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Robust Change Vector Analysis (RCVA) for multi-sensor very high resolution optical satellite data

Frank Thonfeld[a,b,*], Hannes Feilhauer[c], Matthias Braun[c], Gunter Menz[a,b]

[a] Remote Sensing Research Group, Department of Geography, Rheinische Friedrich-Wilhelms-Universität Bonn, Meckenheimer Allee 166, 53115 Bonn, Germany
[b] Center for Remote Sensing of Land Surfaces (ZFL), Rheinische Friedrch-Wilhelms-Universität Bonn, Walter-Flex-Str. 3, 53113 Bonn, Germany
[c] Institute of Geography, Friedrich-Alexander-Universität Erlangen-Nürnberg, Wetterkreuz 15, 91058 Erlangen, Germany

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ABSTRACT

The analysis of rapid land cover/land use changes by means of remote sensing is often based on data acquired under varying and occasionally unfavorable conditions. In addition, such analyses frequently use data acquired by different sensor systems. These acquisitions often differ with respect to sun position and sensor viewing geometry which lead to characteristic effects in each image. These differences may have a negative impact on reliable change detection. Here, we propose an approach called Robust Change Vector Analysis (RCVA), aiming to mitigate these effects. RCVA is an improvement of the widely-used Change Vector Analysis (CVA), developed to account for pixel neighborhood effects. We used a RapidEye and Kompsat-2 cross-sensor change detection test to demonstrate the efficiency of RCVA. Our analysis showed that RCVA results in fewer false negatives as well as false positives when compared to CVA under similar test conditions. We conclude that RCVA is a powerful technique which can be utilized to reduce spurious changes in bi-temporal change detection analyses based on high- or very-high spatial resolution imagery.

1. Introduction

Change detection is a key application of remote sensing technology (Hecheltjen et al., 2014). With increasing availability of multi-sensor imagery, the variety of change detection applications and methods continues to grow. Comprehensive reviews of change detection techniques can be found e.g. in Coppin et al. (2004), Hecheltjen et al. (2014), Lu et al. (2004), Radke et al. (2005), and Singh (1989). Change detection using multi-sensor satellite data has some specific challenges as the multi-temporal image data set can be affected by various factors which may lead to the identification of spurious changes. These sources of systematic errors can be related to the sensor properties or to environmental conditions. The latter include atmosphere, vegetation phenological stage, soil moisture, and tidal stage; all of which can interact and affect the detection of land cover changes in various ways (Jensen, 1996). Coppin et al. (2004) recommended to use data taken on the same day of year to minimize differences in reflectance caused by varying phenological conditions and different sun azimuth and sun zenith angles. Due to their relative phenological stability, summer or winter scenes should be preferred for bi-temporal change detection (Häme, 1991). However, the use of winter acquisitions may be limited by other phenomena such as variable snow cover, low sun elevation angles (resulting in large shadows), and leaf-off conditions. In regions without regular seasonal patterns, identifying appropriate data sets may be even more difficult.

Off-nadir capabilities of modern satellite sensors enable image acquisitions in short intervals, sometimes even daily revisits. This allows for the identification and assessment of fast changes such as floods, earthquakes, tsunamis, fires, and urban infrastructure construction and damage. Using anniversary data is often inappropriate for these applications since data availability is more important than perfect image conditions to ensure appropriate temporal coverage. These circumstances thus require a change detection approach that is capable of dealing with data that have been acquired under varying sun position and viewing angles as well as differing atmospheric and phenological conditions. When using data acquired by multiple sensors, differences in spatial, spectral, and radiometric resolution must be considered as well. Along with specific environmental conditions that affect change detection

* Corresponding author at: Remote Sensing Research Group, Department of Geography, Rheinische Friedrich-Wilhelms-Universität Bonn, Meckenheimer Allee 166, 53115 Bonn, Germany.
E-mail address: frank.thonfeld@uni-bonn.de (F. Thonfeld).

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and may be captured in any image data, off-nadir imagery typically includes additional unique characteristics. Due to differing viewing angles, off-nadir images may capture surface geometric phenomena such as horizontal layover of protruding objects, including buildings and trees (Im and Jensen, 2005). Illumination effects also impede change detection, especially under different sun positions and with increasing spatial resolution.

The majority of established change detection methods require high geometric registration accuracy at subpixel level. Image misregistration may cause image object properties to be evaluated at incorrect locations. This can lead to identification of pseudo-changes as well as the failure to identify genuine changes due to even slight dislocations of image objects (Townshend et al., 1992). Due to random platform shifts between different acquisitions, the footprints of coincident pixels of images from the same sensor are not necessarily identical, thus further complicating exact registration (Bruzzone and Cossu, 2003). Chen et al. (2014) examined misregistration effects on object-based change detection and concluded that even subpixel registration errors can result in substantial overestimation of change. A number of methods have been developed to reduce the effects of registration noise in remote sensing change detection (Bruzzone and Cossu, 2003; Gong et al., 1992; Stow, 1999). Dai and Khorram (1998) showed that precise image registration is required to achieve accurate results in per-pixel change detection, especially when using very high spatial resolution imagery with pixel sizes smaller than 10 m × 10 m. Per-pixel approaches should thus be used carefully. Carvalho et al. (2001) developed a multiresolution wavelet based change detection method that is less sensitive to registration noise and can be applied on images with different spatial resolution. Several methods were developed to consider the pixel neighborhood, for example through filtering of the difference image to reduce registration noise (Gong et al., 1992). In another approach registration noise is estimated from the contextual information in a quantized magnitude-direction space (Bruzzone and Cossu, 2003). The registration noise probability is subsequently considered for the final change/no-change decision. Im and Jensen (2005) calculated multiple correlation images in several neighborhood configurations and subsequently classified from/to changes. Castilla et al. (2009) calculated the least difference of a single band in a predefined neighborhood. Object-based approaches (Chen et al., 2014, 2012; Desclée et al., 2006; Hall and Hay, 2003; Hussain et al., 2013; Walter, 2004) are sometimes preferred over pixel-based approaches, as "sliver" polygons that show spurious changes may be distinguished from real change polygons in GIS analyses (Chen et al., 2012). Since object-based analyses require appropriate segmentation techniques to assure meaningful image objects, pixel-based change detection with subsequent segmentation of changes is an adequate alternative.

During the last years, access and availability of appropriate data sets triggered time series based change detection (Wulder et al., 2012). Time series are an adequate means to reveal and characterize processes leading to changes whereas bi-temporal change detection highlights the results of processes. Each of the methods, time series analysis and bi-temporal change detection, are reasonable in their application domain with specific pros and cons (Thonfeld et al., 2015). Here, we focus on bi-temporal change detection based on images taken under varying acquisition conditions.

Change vector analysis (CVA) (Malila, 1980) is a widely used and robust method which produces two types of change information: (1) change *magnitude* which represents the intensity of change; and, (2) change *direction* which provides information about the spectral behavior of the change vector. Although change direction information is sometimes disregarded in change detection applications, selected studies have examined it and documented its efficiency (Allen and Kupfer, 2000; Chen et al., 2003; Johnson and Kasischke, 1998; Landmann et al., 2013). Bovolo and Bruzzone (2007) provided a comprehensive theoretical framework for CVA. CVA is sensitive to radiometric and geometric distortions. Here, we aim to improve the concept by considering pixel neighborhood in the change detection methodology. The objective of this study is to combine the advantages of CVA, i.e., providing information about intensity and nature of change, and robustness to differences in viewing geometries or registration noise. This extended CVA-based change detection method is called Robust Change Vector Analysis (RCVA).

Table 1
Sensor and acquisition characteristics of Kompsat-2 and RapidEye.

	Kompsat-2	RapidEye (RE-2)
date of acquisition	2010/04/06	2009/24/05
acquisition time (UTC)	08:57:35	11:29:16
off-nadir angle	10.19° (east)	8.28° (east)
orbit	ascending	descending
spatial resolution	4 m (1 m pan)	6.5 m
blue	450–520 nm	440–510 nm
green	520–600 nm	520–590 nm
red	630–690 nm	630–685 nm
red edge	–	690–730 nm
nir	760–900 nm	760–850 nm
pan	500–900 nm	–
radiometric resolution	10 bit	12 bit

2. Data and study site

Our study site includes parts of the city of Cologne, North Rhine-Westphalia, Germany. The site covers an area of 8.25 × 4.25 km^2. It is composed of several land cover and land use types including densely populated urban areas, rural settlements, industrial districts, transportation infrastructure, parks and recreation areas, water bodies, and agricultural fields. The site was selected because changes due to the phenological stage of the vegetation and building construction occurred during the study period.

A RapidEye scene from May 24, 2009 and a Kompsat-2 image acquired on June 4, 2010 were used for this exemplary analysis. The sun-target-sensor geometries of the two images differ considerably. Although the image dates are close to the anniversary, the images show a 2.5 h difference in acquisition time of day. In addition, the two scenes were acquired in different orbital path directions: RapidEye on descending, Kompsat-2 on ascending path. This leads to a rather complex sun-target-sensor constellation (Fig. 1). As shown in Fig. 1, distinct viewing angles θ and θ' and azimuth angles α and α' caused by the different overflight paths and times lead to dislocation of identical features and to different shadow proportions and positions. RapidEye and Kompsat-2 also have distinct spectral coverage and spatial resolution characteristics (Table 1). Image bands with similar spectral definitions (blue, green, red, and near infrared) were selected for use in the analysis. The Kompsat-2 panchromatic band and the red-edge band of RapidEye were not utilized.

3. Methods

3.1. Problem formulation

Off-nadir sensing is a common capability in recent satellite sensor systems. However, the sensor viewing angle has a significant effect on the orthorectification of remotely sensed images (Aguilar et al., 2013; Toutin, 2004). Assuming identical environmental conditions for both data sets used in bi-temporal change detection, sun-target-sensor geometry becomes the critical variable affecting distortions in the satellite imagery. In general, the sun-target-sensor geometries of two images to be compared are