International Journal of Remote Sensing
Vol. 28, No. 22, 20 November 2007, 5167–5173

Letter

Object-based classification of residential land use within Accra, Ghana based on QuickBird satellite data

D. STOW*, A. LOPEZ, C. LIPPITT, S. HINTON and J. WEEKS
Department of Geography, San Diego State University, San Diego, CA 92182-4493, USA

(*Received 23 May 2007; in final form 31 July 2007*)

Downloaded By: [Ingenta Content Distribution TandF titles] At: 22:33 8 April 2009

A segmentation and hierarchical classification approach applied to QuickBird multispectral satellite data was implemented, with the goal of delineating residential land use polygons and identifying low and high socio-economic status of neighbourhoods within Accra, Ghana. Two types of object-based classification strategies were tested, one based on spatial frequency characteristics of multispectral data, and the other based on proportions of Vegetation–Impervious–Soil sub-objects. Both approaches yielded residential land-use maps with similar overall percentage accuracy (75%) and kappa index of agreement (0.62) values, based on test objects from visual interpretation of QuickBird panchromatic imagery.

1. Introduction

Recent studies suggest that intra-urban variations of poverty and health in developing countries may be greater than differences between urban and rural populations (Montgomery and Hewett 2005). Ongoing studies based on census and health surveys attempt to integrate fine spatial resolution satellite data to assess spatial variations in poverty and health within Accra, Ghana (Weeks *et al.* 2006, 2007). However, reporting units associated with census and health data for Accra cover different spatial extents, creating the phenomenon known as the Modifiable Area Unit Problem (MAUP) (Openshaw 1983). This means that disparate data sets should be aggregated and analysed at a common spatial scale. Residential land-use data may be an effective basis for generating analytical units, since the location where people reside is the primary basis for capturing census and individual health data. Alternatively, the proportion of residential land use within analytical units may offer an effective means to standardizing census and health data. There are many other reasons for mapping residential land-use distribution, and differences in the socio-economic characteristics of neighbourhoods will permit more accurate estimates of population distributions and more reliable identification of residential areas most in need of public health interventions. Image segmentation and object-based classification processes applied to fine spatial resolution satellite imagery provide a promising approach to creating maps of urban land use (Herold *et al.* 2003).

The primary objective of this Letter is to assess the effectiveness of image segmentation and hierarchical classification applied to fine spatial resolution satellite

*Corresponding author. Email: stow@mail.sdsu.edu

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online © 2007 Taylor & Francis
http://www.tandf.co.uk/journals
DOI: 10.1080/01431160701604703

data for delineating residential land use polygons and identifying socio-economic status. A secondary objective is to determine appropriate image input features for classifying residential land use and socio-economic status. The question of whether residential land-use objects are best categorized by directly incorporating multi-spectral data, or indirectly by first delineating and classifying land-cover sub-objects and then estimating land-cover proportions is addressed. Definiens (formerly known as eCognition) commercial image-classification software was applied to QuickBird multispectral satellite data covering most of the city of Accra, Ghana.

2. Data and methods

A cloud-free QuickBird satellite image captured on 12 April 2002 was purchased that covers an extent of 18 km (E–W) $\times$ 13 km (N–S), encompassing all but approximately 20% of the Accra Metropolitan Area (AMA). Both multispectral (2.4 m) and panchromatic (0.6 m) images were purchased, with the multispectral data being used for image-classification tests and the panchromatic data for validation. 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 classification.

A bottom-up, hierarchical segmentation strategy with three levels of image objects was implemented. Such an approach may be appropriate for fine spatial resolution data of urban scenes, where land-use objects are composed of numerous land-cover sub-objects that exhibit a wide range of spectral signatures. The finest level (Level 1) represents land-cover sub-objects in the urban scene, Level 2 corresponds to land-use sub-objects, and Level 3 to the final land-use map objects (i.e. polygons). (This numerically bottom-up hierarchical scheme follows that of the Definiens software documentation and is opposite to the top-down numbering convention of the United States Geological Survey Land Use/Land Cover Classification system (Anderson *et al.* 1976).) A bottom-up hierarchical structure is appropriate here, as a key component of this study is whether or not image-derived objects can be classified with greater accuracy when based on the amount and distribution of land-cover patches contained with land-use polygons. For example, in Accra, land-use polygons for high socio-economic areas tend to have more patches of landscape vegetation, while low socio-economic residential polygons contain many small patches of soil and impervious land covers.

Image inputs (i.e. features) to segmentations at Levels 1 and 2 were the four multispectral wavebands, NIR, red, green, and blue (in order of input). The segmentation routine is based on a fractal net evolution algorithm, a type of region growing approach (Yu *et al.* 2006). It is controlled by both scale (size of segment) and shape (compactness and smoothness characteristics of segments) parameters that are adjusted in an interactive, trial-and-error fashion. For Level 1 segmentation, these parameters were modified to achieve a realistic segmentation of land-cover sub-objects, such that the roofs of the smallest residential dwellings were delineated. This was achieved with a Scale Factor of 10 and Shape Factor of 0.7, with equal (0.5) Compactness and Smoothness parameters. For Level 2, parameters were optimized interactively by delineating the smallest residential land-use units (i.e. small neighbourhoods), resulting in the selection of Scale Factor=150, Shape Factor=0.7, with Compactness and Smoothness set at 0.5.

Downloaded By: [Ingenta Content Distribution TandF titles] At: 22:33 8 April 2009

Downloaded By: [Ingenta Content Distribution TandF titles] At: 22:33 8 April 2009

Two types of object-based classification strategies were tested, one based on spatial frequency characteristics of multispectral data for pixels within neighbourhood-size segments, and the other on proportions of Vegetation–Impervious–Soil (V–I–S) sub-objects (e.g. smaller segments) within neighbourhood-size segments. The first strategy (Strategy 1) is simpler and involves less processing (i.e. negates the need for the Level 1 segmentation and classification steps), while the second strategy (Strategy 2) attempts to exploit the hierarchical nature of land-cover objects nested within land-use objects.

Segments (objects) were classified using the fuzzy membership function classifier. (A standard nearest-neighbour classifier was also tested, but preliminary classification trials showed that the fuzzy membership classifier yielded superior results.) Level 1 classes used in classification Strategy 2 consisted of three land-cover types, Vegetation (V), Impervious (I), and Soil (S), following the V–I–S urban land-cover system developed by Ridd (1995). Two Impervious subclasses, Dark and Bright, were also included. Mean segment values for the four QuickBird multispectral wavebands were the primary image features incorporated in the Level 1 classification. Specific statistical features and membership functions utilized for the classification phase were based on graphical and statistical analyses of training sample data.

Level 2 categories were Low Residential, High Residential, and Non-residential, where Low and High refer to socio-economic status. Due to the diversity in non-residential land use/land-cover types within Accra, the Non-residential class consisted of five subclasses, Agriculture, Parks and Forests, Wetlands, Major Roads, and Industrial/Commercial/Institutional. As with the Level 1 classification, mean values of the four QuickBird wavebands were incorporated as image features for classifying Level 2 objects for Strategy 1. Proportions of V–I–S sub-objects within the Level 2 objects were also tested as input features for Strategy 2, with both presence/absence rules and graded membership functions being incorporated. The supervised optimization routine of Definiens software (called Feature Space Optimization) was utilized for both Level 2 classification approaches to guide interactive adjustment of fuzzy membership functions. The Level 3 (final) product was generated by merging adjacent segments belonging to the same class.

Final products resulting from the two classification strategies were subjected to an object-based accuracy assessment and to an alternative validation approach. Reference data for the accuracy assessment were based on on-screen, visual interpretation of the QuickBird panchromatic image by an interpreter who is familiar with the land use of Accra. Randomly selected Level 2 objects were delineated on-screen and manually interpreted. The land-use categories determined from the object-based image classification and visual interpretation for each test object were compared to generate an error matrix and accuracy statistics.

Spatial correspondence of the two image-derived maps was compared with each other and with an alternative map of residential socio-economic status based on census data. Census data for reporting units called Enumeration Areas were categorized as Residential or Non-residential based on a population density threshold of 400 people/km^2. A Slum Index map was generated by summing three census variables that UN-Habitat defines as being related to the degree of slum development: (1) percentage of households with running water, (2) percentage of households with a toilet connected to a sewer system, and (3) percentage of households with three or more persons per room, as shown in figure 1(*d*). A Slum

Downloaded By: [Ingenta Content Distribution TandF titles] At: 22:33 8 April 2009

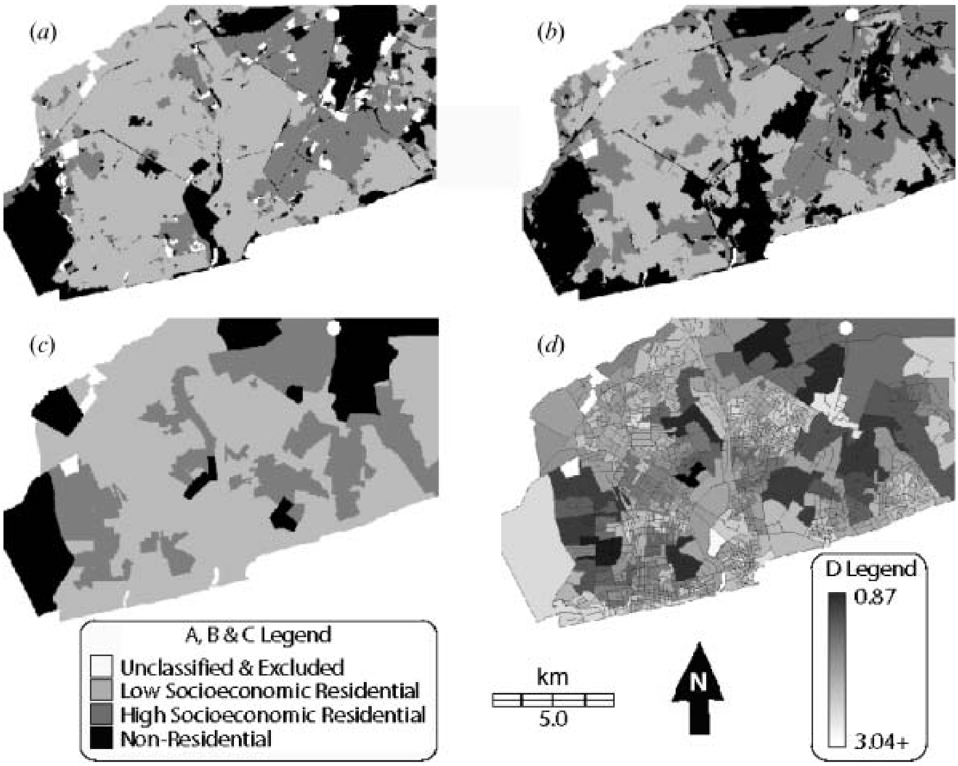

Figure 1. Residential land-use maps of Accra, Ghana. (*a*) Derived from V–I–S sub-objects from QuickBird data; (*b*) derived from multi-spectral QuickBird data; (*c*) derived from categorization of census-based Slum Index; (*d*) continuous value Slum index map derived from census data.

Index threshold of 1.99 (out of 3.00) was selected to separate Low and High Socio-Economic, based on the histogram of Slum Index values for all Residential EAs. The resultant map had the same categories as the image-based classification maps, though the arbitrary map units (Enumeration Areas) were generally larger than land-use objects derived from the QuickBird data. Spatial correspondence between the maps was examined visually and by polygon overlay analysis using Idrisi Andes software.

3. Results and discussion

The residential land-use maps of Greater Accra derived with the multispectral and V–I–S sub-object proportion feature inputs are shown in figures 1(*a*) and 1(*b*), respectively. The object-based classification approach was effective in producing more generalized and realistic-appearing land-use maps that are devoid of mixed- and boundary-pixel effects that result from per-pixel classifiers. While both maps portray realistically the spatial distribution of residential land use and socio-economic household status in Accra, the map based on V–I–S sub-objects contained several unclassified segments due to ambiguous membership scores, while the multispectral-based map had none. A greater proportion of the V–I–S map was classified as Low SE Residential, while High SE Residential and Non-residential proportions were greater on the map derived from multispectral features.

Error matrices and accuracy statistics for the two residential land use maps based on 36 Level 2 test objects (an approximately 1% sample) are presented in tables 1–2. The overall accuracy and kappa index of agreement (KIA) of the two maps were essentially identical, with 75.0% and 0.624 for the map based on multispectral features and 75.0% and 0.619 for the map derived from V–I–S sub-objects, respectively. When based on pixel counts for the same test objects, the overall accuracy and KIA were 80.3% and 0.636 for the map based on multispectral features, and 90.9% and 0.790 for the map derived from V–I–S sub-objects. The pixel count statistics are influenced by the relative size of the test objects, and the higher accuracy estimates suggest that larger test objects were classified more accurately than smaller objects.

The most frequently occurring type of error pertained to the Non-residential class being confused with the two residential types, with minimal confusion between residential types. This confusion between residential and non-residential types likely reflects the common occurrence of mixed residential–commercial land-use types in

Downloaded By: [Ingenta Content Distribution TandF titles] At: 22:33 8 April 2009

Table 1. Accuracy matrix–Class agreement of test segments for residential land-use map derived with QuickBird multi-spectral data and membership function classifier relative to visually interpreted QuickBird panchromatic imagery.

Map/reference	Low SE	High SE	Non-residential	Sum	User's accuracy
Low SE	9	0	0	9	100%
High SE	1	7	4	12	58%
Non-residential	4	0	11	15	73%
Sum	14	7	15		
Producer's accuracy	63%	100%	73%		

Overall agreement=75.0%; Kappa index of agreement=0.624. SE=socio-economic.

Table 2. Accuracy matrix–Class agreement of test segments for residential land-use map derived with land cover sub-objects from QuickBird data and membership function classifier relative to visually interpreted QuickBird panchromatic imagery.

Map/reference	Low SE	High SE	Non-residential	Sum	User's accuracy
Low SE	12	1	3	16	75%
High SE	0	6	2	8	75%
Non-residential	2	0	9	11	82%
Unclassified	0	0	1	1	
Sum	14	7	15		
Producer's accuracy	86%	86%	60%		

Overall agreement=75.0%; Kappa index of agreement=0.619; SE=socio-economic.

Table 3. Results from spatial correspondence analysis between two QuickBird-derived maps and residential land-use map generated from census data.

Residential land-use maps	Overall	KIA
V–I–S vs. slum index	68.4%	0.435
Multi-spectral vs. slum index	56.9%	0.328
Multi-spectral vs. V–I–S	73.8%	0.724

Accra, often within the same building. The higher accuracy of the HSE residential class for both maps is due to the high proportion of landscape vegetation in HSE neighbourhoods, relative to areas with LSE residential and built non-residential land uses that primarily consist of impervious and soil land-cover types.

The spatial correspondence between the two image classification maps and the categorized Slum Index map (shown in figure 1(*c*) and table 3) is modest. The overall and KIA agreement were 66.0% and 0.436 for the map derived using V–I–S features and the map derived from census data, while 56.9% (KIA=0.328) of the map from multispectral classification was in agreement with the census-based map. The agreement and KIA between the two image-derived maps were 71.8% and 0.532, respectively.

Downloaded By: [Ingenta Content Distribution TandF titles] At: 22:33 8 April 2009

4. Conclusions

The key findings from this initial exploration of object-based classification of residential land use and socio-economic status for a major urban centre in equatorial Africa are as follows:

- Image segmentation combined with a hierarchical, object-based classification is an appropriate approach for semi-automated mapping of residential land use based on fine-spatial-resolution multispectral satellite image data, such as from the QuickBird satellite.
- The proportion of V–I–S land-cover sub-objects within Level 2 (neighbourhood scale) objects yielded a map with an accuracy that was essentially identical to the map based on multispectral waveband features as input, though the distribution and patterns of general land-use types were different.
- Though accuracies based on test objects were similar for the two object-based classification products, qualitative and quantitative comparisons with a map generated from census indicators of socio-economic status showed a closer agreement to the map based on V–I–S land-cover sub-objects.
- The primary remotely sensed indicator of residential socio-economic status in Accra is the presence of landscape vegetation.
- Determining residential from other built land-use types in Accra is challenging because of multiple uses of buildings (e.g. commercial and residential).

Acknowledgements

This research was funded partially by grant number R21 HD046612-01 from the National Institute of Child Health and Human Development. Field support in Accra was provided by Raphael Arku and Innocent Deno. Debbie Fugate assisted with census data processing and analysis.

References

Anderson, J.R., Hardy, E.E., Roach, J.T. and Witmer, R.E., 1976, A land use and land cover classification system for use with remote sensor data. *US Geological Survey Professional Paper 964*.

Herold, M., Liu, X. and Clarke, K.C., 2003, Spatial metrics and image texture for mapping urban land use. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 991–1001.

Montgomery, M. and Hewett, P.C., 2005, Urban poverty and health in developing countries: household and neighborhood effects. *Demography*, **42**, pp. 397–425.

Openshaw, S., 1983, *The Modifiable Areal Unit Problem* (Norwich, UK: Geo Books).

RIDD, M., 1995, Exploring a V–I–S (vegetation–impervious surface–soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities. *International Journal of Remote Sensing*, **16**, pp. 2165–2185.

WEEKS, J.R., HILL, A.G., GETIS, A. and STOW, D., 2006, Ethnic residential patterns as predictors of intra-urban child mortality inequality in Accra, Ghana. *Urban Geography*, **27**, pp. 526–548.

WEEKS, J.R., HILL, A.G., STOW, D., GETIS, A. and FUGATE, D., 2007, Can we spot a neighborhood from the air? Defining neighborhood structure in Accra, Ghana. *GeoJournal*, **68**, in press. Available online at www.springerlink.com (accessed 4 October 2007).

YU, Q., GONG, P., CLINTON, N., BIGING, G., KELLY, M. and SHIROKAUER, 2006, Object-based detailed vegetation classification with airborne fine spatial resolution remote sensing imagery. *Photogrammetric Engineering & Remote Sensing*, **72**, pp. 799–811.

Downloaded By: [Ingenta Content Distribution TandF titles] At: 22:33 8 April 2009