Modelling Potential Future Urban Land Use Changes in the Sekondi-Takoradi Metropolitan Area of Ghana*

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Abstract

Land use/land cover (LULC) of Sekondi-Takoradi metropolitan area of Ghana have changed substantially since the 1980s and the patterns of future LULC of the study area will have even greater impacts on the environment, quality of life of residents as well as their health. This study was conducted to model the potential future LULC patterns in the study area to provide information to support effective spatial planning and sustainable development. The study used the Dyna-CLUE model, Markov chain and logistic regression to model potential future LULC patterns. The logistic regression model was used to quantify the relationship between land use change driving factors and land use types, while the Markov chain was applied to estimate two yearly land use demands and the Dyna-CLUE model was applied to model dynamically the spatial patterns of multiple land uses. The results show that eight driving factors namely population density, slope, aspect, elevation, distance from roads, distance from rivers, distance from Takoradi town and distance from major urban centres, significantly drive land use/cover changes in the city, with relative operating characteristic (ROC) statistics ranging between 0.72 and 0.98, while the historical land use model was validated with a Kappa statistic of 49% for the entire map and a user accuracy of 75% for the built up land use, indicating a moderate agreement between predicted and observed land use of 2016. The potential future (2020 to 2050) land use maps showed that the built-up area may increase substantially in the next 30 years, replacing shrubs/farms and secondary forests and potentially intensifying the already existing sprawling in the city.

Keywords: Driving Factors, Dyna-CLUE, Land Use Modelling, Logistic Regression, Markov Chain

1 Introduction

Land use/cover changes are ubiquitous phenomenon in urban areas worldwide, which can affect the quality of the environment if not planned properly. In the developing world, land use changes are characterised by deforestation and urbanisation as a result of changing economic and development policies, rural urban migration and population growth. In West African countries such as Ghana, land tenure also play a role in land use changes; as development on government-owned land is usually planned, but for land owned by individuals, families and chiefs, there is little to no planning for land uses.

To the best of our knowledge, there is no publicly available information on urban land use change and its relationship with socio-economic and biophysical drivers in small metropolis such as Sekondi-Takoradi area of Ghana. Identifying the most significant driving factors of land use change as well as determination of the potential future patterns of land uses, is central to effective land use planning and sustainable urban development in any city. Understanding potential future land use patterns can provide policy makers and urban planners the needed information to effectively plan new development to minimize some of the negative impacts of land use changes, such as sprawling, soil erosion, siltation of rivers, flooding and urban heat islands.

Land use models have been applied for decades to project future land use patterns from local, regional and global scales. There are two main types of land use models, the deterministic and the stochastic models (Park *et al*., 2011b). The stochastic models include logistic regression models, Markov chains, cellular automata, while the deterministic models include the CLUE family of models (e.g. Dyna-CLUE and CLUE-S) and GIS-based models such as SLEUTH and Agent-based models (ABMs). The statistical models use biophysical and socio-economic factors to simulate land use (Bakker and van Doorn, 2009; Arsanjani *et al*., 2013), but they are limited in dynamic modelling of multiple land uses (Verburg *et al*., 2002; Dietzel and Clarke, 2006). Simulation of multiple land use distributions can however be achieved by the combination of stochastic and deterministic land use models as shown in Verburg and Overmars (2009) and they also generate the best land use distributions (Park *et al*., 2011a; Arsanjani *et al*., 2013), using relatively limited datasets. In this study, the Dyna-CLUE model, Markov chain and binary logistic regression have been used to determine significant land use driving factors in the study area to predict the potential future land use of the Sekondi-Takoradi metropolis and surrounding areas in Ghana. Since previous studies (Aduah and Baffoe, 2013) have shown that there is a rapid and unplanned land use changes in the municipality, which have resulted in urban sprawl, the prediction of future land use is aimed at providing further information for planning the development of the metropolis. Availability of

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potential future land use maps will enable authorities to plan the location of new development and reduce future urban sprawling.

2 Resources and Methods Used

2.1 Study Area

Sekondi-Takoradi Metropolis (Fig. 1) comprises of the cities of Sekondi and Takoradi. The Metropolis is located within latitudes 4° 51´ to 4° 56´ North and longitudes 1°41´ to 1°49´ West with a land area of about 206 Km^2 and it is the capital of the Western region of Ghana. The climate is equatorial, with an average annual temperature of about 22 °C. Rainfall is bi-modal, with the major season occurring between March and July and the minor season occurring between August and November. The mean annual rainfall is about 1380 mm. The natural vegetation has largely been degraded and the land use has changed substantially in the last three decades.

Since the discovery of oil in commercial quantities in 2007 in the Cape Three points , off the coast of Ghana, the Sekondi-Takoradi Metropolis have served as the base for oil companies and their workers, which has increased commercial activities and leading to high demand for both commercial and residential accommodation. Between 1988 and 2008, built up areas have increased by two and half fold, grasslands increased by 2%, while forests (evergreen and secondary) reduced by 12% (Aduah and Baffoe, 2013). The municipality is drained by three main rivers; the Anankwari River in the east and the Whin and the Kansawora Rivers to the west, as well as the Essei and the Butre lagoons. Major crops cultivated in the outskirts include cassava, maize, plantain, cocoyam, oil palm, vegetables and coconut and marine fishing.

2.2 Data Acquisition and Land Use Modelling

Dynamic Conversion of Land Use and its Effects modelling framework (Dyna-CLUE) model, was developed by the University of Wageningen, the Netherlands, for land use prediction (Verburg *et al.*, 1999; Verburg *et al.*, 2002; Verburg and Veldkamp, 2004). The model relates land use types and their driving factors as well as dynamic modelling of the competition between different land use types. The Dyna-CLUE model uses the spatial allocation and the non-spatial module. The non-spatial module uses land use demand, which is computed outside the Dyna-CLUE model using models such as Markov chains, econometric or trend analysis, while the spatial allocation module contains routines to spatially allocate the land use demand. The spatial allocation module requires the land use demand, spatial policy restrictions and land use location probabilities. The land use demand is the area of each land use type at a particular point in time, whiles the spatial policy restrictions determine locations where certain land use changes are permitted (Verburg and Veldkamp, 2004).

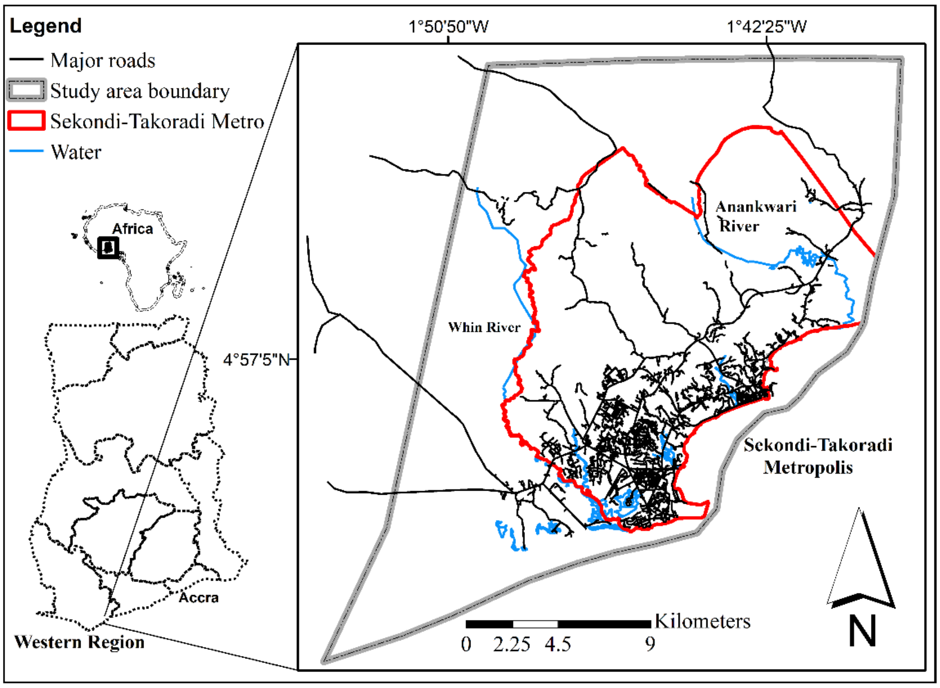

Fig. 1 Map of Sekondi-Takoradi Metropolis and surrounding area, Ghana

In this study, three data inputs were used to implement the spatial policy restrictions; namely area restrictions, land use conversion sequences (conversion matrices) and conversion elasticity. In general, area restrictions are based on a map, which ensures that in certain areas of the study site land use changes are either permitted or not. The area restriction map used in this study prohibited land use changes in three nature reserves in the Sekondi-Takoradi Metropolitan area namely (i) the Takoradi wetlands, (ii) the Monkey hill reserve and (iii) the Nchaban waterworks forest reserve. The conversion matrix influences the simulation of future land use as it specifies changes that are permitted to occur between land use types. The elements of a conversion matrix are derived from observed historical land cover/land use maps. In this study, the possible land use conversions were formulated by inspecting land use change matrix between 2002 and 2016.

Furthermore, based on the historical land use changes and local knowledge of the study area, a land use elasticity rating was created. Land use elasticity ranges from 0 for land use types with lowest conversion costs to 1 for land use types with the highest conversion costs. The conversion cost relates to the difficulty with which one land use type can be converted to the other. For example, the conversion cost of settlement area to another class type is very high, while that of shrubs/farms to settlement is low. The conversion elasticities used in this study were: 1 for built up and water, 0.5 for evergreen forest and shrubs/farms and 0.7 for secondary forest.

2.3 Estimating Land Use Demand

Land use demand or scenarios of land use changes were estimated using Markov chain model (equation (1)), based on observed land use maps of 2002 and 2016 as well as transition probability matrix (Table 1b), derived from a change matrix (Table 1a) between 2002 and 2016 land use/cover. The historical land use demand was estimated on a two yearly interval starting from 2002 (the baseline year) to 2016 (the final year), while the potential future land use demand started from 2016 to 2050, which was based on the statistics used for the historical land use demand estimation. Land cover of 2002 was used as baseline, because its date of capture, compared to other land cover maps, was closest to the date of capture of the population data used in this study. Considering that land cover change is generally stable over short time slices (Hu *et al*., 2013), it was considered reasonable to estimate land cover demand at two yearly intervals using a Markov chain (Equation (1)).

$$X_n = X_{(n-1)}P \qquad (1)$$

Where X_n is land use demand area, $X_{(n-1)}$ is the current land use area and P is the transition probability matrix. The inputs in equation (1) for this study were the initial (2002) land use areas and transition probability matrices, P. The land use transition probability is the probability (Flamenco-Sandoval *et al*., 2007) of one land use type in the initial year to change to another type in the final year. The probability for more than one land use type to change between the initial and the final year is given by a probability matrix. Takada’s software (Takada *et al*., 2010) was used to downscale the probability matrix between the initial (2002) and the final (2016) years (Table 1b) to a two yearly time interval, to capture the dynamics in land use changes occurring in the study area.

2.4 Driving Factors Land Use Demand

Since land use changes at the local scale is primarily dependent on accessibility measures, demographics and economic policies, (Barbier, 2000; Meyfroidt *et al*., 2013), static factors that relate to accessibility to land and resources (e.g. distance to roads, rivers, urban centres, etc), elevation, slope and aspect and a dynamic factor such as population density were selected for simulation. The land use driving factors (Table 2) adopted in this study were selected based on previous studies in Ghana (Braimoh and Vlek, 2005; Aduah *et al*., 2018). The population changes for both the historical and future time steps, was estimated using census data from the Ghana Statistical Service (GSS) database for 2000 and 2010 population and housing census of Ghana (Anon., 2005, 2013). The population changes were estimated based on 3% annual population growth rate for Western region. Other important drivers such as incomes, education and cost of land were not included for lack of data. The selected driving factors were converted to raster maps and imported together with the land use maps to IBM SPSS statistical software. The imported data in IBM SPSS was analysed using binary logistic regression (Equation 2), to estimate the probability of the land use types, based on the driving factors.

$$Log(\frac{P_i}{1-P_i}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (2)$$

where Pi is the probability of land use types in location i, $X_{1, 2 \ldots n}$ are the location factors and $\beta_{1, 2, 3 \ldots n}$ are the logistic regression coefficients. The regression coefficients from equation (2) as well as the land use demands (equation (1)), area restriction files, driving factors, initial land use (2002) and the change matrix, were input in the Dyna-CLUE model, to simulate/model land use.

2.5 Model Calibration and Validation

The logistic regression and the Dyna-CLUE models were calibrated and validated using the Relative Operating Characteristic curve (ROC) statistic, Kappa and overall accuracy, respectively. ROC statistic was used to assess the correlation (Arsanjani *et al*., 2013) between land use types and each driving factor, during the modelling, while the Kappa statistic and the overall accuracy were used after simulation, to assess the correspondence (Congalton, 1991) between observed and simulated land use/cover patterns. During the logistic model calibration, land use/cover driving factors which were not significant at the 95% confidence level were eliminated.

Table 1 (a) Change Matrix (Km^2) and (b) Two Year Transition Matrix

(a)

		From 2002				
	Land cover	Built_up	Water	Evergreen forest	Secondary forest	Shrubs/farms
To 2016	Built-up	75.30	0.41	0.05	2.42	60.06
	Water	2.04	41.16	0.00	0.03	0.24
	Evergreen forest	0.00	0.00	3.16	13.36	2.21
	Secondary forest	0.19	0.00	0.74	64.04	41.14
	Shrubs/farms	3.94	0.10	1.13	58.10	123.08

(b)

		From 2002				
	Land cover	Built-up	Water	Evergreen forest	Secondary forest	Shrubs/farms
To 2016	Built-up	0.97	0.00	0.00	0.00	0.05
	Water	0.00	1.00	0.00	0.00	0.00
	Evergreen forest	0.00	0.00	0.93	0.03	0.00
	Secondary forest	0.00	0.00	0.03	0.87	0.05
	Shrubs/farms	0.01	0.00	0.04	0.12	0.90

Table 2 Land Use Change Driving Factors

Data	Description	Source
Population density	population density (person/sq. Km)	GSS, 2005, 2013
Distance from Takoradi town	distance from centre of largest town	Survey of Ghana
Distance from roads	distance from roads	Survey of Ghana
Elevation	elevation from ASTER GDEM	USGS
Distance from rivers	distance from main rivers	Survey of Ghana
Aspect	aspect derived from ASTER GDE	Survey of Ghana
Slope	slope derived from ASTER GDEM (%)	Survey of Ghana
Distance from urban centres	distance from major urban centres	Survey of Ghana

all euclidean distances were measured in metres

3 Results and Discussion

3.1 Results

3.1.1 Model Validation and Simulated Land Use

Table 3 shows statistics of the binary logistic regression between the driving factors and land use types for the Sekondi-Takoradi metropolis and surrounding areas. Table 3 indicates that the relationship between the land use types and the driving factors is significant at 95% confidence level and the ROC statistics were above 0.7. The logistic regression further shows that increasing population density, distance from Takoradi township and distance from rivers were significantly related to increased built-up areas. For the forest land use, population density increase, increase in distance from Takoradi township and increase in slope influenced reduction in evergreen forests.

Table 3 Statistics of the Relationship between Land Use and Driving Factors

	Built_up	Water	Evergreen forest	Secondary forest	Shrubs/farms
Factor	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Population density	0.0018	0.0005	-0.00137	-0.00207	-0.0008
Aspect	0.0023	-0.00589	0.00101	-0.00023	0.0010
Distance from Takoradi town	0.0001	-0.00004	-0.00011	-0.00003	0.0000
Distance from urban centres	-0.0009	0.00088	0.00021	0.00025	-0.0002
Distance from rivers	0.0007	-0.0014	0.00002	-0.00033	-0.000
Distance from roads	-0.0009	0.00086	0.00006	-0.00019	0.0000
Elevation	-0.0148	-0.31742	0.01683	0.03193	-0.0010
Slope	-0.0106	0.28677	-0.00254	-0.00769	-0.0036
Constant	-1.8753	-0.58288	-2.24354	-0.81332	0.3403
ROC statistic	0.9268	0.98355	0.82083	0.77852	0.7174

all coefficients in the table are significant at $P<0.05$

For Secondary forest, the relationships between the driving forces was quite different from that of the evergreen forest. Secondary forests reduced as population density, aspect, distance from Takoradi township, distance from rivers, distance from roads and slopes increased. However, increase in aspect, distance from Takoradi township and distance from roads influenced increased shrubs/farm area, but increased population density, distance from urban centres, distance from rivers, elevation and slope influenced reduction in the area of shrubs/farms. The binary logistic regression model show that as population density increased, the built up area increased, while the vegetated area decreased.

Fig. 2 presents the comparison of the observed and simulated land cover map for 2016. The Kappa statistic of the comparison between simulated and observed land use/cover map was 0.49, which indicates a moderate agreement, according to the rating by Landis and Koch (1977) and Congalton (1991). Further, an overall accuracy of 63% and user/producer accuracy of 75% for the land use map and the built-up area, respectively, were obtained.

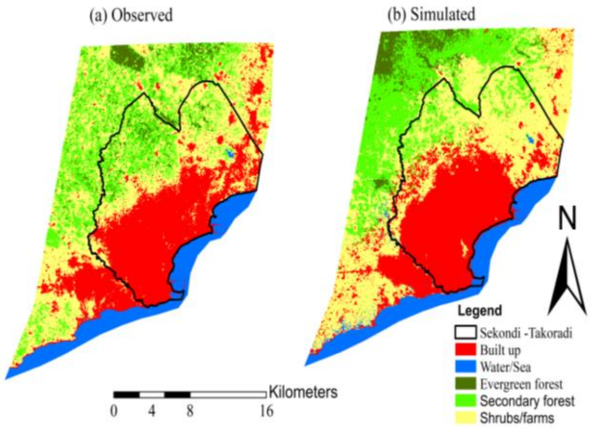

Fig. 2 Observed and Simulated Land Use Maps of 2016

Table 4 also presents a comparison between the land use demand and the actual allocated land use areas after simulation. Table 4 indicates that in this study the non-spatial allocation, based on Markov chain, was more accurate, compared to the spatial allocation, based on the Dyna-CLUE, as the observed demand values corresponded well with the simulated, but a comparison between the observed and simulated maps shows that some sections of the study area were wrongly allocated with land uses.

Table 4 Modelled and Observed Land Use Demand for 2016

Land use/cover	Observed area (Km^2)	Simulated area (Km^2)	Difference (Km
Built-up	138.24	135.80	-2.
Water/sea	43.47	44.09	**0.**
Evergreen forest	18.74	21.75	3.
Secondary forest	106.11	105.11	**-1.**
Shrubs/farms	186.36	186.15	-0.
Total	492.91	492.91	

Since the above statistics (Table 3) and maps (Fig. 2), provides a moderate validation of the Dyna-CLUE model, the model can be used to project future land use patterns for purposes of understanding land use trajectories and assessing their potential impacts in the Municipality and the surrounding areas. Fig. 3 presents potential future land use/cover maps, which shows that the built up areas in Sekondi-Takoradi and surrounding areas (STMA) may substantially increase in the next three decades. Fig. 3 further show that built up areas in STMA may increase from 30% in 2020 to about 40% in the middle of the century, while secondary and evergreen forest may reduce to 15% and 7%, respectively. The maps also show that built up area increased at the expense of shrubs/farm areas and secondary forests. The shrubs/farms reduced from 36% in 2020 to 27% in 2050, while secondary forests reduced from 20% in 2020 to 15% in 2050.

3.2 Discussion

This study has shown that population density, distance from Takoradi town, distance from roads, elevation, distance from rivers, aspect and slope, significantly influence land use allocation in the Sekondi-Takoradi Metropolis and surrounding areas (STMA). The study has also demonstrated that with scarce data, the Dyna-CLUE model can be used to model land use in the STMA. Binary logistic regression between selected driving factors and land use was significant with ROC statistics above 0.7 and the comparison of observed with simulated land use produced moderate Kappa (Fig. 2) and the simulated demand corresponded well with the observed land cover areas (Table 4). The potential future land use simulation was based on business as usual scenario, where the historical land use change trend, based on land cover maps of 2002 and 2016, was assumed to continue into the future. The study has shown that from 2020-2050, the urban area of STMA and its surrounding areas may increase significantly at the expense of shrubs/farms and secondary forests.

The potential future maps depict landscape where large vegetated areas may be replaced by built up areas, which can reduce land available for the mainly subsistence agriculture and leading to potential food security challenges. Changes of vegetated land use to mainly built up at a relatively short time as depicted in the potential future land use maps illustrates that urban sprawling reported by Aduah and Baffoe (2013) may be intensified in the future and make it challenging for authorities to manage the metropolis. With increasing urbanisation and sprawling, land use change impacts such as flash floods, urban heat islands and poor sanitation, could dominate the environment and create conditions for increased mosquito habitats and increased malaria prevalence. With increasing urbanisation, it may be necessary to re-organise the STMA Metropolis and its surrounding areas into a number of small manageable administrative municipalities, to ensure effective urban management to promote sustainability and conducive environment for urban dwellers and businesses.

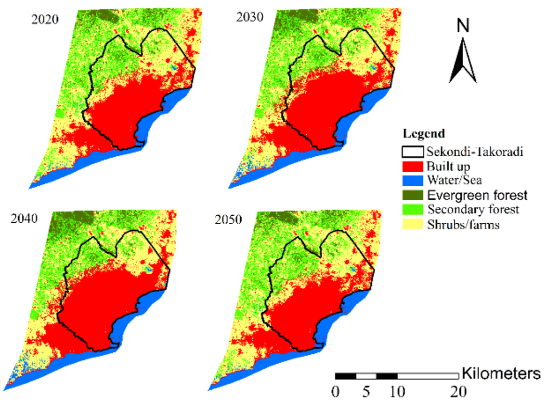

Fig. 3 Potential Future Land Use Maps

4 Conclusions

This study has simulated land use change patterns in the STMA and its surrounding areas using binary logistic regression, Markov chain and the Dyna-CLUE model framework. The simulation has shown that significant driving factors for land use changes in the study area include distance to roads, distance to Takoradi township, distance to urban centres, ground elevation and population density. The potential future land use maps simulated show a sharp increase in urban areas and the reduction of vegetated areas, consistent with the current trend of land use changes as depicted by land use maps derived from satellite images. The projection of the potential future land use maps in this study is critical to the development of STMA and its surrounding areas as the maps can be used to ascertain the possible location of urban areas in the future and to enable planners to control the development for sustainability of the Metropolis. Although the accuracy of the simulations were only moderate, the study provides a contextualized scenario of what may occur given the current trends of land use changes, and is also based on biophysical and socio-economic driving factors. Land use/cover simulation conducted in this study is more objective, compared to expert judgment, which is largely subjective. However, one of the limitations of the study is that it was assumed that during simulation no new land cover class will emerge, as the Dyna-CLUE model cannot introduce new land cover classes, which have no precedence. The study also suffered from lack of detailed census population data at the sub-community level, which resulted in less accurate population density maps. It is recommended that future population and housing census should be based on smaller community polygons, so as to enable accurate population density maps to be prepared. Since the STMA and its surrounding area is fast growing with its attendant sprawling, it is suggested that the polycentric approach to city planning be adopted to among others things avoid congestion in the near future.

References

Aduah, M. S. and Baffoe, P. E. (2013), "Remote Sensing for Mapping Land-Use/Cover Changes and Urban Sprawl in Sekondi-Takoradi, Western Region of Ghana", *The International Journal of Engineering And Science*, Vol. 2, No. 10, pp. 66-73.

Aduah, M. S., Toucher, M. L. and Jewitt, G. P. W. (2018), "Estimating potential future land use in the Bonsa catchment, Ghana, West Africa", *South African Journal of Geomatics* Vol. 7, No. 3, pp. 13.

Anon., (2005), "Population and Housing Census, Analysis of District Data and implications for Planning, Western Region, Ghana". In: Twum-Baah, KA, Kumekpor, TKB and Addae-Mensah, I (eds.). *Ghana Statistical Service, Accra, Ghana*, pp. 1-131.

Anon., (2013), "Population & housing census, National analytical report". In: Awusabo-Asare, K (ed.). *Ghana Statistical Service, Accra, Ghana*, pp. 1-430.

Arsanjani, J. J., Helbich, M., Kainz, W. and Boloorani, A. D. (2013), "Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion", *International Journal of Applied Earth Observation and Geoinformation*, Vol. 2, No. 1, pp. 265-275.

Bakker, M. M. and van Doorn, A. M. (2009), "Farmer-specific relationships between land use change and landscape factors: Introducing agents in empirical land use modelling", *Land Use Policy* Vol. 26, No. 3, pp. 809-817.

Barbier, E. B. (2000), "Links between economic liberalization and rural resource degradation in the developing regions", *Agricultural Economics*, Vol. 23, No. 3, pp. 299-310.

Braimoh, A. K and Vlek, P. L. G. (2005), "Land-cover change trajectories in Northern Ghana", *Environmental Management,* Vol. 36, No. 3, pp. 356-373.

Congalton, R. G. (1991), "A review of Assessing the Accuracy of Classification of Remotely Sensed Data", *Remote Sensing of Environment*, Vol. 37, pp. 35-46.

Dietzel, C. and Clarke, K. (2006), "The effect of disaggregating land use categories in cellular automata during model calibration and forecasting", *Computers Environment and Urban Systems*, Vol. 30, No. 1, pp. 78-101.

Flamenco-Sandoval, A., Martinez Ramos, M. and Raul Masera, O. (2007), "Assessing implications of land-use and land-cover change dynamics for conservation of a highly diverse tropical rain forest", *Biological Conservation*, Vol. 138, pp. 1-2, 131-145.

Hu, Y., Zheng, Y. and Zheng, X. (2013), " CLUE-S and Markov composite models", *Chinese Geographical Science*, Vol. 23, No. 1, pp. 92-100.

Landis, J. R. and Koch, G. G. (1977), "The measurement of observer agreement for categorical data", *Biometrics,* Vol. 33, No. 1, pp. 159-174.

Meyfroidt, P., Lambin, E. F., Erb, K. H. and Hertel, TW. (2013), "Globalization of land use: distant drivers of land change and geographic displacement of land use", *Current Opinion in Environmental Sustainability*, Vol. 5, No. 5, pp. 438-444.

Park, J. Y., Park, M. J., Joh, H. K., Shin, H. J., Kwon, H. J., Srinivasan, R. and Kim, S. J. (2011a), "Assessment of MIROC3.2 HIRES climate and CLUE-S land use change impacts on watershed hydrology using SWAT", *Transactions of the Asabe*, Vol. 54, No. 5, pp. 1713-1724.

Park, S., Jeon, S., Kim, S. and Choi, C. (2011b), "Prediction and comparison of urban growth by land suitability index mapping using GIS and RS in South Korea", *Landscape and Urban Planning* Vol. 99, No. 2, pp. 104-114.

Takada , T., Miyamoto, A. and Hasegawa, S. F. (2010), "Derivation of a yearly transition probability matrix for land-use dynamics and its applications", *Landscape Ecology,* Vol. 25, pp. 561-572.

Verburg, P. and Veldkamp, A. (2004), "Projecting land use transitions at forest fringes in the Philippines at two spatial scales", *Landscape Ecology*, Vol. 19, No. 1, pp. 77-98.

Verburg, P. H., de Koning, G. H. J., Kok, K., Veldkamp, A. and Bouma, J. (1999), “A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use”, *Ecological Modelling* Vol. 116, No. 1, pp. 45-61.

Verburg, P. H. and Overmars, K. P. (2009), “Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model”, *Landscape Ecology*, Vol. 24, No. 9, pp. 1167-1181.

Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V. and Mastura, SSA. (2002), “Modeling the spatial dynamics of regional land use: The CLUE-S model”, *Environmental Management*, Vol. 30, No. 3, pp. 391-405.

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