MERGING LANDSAT IMAGE INFORMATION WITH GEOREFERENCED BIOPHYSICAL AND SOCIO-ECONOMICAL DATASETS TO DESCRIBE FOREST COVER CHANGE IN A PHILIPPINE PROVINCE

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ABSTRACT: This paper describes a combined remote sensing-GIS-logistic regression approach of merging extracted information from Landsat images with georeferenced biophysical and socio-economic datasets in the detection and analysis of the driving forces of forest cover change in Agusan del Norte (ADN) in Mindanao Island, Philippines, a province where forest resource use have been historically extensive. Year 1976 Landsat 2 MSS and year 2001 Landsat ETM+ images were independently classified using Support Vector Machines (SVM) to produce land cover maps with overall classification accuracies of 95% and 98%, respectively. Changes in forest cover and other types of land-cover change in the 25-year period were then detected from these maps through post-classification comparison in a GIS. To investigate what has driven these conversions, the associations between these changes and a selection of biophysical and socio-economical variables were explored through logistic regression analysis. The results show that while both the biophysical and socio-economical variables were significantly associated with the occurrences of forest cover change, the models containing only the socio-economical variables predict better the occurrences of change than those containing only the biophysical variables. This implies that most of the forest cover change detected in the year 2001 in ADN is much more a socio-economical matter, and is less forced by biophysical limitations. With these results, this study demonstrated the usefulness of RS, GIS and statistical analysis as exploratory tools in understanding the underlying processes and identification of driving forces of forest cover change, especially in areas of extensive forest resource use.

1. INTRODUCTION

Understanding the underlying processes and identification of the driving forces of land-cover change presently remains to be a very active area of research. Forest cover change, in particular, has constantly attracted interests among a wide variety of researchers perhaps due to the fact that identification of factors contributing to forest cover change is a first step in controlling forest loss (Grainger, 1993) and is necessary in comprehensive forest management planning and formulation of appropriate forest use policy (Apan and Peterson, 1996).

Remote Sensing (RS) and Geographic Information System (GIS) and statistical analysis techniques have contributed significantly in studying the dynamics of land-cover change (Liu et al., 1993; Apan and Peterson, 1996; Coppin et al., 2004; Hung and Wu, 2005; Millington et al., 2007). Imageries from satellite RS platforms provide valuable sources of multi-temporal land-cover information especially in areas which are difficult to monitor and could be very expensive when using conventional techniques. With GIS, land-cover change could be quantified and visualized to generate primary data on the location, type, and rate of change and, in turn, provide a basis for analyzing the impacts of these changes not only on socio-economic processes but also on such environmental processes as energy flux, runoff, erosion, air and water quality, and biodiversity. With statistical analysis, the detected changes could be examined further to describe the association of various biophysical and socio-economical factors that may have caused the changes.

In northeastern Mindanao, Philippines, the province of Agusan del Norte (ADN) (Figure 1) is widely known for its rich forest resource and one of the major timber producers in the whole country since the 1950s up to the present. In fact, the province belongs to the so-called “Eastern Mindanao Corridor” where 75 percent of the country’s timber extraction comes from (CEPF 2005). The province has utilized its forest resources extensively resulting from the establishment of logging and timber industries way back in the 1950s (Paler et al., 1998) that continue to operate until this time by way of forest license agreements issued by the Philippine government to private corporations and non-government organizations. These industries have contributed greatly to the economy of the province and to the Philippines as a whole; however, they are often blamed for decades of rampant upland forest destruction and significant changes in land-cover whose ecological aftermath continues to unfold in the valleys below. In fact, logging in the primary watersheds of ADN between the 1950s and 1990s has resulted in massive upland erosion and lowland siltation, combined with rapid runoff and flooding (SASFMN, 1993). Recently, the same environmental impacts of deforestation and land-cover change are still a common problem that environmentalists, watershed planners, and policy makers face today in the ADN (ADB, 2004).

While several studies have been conducted to detect and analyze land cover change in the Philippines (e.g. Kummer, 1990; Liu et al., 1993; Apan and Peterson, 1996; Verburg et al., 2006), none have been done so far in a forest resource rich province like ADN. The lack of reliable statistics on land cover change, especially forest cover change, has limited the integration of such knowledge into land use and conservation planning in ADN. Moreover, while the logging industries may have direct connection to deforestation and other types of land-cover changes in ADN, the contributions of other equally relevant factors associated with deforestation such as agricultural expansion, wood extraction, expansion of infrastructure, population growth, and bio-physical environment, among many others (Geist and Lambin, 2002) maybe overlooked. Hence, there arises a necessity to ascertain what were the factors associated with deforestation in this province.

The objective of this study is to detect and analyze forest cover change in ADN. Through a combined remote sensing-GIS-statistical approach, land cover information detected from Landsat images will be merged with georeferenced biophysical and socio-economic datasets to statistically analyze the driving forces of forest cover change in ADN.

2. THE STUDY AREA

ADN has a total land area of 2,590.52 sq. km. where 26% of it is classified as alienable and disposable while 74% are classified as forestlands [81]. The province is consists of 10 municipalities and two cities (Butuan and Cabadbaran). From 1975 to 2000, population of ADN has increased to 250,768 (or 83%). Climate in the province is moderate, having no definite dry season. Due to the vast forest resource of ADN, several privately owned companies and community-based organizations applied and were awarded with different forest licenses in ADN from the years 1959-2001. These include Timber License Agreement (TLA), Integrated Forest Management Agreement (IFMA), Community-Based Forest Management Agreement (CBFMA), and Community-Based Resource Management (CBRM). About 77% of the forestlands of ADN were under TLAs specifically in the years 1959-1989 which indicated a very intensive forest resource extraction in the province during this period. Records of the Department of Environment and Natural Resources-Forest Management Bureau (DENR-FMB) showed that the log production of ADN reached its peaked from the years 1984 to 1992. After year 1992, the log production of Agusan del Norte was observed to decline rapidly. This may be due to the implementation of the total log ban in the year 1992.

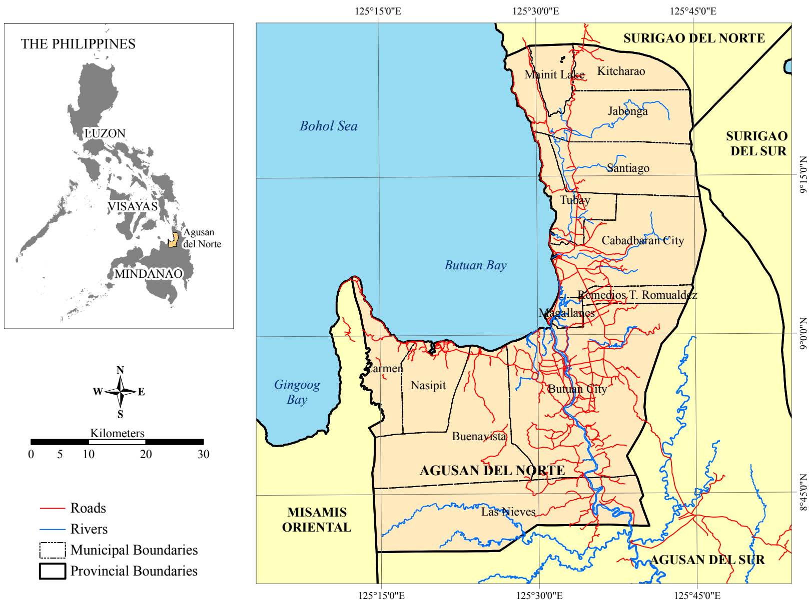

Figure 1. Map of Agusan del Norte, a province located on the northeastern part of Mindanao Island, Philippines.

3. METHODS

3.1 Landsat Image Analysis and Land-cover Classification

Landsat 2 MSS image acquired on April 17, 1976 covering the study area was downloaded from the University of Maryland - Global Land Cover Facility (GLCF) website (http://glcf.umiacs.umd.edu), while Landsat 7 ETM+ image acquired on May 22, 2001 was obtained from the U.S. Geological Survey (http://edcsns17.cr.usgs.gov/EarthExplorer/). These 8-bit images, with pixel resolutions of 57 and 30 meters, respectively, were already orthorectified. Prior to image classification, the images were subjected to radiometric calibration, atmospheric correction using dark object subtraction, and geometric assessment to determine if they are co-registered. The details of the image pre-processing are discussed in Santillan et al. (2011). Cloud and cloud-shadows were also removed from the images using a cloud and shadow masking algorithm (Makinano et al., 2010) to eliminate the error and confusion that they may introduce to the extraction of land-cover information during the image classification process. These steps as well as subsequent image analyses were done using Environment for Visualizing Images (ENVI) Version 4.4.

The pre-processed and cloud-and-shadow free Landsat images (as well as other by-products such as NDVI) were subjected to supervised classification to derive the 1976 and 2001 land-cover (LC) maps. Eight (8) land-cover classes namely, Forest, Rangeland, Built-up, Palm Trees, Cropland, Bare Soil, Exposed Rocks and Water, were identified from the images through visual interpretation using existing LC maps of the DENR, topographic maps and Google Earth images as references. Representative samples of each class were collected from the images for supervised image classification and accuracy assessment. The classification algorithms included traditional classifiers such as Minimum Distance, Mahalanobis Distance and Maximum Likelihood and the recently developed Support Vector Machines (SVM) classifier. SVM was implemented as a non-linear classifier using the Radial Basis Functions (RBF) kernel available in the ENVI 4.4 image analysis software. For both the 1976 and 2001 image dataset, each classifier was implemented using various combinations of input bands. The use of 4 classifiers and various combinations of image bands and by-products was done to generate several classified images and selecting from these outputs the best classified image in terms of classification accuracy. A digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM) was also included as additional band during image classification.

3.2 Land-cover Change Detection

The two LC maps derived were then subjected to post-classification comparison change detection analysis (Coppin et al., 2004) using Arcview GIS 3.2 to examine the location, extent and distribution of land-cover change in the study area. The 2001 land-cover map was first re-sampled to 57-m resolution using nearest neighbor method prior to change detection. Because of cloud and shadows present in the images used ("No Data" in the LC maps), only portions of the LC maps that both have data in 1976 and 2001 were subjected to change detection analysis. The 25-year land-cover change maps and statistics were then derived, which includes a general deforestation (DEFOR) map containing change and no-change in forest cover, and four (4) maps of major forest cover changes: forest to bare soil (FOR2BS), forest to cropland (FOR2CL), forest to palm trees (FOR2PT) and forest to rangeland (FOR2RL).

3.3 Statistical Analysis of Forest Cover Change by Logistic Regression

Binary logistic regression analysis was carried out to test the association of forest cover changes with biophysical and socio-economical variables. These descriptive (or independent) variables are listed in Table 1. The logistic regression approach implemented by Van Doorn and Bakker (2007) was adopted in the analysis to identify the contribution of individual descriptive variables as well as groups of descriptive variables (i.e. biophysical and socio-economical) to the description of forest cover change in general (DEFOR) and of the four investigated forest cover changes (FOR2BS, FOR2CL, FOR2PT and FOR2RL) in particular. The multivariate logistic regression equation used is of the form (Millington et al., 2007):

$$\pi(x) = \frac{e^{\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n}}{1+e^{\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n}} \quad (1)$$

where $\pi(x)$ is the probability that the dependent or response variable equals 1, α is a constant and $\beta_1, \beta_2, \ldots, \beta_n$ are the regression coefficients of the predictor variables $x_1, x_2, \ldots, x_n$. Each of the regression coefficients describes the size of the contribution of that variable to the outcome. In this study, the modeled "outcome" is change in forest cover. The logistic regression coefficient, β was primarily used in explaining the relative influence of the variables to the forest cover change in the area. A positive regression coefficient implies that the variable increases the probability of forest cover change, while a negative regression coefficient indicates the variable decreases the probability of forest cover change.

To implement the logistic regression analysis, the forest cover change maps were converted into binary response variable maps with each pixel in the maps representing the presence/absence (1/0) of the change, whereby the zeroes are observations of forest cover that has not changed during the 25-year period. The proportions of change and no-change in forest cover were computed for each of the binary response variable maps. For each change type, five percent of the response variable with the lowest proportion (i.e. least abundant) were computed and served as the number of samples that will be selected from each change/no change class in the binary maps. This sampling size is large enough to satisfy the minimum number of samples required for logistic regression (Peduzzi et al., 1996).

Finally, the samples that were randomly selected for the four forest cover change logistic regression datasets were merged to create a general DEFOR logistic regression dataset. This study utilized equal number of samples each for the change/no change response variables to avoid erroneous fit of the models which may occur when the ratio 1/0 observations for the response variable is out of proportion, meaning an excess of 1's compared to 0's or the other way around (Van Doorn and Bakker, 2007).

Table 1. Biophysical and socio-economical variables used for the logistic regression analysis.

Type	Variables	Description	Source
Biophysical	*ELEV*	Elevation in meters above mean sea level; continuous variable.	Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM), calibrated with spot heights from topographic maps.
	SLOPE	Slope, in percent; continuous variable.	Computed from the SRTM DEM
	SOILQUAL	Soil type ranked according to increasing quality for agricultural use; Categorical variable: 1=low, 2=medium, 3=high.	Soil Type Map published by the Bureau of Soils and Water Management of the Philippine's Department of Agriculture.
	DISTRIV	Distance to rivers and streams, in meters; continuous variable.	Distance grid computed from rivers and streams digitized from topographic maps.
Socio-economical	*DISTROAD*	Distance to roads, in meters; continuous variable.	Distance grid computed from road network digitized from topographic maps and from the 2001 Landsat images.
	POPDEN	Population density; number of persons per square km; continuous variable.	National Statistics Office, Year 2000 Census
	LAND_LOG	Lands subjected to logging activities; categorical variable: 0 = outside logging area; 1 = inside logging area	Maps of TLA, IFMA, CBFMA and CBRMA; Source of maps: Forest Management Bureau, Department of Environment and Natural Resources
	LAND_PROT	Lands classified as protected area; categorical variable: 0 = outside protected area; 1 = inside protected area	Maps of lands classified as protected areas under the National Integrated Protected Areas System (NIPAS) Act of 1992; Source of maps: Department of Environment and Natural Resources.
	DISTLOG	Distance to logging areas, in meters; continuous variable.	Distance grid computed using the LAND_LOG map.

The values of the biophysical and socio-economical variables were computed for each sampling point. Tests for collinearity of the descriptive variables using Pearson correlation coefficient (R^2), Tolerance Statistics and Variance Index Factor (VIF) were made to ensure that descriptive variables are not correlated with each other. Goodness-of-fit of the logistic regression models is evaluated by the chi-square (χ^2) test, applied to the difference in the (-2Log) maximum likelihood of a model with descriptive variables to a model with less or no descriptive variables (Van Doorn and Bakker, 2007). The χ^2 test was applied to identify the relative importance of the biophysical and socio-economical variables. For this purpose, three models for every forest cover change were tested and the goodness of fit was evaluated: 1) a full model including all the biophysical and socio-economical variables, 2) a model with biophysical variables only, and 3) a model with socio-economical variables only. The χ^2 values of the three models were then compared to assess the descriptive powers of the biophysical and socio-economical variables. The greater the χ^2 value the stronger the forest cover change is associated with the set of descriptive variables. When the sum of χ^2 values of models 2 and 3 is higher than the χ^2 of the full model, it can be concluded that there exist an overlap between the descriptive powers of the two groups of variables. It is not possible to assign the descriptive power to one of the groups (Bakker et al., 2005; Van Doorn and Bakker, 2007).

4. RESULTS AND DISCUSSION

4.1 Forest Cover Change in ADN

The land-cover maps of ADN for 1976 and 2001, showing areas with data common to both year (i.e., cloud and shadow covered areas in 1976 and 2001 were excluded), are depicted in Figure 2. These land-cover maps have overall classification accuracies of 94.99% and 98.25% for 1976 and 2001, respectively. The 1976 land-cover map was the result of SVM-RBF classification of band combinations of Landsat MSS surface reflectance bands (Bands 4, 5 6 and 7), NDVI and DEM. This result was the highest among 32 classifications that utilized 6 various combinations of inputs bands subjected to four classifications algorithms. On the other hand, the 2001 land-cover map was the result of SVM-RBF classification of Landsat ETM+ surface reflectance & temperature bands (Bands 1-7) and DEM; this has the highest classification accuracy among 8 classifications that utilized 2 various combinations of inputs bands subjected to 4 classification algorithms.

Changes in land-cover of Agusan del Norte from 1976-2001 is very evident in the areas surrounding Butuan City. This is where drastic increases in built-up, cropland and water (e.g., expansion of fishpond) areas can be found. Yet, the most pronounced change in land-cover is that of forest and rangeland. Quantitative assessments through change detection using the land cover change map (93.33% accurate) show significant decrease in forest cover by 32% (or about 255.30 sq. km.) while rangeland areas increased by 92% (about 327.86 sq. km.) during the 25-year period. Forest to rangeland is the major land-cover change in Agusan del Norte from 1976 to 2001. Although deforestation due to increase in rangeland is significantly evident, "re-forestation" of rangeland areas from 1976 to 2001 was also present. The total re-forested area was approximately 101 sq. km. It was also observed that large tract of lands planted with palm trees in 1976 have been converted into croplands in 2001.

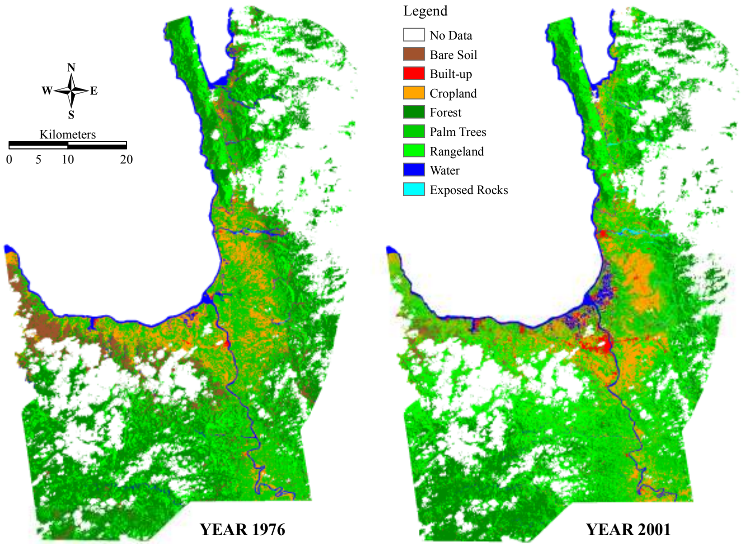

Figure 2. The 1976-2001 land-cover maps of ADN. Areas with data (not covered by clouds and shadows) comprise 66.98% (or 2044.67sq.km.) of ADN.

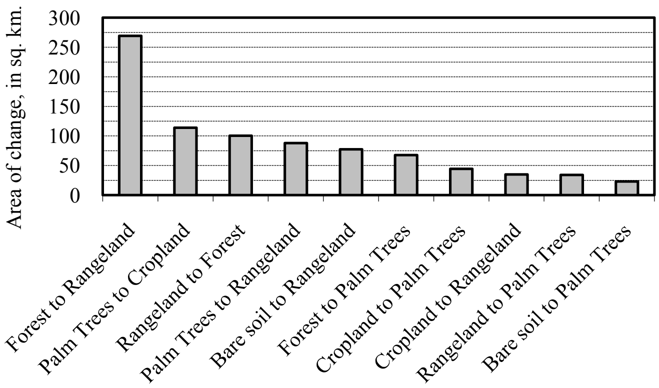

Figure 3. Top 10 land-cover change types in ADN province from 1976-2001 for cloud-free areas only.

Examining the specific changes in the 1976 forest cover showed a decrease in forest area due to their conversion to rangeland (34%), palm trees (8%), cropland (2%) and bare soil (2%). Conversions to built-up, water and exposed rocks amounted to less than 1% of the 1976 forest cover. It can be deduced from the computed land-cover change statistics that forest cover in Agusan del Norte have been drastically reduced by conversion to rangeland. This may have been due to unsustainable logging activities, where, after the trees have been harvested, the logged-over areas were left behind without replanting that made it suitable for grasses to grow. The overall forest cover change in ADN was significant, with only about 54% of its initial forest cover in 1976 remaining. The forest cover change statistics further showed that conversion to rangeland, palm trees, bare soil and cropland are among the four major contributors to forest cover reduction in this province.

4.2 Logistic Regression Analysis of Forest Cover Change: Major Results

Table 2 and Figure 3 summarize the results of the logistic regression analysis of forest cover change in ADN. The analysis showed the relative importance of the biophysical and socio-economical variables to the occurrence of forest cover change in ADN.

Looking into the general scenario of forest cover change (DEFOR), the results of the χ^2 analysis revealed that forest cover change in ADN is governed by both biophysical and socio-economical variables. However, the model χ^2 values suggest that socio-economical variables better describe the occurrence of forest cover change than the biophysical variables because of the former's greater χ^2. There is an overlap between the two sets of variables and it is difficult to associate the changes among the two. The DEFOR model regression coefficients indicate the negative contributions of variables *ELEV*, *SLOPE*, *SOILQUAL*, *DISTROAD* and *LAND_PROT* to the occurrence of forest cover change. This means that increasing the values of these variables will also decrease the occurrence of forest cover change.

Positive coefficients where obtained for the remaining variables *DISTRIV*, *POPDEN*, *LAND_LOG* and *DISTLOG*. This clearly indicates that forest lands in ADN with lower elevation, lesser slope, lesser soil quality, nearer to roads and not located within protected areas were the most prone to forest cover change. The probability of forest cover change is further increased if it is far from rivers and logging areas, and located within an area with higher population density. It can be stated that while the variables *SOILQUAL*, *LAND_LOG*, and *LAND_PROT* are significant in explaining the forest cover change process, their contributions is very minimal because of their near zero coefficient values. The positive coefficient values for *DISTRIV* and *DISTLOG* is quite contrary to what is expected. The general understanding is that a forestland is more prone to be deforested if it is nearer to rivers and logging areas. However, the results of the logistic regression analysis showed otherwise. A plausible explanation for this maybe the historical deforestation that had occurred during the 1950s to the 1970s in ADN, most especially in the upland watersheds (SASFMN, 1993). During this period, forestlands near rivers and logging areas may have been drastically harvested and very little were left to regenerate. As a consequence, forestlands from 1970s onwards can no longer be found near rivers or in logging areas but rather in areas far from these variables.

Table 2. Results of logistic regression analysis of forest cover change in ADN.

A. *Model Chi-square (χ^2) Values*

Type of Model	*DEFOR*	*FOR2BS*	*FOR2CL*	*FOR2PT*	*FOR2RL*
Biophysical + Socio-economical (Full)	2,753	255	531	1,718	1,370
Biophysical Variables Only	1,424	183	290	929	736
Socio-economical Variables Only	1,863	130	382	1,058	863

B. *Logistic Regression Model Coefficients*

Variables		DEFOR	FOR2BS	FOR2CL	FOR2PT	FOR2RL
Bio-physical	*ELEV*	-3.219	-5.160	-81.773	-41.201	-1.620
	SLOPE	-1.619	-2.740	7.666	2.392	-1.397
	SOILQUAL	-0.310	-0.983	1.305	1.259	-0.489
	DISTRIV	4.94	8.119	10.303	5.148	4.896
Socio-economical	*DISTROAD*	-1.345	-0.203	-4.209	-1.745	-1.345
	POPDEN	2.497	3.889	6.624	4.731	2.107
	LAND_LOG	0.544	0.296	2.881	2.268	0.428
	LAND_PROT	-0.517	-1.774	0.753	0.155	-0.628
	DISTLOG	2.839	3.083	14.006	11.252	1.211

In the FOR2BS analysis, the results showed that forest to bare soil conversion is more directed by the set of biophysical variables. The probability of this conversion is greater on highly elevated areas with steep slopes and with a soil that has low qualities for agriculture. This suggests that the biophysical constraints of these areas are that strong that it is unfavorable for other conversions to happen.

The results of the regression analyses of FOR2CL and FOR2PT show the greater influence of socio-economical variables than the biophysical ones. In FOR2CL and FOR2PT, the positive model regression coefficients of *POPDEN*, *LAND_LOG* and *DISTLOG* and the negative coefficient of *DISTROAD* are very indicative of their relative influence to the conversions of forests to cropland and palm trees: forestlands nearer to roads but far from logging areas and with higher population density are the more prone to these conversions. The positive coefficients of biophysical variables *SOILQUAL* is also expected as these kinds of conversions occur in forestlands of better soil quality, especially for soils suitable for cultivation. The influence of elevation is consistent as expected, with highly elevated areas less prone to the conversions. However, the contribution of *SLOPE* is not clear. The positive coefficient of *SLOPE* seems to suggest that a certain criteria for slope must be met for the conversions to cropland and palm trees to occur. Further study is necessary to better understand this finding.

The result of the regression analysis of FOR2RL is similar to that of FOR2BS. The only difference is that the conversion of forest to rangeland is more driven by socio-economic variables. From the regression coefficients, it is evident that more accessible forestlands (e.g. very near roads, low elevation, not sloping, and not within protected areas) were the ones prone to be converted to rangeland. Soil quality also plays a significant role, with forestlands with lesser soil quality more prone to the conversion.

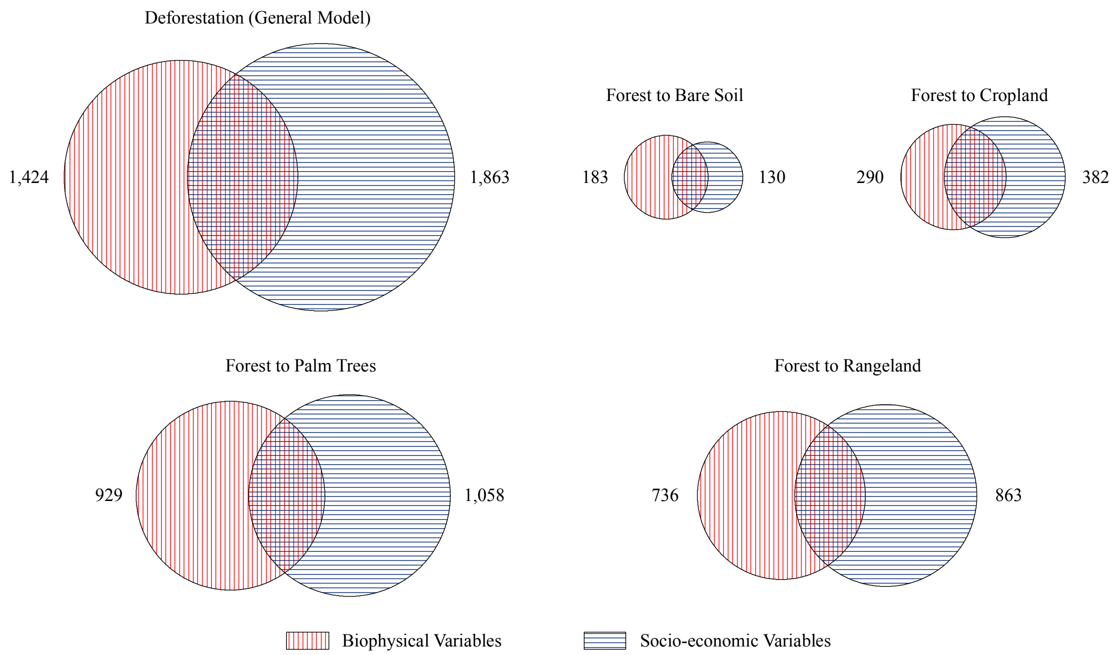

Figure 3. Visualization of the contribution and overlap to forest cover change of the biophysical and socio-economical variables based on the chi-square values. (Visualization adopted from Van Doorn and Bakker, 2007.)

SUMMARY AND CONCLUSIONS

This paper describes a combined remote sensing-GIS-logistic regression approach of merging extracted information from Landsat images with georeferenced biophysical and socio-economic datasets in the detection and analysis of the driving forces of forest cover change in Agusan del Norte (ADN) in Mindanao Island, Philippines, a province where forest resource use have been historically extensive. The Landsat image analysis and classification using SVM-RBF generated highly accurate land-cover maps that were then subjected to change detection and statistical analysis. The most significant land-cover change in ADN was found to be the conversion of forest to rangeland. By merging the forest cover change information with georeferenced biophysical and socio-economical datasets, an explanatory picture of the forest cover change process in ADN was obtained. The results of the χ^2 analysis of the various logistic regression models show that while both the biophysical and socio-economical variables were significantly associated with the occurrences of forest cover change, the models containing only the socio-economical variables predict better the occurrences of change than those containing only the biophysical variables. This implies that most of the forest cover change detected in the year 2001 in ADN is much more a socio-economical matter, and is less forced by biophysical limitations. Although the range of biophysical and socio-economical variables was limited, the study was able to identify some important factors in the forest cover change process. Similar to an earlier study by Van Doorn and Bakker (2007), the statistical analysis employed in this study has been shown to be suitable for describing forest cover change using a variety of different types of data, and thus is considered to be useful in research that aims to integrate spatially explicit biophysical and socio-economic data. Overall, this study demonstrated the usefulness of RS, GIS and statistical analysis as exploratory tools in understanding the underlying processes and identification of driving forces of forest cover change, especially in areas of extensive forest resource use

REFERENCES

Apan, A., Peterson, J., 1996. Probing tropical deforestation: the use of GIS and statistical analysis of georeferenced data. Applied Geography, 18, pp. 137-152.

ADB (Asian Development Bank), 2004. Technical Assistance to the Republic of the Philippines for a Master Plan for the Agusan River Basin. Mandaluyong City, Philippines.

Bakker, M. M., Govers, G., Kosmas, C., Vanacker, V., Oost, K. V., Rounsevell, M., 2005. Soil erosion as a driver of land use change. Agriculture, Ecosystems and Environment, 105, pp. 467-481.

CEPF (Critical Ecosystems Partnership Fund), 2005. An Overview of CEPF's Portfolio in the Philippines Hotspot: Creating Corridors and Alliances, Improving Linkages Between CEPF and World Bank Operations, Asia Forum, Medan, Indonesia.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., 2004. Digital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25, pp. 1565–1596.

Geist, H.J., Lambin, E.F., 2002. Proximate causes and underlying driving forces of tropical deforestation. Bioscience, 52, pp. 143–150.

Grainger, A., 1993. Controlling Tropical Deforestation. Earthscan Publications.

Hung, M.C., Wu, Y.H., 2005. Mapping and visualizing the Great Salt Lake landscape dynamics using multi-temporal satellite images, 1972-1996. International Journal of Remote Sensing, 26(9), pp. 1815-1834.

Kummer, D., 1990. Deforestation in the Post-War Philippines. University Microfilms International, Ann Arbor, Michigan, USA.

Liu, D., Iverson, L., Brown, S., 1993. Rates and patterns of deforestation in the Philippines: application of geographic information system analysis. Forest Ecology and Management, 57, pp. 1-16.

Makinano, M., Santillan, J., Paringit, E., 2010. Detection and analysis of deforestation in cloud-contaminated Landsat images: a case of two Philippine provinces with history of forest resource utilization. In: Proceedings of the 31st Asian Conference on Remote Sensing, Hanoi, Vietnam, November 1-5.

Millington, J., Perry, G., and R. Romero-Calcerrada, 2007. Regression techniques for examining land use/cover change: a case study of a Mediterranean landscape. Ecosystems, 10, pp. 562-578.

Paler, D., Shinohara, T., del Castillo, R. and I. Nomura, 1998. Development of industrial tree plantation in the Administrative Region No. 10 in Mindanao Island, Philippines: with two case studies, Journal of Forest Research, 3, pp. 193-197.

Peduzzi, P., Concato, J., Kemper, E., Holford, T.R., Feinstein, A. R., 1996. A simulation study of the number of events per variable in logistic regression analysis. Journal of Clinical Epidemiology, 49, pp. 1373-1379.

Santillan, J., Makinano, M., Paringit, E., 2011. Integrated Landsat image analysis and hydrologic modeling to detect impacts of 25-year land-cover change on surface runoff in a Philippine watershed. Remote Sensing, 3(6), pp. 1067-1087.

SASFMN (Southeast Asia Sustainable Forest Management Network), 1993. Upland Philippine Communities: Guardians of the Final Forest Frontiers. Center for Southeast Asia Studies, International and Area Studies, University of California, California, USA.

Van Doorn, A. M., Bakker, M. M., 2007. The destination of arable land in a marginal agricultural landscape in South Portugal: an exploration of land use change determinants. Landscape Ecology, 22, pp. 1073-1087.

Verburg, P.H., Overmars, K.P., Huigen, M.G., de Groot, W.T., Veldkamp, A., 2006. Analysis of the effects of land use change on protected areas in the Philippines. Applied Geography, 26, pp. 153–173.