SPATIAL ANALYSIS OF THE CHANGE IN LAND COVER AND HUMAN WELL-BEING IN THE BLACK-BELT COUNTIES OF ALABAMA

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ABSTRACT

Previous studies at the county level have found an increase in forest cover, urbanization, and water structures in the Black Belt counties of Alabama and have documented the connection between such increase and socioeconomic development in the region. However, such findings have limited inferences as the studies did not address the variations in demographic, socio-economic, and land cover attributes within the counties. A better understanding of such linkage is to integrate socio-economic and land cover information available at a finer geographic scale and use them in developing spatial predictive models. Using satellite images and U.S. census data, we quantified changes in land cover and human well-being matrices for census block-groups for 1990 and 2000 and examined spatial regression models relating changes in human well-being index to the changes in major land cover types. Results suggest that weak relationship between human well-being and land cover types was improved significantly after accounting for spatial correlations.

KEYWORDS. Black Belt region, census block-group, land cover, spatial model, well-being.

INTRODUCTION

Studies at county level have found an increase in forest cover, urbanization, and water structures in the Black Belt region of Alabama in the last four decades, and have documented connection between such increase and socioeconomic development of the region (Wear and Greis, 2002). However, such findings have limited inferences as the studies have not addressed the variations in demographic, socio-economic, and land cover attributes within the counties. Although county level analysis provides good sources of information for many diverse sets of demographic, socioeconomic, and geographic data, these data are quite heterogeneous (Crandall and Weber, 2004). County level data have a greater likelihood of spatial aggregation bias. The aggregation could result in the loss of information or patterns observable at finer scales. Also, due to the

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spatial nature of the data, "spatial dependence" often exists among the sample units for which the data are collected (Fotheringham et al., 2002; Isaaks and Srivastava, 1989). Use of the data available at the sub-county level could help to detect 'spatial dependence' and explore differential impacts at the local level (Fraser et al. 2005; Rupasingha and Goetz, 2003).

Alabama's Black Belt region displays evidence of the clustering of the demographic, socioeconomic, and landscape characteristics. The distribution of deciduous and evergreen forests shows spatial pattern. Evergreen forests (mostly pines) are located in the southern and northern part and some part of the southwest corridor of the Black Belt. The deciduous forests are located in the eastern and south central part of the region. Wetlands extend along the Tombigbee River and along the Alabama River. Pasture and crop lands are located in the middle and eastern part of the Black Belt, in the northern part of Sumter and southern part of Perry and Dallas Counties. Such uneven distribution and concentration of the major types of land covers creates clustering of similar values of each land cover in the areas of their dominance. If these unequal variations are not controlled for in statistical analysis, the reliability of "average values' as representatives of the land cover types will decrease (Fotheringham et al., 2002).

Context of the Study

Forces of change in land use and land cover affects the livelihood of people at two levels. At the smaller scale, effects on landowners' economic interests such as choice of crops or forest species and their compositions, and employment opportunities (labor requirement for planting, thinning, harvesting, logging). Research around the globe suggests that maintaining forest resources at a certain level in rural areas ensures the constant flow of raw materials for use in production of timber and forage as well as providing locations for numerous outdoor activities such as recreation, fishing, and hunting. The Millennium Ecosystems Assessment (MEA) study (2003) has classified these contributions into four types: provisioning, regulating, cultural, and supporting services. The MEA suggests that these four services need to be regulated at an optimum level to meet the growing demands of the human population for food, fiber and health, the basic tenets of human-well being.

Changes in land cover also create land fragmentation or consolidation and modify land-based economic activities such as the amount of technical services and subsidies. Consequently, these effects will have aggregated impacts on the livelihood of people and the development of communities.

There are very limited studies of the relationship between human well-being and land cover changes, especially forest types, at the micro level. Many national and global research findings suggest that resource-dependent communities are among the poorest places in the United States and in the world. Research in Appalachia where mining activities dominate, or Southeastern U.S. counties where forests dominate, or coastal regions where fisheries dominate, all suggest relatively high levels of unemployment, low median income, lower education level and substandard housing (Rural Sociology Task Force on Persistent Rural Poverty, 1993). Freudenburg and Wilson (2003) found that mining dependency is more likely to be associated with decreased human well-being. In another study, Elo and Beale (1985) found that forest-dependent counties had higher scores on educational attainment, median household income, but lower scores on poverty rates than the non-forest-dependent counties. However, unemployment was higher in forest-dependent counties. In the Southeastern Region, Norton et al. (2003) detects the negative correlates of timber dependency, which are poverty, lack of economic development, and poor community infrastructure.

In the Black Belt counties, about 70 percent of the land is covered by forest. Pasture and agricultural land account for most of the remaining land (Hartsell and Brown, 2000). Over the past 50 years loblolly pine plantations have become one of the dominant land covers in the region. Forest industry is the leading industry in the state's economy (Abt et al., 2002; Howze et al. 2003) and about 70% of the landowners have some forest land (Gan et al., 2003). Forest lands provide income to landowners from harvesting, hunting leases, or rental payment from participating in cost-share programs.

During 1950s and 1960s, Alabama state agencies prioritized forest-based economic development strategies with the expectation that this would help to create wealth while assisting in economic and infrastructural development. However, this strategy had limited success as measured by low well-being indicators based on education, income, employment, and human capital development (Joshi et al., 2000). Researchers (Bliss et al. 1998; Howze et al. 2003; Joshi et al. 2000; Zabawa, 1991) have consistently found higher poverty in the forest-dependent counties of Alabama.

The objective in this study was to understand the spatial dimension of the relationship between well-being indicators and change in land cover types. This is the first attempt to use census block-group (CBG) level data to examine the relationship between poverty and land covers. The study identifies the strength of spatial effects on the well-being of communities and how changes in land cover may have affected well-being at CBG level over a 10-year period.

The remaining part of this paper is organized into four sections. In the empirical model section, we briefly discuss the conceptual framework and specify the spatial lag model. In the methods section, we discuss the study area, data preparation and description, and descriptive statistics of the data. In the results section, we discuss and compare the empirical results of ordinary least square regression model and spatial lag model. The last section will cover the discussion and conclusion.

EMPIRICAL MODEL

Differences in person-specific and place-specific characteristics contribute to the variation in economic development across geographic areas (Levernier, 2000). An area may be poor simply because it shares a higher proportion of minority, poorly educated, and unemployed groups, which tend to have higher poverty rates. On the other hand, place-based characteristics, such as the degree of availability and use of different forms of community capitals and natural resources available in the specific area, play important roles in the development of communities. Previous research has used demographic, economic, and institutional variables to examine poverty, but none of the studies have included land cover type variables and the spatial dimension of their distribution. Our model focuses on types of land cover such as forest, agriculture, water system, residential growth, and neighborhood effects as determinants of change in a human well-being index between 1990 and 2000. The following spatial model is specified.

$$Y = \alpha + \rho W_1 Y + \beta X + \varepsilon$$

Where Y is the vector of changes in the dependent variable (CBG's well-being index) between 1990 and 2000. W_1 represents row-standardized spatial weight matrices that contain first-order contiguity data for each observation (LeSage, 2006). The spatial lag operator, $\rho W_1 Y$, uses the average neighboring value of the dependent variable for each CBG as an independent variable; the parameter ρ thus represents the spatial dependence inherent in the data (LeSage, 2006). The vector X represents independent variables included in the model. If ρ equals zero, it means there is no spatial dependence, and the model can be estimated through OLS.

This model will explore the contributing role that neighboring CBGs may play in improving or worsening the well-being index of any given CBG. Increase or decline in well-being index in one CBG is expected to be influenced by the change in well-being index in its neighbors. Use of spatial lag operator, $\rho W_1 Y$ helps us find this dependence between CBGs. Our assumption is that the well-being of a community depends upon the operation of the explanatory variables beyond the boundaries of CBGs, much larger than the CBG level aggregation of the land cover types.

METHODS

Study Area

We selected eight counties (Dallas, Hale, Greene, Lowndes, Marengo, Perry, Sumter, and Wilcox) in the Southwest Region of Alabama with a total area of 6,479 square miles (Figure 1). Well-being index and land cover types were measured and analyzed at the CBGs level. CBG is the lowest unit for which US Census Bureau makes most of the census data available to the public. A CBG lies in between Census Tract (higher level) and Census Blocks (lower level) and is a cluster of census blocks. Census Block Groups generally contain between 600 and 3,000 people, with an optimum size of 1,500 people. Geolytics, Inc. (2005), an authorized contractor of the U.S. Census Bureau), has reprojected the Census data of 1970 and 1980, and 1990 into the 2000 boundaries. There are 161 CBGs in the eight counties. However, the analysis is based on 147 CBGs because 14 CBGs did not have any forest cover.

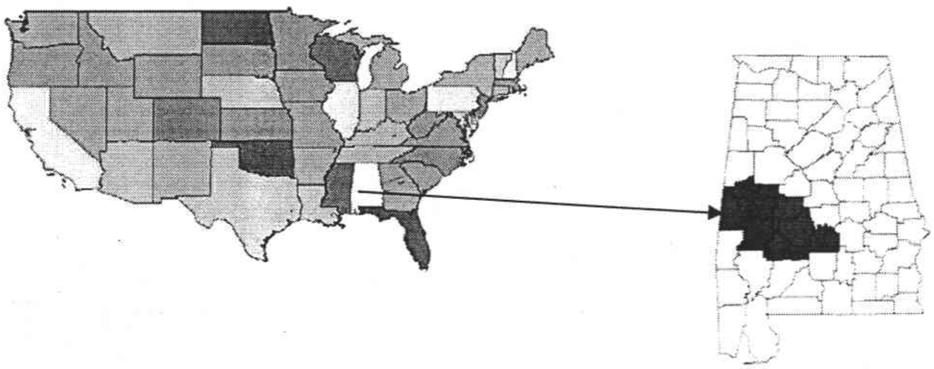

Figure 1: Study area.

Data Description and Preparation

The dependent variable (well-being index) was created using major indicators of well-being such as income, education, and employment. Similarly, the independent variables (different types of land cover such as forest cover types, cropland, pasture land, residential lands, and water system) were extracted from the USGS's National Land Characterization Dataset (NLCD) of 1992 and 2001 (USGS, 2005). The data was analyzed using ArcGIS 8.9, ERDAS Imagine 8.7, and GeoDa Spatial Analysis 0.9.5-I (Beta version).

Human Well-being Index

Many studies have used income, education, and employment, as the major components of well-being index (Bukenya and Fraser, 2003; UNDP, 2005). Gasper (2004) suggested that aggregating income with other variables such as education and employment that are related to aspects of well-being may be a good way to construct a 'well-being' index. We take advantage of readily available U.S. census data on income, education, employment and non-poor population to develop a 'well-being' index for 1990 and 2000. The measure of education is the percentage of 'over 24 years older total population' who graduated from college. The measure of income is the per capita income and median household income in dollars. The employment measure is represented by the percent of 16 years and older population employed full-time, and non-poor population is the percentage of total population above poverty level. Principal Component Analysis (PCA) with varimax rotation was used to create a composite index of "well-being" from these four variables. The composite well-being index represents the "shared variance" originated from all four variables. The loadings of income-related variables (such as per capita income, median household income, and non-poor population) were higher (0.87) followed by employment (0.80) and education (.65) for both years. The well-being index was standardized relative to the range.

Change in Land Cover Types

The National Land Cover Data of 1992 and 2001 were used to derive the information on major land cover types (Figure 2). One of the primary goals of the NLCD project is to generate current, consistent, seamless, and accurate land cover data for the United States at medium spatial resolution. The information on data quality for mapping zone 54 was generated by the Decision Tree algorithm that conducts a cross-validation for assessing classification and prediction reliability. Table 1 shows the NLCD classification scheme and distinctive characteristics of each land cover class in the classification scheme.

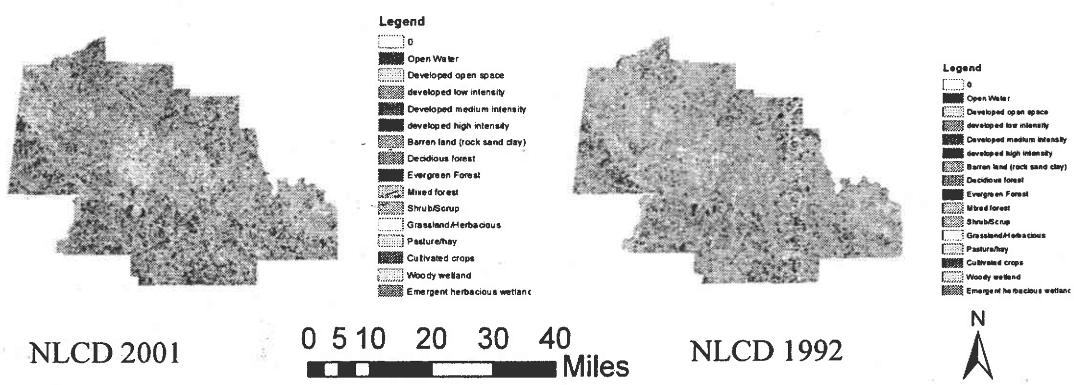

Figure 2. Land cover in the study area, from the National Land Cover Dataset.

Table 1. Description of NLCD land cover types.

NLCD Codes	Cover Types	Description
11	Open Water	All areas of open water, generally with less than 25% cover of vegetation or soil.
22, 23, 24	Residential	Includes areas with a mixture of low, medium and high intensity developed areas. Impervious surfaces account for 20-79 percent of total cover. These areas most commonly include single-family housing units, highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses, and commercial/industrial areas.
41, 90	Deciduous Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75 percent of the tree species shed foliage simultaneously in response to seasonal change. This class also includes woody wetlands.
42	Evergreen Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.
43	Mixed Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are grater than 75 percent of total tree cover.
81	Pasture/Hay	Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crop, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20 percent of total vegetation.
82	Cultivated Crops	Areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20 percent of total vegetation. This class also includes all land being actively tilled.

We used seven major land cover types (1) evergreen forests, (2) deciduous forests, (3) mixed, (4) pastures, (5) croplands, (6) residential, and (7) water (includes lakes, rivers, fish ponds and reservoirs).The area of each land cover type in each CBG was extracted using the spatial analyst extension in ArcGIS 9.1. The change in land cover type in a CBG represents the percentage change in each land cover type. This was obtained by dividing the difference in the area covered by the land type between 2001 and 1992 by the area of the same land cover type in 1992. Table 2 shows the descriptive statistics of the change in land cover type between 1992 and 2001.

<u>Descriptive Statistics</u>

Change in Human Well-being Index

Although the Black Belt region experienced major gains in education, income, and above-poverty level population between 1990 and 2000, the growth in employment, and the well-being index declined (average employment reduced by 4 percent, and average well-being index by 0.07 (Table 2). Of the 147 CBGs, 89 CBGs showed negative gain in well-being index and 58 CBGs showed positive gains in well-being index. These variations suggest that 40% of the area did very well but other areas did not do well over the 10-year period.

Table 2. Descriptive statistics of the well-being indicators and well-being index of 1990 and 2000.

Well-being index	Minimum		Maximum		Mean		Std. Deviation	
	1990	2000	1990	2000	1990	2000	1990	2000
Bachelor Degree	0.00	0.00	24.40	26.78	7.07	7.33	5.09	5.05
Employed%	20.17	23.70	76.68	70.25	47.41	43.38	10.03	9.26
Median HH Income ($$)	5,226	10,000	51,060	66,739	16,532	24,482	7,933	10,876
Per Capita Income ($$)	3,046	5,735	23,688	42,986	8,163	13,398	3,454	5,056
Above poverty%	26.84	26.18	97.10	100	64.83	69.27	15.79	13.58
Well-being Index	0.00	0.01	1.00	1.00	0.42	0.35	0.18	0.18
Change in Well-being Index	-0.81		0.65		-0.07		0.28	

Change in Land Cover Types

Increases in the average value of all land cover types except mixed forests and crop lands were noticed over the 10-year period (Table 3). Evergreen forest increased by 8% between 1992 and 2001 suggesting an increase in pine plantation. However, mixed forest decreased by 54 percent over the same period. In 1991, eight CBGs had zero value for residential cover type whereas in 2001, all CBGs had at least some acres of residential land. Residential area in 2000 was increased by 32% (from the mean value of 4.29 in 1992 to 5.67 in 2001). These changes occurred in the Selma Demopolis corridor along the Highway 80. Crop lands declined by 57% as most of these lands were either converted to forest, pasture, or residential land.

Table 3. Descriptive statistics of the major land cover types of 1992 and 2001 in 147 CBGs.

	Minimum		Maximum		Mean		Std. Deviation	
Land Cover Types	**1992**	**2001**	**1992**	**2001**	**1992**	**2001**	**1992**	**2001**
Evergreen	0.00	0.00	44.31	43.22	14.19	15.45	10.96	10.11
Deciduous	7.40	1.57	64.39	58.16	29.44	30.57	11.70	11.68
Mixed	5.00	0.00	41.38	38.16	21.45	9.78	9.77	7.57
Pasture Land	0.00	0.00	55.25	58.74	13.71	14.26	12.66	13.24
Crop Land	0.39	0.00	34.64	20.05	10.00	4.27	7.32	4.21
Water	0.00	0.00	15.99	17.41	1.78	2.42	2.62	3.07
Residential	0.00	0.02	63.74	66.60	4.29	5.67	10.70	12.49

Correlation between the changes of Human Well-being and Land Cover Type

Table 4 shows the correlation coefficients of the changes of human well-being index and land cover type variables. The human well-being index has significant negative relationship with deciduous forest. That is, significant positive changes in well-being are associated with negative changes in deciduous forests. At the same time, positive changes in deciduous forest are significantly correlated with negative changes in pastures and positive changes in cropland and water.

Table 4. Correlation coefficients of the change in well-being and land cover types.

Variables	Well-being	Evergreen	Deciduous	Mixed	Pasture	Cropland	Water
Evergreen	0.061						
Deciduous	-0.305*	-0.176*					
Mixed	0.023	-0.112	0.017				
Pasture	0.007	-0.163	-0.183*	-0.050			
Crop	0.028	-0.147	0.182*	0.016	-0.152		
Water	-0.068	-0.154	0.190*	0.088	0.170*	0.075	
Residential	0.038	-0.021	0.014	-0.136	-0.084	0.156	-0.112

* Significant at 5% probability level

RESULTS

We examined the relationship between changes and well-being index and changes in land cover types using ordinary least square (OLS) and spatial lag regression models. We performed these models for 89 CBGs that had negative and 58 CBGs that had positive change in well-being index separately.

Base Model (OLS) Results

The regression model for the CBGs with the negative change in well-being (dependent variable) and land cover type change (independent variables) was significant (F (7, 81) = 1.80, P<.01) (Table 5). However, the adjusted R^2 value (0.135) suggests that only 13.5% of the total variation in the change in well-being was explained by independent variables. Among the seven land cover type change variables, only pasture land significantly contributed to the model. There is a negative relationship of the change in pasture land (β = -0.155, t =2.50, p = .014) with respect to well-being changes. That is the increase in pasture land was significantly correlated with the decrease in well-being in those 89 CBGs.

Table 5. Base model (OLS) results.

Variable	Negative change in well-being (89CBGs)		Positive Change in Well-being (58 CBGs)	
	Estimate	*t*-Statistics	Estimate	*t*-statistics
Intercept	-0.151	-2.670	-0.242	3.07
Evergreen	0.002	0.540	-0.004	-1.23
Deciduous	-0.063	-1.034	-0.197*	-3.181
Mixed	0.136	1.568	0.037	0.382
Pasture	-0.155*	-2.509	-0.015	-0.722
Crop	0.017	0.426	0.048	0.684
Water	0.013	0.837	0.012	0.434
Residential	0.001	0.392	0.001	0.093
Adjusted R^2	0.060		0.075	
F value	1.80*		1.66	

* Significant at 5% probability level, ** Significant at 1% level

The base model for CBGs with positive change in well-being was not significant (F (7, 50) = 1.66, P<.150). The adjusted R^2 value (0.189) suggests that 18.9% of the total variation in the negative change in well-being was explained by independent variables. The deciduous forest type was the only significant variable (β =-0.197, t = 3.181, p = .05) as the only significant variable. This result suggested that an increase in the deciduous forest would predict the decrease in the positive change in well-being index.

The spatial lag model for CBGs with negative and positive change in well-being index showed high autocorrelation (Moran's I value = 0.403 and 0.246), respectively, an indicator of presence of spatial dependence. The negative well-being change model was significant (Likelihood ratio test value: 37.54, P =<.001) and accounted 50.6% of the total variance after taking into account the spatial dependence. The spatial lag variable has a significant positive effect (ρ= 0.679) suggesting that neighborhood changes in well-being index are positively related. The high ρ value also indicates that the CBGs with high negative change in well-being are also likely to be spatially near other CBGs with high negative change in well-being index.

The spatial lag model for the positive change in well-being is also significant and showed the strong spatial effect on the relationship (Likelihood ratio test value = 15.74, P =<0 .001, R^2 = 0.442). The spatial lag also showed positive correlation effect (ρ = 0.621).

The significant variables (pasture and deciduous forest) in the base model were still the significant variables in spatial lag models for negative and positive well-being change models, respectively. However, their coefficients became smaller after accounting for spatial correlation. The β coefficient of pasture in the negative well-being index model reduced from -0.155 in OLS model to -0.098 in spatial lag model. Similarly, the β coefficient of the deciduous forest variable in the positive well-being index model declined from -0.197 in OLS model to -0.096 in spatial lag model. These lower values suggest that deciduous and pasture land's contributions were weaker in the spatial lag models when compared to the base models.

Table 6. Spatial lag model results.

Variable	Negative change in well-being (89CBGs)		Positive Change in Well-being (58 CBGs)	
	Estimate	t-Statistics	Estimate	t-statistics
Intercept	-0.034	-0.809	0.114	1.838
Evergreen	0.002	0.823	-0.003	-1.455
Deciduous	-0.043	-0.968	-0.096*	-2.015
Mixed	0.061	0.984	0.076	1.014
Pasture	-0.098*	-2.195	-0.016	-1.004
Crop	0.022	0.771	0.018	0.330
Water	0.016	1.365	0.005	0.250
Residential	-0.004	-0.157	0.001	1.118
Spatial lag (ρ)	0.679**	9.098	0.621**	7.120
R^2	0.506		0.442	
Likelihood Ratio Test	37.54**		15.74**	
Moran's I value	0.403		0.246	

*Significant at 5% probability level, ** significant at 1% probability level

Discussion and Conclusion

This paper examined the relationship between land cover types and human well-being, using the sub-county level CBG data in the Black Belt region of Alabama between 1990 and 2000. Human well-being was measured by a composite index of income, employment and education attributes. The major land cover types considered in the analysis were evergreen, deciduous, mixed forests, pasture, crop, water, and residential lands. The study site was the evident of high clustering of land cover types and well-being indicators. The human well-being index declined slightly over the 10 years period. The area coverage of evergreen, deciduous, pasture, residential and water lands increased slightly in 2001 compared to 1992. Pine plantations increased due to the reversion of crop lands and mixed forests.

The initial analysis indicated a weak relationship between human well-being and land cover types. Among the seven land cover type variables, only deciduous forests and pasture lands were significant predictors of positive change in well-being and negative change in well-being regression models, respectively. However, the analysis shows strong spatial effects indicating high spatial dependence in the well-being and land cover types attributes among the neighboring CBGs. When spatial correlation effects were taken into account, the relationship between human well-being and land cover types was improved.

In conclusion, land cover type changes do have a mixed relationship with the socioeconomic development of the study area. The significant negative coefficients of deciduous forest lands change suggest that deciduous forests had a negative effect on the economic growth of the region. Evergreen forest area (pine plantations) was not significant, but had positive correlation with the well-being index. Due to the increasing trend of pine plantations over decades, it has potential to contribute to the socioeconomic growth of the region. Likewise, inland water systems may result positive impacts on well-being as number of newly built fish ponds are replacing less productive pasture and agricultural lands.

The negative association of both pasture lands and deciduous forests may suggest that major source of income and employment of the majority of the population is other than land-based activities. Exogenous factors such as ownership types of the forests lands, amount of the lands owned by absentee owners, and different forms of community capital such as financial, infrastructure, political capitals, may have important contribution in determining the well-being index of the region. The recognition of the neighborhood effects is imperative when we use spatial data. Also, this study brought to light the difference between conducting study using county and sub-county level data (such as CBG). This study performed at CBG level suggested a weak relationship between major land covers and human well-being which contradicts the results of previous county-level studies that suggested that forestry has contributed positively in improving socioeconomic condition of the region (Wears and Greis, 2002). The implication of this finding is the need for researchers and policy makers to explore the role of forestry in the economic development at the sub-county level by considering the spatial pattern of the distribution of forestry and its implication to socioeconomic development of the region.

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