Scale-Dependent Relationships between Land-Use Change and Its Determinants in the Volta Basin of Ghana

Ademola K. Braimoh* and Paul L.G. Vlek

Center for Development Research, University of Bonn, Bonn, Germany

Received 26 September 2003; accepted 7 December 2003

ABSTRACT: Relationships between cropland change and presumed determinants were analyzed at scales ranging from 30 to 5100 m using logistic regression. The plot of the odds ratio across the spatial scales indicated that both biophysical and social variables were important in explaining cropland change. In the first period (1984–92), biophysical factors were the dominant factors, while market-related variables were more dominant between 1992 and 1999. Response to changing economic opportunities was the underlying cause of this trend. Policies that would make commercialization of agriculture viable are required in the Volta basin of Ghana.

KEYWORDS: Land use

1. Introduction

Land use is determined by biophysical and social variables interacting in space and time (Turner et al., 1995). Descriptive models of land-use and land-cover change

* Corresponding author address: Ademola Braimoh, Center for Development Research, University of Bonn, Bonn D-53113, Germany.

E-mail address: abraimoh@uni-bonn.de

(LUCC) are useful when trying to determine the relationship between LUCC and the driving forces. They also improve our understanding of the functioning of land-use systems for planning and policy formulation. To be of value in planning, models that quantify such relationships at different spatial scales are required (Veldkamp et al., 2001).

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 therefore implies that theories developed in social and natural sciences are adapted for case studies of LUCC (Veldkamp et al., 2001). A landscape ecology paradigm of land use provides a suitable framework for studying the scale dependency of land use and its determinants. It draws upon ecology and system theories to describe the complex interactions between people and their environment (Allen and Walsh, 1996). 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. Second, the land-use system is *structurally* complex in the sense that patterns and processes are scale dependent (Forman and Godron, 1986). Previous studies (e.g., de Koning et al., 1999; Walsh et al., 1999; Walsh et al., 2001) have noted the challenges inherent in analyzing patterns and processes. Certain patterns are visible as spatial extent increases, whereas they are obscure at a small extent, leading to the conclusion that relationships could not be generalized across spatial scales.

This study builds on this body of knowledge by deriving relationships between cropland change and its determinants using logistic regression. The landscape, human, and political ecology paradigms were used to frame the LUCC analysis. 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) 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 spatial scales corresponding to the level of activity of land users or managers. By analyzing cropland change at scales compatible to the level of activity of different land users, this study aims to provide relevant information for land-use planning. The specific objectives of the study include determination of variables that are important to cropland change at different scales and the relative importance of these variables in explaining cropland change at specific periods between 1984 and 1999.

2. The study area

The study area (~5400 km^2) is within the Volta basin in northern Ghana. The Volta Lake is the largest man-made lake. It drains about 400 000 km^2 including 70% of mainland Ghana (Figure 1). More than 80% of the basin is located in the savannah. The Volta Lake is the source of hydroelectric power for the country, while economic activities such as fishing and irrigation also depend largely on the

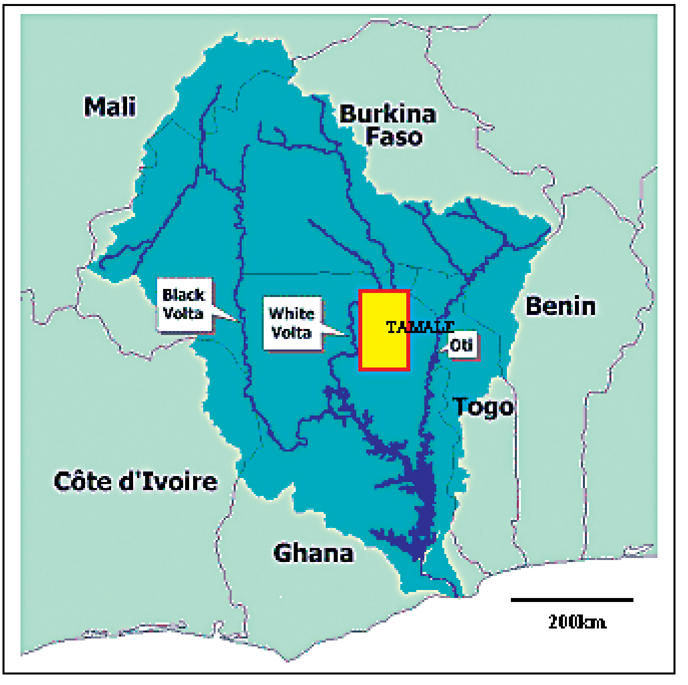


Figure 1. Extent of the Volta River basin. The main tributaries of the Volta Lake are shown, while the study area is within the rectangle enclosing Tamale.

Volta. There is a high level of poverty in the largely rural area, with a population growth rate of about 3%. Two major macroeconomic periods in Ghana fairly correspond to the period under study.

1) Between 1983 and 1991, the government of Ghana embarked upon a stabilization/structural adjustment program that led to a decrease in protection of the food sector. The currency was progressively devalued from 2.75 to 90 Ghanaian cedis per U.S. dollar (Tshikata, 1999). There was also liberalization of the food trade, and the substantial importation of fertilizers and other agricultural inputs continued. Removal of subsidies on fertilizers and other inputs greatly increased the prices of these inputs to farmers due to the devaluation of exchange rates. Trade liberalization exposed the food sector to strong competition with imported food items, whereas currency devaluation made imported food relatively more expensive than domestic food, giving local producers a competitive advantage (Abdulai and Huffman, 2000).
2) The poststructural adjustment period (1992 to the present) has been characterized by recurrent fiscal imbalances. The beginning of the period witnessed a large wage increase in the public sector, and excessive spending on capital budgets, particularly roads. The government of Ghana also pursued initiatives to enhance the efficiency of the tax system.

The response of the populace to these reforms included widespread internal migration, agricultural diversification, and the coexistent processes of agricultural extensification and intensification (Horton et al., 1994; Abdulai and Hazell, 1995; Braimoh, 2004) The dominant land-cover change process in the study area involved the conversion of woodland to cropland at an annual rate of 5% between 1984 and 1999. Such a high rate of change was primarily driven by population growth, population migration, and commercialization of household agriculture (Braimoh, 2004).

The Volta basin of Ghana is currently undergoing tremendous environmental changes. 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. Sustainable development of the largely rural Volta basin therefore depends on effective management of land and water resources. The GLOWA project (more information available online at http://www.glowa-volta.de) was set up to develop a decision support system (DSS) for water management in the Volta basin. LUCC information is crucial for the envisaged DSS for two reasons. First, land surface determines how much of the rainfall evaporates and how much becomes available as groundwater. Second, land cover determines the energy exchange between land and atmosphere and therefore local weather patterns. The current research provides land-use data for integration with other data for the envisaged DSS.

3. Methods

3.1. Data sources

Landsat Thematic Mapper (TM) data acquired on 5 November 1984, 21 December 1992, and 7 November 1999 were used. The images were georeferenced to Universal Transverse Mercator (UTM) projection, with the root-mean-square error below pixel size. Radiance values for 1984 and 1992 images were normalized to the 1999 image following Hall et al. (Hall et al., 1991). Land-cover classification was performed using the maximum likelihood algorithm. Six classes were discriminated: closed woodland, open woodland, grassland, cropland, built-up area, and water. Classification accuracies were assessed using 312 independent observations (measuring approximately 50 m × 50 m each) from field studies and aerial photos taken in 1992. Classification accuracies were 85%, 81%, and 88% for 1984, 1992, and 1999, respectively. These improved to 91% for 1984, 90% for 1992, and 94% for 1999 after merging the classes to a binary cropland/noncropland map. Change detection to derive the dependent variable was based on postclassification comparison and image differencing.

Other spatial data (independent variables) were created for use in the models. Linear regression of one independent against the others was used to investigate multicollinearity. After removal of strongly multicollinear variables ($R^2 > 0.8$), 14 variables summarized in Table 1 were retained for modeling.

3.2. Modeling conversion to cropland

Logistic regression was used to model the probability of a pixel being converted to cropland as a function of the explanatory variables in Table 1. That is, the logistic

Table 1. Independent variables list.

Variables	Description
ALTITUDE	DEM was derived from 50-ft vertical interval contour lines.
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 percent.
TEMP	Temperature zones mapped as binary layer with TEMP=1 if long-term mean annual temperature $>$ 28°C and 0 otherwise. The threshold of 28°C is one of the criteria used to classify the study area into dry and wet savannah agroecological zones (EPA, 1999).
RAIN	In the study area, wet savannah is distinguished from dry savannah using a threshold of long-term mean annual rainfall of 1100 mm. Thus, rainfall zones were mapped as a binary layer with RAIN=1 if rainfall >1100 mm and 0 otherwise.
LI	Agricultural land suitability index on a continuous interval scale [0,1].
WATER	Distance from permanent water bodies.
DOMINANCE	Landscape index calculated for 3 × 3 kernel size of land-cover map as $$\text{DOMINANCE} = In(n) - \left(-\sum_{i=1}^{n} p_i[In(p_i)]\right),$$ where p_i is the proportion of each class i in the kernel and n is the number of classes present. For the first period (1984–92), DOMINANCE was calculated at the start of the period, that is, using land-cover map for 1984, whereas for the 1992–99 model, the 1992 land-cover map was used to calculate the variable.
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 1984–92.
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.

regression model answers the question, What are the factors that determine the conversion of a location to cropland*?* Modeling was performed for 1984 and 1992, and 1992 and 1999 at six spatial resolutions, which are spatially aggregated multiples of the 30-m basic resolution of Landsat TM. The major objective was to ascertain the relative importance of the variables in explaining conversion to cropland at different scales. Cells at aggregated scales were derived from nearest neighbor resampling of the $n \times n$ subpixels for binary variables, while spatial mean was used for continuous variables. For each degradation of spatial resolution, the basic Landsat TM pixel was used. 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), the sizes of commercial farms; and "large" (100 and 170), the sizes of agricultural area for localities. The dependent variable for logistic regression y was a binary presence or absence event, where $y = 1$ means conversion to cropland for the period 1984–92, and $y = 0$, otherwise. The probability p of observing cropland in a pixel is given by

$$p = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n+e}}{1 + e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n+e}}, \tag{1}$$

where β_0 is the intercept, β_n are slope parameters, and e, the residual.

Interpretations of the logistic regression model can be made 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. 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. Thus, the p values were used to identify the variables that are essential in explaining cropland change across scales.

In logistic regression, the odds ratio quantifies the relationship between the dependent and independent variables. If p is the probability that an event will occur, then the odds of the event are $p/(1 - p)$. The 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, the odds ratio, OR, is defined as (Newton, 2000)

$$\mathrm{OR} = \frac{P(\mathrm{event}|x+1)/(1 - P(\mathrm{event}|x+1)}{P(\mathrm{event}|x)/(1 - P(\mathrm{event}|x)}, \tag{2}$$

where $P(\mathrm{event}|x)$ is the probability of the event given x. In the case of a binary variable, the odds ratio measures the effect on the dependent variable if the independent variable belongs to a category other than the reference category. The 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. Last, 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 Equation (1), the β_ns are also referred to as the logit or effect coefficients and correspond to the unstandardized βs of the ordinary least squares regression. A logit coefficient is simply the natural log of the odds ratio; thus, the odds ratio and logit coefficient measure the same thing, that is, the strength of relationship between dependent and independent variables (Hosmer and Lemeshow, 2000). The odds ratio is more intuitive than the logit coefficient, as we are rarely inclined to reason on the logit scale. The 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 are 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.

3.3. Model prediction and validation

The logistic regression only estimates the suitability of a pixel for conversion to cropland in probability terms. The quantity of cells to be converted to cropland after a simulation period still has to be determined. 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 1992–99. 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. Location error occurs when a point of a given category is assigned to a location different from its actual location on the landscape, whereas quantification error occurs when a model assigns a given point on the landscape to a category different from its real category (Pontius, 2000). The first validation procedure involved the use of relative operating characteristics (ROCs), which range from 0.5 (for a model that assigns location at random) to 1 (for a model that assigns location perfectly). Last, 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 were kappa for location (κ_{loc}) and kappa for quantity (κ_q).

4. Results and discussion

4.1. Relationships at the basic Landsat TM scale

Logistic regression results for the two periods are presented in Table 2. For the basic 30-m Landsat TM resolution (scale 1), the likelihood of conversion to cropland increased by more than 4 times in the zone where the rainfall was equal to or more than 100 mm in the first period (1984–92), whereas it increased by about 6 times in the second period (1992–99). 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 kilometer increase in the distance from water in the first period. This may be associated with avoidance of risk of flooding, which is usually high at the beginning of the rainy season. 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 from roads decreased the likelihood of conversion to cropland by a factor of 0.9 in the first period, whereas in the second period an 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 and 0.9 for every kilometer away from the main market (Tamale, Ghana) 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. First, it is likely that additions to population did not increase proportion of the agricultural labor force,

Table 2. Logistic regression results for the six spatial scales for the two periods.

(a) Spatial scale 1:30 m (n = 10 000) Variables	β	Std error S.E$_\beta$	Prob.	e^β
1984–92				
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	—
1992–99				
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 5:150 m (n = 10 000) Variables	β	Std error S.E$_\beta$	Prob.	e^β
1984–92				
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	—

Table 2. (*Continued*)

Variables	β	Std error $S.E_{\beta}$	Prob.	e^{β}
1992–99				
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 10:300 m (n = 5000) Variables	β	Std error S.Eβ	Prob.	e^{β}
1984–92				
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	—
1992–99				
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	—

Table 2. (*Continued*)

(d) Spatial scale 35:1050 m (n = 5000) Variables	β	Std error S.E$_{\beta}$	Prob.	e^{β}
1984–92				
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	—
1992–99				
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 100:3000 m (n = 2500) Variables	β	Std error S.E$_{\beta}$	Prob.	e^{β}
1984–92				
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	—

Table 2. (*Continued*)

Variables	β	Std error S.E$_\beta$	Prob.	e^β
1992–99				
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 170:5100 m (n = 2500) Variables	β	Std error S.E$_\beta$	Prob.	e^β
1984–92				
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	—
1992–99				
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	—

Table 3. Variables that were significant at $p<0.05$.

(a) 1984–92

	SCALES					
Variables	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) 1992–99

	SCALES					
Variables	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						

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. Second, it may indicate the availability of nonfarm employment opportunities for the working population. Third, the negative relationship suggests the substitution of labor for other inputs.

The model explains that agriculture more likely developed on less suitable soils between 1984 and 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 nonfarm economic opportunities, but with soils of lower fertility (Braimoh et al., 2004). 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 on an elevation 50 m higher 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 50 m increased the likelihood of conversion to cropland by 15%. This trend could exacerbate erosion in the study area.

4.2. Necessary variables for models

The variables that are essential in explaining cropland change across scales are marked with an "x" in Table 3. Both biophysical and socioeconomic variables were significant at all scales ($p<0.05$), though to varying degrees. In the first period (1984–92), 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. 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 socioeconomic variables (five out of six spatial scales), while land tenure and population variables were the least (two out of six).

In the second period (1992–99), change in population density was significant at all the spatial scales. Land suitability index (LI) and distance to villages (VILLAGES) were significant at five out of six spatial scales. ROADS and ASPECT were significant at only one scale, whereas SLOPE and TENURE were significant at none.

In Figure 2 a clear difference is shown in the statistical significance of the variables in time across scales. In the first period, the statistical significance of socioeconomic variables generally decreased with increasing spatial extent (Figure 2a). A similar trend is observed from scales 1 to 35 for biophysical variables. With the exception of scale 100, the proportion of significant socioeconomic variables is higher for the investigated spatial scales. Thus, the number of variables essential in explaining cropland change generally decreased across scales. Ardayfio-Schandorf (Ardayfio-Schandorf, 1996) observed that in the predominantly agricultural society of Ghana, individuals and households carry out most land-use decisions. This group of people usually has 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 (one to five) in the first period.

In the second period (Figure 2b), the proportion of significant socioeconomic variables was higher at scales 10–170. This shows that generally, more socioeconomic 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

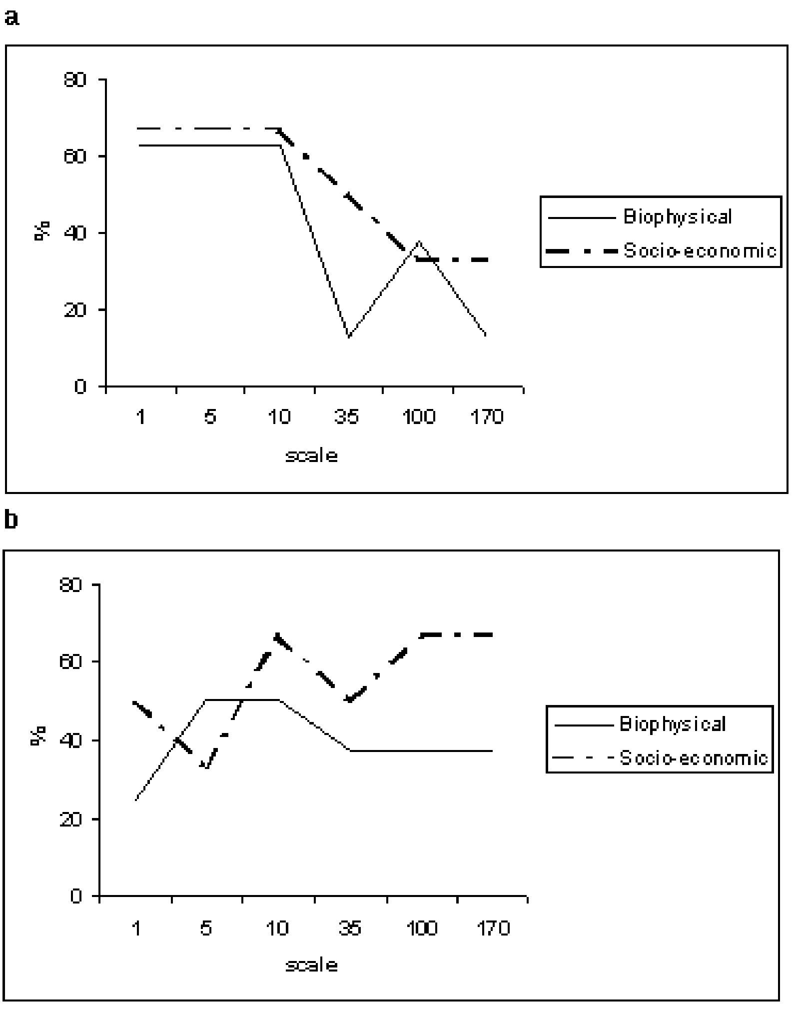


Figure 2. Proportions of significant variables ($p<0.05$) across spatial scales: (a) 1984–92 and (b) 1992–99.

area. It may also be due to interaction among 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 a sort of macroscopic social pattern (Epstein and Axtell, 1996).

Changes in the proportion of significant variables in time at different spatial scales may also be due to the reaction of the dependent variable (cropland change) to changes in the individual spatial scales of variation of the independent variables

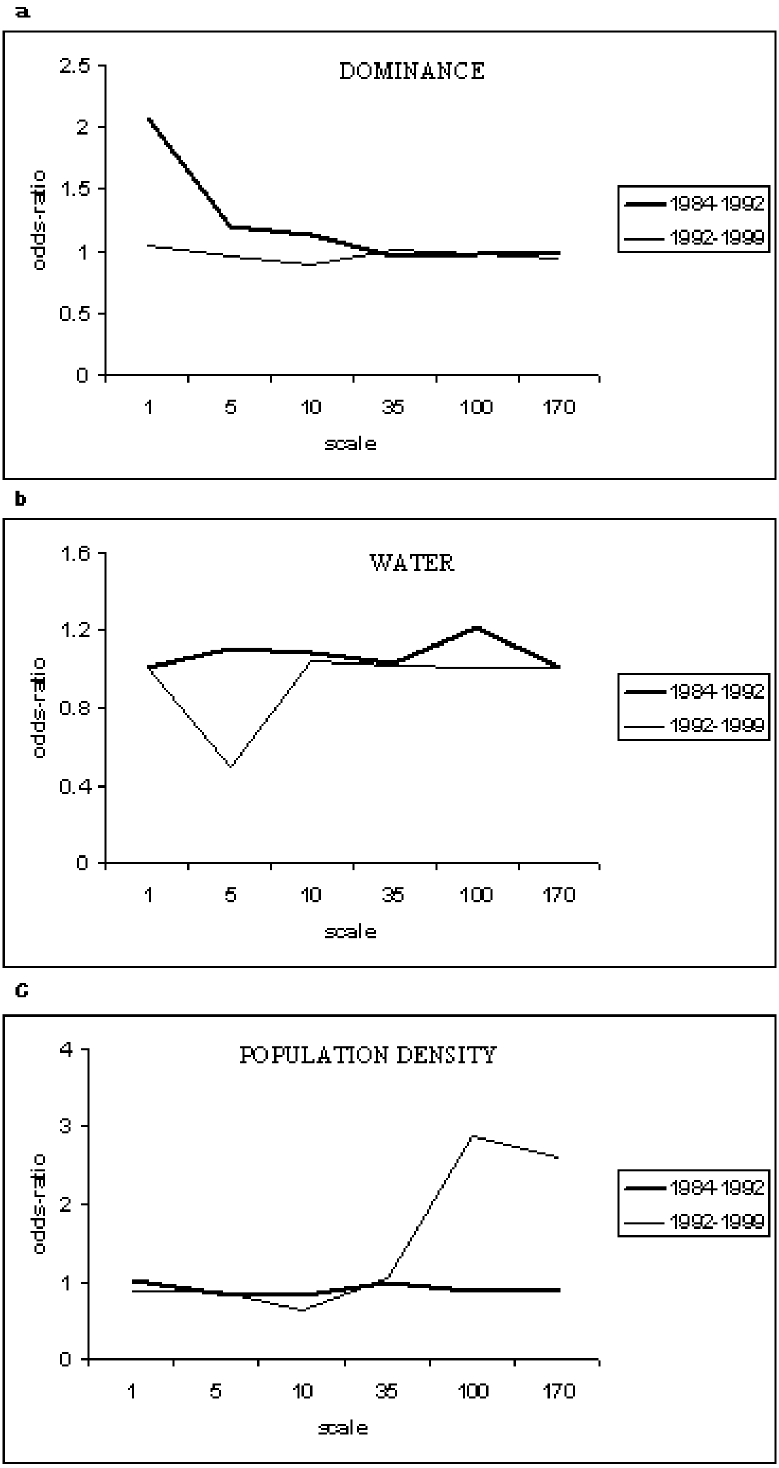
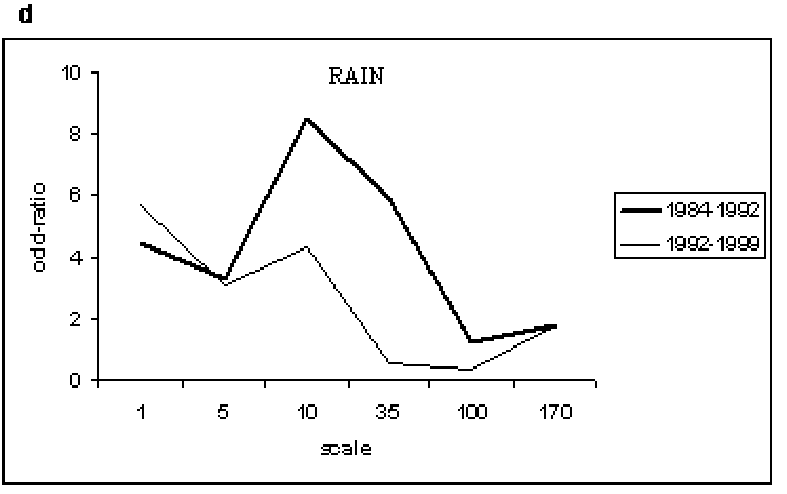


Figure 3. Changes in the odds ratio in space and time for selected variables.



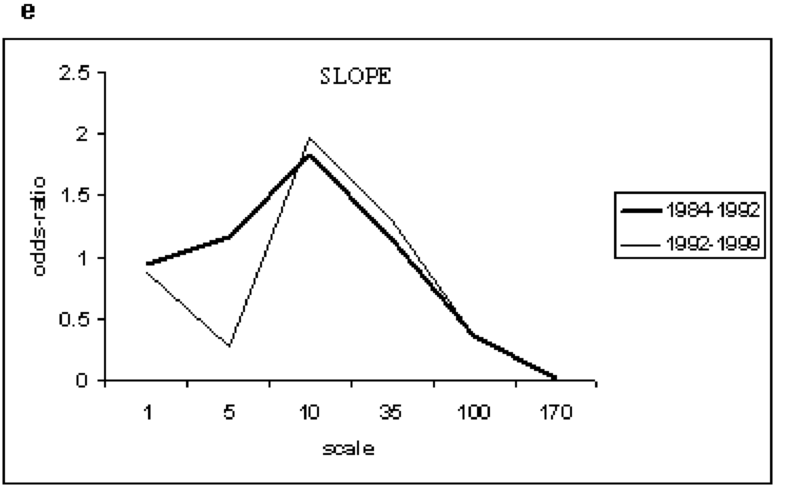


Figure 3. (*Continued*)

over time. The spatial structure of the driving forces of land use typically reflects in the pattern of that land use. When a given dataset exhibits high variability at a detailed scale, it may be possible to detect some patterns up to a certain level of aggregation. On the contrary, when the level of data aggregation exceeds the spatial scale of variation of the variables, the patterns may be obscure (Overmars et al., 2003). While the analysis of the spatial scales of variation of the variables is beyond the scope of this paper, Figure 3 suggests that the spatial scales of variation of some of the variables (e.g., DOMINANCE, WATER, POPULATION DENSITY) probably changed within the two periods, whereas those of others (e.g., RAIN, SLOPE) probably remained constant, resulting in changes in the odds ratio in space and time.

For both periods, biophysical variables generally had the lower frequency of significance. This is largely due to the nature and effects of environmental variables on land changes that tend to occur at a slow pace. Furthermore, Geist and Lambin

Table 4. Intervals for classification of the odds ratio and interpretation of effects on the likelihood of cropland change.

Class	Increase in the likelihood of change		Decrease in the likelihood of change	
	Odds ratio	Symbol	Odds ratio	Symbol
Low	< 2.49	⊕	< 0.33	⊖
Medium	$2.49 - 4.98$	⊕⊕	$0.33 - 0.66$	⊖⊖
High	> 4.98	⊕⊕⊕	> 0.66	⊖⊖⊖

(Geist and Lambin, 2001) noted that biophysical variables such as topography might not necessarily drive, but shape, LUCC.

4.3. Relative importance of the variables

The relative importance of significant variables was reclassified into low, medium, and high following an equal interval classification technique (Table 4). The equal interval classification requires the minimum ($\mathrm{OR}_{\min}$) and maximum ($\mathrm{OR}_{\max}$) odds ratio to determine the interval (C_{int}) of each class:

$$C_{\mathrm{int}} = \frac{\mathrm{OR}_{\max} - \mathrm{OR}_{\min}}{n}, \tag{3}$$

where n is the number of classes. The asymmetric property of the 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.

The resulting classification of the degree of importance of significant variables to cropland change is shown in Table 5.

Table 5a reveals that in the first period (1984–92), 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 30 m, that is, scale 1. A unit increase in each of these variables decreased the likelihood of cropland change by a factor ranging from 0.7 to 0.9. Table 5a 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 and 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 to 0.9.

In the second period (1992–99), rainfall zone (RAIN), 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 5b). A unit increase in distance to market and villages decreased the likelihood of conversion to cropland by a factor ranging from 0.7 to 0.9. A pixel located in the zone where annual rainfall exceeds 1100 mm was at least 5 times more likely to be converted to cropland than another located in the zone where annual rainfall is less than 1100 mm. Distance from villages was generally the most important socioeconomic variables across scales in the second period, reflecting the importance of transportation cost to land users. A unit increase in the variable decreased the

Table 5. Degree of importance of the variables.

(a) 1984–92	Scales					
Variables	1	5	10	35	100	170
Biophysical						
ALTITUDE	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖			
ASPECT						
SLOPE			⊕			
RAIN	⊕⊕	⊕⊕	⊕⊕	⊕⊕⊕		
TEMP					⊕⊕⊕	⊖
LI	⊖⊖⊖	⊖⊖⊖			⊖⊖⊖	
WATER	⊕	⊕	⊕		⊕	
DOMINANCE	⊕	⊕	⊕			
Socioeconomic						
ROADS	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖			
TAMALE	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖	
VILLAGES	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖		⊖⊖⊖
POPD84		⊖⊖⊖	⊖⊖⊖			
POPD92–84	⊖⊖⊖					⊖⊖
TENURE				⊕⊕	⊖	

(b) 1992–99	Scales					
Variables	1	5	10	35	100	170
Biophysical						
ALTITUDE				⊖⊖	⊖	⊖⊖⊖
ASPECT		⊖⊖⊖				
SLOPE						
RAIN	⊕⊕⊕	⊕⊕	⊕⊕		⊖⊖	
TEMP			⊖	⊖⊖		⊕⊕
LI	⊕⊕⊕	⊕⊕⊕	⊕⊕⊕	⊕⊕⊕	⊕	
WATER		⊖⊖	⊕	⊕		
DOMINANCE						⊖⊖⊖
Socioeconomic						
ROADS			⊖⊖⊖			
TAMALE	⊖⊖⊖	⊕		⊕		⊖⊖⊖
VILLAGES	⊖⊖⊖		⊖⊖⊖	⊖⊖⊖	⊖⊖⊖	⊖⊖⊖
POPD92			⊖⊖		⊕⊕	⊕⊕
POPD2000–92	⊕	⊕	⊕	⊕⊕	⊖⊖⊖	⊖⊖
TENURE						

likelihood of conversion to cropland by 0.7–0.9. The 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.

A paired-sample t test was used to compare the mean odds ratio across scales for the two periods (Table 6). 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 6 shows that the likelihood of cropland change given a unit increase in 7 out of the 14 variables was higher in the first period. They were predominantly biophysical variables (six out of eight of the biophysical variables). Thus, biophysical variables were generally more important in explaining cropland change in the first period. Socioeconomic variables were generally more important

Table 6. Comparison of the mean odds ratio across scales for the two periods. Variables that are significant across scales (p<0.1) are shown in boldface.

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

across scales in the second period, as five out of six socioeconomic variables have a negative t value. This may be related to increasing commercialization of household agriculture in the study area. 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 LI, ROADS, and VILLAGES.

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

- First, inclusion of potential biophysical and socioeconomic driving forces in modeling is essential, as this leads to an improved understanding of relationships between land-use change and its determinants across scales.
- Second, the importance of most variables (as illustrated by the 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. We further hypothesize that the changes may be due to changes in the spatial scale of variation of the independent variables over time.
- Third, 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.

4.4. 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 (OLS) regression, 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, that is, the overall fit. The pseudo R^2 in a logistic regression is usually much lower than the R^2 in OLS regression.

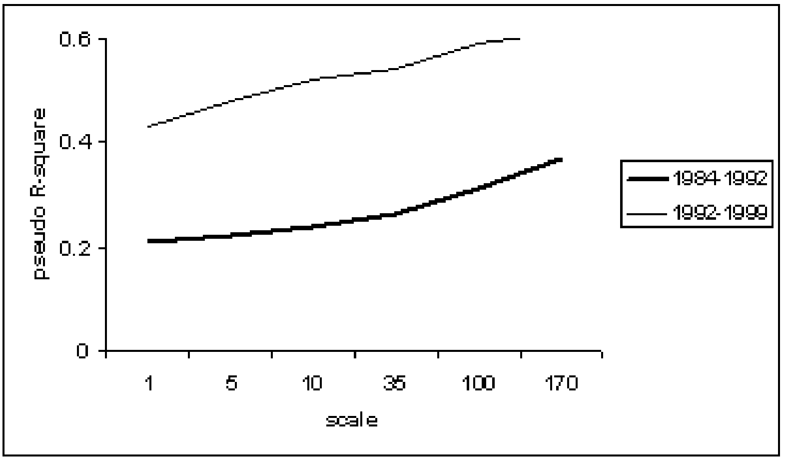


Figure 4. Goodness of fit at different scales.

Changes in pseudo R^2 across scales are shown in Figure 4. 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.

4.5. Validation of models

Relative operating characteristics increased from 0.78 for scale 1 to 0.92 for scale 6 (Table 7). This shows better correspondence in observed and simulated conversion to cropland as spatial extent increases. Different values of κ_{loc} and κ_q were observed across scales. Average values of κ_q were 0.75 (small scales), 0.98 (medium scales), and 0.64 (large scales). Thus, ability of the models to correctly specify quantity across scales is in the order medium>small>large. Average values of κ_{loc} were 0.82 (small scales), 0.94 (medium scales), and 0.99 (large scales), indicating that ability to correctly specify location is large>medium> small.

Table 7. Model validation parameters at different scales.

Scales		ROC	κ_{loc}	κ_q
Small	1	0.78	0.66	0.94
	5	0.83	0.98	0.55
Medium	10	0.88	1.00	0.97
	35	0.91	0.87	0.98
Large	100	0.92	1.00	0.93
	170	0.92	0.99	0.35

5. Conclusions

This study shows that the scale of observation is important in the study of the interrelationship between land-use change and its determinants. Scaling enables the assessment of the role of social relations within which land users interact, leading to changes in land use and land cover. In the Volta basin of Ghana, natural and social processes are altering the land cover in response to macroeconomic changes. In the first period (1984–92), the strategic importance of Tamale as the main market center and major source of nonfarm employment made distance from Tamale (TAMALE) an important determinant of land-use change. However, reduction in economic opportunities especially in the poststructural adjustment period reduced the importance of TAMALE across scales as a determinant of land-use change between 1992 and 1999. The importance of the rainfall zone (RAIN) in the models in both periods suggests the continuous expansion of the agricultural frontier to the wetter part of the landscape. The positive correlation of the land suitability index with cropland change in the second period also indicates the expansion of cultivation to areas that are more suitable for agriculture. This is plausible, as reduction in nonfarm employment opportunities has led to out-migration from Tamale (Braimoh, 2004).

Two major issues remain to be tackled in our future research in this environment where response to changing fiscal environment is altering livelihood strategies and hence the populated landscape in an unprecedented manner. First, there is the need to adequately characterize the emergent properties of the land-use systems using landscape metrics (Pontius, 2000). Second, there is also the need to investigate the effects of the spatial structure of the independent variables on land-use change at different spatial scales through geostatistical or autoregressive techniques.

Unlike previous studies (e.g., Walsh et al., 1999) that noted the dominance of biophysical variables at coarser scales in explaining LUCC, this study shows that both biophysical and social variables are equally important across scales. The study also stresses the importance of multitemporal analysis, as effects on LUCC may not be constant in time. With respect to time, biophysical factors were the dominant factors affecting agricultural land change in the first period. In the second period, market-related variables were clearly the most important factors. Response to changing economic conditions in the form of market-based agriculture was the primary cause. For instance, related research (Braimoh, 2004) indicated an increase in the area devoted to rice production owing to the prohibitive costs of imported rice since trade liberalization. Analyses of the patterns of LUCC as carried out in this study could provide relevant information for policy makers. As agricultural commercialization cannot be successful if left to the forces of demand and supply alone, policies relating to rural infrastructure development as well as institutional arrangements to strengthen the process are required.

Acknowledgments. The GLOWA project was funded by the German Federal Ministry for Education and Research and the Ministry for Schools, Science and Research of North Rhine Westphalia, Germany. The first author also thanks the German Academic Exchange Service for a scholarship award. We thank two referees for their constructive comments on an earlier draft of the paper.

References

Abdulai, A., and P. Hazell, 1995: The role of agriculture in sustainable development in Africa. *J. Sustainable Agric.,* **7,** 101–119.

Abdulai, A., and W. Huffman, 2000: Structural adjustment and economic efficiency of rice farmers in northern Ghana. *Econ. Develop. Cultural Change,* **48,** 503–520.

Allen, T. R., and S. J. Walsh, 1996: Spatial and compositional structure of the alpine treeline ecotone. *Photogramm. Eng. Remote Sens.,* **62** (11), 1261–1268.

Ardayfio-Schandorf, E., (Ed.), 1996: *The Changing Family in Ghana*. Ghana University Press, Accra, Ghana, 245 pp.

Braimoh, A.K., 2004: Seasonal migration and land-use change in northern Ghana. *Land Degrad. Dev.,* **15,** 37–47.

Braimoh, A.K., P.L.G. Vlek, and A. Stein, 2004: Land evaluation for maize based on fuzzy set and interpolation. *Environ. Manage.,* in press.

de Koning, G.H.J., P.H. Verburg, A. Veldkamp, and L.O. Fresco, 1999: Multi-scale modeling of land-use change dynamics in Ecuador. *Agric. Syst.,* **61** (2), 77–93.

Epstein, J. M., and R. Axtell, 1996: *Growing Artificial Societies: Social Science from the Ground up*. Brookings Institution Press, Washington, D.C., 208 pp.

Forman, R.T.T., and M. Godron, 1986: *Landscape Ecology*. John Wiley and Sons, New York, 620 pp.

Geist, H.J., and E. F. Lambin, 2001: What drives tropical deforestation? *LUCC Report Series No. 4,* Land Use and Land Cover Change (LUCC), International Geosphere–Biosphere Programme, 116 pp.

Hall, F.G., D. E. Strebel, J. E. Nickeson, and S. J. Goetz, 1991: Radiometric rectification: Toward a common radiometric response among multidate, multisensor images. *Remote Sens. Environ.,* **35,** 11–27.

Horton, S., R. Kanbur, and D. Mazumadar, (Eds.), 1994: *Labour Markets in an Era of Adjustment,* Vols. I and II. Economic Development Institute of the World Bank, Washington, D.C., 1040 pp.

Hosmer, D.W., and S. Lemeshow, 2000: *Applied Logistic Regression*. 2d ed. Wiley-Interscience, New York, 373 pp.

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

Menard, S., 1995: *Applied Logistic Regression Analysis*. Quantitative Applications in the Social Sciences, Vol. 106, Sage Publications Series, 98 pp.

Newton, H.J., (Ed.), 2000: STATA Technical Bulletin, STB 53, 18–29.

Overmars, K.P., G.H.J. de Koning, and A. Veldkamp, 2003: Spatial autocorrelation in multi-scale land use models. *Ecol. Modell.,* **164,** 257–270.

Parker, D.C., T. Berger, and S. Manson, (Eds.), 2002: Agent-based models of land use/land cover change. *LUCC Rep. Series No. 6,* International Human Dimensions Programme on Global Environmental Change (IHDP), 124 pp.

Pontius, R.G., 2000: Quantification versus location error in comparison of categorical maps. *Photogramm. Eng. Remote Sens.,* **66** (8), 1011–1016.

Tshikata, Y.M., cited 1999: Aid and reform in Ghana. [Available online at http://www.worldbank.org/aid/africa/ghana.pdf.]

Turner, B.L., II, D. Skole, S. Sanderson, G. Fischer, L. Fresco, and R. Leemans, 1995: Land-use and land-cover change science/research plan. *IGBP Rep. 35 and HDP Rep. 7,* International Geosphere-Biosphere Programme, Stockholm, Sweden, and the Human Dimensions of Global Environmental Change Programme, Geneva, Switzerland, 132 pp.

Veldkamp, A., P.H. Verburg, K. Kok, G.H.J. de Koning, J. Priess, and A.R. Bergsma, 2001: The need for scale sensitive approaches in spatially explicit land use change modeling. *Environ. Model. Assess.,* **6,** 111–121.

Walsh, S. J., T.P. Evans, W. F. Welsh, B. Entwisle, and R. R. Rindfuss, 1999: Scale-dependent relationships between population and environment in northeastern Thailand. *Photogramm. Eng. Remote Sens.,* **65,** 97–105.

Walsh, S. J., T. W. Crawford, K. A. Crews-Meyer, and W. F. Welsh, 2001: A multiscale analysis of land use/land cover change and NDVI variation in Nang Rong district, northeast Thailand. *Agric. Ecosyst. Environ.,* **85,** 47–64.