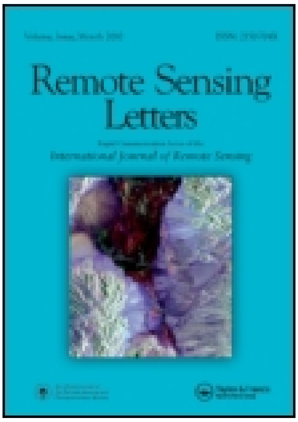


Remote Sensing Letters
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/trsl20

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

Christopher D. Lippitt [a] , Lloyd L. Coulter [a] , Mary Freeman [a] , Jeffrey Lamantia-Bishop [a] , Wyson Pang [a] & Douglas A. Stow [a]
[a] Department of Geography, San Diego State University, San Diego, CA, 92182, USA

Available online: 24 Mar 2011

*Remote Sensing Letters*
Vol. 3, No. 1, January 2012, 21–29

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

CHRISTOPHER D. LIPPITT*, LLOYD L. COULTER, MARY FREEMAN, JEFFREY LAMANTIA-BISHOP, WYSON PANG and DOUGLAS A. STOW
Department of Geography, San Diego State University, San Diego, CA 92182, USA

(*Received 9 June 2010; in final form 4 October 2010*)



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. 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). Although 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 the 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 the 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 hypothesis, 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

*Corresponding author. Email: lippitt@rohan.sdsu.edu

*Remote Sensing Letters*
ISSN 2150-704X print/ISSN 2150-7058 online 
http://www.tandf.co.uk/journals
DOI: 10.1080/01431161.2010.531059

remote sensing data are explored: principal component 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 the 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 neighbourhoods of the Accra metropolitan area for use as indicators of social phenomena relating to health outcomes (Stow *et al.* 2010).



## 2. 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 'colour', '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. colour 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.*

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 |

Notes: '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



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. Methods

QuickBird multispectral image data with 2.4 m spatial resolution were acquired on 12 April 2002 for most of Accra, Ghana (see figure 1), and used to derive transformations for all segmentation and classification analyses. Linear spectral unmixing (an approach to SMA) was conducted on a per-pixel basis using four *in situ* end-members: 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 (ERDAS Inc., Norcross, GA, USA), whereas SMA was conducted in ENVI 4.5 (ITT Visual Information Solutions, Boulder, CO, USA).

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 colour infrared composite images. Selection of calibration objects for segmentation was constrained to objects ranging from 40 to 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 (Definiens, München, Germany), multi-resolution segmentation parameters (i.e. *scale*, *shape/colour* 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 ten randomly selected independent reference objects for each object type. Segmentation validation objects were selected

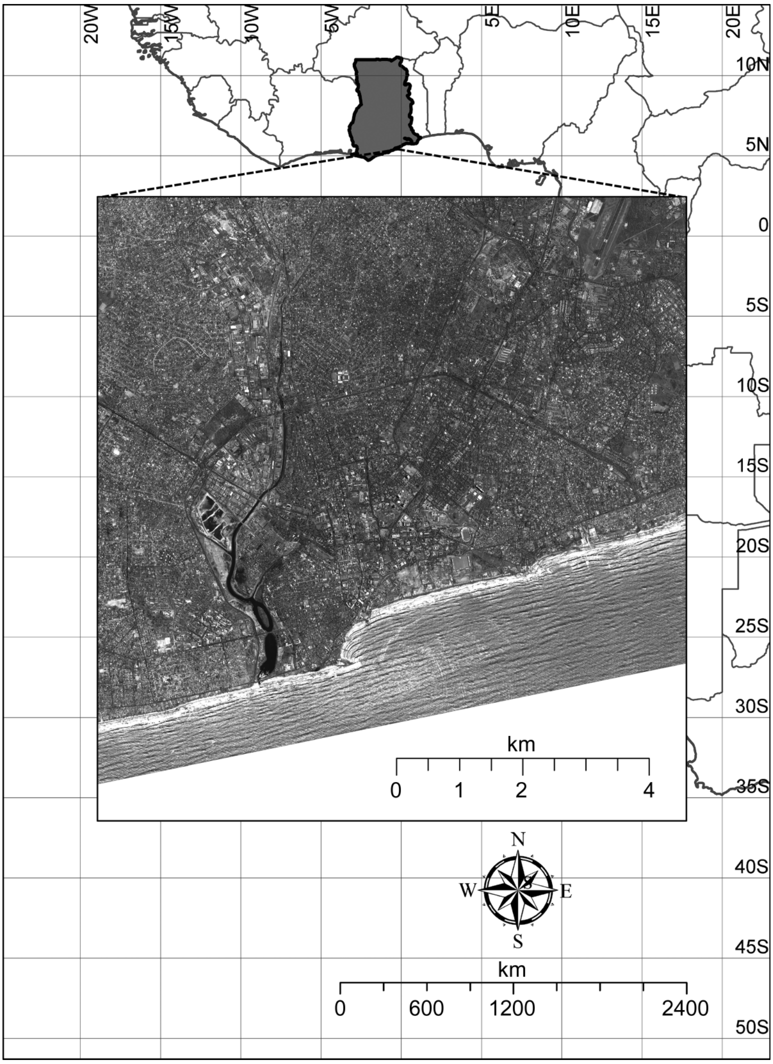


Figure 1. QuickBird panchromatic waveband of the study region of Accra, Ghana.

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 |

Note: Refer table 1 for variable definitions.

under the same constraints as segmentation calibration objects. Objects of maximum overlap were compared with 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 neighbour (Euclidean distance) classifier on the four multispectral segment means, to ensure that differences in final product accuracy are attributable only to the differences in the 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. Although 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 ten randomly selected independent ground reference objects per class. Per-pixel error analysis (overall map accuracy and kappa



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 |

Note: Refer table 1 for variable definitions.

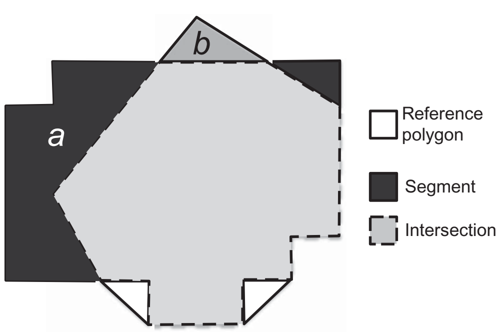


Figure 2. Schematic demonstrating the estimation of segmentation product accuracy; commission (*a*), omission (*b*) and intersection estimated by comparing percentage agreement and disagreement between segment (dark) and reference objects (white).

index of agreement) was conducted for all classes. Given that the desired information product is the relative proportion of Trees and Buildings per neighbourhood 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 through least squares linear regression.

## 4. 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 compared with multispectral data inputs, 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%) compared with building objects (24% and 27%, respectively), whereas principal component transformations resulted in higher building object segmentation accuracies compared with trees (table 3). Relative to spectral bands, only SMA feature inputs yielded higher segmentation accuracies for buildings, whereas 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).

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 |

Note: Refer Table 1 for variable definitions.

## 5. Discussion and 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 have an effect on 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 with, 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.



### Acknowledgement

This research was funded partially by grant number R21 HD046612-01 from the National Institute of Child Health and Human Development.

### References

Abkar, A.-A., Sharifi, M.A. and Mulder, N.J., 2000, Likelihood-based image segmentation and classification: a framework for the integration of expert knowledge in image classification procedures. *International Journal of Applied Earth Observation and Geoinformation*, **2**, pp. 104–119.

Adams, J.B., Smith, M.O. and Johnston, P.E., 1986, Spectral mixture modeling: a new analysis of rock and soil types at the viking lander site. *Journal of Geophysical Research*, **91**, p. 14.

Addink, E.A., De Jong, S.M. and Pebesma, E.J., 2007, The importance of scale in object-based mapping of vegetation parameters with hyperspectral imagery. *Photogrammetric Engineering & Remote Sensing*, **73**, pp. 905–912.

Baatz, M. and Schape, A., 2000, Multiresolution segmentation – an optimization approach for high quality multi-scale image segmentation. In *Angewandte Geographische Informationsverarbeitung*, **XII**, pp. 12–23.

Benz, U.C., Hoffman, P., Willhauck, G., Lingenfelder, I. and Heynen, M., 2004, Multiresolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, **58**, p. 19.

Blaschke, T., Lang, S. and Hay, G.J., 2008, Object-based image analysis: spatial concepts for knowledge-driven remote sensing applications. In *Lecture Notes in Geoinformation and Cartography*, p. 818, (London: Springer).

Blaschke, T. and Strobl, J., 2001, What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *GIS – Zeitschrift für Geoinformationssysteme*, **14**, pp. 12–17.

Bocka, M., Xofisb, P., Mitchleyb, J., Rossnerc, G. and Wissenc, M., 2005, Object-oriented methods for habitat mapping at multiple scales – case studies from Northern Germany and Wye Downs, UK. *Journal for Nature Conservation*, **13**, p. 14.

Definiens, 2003, *Definiens User Guide 4.0* (Munich, Germany: Definiens).

Gitelson, A.A., Stark, R., Grits, U., Rundquist, D., Kaufman, Y. and Derry, D., 2002, Vegetation and soil lines in visible spectral space: a concept and technique for remote estimation of vegetation fraction. *International Journal of Remote Sensing*, **23**, pp. 2537–2562.

Hay, G.J., Blaschke, T., Marceau, D.J. and Bouchard, A., 2003, A comparison of three image-object methods for the multiscale analysis of landscape structure. *ISPRS Journal of Photogrammetry and Remote Sensing*, **57**, pp. 327–345.

Kim, M., Madden, M. and Warner, T.A., 2009, Forest type mapping using object-specific texture measures from multispectral Ikonos imagery: segmentation quality and image classification issues. *Photogrammetric Engineering & Remote Sensing*, **75**, pp. 819–829.

Liu, D. and Xia, F., 2010, Assessing object-based classification: advantages and limitations. *Remote Sensing Letters*, **1**, pp. 187–194.

Lucieer, A. and Stein, A., 2002, Existential uncertainty of spatial objects segmented from satellite sensor imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **40**, pp. 2518–2521.

Moller, M., Lymburner, L. and Volk, M., 2007, The comparison index: a tool for assessing the accuracy of image segmentation. *International Journal of Applied Earth Observation and Geoinformation*, **9**, pp. 311–321.

Neubert, M. and Meinel, G., 2003, Evaluation of segmentation programs for high resolution remote sensing applications. In *Proceedings of the Joint ISPRS/EARSeL Workshop 'High Resolution Mapping from Space 2003*', 6–8 October 2003, Hannover, Germany, p. 8.

Openshaw, S., 1984, Ecological fallacies and the analysis of areal census-data. *Environment and Planning A*, **16**, pp. 17–31.

Pereira, J.M.C., 1999, A comparative evaluation of NOAA/AVHRR vegetation indexes for burned surface detection and mapping. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 217–226.

Ridd, M.K., 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.

Rogan, J., Franklin, J. and Roberts, D.A., 2002, A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. *Remote Sensing of Environment*, **80**, pp. 143–156.

Rosenfeld, A. and Davis, L.A., 1979, Image segmentation and image models. *Proceedings of the IEEE*, **67**, p. 8.

Small, C., 2001, Estimation of urban vegetation abundance by spectral mixture analysis. *International Journal of Remote Sensing*, **22**, p. 29.

Stow, D., Lippitt, C.D. and Weeks, J., 2010, Delineation of neighborhoods of Accra, Ghana based on Quickbird satellite data. *Photogrammetric Engineering & Remote Sensing*, **76**, pp. 907–914.

Stow, D., Niphadkar, M. and Kaiser, J., 2005, MODIS-derived visible atmospherically resistant index for monitoring chaparral moisture content. *International Journal of Remote Sensing*, **26**, pp. 3867–3873.

Strahler, A.H., Woodcock, C.E. and Smith, J.A., 1986, On the nature of models in remote-sensing. *Remote Sensing of Environment*, **20**, pp. 121–139.

Trias-Sanz, R., Stamon, G. and Louchet, J., 2008, Using colour, texture, and hierarchial segmentation for high-resolution remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, **63**, pp. 156–168.

Woodcock, C. and Harward, V.J., 1992, Nested-hierarchical scene models and image segmentation. *International Journal of Remote Sensing*, **13**, pp. 3167–3187.

Wu, C. and Murray, A.T., 2003, Estimating impervious surface distribution by spectral mixture analysis. *Remote Sensing of Environment*, **84**, pp. 493–505.

Zhan, Q.M., Molenaar, M., Tempfli, K. and Shi, W.Z., 2005, Quality assessment for geo-spatial objects derived from remotely sensed data. *International Journal of Remote Sensing*, **26**, pp. 2953–2974.