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The effect of input data transformations on object-based image analysis

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Abstract

The effect of using spectral transform images as input data on segmentation quality and its potential effect on products generated by object-based image analysis are explored in the context of land cover classification in Accra, Ghana. Five image data transformations are compared to untransformed spectral bands in terms of their effect on segmentation quality and final product accuracy. The relationship between segmentation quality and product accuracy is also briefly explored. Results suggest that input data transformations can aid in the delineation of landscape objects by image segmentation, but the effect is idiosyncratic to the transformation and object of interest.

1.0 INTRODUCTION

In response to the broad availability of high spatial resolution remote sensing data and the subsequent evocation of the “H” resolution scene model (Strahler et al. 1986), object-based image analysis (OBIA) is becoming more prevalent than at any other time in its greater than 30-year history (Rosenfeld and Davis 1979, Woodcock and Harward 1992, Blaschke and Strobl 2001, Benz et al. 2004, Blaschke et al. 2008). While a variety of techniques and software have been presented as OBIA (See Blaschke et al. 2008 for review), the regionalization (i.e., segmentation) of image data is a principal step to OBIA, typically followed by classification and generalization operations (Rosenfeld and Davis 1979). Segmentation determines the spatial units, and subsequently the scale at which image analyses are conducted, and therefore has potential to affect the accuracy of all subsequent analysis and final products (Openshaw 1984, Addink et al. 2007). Image segmentation is the foundation to most OBIA; the effect of segmentation quality on potential OBIA product accuracy has recently been noted by several authors (e.g., Addink et al. 2007, Kim et al. 2009, Liu and Xia 2010).

This study investigates the effect of incorporating spectral transform images on the accuracy of segmentation (i.e., how well segmentation boundaries reflect the boundaries of objects of interest in the scene) and final product accuracy. We hypothesize that spectral transformations (e.g., principal components, vegetation indices, material fractions derived through spectral mixture analysis) can improve segmentation accuracy, and subsequently final product accuracy, when compared to spectral data alone. To test this hypotheses, we compare segmentations of QuickBird multispectral imagery of Accra, Ghana in the context of mapping urban land cover objects. Several data transformations commonly used to enhance landscape object discrimination in remote sensing data are explored: principal

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components analysis (PCA), spectral mixture analysis (SMA) (Adams et al. 1986) of vegetation, impervious, and soil fractions, and two common vegetation indices: normalized difference vegetation index (NDVI), and visible atmospherically resistant index (VARI) (Gitelson et al. 2002). To permit quantitative comparison of segmentation results we validate segmentation quality using an area-based error analysis in a manner proposed by Zhan et al. (2005). The relationship between segmentation accuracy and final product accuracy is preliminarily assessed using least squares regression. Collectively, this research explores the effect of varying input data on segmentation quality and, subsequently classification products generated using OBIA techniques.

This study was conducted within the context of a larger effort to assess the feasibility of mapping health indicators in Accra, Ghana using remote sensing data. Specifically, the study is motivated by the need to accurately delineate the relative proportion of trees and buildings within neighborhoods of the Accra metropolitan area for use as indicators of social phenomena relating to health outcomes (Stow et al. 2010).

2.0 BACKGROUND

OBIA offers profound advantages over traditional pixel-based classification methods, particularly for high spatial resolution image data. It permits the use of image information beyond 'color', 'tone', and 'time' (e.g., shape, pattern, shadow, association/site) (Benz et al. 2004), represents an explicit implementation of the H-resolution scene model (Strahler et al. 1986), and has been shown to offer improved classification accuracies over pixel based approaches in many applications (Neubert and Meinel 2003, Bocka et al. 2005).

Most OBIA techniques rely on image segmentation to delineate image regions, on which all subsequent analyses are performed (Abkar et al. 2000, Baatz and Schape 2000, Blaschke and Strobl 2001, Hay et al. 2003, Benz et al. 2004). The segments define the unit of analysis, and therefore affect not only the accuracy of classification results (Addink et al. 2007), but according to modifiable area unit problem (MAUP), can determine the results (Openshaw 1984). There have been attempts to identify the "intrinsic scale" of image objects (Hay et al. 2003, p. 328), but most research has relied on trial and error to set parameters that delineate regions corresponding to landscape objects of a given minimum mapping unit (Benz et al. 2004, Moller et al. 2007).

Definiens multi-resolution (Baatz and Schape 2000, Benz et al. 2004) segmentation results are affected by both user specified constraint parameters (i.e., scale factor H , shape vs. color weighting, and compactness vs. smoothness weighting) and the data on which segmentation is based. The multi-resolution image segmentation algorithm within Definiens employs a region-based, local mutual best fitting approach (see Baatz and Schape 2000 for details). Several authors have investigated the effect of the Definiens multi-resolution user parameters on segmentation and classification accuracy (Lucieer and Stein 2002, Neubert and Meinel 2003, Moller et al. 2007), but research interrogating the utility of spectral transformations for image segmentation is rare (Trias-Sanz et al. 2008).

Segmentation is typically performed on panchromatic or multi-spectral waveband inputs (Definiens 2003, Hay et al. 2003, Benz et al. 2004), but there is evidence that spectral transform inputs may yield more reliable image segmentation results (Trias-Sanz et al. 2008). Given this, and the established ability of input transformations to improve image classification (Pereira 1999), change detection (Rogan et al. 2002), and image based material measurement, (Small 2001, Stow et al. 2005), we investigate the effect of several common remote sensing data transformations (i.e., SMA, PCA, NDVI, and VARI) on segmentation and final OBIA product accuracy. Table 1 provides a summary of the spectral transformations tested in this study.

3.0 METHODS

QuickBird multispectral image data with 2.4 m spatial resolution were acquired 12 April 2002 for most of Accra, Ghana (see Figure 1) and used to derive transformations for all segmentation and classification analysis. Linear spectral unmixing (an approach to SMA) was conducted on a per-pixel basis using four *in situ* endmembers: Vegetation, Dark Impervious, Bright Impervious, and Soil (Ridd 1995, Wu and Murray 2003). Vegetation indices and principal components 1-3 were derived using ERDAS Imagine 9.3, while SMA was conducted in ENVI 4.5.

Pan-sharpened (~ 0.6 m) multispectral data were used to derive reference data for the segmentation and classification processes. Ten segmentation calibration objects for each of the two dominant landscape features, trees and buildings, were generated by heads-up digitizing based on visual interpretation of pan-sharpened Quickbird false color infrared composite images. Selection of calibration objects for segmentation was constrained to objects ranging from 40-80 pan-sharpened multispectral (0.6 m) pixels in size and were selected to represent the various object-background combinations represented in the scene.

Each transformed image was segmented individually. Within the Definiens professional 5.0 software, multi-resolution segmentation parameters (i.e., *scale*, *shape/color*, and *smoothness/compactness*) were manipulated iteratively to optimize the segmentation products through visual comparison with associated calibration objects by boundary coincidence with the segment of dominant overlap. Table 2 shows the parameters used to generate the “optimal” segmentation for each transformation input type.

Segmentation products were validated using 10 randomly selected independent reference objects for each object type. Segmentation validation objects were selected under the same constraints as segmentation calibration objects. Objects of maximum overlap were compared to reference objects and area of overlap, omission error, and commission error were calculated as percentages of the union of reference and segmented objects and are summarized in Table 3. Figure 2 illustrates the calculation of area overlap, omission error, and commission error.

Land cover classification was conducted on all segmentation results using a nearest neighbor (Euclidean distance) classifier on the four multispectral segment means, to ensure that differences in final product accuracy are attributable only to differences in segmentation. Ten sample objects per class were identified based on maximum overlap with reference polygons described above. The mapped classes include: Trees, Grass, Water, Bare Soil, Asphalt, and Building. The Building class was classified as Bright Building, Dark Building, and Composite Building sub-classes, and grouped into a single Building class in the post-classification generalization phase. While Tree and Building were the target classes, Grass, Water, Bare Soil, and Asphalt were included to improve the definition of Tree and Building classes in feature space.

OBIA products were validated using 10 randomly selected independent ground reference objects per class. Per-pixel error analysis (overall map accuracy and Kappa index of agreement) was conducted for all classes. Given that the desired information product is the relative proportion of Trees and Buildings per neighborhood and not an exact representation of the size or shape of these objects, pixel-based accuracy assessment is appropriate. Segmentation “accuracy” was then related to classification accuracy and kappa index of agreement for the Tree and Building classes via least squares linear regression.

3.0 RESULTS

Segmentation accuracy results for the Tree and Building classes are presented in Table 3. Overall classification accuracy results and results for Tree and Building classes are summarized in Table 4. Spectral transform images yielded higher segmentation accuracy when compared to multispectral data inputs (hypothesis 1), but the effect is dependent on the object and class of interest. Most transform inputs achieved higher accuracy for either tree or building segmentation at the expense of the other.

Vegetation indices resulted in relatively high tree object segmentation accuracies (NDVI = 59%, VARI = 52%) when compared to building objects (24% and 27%, respectively), while principal components transformations resulted in higher building object segmentation accuracies when compared to trees (Table 3). Relative to spectral bands, only SMA feature inputs yielded higher segmentation accuracies for buildings, while SMA and NDVI resulted in higher segmentation accuracies for trees. This suggests that transformations developed to enhance the discrimination of landscape features using pixel based techniques can aid in the delineation of those features using OBIA techniques.

Objects segmented using spectral data showed the highest overall classification accuracy and kappa (Table 4). VARI yielded higher tree class kappa values than spectral data (0.95 and 0.90 respectively). Products generated through segmentation of the first three principal components had a higher building class kappa value (0.94) than the other transformations (0.75-0.81).

Least squares trends between segmentation accuracy and overall kappa classifications suggest that there is a positive relationship between segmentation and classification accuracy, but more samples would be required to test the significance of that relationship. Positive trend lines for both the tree and building classes support the hypothesis that final product accuracies are dependent on segmentation quality, supporting the findings of other recent research (e.g., Addink et al. 2007, Liu and Xia 2010).

4.0 DISCUSSION & CONCLUSIONS

In summary, spectral transformations can improve segmentation accuracy but the improvement seems to be idiosyncratic to the object of interest and the type of transformation. The identification of image transformations appropriate for the delineation of specific landscape objects seems particularly promising; further investigation into the use of image transformations to improve segmentation quality is warranted. Segmentation accuracy can effect classification accuracy, highlighting the need to explore the quantification of segmentation quality and to define rigorous procedures for optimizing image segmentation based on the objects and scale of interest.

The correlation between segmentation accuracy and kappa for the final OBIA product is weaker than one would reasonably expect (Addink et al. 2007), particularly for the tree class; in one case (i.e., PC1, trees) a segmentation accuracy of 34% produced a kappa of 0.87. At first glance this would seem to refute the logical conclusion that product accuracy is dependent on segmentation quality (Addink et al. 2007). Note however, that segments may have been, and in many cases were, smaller than the reference object they were compared to, resulting in high omission error (e.g., PC1 and PC1-3). For segmentations that are finer scale than the objects of interest, however, there is not necessarily a loss in classification accuracy (Liu and Xia 2010), suggesting that a commission error only accuracy metric may be more appropriate for assessing the relationship between segmentation quality and final product accuracy.

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Figure 1.
Quickbird panchromatic waveband of the study region of Accra, Ghana.

Figure 2. Schematic demonstrating the estimation of segmentation product accuracy; commission (A), omission (B), and intersection estimated by comparing percentage agreement and disagreement between segment (dark) and reference objects (white).

Table 1

Description of input data transformations.

	Feature of Interest	Input Spectral Wavebands	No. of Output Data Layers
Spectral	-	1-4	4
SMA-VIS	Tree/Building	1-4	4
NDVI	Tree	3,4	1
VARI	Tree	1-3	1
PC1	Building	1-4	1
PC1-PC3	-	1-4	3

'Spectral': Quickbird multispectral wavebands 1-4

'SMA-VIS': Vegetation, Dark Impervious, Light Impervious, and Vegetation fractions produced by linear spectral unmixing

'NDVI': Normalized difference vegetation index

'VARI': Visible atmospherically resistant index

'PC1': First principal component

'PC1-PC3': First three principal components

Table 2

Definiens segmentation parameters for each spectral transformation input type.

	Scale	Shape	Compactness
Spectral	13	0.5	0.3
SMA-VIS	1	0.1	0.2
NDVI	10	0.1	0.5
VARI	10	0.1	0.5
PC1	7	0.1	0.2
PC1-PC3	5	0.1	0.2

Refer to Table 1 for variable definitions.

Table 3

Segmentation accuracy percentages based on correspondence with ten validation objects for each object type and spectral transformation.

	Buildings			Trees		
	Correct (%)	Commission Error (%)	Omission Error (%)	Correct (%)	Commission Error (%)	Omission Error (%)
Spectral	60	20	20	52	36	12
SMA-VIS	62	8	30	65	15	20
NDVI	24	74	3	59	24	17
VARI	27	70	4	52	13	35
PC1	35	8	57	35	22	43
PC1-PC3	55	7	38	47	8	45

Refer to Table 1 for variable definitions.

Table 4

Classification accuracy statistics

	5-Class Overall (%)	5-Class Kappa Index	Trees Kappa Index	Buildings Kappa Index
Spectral	94	0.92	0.90	1.00
SMA- VIS	85	0.81	0.86	0.81
NDVI	85	0.80	0.90	0.75
VARI	86	0.82	0.95	0.77
PC1	81	0.76	0.87	0.81
PC1-PC3	87	0.83	0.75	0.94

Refer to Table 1 for variable definitions.