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# Optimal Methodology for Detecting Land Cover Change in a Forestry, Lakeside Environment Using NAIP Imagery

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## ABSTRACT

Mapping land cover change is useful for various environmental and urban planning applications, e.g. land management, forest conservation, ecological assessment, transportation planning, and impervious surface control. As the optimal change detection approaches, algorithms, and parameters often depend on the phenomenon of interest and the remote sensing imagery used, the goal of this study is to find the optimal procedure for detecting urban growth in rural, forestry areas using one-meter, four-band NAIP images. Focusing on different types of impervious covers, the authors test the optimal segmentation parameters for object-based image analysis, and conclude that the random tree classifier, among the six classifiers compared, is most optimal for land use/cover change detection analysis with a satisfying overall accuracy of 87.7%. With continuous free coverage of NAIP images, the optimal change detection procedure concluded in this study is valuable for future analyses of urban growth change detection in rural, forestry environments.

## KEYWORDS

Change Detection, Land Cover Classification, NAIP, Object-Based, Random Tree

## INTRODUCTION

Land use and land cover (LULC) change reflects complex relationships and interactions between human activities and natural environment. Knowing and modeling LULC change can help develop related policies and satisfy important social needs, e.g. transportation planning, land management, forest conservation, ecological assessment, and urban growth management. Although land cover changes can be monitored through field survey, remote sensing imagery and methods have been widely adopted due to the capability of acquiring up-to-date information over large areas promptly. In the past, remotely sensed imagery used for LULC mapping included landsat thematic mapper (TM), Satellite Probatoired' Obsevation de la Terre (SPOT), advanced very high resolution radiometer (AVHRR), and new generation aerial photography, such as digital orthophoto quarter quads (DOQQs). Past research has proposed and tested a variety of methods and techniques for LULC change detection (Singh, 1989; Lu et al., 2004; Hussain et al., 2013). Due to the complexity of the phenomena under

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study and variations of the image used, the consensus is that different change detection approaches have different strength and weakness, and that the optimal, most applicable method often depends on the phenomenon of interest, remote sensing data used, the nature of study site, and users' needs (Ban & Yousif, 2016; Deilami et al., 2015; Tewkesbury et al., 2015).

The goal of this study is to find optimal methodology for detecting changes in a forestry, lakeside environment using 1-m, 4-band (RGB visible bands and a near infrared band) images from the National Agriculture Imagery Program (NAIP). The NAIP imagery is produced by U.S. Department of Agriculture initially for the purpose of monitoring crop growth; the imagery has the infrared band that is suitable for detecting vegetation growth and therefore is taken during the months of July or August. The advantage of using NAIP for change detection is that the images are freely available to the public and have been consistently produced every two years recently for the entire U.S. The NAIP imagery is ortho-rectified with 1-m resolution that is suitable for detecting changes at the building scale. This study intends to establish an efficient and effective procedure for future change detection using NAIP imagery.

There are two types of approaches for determining LULC distribution and change at local level: pre-classification and post-classification (Yuan et al., 1998). Two major groups of pre-classification approach are algebra-based detection and transformation-based detection. Algebra-based change detection focuses on spectral values, backscatter values, indices, texture features, and other properties, and specific methods include image differencing, changing image ratio, and change vector analysis (Chen et al., 2003). Transformation-based change detection reduces data redundancy between spectral bands and emphasizes information difference in derived components, e.g. principal component analysis (PCA) (Eklundh & Singh, 1993), iteratively-reweighted multivariate alteration detection (IR-MAD) (Griffiths et al., 2012), and minimum noise fraction (MNF) (Luo et al., 2016). These methods can detect the change but cannot provide detailed information regarding how each LULC type changes.

In contrast, post-classification comparison (PCC) methods first classify multi-temporal images individually to generate LULC maps, from which "from-to" change information is then produced (Chen et al., 2003; Singh, 1989; Van Oort, 2007). It is generally agreed that post-classification comparison is more suitable with sufficient training samples available. PCC minimizes the impacts of atmospheric, sensor and environmental differences between multi-temporal images, and provides a complete change confusion matrix. However, the accuracy of PCC is highly dependent on the result of individual classification. Classification errors may due to uncertainties in the measured phenomenon/classes, noise and distortions in images, sensor limitations in resolution (spatial, spectral, radiometric, and temporal) in detecting objects or differences (Powell et al., 2004; Ban & Yousif, 2016). Edge effects and registration errors can also cause possible errors in the classification process.

Researchers have utilized and experimented a variety of feature extraction and classification techniques for the past several decades. Traditional classification methods assign individual pixels to a specific class based on spectral and textual signature to produce LULC maps by using medium-resolution imagery, e.g. Landsat and SPOT imagery. This medium-resolution imagery often results in mixed pixels problems, in which image pixels contain two or more land classes causing confusion in classification. Mixed pixels often occur at the borders between two classes or along linear features (Powell et al., 2004; Choodarathnakara et al., 2012).

With the availability of very high spatial resolution (VHSR) imagery, e.g., IKONOS, QuickBird, and GeoEye imagery, mixed pixels problems may be reduced. Particularly, object-based image analysis (OBIA) has been used to derive detailed LULC information with higher accuracy than traditional pixel-based methods (Ardila et al., 2012; Pu et al., 2011; Puissant et al., 2012). OBIA works well on VHSR imagery in that it allows for additional variables such as shape, texture, size, and contextual information integrated for image segmentation and feature extraction (Jensen, 2009). Random trees, decision trees and nearest-neighbor classifier are typical machine learning methods for classifying objects. The accuracy and efficiency of these classification methods often depend on the imagery used. OBIA have been utilized on NAIP (National Agriculture Imagery Program) digital aerial photographs