Urban Vegetation Cover and Vegetation Change in Accra, Ghana: Connection to Housing Quality

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The objectives are to (1) quantify, map, and analyze vegetation cover distributions and changes across Accra, Ghana, for 2002 and 2010; and (2) examine the statistical relationship between vegetation cover and a housing quality index (HQI) for 2000 at the neighborhood level. Pixel-level vegetation cover maps derived using threshold classification of 2002 and 2010 QuickBird normalized difference vegetation index images have very high overall accuracies and yield an estimate of 5.9 percent vegetation cover reduction over the study area between 2002 and 2010. A high degree of variance in vegetation cover for individual dates is explained by HQI at the neighborhood level, although minimal covariability between absolute or relative vegetation cover change and HQI for 2000 was observed. **Key Words: Accra, Ghana, remote sensing, satellite, socioeconomic status, urban vegetation.**

本文的目的是：（1）量化，绘制，以及分析加纳首都阿克拉在 2002 年和 2010 年的植被分布和变化；（2）审查在街区一级 2000 年的植被和住房质量指数（HQI）之间的统计关系。使用 2002 年和 2010 年高精度的快鸟卫星归一化差异植被指数图像的阈值分类，制作像素级的植被覆盖图，得出在 2002 年和 2010 年之间，在该研究地区植被覆盖减少了 5.9%。虽然观察到 2000 年在绝对或相对的植被覆盖变化之间的协变性最小，但是街区一级的 HQI 解释了植被覆盖在个别日期的高度差异。**关键词：阿克拉，加纳，遥感，卫星，社会经济地位，城市植被**。

Los objetivos son (1) cuantificar, mapear y analizar las distribuciones y cambios de la cubierta vegetal a través de la ciudad de Accra, Ghana, entre 2002 y 2010; y (2) examinar la relación estadística entre la cubierta vegetal y un Índice de Calidad de la Vivienda (ICV) calculado para el 2000, a nivel de vecindario. Los mapas derivados de la cobertura vegetal a nivel de pixel, usando la clasificación de umbrales de imágenes índice normalizadas del QuickBird sobre diferencias de la vegetación de 2002 y 2010, tienen, en general, muy altas fidelidades y rinden un estimativo del 5.9 por ciento de reducción de la cubierta vegetal del área de estudio en el período estudiado. Un alto grado de varianza en la cubierta vegetal para fechas individuales se explicado por el ICV a nivel de vecindario, aunque se observó mínima covariabilidad entre el cambio de la cubierta vegetal absoluto o relativo y el ICV para 2000. **Palabras clave: Accra, Ghana, percepción remota, satélite, estatus socioeconómico, vegetación urbana.**

The populations of cities in developing countries are growing rapidly, as a result of rural-to-urban migration in combination with an excess of births over deaths in cities. In fact, cities in developing countries are expected to absorb nearly all of the global increase in population over the next several decades (United Nations Population Division 2010). Given this and that cities have historically provided the kind of economic and employment growth needed for people to rise above the poverty level (Weeks 2011), cities in developing countries warrant an increasing amount of our attention. Our focus in this article is on Accra, the capital city of Ghana, which is in the middle of a major transition from a predominantly rural to predominantly urban society. Population growth in rural areas is

The Professional Geographer, XX(X) XXXX, pages 1–15
Initial submission, July 2011; revised submission, October 2011; final acceptance, December 2011.
Published by Taylor & Francis Group, LLC.

absorbed by cities as the redundant rural population seeks jobs in urban places. Urban growth is likely to lead to urban sprawl, which can convert arable agricultural land to urban land uses. Land beyond the former urban periphery can then, in turn, be converted to agriculture. At the same time, housing and occupancy rates of previously developed urban areas are becoming denser. The rapid growth of Ghanaian cities is characterized by a high degree of informality and a low level of formal infrastructure. This means that land cover and land use in urban areas is changing and this transformation of the built environment will almost certainly be associated with increasing spatial inequalities in social, economic, and health conditions.

The local context in a city influences quality of life, and particularly health, indirectly by promoting or constraining the knowledge of disease transmission mechanisms and the ability to access health providers and directly by placing people at risk from environmental hazards. Both the direct and indirect contextual influences are related closely to socioeconomic status: Lower socioeconomic status (SES); lower SES is almost always associated with poorer health. Because people of similar SES tend to live in proximity to one another (although there are exceptions to this pattern), identifying regions of the city by their SES provides an important clue to the health of the population in those areas (Weeks et al. forthcoming). Thus, if we know the SES of a neighborhood within a city, we will be in a good position to draw inferences about the relative levels of health of people living in that neighborhood.

Accra has a population of almost 4 million people within the Greater Accra Metropolitan Area that spreads along the Atlantic coast near the confluence of the equator and prime meridian. The city has expanded and become more densely settled in the last decade, primarily from in-migration. The population of the Accra Metropolitan Area (our study site within the Greater Accra region) grew almost half a million from 2000 to 2010. A majority of Accra's inhabitants are poor and live in low-SES neighborhoods, with 58 percent of the population in neighborhoods classified as slums (UN-Habitat 2009). Most of these slums have informal, high-density housing settlements with small vegetation coverage and a high percentage of impervious land cover. Accra experiences two rainy seasons, one from May to July and the other one from August to October. Higher SES neighborhoods tend to be located at higher elevations where they are less prone to flooding from the short but intense tropical rains (Rain et al. 2011).

Vegetation cover in Greater Accra is associated with landscaping, parks, urban agricultural plots, regrowth following clearing, some remnant forests, and wetland vegetation surrounding lagoons. As a capital city, the urban core of Accra consists of large government compounds that are heavily landscaped with trees and lawns. Our field observations suggest that the amount of vegetation cover in residential areas tends to be associated with SES, such that higher SES residences have higher amounts of landscape vegetation, whereas lower SES areas have lesser (often no) vegetation cover. The abundance of vegetation cover and size of building structures indicate differences in SES of residential areas (Stow et al. 2007; Stow, Lippitt, and Weeks 2010; Lippitt et al. 2012), although these relationships have not been heretofore confirmed statistically. As the population of Greater Accra increases, change in vegetation cover should be one of the strongest signals of land cover and land use change and might signal changes in SES and health levels.

Remote sensing can play an important role in urban demographic and health studies by providing spatially explicit data on land surface properties and phenomena that could directly or indirectly pertain to the SES and thus potentially the health of urban dwellers. Our broader research agenda (beyond the scope of this article) involves explorations of satellite image data for delineating neighborhoods (Stow et al. 2007; Stow, Lipitt, and Weeks 2010; Lippitt et al. 2012); mapping urban agriculture plots that are breeding grounds for *Anopheles gambiae*, a mosquito vector for malaria (Klinkenberg et al. 2005; Stoler et al. 2009); and mapping land cover features such as landscape vegetation and residential dwellings that indicate SES and potential health risks for Accra, the capital city of Ghana (Weeks et al. 2010). Here we explore the utility of multitemporal high-spatial-resolution satellite image data for quantifying the distribution of urban vegetation in Accra and comparing such distributions and their temporal changes with spatial patterns of

SES, from which we infer spatial patterns of inequality in health.

Mapping and monitoring urban vegetation cover is a well-developed and reliable application of remote sensing (Kwarteng and Small 2010). Prior studies have analyzed and exploited high to moderate spatial resolution satellite multispectral data for analyses of urban vegetation within major cities of developing countries in the context of disease transmission (Fuller et al. 2010; Machault et al. 2010), food production and population change (Forkuor and Cofie 2011), neighborhood delineation (Stow, Lippitt, and Weeks 2010), and urban climate modification and urban ecology (Wei et al. 2007). Image processing and classification approaches to mapping vegetation cover can vary between per pixel image classification (of which a multitude of image classification algorithms have been developed; Fuller et al. 2010), object-based image analysis (OBIA; Cohen et al. 2010; Zhang, Feng, and Jiang 2010), and spectral mixture analysis (Yunhao et al. 2006).

The highly reflective nature of vegetation in near-infrared (just beyond visible) wavelengths relative to other land surface material types means that the presence or amount of projected vegetation cover can be reliably mapped and monitored by imaging systems that can sense near-infrared radiance (NIR). The contrast or difference of the near-infrared and red radiance measured by a remote sensing instrument is particularly sensitive to presence and amount of vegetation cover. This spectral radiance contrast is commonly measured using the normalized difference vegetation index (NDVI), which is derived with the formula NDVI = (NIR − Red) / (NIR + Red). Here, NIR and Red refers to digital number, spectral radiance, or spectral reflectance values for the NIR and red wavelength bands, depending on the level of calibration and radiometric processing of the remotely sensed data that are utilized. High NDVI values correspond to pixels that represent areas of high amounts of photosynthetically active vegetation cover.

High-spatial-resolution satellite systems with multispectral sensors provide a potentially valuable source of remote sensing data for mapping vegetation cover and monitoring vegetation changes across major urban areas. Most of these satellite systems are commercially operated, with the first (IKONOS) being launched in 1999. They provide multispectral image data with visible and near-infrared spectral bands, high radiometric resolution (e.g., 10- and 11-bit quantization levels), and nominal spatial resolutions between 1.65 and 4 m. A single, broad panchromatic band image is also captured by these systems with spatial resolutions between 0.4 and 1 m. The QuickBird satellite was launched shortly after IKONOS and for most of the 2000 decade provided the highest spatial resolution multispectral data available at 2.4 m. The advantages of high-spatial-resolution satellite data over the more readily available moderate-resolution systems such as Landsat Thematic Mapper and SPOT High Resolution Visible are the higher spatial and radiometric resolutions that enable finer and more accurate measurements of vegetation cover. The relative disadvantage is that the cost per unit area is higher and the extent of coverage per satellite image capture is substantially smaller, sometimes requiring multiple passes and dates of acquisition to cover an entire metropolitan area.

The primary objectives of this study are to (1) quantify, map, and analyze vegetation cover distributions and changes across Accra, Ghana, for 2002 and 2010; and (2) examine the statistical relationship between vegetation cover and SES at the neighborhood level, from which we will draw inferences about the spatial inequality in health in the city. QuickBird multispectral data for 2002 and 2010 are utilized to generate NDVI images and vegetation cover maps through image classifications. Demographic data from the 2000 Ghana Census of Population and Housing provide the basis for deriving a Housing Quality Index (HQI), which is used as a metric of SES. Spatial covariation in vegetation cover and HQI is quantified statistically at the neighborhood level.

Data and Methods

The study area is a 121 km^2 portion of the Accra, Ghana, metropolitan area defined as the common area between coverage of QuickBird satellite images captured in 2002 and 2010, delineated in Figure 1. The study area captures 65 percent of the Accra Metropolitan Area (AMA)

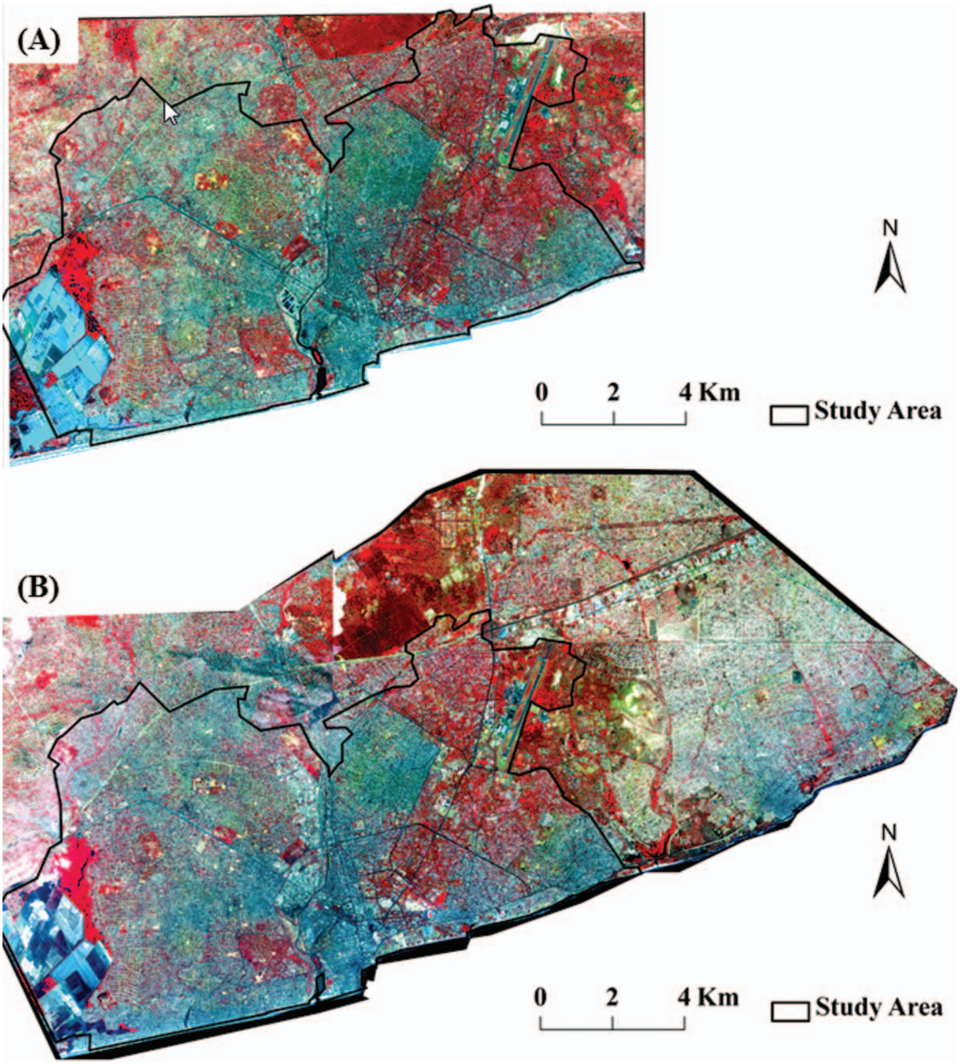

Figure 1 *QuickBird multispectral images of Accra, Ghana, displayed in false color infrared format with study area delineated. (A) 12 April 2002. (B) 27 January 2010. (Color figure available online.)*

land area and 83 percent of the population as enumerated in the 2000 census.

An HQI was created by means of a principal components analysis (PCA). We began with a set of dummy variables for all characteristics of housing and infrastructure available to us from the 2000 census at the housing unit level. (Note that data are not yet available from the 2010 census.) Thus, the unit of analysis for the PCA was the individual household. The variables included type of floor (focusing on dirt floors, which are associated with poor health), whether or not the house has electricity, the source of water to the house, the type of toilet used by the household, the type of bathing facility available to the household, how both liquid and solid waste are disposed of, the type of fuel used for cooking, the type of kitchen facility used for cooking, and the number of persons per sleeping room.

Over all, there were twenty variables entered into the PCA, from which nine components with an eigenvalue greater than one were extracted, explaining 73 percent of the variance in the set of variables. We used only the first component because its eigenvalue of 4.5 was significantly higher than the second through ninth components. It alone accounted for 22 percent of the variance and included seven variables that loaded with coefficients above 0.50. The four highest loading variables (with coefficients at or above 0.70) were whether a house had its own toilet, put its liquid waste in a sewer, had a separate room for cooking, and used gas for cooking. The presence of these characteristics, in particular, was indicative of the highest quality housing. Because factor scores are centered around a mean of zero, with a minimum score in this case of –2.22, we added a constant to each score so that the range was from zero for a house with the lowest quality of housing to a score slightly above five for the highest quality. These scores were then averaged for any given spatial unit of analysis, which for this study is the vernacular neighborhood, as described later. Thus, the SES scores used in this analysis represent the average HQI score for housing units in each neighborhood of Accra.

A digital map of vernacular neighborhoods (Figure 2) was used as the basis for quantifying vegetation cover and change and for statistical comparison of the vegetation quantities versus HQI. Census data are aggregated to the level of the enumeration area (EA), but EAs in Accra are designed to encompass approximately 1,000 persons and are generally too small in area, population, or both to be considered a neighborhood, leading to the necessity of agglomerating them to create neighborhoods. An important set of such neighborhoods is what have been called “vernacular” neighborhoods, which refer to

> neighborhood boundaries that are broadly recognized and agreed to by residents of a given city—in this case Accra, Ghana—even if they may have no premeditated and formal definition. These are the place names, for example, that would be provided to a taxi driver, especially since there is no comprehensive street address system in Accra. In Accra, 88 of these neighborhood boundaries have been created by Ghana Statistical Service (GSS) by grouping together contiguous EAs. (Weeks et al. 2010, 563)

These boundaries are generally similar to those generated on the basis of local knowledge without access to GSS census data (Songsore et al. 2005; Agyei-Mensah and Owusu 2010).

We analyzed vegetation cover distributions and change in Accra by obtaining, processing, and analyzing QuickBird satellite multispectral image data for April 2002 and January 2010 (portrayed in Figure 1), two of the only available cloud-free, high-spatial-resolution satellite images that cover most of Accra. This high-spatial-resolution (2.4 m) multitemporal image data set enables detection of fine-scale land cover changes such as clearing of vegetation and construction of small residential dwellings. Both images had been georeferenced independently to the Universal Transverse Mercator map projection by a third-party company (i-cubed) at Digital Globe’s (QuickBird image vendor) standard processing level (CE90 = 23 m; root mean square error [RMSE] = 14 m). Ocean and inland waters were masked prior to image analyses. We used an empirical line normalization approach to radiometrically normalize the two dates of imagery (Yuan and Elvidge 1996).

A simple threshold-based classification of NDVI values was implemented to derive maps of vegetation proportions for both image dates. Red and NIR band digital number values for both dates of the geometric and radiometric corrected QuickBird imagery were used to generate NDVI images. Two analysts interactively and independently determined the same threshold NDVI value to classify vegetation (NDVI $>$ 0.2) and nonvegetation (NDVI $<$ 0.2) land cover on a per pixel basis. We also tested two more complicated classification approaches available through commercial software packages: (1) a spatial contextual neural network classifier in Feature Analyst and (2) a geographic object-based image analysis (GEOBIA) approach in eCognition. We visually analyzed and compared mapped vegetation objects represented on products derived from the spatial contextual and GEOBIA software relative to the QuickBird multispectral image displayed in false color infrared format. On doing so, it was readily apparent that errors (e.g., commission and omission) in those

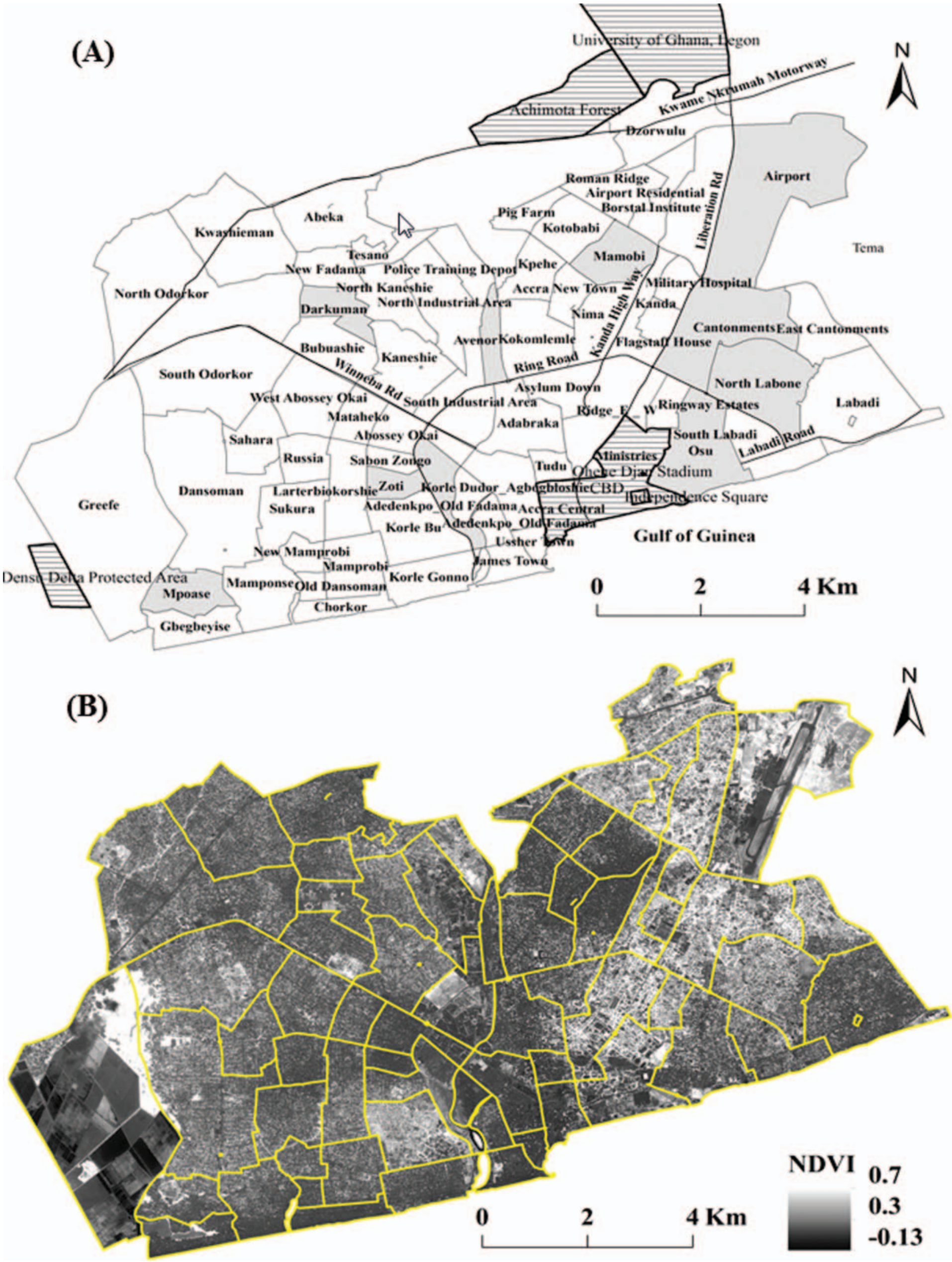

Figure 2 *Map of vernacular neighborhoods in Accra, Ghana. (A) Boundaries with neighborhood labels, with neighborhoods subjected to detailed visual image change analysis shaded in gray and important geographic features annotated. (B) Boundaries overlaid on 2010 normalized difference vegetation index (NDVI) image. (Color figure available online.)*

products were more prevalent than for the simple per pixel NDVI threshold classification product. The latter NDVI threshold classification product was used for subsequent analyses given these qualitative observations, the simplicity of the classification approach, and the very high quantitative accuracies (reported in the Results section).

We somewhat arbitrarily chose 1,000 randomly generated pixels (representing 0.005 percent of the study area) for each image date and one of the authors visually interpreted the QuickBird multispectral images. As shown in the results, the sample size was more than adequate for estimating map accuracy with a very narrow uncertainty range at the 95 percent confidence interval (Jensen 2005). We then used these observations as reference data for assessing the accuracy of the 2002 and 2010 vegetation maps at the pixel level. Clearly, the reference data are not completely independent, but no other sources of independent image data are available for corresponding dates. True ground reference data would be impossible to obtain for 2002, would be expensive to collect for such a large sample size (e.g., 1,000 points), and would result in greater uncertainty due to colocation issues between field observations and pixels. The author and analyst independently determined whether the randomly selected pixels predominantly consisted of vegetation or nonvegetation cover. The class assigned from the per pixel classification was cross-tabulated with the reference data class for each sample pixel to develop an accuracy matrix. Overall, user's and producer's accuracy measures were generated from the accuracy matrices for the 2002 and 2010 land cover products. Estimates of the change in vegetation cover between 2002 and 2010 from the reference data and image classification products were also compared.

The proportion of vegetation cover was estimated for vernacular neighborhood units of Greater Accra that were imaged in both 2002 and 2010 by summing the number of pixels classified as green vegetation and dividing by the total number of pixels contained within each neighborhood for both 2002 and 2010. Absolute percentage change in green vegetation proportions between 2002 and 2010 and relative percentage change derived as the absolute change divided by vegetation proportions in 2002 were calculated for each neighborhood.

In addition, an analyst conducted a structured qualitative image analysis to better understand the nature of vegetation change throughout the Accra study area. Two to four neighborhoods (approximately a 14 percent sample) were randomly selected from three strata that were based on the neighborhood-level vegetation change products (described later in the Results section). The three strata were associated with (1) vegetation increase, (2) median vegetation change (slight decrease), and (3) high vegetation decrease categories. The image analyst examined the vegetation cover maps and a false-color infrared composite image from both dates of the QuickBird data from which the vegetation maps had been derived. Because most of the vegetation change pertained to vegetation removal, the analyst tabulated the type of land cover that occurred in 2010 following devegetation since 2002.

Ordinary least squares regression analysis was performed to assess the strength of relationships between HQI derived from the 2000 census data versus vegetation cover for both 2002 and 2010 and for absolute and relative vegetation change percentages at the neighborhood level. Diagnostics were conducted in GeoDa (Anselin, Syabri, and Kho 2005) on the standardized residuals for the presence of spatial autocorrelation (based on global Moran's *I*) and heteroscedasticity (based on the Breusch–Pagan and Koenker–Bassett tests).

Results

Accuracy measures of pixel-level vegetation cover (presence) maps derived from the NDVI threshold classification of 2002 and 2010 QuickBird multispectral images are provided in Tables 1 and 2. Overall accuracies are 93.8 + 1.5 percent and 96.1 + 1.2 percent for the 2002 and 2010 maps, respectively, based on the independent visual interpretation of 1,000 randomly selected pixels. User's accuracies (accounting for errors of commission) ranged between 93 and 97 percent for vegetation and nonvegetation classes for both dates, and producer's accuracy (accounting for errors of omission) ranged between 90 and 96 percent. Given the high overall and categorical accuracies, the maps were considered to be acceptably reliable at the pixel level and certainly reliable

Table 1 *Error matrix for 2002 classification*

Classification	Reference: Vegetation	Reference: Nonvegetation	User's accuracy
Vegetation	326	25	92.90%
Nonvegetation	37	612	94.30%
Producer's accuracy	89.80%	96.10%	Overall accuracy
	$N = 1,000$		93.80%

in terms of portraying the spatial distribution and change in vegetation cover at the neighborhood level and coarser.

The magnitude and sign of vegetation change from 2002 to 2010 for the entire study area was estimated from the 1,000 samples (pixels) of the reference and image classification data, as shown in Table 3. The estimate from the reference data is –7.4 percent (net loss) of the study area, whereas the image-derived maps yield an estimate of –5.9 percent. This suggests that postclassification comparison of the image-derived maps yields a change map with a bias of +1.5 percent, meaning that vegetation loss is slightly underestimated. Assuming that the reference data are more reliable than the image classification product, a 7.4 percent reduction in vegetation cover for the study area is equivalent to loss of almost 9 km^2. This estimate is based on the reality that a pixel classified as vegetation represents a land surface area that is mostly but not necessarily fully covered by vegetation and one classified as nonvegetation contains minimal vegetation and the assumption that biases associated with these discrete classifications for both years balance out.

Maps depicting pixel-level vegetation cover in Accra for 2002 and 2010 are shown in Figures 3A and 3B, respectively. Vegetation cover exhibits high spatial variability with high concentrations in the northeastern and far western portions of the study area and very low amounts along most of the coastal strip and much of the central part of Accra. This spatial pattern of vegetation cover matches the general pattern of land use and SES across Accra, where undeveloped, government institutional, high-SES residential and planted urban agricultural plots have high vegetation cover and low-SES residential and fallow urban agricultural plots exhibit low vegetation cover.

Through visual comparison of Figures 3A and 3B, one can see that reduction of vegetation cover was pervasive throughout much of Accra in the period from 2002 to 2010, as is also indicated by the estimates for the overall study area based on both the reference and image classification data. Reduction in vegetation cover is particularly evident along the coastal strip that already had limited vegetation cover in 2002 and throughout the southeastern portion of the study area. A few areas of vegetation expansion are evident in areas to the far west and near the airport in the northeast portion of the study area, which have lesser amounts of development and are mostly covered by natural vegetation.

Maps depicting percentage vegetation cover at the neighborhood level in Accra for 2002 and 2010 are shown in Figures 4A and 4B, respectively. Absolute percentage change in vegetation and relative change as a percentage of

Table 2 *Error matrix for 2010 classification*

Classification	Reference: Vegetation	Reference: Nonvegetation	User's accuracy
Vegetation	271	21	92.80%
Nonvegetation	18	690	97.50%
Producer's accuracy	93.80%	97.00%	Overall accuracy
	$N = 1,000$		96.10%

Table 3 *Comparison of percentage of image classified as vegetation and nonvegetation for 1,000 samples of reference data and image classification product*

	Reference		Classification	
Image year	**Vegetation (%)**	**Nonvegetation (%)**	**Vegetation (%)**	**Nonvegetation (%)**
2002	36.3	63.7	35.1	64.9
2010	28.9	71.1	70.8	29.2
2010–2002	−7.4	+7.4	−5.9	+5.9
Change bias			+1.5	−1.5

2002 cover are illustrated in Figures 4C and 4D, respectively. The large majority of neighborhoods, particularly those in the more densely settled portions of the city, exhibit an absolute loss of vegetation cover of up to 10 percent, with several neighborhoods showing more than 10 percent vegetation loss. Similarly, a majority of neighborhoods experienced a reduction of vegetation cover of at least 10 percent relative to their 2002 amount, with most of the western portion of the study area showing greater than 25 percent relative change.

Visual analysis of the QuickBird color infrared composite images and resultant vegetation maps for both dates and selected neighborhoods enabled a more nuanced assessment of the land cover transition sequences associated with vegetation cover changes in Accra. An example of one of the image and map sets for the Darkuman neighborhood (representative

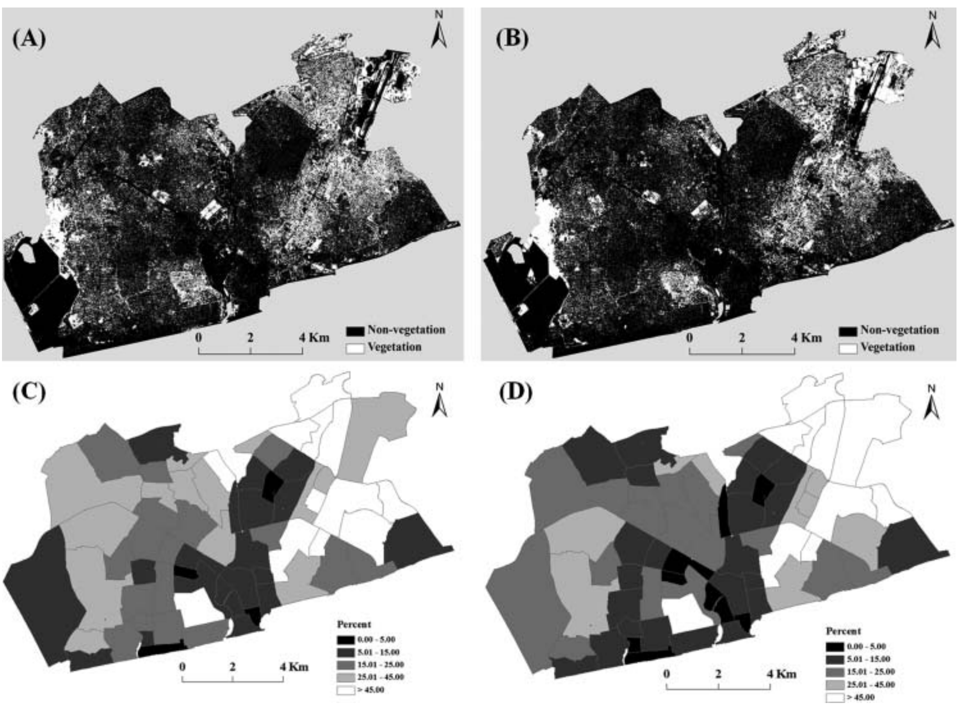

Figure 3 *Vegetation cover presence map derived from QuickBird normalized difference vegetation index classification. (A) 2002 pixel level; (B) 2010 pixel level; (C) 2002 neighborhood level; (D) 2010 neighborhood level.*

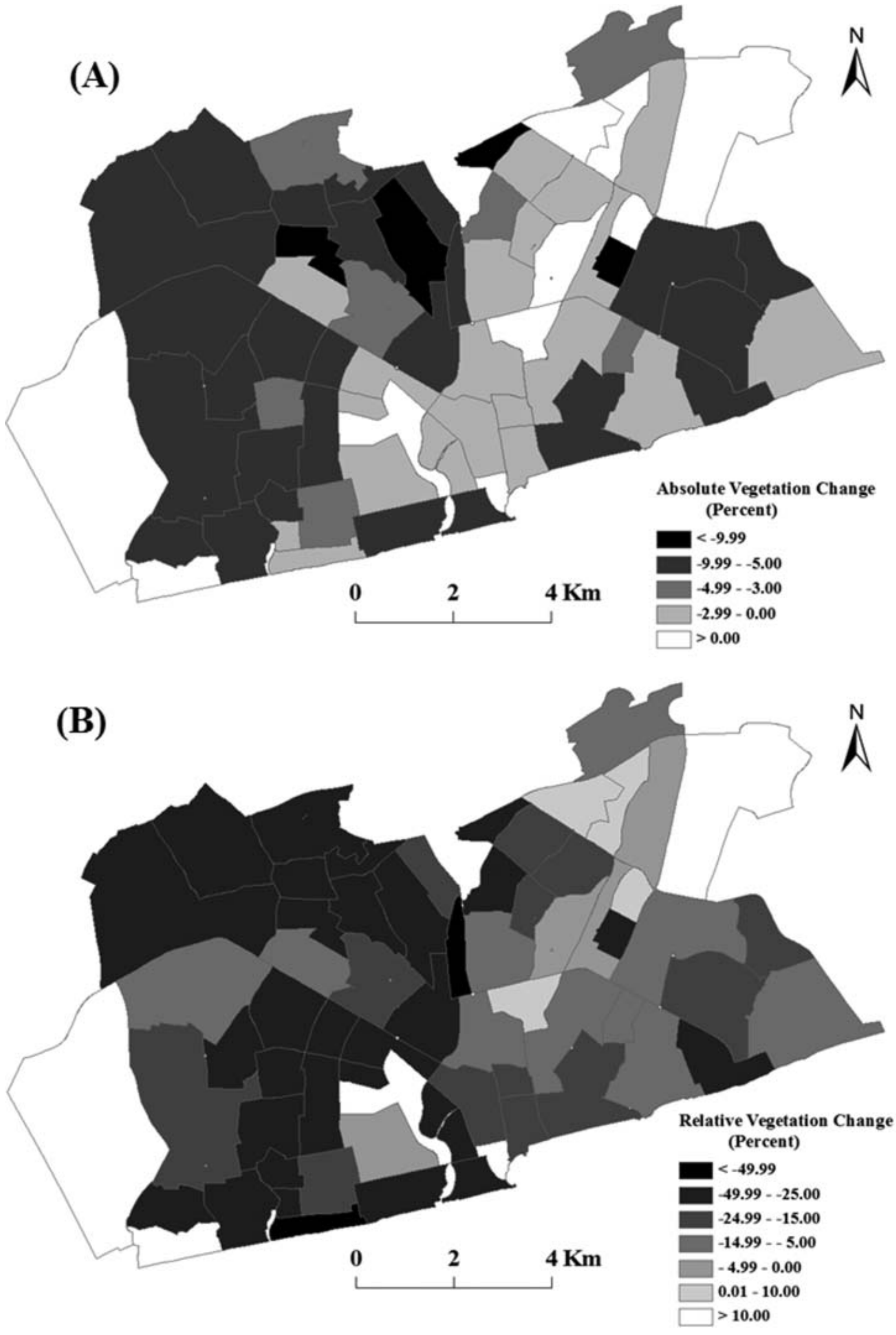

Figure 4 *Vegetation change percentages by neighborhood. (A) Absolute change (percentage vegetation cover in 2010 – percentage vegetation cover in 2002). (B) Relative change (percentage of vegetation cover in 2010 – percentage of vegetation cover in 2002/percentage of vegetation cover in 2002).*

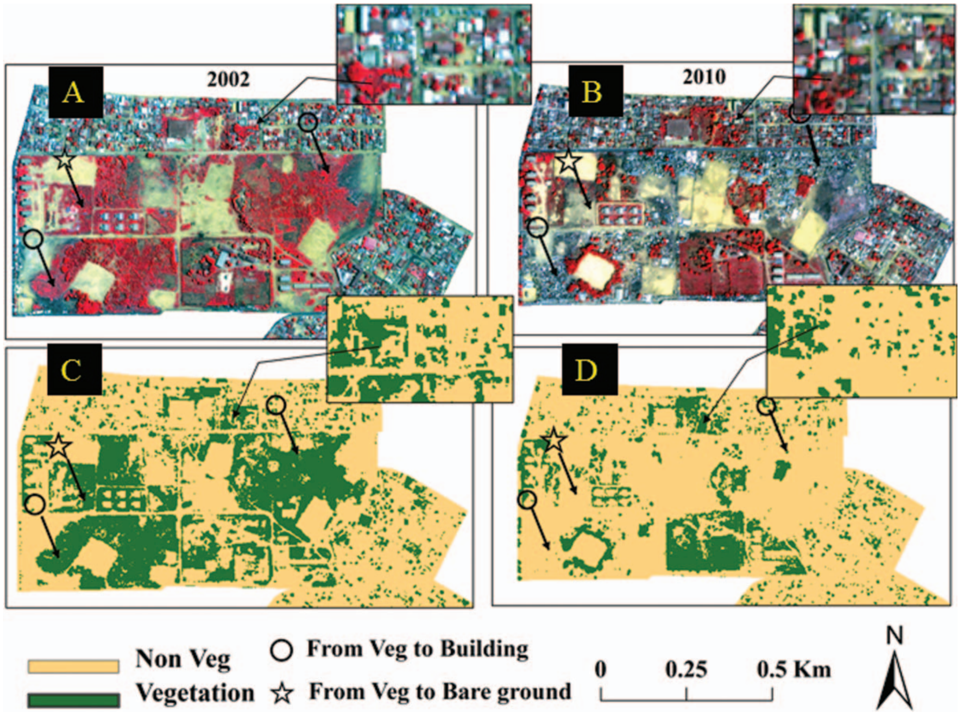

Figure 5 *Example of interpreter-based image assessment of vegetation changes for Darkuman neighborhood. (A) Subset of QuickBird color infrared composite image April 2002. (B) January 2010 image subset. (C) Classification product subset derived from April 2002 QuickBird image. (D) January 2010 classification subset. Substantial vegetation loss is observed for this neighborhood, associated with clearing, new building construction, and urban building densification. (Color figure available online.)*

of substantial vegetation reduction) is shown in Figure 5. Table 4 provides a summary of the transition sequences for the nine neighborhoods that were analyzed.

For the seven sampled neighborhoods that had experienced a net decrease in vegetation cover, approximately 63 percent of the devegetation was associated with completed

Table 4 *Neighborhood-level land cover change to and from vegetation for randomly selected neighborhoods within three vegetation change strata: large decrease, small decrease, and small increase*

Vegetation change	Absolute change (%)	Relative change (%)	Transition to
Large decrease			
Avenor	−5.6	−53	Building (20%), Impervious/soil (40%), Water (40%)
Darkuman	−13.7	−46	Building (80%), Impervious/soil (20%)
Mposae	−8.8	−29	Building (70%), Impervious/soil (30%)
Small-medium decrease			
Cantonments	−7.71	−12	Building (85%), Impervious/soil (15%)
Mamobi	−2.1	−20	Building (40%), Impervious/soil (60%)
North Labone	−8.1	−17	Building (70%), Impervious/soil (30%)
Osu	−1.6	−7	Building (55%), Impervious/soil (45%)
Small increase			
Airport	+8.1	+18	Tree expansion/growth
Zoti	+1.8	+12	Herbaceous regrowth

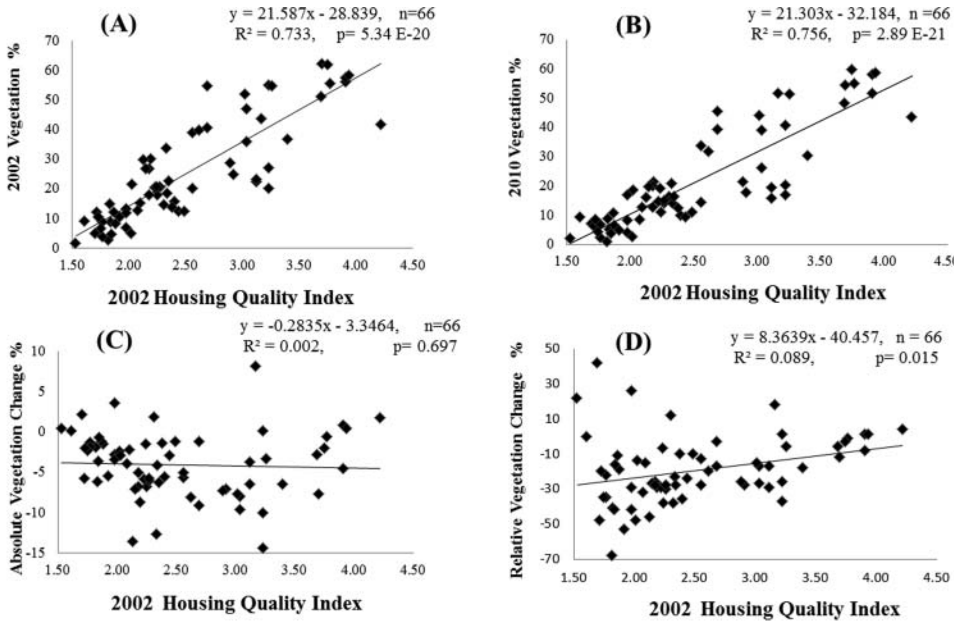

Figure 6 *Scatterplots, least squares line, and regression statistics for neighbor-level analyses of (A) Housing Quality Index (HQI) versus 2002 vegetation cover; (B) HQI versus 2010 vegetation cover; (C) HQI versus absolute percentage vegetation change; and (D) HQI versus relative percentage vegetation change.*

building, with most of the buildings being residential dwellings. Slightly more than 30 percent of removed vegetation was replaced by impervious materials or soil (which were difficult to separate visually) in the form of streets, incomplete building construction, or bare soil. A little less than 6 percent of devegetation was associated with removal or inundation of water, which is likely biased by the random selection of the Avenor neighborhood in which a canal had been widened.

Few of the neighborhoods exhibited net vegetation expansion over the eight-year study period and the two neighborhoods selected for analysis showed less than 10 percent absolute and between 10 and 20 percent relative increase in vegetation cover. Minimal development occurred within the Airport neighborhood and most of the vegetation increase was associated with tree growth. The increased vegetation cover for the Zoti neighborhood resulted from regrowth of herbaceous vegetation in areas that had been cleared prior to the 2002 image acquisition.

Scatterplots and statistical results from regressing HQI against percentage vegetation cover at the neighborhood level are shown in Figures 6A and 6B. A high degree of spatial covariability for HQI and vegetation cover is evident based on r^2 values of 0.73 ($n = 66$, $p = 0.00$) and 0.76 ($n = 66$, $p = 0.00$) for 2002 and 2010 vegetation percentages, respectively. Interestingly, a slightly higher (albeit not statistically significantly higher) r^2 value resulted for the 2010 vegetation proportions than those for 2002 even though HQI is derived from 2000 census data. These results suggest that the relationship between HQI and vegetation is sufficiently robust as to be relatively unaffected by changing vegetation over the span of time covered in this analysis. No spatial autocorrelation effect or heteroscedasticity was identified based on an analysis of the standardized residuals from the regression model. We also regressed HQI on absolute and relative percentage vegetation change, with scatterplots and statistical results shown in Figures 6C and 6D, respectively. No trend or significant relationship was found for either of these regressions. It is not yet possible to test the relationship between change in HQI versus percentage vegetation change, as change in HQI cannot be derived until the 2010 Ghana census data have been released.

Discussion and Conclusions

Green vegetation is a readily detectable land cover type relative to a background composed of impervious and soil cover types in an urban setting such as Greater Accra, due to its very high near-infrared and low visible spectral reflectance. This is particularly the case with the 2.4-m spatial resolution QuickBird multispectral data, where even small trees and vegetation patches can compose most of the ground resolution element associated with a QuickBird pixel. This explains why the simplistic NDVI threshold-based classification yielded very accurate maps (94–96 percent overall accuracy) of vegetation cover presence and why our limited evaluation of more advanced OBIA and spatial contextual approaches showed that the more parsimonious NDVI threshold approach yielded equally if not more reliable maps.

Although originally covered by tropical forests, agricultural clearing and urban development have greatly modified the vegetation composition of Greater Accra and Herbaceous and shrub vegetation are predominant in sparsely settled areas. The equatorial climate of the area is conducive to rapid regrowth after clearing. The few neighborhoods that exhibited increases in vegetation cover were on the periphery of Greater Accra and had minimal residential development, and vegetation cover increased mostly through regrowth following clearing.

Despite these vegetation dynamics and the difference in the seasonal dates of the two QuickBird images (April 2002 and January 2010), we found little evidence of bias or artifacts in the resultant vegetation maps that might have influenced estimates of vegetation cover and change. Visual analyses of multidate images and derived vegetation maps at or near the pixel level (i.e., zoomed in so that individual pixels are resolvable) revealed consistent representation of persistent vegetation objects, expansion of some tree objects from 2002 to 2010 (indicating tree growth) and minimal differences associated with cast shadows and canopy illumination variability. As a normalized difference index, NDVI tends to be effective at normalizing illumination and shadowing effects, particularly those associated with vegetation canopies (Holben and Justice 1981). Persistent vegetation objects between years showed no substantial difference in visual appearance on color infrared images, NDVI values, or classification results associated with the three-month difference in the time of year of image acquisition.

The most revealing difference between Accra residential neighborhoods of varying SES is the relative abundance of vegetation cover and the size and density of residential structures. High-SES areas tend to have a high proportion of landscape vegetation cover, whereas low-SES areas have little. Slum-like areas exhibited low amounts of vegetation cover and the greatest relative decrease in vegetation cover (and increase in density of residential buildings) during the eight years between imaging, despite having low vegetation cover and high dwelling density in 2002. Densification was prevalent in low-SES neighborhoods, particularly those along the coast of the Gulf of Guinea, as much of the limited vegetation cover existing in 2002 was removed and replaced mostly by small residential structures.

Neighborhoods in western and north-central Accra having the lowest HQI have less than 5 percent vegetation cover, with the proportion of vegetation cover being less than 15 percent for much of western Accra. Urban vegetation is known to have many positive effects on urban residents and their environments, including shading, absorption of gaseous air pollutants, attenuation of noise, interception and storage of precipitation, evapotranspiration, and aesthetics, to name a few (Emmanuel 1997; Jonsson 2004; Solecki et al. 2005; Nowak, Crane, and Stevens 2006; Souch and Grimmond 2006; Bell, Wilson, and Liu 2008). Low amounts of vegetation in these neighborhoods are consistent with our inference of an overall low quality of life for their inhabitants, both directly because of a lack of vegetation and indirectly through its high relationship with low-quality housing, our proxy measure for neighborhood SES. These findings provide further evidence that proxy measures derived from remote sensing enable spatially explicit and temporally frequent monitoring of conditions associated with quality of life of urban inhabitants of developing countries.

Our plans for follow-up research are threefold. We will attempt to determine whether the hard/discrete, per pixel classification of vegetation and nonvegetation categories yields biases in estimating areal amounts of vegetation change. Our initial analyses of this potential for bias revealed that the use of QuickBird panchromatic (with 0.6-m spatial resolution) was not sufficient to determine fractional vegetation cover amounts of multispectral pixels (2.4 m spatial resolution). We will also examine spatial and temporal patterns of HQI for 2000 and 2010 and changes in HQI relative to vegetation cover change when the 2010 census data become available from GSS. Finally, we will examine women's and children's health outcomes relative to vegetation cover and change based on satellite-derived vegetation data for zones surrounding 2,800 individual households that we surveyed in 2008 and 2009 as part of the Women's Health Survey of Accra (Weeks et al. forthcoming). ■

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