Object-Based Change Detection

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Abstract

Characterizations of land cover dynamics are among the most important applications of Earth observation data, providing insights that inform management, policy and science. Recent progress in remote sensing and associated digital image processing offers unprecedented opportunities to more accurately detect changes in land cover over increasingly large areas, with diminishing costs and processing time. The advent of high spatial resolution remote sensing imagery further supports opportunities to apply change detection with object-based image analysis, i.e. object-based change detection – OBCD. Compared to the traditional pixel-based change paradigm, OBCD has the ability to improve the identification of changes for the geographic entities found over a given landscape. In this article, we present an overview of the main issues in change detection, followed by the motivations for using OBCD as compared to pixel-based approaches. We also discuss challenges that are raised due to the use of objects in change detection, and provide a conceptual overview of solutions, which are followed by a detailed review of current OBCD algorithms. In particular, OBCD offers unique approaches and methods for exploiting high spatial resolution imagery, to capture meaningful detailed change information in a systematic and repeatable manner, corresponding to a wide range of information needs.

1. Introduction

Since the advent of satellite based Earth observation, land cover change detection has been a major driver of developments in the analysis of remotely sensed data (Anuta and Bauer 1973, Anderson 1977, Nelson 1983, Singh 1989, Lu *et al.* 2004, Aplin 2004, Coppin *et al.* 2004). More recently, high spatial resolution imagery has been available from commercial operators providing unique opportunities for detailed characterization and monitoring of forest ecosystems (Wulder *et al.* 2004, 2008c, Hay *et al.* 2005, Falkowski *et al.* 2009), urban areas (Herold *et al.* 2002, Hay *et al.* 2010) and additional applications developed to address increasingly detailed information needs (Castilla *et al.* 2008, Chen *et al.* 2011). Land cover change refers to variations in the state or type of physical materials on the Earth's surface, such as forests, grass, water, etc., which can be directly observed using remote sensing techniques (Fisher *et al.* 2005). As human induced change occurs at an increasingly rapid pace, and as Earth observation data become ubiquitous,

remote sensing based monitoring systems are expected to further play crucial roles in environmental policy and decision making.

Accurately monitoring land cover is a matter of utmost importance in many different fields. Satellite or airborne based monitoring of the Earth's surface informs on interactions between anthropogenic and environmental phenomena, providing the foundation to better use natural resources (Lu *et al.* 2004). It enables refined policy development and the capacity to address otherwise inaccessible science questions (Cohen and Goward 2004). Remote sensing *change detection*, defined by Singh (1989) as "*the process of identifying differences in the state of an object or phenomenon by observing it at different times*", provides a means to study and understand ecosystems' patterns and processes at a range of geographical and temporal scales. While knowledge of land cover conditions at a given point in time is important, the dynamics or trends related to specific change conditions offer unique and often times important insights, ranging from natural disaster management to atmospheric pollution dispersion. Indeed, remotely sensed imagery is really an important source of data available to systematically and consistently characterize change in terrestrial ecosystems over time (Coops *et al.* 2006).

The capacity for large geographical coverage, high temporal frequency, and low cost, combined with an increasingly wide selection of spatial and spectral resolution options, further enhances the use of remotely sensed imagery for land cover change detection. Over the past three decades, numerous studies have been conducted to explore the feasibility and accuracy of image analysis applications for monitoring land cover change (Singh 1989, Coppin and Bauer 1996, Mas 1999, Lu *et al.* 2004, Aplin 2004, Coppin *et al.* 2004). However, the availability of high spatial resolution imagery from satellite and airborne platforms has resulted in a need to reconsider these traditional change detection image processing approaches.

Traditionally, change detection techniques have used individual pixels as their basic units of analysis, which we refer to hereafter as *pixel-based change detection*. Recently, high-performance computing systems and efficient software algorithms enable increased opportunities for segmentation and feature extraction from multispectral and multiscale remotely sensed imagery, which in turn facilitate the seamless integration of raster-based image processing and vector-based GIS (Geographic Information System) functionalities (Blaschke 2010). These developments have also enabled the implementation of a recent change detection approach, referred to as *Object-Based Change Detection* (OBCD) (Hall and Hay 2003, Blaschke 2005).

OBCD has evolved from the concept of *Object-Based Image Analysis* (OBIA), [more recently referred to as *Geographic Object-Based Image Analysis* (GEOBIA) (Hay and Castilla 2008)], which combines segmentation, spatial, spectral and geographic information along with analyst experience derived from *image-objects* in order to model geographic entities (Blaschke and Hay 2001, Hay and Castilla 2008). Image-objects are groups of pixels in the image that represent meaningful objects in the scene. A feature of OBCD is to extract meaningful image-objects by segmenting (two or more) input remote sensing images; which is consistent with the original notion of using change detection to identify differences in the state of an observed "*object or phenomenon*" (Singh 1989). To better understand the concept of OBCD, we define it as 'the process of identifying differences in geographic objects at different moments using object-based image analysis'.

As the spatial and temporal resolution of remote sensing technologies increases, so too do the demands of users for timely and relevant geospatial change information that is object-based and able to seamlessly work with existing geospatial analytical platforms. The challenge then becomes knowing which data, tools and methods provide the best solutions for specific problems and what limitations still need to be addressed? In response to these concerns, Section 2 provides a brief overview of main issues in change detection. Section 3 outlines the motivations of using image-objects over pixels to better deal with some of those issues. We also note that new challenges are further raised in OBCD. Section 4 provides a conceptual overview of these challenges and possible solutions based on the literature. In Section 5, we summarize and review recent OBCD algorithms, followed by the conclusion to this review in Section 6.

2. Main issues in change detection

The accuracy of change detection using remotely sensed imagery depends on many important factors. Change detection algorithm is an apparent one; however, no specific algorithm has claimed to be suitable for all projects. Meanwhile, several other main issues should also be carefully considered before/while conducting change detection, as the neglect of these issues is unlikely to produce a satisfactory change detection result. In subsequent sections, six main issues are briefly discussed.

2.1. Spatial scale

In the context of remote sensing, spatial scale typically corresponds to spatial resolution, i.e., pixel size (Woodcook and Strahler 1987). As the most significant spatial element in remote sensing, spatial scale represents a window of perception through which a landscape is viewed (Marceau and Hay 1999, Aplin 2006). Typically, low resolution images are able to efficiently monitor the changing Earth's surface over large areas. However, this can also result in mixed pixels that represent a weighted average of the spectral response of various land cover types (Aplin 2006), causing difficulties to accurately define specific changes. High spatial resolution imagery may be sufficient to delineate the individual geographic objects of interest, whereas high spectral variation within objects is also generated. In this case, a large amount of small spurious changes are possibly produced. A further note on high resolution is that it is more difficult to perform an accurate image registration than using low resolution, resulting in the decrease of change detection accuracy (refer to Section 2.4 for details).

2.2. Temporal scale

Temporal scale is also called temporal resolution, which refers to the time interval between successive image acquisitions at the same site (Mather 2004). It is critical for analysts to understand the project objective and be familiar with the characteristics of geographic objects of interest before collecting remote sensing imagery. For example, anniversary images are suitable to monitor forest changes in long-term trends, such as the changes induced by human activities, as the seasonal phonological differences can be minimized. However, a short-term phenomenon, such as forest fires, requires imagery to be acquired at finer temporal scales. As Coppin *et al*. (2004) argued that the proper understanding the nature of the change is more sophisticated than the simple detection of change itself.

2.3. Viewing geometry

The collection of multi-temporal imagery requires the consideration of both look angle and Sun angle, which are critical factors impacting the reflectance of geographic objects on Earth's surface. Ideally, only the tops of these objects are visible, if the remote sensing imagery is acquired directly at nadir (i.e. 0º off-nadir look angle). However, the sensors can tilt as much as 20º for some systems, e.g. SPOT, IKONOS and Quickbird (Jensen 2005). Consequently, both the object tops and their sides are recorded, where the increase of sensor off-nadir look angle

enables collecting more object side information and decreasing image spatial resolution. Similarly, the reflectance of geographic objects also varies with the change of Sun angle. For example, a low Sun angle typically contributes to a severe shadow effect in a high spatial resolution image, especially when a ground object (e.g., urban skyscraper) is much taller than the neighbours. It is therefore suggested that data collected for change detection should use approximately the same sensor look angle and Sun angle (Jensen 2005).

2.4. Image registration

As an essential pre-processing for change detection, multi-temporal image registration ensures that the changes detected are not because we compare land surface objects at different geographic locations between one time and another (Townshend *et al*. 1992). The performance of image registration is typically related to two factors: image spatial resolution and the structure of geographic objects of interest. For example, misregistration is possibly to occur at the pixel level using very high spatial resolution imagery (e.g., 1 m IKONOS), while it is easier to achieve registration accuracy at the subpixel level using relatively low resolution data (e.g., 30 m Landsat). In addition to spatial resolution, Dai and Khorram (1998) have further proven that the finer the spatial frequency in the images, the greater the effects of misregistration on change detection accuracy. In their tests, the registration accuracy of less than one-fifth of a pixel was required in order to detect 90% of the true changes (Dai and Khorram 1998).

2.5. Radiometric correction or normalization

Radiometric correction is another critical pre-processing for change detection, because images captured on multiple dates may have radiance or reflectance differences due to (i) the improperly functioning of the remote sensing system, and/or (ii) atmospheric attenuation caused by absorption and scattering in the atmosphere (Jensen 2005). Readers may refer to Lu et al. (2004), Coppin et al. (2004) and Jensen (2005) for thorough review of radiometric correction methods used in recent change detection. Additionally, it has been confirmed by several studies that absolute or complicated radiometric correction algorithms may not lead to significantly improved change detection accuracy; thus, the use of relative radiometric correction to normalize intensities of bands of multi-temporal imagery to a reference scene is sufficient for many change detection applications (Collins and Woodcock 1994, Song *et al*. 2001, Coppin *et al*. 2004).

2.6. Features applied in change detection schemes

Change detection can be directly conducted comparing spectral bands (e.g., image differencing or ratioing). However, extra features extracted from the spectral information are increasingly applied to improve change detection accuracy. Of these features, the most important one is image-texture, which normally refers to the measurements of the spatial variability of neighbouring pixels within a moving window/kernel assessed across the image. Recently, the addition of image-texture has proven more effective than using spectral bands alone for change detection (Ward *et al*. 2000, Li and Leung 2002, Wu *et al*. 2010). A commonly used image-texture in the remote sensing community is the statistical approach, which includes first-order (e.g., standard deviation and skewness) and second-order [e.g., grey level co-occurrence matrix (GLCM) and semivariance] statistics (Haralick *et al.* 1973, Tuceryan and Jain 1998, Atkinson and Lewis 2000). Additionally, it should be noted that several other features, such as the vegetation index of NDVI and bands of principal component analysis (PCA), can also facilitate the improvement of change detection performance (Ward *et al*. 2000, Deng *et al*. 2008).

3. Image-objects in change detection: motivations

For over three decades, pixel-based change detection has been, and remains an important research topic in remote sensing. Several review papers have presented thorough explorations of pixel-based change detection techniques and their related applications (Singh 1989, Lu *et al*. 2004, Aplin 2004, Radke *et al*. 2005). According to these papers, critical issues persist, some of which are associated with data quality and landscape complexity, while others are related to the nature of pixel-based algorithms. Recent studies have demonstrated that OBCD characteristics can provide improvements over pixel-based change detection by solving or partially solving several change detection issues using pixels, especially when high spatial resolution imagery is used. In the following sub-sections, we outline these specific issues that are also related back to the previous Section 2, and discuss the motivations of using the object-based paradigm with a comparison to pixel-based change detection.

3.1. Spatial multiscale analysis

As objects of interest exist within a scene, often within a range of different sizes, shapes and times, no single spatial resolution is sufficient to capture all of their characteristics (Woodcock

and Strahler 1987, Hay *et al.* 1997). From a pixel-based perspective this also means that it is difficult to define a unique spatial resolution to accurately monitor the changes of all types of geographic objects (Marceau *et al.* 1994). To address this challenge, the object-based paradigm enables the characterization of different landscape features within the same image using different object sizes, each of which are composed of pixels with the same spatial resolution. *Scale parameters*, which define the mean, minimum, and maximum object size, are often used to optimize the delineation of individual features, resulting in improved change detection accuracy (Hall and Hay 2003, Laliberte *et al.* 2004, Hese and Schmullius 2004, Durieux *et al.* 2008, Johansen *et al.* 2008). A typical example is the change detection using multiscale object-based classification results of multiple dates, where a high accuracy classification definitely facilitates the improvement of change detection performance. Figure 1(a) represents a wildland-urban interface area that has been classified using a two-scale object-based approach (Cleve *et al.* 2008). A small scale was applied to delineate houses, while a large scale was more appropriate to capture vegetation patches. The classification accuracy improved by 18% compared to that using the pixel-based approach [Figure 1(b)] (Cleve *et al.* 2008).

3.2. Reduction of small spurious changes

When observing a common scene, a high spatial resolution image provides more details than a lower spatial resolution image. However, this increased spatial resolution generates high spectral variability within geographic objects, which typically reduces change detection (and classification) accuracy when using pixel-based algorithms. Isolated pixels or holes (also known as the *salt-and-pepper* effect) often occur (Marceau *et al.* 1990, Desclée *et al.* 2006, Bontemps *et al.* 2008, Hofmann *et al.* 2008). As an alternative, OBCD monitors the change of meaningful image-objects, which model actual geographic entities (Castilla and Hay 2008). Each image-object is considered as one single study unit. Detected small spurious changes that are due to high spectral variability, therefore, are reduced by smoothing out small changes within the extent of each geographic object. Objects that are smaller than a specified size can simply be merged into the matrix. For example, when monitoring land cover dynamics in an urban area, Zhou *et al.* (2008) compared the object-based and pixel-based change detection approaches. Figure 2 shows that a large number of small spurious changes have disappeared by using image-objects, which achieved an accuracy that was 9% higher than using pixels (Zhou *et al.* 2008).

Both anthropogenic and natural landscape features often show heterogeneous internal reflectance patterns (e.g. shadowing effects) that are not constant through time due to variations in sun-surface-sensor geometry inherent to multitemporal image acquisitions (Wulder *et al.* 2008a). Change detection using image-objects may provide better solutions to mitigate the effect of illumination changes. For example, Wulder *et al.* (2008b) describe a method to track changes in vegetation health status at an individual tree level from four years of Quickbird imagery, acquired with different viewing geometries (Figure 3). Statistical analysis demonstrated that while individual trees may not be tracked over time, the segment level tree counts were not statistically different (Figure 4). Consequently, when incorporated with spectral measures of vegetative health, the segment level tree counts could be combined to inform on the nature of insect population dynamics over time.

Misregistration between the same features on multitemporal images is a further critical source of error. As stated by Mäkelä and Pekkarinen (2001) and Desclée *et al.* (2006), segmentation that generates image-objects is less sensitive to misregistration errors than traditional pixel-based approaches. Blaschke (2005) further recommends a GIS framework to deal with this issue. For example, Figure 5 shows that two types of image-objects (i.e., rectangular and circular) both have a slight misregistration error between two-date images. The small spurious changes could be distinguished from real changes after a GIS analysis is performed, where several object characteristics (e.g., area, shape and perimeter) can be considered.

3.3. Object-based features

Rather than concentrating on isolated pixels of varying color, remote sensing image analysis using objects allows for the extraction of sophisticated geospatial information with unique object-based features, such as geometry, texture and context (Hay and Castilla 2008, Blaschke 2010). Although pixel-based approaches also generate texture, the neighbourhood used to retrieve spatial information is typically defined by a square window of fixed size (e.g. 5 by 5 pixels), which is passed across the entire dataset. Though square windows are trivial to implement, they are biased along their diagonals, and will likely straddle the boundary between two landscape features, especially when a large window size is used (Laliberte and Rango 2009). As a result, it has been argued that the traditionally unsophisticated extraction and use of spatial

information remains a critical drawback to pixel-based image processing routines in change detection (McDermid *et al.* 2003). Object-based approaches have an advantage of being able to define window size and shape based upon local object characteristics from which to extract spatial information. Thus, image-objects generated through the segmentation process in turn serve as contextual windows. Besides the texture extracted within individual image-objects, a higher order of texture that takes into consideration the spatial distribution of adjacent objects can also be generated (Figure 6, Chen and Hay 2011). In a case study of modelling forest canopy height, Chen *et al*. (2011) found that the adding of object-based texture better facilitates the improvement of model performance than using the traditional square windows at most evaluated scales. The effectiveness of using object-based features has also been proven by recent change detection studies, including urban land use change (Herold *et al*., 2002), shrub encroachment (Laliberte *et al*. 2004), mangrove ecosystem dynamics (Conchedda *et al*. 2008), forest death monitoring (De Chant and Kelly, 2009), etc. We further note that many object-based features are already available in commercial remote sensing software, such as eCognition suite (Definiens Imaging GmbH, Munich, Germany), the ENVI EX module (ITT Visual Information Solutions, Colorado, USA), the ERDAS IMAGINE Objective module (ERDAS Inc. Norcross, USA) and PCI's FeatureObjeX (PCI Geomatics, Ontario, Canada).

4. Challenges and opportunities in OBCD

To represent geographic objects in OBCD, remote sensing imagery are typically segmented resulting in 'segments' from which meaningful image-objects can be generated, based on their spatial and spectral attributes and user experience (often in the form of rule-sets). Change detection is performed by tracking the objects that show differences in their spatial and/or spectral attributes over time. Not only do many segmentation algorithms exist (Pal and Pal 1993) that affects the resulting object geometries, but many pixel-based change detection algorithms can also be transferred to the object domain. For example, the idea of comparing pixel values can be used to compare object values. However, users must be aware that objects in OBCD are of various sizes and shapes, which require specific solutions to deal with their object-related characteristics. Based upon the previous research activities in OBCD, the following sub-sections provide a conceptual overview of object-based challenges and opportunities.

4.1. Comparison of image-objects

Since image-objects are used as the basic study units in OBCD, the most important issue that needs to be dealt with is how to define changes between them. An immediate solution is the comparison of image-objects of multitemporal dates at the same geographic location, as does in pixel-based change detection. Typically, image-objects can be either (i) directly compared using object spectral information and/or associated features (Hall and Hay 2003, Miller *et al.* 2005, Chen and Hutchinson 2007, Lefebvre *et al.* 2008, Gong *et al.* 2008), or (ii) compared after an object-based classification (Willhauck *et al.* 2000, Laliberte *et al.* 2004, Walter 2004, Owojori and Xie 2005, Blaschke 2005, Durieux *et al.* 2008, De Chant and Kelly 2009). Statistics or GIS functions are typically used in the comparison of image-objects. Different from pixel-based approaches, the majority of OBCD algorithms mentioned above have employed object-based features (e.g. geometry, texture and context), which provide great opportunities to better monitor land cover changes than using spectral information alone.

Another type of OBCD algorithms has managed to derive image-objects by segmenting all multitemporal states of the scene in one step (Desclée *et al.* 2006, Bontemps *et al.* 2008, Conchedda *et al.* 2008, Stow *et al.* 2008, Duveiller *et al.* 2008, Park and Chi 2008, Im *et al.* 2008). Consequently, the comparison of image-objects is more straightforward than the algorithms aforementioned, as the geometry (e.g. shape or size) difference of multitemporal image-objects (at the same geographic location) does not demand further considerations.

Several previous studies have also confirmed the effectiveness of incorporating pixel-based procedures into object-based schemes (Carvalho *et al.* 2001, Al-Khudhairy *et al.* 2005, Niemeyer *et al.* 2005, McDermid *et al.* 2008, Linke *et al.* 2009). These OBCD algorithms usually obtain preliminary change results using pixels. The object-based paradigm is further applied to improve the change detection performance.

4.2. Sliver polygons

Sliver polygons typically refer to small overlap areas or gaps, which result from errors in the overlay of two or more GIS coverages (Goodchild 1978). Change detection with image-objects inevitably generates sliver polygons, when these objects are individually derived and compared. This is typically due to image misregistration and inconsistent segmentation. As image misregistration is an apparent reason, the inconsistent segmentation is further discussed. Due to

the reason that multitemporal images are taken at different times, even if no land cover change occurs within the considered time interval, the images tend to be different due to variations in Sun angle, sensor look angle, cloud coverage, etc. Consequently, it is almost impossible to independently generate exactly the same image-object boundaries for the same landscape features in multitemporal images.

An ideal solution is to develop a robust segmentation algorithm by replicating human interpretation. However, such an algorithm is and will still be unfeasible in the long term. Recent studies have provided several realistic solutions. For example, McDermid *et al.* (2008) and Linke *et al.* (2009) generated annual maps by updating and backdating their existing object-based reference maps. A prerequisite to applying this approach is to have high-accuracy reference maps, as changes are examined against these pre-existing conditions. Another type of solution was initially provided by Desclée *et al.* (2006) by segmenting multitemporal images in one step. This basic idea has been followed by many other OBCD studies (Bontemps *et al.* 2008, Conchedda *et al.* 2008, Stow *et al.* 2008, Duveiller *et al.* 2008, Park and Chi 2008, Im *et al.* 2008, Huo *et al.* 2010). Concurrent to developments in OBCD, image processing techniques have also been developed that allow slivers to be treated as information rather than as noise. For example, if we consider an insect infestation over time, an impacted area can be expected to fluctuate. Thus, spatio-temporal methods may be applied to the (sliver) polygons to determine if a particular object is stable, expanding, or contracting (Robertson *et al.* 2007).

4.3. Evaluation of change results

The commonly used accuracy assessment elements in pixel-based change detection include: overall accuracy, producer's accuracy, user's accuracy and the Kappa coefficient (Lu *et al.* 2004). When pixels are considered the basic study units, it is reasonable to use the pixel-level truth data to evaluate the change results. However, this is not the case when assessing object change accuracy [with comparison issues described in Wulder *et al.* (2006)]. Although the accuracy assessment elements used in pixel-based change detection have been directly applied to evaluate the OBCD performance, the critical difference is the reference data type, which can be either points (i.e. pixels) or objects. Some studies used point data to check the change accuracy (McDermid *et al.* 2003, He *et al.* 2005, An *et al.* 2007, Im *et al.* 2008, Conchedda *et al.* 2008, Linke *et al.* 2009). The advantage is that points are relatively easy to acquire and simple to

overlay onto change images. However, Biging *et al.* (1999) argued that pixel-based accuracy assessments tend to underestimate object-based map accuracy. Other researchers have used objects as their reference data (Yu *et al.* 2004, Al-Khudhairy *et al.* 2005, Desclée *et al.* 2006, Durieux *et al.* 2008, Stow *et al.* 2008, Bouziani *et al.* 2010). Their results show that objects may be well suited to quantify changes when only one class of the landscape feature (e.g. shrub, building or tree) is the research emphasis, although the change detection accuracy evaluated with objects is more complicated than using pixels.

Unlike pixel-based change metrics, beyond disappearance or emergence of features, geographic objects can also partially change (e.g. minor, moderate or major changes). For example, one homogeneous forest stand may be entirely removed to form a cutblock, or partially modified due to seasonal dynamics. OBCD offers opportunities to evaluate different change levels by using object-related characteristics, such as size, shape and variability within the boundary extent, although few studies have considered this reality (Chen and Hutchinson 2007).

5. A review of OBCD algorithms

In this section, we explore the state-of-the-art OBCD algorithms by classifying them into four categories: (i) *image-object*, (ii) *class-object*, (iii) *multitemporal-object*, and (iv) *hybrid change detection*.

5.1. Image-object change detection

Similar to pixel-based change detection, OBCD can be performed by directly comparing image-objects defined by a threshold. Typically, multitemporal images are segmented separately with changes analyzed based on object's spectral information (e.g. averaged band values) or other features extracted from the original objects (e.g. image-texture and geometry). In this review, the OBCD algorithms which emphasize direct image-object comparisons are grouped as *image-object change detection*.

Miller *et al.* (2005) presented an OBCD algorithm to detect the change of significant blobs (i.e. objects) between a pair of gray-level images. Two main steps were used. First, objects were extracted by using a connectivity analysis. Second, each object from the base image was searched for a corresponding object in another image. To detect whether two corresponding objects were really different (i.e. changed) or not, a matching method was used to capture the

relationship between two object boundary pixels. By applying this object-based concept, the authors argued that the proposed algorithm worked for noisy input images and that no pre-defined windows were required, as processing was directly undertaken on the extracted objects. Lefebvre *et al.* (2008) further evaluated the use of geometry (i.e. size, shape and location) and content (i.e. wavelet transform-derived texture) information in OBCD. Their qualitative results indicated that both object contour and texture features were effective to detect changes in very high resolution airborne images at the sub-meter level, and further recommended the application of their algorithm to spaceborne images.

Aforementioned studies have been conducted at one certain scale. To delineate image-objects and identify their change through scales, Hall and Hay (2003) developed an OBCD framework by first segmenting panchromatic SPOT scenes from two dates, and then directly applying an image differencing method to detect object changes at different up-scaled resolutions. To avoid subjective change threshold decisions, a non-parametric and unsupervised method proposed by Otsu (1979) was used, to automatically select thresholds. Their results revealed that the sensor related striping noise was effectively ignored; and a foundation for exploring both fine and coarse scales was established. Gong *et al.* (2008) also used the multiscale logic. However, rather than simply changing image resolution, they created a full-scale object tree by extracting all segmented objects using a hierarchical structure; where all objects of different scales were segmented from a single scene. Spatially corresponding (artificial) objects from two-date images were then compared to detect their structural changes. Compared to the typical multiscale segmentation, their objects were more accurately extracted, which improved the change detection performance.

Compared to the approaches with ideas directly borrowed from the pixel-based change detection, OBCD may need unique solutions to deal with specific conditions. For example, Chen and Hutchinson (2007) made a comparison of three types of OBCD algorithms, i.e. correlational analysis, PCA (principle component analysis) and boundary compactness analysis. The first two algorithms performed similar to pixel-based change detection; however, objects were used rather than pixels. The third algorithm (boundary compactness) was presented to deal with their specific change detection problem – earthquake-caused urban damage. The hypothesis used in this algorithm was that the boundary of a before-damage structure had a continuously closed edge, while this characteristic dramatically weakens after damage. Compared to the previous two

algorithms, this new approach of using boundary information provided a better agreement with the manually derived reference map, though a threshold had to be defined.

The major advantage of image-object change detection is the straightforward comparison of objects. The algorithms are also easy to implement. Typically, all objects are directly extracted through image segmentation, and steps, such as image differencing, are similar to those in pixel-based change detection or simple GIS intersection operations. However, as objects are of different sizes and shapes, a critical procedure is the search for spatially 'corresponding' objects in multitemporal images. Errors in locating these objects will potentially lead to incorrect change detection results. This might explain the reason why the direct comparison approach is suitable for detecting specific objects of interest, such as artificial landscape features (Miller *et al.* 2005, Gong *et al.* 2008). Another challenge with image-object change detection is the requirement to select an appropriate change threshold. Since the threshold value is often intuitively defined by researchers, a bias may be introduced. However, we note that this challenge also exists in pixel-based change detection, where change/no-change thresholds must be defined.

5.2. Class-object change detection

A direct comparison of image-objects cannot readily indicate the 'from-to' change of landscape classes (i.e. from clear-cut to vegetation), which requires additional classification information. In this review, *class-object change detection* represents a group of OBCD algorithms that detect landscape changes by comparing the independently classified objects from multitemporal images. Since each object belongs to a specific class, the object comparison step in OBCD has no need to consider features such as object spectral and texture values.

The update of existing maps or GIS layers is an immediate application for using class-object change detection. Durieux *et al.* (2008) applied an object-based classification approach (using fuzzy membership functions) to a 2.5 m SPOT mosaic covering an entire island of 2,512 km^2. The extracted buildings were compared with the old reference maps to monitor the urban sprawl over six years. Similarly, Walter (2004) evaluated the importance of using different input channels (i.e. spectral, vegetation indices and texture) in an object-based classification, which led to different results when updating GIS layers. They suggested that the assessment of additional object characteristics, derived from laser data, texture measures, and multitemporal data would improve both classification and change detection performance. We note that in the

aforementioned studies GIS polygons (or existing maps) were considered as the base layer, with the change classes updated from a comparison with single date imagery. However, this is not the case in many other studies, which require creating objects from multitemporal remote sensing images. Laliberte *et al.* (2004) conducted an object-based classification on 11 aerial photos and one QuickBird image spanning 67 years. As the authors were only interested in the change of vegetation area, the total change values were calculated without considering their change in spatial distribution. In related studies, the results only involved a change map by directly overlaying two-date classified images or several change metrics, such as total area, mean nearest neighbour distance and mean elevation (Willhauck *et al.* 2000, Owojori and Xie 2005, Mouflis *et al.* 2008). Although multitemporal data were processed in these studies, the change detection procedure emphasized the use of object statistics.

To better understand how an individual object changes over time (such as spatial distribution, total area, perimeter, shape, complexity, etc.), additional efforts are required to compare each pair of the correspondingly classified objects. However, as discussed by Blaschke (2005), it is difficult to distinguish whether the object difference is due to real change or geometric inconsistence (e.g. caused by a misregistration error or a segmentation-induced difference). This lead to the development of a GIS conceptual framework, where a series of rules were defined by taking into account object size, shape and location (Blaschke 2005). Similar ideas were also applied in many other independent studies (Hazel 2001, Li and Narayanan 2003, Gamanya *et al.* 2009, Grenzdörffer 2005, De Chant and Kelly 2009); with specific rules adapted to particular conditions. For example, since forest gap dynamics are important to monitor tree diseases, De Chant and Kelly (2009) converted raster polygons classified as gaps, to vector layers and performed object intersection functions with GIS software. Changes were tracked by analyzing object metrics including perimeter, area, shape and Euclidean nearest neighbour. To detect military object changes, Hazel (2001) compared corresponding objects derived from two dates by calculating *association confidence*, which includes the spatial distance between the object centroids, the degree of spatial overlap, a distance between spatial and spectral feature vectors, and differences in assigned classification and classification confidence. Similarly, Li and Narayanan (2003) quantified lake change using a shape similarity measure.

In addition to geometric information, it is still valuable to use spectral and/or texture measures to compare the classified objects. In the studies conducted by He *et al.* (2005) and An

et al. (2007), an object-based classification was simply used to detect 'possible' changed objects (e.g. non-urban to urban). A further verification of whether the change was real or not, involved the calculation of *object similarity* using spectral and texture characteristics.

Change detection based on classified objects is a common type of OBCD approaches which can produce straightforward results (e.g. a change matrix) indicating the 'from-to' landscape change. However, specific rules have to be defined to compare objects when GIS processing is involved. One interesting idea, referred to as *object-fate* (Schöpfer *et al.* 2008) is to define buffers of possibility, or states of change around each object. Similar to pixel-based change detection, the performance of OBCD is also strongly influenced by the initial classification procedure. Details of pixel-based classification accuracy assessment have been discussed by Foody (2002) and Fuller *et al.* (2003). As for the object paradigm, classification accuracy is also related to the selection of appropriate image segmentation techniques, of which many exist (Pal and Pal 1993). Practitioners must also note that error propagation in both segmentation and classification will affect the OBCD performance.

5.3. Multitemporal-object change detection

Images acquired from different dates rarely capture the landscape surface the same, due to many factors including illumination conditions, view angles and meteorological conditions (Wulder *et al.* 2008a). Thus, segmentation generated image-objects from different dates often vary geometrically, even though they represent the same geographic feature(s). Instead of separately segmenting multitemporal images, the concept of multitemporal-*object change detection* takes advantage of all multitemporal states of the scene. Specifically, temporally sequential images are combined and segmented together producing spatially corresponding change objects.

The pioneering work of Desclée *et al.* (2006) presented an explicit algorithm to implement a multitemporal-object change detection approach. The authors segmented an entire multi-date image-set together followed by a calculation of its spectral features (i.e. mean and standard deviation) from each date for all image-objects. Finally, discrimination between changed and unchanged objects was performed using a statistical analysis based on the chi-square test. Using this approach, the authors reported high detection accuracy (> 90%) and overall Kappa (> 0.80). Following a similar approach, additional studies developed OBCD algorithms with an emphasis on developing new ways to characterize object-level change.

Bontemps *et al.* (2008) integrated the Mahalanobis distance calculation and a thresholding method to identify change objects. Conchedda *et al.* (2008) used a nearest neighbour supervised classification approach and reference data to quantify changes. Similarly, Stow *et al.* (2008) compared a nearest neighbour classifier and fuzzy membership functions to monitor shrub change, with results demonstrating superior performance using the nearest neighbour classifier. Other studies evaluated several unsupervised solutions with the ISODATA classification algorithm (Duveiller *et al.* 2008), and change vector analysis (CVA) (Park and Chi 2008). In addition to comparing different classifiers, Im *et al.* (2008) evaluated the performance of adding *object correlation images* and *neighbourhood correlation images* within the classification feature space. Their results revealed that the incorporation of these new features produced more accurate change feature classes (Kappa > 0.85). Rather than conducting a combined segmentation of multitemporal images, Li *et al.* (2009) describe an incremental segmentation procedure designed for radar imagery, where they started by (i) segmenting the first-date image, (ii) treating the result as a thematic layer, then (iii) segmenting the derived layer together with the second-date image. Their intent was that the previous segmentation would constrain each subsequent segmentation so as to avoid inconsistent results when using unique segmentations (e.g. objects with varied boundaries).

A single segmentation step using all multitemporal images facilitates OBCD by creating consistent image-objects in size, shape and location coordinate over time. However, it is unclear whether this form of change detection is influenced by segmenting before- and after-change images together, as the same geographic location may have different objects. Similarly, the effect of mixed object spectral information (from different atmospheric, meteorological, illumination and viewing angle, etc.) on change results remains to be explored.

5.4. Hybrid change detection

Unique from the algorithms we have previously discussed, are methods which involve the use of both object and pixel paradigms. These, we refer to as *hybrid change detection*. A widely used hybrid approach comes from the idea that the preliminary change information should be derived from pixels; while object schemes are subsequently applied to better extract the change results.

A novel hybrid change detection algorithm was proposed by Carvalho *et al.* (2001). The authors showed that wavelet inter-scale correlation computed from pixel-based difference images

(e.g. differencing, rationing, PCA, CVA) were effective to identify all land cover changes over a study area. Region growing segmentation was then performed to extract objects solely where changes occurred, avoiding the time-consuming task of segmenting all remotely sensed images. The authors concluded that this approach was insensitive to geometric misregistration and atmospheric discrepancies between the multitemporal images, as well as to differences in the phenological state of vegetation patches. This procedure aids automation, and since 2003 has been used on an operational basis by the government of Minas Gerais, Brazil, to update vegetation maps. In another study, Al-Khudhairy *et al.* (2005) applied pixel-based PCA and image differencing to high spatial resolution imagery. The change images were then analyzed by an object-based classification, which improved upon the pixel-based change detection. In the studies conducted by McDermid *et al.* (2008) and Linke *et al.* (2009), multispectral images were transformed into wetness bands, which were effective for detecting forest disturbance (Franklin *et al.* 2001). This transformation was followed by a pixel-based image differencing using wetness information with an object-based classification applied to the changed areas. Niemeyer *et al.* (2005) used a similar procedure; however, their research emphasized on the creation of pixel-based mutually orthogonal difference images, rather than employing the traditional image differencing method. Yu *et al.* (2004) applied segmentation to a difference image from a forest canopy height model, generated from a small footprint, high sampling density lidar (light detection and ranging). Results showed that individually harvested trees were accurately delineated.

The *hybrid algorithms* that combined pixel- and object-based schemes successfully reduced noisy changes, as well as the small and spurious changes introduced by the inconsistent delineation of objects (McDermid *et al.* 2008). However, as many steps are involved in hybrid change detection, it remains unclear how the final change results are influenced by the different combinations of pixel-based and object-based schemes.

6. Conclusions

Accurate and rapid acquisition of landscape change facilitates decision-making and supports sustainable development. Over three decades, activities using remotely sensed imagery to monitor Earth's surface change have proven effective in a variety of fields, thanks to distinctive remote sensing characteristics, such as large geographical coverage, high temporal frequency,

low cost and increasingly spatial resolution. Among them, the recent feature of high spatial resolution provides a remarkable potential to monitor our land use changes with much more detail than ever before. To successfully achieve this goal, however, a reconsideration of traditional pixel-based change detection approaches is also an essential.

In the last decade, an object-based paradigm of modelling geographic entities by combing segmentation, spatial, spectral and geographic information along with analyst experience derived from image-objects has drawn high attentions in the remote sensing community. Incorporating this new paradigm into change detection – object-based change detection (OBCD) – meets the objective of identifying differences in geographic objects, i.e., meaningful image-objects (Castilla and Hay, 2008). Specifically, OBCD has demonstrated particular strengths over pixel-based approaches in dealing with several critical issues in change detection enabling: (i) spatial multiscale analysis to optimize the delineation of individual landscape features, while the spatial scale of pixels is predefined by the sensor resulting in reduced change detection accuracy; (ii) reduction of small spurious changes due to high spectral variability in high spatial resolution imagery, change of viewing geometry, and slight misregistration between multitemporal images, while applying pixels as the basic units tends to produce more salt-and-pepper noises; (iii) object-based features to facilitate change detection that not only provides more metrics (e.g. shape and size) than those from pixels, but also generates more meaningful object-adaptive windows/kernels than the ones heuristically/arbitrarily defined.

The new features of image-objects, however, raise new challenges in OBCD. Research endeavours to deal with these challenges are summarized in four groups: image-object, class-object, multitemporal-object, and hybrid change detection. Compared to traditional pixel-based change detection, OBCD algorithms have to consider not only spectral and/or texture information, but also object geometry. Statistics or GIS functions facilitate the implementation of image-object comparison, although heuristically defined thresholds are often needed. We further note that, image-objects independently derived from multitemporal imagery rarely have the same object boundaries for the same landscape features, due to the variations in viewing geometry, illumination, etc. As a result, silver polygons are generated by differencing two or more image-objects. Recent solutions include segmenting all multitemporal images at one step and backdating or updating one-date land cover maps. However, limitations remain in these approaches, which either rarely consider the influence of segmenting before- and after-change

images together, as the same geographic location may have different objects, or rely on well-developed high-accuracy reference maps. The evaluation of OBCD results is another critical issue that has raised researchers' attention. Preliminary results show that objects may be well suited to quantify changes when only one class of the landscape features is the research emphasis. However, a system and thorough comparison of using points and objects in OBCD accuracy assessment for various types of landscape features remains to be completed.

Most OBCD algorithms have been developed fairly recently with the published literature describing applications over a variety of fields, including (i) vegetation change, (ii) urban change, and (iii) other applications. Specifically, (i) many researchers have focused on OBCD in defining the dynamics (e.g. disturbance and recovery post-disturbance) occurring over boreal (Hall and Hay 2003, McDermid *et al.* 2003, 2008, Hese and Schmullius 2004, Yu *et al.* 2004, Desclée *et al.* 2006, Wulder *et al.* 2008b, Middleton *et al.* 2008, Linke *et al.* 2009), tropical (Carvalho *et al.* 2001, Bontemps *et al.* 2008, Duveiller *et al.* 2008), and temperate (Willhauck *et al.* 2000, DeChant and Kelly 2009) forest ecosystems. OBCD has also been applied to detect changes occurring over savannah (Carvalho *et al.* 2007), mangrove (Conchedda *et al.* 2008), and riparian (Johansen *et al.* 2010) ecosystems, with additional investigations upon shrub encroachment (Laliberte *et al.* 2004) and retreat (Stow *et al.* 2008). (ii) OBCD is well suited to portray urban change, as anthropogenic objects (e.g. buildings, roads and parking lots) have distinct boundaries and are relatively internally homogeneous. Application examples are geographically disparate, including Africa (Durieux *et al.* 2008, Gamanya *et al.* 2009, Bouziani *et al.* 2010), Asia (He *et al.* 2005, An *et al.* 2007, Li *et al.* 2009), Europe (Grenzdörffer 2005, Walter 2005, Doxani *et al.* 2008), and North America (Owojori and Xie 2005, Im *et al.* 2008, Gweon and Zhang 2008, Zhou *et al.* 2008, Bouziani *et al.* 2010). Urban change may also refer to defining structural damage (e.g. building collapse). Compared to urban development, structural damage is somewhat more difficult to detect using OBCD, as the post-damage images relate discrete and unclosed building edges (Chen and Hutchinson 2007). Recent studies have assessed the use of OBCD algorithms to interpret various types of urban damage caused by natural disasters (e.g. earthquakes or tsunamis) or humanitarian crises (Al-Khudhairy *et al.* 2005, Chen and Hutchinson 2007, Gong *et al.* 2008, Tanathong *et al.* 2009). (iii) In addition to the applications related to vegetation dynamics or urban areas, OBCD has also been evaluated to detect feature change with military vehicles (Hazel 2001), lakes (Li and Narayanan 2003),

nuclear facilities (Niemeyer and Canty 2003, Niemeyer *et al.* 2005), quartzite (Carvalho *et al.* 2001) and marble quarries (Mouflis *et al.* 2008), landslide-prone areas (Park and Chi 2008), and coastal regions (Berberoglu and Akin 2009).

Apparently, recent research efforts to develop OBCD algorithms for different application domains have dramatically advanced change detection studies using the object-based paradigm. However, challenges remain. For example, (i) OBCD has difficulties to detect changes in continuous geographic variables (e.g. NDVI and land surface temperature), as no precise boundaries of these variables can be defined (Bian, 2007). Thus, users should be mindful that objects portraying continuous spatial phenomena may be inconsistently generated. (ii) Beginning with the premise that landscape features can be delineated with objects, the performance of recent computer-aided segmentation algorithms is highly dependent on the specified task, where no single algorithm is appropriate under all conditions. Thus, a 'trial-and-error' approach is typically used to optimize the parameters. Errors from segmentation propagate through change detection. For example, changes smaller than the object size could not be detected (Desclée *et al.* 2006). Even though geographic objects are perfectly delineated at one date, the handling of partial (i.e. sub-object area) changes has rarely been addressed (Chen and Hutchinson 2007, Gamanya *et al.* 2009). (iii) There remains little discussion on feature selection techniques, which is an important part of OBCD. Compared to the pixel-based change detection, OBCD benefits from a wider range of features to choose from, including spectral information, image-texture, geometry and relation to sub-/super-objects. On the other hand, this also increases the difficulty of choosing the most appropriate features for OBCD. In particular, when multitemporal and multiband images are used, the number of features further dramatically increases with the number of dates and bands. (iv) SAR (synthetic aperture radar) is another important remote sensing system; however, the application of SAR imagery in OBCD has been limited by the unsatisfied performance of the commonly-used commercial segmentation software due to the presence of speckle that can be modeled as strong noise (Rignot and van Zyl 1993, Ayed *et al.* 2005). It is expected that the incorporation of more sophisticated algorithms, such as the MRF (Markov random field) approach (Smits and Dellepiane, 1997), the global maximum *a posteriori* (MAP) estimation (Caves *et al.* 1998) or spectral clustering ensemble (Zhang *et al.* 2008), in commercial software will support a better use of SAR imagery in OBCD.

Despite challenges in OBCD remain to be addressed, the research activities of incorporating the object-based paradigm in change detection offer unique approaches and methods for exploiting high spatial resolution imagery, to capture meaningful detailed change information in a systematic and repeatable manner, corresponding to a wide range of information needs.

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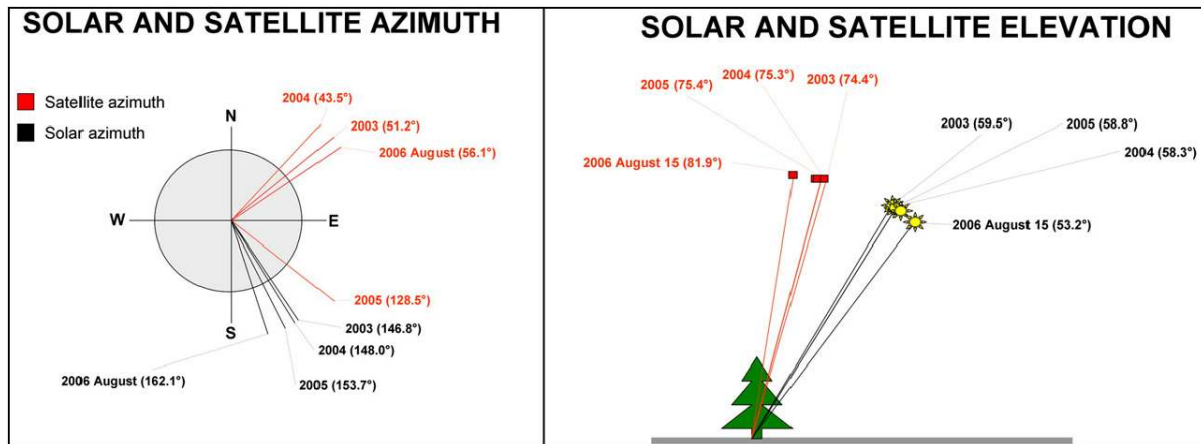
List of Figures:
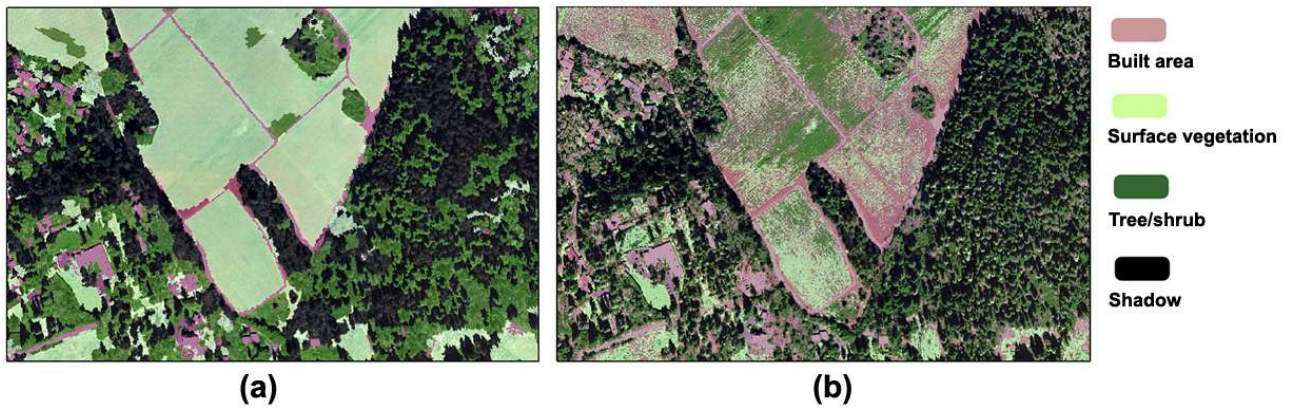
Figure 1: Comparison of classified maps using (a) a multiscale object-based, and (b) a pixel-based approach (modified from Cleve *et al*. 2008).
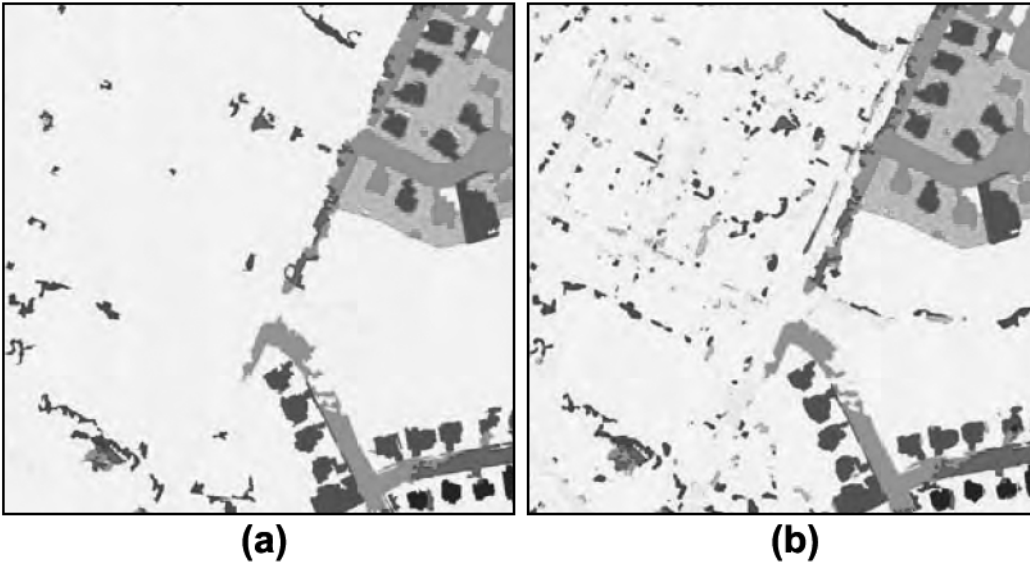
Figure 2: Comparison of change detection results using (a) an object-based and (b) a pixel-based approach (modified from Zhou *et al*. 2008).

Figure 3: Illustration of the different viewing geometries under which the four years (2003, 2004, 2005 and 2006) of images were collected (adapted from Wulder *et al*. 2008b).
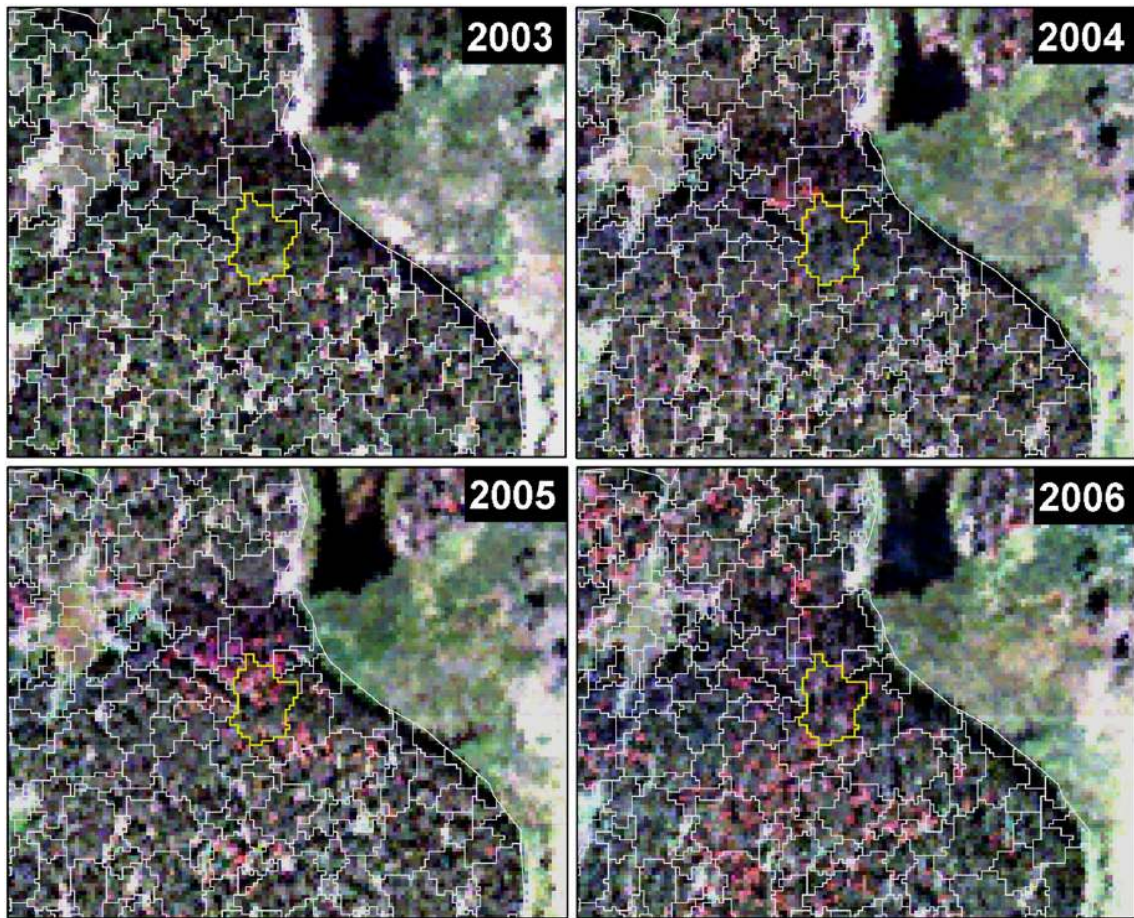
Figure 4: A forest stand covered by image-objects (with white and yellow boundaries), where the yellow object tacks tree counts and vegetation health over the same geographic area (adapted from Wulder *et al.* 2008b).
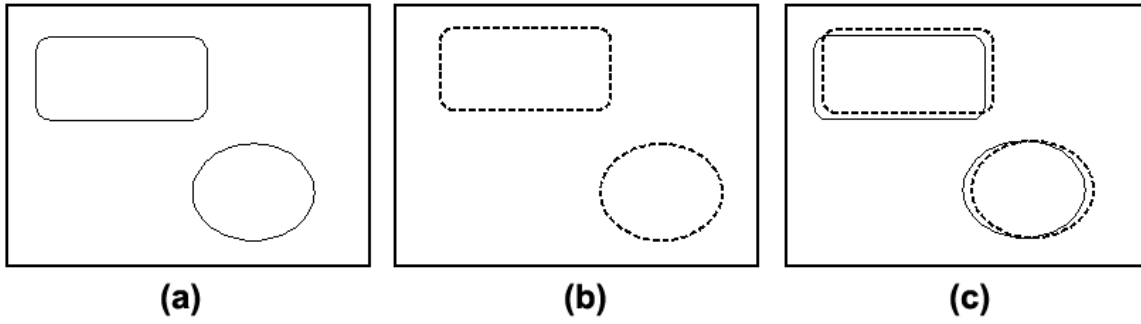
Figure 5: Two hypothetical image-objects extracted separately from (a) date 1 and (b) date 2, and (c) their overlay showing displacement due to image misregistration.
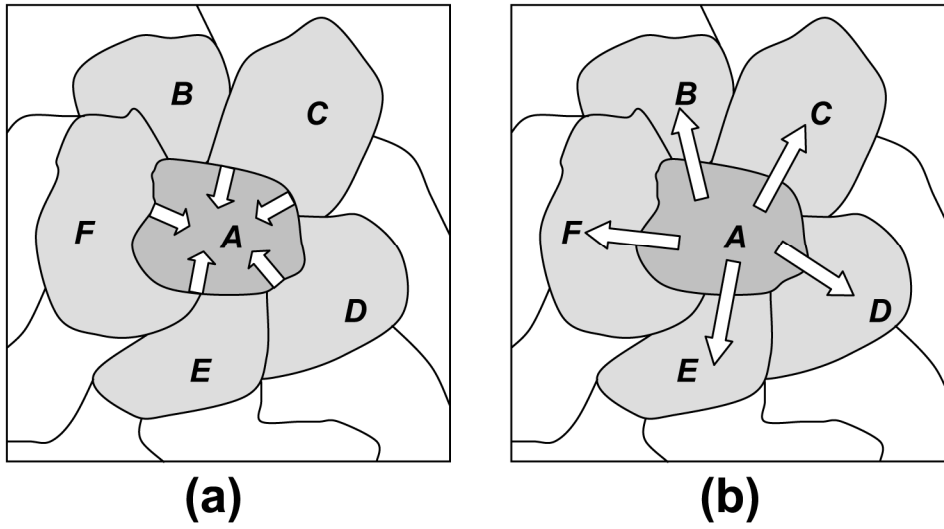
Figure 6: Object-based texture calculated within (a) individual object A or (b) neighbouring objects – A, B, C, D, E and F (adapted from Chen and Hay, 2011).