Geographic Object-based Delineation of Neighborhoods of Accra, Ghana using QuickBird Satellite Imagery

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Abstract

The objective was to test GEographic Object-based Image Analysis (GEOBIA) techniques for delineating neighborhoods of Accra, Ghana using QuickBird multispectral imagery. Two approaches to aggregating census enumeration areas (EAs) based on image-derived measures of vegetation objects were tested: (a) merging adjacent EAs according to vegetation measures, and (b) image segmentation. Both approaches exploit readily available functions within commercial GEOBIA software. Image-derived neighborhood maps were compared to a reference map derived by spatial clustering of slum index values (from census data), to provide a relative assessment of potential map utility. A size-constrained iterative segmentation approach to aggregation was more successful than standard image segmentation or feature merge techniques. The segmentation approaches account for size and shape characteristics, enabling more realistic neighborhood boundaries to be delineated. The percentage of vegetation patches within each EA yielded more realistic delineation of potential neighborhoods than mean vegetation patch size per EA.

Introduction and Background

Neighborhood is a term that is common in both academic and lay vernaculars, but it may have many different meanings or usages (Sampson *et al.*, 2002; Talen, 1999; Warren, 1978). Normally, a neighborhood is considered to be a spatial unit within a city or urban area. But in reality, neighborhoods are social constructs, and there are no precise definitions or delineations for them in physical space. Here we define neighborhoods to be a spatial unit within which urban residents share common social-cultural behaviors and identities. Overall, our interest in delineating neighborhoods is two-fold. First, we are interested in the manner in which neighborhood dwellers share information about health practices and outcomes, and are similarly exposed to environmental factors that may influence the health of an individual living within the neighborhood. Second, we are interested in delineating spatial units at the neighborhood scale for which disparate socio-economic, health, and environmental data can be optimally summarized to support spatial statistical analyses. The emphasis here is on the second objective.

Recent studies suggest that intra-city variations in poverty and health in developing countries, such as most of Africa, may be greater than differences between urban and rural populations (Montgomery and Hewett, 2005; Weeks *et al.*, 2006). Accra, Ghana is an excellent city to study neighborhood effects on health and poverty because of its disparate socio-economic and health conditions, and because relatively recent and rich census and women's health data sets are available (Weeks *et al.*, 2006; Weeks *et al.*, 2007). As is generally the case for these types of urban data sets, the census and health data are summarized and reported by spatial units that vary in size and shape. This leads to the modifiable areal unit problem or ecological fallacy (Openshaw, 1983), when attempts to draw statistical inferences from and between these data sets are compromised or biased by the irregular reporting units. Thus, delineating neighborhoods in Accra may be a useful means for deriving analytical units for subsequent statistical analyses, and enable an evaluation of possible neighborhood effects on health practice and outcomes.

A means for delineating neighborhoods is through a regionalization process applied to geospatial data that are recorded at finer spatial scales than potential neighborhoods and that have attributes that are relatively homogenous within neighborhoods. By a potential neighborhood, we are referring to a spatial urban unit that is delineated through a regionalization process, which may or may not conform to an actual neighborhood in terms of its residents sharing common behaviors and identities. For instance, potential neighborhoods could be delineated through spatial aggregation of socio-economic measures from census data that are recorded for census reporting units. In Accra, the finest level of census reporting unit is called an Enumeration Area (EA). EA-level census data can be aggregated to a coarser level to delineate potential neighborhoods. However, census data are expensive to capture and organize, are not available for most cities in developing countries, and can become rapidly out of date, such as is the case for Accra. Also, if census data were to be aggregated to form analytical units for subsequent statistical analysis, a less biased approach to delineating these analytical units would be to use an alternative source of data for regionalization.

Remote sensing provides a primary source of geospatial data for regionalization (Tian *et al.*, 2005) and/or delineation of potential neighborhoods. Remotely sensed images have been used for regionalization purposes in the field of

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hydrology (Boulet *et al.*, 2000; Brunner *et al*, 2004), but apparently, in a very limited manner for intra-urban studies or delineating neighborhoods *per se* (Zhou, 2006). However, several previous studies have evaluated urban socio-economic conditions using high spatial resolution satellite image data (Bjorgo, 2000; Giada *et al.*, 2003; Stow *et al.*, 2007). For remotely sensed images to be useful for urban regionalization and neighborhood delineation, some physical environmental and/or urban infrastructural characteristics of neighborhoods must be identifiable and unique (Rashed, in press). The urban vegetation-impervious-soil (V-I-S) model of Ridd (1995) provides a potentially useful remote sensing approach to deriving geospatial measures that may be used for regionalization purposes. By combining the V-I-S model with GEographic Object-based Image Analysis (GEOBIA; Casilla and Hay, 2008), proportions, sizes, and shapes of basic urban materials and structures may provide the link between the biophysical urban landscape and neighborhoods (Stow *et al.*, 2007).

Accra is a city of around two million people that has grown rapidly in the last decade (Ghana Statistical Services, 2002). While a majority of Accra's inhabitants are poor and live in low socio-economic status (SES) neighborhoods, most of the slums of Accra consist of formal, high density housing settlements, and few informal slums or camps exist currently. In many cases moderate to high SES neighborhoods are juxtaposed with slums, and tend to be located at higher elevations where in-flooding from tropical rains is less common. While size of house structures and properties tend to indicate differences in SES of residential areas (e.g., larger houses and properties indicate higher SES), structures in slum areas often consist of large networks (e.g., compounds) of connected or closely separated single story dwellings that can appear on high spatial resolution imagery to be large buildings.

The most striking and revealing difference between residential areas of varying SES is the relative abundance of vegetation cover. High SES areas have a high proportion of landscape vegetation cover while low SES areas have little (Lo and Faber, 1997). Thus, the proportion or size of vegetation objects may be effective criterion for delineating Accra neighborhoods. The greatest potential confusion occurs between High SES residential areas and institutional land-use, such as the national government building complexes, that both contain large amounts of landscape vegetation. Another complication is that land-use is often "mixed use," such that buildings may be used both for residential and commercial purposes.

The objective of this study was to test approaches to delineating neighborhoods of Accra based on high spatial resolution multispectral image data from the QuickBird satellite system and GEOBIA. Specifically, we evaluate two parsimonious approaches to regionalizing EAs by using quantitative measures of vegetation objects as the aggregation metrics and constraining the aggregation/segmentation process using EA boundary data. Both approaches exploit readily available functions within the commercial GEOBIA software called Definiens (Version 5); one by merging EAs according to similarity of vegetation objects and the other by image segmentation.

Data and Methods

We test the two parsimonious approaches to delineating neighborhood units based on QuickBird satellite image data and GEOBIA. EAs were used as the basic spatial unit of analysis and were aggregated in an attempt to form neighborhood units, based on similarity in vegetation patch proportions or mean patch size derived from GEOBIA. Digitized EA boundaries were initially georeferenced only approximately, so the georeferenced QuickBird image was used as a base for fine-tuning the georeferencing of the EA boundaries and ensuring high registration precision between the two data sets. Two approaches to spatial aggregation were tested: (a) polygon merging, and (b) image segmentation. Image-derived neighborhood maps were compared with the reference map derived using the slum index (Weeks *et al.*, 2007) and a spatial data aggregation procedure (Duque, 2007a) described below to provide a relative assessment of potential map utility. A flow chart portraying the data processing and analysis steps is shown in Figure 1.

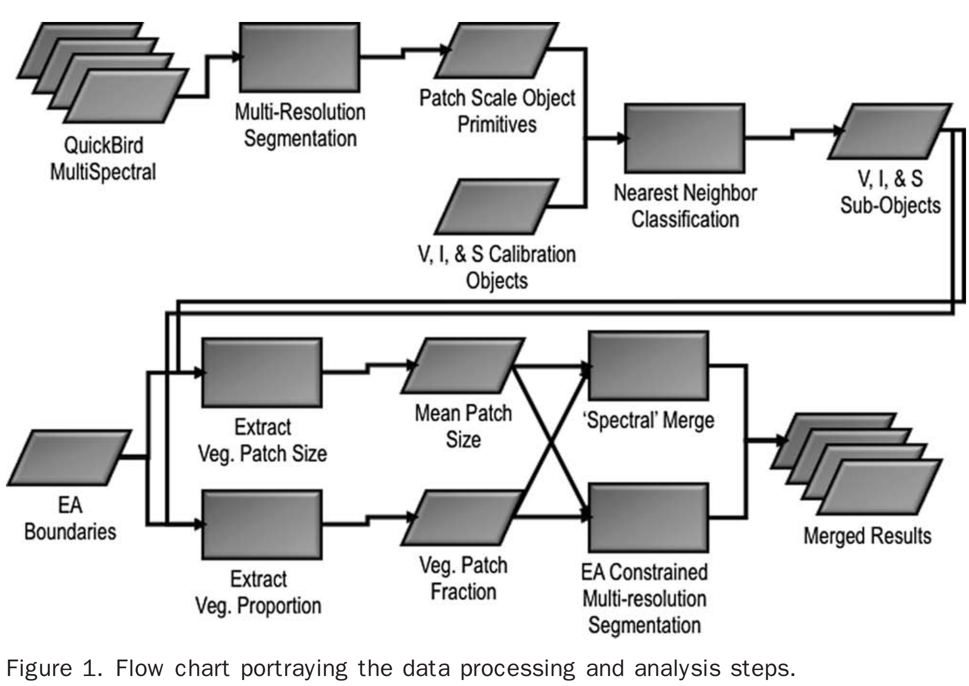

Figure 1. Flow chart portraying the data processing and analysis steps.

A cloud-free QuickBird satellite multispectral with a 2.4 m nominal ground sampling distance (GSD) captured on 12 April 2002 was utilized. The full image covers an 18 km (E to W) × 13 km (N to S) area, which is approximately 80 percent of the Accra Metropolitan Area (AMA). For this study we used a 6 km (E to W) × 5 km (N to S) subset of the QuickBird image (shown in Figure 2) that contained most of the neighborhood and land use types found within Accra. The imagery had been georeferenced to the Universal Transverse Mercator map projection by DigitalGlobe at the Standard processing level (CE90 = 23 m; RMSE = 14 m). Ocean and inland waters were masked prior to image analyses.

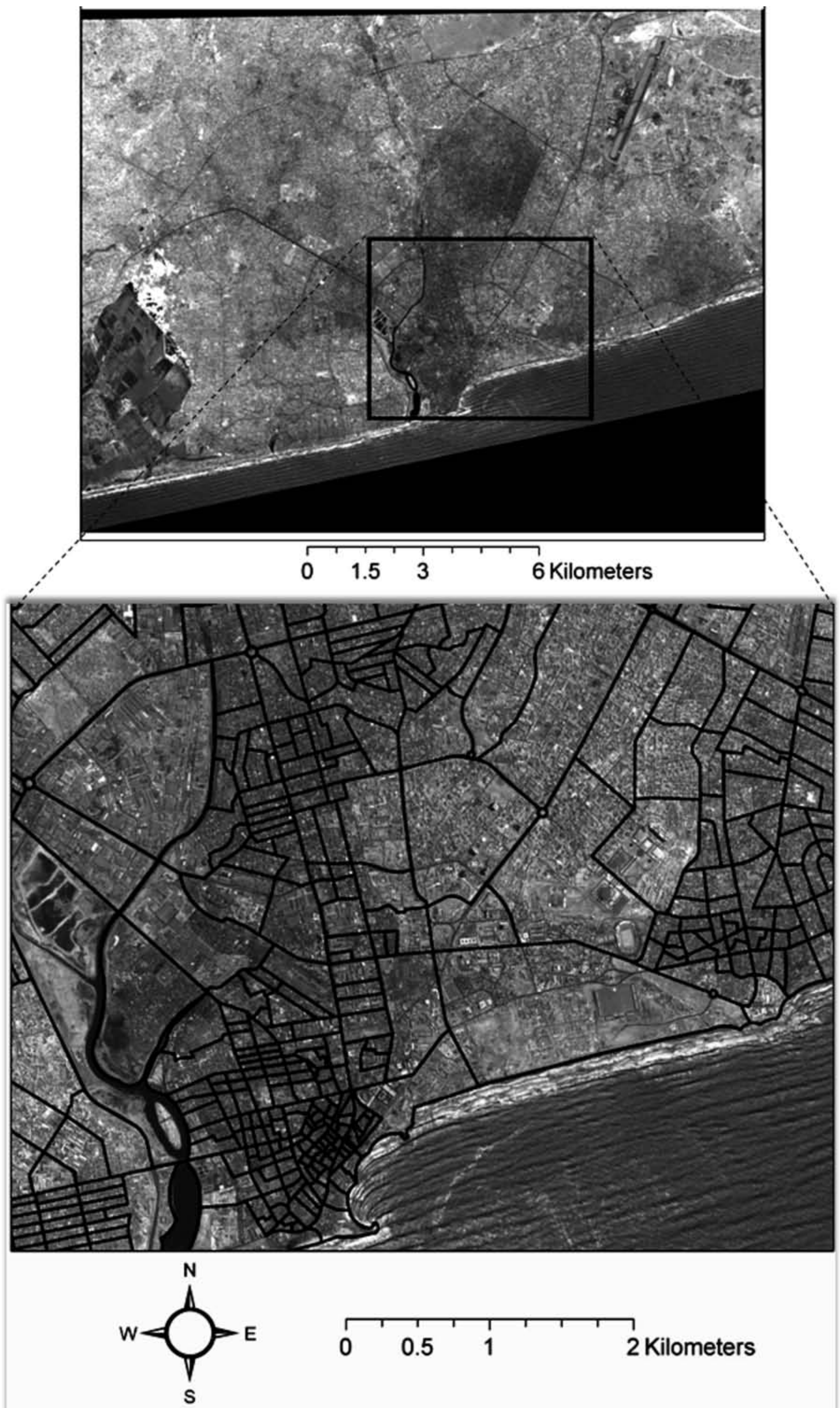

Figure 2. Full extent of QuickBird near infrared waveband image covering Accra, Ghana (top) with enlarged subset of the study area (bottom). Image was captured 12 April 2002. Polygons displayed on subset image represent georeferenced census enumeration area (EA) boundaries.

A map that had been generated through GIS and spatial aggregation modeling of census data was utilized as reference data for a relative assessment of the utility of image-derived neighborhood maps. Figure 2 contains a map of EA boundaries, and the reference map is displayed in Figure 4f. The reference map was based on a slum index that was calculated for each EA by summing five census variables for each housing unit based on UN-Habitat (2006) definitions of slums as representing place that have one or more of the following characteristics: (a) no running water inside the house, (b) no toilet connected to sewer system, (c) three or more persons per room, (d) roof of non-durable material, and (e) insecure tenure (e.g., squatting) (Weeks *et al.*, 2007). Each housing unit was scaled from 0 to 5, where zero indicates no slum characteristics and five indicates all slum characteristics. The average score for housing units in an EA is the slum index for that EA.

The EA-level map of slum index was subjected to a polygon spatial aggregation procedure called the Max-P-Region (Duque *et al.*, 2007a) to produce 277 "analytical regions." In this method, the problem of aggregation of spatial data is conceptualized as a special case of clustering in which the geographical contiguity between the elements to be grouped are considered. This particular case of clustering methods is usually known as contiguity-constrained clustering or simply the regionalization problem (Duque *et al.*, 2007b). Each EA is compared to its neighbors to see if the neighbors are more like the "kernel" EA than would be expected by chance alone. If so, the neighbor is attached to the kernel EA, and then this new agglomerated EA is compared with neighbors. The process is iterative, working toward a stable solution in which all agglomerations (analytical regions) represent the maximum homogeneity within neighborhoods, and the maximum heterogeneity between neighborhoods.

Of particular importance is that the method is multivariate, taking into account several different variables at a time, and thus, it is an improvement on an earlier agglomeration method using similar data. In this instance, each of the five slum characteristics of the housing units in an EA was evaluated against the values for neighboring EAs in order to make a decision about agglomerating one EA with another. A series of random permutations was run to confirm that the results were significantly different from results that could be obtained by chance alone.

A bottom-up, hierarchical segmentation strategy with two levels of image objects (Stow *et al.*, 2007) was implemented for the image-based derivation of potential neighborhoods. Definiens uses a region-based local mutual segmentation routine, a type of region growing approach, to generate image objects (Baatz *et al.*, 2000; Benz *et al.*, 2004; Yu *et al.*, 2006). We controlled segmentation by both scale (size of segment) and shape (compactness and smoothness characteristics of segments) parameters in an interactive, trial-and-error fashion.

The first and finest segmentation (Level 1) consisted of potential V-I-S patches, where our primary interest was to delineate vegetation patch objects. Image inputs (i.e., spectral features) for the Level 1 segmentation were the four QuickBird multispectral wavebands, NIR, red, green, blue (in order of input) (Stow *et al.*, 2007). Level 1 segmentation was optimized based on visual inspection of training objects (e.g., trees and buildings) on segmentation products generated iteratively by altering segmentation parameters. We used a supervised classification of V-I-S classes based on a standard nearest neighbor (a.k.a., minimum distance to mean) classifier. Input features were selected using a statistical separability measure embedded in the Definiens routine known as Feature Space Optimization. The selected "optimal" features are listed and described in Table 1.

TABLE 1. INPUT FEATURES USED IN LEVEL 1 SEGMENT CLASSIFICATION

Selected Features	Feature Description
Brightness	Sum of digital numbers of all bands
Compactness	Length*width/number of pixels
Shape Index	Border length/4*object area$^{1/2}$
Mean Red Band	Mean red band value
Mean NIR Band	Mean NIR band value
Std. Dev. Blue Band	Standard deviation of blue band
Std. Dev. NIR Band	Standard deviation of NIR band
Length/Width	Object length divided by object width

Vegetation objects from the Level 1 segmentation and classification were used to derive vegetation metrics at the EA level. Values for the proportion of vegetation patches and mean size of vegetation patches were derived for each EA and are depicted in Figure 3.

The second segmentation was at a coarser level (i.e., larger objects) at which EAs were grouped in an attempt to form neighborhood units. For Level 2 segmentation, feature inputs were either vegetation patch fraction or vegetation patch size features. To allow segmentation of the Level 1 summary results directly, it was necessary export the Level 1 objects into an ArcGIS® shapefile (*.shp), convert them to a raster layer, and import them back into Definiens as if they were a spectral layer. To constrain the Level 2 segmentation, the EA boundary file was imported in vector format and was an input to the segmentation routine as a thematic layer (along with the vegetation patch features). A large scale parameter was used to generate objects that were only limited in size by the EA boundaries. This ensured that aggregated segments conformed to EA boundaries and that resultant segmentation products directly represented maps depicting potential neighborhood boundaries.

To limit the generation of unrealistically large neighborhood objects, a size-constrained iterative segmentation procedure was also tested. After initial segmentation using a scale factor of 15 (Shape = 0.3; Compactness = 1.0), objects smaller than an empirically defined threshold (200,000 m^2) were allowed to aggregate further in subsequent segmentations. The scale factor was increased sequentially from 100 to 1,000 in increments of 100.

A simpler and more direct approach to aggregating EAs was also tested using the Merge function of Definiens software. This function employs topological and feature similarity criteria to group adjacent image segments. The topological criterion is simply that only objects sharing a common boundary can be merged and the spectral criterion is a simple linear distance measure for input features. In this case, the features were vegetation patch proportion and mean patch size for each EA. As with the selection of segmentation parameters, the merge distance factor was optimized through interactive modification according to visual examination of aggregated EA boundaries. The objective was to minimize the number of newly formed neighborhood objects, while avoiding elongated or low compactness objects.

Spatial correspondence of the five image-derived neighborhood maps was compared with the reference map that had been derived from the spatially aggregated slum index (census-based) data. This provided a relative assessment of the potential utility of the image-derived maps for representing actual neighborhoods in Accra, given that there is no absolute definition or delineation of neighborhoods at this time. We assessed spatial correspondence by comparing summary statistics and through spatial correspondence overlay analysis. Summary statistics included number, mean

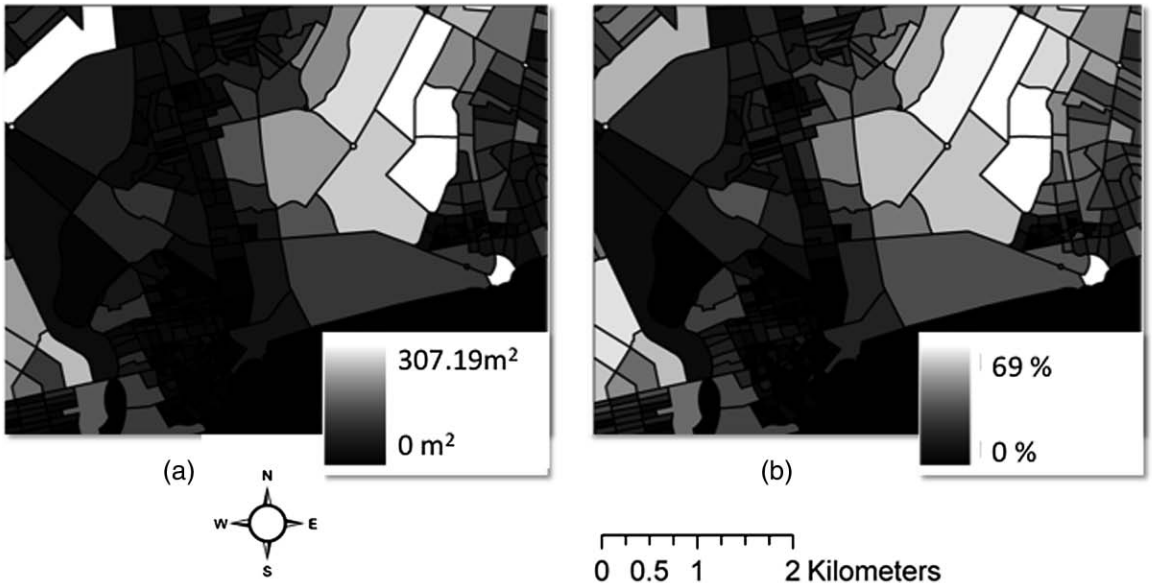

Figure 3. Maps of (a) mean vegetation size, and (b) vegetation proportion and for EAs within the Accra, Ghana study area. Vegetation proportions and size data were estimated from patch-level segmentation and classification of QuickBird multi-spectral image data.

size, and range of sizes of neighborhood units. Spatial correspondence analysis was challenging to perform since the image-derived and reference maps represent polygons that delineate possible neighborhoods, but have no attributes or labels associated with them. With the census-derived map as the reference, the mean number of image-derived neighborhood polygons contained within each reference map polygons was tabulated by determining centroids for image-derived polygon and counting centroids contained within each reference polygon. A smaller average number of contained centroids indicates greater correspondence with the reference map, since the image-derived maps tended to represent a greater number of neighborhood polygons (i.e., fewer EAs were aggregated).

Results

The five image-derived maps representing potential neighborhood boundaries are shown relative to the reference map in Figure 4f. It is apparent in Figure 4 that more neighborhoods are portrayed on the image-derived maps than the reference map, except for the map derived by size-constrained iterative segmentation. Stated differently, fewer EA aggregations resulted from the merging or segmentation of the QuickBird-generated vegetation patch objects than for the aggregation of the Slum Index. The map generated from the size-constrained iterative segmentation procedure applied to QuickBird-estimated vegetation proportions is visually most similar to the reference map. This is the case because the procedure aggregated more EAs than those used to generate the other image-based maps. In general, maps derived using segmentation were more similar to the reference map than those generated with the merge approach, and maps based on vegetation proportion inputs were more similar to the reference map than those based vegetation size feature inputs.

The size-constrained iterative segmentation map and the reference map appear to represent similar size units that have different shape configurations, but neither map appears to better represent actual neighborhoods. The size-constrained iterative segmentation approach better identified EAs that mostly consisted of government and other institutional land-use from residential areas, whereas the slum index map tended to group these units with EAs composed of high SES residential areas. Low SES neighborhoods seem to be more fragmented on all maps than our ground reconnaissance suggests is realistic, as a consequence of incomplete aggregation of numerous small EAs in these densely populated areas. The shape representation criteria of the image segmentation approach to aggregation yielded neighborhood units that have more smoothly varying boundaries than those depicted on the reference map or the spectral merge products.

Table 2 lists summary statistics and Table 3 spatial correspondence analysis results from the comparison of the five image-derived maps of neighborhood units with the reference map. Both tables substantiate the findings from the visual analysis of map products. The map based on size-constrained iterative segmentation of vegetation proportions was more similar to the reference map in terms of the number and size of potential neighborhoods, while the other four image-derived maps depicted many more, smaller units. Spatial correspondence analysis results show that the map derived with size-constrained iterative segmentation was similar in terms of number and size of units, and on average, 1:1 image-derived units were contained within a reference map unit, which implies a high level of agreement. However, the only exact, one-to-one matches were larger EAs that had not been aggregated.

Conclusions

Our evaluation of approaches to delineating neighborhoods of a large city in a developing country is a unique application of GEOBIA. In fact, few attempts at delineating neighborhoods based on remotely sensed imagery (Zhou, 2006) and none pertaining to intra-urban regionalization studies are evident in the remote sensing literature. Such an application

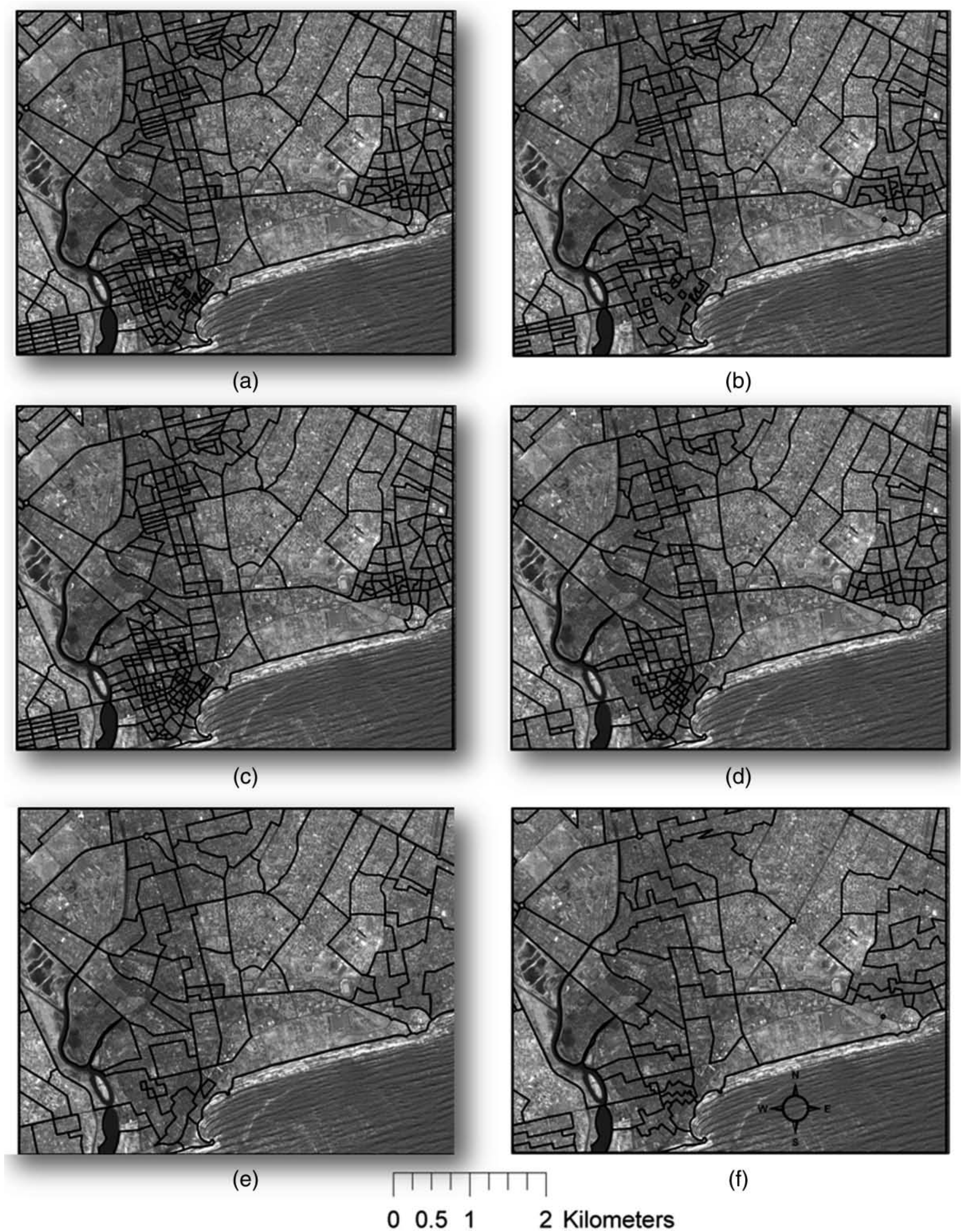

Figure 4. QuickBird image-derived and census-derived maps of potential neighborhood units based on aggregation of enumeration areas (EAs) for the Accra study area: (a) feature distance merge approach based on vegetation patch proportions, (b) feature distance merge approach based on mean vegetation patch sizes, (c) segmentation approach based on vegetation patch proportions (d) segmentation approach based on mean vegetation patch sizes, (e) size-constrained iterative segmentation approach based on vegetation patch proportions, and (f) reference map derived with EA Slum Index values (based on census data) and aggregation using the Duque (2006) spatial clustering technique.

Table 2. Summary Statistics for Polygon Units in Neighborhood Maps

Aggregation approach-Feature input	No.	Mean Size (m^2)	Std. Dev. Size (m^2)
Reference	79	273,827	429,728
Spectral merge-veg %	286	115,441	234,821
Spectral merge-veg size	432	68,892	152,561
Segmentation-veg %	184	116,701	240,995
Segmentation-veg size	309	69,565	159,124
Size-constrained iterative segmentation-veg %	69	314,068	330,642

Table 3. Spatial Overlay Correspondence of Image-derived Neighborhood Maps Relative to the Reference Map. Values Represent Number of Image-derived Polygon Centroids within Reference Polygons. Smaller Values Imply Greater Spatial Correspondence.

Aggregation approach-feature input	Mean	Standard Deviation	Maximum
Spectral merge-veg %	2.53	2.64	16
Spectral merge-veg size	4.14	3.82	23
Segmentation-veg %	2.47	2.27	9
Segmentation-veg size	4.08	3.38	11
Size-constrained iterative segmentation -veg %	1.01	1.42	8

is particularly challenging given the vagueness associated with the meaning and definitions of neighborhoods and therefore, the difficulty in assessing the validity and utility of image-derived maps of neighborhoods. Even the map evaluation phase of this study required development of novel methods for comparing maps of neighborhood boundaries.

We tested two approaches to aggregating census units (EAs) to form potential neighborhoods, based on commercial GEOBIA software. An EA-constrained image segmentation approach to aggregation was more successful than a simple polygon merge technique that was based solely on the similarity of image-derived features between contiguous EAs. The segmentation approach is capable of accounting for size and shape characteristics, which enables more realistic neighborhood boundaries to be delineated. Further refinement of the EA-constrained segmentation procedure was required to achieve a reasonable map of neighborhood boundaries that more closely approximated a reference map. The refinement entailed constraining or limiting the size of EAs that were aggregated through segmentation, and sequentially increasing the size constraint in an iterative fashion. The reference map was derived from census data by calculating a slum index and then spatially aggregating EAs using spatial clustering routine.

While many image-derived feature inputs were explored initially, two vegetation features based on patch-level segmentation of urban objects showed the most promise and were tested. The percentage of vegetation patches within each EA was a better discriminant for delineating potential neighborhoods than mean vegetation patch size per EA. Vegetation proportions within residential neighborhoods tend to be greater for higher SES residential areas and can be readily estimated and mapped using QuickBird or other visible/NIR optical image data.

This study is a first step towards semi-automated, image-based delineation of urban neighborhoods based on high spatial resolution image data. While it is appropriate to start with a parsimonious approach that is based on aggregation of EAs, particularly when the primary available reference data were derived in a similar manner, the ultimate objective is to delineate neighborhoods from the pixel up, based on GEOBIA techniques. Until such objectives are realized, visual image interpretation of high spatial resolution imagery provides an immediately available and likely successful means for delineating neighborhoods, particularly when conducted by interpreters who are generally familiar with the neighborhoods of a city. As neighborhood definitions become more specific and train/test data are available through field surveys and resident interviews, the ability to more automatically delineate neighborhoods will likely be realized.

Acknowledgments

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