources of Growth in East Africa Agriculture. *Mardia Discussion Paper No 4*, World Bank.

Macleod RD and Congalton RG (1998) A Quantitative Comparison of Change Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data. *Photogrammetric Engineering and Remote Sensing*. Vol. 64. No. 3. p. 207 - 216.

Malthus TR (1967) *Essay on the principle of population*. 7th edition, Dent, London.

Manson S (2001) Simplifying complexity: A review of complexity theory. *Geoforum* 32 (3), 405–414.

McBratney AB and Odeh IOA (1997) Application of fuzzy sets in soil science: fuzzy logic, fuzzy measurement and fuzzy decisions *Geoderma* 77: 85-113.

McCullaugh P and Nelder JA (1989) *Generalized linear models*. Chapman Hall, NY.

Menard S (1995) *Applied Logistic Regression Analysis*. Sage Publications Series: Quantitative Applications in the Social Sciences, No. 106.

Mercer-Quarshie H. (2000) The lowland rice development project. In *National Workshop on Rice Production in Ghana*. Sponsored by the Overseas Development Institute, November 2000, Ho, Upper East Region pp 29-33

Merchant C (1990) The Realm of Social Relations: Production, Reproduction, and Gender in Environmental Transformations. In *The Earth as Transformed by Human Action*, eds. B.L. Turner, II, W.C. Clark, R.W. Kates, J.E. Richards, J.T. Mathews, and W.B. Meyer, 672-684. Cambridge: Cambridge University Press.

Mertens B and Lambin EF (2000) Land-cover change trajectories in Southern Cameroon. *Annals of the Association of American Geographers* 90(3): 467-494.

Mertens B, Sunderlin WD, Ndoye O and Lambin E (2000) Impact of macroeconomic change on deforestation in *South* Cameroon: Integration of household survey and remotely-sensed data. *World Development* 28(6): 983-999.

Meyer WB and Turner II BL (1994) *Changes in land use and land cover: a global perspective*. Cambridge University *Press*, Cambridge, UK.

Mortimore M (1993) Population Growth and Land Degradation. *GeoJournal* 31(1): 15-21.

Munsell Color Company (2000) *Munsell Soil Color Charts Rewashable Edition* (2000) GretagMAcbeth, 617 Little Britain Road, New Windsor NY12533

Nelson DW and Sommers LE (1982) Total carbon, organic carbon, and organic matter. In: Page A.L., et al., ed. *Methods of soil analysis*. Part 2. 2nd ed. *Agron. Monogr*. 9. Madison, WI: ASA and SSSA, pp 581-594

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

Newton HJ (ed) (2000) STATA Technical Bulletin, STB 53:18-29, January 2000.

Nyanteng VK and Asuming-Brempong S (2003) The Role of Agriculture in Food Security in Ghana. *Roles of Agriculture Project International Conference* 20-22 October, 2003 Rome, Italy

Nye PH and Stephens D (1962) Soil Fertility *in* Wills J.G. (ed) *Agriculture and Land-use in Ghana* pp 127-143 Oxford University Press, London

O'Neill RV (1988) Hierarchy theory and global change. In: Rosswall, T., Woodmansee, R.G., Risser, P.G. (Eds.), *Scales and global change. Spatial and temporal variability in biospheric and geosphericprocesses. SCOPE 35*, John Wiley & Sons Ltd., Chichester, pp. 29-45.

Ofori F (1998) *Managing the soil resources base for accelerated agricultural growth in Ghana*. Directorate of Crop Services, Ministry of Food and Agriculture, Accra p.26

Ogunkunle A.O. (1993) Soil in land suitability evaluation: an example with oil palm in Nigeria. *Soil Use and Management* 9: 37-42

Overmars KP, de Koning GHJ and Veldkamp A (2003) Spatial autocorrelation in multi-scale land use models *Ecological Modelling* 164: 257-270 (2003)

Overseas Development Institute (1999) Rethinking Natural Resources Degradation in Semi-Arid Sub-Saharan Africa: The case of Semi-Arid Ghana. *ODI Rural Policy and Environment Group*, UK

Øygard R, Vedeld T and Aune J (1999) *Good Practices in Drylands Management*. Noragric Agricultural University of Norway, As, Norway.

Palm CA, Myers RJK and Nandwa SM (1997) Combined Use of Organic and Inorganic Nutrient Sources for Soil fertility Maintenance and Replenishment In Buresh R.J., Sanchez P.A. and Calhoun F (eds) Replenishing Soil Fertility in Africa *SSSA Special Publication No 51*, Madison, Wisconsin USA pp 193-217.

Parker DC, Berger T, and Manson S (eds., 2002) Agent-Based Models of Land Use / Land Cover Change. LUCC Report Series No. 6, International Human Dimensions Programme on Global Environmental Change (IHDP)

Pearce R (1992) 'Ghana' In Duncan A. and Howel J (eds) Structural Adjustment and the African Farmer Overseas Development Institute, London

Perz SG (2002) Household Demography and Land use allocation among Small Farms in the Brazilian Amazon *Human Ecology Review* 9(2): 1-16

Petit C, Scudder T and Lambin EF. (2001) Quantifying processes of land-cover change by remote sensing: resettlement and rapid land-cover changes in southeastern Zambia. *International Journal of Remote Sensing* **22**(17): 3435-3456.

Petschel-Held G, Block A, Cassel-Gintz M, Kropp J, Ludeke MKB, Moldenhauer O, Reusswig F, and Schellnhuber HJ (1999) Syndromes of Global Change: A Qualitative Modelling Approach to Assist Global Environmental Management *Environ. Model. Assess.* **4**, 295–314.

Pfaff ASP (1999) What Drives Deforestation in the Brazilian Amazon? Evidence from Satellite and Socioeconomic Data. *Journal of Environmental Economics and Management* 37, 25-43.

Pilon P, Howarth P, Bullock R, and Adeniyi P (1988) An enhanced classification approach to change detection in the semi-arid environments. *Photogrammetric Engineering and Remote Sensing*, 55:1709--1716.

Pontius RG (2000) Quantification error vs. location error in comparison of categorical maps. *Photogrammetric Engineering and Remote Sensing* 66 (8), 1011–1016.

Rouchier J, Bousquet F, Requier-Desjardins M. and Antona M (2001) A multi-agent model for describing transhumance in North Cameroon: comparison of different rationality to develop a routine. *Journal of Economic Dynamics and Control* 25: 527-559.

Ruben R, Kuyvenhoven A and Hazell P (2003) Investing in Poor People in Less-Favoured Areas: Institutions, Technologies and Policies for Poverty Alleviation and Sustainable Resource Use. *Contributed Paper for International Conference on Staying Poor: Chronic Poverty and Development Policy IDPM Manchester, 7-9 April 2003* pp20

Runge-Metzger A and Diehl L (Eds.) (1993) Farm Household Systems in Northern Ghana. Verlag Josef Margraf, Germany.

Sanchez P, Izac AM, Buresh R, Shepherd K, Soule M, Mokwunye U, Palm C, Woomer P, and Nderitu C (1997) Soil Fertility Replenishment in Africa as an Investment in Natural Resource Capital p 1-46. In Replenishing Soil Fertility in Africa, R. Buresh and P. Sanchez, (eds.) SSSA Special Publication 51. Madison, WI: Soil Science Society of America (SSSA)

Schabenberger O and Pierce FJ (2002) Contemporary Statistical Models for the Plant and Soil Sciences

Scoones I (1998) Sustainable Rural Livelihoods: A Framework for Analysis *IDS Working Paper 72*.

Smith L (1991) Agricultural Labour Markets and Structural Adjustment in Sub-Saharan Africa. *Economic and Social Development Paper No 99*, FAO, Rome

Soil Research Institute (2001) Soil map of Ghana. Soil Research Institute, Accra, Ghana

Soil Survey Staff (1994) Keys to Soil Taxonomy. Sixth Edition. USDA-SCS. Government Printing Office, Washington DC.

Stein A, Riley J and Halberg N (2001) Issues of scale for environmental indicators. *Agriculture, Ecosystems and Environment* 87(2001): 215-232

Stéphenne N and Lambin EF (2001) A dynamic simulation model of land-use changes in Sudano-sahelian countries of Africa (SALU), *Agriculture Ecosystems and Environment* 85 (2001) 145–161.

Story M. and Congalton R (1986) Accuracy assessment: A user's perspective. *Photogrammetric Engineering and Remote Sensing*. Vol. 52, No. 3. pp. 397-399.

Swain PH and Davis SM (eds), (1978) Remote Sensing: The Quantitative Approach. McGraw-Hill, New York.

Sys C (1985) *Land evaluation*. Ghent: State University of Ghent.

Tang H and Van Ranst E (1992) Testing of fuzzy set theory in land suitability assessment for rainfed maize production. *Pedologie* 17: 129-147

Thomas GW (1982) Exchangeable cations. *In*: Page et al A.L., ed. Methods of soil analysis. Madison, WI: Part 2. 2nd ed. *Agron. Monogr.* 9. ASA and SSSA. pp:159-165.

Thornton P and Jones PG (1998) A conceptual approach to dynamic agricultural land use modeling. *Agricultural Systems* 57:505-521.

Tiffen M, Mortimore M. and Gichuki F (1994) *More people less erosion: environmental recovery in Kenya*. London: John Wiley.

Tshikata YM (1999) Aid and Reform in Ghana. http://www.worldbank.org/ research /aid/ africa/ghana. pdf cited on 26 May 2002.

Tsigbey FK and Clottey VA (2003) Peanut production methods in Northern Ghana and some disease perspectives. *Proceedings of Sod Based Cropping Systems Conference*, North Florida Research and Education Center-Quincy, University of Florida, Feb. 20-21, 2003. pp. 214-222

Tucker CJ, Dregne HE and Newcomb WW (1991) Expansion and contraction of the Sahara desert from 1980-1990. *Science* 253: 299-301.

Turner II BL. and Ali AMS (1996) Induced intensification: Agricultural change in Bangladesh with implications for Malthus and Boserup. *Proc. Natl. Acad. Sci. USA*. Vol. 93, pp. 14984–14991, December 1996

Turner II BL, 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 and HDP Report No. 7*. International Geosphere-Biosphere Programme and the Human Dimensions of Global Environmental Change Programme, Stockholm and Geneva.

Turner II BL, Hyden G and Kates R (eds) (1993a) Population growth and Agricultural change in Africa. Gainesville, FL: University Press of Florida

Turner II BL, Moss RH, and Skole DL (1993b) Relating Land Use and Global Land-Cover Change: A Proposal for an IGBP-HDP Core Project. *IGBP Report 24 and HDP Report 5*. IGBP Stockholm.

Van Ittersum MK, Rabbinge R, and Van Latesteijn HC (1998) Exploratory land use studies and their role in strategic policy making. *Agricultural Systems* 58, 309-330.

Vanlauwe B., Diels J., Saginga N. and Merckx R (eds) (2002) *Integrated Plant Nutrient Management in Sub-Saharan Africa*. CABI Publishing.

Veldkamp A and Fresco LO (1996) CLUE: a conceptual framework to study the Conversion of Land Use and its Effects. *Ecological modelling*, 85: 253-270.

Veldkamp A, Verburg PH, Kok K, de Koning GHJ, Priess J, and Bergsma AR (2001) The need for scale sensitive approaches in spatially explicit land use change modeling. *Environmental Modeling and Assessment*. 6: 111-121.

Verburg PH, Schot P, Dijst M, and Veldkamp A (2003) Land use change modelling: current practice and research priorities *Geojournal* in press.

Vitousek PM, Mooney HA, Lubchenco J, and Melillo JM (1997) Human Domination of Earth's Ecosystems. *Science* 277: 494-499, 25 July 1997

Vlek PLG, Kühne RF and Denich M (1997) Nutrient resources for crop production in the tropics. *Phil. Trans. R. Soc. Lond.* B 352. 975 - 985.

von Braun J and Kennedy E (eds) (1994) Agricultural Commercialization, Economic Development, and Nutrition, The Johns Hopkins University Press, 2715 North Charles Street, Baltimore, Md. 21218, U.S.A.

Walker HO (1962) Weather and Climate, *in* Wills JG (ed) *Agriculture and Land-use in Ghana* pp 7-50 Oxford University Press, London

Walsh SJ, Crawford TW, Crews-Meyer KA and Welsh WF (2001) A Multi scale Analysis of Land use Land cover change and NDVI Variation in Nang Rong District, Northeast Thailand. *Agriculture, Ecosystems and Environment* 85, 47-64.

Walsh SJ, Evans TP, Welsh WF, Entwisle B, and Rindfuss RR (1999) Scale-Dependent Relationships between Population and Environment in Northeastern Thailand. *Photogrammetric Engineering &Remote Sensing* 65, 97-105.

Zadeh LA (1965) Fuzzy Sets. *Information and Control* 8: 338-353

Dedication

To the Good, Great and Gracious God
Whose Divine assistance in this work I gratefully acknowledge

Acknowledgements

I thank God, the Almighty for the successful completion of this work. Without His divine assistance nothing could have been achieved. I also thank my Supervisor, Prof Paul Vlek for his advice, support, and encouragement at all stages of the work. I have benefited immensely from his excellent, erudite proficiency. My sincere gratitude also goes to Prof Gunter Menz for his support and sustained interest in my research. I thank Prof Alfred Stein, my Spatial Statistics teacher for his invaluable suggestions. I also thank Prof Armin Skowronek for the valuable information on pedology and soil resources in the tropics. I thank the DAAD for supporting me with funds for the PhD program. The support of the German Federal Ministry for Education and Research and the Ministry for Schools, Science and Research of Northrhine Westphalia who funded the GLOWA project is also acknowledged. I also thank the GLOWA Project coordinators- Drs Nick van de Giesen, Marc Andreini and Mathias Fosu for the opportunity to work on the project.

Special thanks to Dr Günther Manske, Hanna Peters, Sina Bremer, Sabine Aengenendt-Baer, Inga Haller, Andrea Berg for help with many administrative matters. I thank Margaret Jend for translating the German Abstract. I thank my colleagues at ZEF for the camaraderie, in particular Ayo Ajayi, Steve Duadze, Philip Oguntunde, Jens Liebe, Jan Friesen, Wilson Agyare, Nii Codjoe, Isaac Osei-Akoto, Adama Konseiga Khalid Khalafalla and Fabio Vescovi. I also thank Marina and Marc Dahmann for their concern for my welfare in Germany.

I am grateful to Prof J Nabilla, Dr A. Salifu, Dr V. Clottey, Cecil Ossei, Robert Owusu, Isaac Acquah and all members of the Savannah Agricultural Research Institute, for their help during the field studies in Ghana. I also thank Nicholas Breslyn and other members of the household survey team for their help.

The prayerful support of Felicia Braimoh, Boboye and Tayo Ekundayo, Oladele and Funmi Braimoh, Paul and Dorcas Fasuyi-Steele, Prof Ayo and Dr Toyin Ogunkunle, Femi and Rachel Omiyale, Jibola and Ayo Adeyemi, Ade and Comfort Adesina, Dr and Mrs G.O. Adeoye, Dr and Mrs. Akinbola, Olu, Kenny and Ope Amusan, Tunrayo and Jumoke Alabi, Robert and Abike, Jire and Bola Fagbola, Victor and Toyin Okwunwa, Idowu and Sade Oladele, Dipo and Bunmi Fanimo and many others is sincerely acknowledged. I also thank Ferdinand and Julienne Ngo-Ngaka, Grace Ngo-Ngaka, Ernestine Ekoudi, Sosthene Evina for the sweet fellowship. My special thanks to others not mentioned for their tremendous help.

Finally, I thank Lola, my loving wife, for standing by me throughout the program. Her prayers, support, patience, care and encouragement have contributed immensely to my achievements. I also thank our wonderful children Theophilus Ore-Oluwa and Eunice Ike-Oluwa for being a source of inspiration.