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Assessment of the image misregistration effects on object-based change detection

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A B S T R A C T

High-spatial resolution remote sensing imagery provides unique opportunities for detailed characterization and monitoring of landscape dynamics. To better handle such data sets, change detection using the object-based paradigm, i.e., object-based change detection (OBCD), have demonstrated improved performances over the classic pixel-based paradigm. However, image registration remains a critical pre-process, with new challenges arising, because objects in OBCD are of various sizes and shapes. In this study, we quantified the effects of misregistration on OBCD using high-spatial resolution SPOT 5 imagery (5 m) for three types of landscapes dominated by urban, suburban and rural features, representing diverse geographic objects. The experiments were conducted in four steps: (i) Images were purposely shifted to simulate the misregistration effect. (ii) Image differencing change detection was employed to generate difference images with all the image-objects projected to a feature space consisting of both spectral and texture variables. (iii) The changes were extracted using the Mahalanobis distance and a change ratio. (iv) The results were compared to the 'real' changes from the image pairs that contained no purposely introduced registration error. A pixel-based change detection method using similar steps was also developed for comparisons. Results indicate that misregistration had a relatively low impact on object size and shape for most areas. When the landscape is comprised of small mean object sizes (e.g., in urban and suburban areas), the mean size of 'change' objects was smaller than the mean of all objects and their size discrepancy became larger with the decrease in object size. Compared to the results using the pixel-based paradigm, OBCD was less sensitive to the misregistration effect, and the sensitivity further decreased with an increase in local mean object size. However, high-spatial resolution images typically have higher spectral variability within neighboring pixels than the relatively low resolution datasets. As a result, accurate image registration remains crucial to change detection even if an object-based approach is used.

1. Introduction

Over the past decades, the global landscape has been continuously reshaped by rapid environmental change (Turner et al., 2007). Therefore, accurate global and regional measures of the landscape state over time are important to improve models and our understanding of the mechanisms causing this change. To date, one of the most widely used technologies for this purpose is remote sensing change detection, which takes advantage of the remote sensing capacities for broad-area synoptic coverage, high temporal frequency and relatively low-cost data acquisition, as well as the advances in digital image processing (Chen et al., 2012).

Multitemporal image registration is an essential pre-process in change detection for ensuring that detected changes are meaningful, and not simply the product of comparing two land-surface objects at different geographic locations (Townshend et al., 1992). Therefore, misregistration errors, if not adequately minimized, can severely compromise the change detection accuracy (Townshend et al., 1992; Dai and Khorram, 1998; Stow, 1999; Roy, 2000; Farin and de With, 2005). Independent studies from Townshend et al. (1992) and Dai and Khorram (1998) demonstrated that a registration accuracy of at least 0.2 pixels is required in order to achieve a change detection with less than 10% error. However, their findings were limited to the use of relatively medium- and low-spatial resolution remote sensing imagery, e.g., 28.5 m Landsat TM and 250/500 m MODIS, and classic pixel-based methods.

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Over the last decade, the amount and accessibility of high-spatial resolution (hereafter referred to as h-res) remote sensing images collected from commercial satellites and airborne platforms continued to proliferate globally. While such data sets provide us with unique opportunities for detailed characterization and monitoring of our landscape, the accuracy of change detection algorithms using the classic pixel-based methods is usually reduced by numerous small spurious changes, also called the "salt and pepper" effect (Desclée et al., 2006). To address this issue, the concept of *object-based image analysis* (OBIA) [more recently referred to as *geographic object-based image analysis* (GEOBIA)] was introduced to the change detection domain – *object-based change detection* (OBCD), where image-objects (groups of pixels) are used to model meaningful geographic objects and the task then becomes estimating the changes of image-objects rather than individual pixels (Hall and Hay, 2003; Blaschke, 2010). Improved change detection accuracies were obtained in a range of research fields, such as monitoring forest disturbances, urban development, and natural disasters (Water, 2004; Desclée et al., 2006; Chen and Hutchinson, 2007; Im et al., 2008; Li et al., 2009; Chen et al., 2012). Although OBCD appears promising, image registration remains a critical pre-process, where new challenges are also raised. Specifically, the high spatial and spectral variability of h-res imagery make it sensitive to geometric and radiometric corrections (Baltsavias et al., 2001; Chen and Hay, 2011). As a result, the same level of registration efforts may induce an even higher level of change detection error using h-res imagery. On the other hand, image-objects have proven effective in reducing small spurious changes. An immediate question is: how much these image-objects can compensate for the errors introduced by using the h-res data? It should also be noted that, different from pixels, image-objects are of various sizes and shapes, which may influence change detection accuracy in different ways, although less consideration was given to the quantitative analysis of this effect.

The primary objective of this study was to assess the impacts of misregistration on OBCD using multitemporal h-res imagery. To do so, three types of landscapes dominated by urban, suburban and rural features, were chosen to represent geographic objects of different sizes (small to large) and shapes (simple to complex). Multitemporal images were intentionally misregistered at different errors. Two change detection algorithms based on image-objects and individual pixels were applied to the study areas. Their change detection accuracies were compared and the relationships between object (size and shape) and misregistration were investigated.

2. Methods

2.1. Study areas

Three study areas, located in three counties of North Carolina, USA, were chosen to represent local major land-use/land-cover types, including (i) an urban area (4500 ha) in Mecklenburg County, (ii) a suburban area (4500 ha) in Gaston County, and (iii) an agricultural area (4500 ha) in Lincoln County (Fig. 1). These areas also signified different styles of geographic objects: (i) the urban area (City center of Charlotte and its neighbor) was characterized by high-density anthropogenic features (e.g., large commercial buildings), most of which were compact and had relatively simple roof boundaries as synoptically viewed from the sensor. The changes were mainly caused by converting old buildings/open lands into new multi-story buildings. (ii) The suburban area (south of the City of Gastonia) was dominated by low-density residential communities. High spatial interaction between anthropogenic and natural features was evident by the recent development of urban forests into single-family homes. Consequently, geographic objects, when visualized synoptically, tended to be mixed and the placement of their boundaries was more complex. (iii) The agricultural area was characterized by large farmland, where the size of each land was large and its boundary could be drawn with simple and near-linear lines. The changes were mainly attributed to phenological dynamics of local crops.

2.2. Data and preprocessing

Since all three study areas were within the extent of one SPOT image scene, this research used two dates of SPOT 5 images that were acquired on March 5, 2006 and August 2, 2011. Both images were cloud-free with similar incidence angles of 16.4° and 16.5°, and each one consisted of four 10 m multispectral bands (i.e., green, red, near infrared, and short-wave infrared) and one 5 m panchromatic band.

To retain both the image spectral values and its high-spatial resolution, a Gram–Schmidt algorithm was used to effectively fuse the multispectral channels with the panchromatic band (Laben et al., 2000; Powers et al., 2012). Although a level 2A preprocessing of radiometric and geometric corrections was applied to the individual scenes by the data vendor, minimizing spatial and spectral differences between images taken at different dates was also critical to accurate change detection. In this study, three subsets of the SPOT imagery were extracted to cover the three study areas, with each area covering 4500 ha. Each of these subsets (hereafter *image pairs*) was processed separately using the following steps. The registration was conducted using a second-order affine polynomial and a nearest-neighbor resampling method for RMSEs of 0.28, 0.25 and 0.24 pixels. Although errors still existed, they were comparatively small. In the relative radiometric normalization, linear regression was applied to match the spectral responses of the two-date images based on the digital numbers of unchanged training pixels, located mainly in the regions covered by pavements, buildings and water. This method has proven effective at correcting SPOT 5 time series, with results comparable to those using more rigorous methods, such as the classic 6S model, although fewer parameters are required in the linear regression (El Hajj et al., 2008).

2.3. Simulation of image misregistration

Geometrically, multitemporal images may contain scaling, rotation, translation, and skewing differences (Dai and Khorram, 1998), which are typically caused by one or more factors during data acquisition, such as the differences between sensor's altitudes and attitudes, other than actual landscape changes. In this research, we simplified the misregistration effect by assuming that the errors are equally distributed over the study areas. For each of the three image pairs, the simulation was conducted by intentionally shifting one image against the other at 45° with 30 different errors of $\sqrt{2}i$ pixels ($i = 1,2,\ldots,30$) in distance. For example, a pixel at the location of (x, y) was shifted to new locations of ($x + i$, $y + i$) after misregistration. This method followed a similar strategy employed by Townshend et al. (1992) and Dai and Khorram (1998). Subpixel misregistration was not performed, as the comparison of two images technically requires their basic sampling units (i.e., pixels) to spatially correspond. Thus, the shifted image will need to be resampled in a subpixel test, and altered pixel spectral values will introduce additional change detection error.

2.4. Change detection

One of the most widely used change detection methods is image differencing, where a predefined threshold is used to separate