Integrating rule-based approach and urban density index for improving object-based urban land cover classification using WorldView-2 Data

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Abstract

This study aimed at evaluating the potential of using WorldView-2 high resolution multispectral data in detailed urban land cover classification. The classification was performed in three stages. The first stage consisted of object-based support vector machine (SVM) classification resulting in eleven land cover classes with 88.48% overall accuracy and 0.86 Kappa coefficient. The generated land cover classes include high and low density built-up areas, open and bare land, forest, paved and unpaved road, urban green space, water and flooded wetland. The second stage aimed at developing and applying a series of geometric rules for classification refinement. A slight increase of classification accuracy with 1.75% was achieved and the confusion between low and high density built-up areas could be decreased significantly. The third stage consisted of developing an urban density index based on post-classification segmentation performed based on a road network classified during the first stage. The proportion occurrence of land cover categories in each produced segment was determined and a 0.65 threshold value was empirically chosen for assigning value to either urban or non-urban class. This resulted in increasing the classification from 88.4% to 90.7% and in decreasing the confusion between low and high density built-up areas by 20%. It was found that the synergy among trained multispectral and panchromatic bands, ruleset, texture features and urban index led to higher classification accuracies and reduction in spectral variability within each land cover class.

Keywords: Object-based image analysis, Rule-based approach, Urban density index, Kigali, Rwanda

1 Introduction

Since 2015, 54% of the 7.3 billion World population are residing in urban areas and it is expected that 66% of the world's population will be urban by 2050 (United Nations, 2015). In 2016, 512 cities with more than 1 million inhabitants were globally inventoried including 31 megacities (cities with more than 10 million residents). By 2030, 662 cities will have at least 1 million residents and megacities will increase up to 41 (United Nations Department of Economic and Social Affairs Population Division, 2016). Apart from being engines of economic development, cities' expansions are seen as threat to environmental sustainability (Girard et al., 2003; Kleniewski & Thomas, 2010). Land cover fragmentation, cropland reduction and impervious surface sprawl are among the associated urbanization effects. Urban footprints are also putting stress on human well-being and contribute to the deterioration of the quality of life, especially in deprived urban areas. Therefore, tracking urban development trajectories is essential for managing urbanization side-effects and for dealing with pressing urban land administration and management challenges. Up-to-date data and cost effective methods are essential for detailed urban land cover analysis, which can help in policy implementation pertaining to sustainable urban dynamics.

With the emergence of high resolution satellite data and advances in geo-computation, the production of urban land cover maps from remotely sensed images at very fine resolution is possible (Zhou & Wang, 2008). Traditional methods for information extraction from satellite images are using pixel based methods either through supervised or unsupervised classifications (Lillesand et al., 2008). Since around 2000, object-based image analysis (OBIA) is widely used for urban land cover mapping especially when processing high resolution data (Blaschke, 2010). However, the extraction of urban land cover on very high resolution data using OBIA is constrained by high variability in the same land cover class (Asner & Warner, 2003; Lu et al., 2010). Therefore, extended methods beyond training merely image bands during classification could enhance the quality of produced land cover maps. In this short communication, an extended method integrating a rule-based approach and urban density index based on a WorldView-2 multispectral high resolution image and OBIA for enhancing urban land cover classification is explored.

2 Study area and data description

The testing area in the present study was Kigali City in Rwanda. Kigali is Rwanda's capital and largest city with an estimated area covering 730km² with a population of more than 1 million (National Institute of Statistics of Rwanda, 2012). Kigali's population quadrupled from estimated 200 000 in 2002 to 1.135 million in 2012 (National Institute of Statistics of Rwanda, 2012). Urban sprawl in the urban fringe area, land cover conversion, inner city redevelopment and

impervious surface development are key transformations taking place in Kigali.

Eight spectral bands of a WorldView-2 image covering the central and Eastern part of Kigali were used in this study. The image was acquired on 15 July 2015. The study area is covering an estimated area of 281km2. A 10 by 10-meter Digital elevation model (DEM) was added the WorldView-2 multispectral bands. All inputs data were projected in Universal Transverse Mercator-36 South zone. Figure 1 represents the study area.

Figure 1: Location of the study area



Except Coastal and Red Edge all spectral bands were use in training and SVM classification. The choice of input bands was motivated by the need for reducing data dimensionality and redundant information. Table 1 summarizes the WorldView-2 spectral and spatial resolution specifications.

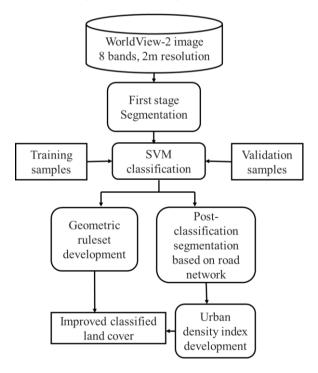
Table 1: Specifications of WorldView-2 spectral bands			
-	Spectral	Wavelength	Spatial
	bands	range (in nm)	resolution (in
_			m)
	Coastal	400 - 450	2
-	Blue	450 - 510	2
-	Green	510 - 580	2
-	Yellow	585 - 625	2
-	Red	630 -690	2
-	Red Edge	705 - 745	2
-	NIR 1	770 - 895	2
-	NIR 2	860 - 1 040	2
	Panchromatic	450 - 800	0.5

3 Methods

The image was first segmented using eCognition software for generating primitive objects (segments) that served in

selecting training samples and applying the classifier. Multiresolution segmentation algorithm was used at this stage. Selected training samples were applied using support vector machine (SVM) classifier and first step land cover map was generated with 11 land cover classes including high and low density built-up areas, open land, forest, water, paved and unpaved roads, bare land, flooded and drained wetlands and urban green space. A series of geometric rules were developed and applied for improving the first land cover map that was suffering from confusion and overlapping in land cover classes. For further classification refinement, a postclassification segmentation was performed using classified road network as inputs and urban density index map was developed. The urban density score was determined by calculating the mean value of proportional land cover type(s) in each generated segments and reclassifying the results using linear transformation with ranging value from non-urban (0) to urban (1). The 0.65 threshold value was judged appropriated for assigning an object either to urban or nonurban class. Improved land cover classification was generated after accuracy assessment and classification refinement. Figure 2 illustrates the methodology used in the present research.

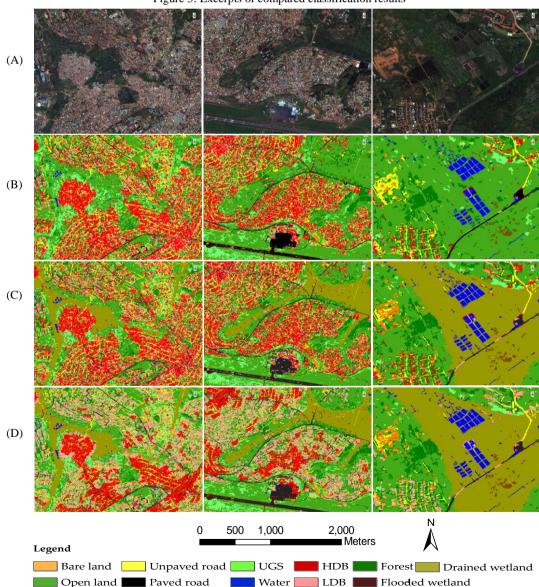
Figure 2: Methodological flowchart

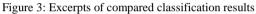


4 Results and Discussion

Training and application of SVM on segments generated based on merely multispectral band of Worldview-2 images resulted in a land cover classification with an overall accuracy of 88.49% and 0.86 Kappa Coefficient. However, low accuracy in low density built-up areas (18.9% producer's accuracy against 23.17% user's accuracy) and high overlap between high and low density built-up areas were the main drawback. While applying the geometric rules on classified land cover, the overall accuracy improved by 2% increase and the Coefficient became 0.88. The introduction of urban density index for final classification refinement resulted into 90.7% overall accuracy and 0.89 Kappa Coefficient.

Furthermore, integration of the geometric ruleset and urban density index increased the producer and user's accuracies in low density built-up areas to 64.91% and 53.8%, respectively. The overlapping between high and low density built-up classes improved significantly. Increased class separabilities are also observed in other land cover categories. In Figure 3, row (A), Worldview-2 image excerpts are shown; (B) represents the classification result without ruleset; and (C) the improved ruleset classification, especially in terms of drained wetland detection. Finally, the ruleset combined with an urban density index enhanced the over-estimation of high density built-up areas and under-estimation of low density built-up area as portrayed in (D). By referring to the research findings, detailed land cover classification with high accuracies in a complex urban environment with multiple land cover categories can hardly be achieved from high-resolution multispectral data alone when merely relying on spectral bands. Successful urban land cover classification would involve combination of different methods and techniques beyond training original bands in supervised classification approaches, given the high variability and confusion of spectral properties within the same land cover classes as recalled by (Herold et al., 2003; Lu et al., 2010). Often, improved and detailed urban land cover classifications are resulting from synergies between ruleset integration, urban index, trained visible, near-infrared and panchromatic bands, and the features included in training the object-based SVM.





5 Conclusion

The present study explored the impact of integrating geometric ruleset with urban density index for minimizing the effect of spectral variability in the same land cover class and improving the classification using a supervised support vector machine classifier. It was found that complex urban land cover environments are challenging while classifying urban features. High spatial resolution data such as WorldView-2 imagery were identified as useful input for extracting high quality information given their rich and detailed spatial information content. Nevertheless, high resolution data are affected by the spectral variability in the same land cover class while performing land cover classification. Extended method such as integration of geometric ruleset and developed urban density index are found worthwhile in urban land cover disaggregation. Advanced classifiers like support vector machine (SVM) were found robust in separating land cover class in high spectral dimensional feature space. While comparing object-based classification based on merely spectral bands and the combination of rule-based approach and urban density index, it was remarked that an improvement in land cover class separability and in overall accuracy of are achieved with integrated methods i.e. combination of spectral data with geometric ruleset and urban density index.

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References

Asner, G. P., & Warner, A. S. (2003). Canopy shadow in IKONOS satellite observations of tropical forests and savannas. *Remote Sensing of Environment*, 87(4), 521-533.

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS journal of photogrammetry and remote sensing*, 65(1), 2-16.

Girard, L. F., Forte, B., Cerreta, M., Toro, P., & Forte, F. (2003). *The human sustainable city: challenges and perspectives from the habitat agenda*: Ashgate Aldershot.

Herold, M., Liu, X., & Clarke, K. C. (2003). Spatial metrics and image texture for mapping urban land use. *Photogrammetric Engineering & Remote Sensing*, 69(9), 991-1001.

Kleniewski, N., & Thomas, A. (2010). *Cities, change, and conflict:* Nelson Education.

Lillesand, T., Kiefer, R., & Chipman, J. (2008). Digital image interpretation and analysis. *Remote Sensing and Image Interpretation*, 6, 545-581.

Lu, D., Hetrick, S., & Moran, E. (2010). Land cover classification in a complex urban-rural landscape with QuickBird imagery. *Photogrammetric Engineering & Remote Sensing*, 76(10), 1159-1168.

National Institute of Statistics of Rwanda. (2012). 2012 Population and Housing Census: Results. Kigali, Rwanda. United Nations. (2015). World population prospects: The 2015 revision (pp. 66). New York: Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, Department of Economic and Social Affairs.

United Nations Department of Economic and Social Affairs Population Division. (2016). The World's Cities in 2016 – Data Booklet (ST/ESA/ SER.A/392): United Nations.

Zhou, Y., & Wang, Y. (2008). Extraction of impervious surface areas from high spatial resolution imagery by multiple agent segmentation and classification. *Photogrammetric Engineering & Remote Sensing*, 74(7), 857-868.