lands are also considerable. The total depleted forested areas are more than 60 % of these forested land classes. Savannah land classes on the other hand, are less affected. Recorded changes within these classes cover an area of 331 ha which corresponds to 3 % of the key site. Fig. 4 highlights the magnitude of changes in term of net change within the key study area and also within the LUC class.

The result is presented in Table 5. The correlation between variables FORA and NFAR is negative (r = -1) and highly significant at 0.01 levels.

Correlation between FORA and Cotton area, FORA and Built-up as well as Built-up and caring capacity is negative and significant at 0.05 level. On the other hand, correlations are positive and significant at 0.05 level for the relationship between NFAR and Cotton area, NFAR and Built-up area, Cotton area and the distance to farm as well as between the population density and the distance to farm.

As shown in table 6, parameter estimates with their corresponding standard error, t-statistics and significance probability are presented. According to Schneider and Pontius (2001), positive values of estimated coefficients or parameters indicate that larger values of the independent variables increase the likelihood, while negative values indicate the opposite. The significance level of each parameter was estimated by t-statistics. In other words, the t-statistics indicates the relative weight of these independent variables in the model. This allows assessing the role of each variable in the model prediction.

The adjusted R-square (R^2) value was estimated at 0.98. As stated by Kenkel *et al.* (1989), the coefficient of determination (R^2) value indicates the percentage of change of the dependent variable when any variation occurs with the two independent variables: Built-up and Cotton area. The results so far obtained indicate that any variation in the two independent variables will explain 98% of (quantity of) change in FORA. In other words, any expansion of Built-up or Cotton area will induce 98% of change in forested areas.

Model Simulation

Using a stepwise method, results of data simulation are presented in Table 7. One independent variable has shown adequate parameters for the simulation process. The selected variable for the model is the Agricultural area. As shown in Table 6, all regression coefficients related to this independent variable are highly significant with the p-values or probabilities values fairly equal to zero.

From this simulation exercise, future of land use/cover change can be predicted. This study has highlighted that increase in agricultural area would be the principal cause of vegetation destruction or degradation.

Fig. 5 shows observed values of the land use/cover change occurring from 1986 to 1999 and the linear trend extrapolations for 2015 and 2025. The first two bars of the figure show that from 1986 to 1999, farmlands and built-up areas have respectively increased by 18.4 % and 1.35% whereas the forested areas have decreased by 19.76% of the total study area. The third and fourth bars in Fig. 5 show land use/cover shares in years 2015 and 2025 by trend extrapolation assuming that the past rates of changes continue until target years. This shows that farmland and built-up areas would increase greatly whereas the forested areas will continue to decrease.

The results of this study have shown that over an observation period of 13 years, farmlands and built-up areas have increased by 18.4% and 1.35% respectively whereas the forested areas have decreased by 19.76%. The ratios respectively are: (-23); (0.76) and (198) for farmland, built-areas and forested areas.

From Fig. 5, it is clearly demonstrated that built-up area and farmland are estimated to increase while forested lands would decrease. This indicates that further development of land use/cover change would take place at the expense of forested areas. The prospect of farmland increase although is the normal trend in an area where agriculture is the main backbone of economy, there is a necessity to induce some policy options.

Implementation of this conceptual framework would help to manage the natural resources in a way that they meet the population needs. Although the resources are well managed, land use/land cover change are likely to persist (Morita *et al*., 1997). The difference will be in terms of impacts.

Discussion

Developments in geographic information systems and remote sensing techniques have permitted estimation of changes in land use/cover over a selected time period. The data were assembled in matrices often known as change matrix or contingency table. The change analysis allows increasing better understanding of what happened over the study area during the past period of observation. Thus, this approach is by nature retrospective. As the development policy has to be based on predictive analysis, the transition probabilities were calculated and simulation was performed to predict the changes over a time horizon.

One of the short comings of the Markov model used for this study is that the model is linear. According to Kesseler and Greenberg (1981), such a model involves no time delay longer than a single time step. Secondly, the amount of land transferred from one class to another during a time step is simply a portion of the area of each land use/cover class. However, vegetation dynamics are almost certainly non-linear and often involve time delays (Anderson *et al*., 1976). The problem this situation raises is how to use a linear model to deal with a non-linear environment.

Such a situation is possible since by essence, the transition represents a discrete change of state. This means that if a location, such as a point, polygon or pixel at one time is in state A and some other time in state B, then it can be stated that a state change has taken place. In some places, land use/cover transitions are rather more subjective in their classification than this statement implies (Kramer, 1996; Tole, 2002). To support this, it was argued that a wooded forest lot could become the backyard of a residence and change from forest to built-up area. In this case, the changing use does not imply changing cover. Another situation could result from uncontrolled wood harvesting. Although the canopy of the woody stratum remains virtually stable without any noticeable change, the merchantable wood trees could already be removed. This highlights the necessity to link the land change with stock volume estimation through a forest survey using remote sensing.

From above, most authors do not find any inconvenience in this situation that is intrinsic to the nature of both model used and the environment studied. However, to overcome Markov model limitation so far stated, time delays should be incorporated in Markov models by extending them to the second order. But, this becomes too complicated as it needs to use complicated mathematic processes (Fisher *et al.*, 1976, Waddel, 2000; Alexandrov & Hoogenboom, 2000). Analysis of the different transition probabilities helped to establish the land use/cover change trajectory of the study area. One of the reasons for choosing this approach relies on the availability of a time series images of 1986, 1997, and 1999. The images were acquired between December and February, which is the best period for land use classes discrimination on the images.

The adjusted R-square (R^2) value was estimated at 0.98. As stated by Kenkel *et al.* (1989), the coefficient of determination (R^2) value indicates the percentage of change of the dependent variable when any variation occurs with the two independent variables: Built-up and Cotton area. The results so far obtained indicate that any variation in the two independent variables will explain 98% of change in FORA. In other words, any expansion of Built-up or Cotton area will induce 98% of change in forested areas.

As shown in Table 5, all the regression coefficients are highly significant. Coefficients of regression appraised were negative for the two independent variables used for the regression model. From above, it can be deduced that any increase in cotton surface will result in a reduction of FORA variable. The same is observed with Built-up variable. In other words, expansion of cotton cultivation and built-up areas is negatively correlated with forested areas. These relationships confirm that human activities, as stated so far in the last chapter are the main drivers of land use /land cover change. Overall, estimation of land use/cover changes through modeling has provided an important conceptual link that can be used to generate land use/cover change simulation on the basis of land use/cover change predictions.

Conclusion

This study has highlighted how from developments in geographic information system and remotely sensed image analysis, it is possible to calculate changes in land use/cover classes during selected time intervals. It also illustrated techniques for predicting land use/cover in the horizon of 2025 with the assumption that transition probabilities remain constant over time, which is probably a conservative estimate based on a rapidly increasing population in Benin (MPDEAP et PNUD, 2008). Through this modeling activity, the strengths of the relationships between land use/cover change processes and the estimated change in agricultural and other developed land use factors specified in this study suggest that there is prospect for the proposed model approach.

The results of this study have shown that over an observation period of 13 years, farmlands and built-up areas have increased by 18.4% and 1.35% respectively whereas the forested areas have decreased by 19.76%. The ratios are respectively (-23); (0.76) and (198) for farmland, built-areas and forested areas.

The rapid rate of forest loss indicates that actions have to be taken to keep the impacts of the land use/land cover changes to a low level. Policy options for land use/land cover management to control land use/cover change encompass migration control and control of socio-economic studies. Regional planning based on local participation and needs should be set up. Although the Markov model used in this study has demonstrated its efficiency in predicting and simulating land use/land cover changes, further research should include how to map where the changes took places in addition to the simulated changes. In-depth studies on these models will help to adequately locate where the changes take place and to design proper management measures for specific locations.

References

Alexandrov, A & Hoogenboom G. 2000. The impact of climate variability and change on crop yield in Bulgaria. *Agriculture and Forest Meteorology* 104: 315–27.

Anderson, J.R., 1971. Land use classification schemes used in selected recent geographic applications of remote sensing: Photogrammetric Engineering, Vol. 37, N°4 pp: 379-387.

Atkinson, P.M. & Tate, N.J. 2000. Spatial scale problems and geostatistical solutions: A review. *Professional Geographer* 54: 4 607-623.

Barbieri, A.; Monte-Mór, R.; Bilsborrow, R. 2008. Towns in the jungle: exploring linkages between rural-urban mobility, urbanization and development in the Amazon. In: Sherbinin, A.;Rahman, A.; Barbieri, A.; Fotso, J.C.; Zhu, Y.. (Eds.), Urban Population and Environment Dynamics in the Developing World: Case Studies and Lessons Learned. Paris: CICRED. 67p.

Brown, D.G.; Pijanowski, B.C. and Duh, J.D. 2000. Modeling the relationship between land use and land cover on private lands in the upper Midwest, USA. *Journal of Environmental Management* N°59: 17- 24.

Deressa, T. T. 2007. Measuring the Economic Impact of Climate Change on Ethiopian Agriculture: Ricardian Approach. The World Bank Development Research Group Sustainable Rural and Urban Development Team. Policy Research Working Paper 4342, 32p.

Diaconis, P. 2009. The Markov Chain Monte Carlo revolution, *Bulletin of the AMS*, N° 46 Vol 2, 179-205.

Ficher, G.; Ermoliev, Y.; Keyzer, M.A.; Rosenzweig, C. 1996. Simulating the socio-economic and biogeophysical driving forces of land-use and land cover change: The IISA land use change model. IISA Working paper WP-96-010, 83p.

Gilks, W. R., Richardson, S. and Spiegelhalter, D., eds. 1996. Markov Chain Monte Carlo in Practice: Interdisciplinary Statistics, Chapman & Hall/CRC. 46p.

Hsu, L.T and Cheng, C.C., 2000. Integrating landscape models in forest landscape analyses using GIS: an example in Taiwan. Workshop on GIS development, Poster session. 10p.

Kenkel, N.C., Juhasz-Nagy, P. & Podani, J. 1989. On sampling procedures in population and community ecology. : Vegetation N°83, 195-207.

Kessler, R.C. and Greenberg, D.F. 1981. Linear Panel Analysis: Models of Quantitative Change (New York, Academic Press). 124pp.

Kok, K. 1999. Scaling the land use system: A modeling approach with case studies for Central America. Ph.D thesis Wageningen University. 135pp.

Kramer, J. 1996. Integration of a GIS with a local scale self modifying urban growth model in South-eastern Orange County, New-York. M.A Thesis. Hunter College-CUNY. 87pp.

Link, W. A., E. Cam, J. D. Nichols, and E. G. Cooch. 2002. Of Bugs and birds: Markov chain Monte Carlo for hierarchical modeling in wildlife research. *Journal of Wildlife Management* 66:277–291.

Mama, V. J. 2005. Accuracy assessment in improving land-use/cover classification in Benin. *Bulletin de la Recherche Agronomique du Bénin* N°48 :38-45.

Mama, V. J. & Adeniyi, P. 2005. Tree diversity Analysis of a savannah type in Republic of Benin using remote sensing and plant diversity indices. *Environtropica*, Vol. 1 et 2: 29-39.

Mama, V.J and Oloukoi, J. 2003. Evaluation de la précision des traitements analogiques des images satellitales dans l'étude de la dynamique de l'occupation du sol. *Télédétection*, Vol 3, N°5, 429-441. Université de Sherbrooke, Québec, Canada.

Mertens, B. and Lambin, E.F. 2000. Land cover change trajectories in Southern Cameroon. *Annals of the Association of American geographers*, Vol.90, N°3: 467-494.

Morita, H.; Hoshino, S.; Kagatsume, M.; Mizuno, K. 1997. An application of the land use change model for Japan Case Study area. IIASA. Interim Report. IR-97-065. 10p.

MPDEAP et PNUD (2008), Rapport national sur le Développement Humain au Bénin 2007/2008. Responsabilité sociale, corruption et développement humain durable. Ministère de la Prospective, du Développement, et de l'Evaluation de l'Action Publique. Programme des Nations Unies pour le Développement, Bénin. 54p.

Nelson, G. C., 2000. Modelling deforestation and land use change; *Sparse data Environments*. IAAE Spatial Analysis learning Workshop, Berlin. 14p.

Oloukoï, J.; Mama V. J. & Agbo, F. B. 2007. Modélisation de la dynamique de l'occupation des Terres dans le département des collines au Bénin. *Télédétection*, Vol. 6, N° 4: 305-323.

Rubiano, J. 2000. Land Use Change in Tropical Hillsides: the influence of pattern on process. *Advances in Environmental Monitoring and Modelling*, Vol. 1 N°1: 61-79.

Schneider, L.C. & Pontius, Jr.R.G. 2001. Modelling land use change in the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems & Environment* Vol. 85, pp. 83-94.

Skole, D.L., Chomentowski, W.H., Salas, W.A., Nobre, A.D., 1994. Physical and human dimensions of deforestation in Amazonia. *Bioscence* Vol. 44: 314-322.

Tole, L. 2002. An estimate of forest extent and change in Jamaica using Landsat MSS data. *International Journal of Remote sensing*, vol. 23, n° 1: 91-109.

Turner, M.G. 1997. Spatial simulation of landscape changes in Georgia: a comparison of three transition models. *Landscape Ecology* 1:29-36.

Verburg, P.H., Veldkamp, T. A., Bouma, J. 1999. Land use change under conditions of high population pressure: the case of Java. *Global Environment Change* No. 9: 303-312.

Waddell, P. 2000. A behavioural simulation model for metropolitan policy analysis and planning: residential location and housing market components of UrbanSim. *Environment and Planning*, 27: 247-263.

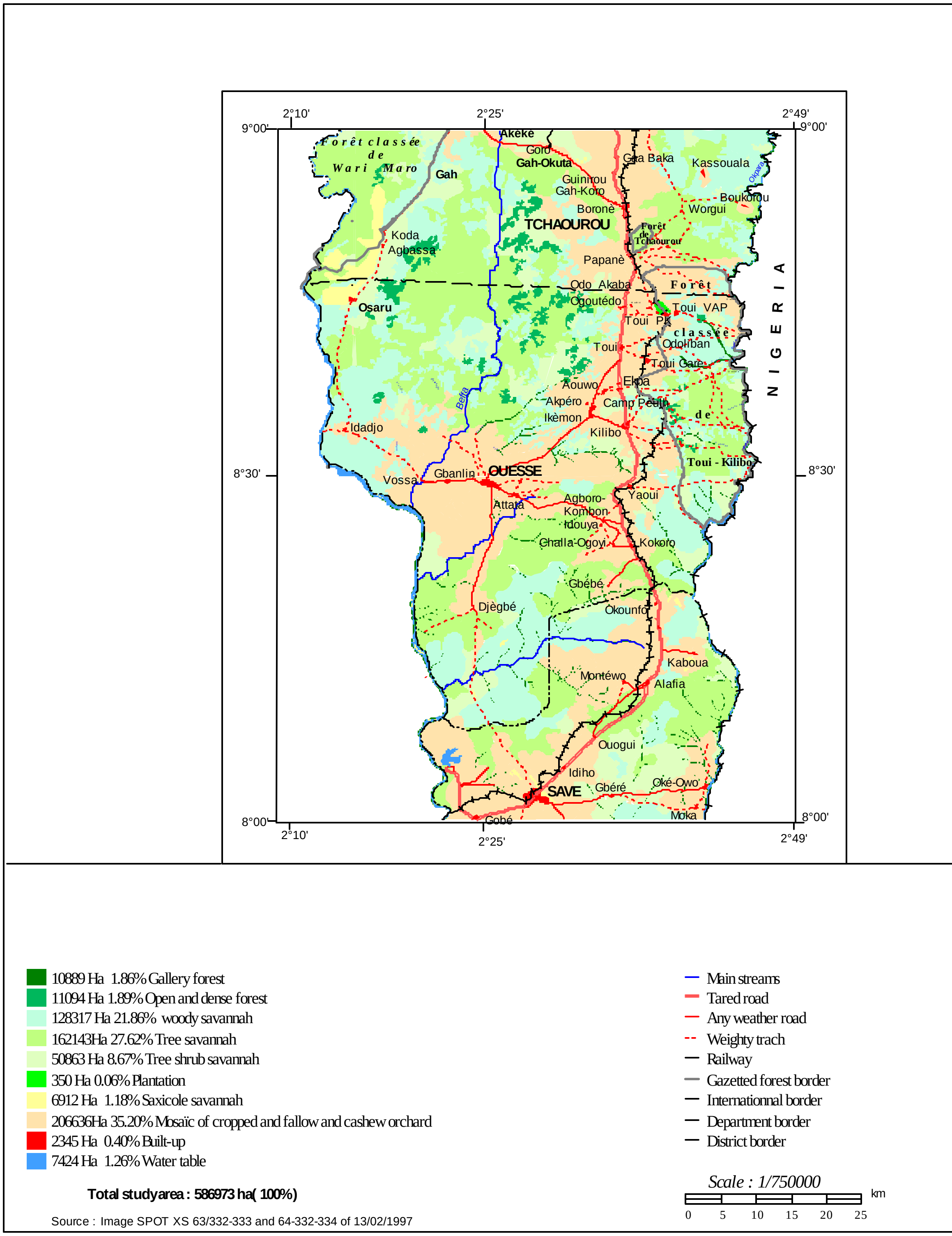
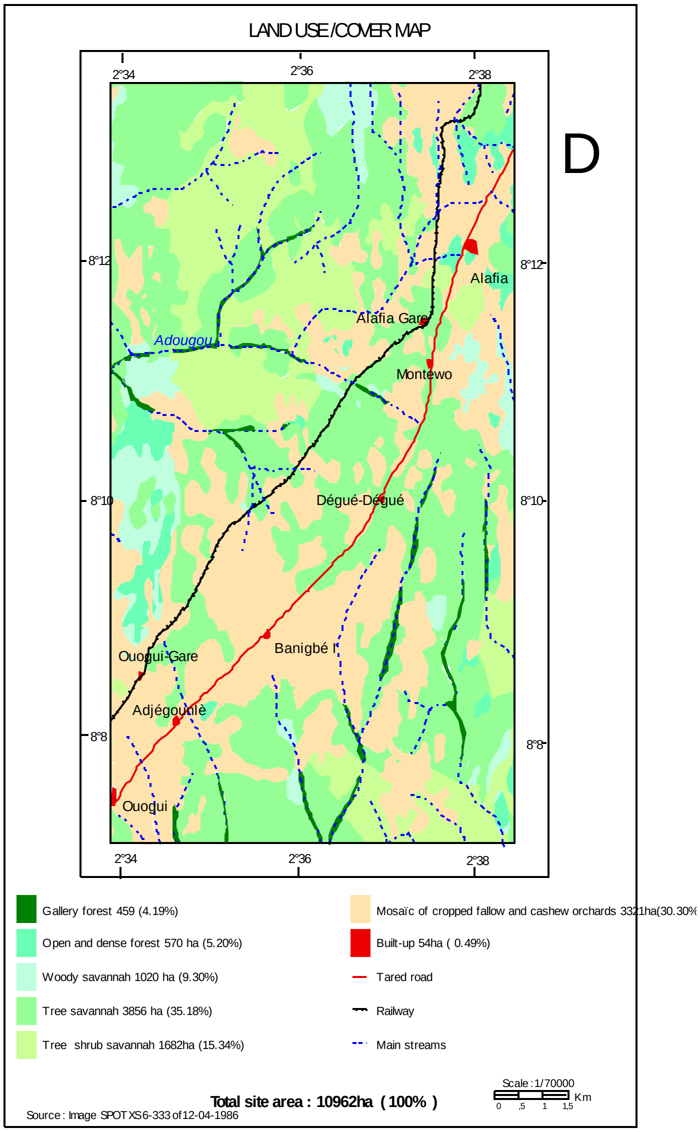


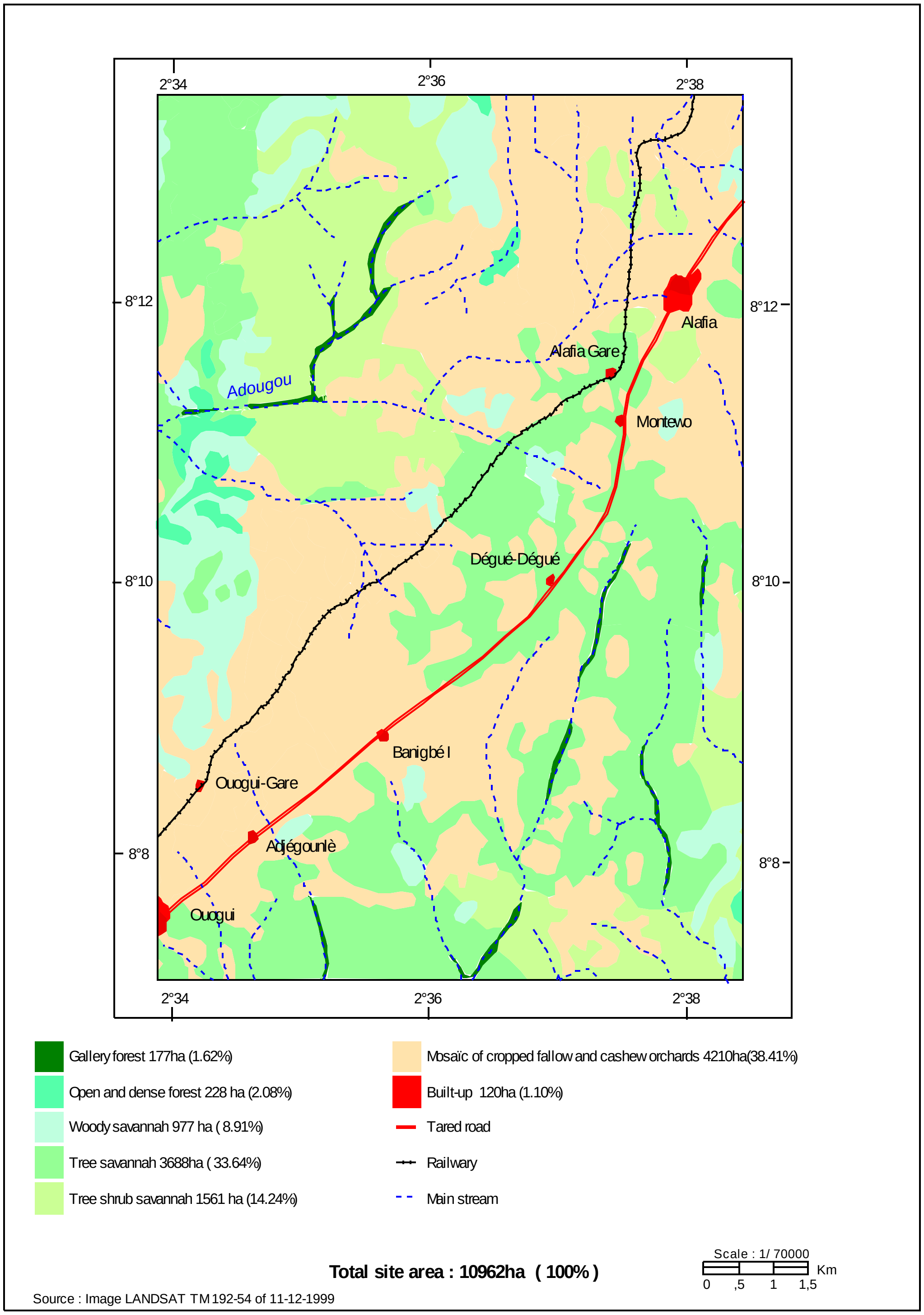
Fig. 1: Site presentation



86

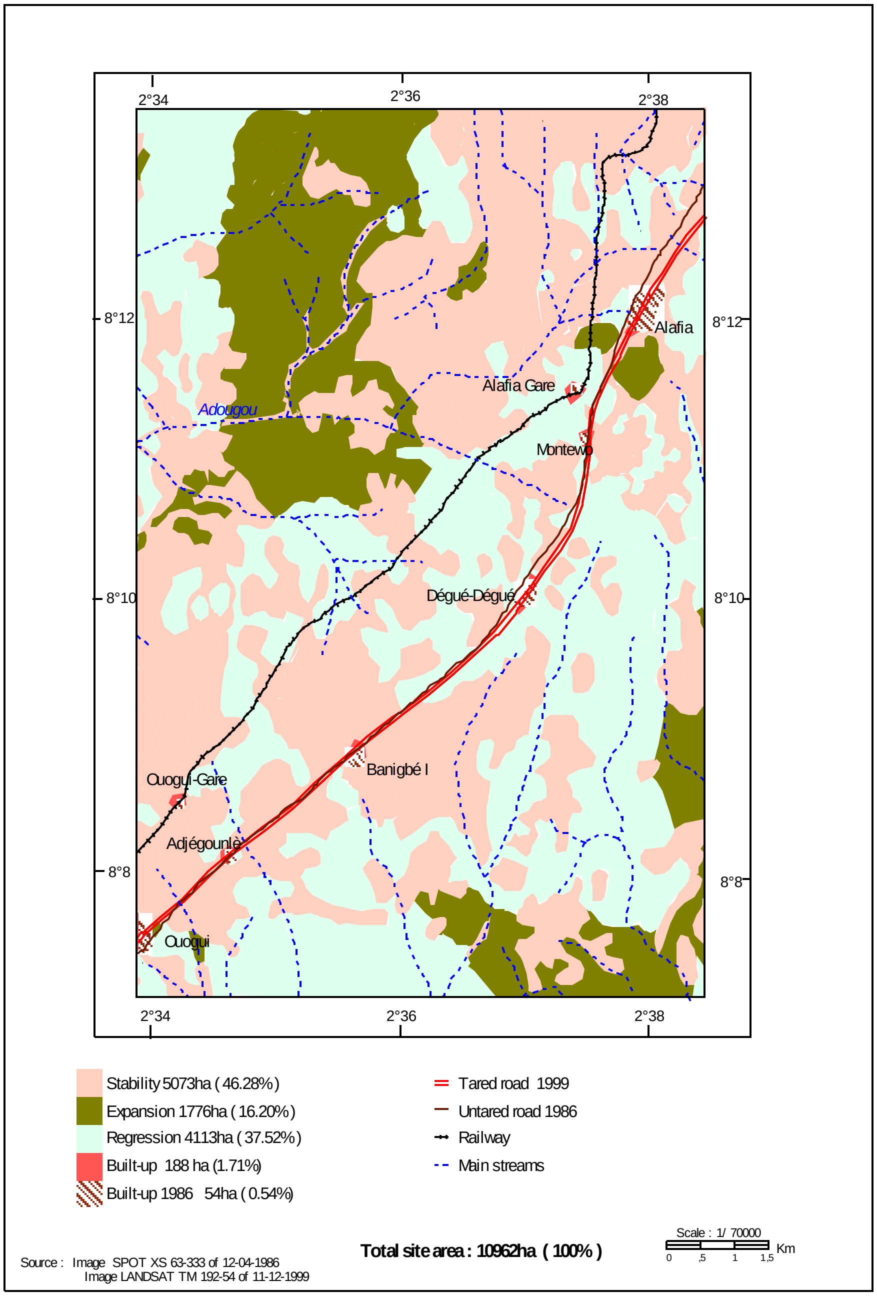
Fig. 2 : Study area

Fig. 3: Study site LUC 1999



Modelling land use and land cover change in a central region of the Republic of Benin, using a Markov Model. Vincent Joseph Mama and Oloukoi, Joseph

Fig. 4: Study site LUC change synthesis 1986-1999



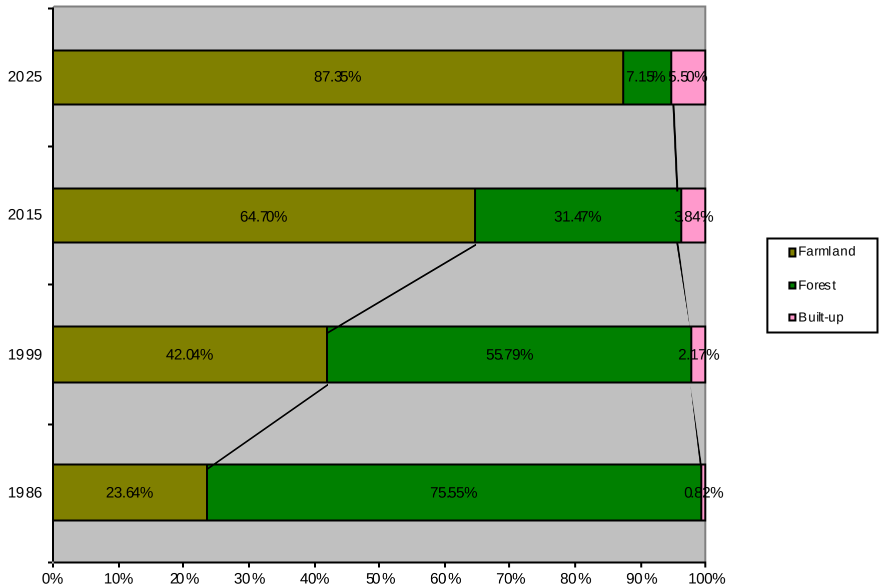


Fig. 5: Estimated land use/cover of the study area share in years 2015 and 2025

Table 1: Satellites images used in this study.

Data Type	**Date**	**Spatial Resolution**	**Identification**	**Acquisition Source**
SPOT XS Image	29/12/1986	20m	kJ 63/332 kJ 64/334	CENATEL archives
	13/02/1997	20m	kJ 63/332 kJ 64/334	CENATEL archives
LANDSAT5TM	11/12/99	30 m	Row 54 Path 192	CENATEL archives
LANDSAT 7 (ETM)	13/12/2000	28,5m		

Table 2: Site variables used

Abbreviation	Description	**1986** Mean	**1999** Mean
Dependent	**Variables**		
FORA	Probability that a forested area transformed to non forested	0.84	0.63
NFAR	Probability that a non forested area transformed to forested	0.16	0.37

Table 3: Explanatory variables

	Socio-economic driving forces	**Acronyms**	**Units**
X1	Agricultural areas	AGRA*	Ha
X2	Built-up areas	BULA*	Ha
X3	Cotton areas	COTA**	Ha
X4	Population density	POPD **	Person/ha
X5	Migrant dwellings	MIGD**	Number
X6	Duration before fallow	DBFA**	Years
X7	Distance to farms	DFAR**	Km
X8	Carrying capacity	CCAP**	Number/ha

* *Data obtained from land use /cover analysis*
** *Data obtained from socio economic survey*

Table 4: Land use classes of the study area

LUC classes	1986		1999		Net Change		% Net Change within LUC class
	Area (ha)	%	Area (ha)	%	Area (ha)	%	
- Gallery Forest	459	4.2	177	1.6	282	2.6	61.5
- Open & dense forest	570	5.2	228	2.1	342	3.1	60
- Woody Savannah	1020	9.3	977	8.9	43	0.4	0.2
- Tree Savannah	3856	35.2	3688	33.6	168	1.5	4.4
- Tree Shrub Savannah	1682	15.3	1562	14.2	120	1.1	7.1
- Agricultural lands	3321	30.3	4210	384	-889	-8.1	-26.8
- Saxicolon Savannah	-	-	-	-	-	-	-
- Built-up	54	0.5	120	1.1	-66	-0.6	-122.2
- Total	**10,962**		**10,962**				

Table 5: Correlation matrix between different variables

	FORA	NFAR	AGRA	BULA	COTA	POPD	MIGD	DBFA	DFAR	CCAP
FORA	1,00	-1,00** (0.00)	-0.24 (0.646)	-0.87* (0.03)	-0.89* (0.02)	-0.66 (0.16)	-0.10 (0.86)	0.61 (0.20)	-0.72 (0.11)	0.68 (0.14)
NFAR	-1.00** (0.00)	1.00	0.24 (0.64)	0.87* (0.03)	0.89* (0.02)	0.66 (0.16)	0.10 (.86)	-0.61 (0.20)	0.72 (0.11)	-0.68 (0.14)
AGRA	-0.24 (0.65)	0.24 (0.65)	1.00	-0.24 (0.64)	0.62 (0.19)	0.66 (0.16)	0.91* (0.01)	-0.64 (0.18)	0.80 (0.06)	0.39 (0.45)
BULA	-0.87* (0.03)	0.87* (0.03)	-0.24 (0.64)	1.00	0.55 (0.26)	0.42 (0.40)	-0.28 (0.59)	-0.19 (0.72)	0.36 (0.49)	-0.82* (0.05)
COTA	-0.885* (0.02)	0.89* (0.02)	0.62 (0.19)	0.56 (0.26)	1.00	0.76 (0.08)	0.45 (0.42)	-0.78 (0.07)	0.86* (0.03)	-0.39 (0.45)
POPD	-0.66 (0.16)	0.66 (0.16)	0.66 (0.16)	0.42 (0.40)	0.76 (0.08)	1.00	0.66 (0.16)	-0.33 (0.53)	0.87* (0.02)	-0.,19 (0.73)
MIGD	-0.10 (0.86)	0.10 (0.86)	0.91* (0.01)	-0.28 (0.59)	0.41 (0.42)	0.655 (0.16)	1.00	-0.42 (0.41)	0.755 (0.08)	0.55 (0.26)
DBFA	0.61 (0.20)	-0.61 (0.20)	-0.64 (0.18)	-0.19 (0.72)	-0.78 (0.07)	-0.33 (0.53)	-0.42 (0.45)	1.00	-0.71 (0.11)	0.07 (0.89)
DFAR	-0.72 (0.11)	0.72 (0.11)	0.80 (0.06)	0.36 (0.49)	0.86* (0.03)	0.872* (0.02)	0.76 (0.08)	-0.71 (0.11)	1.00,	-0.09 (0.87)
CCAP	0.68 (0.14)	-0.68 (0.14)	0.39 (0.45)	-0.82* (0.05)	-0.39 (0.45)	-0.19 (0.73)	0.55 (0.26)	0.07 (0.89)	-0.09 (0.87)	1.00

*** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed); ( ) Probability*

Table 6: Results of the regression analysis

Variables	Estimated coefficient	Standard Error	t-statistic (p-value)
(Constant)	90.84	1.311	69.31 (0.000)
Built-up	-2.53E-02	0.003	-7.44 (0.005)
Cotton area	-3.32E-03	0.001	-8.06 (0.004)

Table 7: Results of regression on simulated data with Markov chain method

Model	Coefficients B	Standard Error	t-statistics	p-values
(Constant)	110.401	.001	4241366.659	.000
Agricultural area	-6.934E-04	.001	-1712919.388	.000