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Review Article

Change detection from remotely sensed images: From pixel-based to object-based approaches

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ABSTRACT

The appetite for up-to-date information about earth's surface is ever increasing, as such information provides a base for a large number of applications, including local, regional and global resources monitoring, land-cover and land-use change monitoring, and environmental studies. The data from remote sensing satellites provide opportunities to acquire information about land at varying resolutions and has been widely used for change detection studies. A large number of change detection methodologies and techniques, utilizing remotely sensed data, have been developed, and newer techniques are still emerging. This paper begins with a discussion of the traditionally pixel-based and (mostly) statistics-oriented change detection techniques which focus mainly on the spectral values and mostly ignore the spatial context. This is succeeded by a review of object-based change detection techniques. Finally there is a brief discussion of spatial data mining techniques in image processing and change detection from remote sensing data. The merits and issues of different techniques are compared. The importance of the exponential increase in the image data volume and multiple sensors and associated challenges on the development of change detection techniques are highlighted. With the wide use of very-high-resolution (VHR) remotely sensed images, object-based methods and data mining techniques may have more potential in change detection.

1. Introduction

In remote sensing (RS) applications, changes are considered as surface component alterations with varying rates. Land-cover (LC) and land-use (LU) change information is important because of its practical uses in various applications, including deforestation, damage assessment, disasters monitoring, urban expansion, planning, and land management. Singh (1989) defined change detection (CD) as *"the process of identifying differences in the state of an object or phenomenon by observing it at different times"*. The CD frameworks use multi-temporal datasets to qualitatively analyze the temporal effects of phenomena and quantify the changes. The RS data has become a major source for CD studies because of its high temporal frequency, digital format suitable for computation, synoptic view, and wider selection of spatial and spectral resolutions (Chen et al., 2012a; Coops et al., 2006; Lunetta et al., 2004). The general objectives of CD in RS include identifying the geographical location and type of changes, quantifying the changes, and assessing the accuracy of CD results (Coppin et al., 2004; Im and Jensen, 2005; Macleod and Congalon, 1998).

Developing CD methods in RS is an ongoing research agenda. The principle behind using RS data for CD is that changes in the object of interest will alter the spectral behavior (reflectance value or local texture) that is separable from changes caused by other factors (e.g. atmospheric conditions, illumination and viewing angles, and soil moistures) (Deer, 1995; Green et al., 1994; Jensen, 1983; Singh, 1989). The CD from RS data is affected by various elements including spatial, spectral, thematic and temporal constraints, radiometric resolution, atmospheric conditions, and soil moisture conditions (Jensen, 2005). Different CD techniques have been developed in the past, depending on the requirements and conditions. However, the selection of the most suitable method or algorithm for change detection is not easy in practice (Lu et al., 2004). Researchers have made enormous efforts in developing various change detection methodologies including both the traditional pixel-based (Mas, 1999) and more recently, the object-based (Araya and Hergarten, 2008).

Various CD reviews based on pixel-based analysis of RS data have been published (see e.g. Coppin et al., 2004; Deer, 1995; Jianyaa et al., 2008; Lu et al., 2004; Mouat et al., 1993; Singh, 1989) which have summarized and categorized CD techniques based on different viewpoints. A common one is grouping them into pre-classification and post-classification CD techniques

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(Chen et al., 2012c). Chan et al. (2001) categorized them as change enhancement techniques and nature-of-change techniques. Lu et al. (2004) presented a comprehensive review and grouped CD techniques into seven categories. They categorized an exhaustive list of CD studies with respect to the change domain or applications aspects. Most of these reviews cover CD techniques for coarse and relatively fine spatial resolution data such as MODIS, Landsat (MSS, TM), SPOT, and radar. However, these reviews do not extensively examine techniques and methods suitable for data from very-high-resolution (VHR) optical satellites such as IKONOS, QuickBird, GeoEye, RapidEye, EROS A and B. The object-based imaged analysis techniques are considered more suitable for VHR image data and some discussion can be found in (Blaschke, 2010; Chen et al., 2012a; Jianyaa et al., 2008; Lang, 2008).

In this paper we place the CD methodologies into two discrete groups based on the unit of image analysis. The first is the traditional/classical pixel-based, employing an image pixel as fundamental unit of analysis. The second group is the object-based method, emphasizing, first, creating image objects and then using them for further analysis. This paper is broadly organized into three parts. First pixel-based change detection (PBCD) methods are discussed followed by object-based change detection (OBCD) techniques. Also, the spatial data mining techniques are discussed for their potential for analyzing changes from RS data. The focus of this paper is to provide a review of commonly used CD methods and techniques in RS, their applications, and related issues.

2. General considerations in change detection from RS

The most generic CD schema in RS comprises, broadly speaking, (a) feature extraction (e.g. difference or ratio), and (b) decision function (operation to produce decision i.e. change vs. no-change). However, not all the methods follow it (Dreschler-Fischer et al., 1993). The CD process can broadly be split into: (a) pre-processing (b) selecting CD technique, and (c) accuracy assessment.

The pre-processing stage handles the issues related to radiometric, atmospheric, and topographic corrections, geometrical rectification and image registration. It is important to consider using data from the same sensor, radiometric and spatial resolutions and near-anniversary acquisition dates to eliminate the effects of sun angle, seasons, and phonological difference (Song and Woodcock, 2003). Corrections are required to minimize the impact caused by these factors. However, Song et al. (2001) argued that atmospheric corrections may not be required when single-date image is used for classification, but is mandatory when multi-temporal or multisensory data are used. Lu et al. (2008) argued that acquiring data from same sensor could be difficult, especially in moist tropical regions which necessitate using data from different sensors. Post-classification comparison for CD, however, does not have some of this strict requirement (Chen et al., 2012c).

Image registration and multi-temporal radiometric corrections are perhaps the most important and indispensable steps in CD methods. Precise geometric registration between multi-temporal images is essential to avoid largely spurious results, as image displacement will cause false change areas in the scene. A sub-pixel level geometrical registration accuracy is generally required by most of the CD studies (Jianyaa et al., 2008). Higher registration accuracy becomes more important when data is from different sensors and at different resolutions. The higher registration accuracy requirement can be avoided in some CD methods such as object-based ones, where "buffer detection" algorithms can be applied to compare the extracted features (Deren et al., 2003).

Radiometric corrections rectify errors caused by the variation in sensor characteristics, atmospheric condition, solar angle, and sensor view angle to maintain the radiometric consistency (Chen et al., 2005; Du et al., 2002). Different radiometric correction methods are developed. The absolute radiometric correction (ARC) extracts the absolute reflectance of scene targets at the surface of the earth. The relative radiometric correction/normalization (RRC) reduces atmospheric and other unexpected variation among multiple images by adjusting the radiometric properties of target images to match a base image (Janzen et al., 2006; Yuan and Elvidge, 1996). The RRC include methods such as dark object subtraction (Chavez, 1988), Pseudo Invariant Features (PIF) (Chen et al., 2005), automatic scattergram controlled regression (ASCR) (Elvidge et al., 1995), Ridge method (Song et al., 2001), and second simulation of the satellite signal in the solar spectrum (6S) (Vermote et al., 1997).

It is also important to consider the change dependency on the temporal factor before collecting RS data for CD. Data collected too early would not cover the slower change process; data collected too late would be prone to excessive omission error and would have a significant impact on the completeness of CD (Lunetta et al., 2004).

Selecting appropriate CD technique is related to the objectivity of the study. Some techniques such as image differing or ratioing can only provide change/no-change (binary) information. If detailed change matrix (change direction) is required for a study, different techniques such as post-classification will be needed. Another viewpoint is to select a CD technique based on the unit of image analysis. Many pixel-based CD methods, which have been used traditionally, are not considered appropriate for VHR RS data, in which object-based analysis may be used more frequently. A variety of algorithms have been developed based on both the pixel- and object-based approach which provide a wider selection range (Lu et al., 2011).

The size of the study area and the spatial resolution can also significantly impact the selection of CD technique. The spatial resolution in RS typically corresponds to the pixel size. The pixel size represents the scale through which landscape is viewed and modeled (Aplin, 2006; Marceau, 1999; Woodcock and Strahler, 1987). Typically, low resolution images are used to monitor the changes over larger areas. At the national and global change mapping, the coarser spatial resolution data, including NOAA's Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), is increasingly used (Coppin et al., 2004). At the regional level, per-pixel based methods, using medium spatial resolution image such as Landsat Thematic Mapper (TM), are used. VHR RS data (e.g. QuickBird, IKONOS, OrbView) is used for local scale studies as it provides greater spatial resolution. The pixel-based techniques face a challenge posed by higher spectral variation and mixed pixels on these VHR data (Aplin, 2006; Chen et al., 2012a). More recently, object-based methods are more commonly used for CD at the local scale (Lu et al., 2011). Table 1 summarizes the different CD techniques.

3. Pixel-based change detection (PBCD) in remote sensing

A pixel has been the basic unit of image analysis and CD techniques since the early use of RS data. An image *pixel* is the atomic analytical unit in these techniques whose spectral characteristics are exploited to detect and measure changes mostly without considering the spatial context. Most often statistical operators are used for evaluating the individual pixel. Researchers have reviewed the pixel-based approaches, in greater depth, summarizing functionalities, advantages and disadvantages (see e.g. Coppin et al., 2004; Deer, 1995; Ilsever and Ünsalan, 2012; Lu et al., 2004; Singh, 1989).

Different pre-classification CD techniques based on image algebra have been developed including: (a) image differencing, (b) image ratioing, (c) regression analysis, (d) vegetation index

Table 1
Summary of different change detection techniques.

Technique	Sub-class	Approach	Advantages	Limitations	Examples
Pixel-based	Direct comparison	Image differencing	• Simple • Easy to interpret results	• No complete matrices of change information • Optimal threshold selection • The difference value is absolute. Therefore same value may have different meaning depending on the starting class • Binary (change vs. no change)	Urban land cover changes at the urban fringe from SPOT HRV imagery (Quarmby and Cushnie, 1989) Change detection in forest ecosystems (Coppin and Bauer, 1996)
		Image ratioing	• It better handles calibration (including sun angle, shadow and topography impact) errors (Rignot and van Zyl, 1993)	• No complete matrices of change information • Non-normal distribution of results • Binary (change vs. no change)	Environmental change using Landsat (Howarth and Wickware, 1981)
		Regression analysis	• It accounts for differences in the mean and variance between pixel values for different dates, therefore reduces the adverse effects by atmospheric conditions and sun angles (Singh, 1989)	• Accurate regression functions for the selected bands needed • It is better suited for measuring the conversion from one type to other and poor for detecting subtle changes (Coppin et al., 2004)	Logistic regression to model changes from forest to non-forest (Ludeke et al., 1990) Tropical deforestation change measuring (Singh, 1986)
	Transformation / from Image	Vegetation index differencing	• Reduces impacts of topographic effects and illumination	• Random or coherence noise • Binary (change vs. no change)	Detection of forest harvest type (Wilson and Sader, 2002) Change detection in a Swedish mountain range (Nordberg and Evertson, 2005) Land cover change in the United Arab Emirates (Sohl, 1999)
		Change vector analysis (CVA)	• Process any number of spectral bands desired • Produce detailed change detection information • Beneficial when; (a) either change of interest and their spectral manifestation are not well-known, (b) change of interest is known or has high spectral variability, and (b) even if the changes in both land cover type and condition may be of interest (Johnson and Kasischke, 1998)	• Difficult to identify land cover change trajectories • Strictly Require the remotely sensed data acquired from the same phonological period (Chen et al., 2003)	Land cover monitoring (Johnson and Kasischke, 1998) Land-Use/Land-Cover Change Detection (Chen et al., 2003) Forest change detection (Nackaerts et al., 2005) Disaster assessment (Bayarjargal et al., 2006)
		Principal component analysis (PCA)	• Data redundancy reduction • Emphasizes different information in the derived components	• Scene dependent making it difficult to interpret and label for different dates • Does not differentiate between change types; rather, it reports on areas that have changed (binary change)	Brush-fire damage and vegetation regrowth (Richards, 1984) Land-cover change (Byrne et al., 1980) land-use change detection and analysis (Deng et al., 2008)
		Tasselled cap transformation (KT)	• Data redundancy reduction • Scene Independent • Produces stable spectral components which allows developing baseline spectral information for long-term studies	• Difficult to interpret and label change information • No complete matrices of change	Analysing forest disturbances (Jin and Sader, 2005) Vegetation change (Rogan et al., 2002)
		Texture analysis based	• Statistical explanation to the spatial distribution of the image pixels • Settlements have higher texture value compared to the non-settlement areas • Measure relative frequency of the spatial adjacency	• Dependent on window size	Urban Disaster Analysis (Tomowski et al., 2011) land use change detection (Erener and Düzgün, 2009)
	Classification based change detection	Post-classification comparison	• Atmospheric, sensor and environmental impact reduction • Complete matrices of change • Also minimizes the impact of using multi-sensor images	• Require accurate and complete training data set • Final accuracy is dependent on classification accuracy of individual image	Land use land cover classification and change (Miller et al., 1998; Yuan et al., 2005) Urban Sprawl measuring (Ji et al., 2006) Change detection by unsupervised classification (2000; Ghosh et al., 2011)
		Multi-date direct comparison	• One classification for stacked data • Atmospheric correction is not needed	• Difficulty in labeling the change classes • Do not provide complete change matrix (Jensen, 2005)	Land-cover change detection (Lunetta et al., 2006)

(continued on next page)

Table 1 (*continued*)

Technique	Sub-class	Approach	Advantages	Limitations	Examples
	Machine Learning	Artificial Neural Network	• ANN is non-parametric supervised algorithm • Estimate data properties based on training data	• The main issues with ANN include: (a) the hidden layer in ANN is not known properly; (b) the amount of training data is important in teaching the network; and (c) ANN functionalities are not common in image processing software	Forest change detection (Woodcock et al., 2001) Urban change model (Pijanowski et al., 2005) Land-cover change (Abuelgasim et al., 1999; Dai and Khorram, 1999) Urban change (Liu and Lathrop, 2002)
		Support Vector Machine	• Non-Parametric and no assumption on data distribution • Able to handle small training data sets and often produces higher classification accuracy than the traditional methods (Mantero et al., 2005) • Theoretically can handle larger data sets with higher dimensionality and is particularly used for hyper-spectral image classification (Melgani and Bruzzone, 2004)	• Difficulty in choosing the best kernel function • The computational time for classification and achieving optimization during the learning phase increases polynomially with the increase of data dimensionality (Habib et al., 2009)	Land cover change detection (Nemmour and Chibani, 2006) Forest cover change analysis (Huang et al., 2008)
		Decision Tree	• Non-Parametric and no assumption on data distribution • Can provide rule set for change and no-change classes	• Sensitive to training data quality and the number of training samples per class, and they can be "over-trained" such that the model is not applicable to datasets from other areas or time periods (Lippitt et al., 2008) • Do not search for optimal fit • Can grow much larger in sizes and make it difficult to interpret	Land cover change analysis (Im and Jensen, 2005)
	GIS	GIS Integration	• Allows to access ancillary data from GIS to help image interpretation and analysis • Updating GIS Database	• Data quality from different sources • Different geometric accuracies	Land use change (Pijanowski et al., 2002) Land cover change (Xiuwan, 2002)
	Advanced Methods	Spectral mixture analysis	• Identifies suitable endmembers • Defines suitable thresholds for each land-cover • The results are stable, accurate and repeatable • Capable to recover natural ecosystem change signals at much finer event scales, e.g. thinning in forest ecosystems (Coppin et al., 2004)	• Complex method • Time-consuming	Land-cover change analysis (Versluis and Rogan, 2009) Post-fire vegetation regrowth detection (Solans Vila and Barbosa, 2010)
		Fuzzy Change Detection	• Objectively defines threshold • Allow a probabilistic class membership may provide a more appropriate representation than a conventional 'hard' classification	• Labeling change among a matrix of many overlapping classes may be difficult or non-informative (Kennedy et al., 2009)	Topographic map revision (Metternicht, 1999) Unsupervised change detection (Bruzzone and Prieto, 2000) Landscape change analysis (Fisher et al., 2006)
		Multi-sensor data fusion for change detection	• Allow to take advantage of different sensor to detect different objects • In time series analysis helpful when one of the sensors may not be available	• Different spatial and spectral resolution need developing fusion strategies	Land use change detection (Deng et al., 2008)
Object based	Direct Object comparison based	Objects extracted from one image and the assigned to or searched from image data from second acquisition	• Straightforward comparison of objects • Ease of implementation • Image objects have same geometric properties at two times • Change geometrical propertied (shape parameters i.e. border length, size) • Change by spectral or extracted features (texture) • Easy integration to GIS	• Dependent on the accuracy of the segmentation • Do not provide 'from–to' change • Difficulty in searching spatially corresponding objects in multi-temporal images • Appropriate threshold selection when comparing objects based on both the geometry and spectral or extracted features	Change detection from pair of Gray-Level Images (Miller et al., 2005) Change detection to grassy strip (Lefebvre et al., 2008) Landscape change detection (Hall and Hay, 2003)
	Object classification comparison based	Two segmentation created separately and compared	• All the available objects could be used for object-based change detection	• Difference in sizes and correspondence of image objects from multi-temporal images because of segmentation	Forest Change detection (Desclée et al., 2006) Land cover and land use change analysis (Gamanya et al., 2009) Updating the Land Cover Database (Xian and Homer,

Table 1 (*continued*)

Technique	Sub-class	Approach	Advantages	Limitations	Examples
			• Allows thematic, geometric and topological change measure • Change based on classification comparison • Completer from-to change matrix (Chen et al., 2012a)	• When searching for objects extracted from one image in a second image, locational error can cause incorrect change results • Dependent on the accuracy of the segmentation • Classification accuracy influences the change detection accuracy	2010)
	Multitemporal-object change detection	Stacked Bi-temporal images	• Single segmentation of all the stacked images • Image objects have same geometric properties at two times • Exploit the geometrical, spectral, and derived features to create change trajectories	• Results in some artifacts that may result from misregistration and differences in shadowing between dates • Do not provide new/different objects that might be created at different times because of change	Forest change detection (Desclée et al., 2006) Change detection from time series(Bontemps et al., 2008)
Spatial data mining	Data mining of remote sensing images		• Allow to search through large data sets • Search for spatio-temporal patterns • Extract knowledge and relationships • Provide advanced clustering and classification algorithms	• Difficult learning curve • No Direct integration of main stream image processing and data mining tools	Land-use change (Dos Santos Silva et al., 2008) Spatiotemporal changes (Boulila et al., 2011) Environmental change detection (Eklund et al., 2000) Combined OBIA and DM (Vieira et al., 2012)

differencing, (e) change vector analysis (CVA), (f) principal component analysis (PCA), and (g) tasselled cap transformation (KT). The level of change information derived from RS images can be categorized as: (i) detecting simple binary change (i.e. change vs. no change) [e.g. a, b, d, f], and (ii) the detailed "from-to" change (e.g. post-classification comparison) (Im et al., 2007). Getting detailed "from-to" change information is mostly required in many change analysis studies; however, a simple binary change vs. no change is often described as sufficient for many studies (Im et al., 2008a).

The classification based comparison to measure detailed change (post-classification comparison and composite or direct multi-date classification) is perhaps the most common methodology adopted in the CD studies that can involve both the pixel and object. Also, machine-learning (such as artificial neural networks, support vector machine, decision tree) and GIS-based methods have been used for change studies. A brief description of different pixel-based CD methods is described in Table 2.

4. Issues with traditional techniques

The decision function is the key element that identifies change from no-change in CD algorithms. One common approach, the application of a threshold value to differentiate change from no-change, is used in most of the CD algorithms. This technique, however, often suffers from mis- or over- detection, and selecting a suitable threshold value to identify change is difficult (Jensen, 2005; Lu et al., 2004; Xian et al., 2009; Zuur et al., 2007). Too low a threshold will exclude areas of change, and too high will include too many areas of change. Selecting an appropriate threshold is generally not clear especially for unsupervised algorithms when ground truth is not available to present prior knowledge. Algorithm fusion techniques can be used select appropriate threshold decision function as it involve in improving overall performance of the decision by combining the individual opinions to derive a consensus decision. This techniques is most often used in improving classification results (Kittler et al., 1998) and can be applied to change detection when change and no-change are treated as a binary classification problem. Melgani and Bazi (2006) fused different thresholding algorithms to achieve a robust unsupervised change detection.

Pu et al. (2008) found that the accuracy of CD was improved by setting different thresholds for positive and negative changes. The optimum threshold(s) are either identified using a trial-and-error manual method or through automatic generation and testing (Im et al., 2007; Lu et al., 2004; Rosin, 2002). The limitations of the first approach include its tendency to be labor intensive and time consuming, using only one image in the analysis, and it tests just a few (e.g., 5–10) discrete thresholds (Im et al., 2008a). Also it does not consider the spatial correlation between the neighboring pixels (Ghosh et al., 2011). Various automated threshold selection algorithms have been proposed, and Rosin and Ioannidis (2003) argued that the performance of these algorithms is scene-dependent. A calibration model that removed the limitations of the traditional approach can be found in Im et al. (2007), where, instead of fewer discrete thresholds, a continuum of thresholds are autonomously tested. Other approaches to improve the threshold selection include: fuzzy set and fuzzy membership functions (Metternicht, 1999), Bayes rule analysis (Bruzzone and Prieto, 2000), and the use of existing objects for automated threshold calculation (Bouziani et al., 2010).

The CD methods that employ classification can use both the supervised and unsupervised algorithms. The accuracy of post-classification CD is a function of the accuracy of the classification on individual images. The errors at each classification will propagate and reduce the overall accuracy of change analysis. The supervised approach uses training sets. The quality, accuracy and completeness of training data are crucial to producing higher-quality (accurate) classification and hence better CD (Erbek et al., 2004; Nackaerts et al., 2005). However, selecting high-quality training sample sets for image classification is often difficult and time-consuming, in particular for historical image data classification.. For unsupervised classification, prior knowledge of the area under investigation is not required, and therefore no prior statistics of the aforesaid classes is needed to be provided to the algorithm (Bazi et al., 2010; Melgani et al., 2002). The unsupervised classification based CD methods face difficulty in identifying and labeling change trajectories (Lu et al., 2004). The other major issue with

Table 2
Brief descriptions of pixel-based change detection techniques.

Technique	Functioning
Image differencing	Two precisely co-registered multi-temporal images are used to produce a residual image to represent changes. The difference can be measured directly from radiometric values of the pixel or on the extracted /derived/ transformed images such as texture or vegetation indices. Mathematically, the difference image is: $I_d(x,y) = I_1(x,y) - I_2(x,y)$, Where I_1 and I_2 are images from time t_1 and t_2 and (x,y) are coordinates and I_d is the difference image. Pixels with no change in radiance are distributed around the mean (Lu et al., 2005), while pixels with change are distributed in the tails of the distribution curve (Singh, 1989). Since change can occur in both directions, it is therefore up to the analyst to decide which image to subtract from which (Gao, 2009).
Image rationing	A ratio between two co-registered images is computed. Mathematically; $Ir = \frac{I_1(x,y)}{I_2(x,y)}$ Unlike in image differencing, the order of the images in the division is not important as the change results are expressed in ratios, and areas that are not changed should theoretically have a value of 1.
Image regression	The image I_2 from time (t_2) is assumed to be a linear function of image $I_1$from time (t_1). The image I_2 is taken as the "reference" image and I_1 as a "subject" image. The subject image is then adjusted to match the radiometric conditions of the reference image. A regression analysis, such as least-squares regression, can help identify gains and offsets by radiometrically normalizing the subject image to match the reference image (Lunetta, 1999). Change (I_d) is detected by subtracting regressed image from the first-date image. $\widehat{I}_d(x,y) = aI_d(x,y) + b$ $I_d(x,y) = I_d(x,y) - \widehat{I}_d(x,y)$
Vegetation index differencing	Vegetation indices are mathematical transformations designed to evaluate the impact of vegetation on observations in multispectral mode. These indices enhance the spectral differences on the basis of strong vegetation absorbance in the red and strong reflectance in the near-infrared band. For CD, generally, the vegetation indices are produced separately for two images and then standard pixel based CD (e.g. differencing or ratioing) are applied. Different vegetation indices have been developed such as: (a) ratio based, including Ratio Vegetation Index (RVI) and the Normalized Difference Vegetation Index (NDVI), (b) orthogonal indices, including Perpendicular Vegetation Index (PVI) and Difference Vegetation Index (DVI), and (c) Soil Adjusted Vegetation Index (SAVI) and modified soil adjusted vegetation index(MSAVI) (Chen et al., 1999). $RVI = \frac{n}{r}$ $NDVI = \frac{n-r}{n_r}$ $TVI = \sqrt{\frac{n-r}{n+r} + 0.5}$ $SAVI = \frac{n-r}{n-r+L}(1+L)$ $MSVI = \frac{2n+1-\sqrt{(2n+1)^2-8(n-r)}}{2}$ Where n is near infrared band and r is the red band. The L in SAVI confirms the same bound between NDVI and SAVI. Unsalan (2007) modifying RVI and NDVI by calculating angle vegetation index (Unsalan and Boyer, 2004) and developed a bi-temporal vegetation Time-Dependent Vegetation Indices (TDVI)
Change vector analysis (CVA)	It allows simultaneous analysis of multiple image bands for CD. The idea behind CVA is that a particular pixel with different values over time resides at substantially different location in the feature space (Jensen, 2005). The pixel values are treated as vectors of spectral bands and change vector (CV) is calculated by subtracting vectors for all pixels at different dates (Malila, 1980). The direction of the CV depicts the type of change whereas the magnitude of the change corresponds to the length of the CV. CVA can also be performed on the transformed data (e.g. Kauth-ThomasTransformation, KTT).
Principal component analysis (PCA)	PCA, mathematically based on "*Principal Axis Transformation*", is a transformation of the multivariate data to a new set of components, reducing data redundancy (Lillesand et al., 2008). PCA uses either the covariance matrix or the correlation matrix to transfer data to an uncorrelated set. The eigenvectors of the resulting matrices are sorted in decreasing order where first principal component (PC) expresses most of the data variation. The succeeding component defines the next largest amount of variation and is independent (orthogonal) of the preceding principal component. In PCA the assumption is that the areas of no change are highly correlated while areas of change are not. In multitemporal image analysis, the PC1 and PC2 tend to represent the unchanged areas, whereas PC3 and later PCs contain the change information (Byrne et al., 1980; Ingebritsen and Lyon, 1985; Richards, 1984). Two PCA based CD approaches are used. The first, *separate rotation,* is to acquire PCs from images separately and then use other CD technique (such as image differencing). The second is *merged approach* where bi-temporal images are merged into one set and PC is applied. The PCs having negative correlation to bi-temporal data correspond to change. Coppin and Bauer (1996) argued to examine the eigen-structure of the data and visual inspection of the combined images to analyze change types. Sometimes, to determine change type, a grouping of values in a PCA ordination plot is done; however, Zuur et al. (2007) argued that it can be inaccurate or misleading without knowledge of the actual change that has occurred.
Kauth-Thomas Transformation (KT)/Tasseled Cap transformation	The KT is orthogonalization (linear transformation) of a multiband, and multi-date dataset and differs from PCA in terms that it is fixed. These output features represent the greenness brightness and wetness. Presented by Kauth and Thomas (1976) it analyzes the structure of the spectral data, which is a function of a particular characteristic of scene classes. Unlike the PCA, MKT is not scene-dependent and uses of stable and calibrated transformation coefficients which ensures that its application is suitable between regions and across time.(Crist, 1985). The change is measured based on the brightness, greenness and wetness values (Lu et al., 2004). Gram-Schmidt (GS) is developed by modifying KT to handle multitemporal data which produce stable components corresponding to multitemporal analogs of KT brightness, greenness and wetness, and a change component (Collins and Woodcock, 1994).
Post-classification comparison	It is arguably the most obvious quantitative CD method because it provides from-to change information (Bouziani et al., 2010; Im and Jensen, 2005; Jensen, 2005). Originally used in the late 70s, it compares two classified images to generate a change matrix, it is often used as a benchmark for the qualitative evaluation of emerging CD techniques (Lunetta, 1999). In this approach, bi-temporal images are first rectified and classified. The classified images are then compared to

Table 2 (*continued*)

Technique	Functioning
	measure changes. The classes for both the images have to be identical to enable one-to-one comparison. The errors from individual image classification are propagated in the final change map, reducing the accuracy of the final CD (Chan et al., 2001; Dai and Khorram, 1999; Lillesand et al., 2008). In order to improve CD results, the classification of individual images has to be as accurate as possible.
The composite or direct multidate classification	The composite or direct multidate classification technique is among the earliest semi-automated approaches to generating land-use and land-cover change maps where a single analysis for multidate datasets is performed (Lunetta, 1999). Multi-temporal and rectified images are first stacked together. PCA technique is often applied to reduce the number of spectral components to a fewer principal components (Mas, 1999; Singh, 1989). The minor components in PCA tend to enhance the spectral contrast and represent changes (Collins and Woodcock, 1996). The temporal and spectral features have equal status in the combined dataset, making it difficult to separate the spectral changes within one multispectral image from temporal changes between images in the classification (Schowengerdt, 1983).
Machine learning	*Artificial neural networks (ANN)* algorithms for image based CD belong to the classification-based CD category. ANN algorithms are nonparametric and make no assumptions about data distribution and independency. They adaptively estimate continuous functions from data without specifying mathematically how outputs depend on inputs (Im and Jensen, 2005). ANN algorithm learns from the training dataset and build relationships (networks) between input (image) and output nodes (changes). The trained network then is applied to the main dataset to create a change map (Dai and Khorram, 1999; Gopal and Woodcock, 1996). The ANN approach can provide better CD results when land-cover classes are not normally distributed (Lu et al., 2004). The *Support Vector Machine (SVM)* is a supervised non-parametric statistical learning technique and makes no assumption about the underlying data distribution. The SVM is based on statistical learning theory which implements structural risk minimization for classification (Vapnik, 2000). When applied to stacked multi-temporal images, the change and no-change is treated as a binary clasiification problem (Huang et al., 2008). The algorithm learns from training data and automatically finds a threshold values (Bovolo et al., 2008) from the spectral features for classifying change from no-change. The *decision tree* (DT) classification algorithms are also non-parametric with no assumption about data distribution and independency. These DT algorithms build a flow-chart-like tree (hierarchical) structure in which each node represents a test on a number of attribute values, each branch represents an outcome of the test, and tree leaves represent classes or class distribution (Han et al., 2011; Larose, 2005). The classification rules at the node of the DT are based on the analysis of attribute values. Once a DT is built it can be used for classifying the unknown cases. Change vs. no-change can be treated as a binary-classification problem or a post-classification comparison can be performed to measure changes. Some other machine learning algorithms used for classification and change monitoring include; genetic programming (Makkeasorn et al., 2009), random forest(Pal, 2005; Sesnie et al., 2008; Smith, 2010), and Cellular automata (Yang et al., 2008).
GIS based	Most of the current image processing systems are either integrated or compatible with geographic information systems (GIS). GIS provides a base for data integrating, visualizing, analyzing and map producing. The flow of the data can be bidirectional, as GIS data can be used to overlay onto an image; alternatively, the results from image analysis and can be used to update the GIS data. For example, the parcel layers stored in a GIS database are used to assist classification and CD from an image (see e.g. Smith, 2008). Similarly, image data is used to update the GIS database. GIS also allows integrating past and current maps for comparison and CD. In such cases, image overlaying and binary masking may help reveal quantitatively the change dynamic in each class. Li (2010) favoured using GIS data and methods such as spatial association, spatial clustering, spatial relation, spatial distribution, spatial evolvement and spatial feature, for CD. Petit et al. (2001) presented a methodology for land cover change detection by integrating the land cover maps derived from image data. The applicability of GIS with RS integration is enhanced by the more frequent use of object-based image analysis techniques. The spatial and aspatial information about objects stored in the GIS database can play an important role when linked to the objects extracted from RS image for CD along with other image analysis (Bouziani et al., 2010). For example, Walter (2004) presented an object-based technique for CD where the training data is extracted from the GIS database to classify the image. The classified objects from the images were then compared against the objects stored in GIS to measure changes.
Texture analysis based change detection	Texture features from images are measured and compared for CD. Texture provides information about the structural arrangement of objects and their relationship with respect to their local neighborhoods (Caridade et al., 2008). Change is measured by comparing the textural values from images. Among several texture measuring algorithms, a common is a greylevel co-occurrence matrix (GLCM) which is a second order statistics (Haralick et al., 1973; Sali and Wolfson, 1992). GLCM examine the spectral as well as spatial distribution of grey values. Rather than per-pixel comparison, the image is normally divided into smaller windows; texture is calculated and comparison is done at window level. He and Wang (1991) emphasized using texture information only in conjunction with spectral data.
Multi-temporal spectral mixture analysis	Spectral mixture analysis (SMA) has been used to address the increased dimensionality (more than one target class in one pixel) because of high spectral resolution. The assumption in SMA is that multispectral image pixels can be defined in terms of their subpixel proportions of pure spectral components which may then be related to surface constituents in a scene. In a simple case, linear mixture model, endmember (scene element with a spectral response that is indicative of a pure cover type) spectra weighted by the percent ground cover of each endmember are linearly combined (Versluis and Rogan, 2009). A linear spectral mixture model is given as: $r_i = \sum_{j=1}^{n} a_{ij} f_j + e_i$ r_i = measured reflectance of a given pixel in spectral band i, n is the number of mixture components, f_j is the areal proportion, or fraction, of endmember j in r_i , a_{ij} is the reflectance of endmember j in spectral band i, and e_i is the residual, the difference between the observed (r_i) and modeled pixel values (Versluis and Rogan, 2009) Solans Vila and Barbosa (2010) argued that it is important to select the number and spectrum of the endmembers for an accurate application of SMA techniques which can be based on the image itself or use field-spectra measures in situ or in labs.

(*continued on next page*)

Table 2 (*continued*)

Technique	Functioning
Fuzzy change detection	Fuzziness deals with the ambiguity of class labeling and implies that the boundaries between different classes and phenomena are fuzzy and that there is heterogeneity within a class perhaps due to the physical differences (Lizarazo and Joana, 2010). This becomes important when there is difficulty in selecting a threshold valued to distinguish change from no-change. The results of fuzzy reasoning are not discrete and crisp, but are, rather, expressed in terms of 'probabilities' (Metternicht, 1999). It can contain elements with only a partial degree of membership. Fuzzy membership differs from probabilistic interpretation as fuzzy set is defined by a membership function (degree of membership) and the class with highest probability is interpreted as actual class. Post-classification comparison can then be applied to measure the change (Eklund et al., 2000; Fisher et al., 2006; Fisher and Pathirana, 1993; Foody and Boyd, 1999).
Multi-sensor data fusion for change detection	Acquiring RS data at varied spatial, spectral and temporal resolutions formulate an image pyramid that allows getting data at different resolutions. The data from different sensors reflect specific aspects of terrain and using data from different sensors might help identify certain properties. Although working with different sensors is not ideal, it is sometimes useful especially when time series analysis is performed and one of the sensors may not be available (Serra et al., 2003). Multispectral RS data is also useful when dealing with heterogeneous land uses and three dimensional structures especially in urban areas (Griffiths et al., 2010; Richards, 2005). Pohl and Van Genderen (1998) had argued that characteristics of fused image data depend upon the applied pre-processing and fusion techniques. The spectral content difference between low and high resolution images causes disturbances. When fusing multi-sensor data for CD the physical characteristics of the input data need to be understood in order to select appropriate processing methods and to judge the resulting data. Different pixel size affects the classification results. The classification of coarser resolution image would miss some elements appearing in VHR images. The pixel size and/or grid origin also causes geometric errors when images are overlay for CD. Petit and Lambin (2001) used GIS to resolve the inconsistencies related to the differences of the sources when they used SPOT XS and aerial photograph for land cover change analysis. They argued that the residual error in CD, attributed to the different sources, is around 3–5% and is mostly due to positional and map-making errors. Deng et al. (2008) used SPOT-5 (XS) and Landsat-7 (ETM+) data and applied PCA based CD. They reported an overall accuracy of 89.54% and 0.88 for kappa coefficient.

unsupervised classification methods, such as clustering, is the selection of the number of clusters or groups. Selecting an inappropriate number of clusters (a few or too many) influences the outcome and produces different results (Richards and Jia, 2006).

When RS data comes from different sensors, some extra problems result. Different pixel sizes affect the classification as land cover is viewed differently with varying details, depending on the pixel size. Classification of coarser resolution image will miss some elements, making it difficult to match to the elements in fine scale RS data. Also, errors in registration and scale difference because of different geometric correction would not allow an accurate overlay. The number of bands and the amount of spectral information is different in different images (Fung, 1992). Working with different sensors is not ideal, but is, however, sometimes unavoidable (Serra et al., 2003). This raises questions about selecting classification algorithms for different sensors and how to consider factors such as spatial resolution. Fung (1992) discussed that change in resolution needs the selection of proper techniques to minimize any error caused by resolution difference. It suggests that direct pixel-comparison such as image differencing and rationing would not be suitable.

The traditional CD algorithms have been commonly implemented for low- to medium- resolution imagery but are not successful for high-resolution images (Im and Jensen, 2005; Lefebvre et al., 2008). The results of pixel-based CD strategies are often limited when applied to very-high-resolution (VHR) imagery. Using VHR image data for change raises a number of challenges: (a) geo-referencing accuracy, (b) larger reflectance variability in each class, and (c) different acquisition characteristics (e.g. sensor viewing geometry, shadow effect, and illumination angle) (Wulder et al., 2008). The increased variability present in VHR images often results in too many changes being detected, known as the "salt and pepper" effect, and decreases the potential accuracy of pixel based CD approaches (Niemeyer et al., 2008).

Another important limitation of the traditional pixel-based CD approaches is the difficulty of modeling the contextual information (Blaschke and Strobl, 2001; Johansen et al., 2010). The spatial aspect of the real-world objects and their spatial relationships, along with their arrangements, are not modeled in the pixel-based analysis. This results in exclusion of the spatial context that otherwise would provide vital clues about the area under investigation. A human operator perceptually takes these parameters into consideration while visually interoperating an image and extracts useful information that is very hard to model in pixel-based strategies. This has led to the development of alternate techniques for CD from RS images.

Pixel-based strategies also lead to noisy outputs like isolated changed pixels, holes in the connected changed components or jagged boundaries (Bontemps et al., 2008). As a result, the traditional image analysis algorithms are either complemented or sometimes replaced by novel approaches.

5. Object-Based Change Detection (OBCD)

The emergence of VHR multispectral imagery and the rapid increase in computational capabilities over the last decade have challenged the traditional pixel-based image analysis (Chen et al., 2012a). It was recognized earlier (Fisher, 1997) that a pixel is not a true geographical object; rather, it is a cell representation of spectral values in a grid whose boundaries lack real-world correspondence. Addink et al. (2012) supported this idea by arguing that a pixel is not the optimal spatial unit for mapping landscape. An early discussion of going beyond pixel-based image analysis and incorporating spectral, spatial, temporal and geometrical aspects for comprehensive representation of urban structure, extraction of accurate and tangible information and CD can be found in (Longley, 2002). The high reflectance variability within individual features and the number of classes present in the high spatial-resolution image has restricted the traditional per-pixel analysis (Johansen et al., 2010). The higher spatial resolution is also linked to the mixed pixel problem, which is considered as one of the largest source of error and uncertainty in land cover CD (Boyd and Foody, 2011). The object-based image analysis (OBIA) techniques have been shown to reduce the effects of geo-referencing, higher spectral variability, and acquisition characteristics.

Object-based change detection (OBCD) techniques are part of the OBIA, (also referred to as *geographic object-based image analysis* (GEOBIA) (Castilla and Hay, 2008), which is not entirely new.

Although it dates back to the 1970s, it was not widely used mainly due to its limitations in spatial data resolution and computation (Platt and Rapoza, 2008). The advances in the recent past in geographical information technologies (GIT) along with some dedicated object-based image analysis system (such as eCognition, IMAGINE Objective, and ENVI's Feature Extraction module) have helped bring object-based image analysis to the mainstream (Addink et al., 2012; Aplin and Smith, 2008; Longley, 2002). OBIA allows the segmentation and extraction of features from VHR data and also facilitates the integration of raster-based processing and vector-based GIS (Blaschke, 2010).

The unit for analysis in the OBIA is an image object which gets richer information including texture, shape, and spatial relationships with neighboring objects and ancillary spatial data for different spatial resolution (Aguirre-Gutiérrez et al., 2012; Bock et al., 2005) allowing the exploitation of the spatial context. This is similar to a human analyst, who intuitively identifies the objects from an image rather than individual pixels by considering the different properties (e.g. size, texture, shape) and spatial arrangements of these objects to understand the semantics (Addink et al., 2012; Marceau, 1999). Inclusion of the contextual information and shape features becomes important as most of the VHR image data consists of only four multi-spectral and one panchromatic band (Johansen et al., 2008). Groups of pixels in an image make image-objects which represent meaningful objects in the scene. Ontologically, this allows the identification and extraction of real-world features more accurately and reliably from RS data on more appropriate scales. Moreover, it provide the opportunity to divide map data into homogenous objects on different spatial scales (Johansen et al., 2010). Based on the concept of image-objects and the change definition by Singh (1989), Chen et al. (2012a) defined OBCD as *"the process of identifying differences in geographic objects at different moments using object-based image analysis"*.

A significant objective of OBIA is to improve the image classification (Johansen et al., 2010; Lizarazo, 2012; Lizarazo and Joana, 2010). The OBIA based classification results are crisp and discrete, making them useful for thematic mapping and CD. OBIA based classification typically comprises: (a) image segmentation, (b) object hierarchy development (based on training data set), and (c) classification (Benz et al., 2004; Blaschke, 2010). The fundamental first step in OBIA and OBCD is extracting image-objects, which is achieved by segmentation or stratification of the images that may be applied using external information to like parcel boundaries (Addink et al., 2012). These image-objects are further used as the basic unit for developing CD strategy.

Image segmentation is at the core of OBIA, and various segmentation techniques have been developed with varying results (Neubert et al., 2006). Segmentation is not entirely new, and early discussion of it can be found in Haralick et al. (1973). The earlier developments in segmentation techniques were in machine vision aiming at the analysis of patterns, the delineation of discontinuities on materials or artificial surfaces, and the quality control of products. These algorithms were not used to classify earth observation data (Blaschke et al., 2006). Functionally, a segmentation process partitions an image into homogenous objects (segments) which are spectrally similar and spatially adjacent (Bontemps et al., 2008). During segmentation, the within-object variation is minimized compared to the inter-object variations. Conceptually, one important aspect of image segmentation is its relevance to spatial scale theory in RS which describe how local variance of image data in relation to the spatial resolution can be used to select the appropriate scale for mapping individual land use class (Woodcock and Strahler, 1987).

Most of the segmentation approaches can be grouped into either boundary or edge-based (discontinuity of pixels) or area-based (similarity of pixels) techniques (Freixenet et al., 2002). Besides these two groups, Blaschke et al. (2006) and Kohler (1981) considered pixel segmentation, which includes threshold-based segmentation, as a third group. The functioning and issues related to different segmentation techniques can be found in Baatz and Schape (2000), Freixenet et al. (2002), Geneletti and Gorte (2003), Haralick and Shapiro (1985), Jain et al. (1995), Jianqing and Yee-Hong (1994), Le Moigne and Tilton (1995), Mason et al. (1988) and Schöpfer et al. (2010).

Stow (2010) grouped OBCD strategies into post-classification comparison and multi-temporal image object analysis. Chen et al. (2012a) grouped them into: (a) image-object change detection, (b) class-object change detection, (c) multitemporal-object change detection, and (d) hybrid change detection. Niemeyer et al. (2008) described how changes in OBIA are measured based on layer features (e.g. mean, standard deviation, ratio, texture), shape features (e.g. area, direction, position), neighboring relations (e.g. sub- and super-objects), and object class membership. The CD strategies are described in Table 3.

5.1. Hybrid change detection (HCD)

Hybrid change detection refers to the use of two or more methods for CD, employing pixel or object, as discussed above. HCD are categorized as: (a) procedure-based (using different detection methods in different detection phases), and (b) result-based (using different CD methods and analyzing their results) (Jianyaa et al., 2008). HCD methods can combine the advantages of the threshold based and classification based CD methods (Lu et al., 2004). However, as several steps are involved in HCD, it remains unclear how the final change results are influenced by the different combinations of pixel-based and object-based schemes (Chen et al., 2012a).

There are various examples of HCD methods. Walter (2004) integrated GIS and OBIA for OBCD and used maximum likelihood classification (MLC). Al-Khudhairy et al. (2005) applied pixel-based PCA and image differencing to VHR Ikonos imagery. The change images were then analyzed by using OBIA, which improved the pixel-based CD. They suggested that the results of the traditional change analysis can effectively be interpreted by supplementing them with object-based post-classification. Niemeyer and Nussbaum (2006) used a combination of pixel- and object-based approaches by first pinpointing change pixels by statistical change detection and object extraction, and subsequently post-classifying the changes based on a semantic model of object features.

McDermid et al. (2008) combined pixel- and object-based techniques to reduce noise in change detection, as well as the small and spurious changes introduced by the inconsistent delineation of objects. Niemeyer et al. (2008) applied an unsupervised procedure to the objects extracted from QuickBird for change detection. They applied Multivariate Alteration Detection (MAD) transformation to detect change, and the change objects were sub-clustered by using fuzzy maximum likelihood estimation. Hofmann et al. (2008) implemented a different change indicator based on a comparison of the input bi-temporal RS data and used in combination with a transition-probability matrix to detect and reclassify potential changes in GIS-objects. Gamanya et al. (2009) applied region-merging segmentation on Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Matter (ETM) and applied a fuzzy-logic model for classification before comparing them to calculate the changes. Yu et al. (2010) performed an object based classification using a support vector machine (SVM) and compared the objects with land use vector data.

Table 3
Brief descriptions of object-based change detection techniques.

Technique	Description
Direct Object change detection (DOCD)	A direct comparison between the image-objects from different dates is performed for CD, which is similar to the pixel-based approaches. Change is detected either by (a) comparing the geometrical properties (width, area and compactness) (Lefebvre et al., 2008; Zhou et al., 2008b), or (b) comparing spectral information (mean band values) (Hall and Hay, 2003), and/or extracted features (e.g. texture) (Lefebvre et al., 2008; Tomowski et al., 2011) of the image objects. Broadly speaking, two strategies are developed. In the first, objects from image at time t_1 are extracted, and are assigned to or searched from image at time t_2 without segmentation (Miller et al., 2005). In the second approach, segments from multi-temporal images are extracted and compared for CD (Niemeyer et al., 2008). The disadvantage of the first approach is that change is linked to only the objects extracted from first image and will not provide new objects that might be created in the second image because of change. The second approach, however, allows using all the objects from both images for change analysis.
Classified Objects change detection (COCD)	Perhaps the most commonly used OBCD methodology that allows the creation of a change matrix indicating the "from– to" changes. OBIA is performed on multi-temporal images to extract objects and independently classify them. The classified objects are compared for a detailed change analysis. Objects are compared based on both the geometry and the class membership (Chant and Kelly, 2009; Hazel, 2001; Jiang and Narayanan, 2003). A theoretical framework of OBCD based on post-classification comparison was provided by Blaschke (2005) for the comparison of multi-temporal map objects to detect and identify changes. Stow (2010) argued that the same segmentation and classification algorithms with similar parameters, class schema and output format should be use in this methodology. Different classification algorithms, such as decision-tree and a nearest neighbor classifier (Im and Jensen, 2005), fuzzy classification (Durieux et al., 2008), and maximum likelihood classification (MLC), are used in OBIA. The classification algorithms used in OBCD incorporate both the spectal information and derived factors such as texture. One of the immediate applications of COCD is updating maps or GIS layers (Hansen and Loveland, 2012; Holland et al., 2008; 2004; Xian and Homer, 2010; Xian et al., 2009). The performance of COCD is strongly related to the performance and accuracy of the classification algorithm, similar to pixel-based approached. The classification accuracy in OBIA is also related to the selection of image segmentation technique which can results objects of different sizes based on different segmentation parameters.
Multitemporal/multidate-object change detection	Image segmentation and classification is applied directly to stacked/ composite multi-temporal images producing spatially corresponding change objects. The composite image may comprise one or more co- registered panchromatic, multi-spectral waveband, texture, and/or spectral transform multi-temporal images. Desclée et al. (2006) stacked multi-date SPOT images and produced segmentation. The extracted objects then were assigned the spectral values (mean and standard deviation) from each image (different dates). A statistical procedure was used to identify changed objects. The abnormal values of reflectance difference statistics corresponded to the changed objects. An error matrix was used for CD accuracy and accuracy. >90% and an overall kappa higher than 0.80 were reported. A similar approach was adopted by Bontemps et al. (2008) which applied segmentation to multitemporal data (12-dimensions comprising red, NIR, and SWIR). Spectral properties were obtained for all the objects, and used a Mahalanobis distance algorithm for CD. Conchedda et al. (2008) and Stow et al. (2008) used multi-temporal composite images in both segmentation and classification phases to map vegetation change objects. Other examples include applying clustering on multi-date objects for analyzing deforestation (Duveiller et al., 2008). The single segmentation of all the stacked imaged results in creating image-objects consistent in size, shape and location coordinate over time. Multitemporal segmentation would also result in some artifacts if there are misregistration and differences in shadowing between dates (Stow, 2010). Another issue pertaining to the use of a single segmentation for all the images is that it will not provide new/different objects that might be created at different times because of change.

6. Challenges for objects-based approaches

Contrary to pixel-based approaches, OBIA uses spectral, textural, spatial, topological, and hierarchical object characteristics to model reality. There are, however, concerns about validation, as Radoux et al. (2010) argued that point-based sampling does not rely on the same concept of objects. Error matrix is still used in most OBCD studies, and Hernando et al. (2012) argued that this is established for pixel-based approach, and that a state-of-the-art approach for object-based accuracy assessment is not available. Few approaches have been developed recently, including *potential mapping accuracy* measure for assessing (with a binary variable) the number of correctly classified pixels segment (Coillie et al., 2008), and an object-based sampling strategy by Radoux et al. (2010). Some researchers used point data to check the change accuracy. It is relatively easy to acquire points and overlay them to change image (Conchedda et al., 2008; Im et al., 2008b). It is possible to evaluate different properties of objects including size, shape, and boundary extent variability and then develop a framework for change-result validation in OBCD studies.

The fundamental assumption in OBIA is that objects derived through segmentation correspond to objects at the surface. However, perfect one-to-one correspondence may not be possible in all instances, particularly if the object is small, or if the resolution of the imagery is too coarse (Lein, 2012). The segmentation algorithms affect the resulting object geometries, which require specific solutions to keep the consistency and reliability in linking the objects extracted from two different times. Albrecht et al. (2010) argued that for spatial accuracy, object boundaries are more critical in OBIA. It becomes important to understand how the configuration of segmentation algorithms will result in accurate and more realistic real-world objects. An important input to the segmentation algorithms is scale parameter which controls the output object size. This makes it difficult to define single or most appropriate segmentation parameters in order to enable the creation of optimized objects reliably and accurately (Hay et al., 2005; Kim et al., 2008). Arbiol et al. (2006) pointed out that semantically significant regions are found at different scales, which makes it important to adjust the scale parameter in segmentation to achieve the optimal results. Mostly, the segmentation parameters are selected by subjective trial-and-error methods. Although different methodologies have been developed to address this issue (see e.g. Drăguţ et al., 2010; Singh et al., 2005; Smith, 2010), it is still an important consideration in OBIA. It has favoured the multiscale object-based approach as being more appropriate (Baatz and Schape, 2000; Hay et al., 1997).

The image segmentation process also suffers from under-segmentation and over-segmentation errors, which would create objects that do not accurately represent real-world features (Möller et al., 2007). Under-segmentation creates bigger objects which cover more than one real-world feature and also cover the mixed classes, whereas over-segmentation creates smaller parts of real-world objects which then need to be merged to create a more realistic representation of actual features (Liu and Xia, 2010). Both under-segmentation and over-segmentation create objects that do not represent the properties of real-world features and may not be useful; this may even reduce the classification accuracy.

Similar to pixel-based approaches, OBIA classification results need to be evaluated to assess their accuracy and reliability. The object extraction in OBIA is scale-dependent, and extracted objects vary in their conceptualization between *bona fide* (tangible and visible in the landscape) and *fiat* (lacking a physical border). There is also a broader ontological spectrum in classification process. The fuzzy transitions in the landscape make it difficult to relate image objects to landscape elements, possibly because of the mismatch between class definition and image object size (Addink et al., 2012). This means that evaluating the OBIA results is hardly a binary (''false'' or ''true'').

In OBIA for classification, the image-objects are first extracted from an image and then classified using different, supervised and un-supervised, classification algorithms. This faces similar challenges as faced by traditional pixel based approach including such as the training set size and its completeness (Congalton and Green, 2009; Lein, 2012; Russell, 2009).

7. Data mining technique and change detection

The analytical framework in RS change detection is becoming more data driven because of a rapid increase in the availability of RS data especially at very high resolution, and increased computational power with more sophisticated algorithms. Huge repositories of image data, which cover larger areas and larger spans of time, are becoming available. The situation has changed from a data and computational-poor scenario to a data-rich and information-poor scenario (Lijuan et al., 2010). The ability to produce and transmit geospatial data is greater than the ability for interpretation and analysis which require new techniques for the automatic or semi-automatic discovery of knowledge. The capability of and the features in data mining (DM) techniques thus can be useful in RS change detection (Barnes et al., 2007).

Data mining (DM) technique is part of a broader framework of knowledge discovery in database (KDD), which consists of techniques and algorithms for extracting non-trivial, and implicit information leading to constructing a knowledge model (Han et al., 2011; Larose, 2005). DM techniques aim at finding facts by inference and finding information in unstructured data or data that is not structured explicitly for the required purposes to meet the challenges of automating the use of data and information. Geographical or spatial data mining (SDM) is regarded as a specialized area of KDD (Miller and Han, 2001) with the fundamental objective of exploring both spatial and non-spatial properties to discover hidden knowledge (Chelghoum et al., 2002).

Image based DM techniques have been used for change detection. For example, Boulila et al. (2011) developed a predictive model for land cover change detection in image time series using DM. The object extract from image at time t is described by a set of features, radiometry, geometry, texture, and spatial relations, and acquired context. The attribute values of this set describe the object status at a given time. Different states of objects are composed (from time t_1 to t_n). A DM algorithm was then applied to develop a model to predict spatio-temporal changes to land uses. Eklund et al. (2000) applied a post-classification comparison for change detection. They extracted interest points and used them in a feature hierarchy. Images were classified using fuzzy algorithm; eight types of ground-covers grouped into three classes, and a set of logical queries were applied for CD. Petitjean et al. (2010) applied mining techniques to 35 images covering 20 years to understand the frequent sequential patterns. The Near Infra-Red (NIR), Red (R), Green (G) and NDVI values were provided to the mining algorithms for all the 35 images and sequential patterns were extracted. Dos Santos Silva et al. (2008) used a data mining framework to explore spatial patterns of land use in order to identify different agents involved in land-use change.

Other important areas of DM application in RS sensing are improving image classification and automatically or semi-automatically selecting a decision threshold for change detection. The thresholds to create decision boundaries are traditionally obtained using knowledge provided by experts and by trial and error. Otukei and Blaschke (2010) presented a method using DM to provide a decision threshold and argued that this is a reliable, transferable and reproducible mechanism which addresses the inconsistency inherent to a human. They applied a decision tree data mining algorithm C4.5 on the principle components, tasselled cap bands, and normalized vegetation index and texture features extracted from Landsat TM to determine threshold value. They concluded that applying DM helped identify the threshold values and also enabled selecting appropriate bands for classification. In a more recent study by Vieira et al. (2012), the objects were extracted from an image using OBIA and then J48 decision tree algorithms from DM (using WEKA data mining package) were used to create two classes. Landsat TM/ETM+ bands (3–5) were used in the classification, and 27 objects attributes covering spectral, spatial, textural and vegetation indices were provided to the DT algorithm. Kappa statistics provided by cross-validation were used to select the most appropriate DT for classification. They reported higher Global Accuracy (93.99%) and Kappa (0.87). The higher accuracy achieved through DM for the objects extracted from images promised better change detection in post-classification comparison.

8. Future remote sensing change detection

Change detection, including both the bitemporal or multitemporal, is one of main applications of remotely sensed data (Campbell and Wynne, 2011). With the development of RS technology and data, the RS-based change detection has witnessed a substantial evolution from traditional pixel-based spectral and statistical analysis to advanced and pioneering techniques, which are still in progress. One may consider three aspects of RS-based change detection – application domain, data, and the techniques – to see the possible future trends in this area.

The majority of traditional RS change detection applications have been on bio-physical, environmental change detection, land use/cover change, and also security related application, although its application domain has been much wider (Kennedy et al., 2009). One can argue that the application domain has guided the maturity and development of RS technology by highlighting the needs and presenting the challenges. On the other hand it would also be valid to argue that the advancements in the technologies in general over the last decades have allowed the applications to go beyond the traditional limits and try new ventures which in turn fed back to the RS technologies for further developments. This trend seems continuing and more applications areas would benefit from the advancements of the technologies and data sources (Blaschke et al., 2011; Weng, 2011).

The early RS data had limited spatial, spectral and temporal resolutions which were the major cause of the limitation in RS based change detection methodologies (Boyd and Foody, 2011). In the past decades a constant increase in the use of RS data at much fine resolutions can be observed. The increased use of RS data is mainly due to the lower cost and the launch of advanced sensors, in private sector, capable of acquiring data at much finer scales. The same evolution trend is expected in the future. Many long term RS data acquisition programs such as Landsat, SPOT, and ANHRR are providing data since last 20–30 years. Such programs seem to continue in the future with improvements in the spatial resolutions. These programs have already results in the data sets spanning longer periods which present a potential for the development of time series analysis for long term change studies. Meanwhile, with the launch of new satellites, change detection will be more often conducted for images from different sensors with different spatial, spectral, and radiometric properties in the future. This represents challenges for developing effective and efficient change detection methodologies and frameworks capable of searching through huge achieve of RS data with different spatial/spectral/temporal resolutions and enable change analysis (Boulila et al., 2011; Min et al., 2010; Qiao et al., 2012; Vieira et al., 2012).

The early and traditional change detection studies using RS data sets are pixel-based spectral and/or statistical methods. It is believed that these pixel-based approaches will still be widely used in the future for time-series images from same or different sensors that can meet basic considerations and assumptions of these approaches. With the increasing availability of multi-sensor images more systematic tests on the sensitivity of different pixel-based change detection approaches should be done using multiple sensor data. More advanced change detection technology focusing on multi-scale statistical, textural, and pattern changes will be needed to overcome the limitations of pixel-based statistical approaches when multiple sensor data are used. Complex techniques will evolve over time with the advanced technologies emerging and the availability of finer resolution data sets and higher computational power in the future. Currently, OBIA based change detection techniques are more frequently used because of their advantages over the traditional techniques in the analysis of high-resolution images. However, these techniques have several questions to answer. Automatically selecting the most appropriate parameters for object extraction (Drăguţ et al., 2010; Martha et al., 2011; Smith, 2010), defining standard framework for object comparison for change detection, and the accuracy assessment for change detection results are among most prominent (Albrecht et al., 2010; Hernando et al., 2012; Lein, 2012). In near future we can expect developments in these areas enabling automation in feature extraction and change detection more reliably and accurately. Other techniques employing advanced computational and data processing algorithms such as AI, knowledge-based expert system, agent-based models and machine learning algorithms represent new directions in change detection studies. The increased use of such algorithms (i.e. decision tree, support vector machine) in the RS based change detection studies can be seen in the literature. One can expect the integration of more machine learning algorithms in the image processing packages for classification and change detection (Chen et al., 2012a,b; Hamedianfar and Shafri, 2013; Vieira et al., 2012).

9. Summary

In this paper we have presented a review of the traditional pixel-based change detection methods and highlighted their functionalities and limitations. This was succeeded by a discussion of object-based change detection from images. Finally we briefly discussed data mining techniques for image analysis and their use in change detection. Change detection from remotely sensed data is a topic of ever-growing interest. Change detection from remotely sensed data is a complicated process, with no single approach optimal and applicable to all cases. It is no wonder that a large number of change detection techniques from remotely sensed data have been developed, and new techniques and methods are still emerging. The traditional pixel-based change detection methods did not fully exploit the spatial context of the real-world objects modeled as pixels in an image. The widely used pixel-based techniques have been, and remain, an important research topic and and were successfully implemented in many areas to measure changes using RS data.

The need to bring the spatial context and relationships into change detection mechanism was appreciated, even in the early attempts; the lack of computational power and the availability of the data were among the major barriers in the early stages of object-based method development. Over the last decade the situation has changed, with enormous leaps in technologies and improvements in many areas related to the research in image processing and analysis. The increase in the capability to gather and manage data at very high resolution challenges the traditional image analysis techniques; the drawbacks in those techniques started to emerge. As result, OBIA techniques were developed to handle the large variations in very-high-resolution data and to get better accuracy both in image classification and change detection. Comparing to pixel-based approaches, OBCD facilitate with the multi-scale analysis to allow delineating landscape features at different levels, and reduces the small spurious changes. Many previous studies have shown that improved results and higher accuracy is achieved when OBIA is used compared to pixel-based approaches. There are several studies which applied both the pixel-based and object-based approaches to compare the CD performance (see e.g. Desclée et al., 2006; Im et al., 2008b; Johansen et al., 2010; Lingcao et al., 2010; McDermid et al., 2008; Robertson and King, 2011; Zhou et al., 2008a).

With the increasing availability of large multi-scale multi-sensor multi-temporal remotely sensed datasets the DM techniques have shown their potential in remote sensing change detection. The DM techniques are developed to address the knowledge extraction from complex and larger data sets which is a helpful feature when considering analysing complex nature of remote sensing data and the required information contacts. With the development OBIA the utility of DM techniques are becoming more apparent. The DM techniques can help improve the classification results when objects are used by exploring different characteristics and understanding the complex relationships. Both object-based image analysis and spatial data mining are now more frequently used; they have great potential for answering the challenges of traditional change detection techniques on very high resolution images.

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