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# REVIEW ARTICLE

# Current situation and needs of change detection techniques

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Research on change detection techniques has long been an active topic and many techniques have been developed. In reality, change detection is a comprehensive procedure that requires careful consideration of many factors such as the nature of change detection problems, image preprocessing, selection of suitable variables and algorithms. This paper briefly overviews the major steps involved in a change detection, summarises major change detection methods, discusses the impacts of scales and complexity of study areas on the selection of remote-sensing data and change detection algorithms and finally discusses the needs of developing new change detection methods. As high spatial resolution images are easily available in the past decade, texture- and object-based methods become valuable to improve change detection performance. At national and global scales, coarse spatial resolution satellite images such as MODIS become important data sources for rapidly detecting land-cover change, but results have high uncertainty. More research is needed to develop new techniques to solve the mixed pixel problem. At regional scale, it is necessary to explore integration of multi-sensor data and multiple algorithms to improve change detection results.

**Keywords:** change detection; remote sensing; land use and land cover

## 1. Introduction

Land use and land cover (LULC) change has been regarded as an important factor influencing climate change and environmental conditions (Grimm *et al*. 2008, Jones *et al.* 2008), and has a close relationship to population migration and economic conditions (DeFries 2013). As a fundamental data source for many studies, timely updating of LULC data sets is necessary. Remote sensing has become a major data source for mapping and monitoring LULC dynamic change over time (Xian *et al.* 2009, Hansen and Loveland 2012), because it can capture land surface information at the time when satellites pass through. In the past four decades, research on LULC change detection has obtained great attention and a large number of techniques have been developed (see the review papers by Singh 1989, Lu *et al*. 2004b, Bhagat 2012, Hussain *et al*. 2013). To date, change detection is still an active research topic (Demir *et al.* 2012, 2013, Volpi *et al*. 2013), and new techniques continue to be developed to effectively employ different features inherent in remote sensing and ancillary data for improving change detection results (Ardila Lopez *et al*. 2012, Chen *et al*. 2013, Hussain *et al*. 2013, Kim *et al*. 2013).

In theory, different LULC types have their own spectral signatures, and change in LULC types will result in change of their spectral signatures. Thus, LULC change can be

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detected through comparing the spectral signatures of two points in time using a suitable algorithm (Lu *et al.* 2004b). However, in practice, many factors, such as the complexity of landscapes and topographic conditions under investigation, the characteristics of selected remote sensing data, quality of image registration and of atmospheric correction or normalisation between multitemporal images, the selected change detection methods and the analyst's skill and experience can affect change detection results (Lu *et al*. 2004b, Jensen 2005). Therefore, change detection is a comprehensive procedure that requires consideration of all these aspects. When the user's needs are clearly described and the study area is selected, selection of variables and corresponding change detection algorithm becomes critical.

In practice, the right choice for implementing change detection in a specific study area is still poorly understood, mainly due to lack of guidelines to design an optimal change detection procedure. It is necessary to better understand which technique is suitable for which kinds of remotely sensed data at different characteristics of the study areas under investigation. Although previous literatures (e.g., Singh 1989, Lu *et al*. 2004b, Hussain *et al*. 2013) have reviewed many change detection techniques, they are more focused on the description of specific techniques. Some important topics such as concerns in major steps involved in a change detection procedure, selection of potential variables and impacts of scale issues have not been fully discussed. This paper will (1) offer a general description of a change detection procedure so that readers can clearly understand major concerns in each step; (2) describe different change categories and overview potential variables for change detection; (3) discuss the impacts of different scales and complexity of a study area on the selection of remote sensing variables and corresponding algorithms, which they have not been fully discussed before; and (4) finally, briefly discuss the needs to develop new methods to effectively employ different remote sensing features.

## 2. A general procedure for conducting a change detection analysis

The major steps and corresponding contents for conducting an LULC change detection analysis is summarised in Table 1. A brief description of each step is provided in the following sub-sections.

### 2.1 *Description of change detection problems*

For a change detection study, it is necessary to clearly define the research problems that need solving, the objectives, location and extent of the study area (Jensen 2005). All the following steps such as selection of remotely sensed data and corresponding algorithms are designed according to the nature of change detection problems. Important issues include definition of a change detection system, extent and complexity of the study area, user's requirements in change detection results, time periods and availability of remote sensing and ancillary data. After clearly understanding user's needs and research problems, a change detection procedure can be designed. The selection of suitable variables from remote sensing data and corresponding change detection algorithms is especially critical in a change detection procedure and they are still active research topics.

### 2.2 *Selection of suitable remotely sensed data*

Remote sensing data have different features in radiometric, spectral, spatial and temporal resolutions and polarisation options (for radar data). Understanding the strengths and

Table 1. Major steps and corresponding contents for conducting change detection analysis.

| Major steps | Main contents |
|---|---|
| Describe the nature of change detection problems | Research problems and objectives |
| | Geographic location and size |
| | Time period |
| | Change detection system |
| | Accuracy requirement |
| Select suitable remotely sensed data | The characteristics of remote sensing data |
| | Consideration of atmospheric & environmental conditions |
| | Characteristics of the landscape under investigation |
| Conduct image preprocessing | Geometric rectification/registration |
| | Radiometric and atmospheric correction |
| | Topographic correction if needed |
| Select suitable variables | Different features inherent remote sensing data |
| | Per-pixel-based variables from image transform or vegetation index |
| | Sub-pixel-based variables from unmixing processing such as spectral mixture analysis |
| | Spatial features such as textural images |
| | Thematic variables from image segmentation or classification |
| Select suitable change detection algorithms | The characteristics of change detection algorithms |
| | Selection of suitable algorithms |
| | Comparison of different algorithms if needed |
| Evaluate change detection results | Determination of sampling strategy and sample size |
| | Collection of reference data |
| | Accuracy assessment |

weaknesses of different types of sensor data is prerequisite for selecting suitable data sets for a specific study (Barnsley 1999, Lefsky and Cohen 2003). User's needs, complexity of landscapes and the areal extent of a study area are important concerns for the selection of remotely sensed data (Lu *et al*. 2004b, Lu and Weng 2007). High spatial resolution images such as IKONOS, QuickBird and Worldview have recently become important data sources for change detection analysis at a local scale (Lu *et al*. 2010). Medium spatial resolution images, especially Landsat images due to their long history of data availability and suitable spectral and spatial resolutions, have become a common data source for regional LULC change detection (Xian *et al.* 2009, Hansen and Loveland 2012). At a continental or global scale, coarse spatial resolution data such as AVHRR, MODIS and SPOT VGT (VEGETATION) may be used (Hansen and DeFries 2004, Bergen *et al*. 2005, Lunetta *et al*. 2006, Hansen *et al*. 2008a, b, Bontemps *et al.* 2012), but present challenges in developing suitable techniques to extract changed features from coarse spatial resolution data. Since a radar can capture land surface information without impacts of atmospheric conditions, its data has become another important source for LULC change detection (Grey *et al.* 2003, Wang *et al*. 2008, Whittle *et al*. 2012, Brisco *et al*. 2013, Nascimento *et al*. 2013), especially when optical sensor data are not available due to the cloud cover problem. Ideally, change detection is conducted with multitemporal images from the same sensor. Yet, the same sensor data may not be obtainable due to the constraints of data availability. In these cases, data from different optical and/or radar sensors are the only solution (Reiche *et al*. 2013). Using multi-sensor images which are acquired at different dates is a challenge in terms of designing a suitable procedure. Caution should be taken to reduce the impact of external factors, such as different atmospheric conditions, states of soil moisture and vegetation phenology between different image acquisition dates, on the change detection analysis (Jensen 2005). Cloud cover is another problem that needs to be taken care of before conducting change detection analysis (Lu *et al*. 2012, Eckardt *et al*. 2013).

### 2.3 *Image preprocessing*

Image preprocessing, including geometric rectification or image-to-image registration and atmospheric calibration, is required before conducting a change detection analysis. Accurate geometric registration between multitemporal images is critical because mis-registration may result in largely spurious results of change detection (Dai and Khorram 1998, Verbyla and Boles 2000, Stow and Chen 2002, Shi and Hao 2013). The atmospheric conditions at different acquisition dates influence spectral signatures for the same invariant objects. Therefore, conversion from raw data to surface reflectance using a proper atmospheric calibration method is needed (Song *et al.* 2001, Du *et al.* 2002, Vicente-Serrano *et al.* 2008, Chander *et al.* 2009). Many algorithms from relative calibration and dark-object subtraction to complex model-based calibration approaches (e.g., 6S – second simulation of the satellite signal in the solar spectrum) have been developed for radiometric and atmospheric correction (Vermote *et al*. 1997, Song *et al*. 2001, Chander *et al.* 2009). The dark-object subtraction approach is commonly used in practice because it is strictly an image-based procedure and corrected for the effects caused by sun zenith angle, solar radiance, and atmospheric scattering (Chavez 1996, Lu *et al*. 2002). In mountainous study areas, topographic correction is also necessary to reduce the impact of topography on reflectance. The topographic correction models, such as Minnaert, and statistical–empirical approaches may be used (Riano *et al*. 2003, Lu *et al*. 2008b).

### 2.4 *Selection of suitable remote sensing variables*

Selection of suitable remote sensing variables to detect changes is fundamental. These variables could be spectral bands and derived variables using different approaches, such as vegetation indices, transformed images, textures, segments, sub-pixel features and classification results. Section 4 discusses the potential variables that may be used for change detection analysis.

### 2.5 *Selection of a change detection algorithm*

Many change detection techniques have been reviewed in the literature (e.g., Singh 1989, Coppin and Bauer 1996, Coppin *et al*. 2004, Lu *et al*. 2004b, Jensen 2005, Kennedy *et al.* 2009, Bhagat 2012, Hussain *et al*. 2013), but which method should be selected for a specific study area and data set is not clear. Depending on the analyst's knowledge, the skills in handling remote sensing data and characteristics of the study areas, several methods are selected for a comparative analysis to identify the best result (Ridd and Liu 1998, Mas 1999, Hayes and Sader 2001, Lu *et al*. 2005, Bucha and Stibig 2008, Berberoglu and Akin 2009). A brief overview of change detection techniques is provided in Section 5.

### 2.6 *Evaluation of change detection results*

The implementation of accuracy assessment for change detection results is a challenge because of the difficulty in collecting reference data at multitemporal periods (Morisette and Khorram 2000, Foody 2010, Olofsson *et al*. 2013). If reference data are available, the traditional error matrix method can be used and this method has been fully described in previous literature (e.g., Foody 2002, Van Oort 2007, Congalton and Green 2008). Biging *et al.* (1999) provided a detailed description of the issues affecting accuracy assessment of LULC change detection. They discussed the factors of a remote sensing processing system that affected accuracy assessment, presented a sampling design to estimate the elements of the error matrix efficiently, illustrated possible applications and gave recommendations for accuracy assessment of change detection. Interested readers should look at the monograph 'Accuracy assessment of remotely sensed-derived change detection' by Biging *et al.* (1999). Different change categories, such as binary change and non-change and detailed 'from-to' change trajectories, required different accuracy assessment methods, including sampling technique (Foody 2010), especially in a large area (Herold *et al*. 2008). In order to improve change detection results, uncertainty analysis is valuable to identify major factors influencing change detection errors to optimise the change detection procedure; however, this kind of research has not been obtained much attention yet.

## 3. A brief overview of change categories

Change detection is generally grouped into two categories – the change between classes and the change within classes. The former is a conversion of a land cover from one category to a completely different category such as deforestation or urbanisation; and the latter is a modification of the condition of a land cover within the same category, such as forest degradation due to selective logging (Lu *et al.* 2004b). A good change detection study should provide information relevant to (1) changed area and rate, (2) spatial distribution of changed types, (3) change trajectories of LULC types, (4) changes in certain specific attributes such as biomass and leaf area index (LAI) and (5) accuracy assessment of change detection results (Lu *et al.* 2004b). In addition to the conversion from one type to another, more research is shifted to examining the disturbance due to fires and insects, or the seasonal change due to phenology (Wulder and Franklin 2007, Verbesselt *et al*. 2010a, b). Before implementing a change detection analysis, it is important to clearly define the kinds of changes to be detected in a given study area. Here, we group the change categories into four types: binary change/non-change, detailed 'from-to' change trajectories, specific change type and continuous variable change, and they are briefly discussed in the following.

### 3.1 *Binary change and non-change category*

Change and non-change detection is usually the initial stage for understanding the amount and spatial patterns of changed areas in a study area within a change detection period. This information is required to be able to design a change detection procedure, including identification of suitable remote sensing variables and change detection algorithms. Threshold-based methods are commonly used to distinguish changed areas from non--changed areas (Lu *et al*. 2005). However, change and non-change detection cannot provide much meaningful information unless a clear definition for detecting the kind of change is provided.

### 3.2 *Detailed 'from-to' change trajectories*

Many change detection studies require detailed 'from-to' change trajectory information. A post-classification comparison approach is commonly used for examining the detailed change trajectories (Lu *et al*. 2004b, 2012). Before conducting the change detection analysis, it is critical to clearly define an LULC classification system and the required change detection system. Different classification systems will considerably affect the classification accuracy, thus influencing change detection accuracy. It is important to highlight interesting and meaningful change trajectories, and to exclude spurious change due to the misregistration. For instance, two six-class (i.e., forest, savanna, other-vegetation, agropasture, impervious surface area, and water) classification images can produce six unchanged types and 30 change trajectories. However, some change trajectories, such as those from impervious surface areas or agropasture to mature forest or to savanna within a few years, are not true. Figure 1 provides an example for highlighting forest deforestation (from forest to agropasture or other-vegetation), savanna deforestation (from savanna to agropasture or other-vegetation), dynamic change between other-vegetation and agropasture and impervious surface expansion (from forest, savanna, other-vegetation or agropasture to impervious surface areas) in the Brazilian Amazon (details were provided in Lu *et al.* 2013a).

### 3.3 *Specific change types*

Not all studies require detailed 'from-to' change trajectory information. In these cases, users want to know specific change types, such as deforestation, urbanisation, agricultural expansion and certain disaster-induced changes (e.g., flooding, earthquake and fire). Deforestation has been regarded as a major factor resulting in carbon emission into the atmosphere (Harris *et al*. 2012, Zarin 2012). Brazil has developed two systems, i.e., PRODES – Program for the Estimation of Deforestation in the Brazilian Amazon (http://www.obt.inpe.br/prodes/) and DETER – Real Time Deforestation Monitoring System (http://www.obt.inpe.br/deter/) to monitor annual deforestation using Landsat and MODIS data, respectively (Hansen *et al*. 2008b, Shimabukuro *et al*. 2013). Figure 2 provides examples illustrating urbanisation in an urban–rural landscape in Mato Grosso State using multitemporal QuickBird images (Lu *et al*. 2010) and deforestation in Machadinho d'Oeste in north-eastern Rondônia State using multitemporal Landsat images (Lu *et al.* 2004a). In this case, one just needs to develop a specific method to extract the land-cover type (e.g., impervious surface area or forest) without a complete LULC classification scheme.

### 3.4 *Continuous variable change*

LULC modification, especially forest disturbance, can be caused by natural (insect/disease, drought and fire) and anthropogenic factors (e.g., selective logging) (Wulder and Franklin 2007, Frolking *et al*. 2009, Spruce *et al*. 2011, Masek and Healey 2013, Souza 2013). This kind of change detection has special requirements, that is, the selected remote sensing variables are sensitive to small quantitative changes in vegetation structure, and the time period is relatively short in order to detect the disturbance. Since Landsat data are available for public access at no cost, time series of Landsat images have been extensively applied to examine forest disturbance (Huang *et al*. 2009, 2010, Kuemmerle *et al*. 2009, Cohen *et al.* 2010, Kennedy *et al.* 2010, Wulder *et al*. 2012,

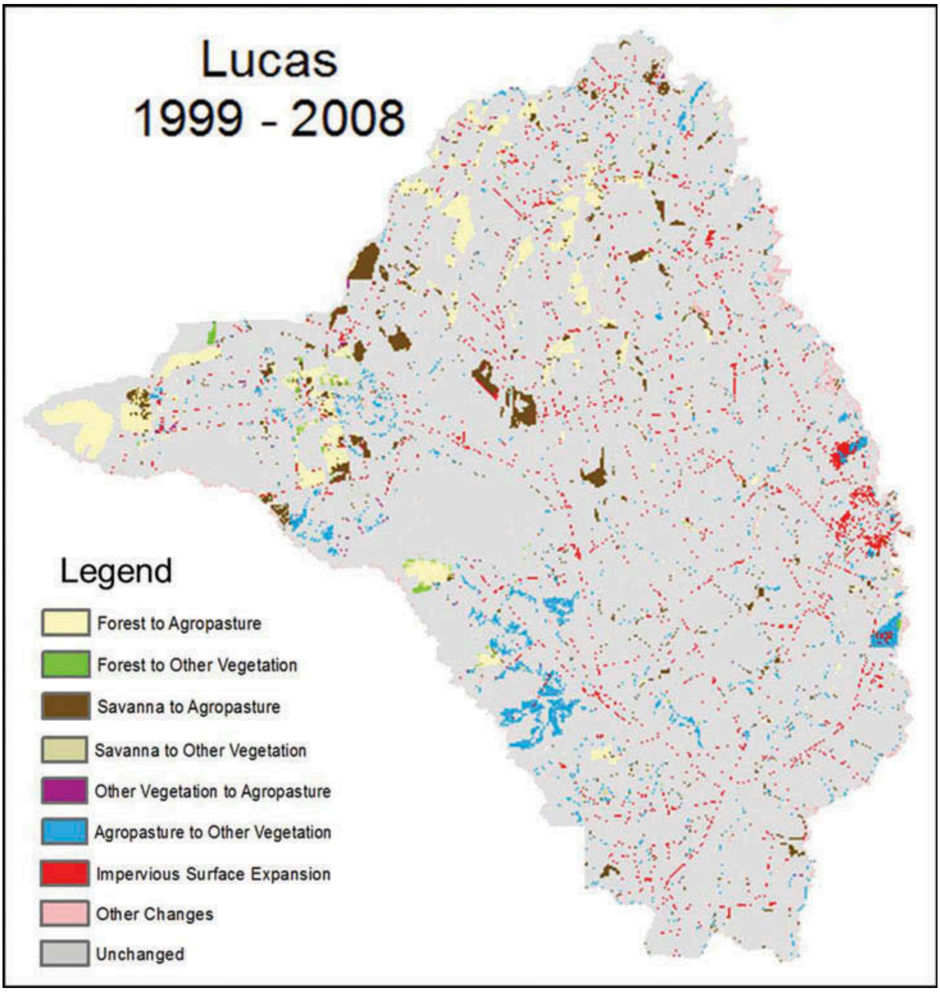


Figure 1. An example showing detailed LULC 'from-to' change trajectories between 1999 and 2008 in Lucas do Rio Verde, Mato Grosso State, Brazil.

Potapov *et al*. 2013). Meanwhile, time series MODIS data provide a new opportunity to examine forest disturbance at regional and national scales (Jin *et al*. 2005b, Verbesselt *et al*. 2010b). The key is to develop suitable techniques to detect the small changes in the mixed pixels due to its coarse spatial resolution. Depending on the factors causing forest disturbance, selection of suitable remote sensing variables and techniques are especially important for detecting the disturbance at different degrees.

## 4. Selection of suitable variables for conducting change detection analysis

The spectral, spatial, temporal, and radiometric resolutions of remotely sensed data have a significant impact on the success of a change detection project. When selecting remote sensing data for change detection applications, it would be ideal to use the same sensor with the same radiometric and spatial resolution at the same time of the year in order to

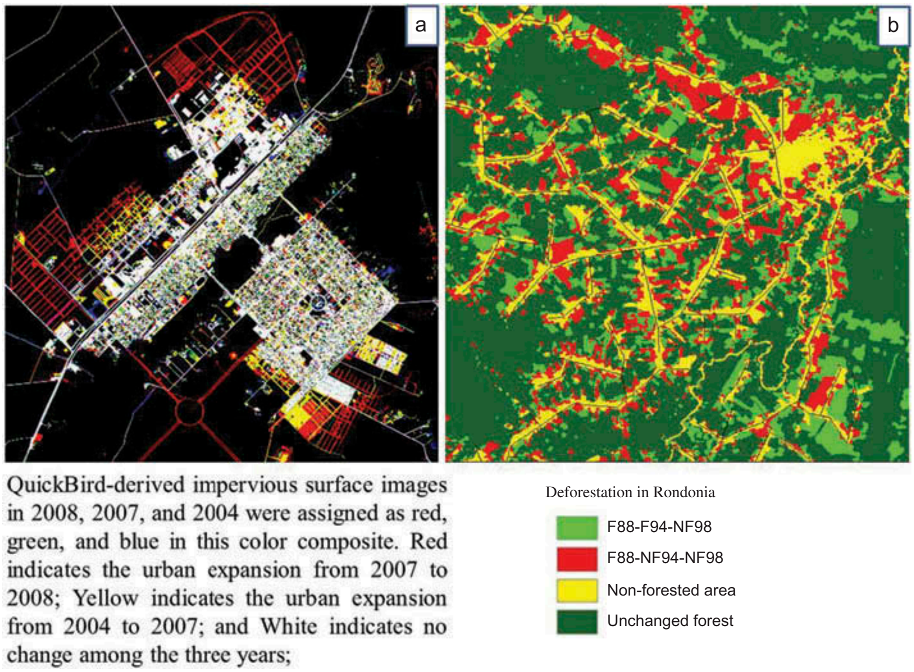


Figure 2. Examples showing (a) urbanisation in Lucas do Rio Verde, Mato Grosso State using QuickBird images in 2004, 2007 and 2008; and (b) deforestation in Machadinho d'Oeste in north-eastern Rondônia State using Landsat images in 1988, 1994 and 1998.

eliminate the effects of external sources such as sun angle and phenological differences. The considerations of remote sensing systems and environmental characteristics before implementing a change detection study were detailed in previous literature (see Coppin and Bauer 1996, Biging *et al*. 1999, Jensen 2005). In reality, selection of the same sensor data in a specific study is difficult, especially in moist tropical regions due to cloud cover problem. For change detection over long-term periods, satellite images may be not available, thus, multi-source data consisting of different satellite images, airborne photographs and existing thematic maps may be used (Petit and Lambin 2001, Ichii *et al.* 2003, Walter 2004, Li 2010, Groen *et al*. 2012, Tian *et al*. 2013). Today's availability of different remote sensing data provides more choices for data collection for a specific study area (Reiche *et al*. 2013), considering the user's needs, extent and complexity of a study area.

The unique features (e.g., radiometric, spectral, spatial and temporal resolutions for optical sensor data and polarisation options for radar data) of remote sensing data make it the primary data source for LULC change detection at various scales (Kennedy *et al.* 2009, Wulder *et al*. 2012). Temporal resolution is an important concern for collecting multitemporal remote sensing data. Relatively low temporal resolution (e.g., revisit interval of 26 days for Landsat MSS in the 1970s, and of 16 days for Landsat TM in the 1980s) makes collection of cloud-free images difficult. Daily availability of some remote sensing data such as RapidEye and MODIS and availability of multi-sensor data provide new opportunities to conduct LULC change detection, especially for modification detection. Improvement in radiometric resolution, from 6 bits in Landsat MSS, and 8 bits in

Landsat TM to 12 bits in Landsat 8 LDCM (Landsat Data Continuity Mission) may provide better separability for different LULC types. Spectral signature is a critical feature for LULC classification. Higher spectral resolution data, such as hyperspectral versus multi-spectral versus panchromatic data, have the potential to better separate different LULC types. In reality, majority of available sensor data are multi-spectral. Spatial resolution determines the ability to distinguish the smallest objects in remote sensing data. At present, spatial resolution has a wide range, from sub-meter (e.g., QuickBird, Worldview), to medium (e.g., 30 m for Landsat images) and coarse spatial resolution images (e.g., MODIS with 250 m to 1000 m). Since radar systems can collect data with different polarisation options without impacts of weather conditions (Kasischke *et al.* 1997), use of radar data becomes important for the study areas where optical sensor data limits usability due to cloud cover problems. However, the incapability of vegetation classification using radar data (Li *et al*. 2012) may be a constraint for successful change detection, especially for detecting vegetation modification due to human or nature-induced factors. The followings discuss each category of the potential variables.

### 4.1 *Direct use of remote sensing spectral features*

Spectral responses are the most common variables for change detection. Much of previous research has indicated that the visible red band, with a wavelength of 620–750 nm, can provide better performance in detecting binary change/non-change categories than other spectral bands due to the highly different spectral signatures between vegetation and other land covers (Chavez and Mackinnon 1994, Lu *et al*. 2005). Vegetation indices or transformed images may further improve change detection performance due to the capability of enhancing features of interest (Lu *et al*. 2005). Because vegetation indices can reduce the variation caused by canopy geometry, soil background, sun view angles and atmospheric conditions, many vegetation indices have thus been developed (Bannari *et al.* 1995, Eastwood *et al*. 1997, McDonald *et al.* 1998) and applied to LULC change detection, especially vegetation change. They have different merits because vegetation indices can enhance some specific vegetation information (Bayarjargal *et al*. 2006). Image transform can concentrate major image information on the first few components, and using these derived components, it may produce better change detection results than using individual bands (Lu *et al*. 2005). Principal component analysis (PCA), tasselled cap and minimum noise fraction (Jensen 2005) are among the most commonly used image transform methods. The wetness component from tasselled cap transform has proven to be valuable for detecting forest disturbance (Healey *et al*. 2005, Jin *et al*. 2005a). The spectral features are especially important for medium and coarse spatial resolution images for conducting change detection, but it is critical to identify proper variables that can better represent the spectral difference between the interested features and others. In practice, researchers examine different variables and compare their results in order to find the best one for a specific study (Lu *et al*. 2005).

LULC change detection is usually conducted with the same sensor data. For many study areas, especially those in moist tropical regions, collection of the same sensor data at different dates may be difficult because of cloud cover and low revisit time of the satellite. In this case, the use of different sensor data for conducting change detection is required (Lu *et al.* 2008a, Qin *et al*. 2013). Although different sensor data (Lefsky and Cohen 2003) provide new opportunities for integrating multi-sensor data in change detection analysis, the differences in spectral, spatial, radiometric and temporal resolutions between different sensor data make change detection using traditional methods difficult.

New methods are needed to conduct change detection based on multiple sensor data. One possible method uses data fusion (Pohl and van Genderen 1998, Lu *et al.* 2008a, Zeng *et al*. 2010, Zhang 2010, Hussain *et al*. 2013, Reiche *et al*. 2013). The key is to select suitable data fusion techniques to highlight the changed areas. Lu *et al.* (2008a) had used Landsat TM and SPOT HRG to examine vegetation change in the Brazilian Amazon based on PCA fusion and image differencing for identifying vegetation degradation/restoration. Data fusion of multi-resolution or multi-sensor images may enhance the spectral information in addition to improving spatial resolution in the newly fused image (Du *et al*. 2013, Reiche *et al*. 2013).

### 4.2 *Use of spatial information*

As high spatial resolution images, such as QuickBird and Worldview, are easily available since the early 2000s, much research has shifted to use of high spatial resolution images for accurate LULC change detection, especially in urban landscapes (Lu *et al*. 2010). This provides a new platform to examine small changes in an urban landscape or to analyse forest disturbance due to selective logging or other disasters. However, directly using spectral signatures generates relatively poor results due to high spectral variation with the same land cover and different shade sizes due to sun elevation angles and azimuths between image acquisition dates, as illustrated in Figure 3. The rich spatial information inherent in high spatial resolution images is an important feature for LULC change detection. Textural images calculated using the GLCM-based methods have been proven to be valuable for change detection (Im *et al.* 2008a, Lam 2008, Lu *et al*. 2010, Wu *et al.* 2010). Many texture measures such as variance, homogeneity, contrast, dissimilarity, entropy, second moment, Markov random field and others (Haralick *et al.* 1973, Marceau *et al.* 1990, Chen *et al.* 2004, Seetharamana and Palanivel 2013) are used for LULC classification (Li *et al*. 2012), but not extensively for change detection yet. The major reason may be the difficulty in identifying the optimal textural images and the reduced separability of some LULC types (Li *et al*. 2012). The performance of a textural image varies with the complexity of a study area under investigation, the texture measure used, the size of moving window and the image itself (Chen *et al.* 2004). Recently, object-based image analysis has been widely explored using high spatial resolution images (Im *et al.* 2008b, Blaschke 2010, Chen *et al*. 2012a). The key is to identify optimal parameters for developing good-quality segmentation imagery suitable for a specific study.

### 4.3 *Use of sub-pixel information*

When medium and coarse spatial resolution images are used in urban landscapes or in a complex landscape covering a large study area, mixed pixels are a major problem affecting the change detection because changed areas are small and scattered in different locations (Lu and Weng 2004, Lu *et al.* 2008a). Direct use of these images at per-pixel level cannot effectively detect the changes or may generate high uncertain results. Sub-pixel information may provide a new platform for detecting modification, especially vegetation disturbance because of the ability to reflect forest stand structure (Lu *et al.* 2003, Souza 2013). Spectral mixture analysis is one of the common methods to produce fractional images for change detection (Haertel *et al.* 2004, Lu *et al.* 2011b, c). The key is to identify suitable endmembers for unmixing multi-spectral images into fractional images (Lu *et al.* 2003). In reality, the application of sub-pixel information for change detection is still very limited. The major problem is the difficulty in generating fractional land-cover

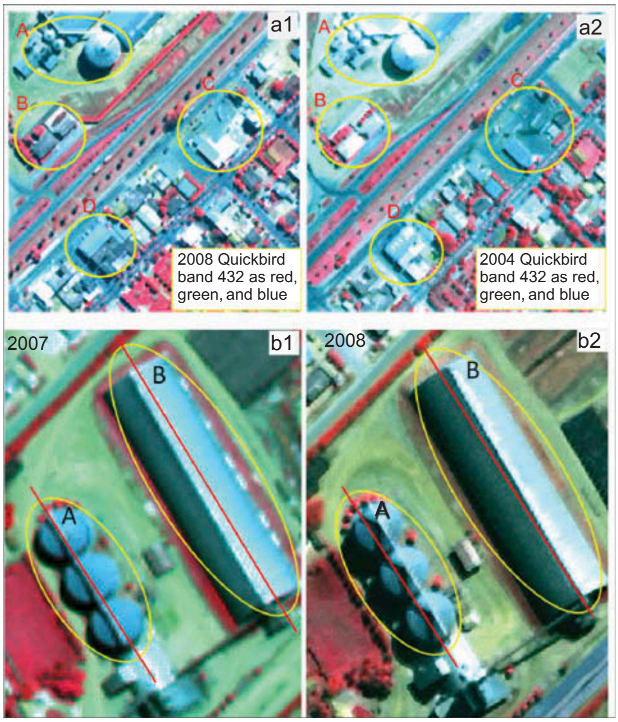


Figure 3. QuickBird false colour compositions showing the high spectral variation in impervious surface areas and shadow (a1 and a2) and displacement problems between different image acquisition dates (b1 and b2).

data from medium or coarse spatial resolution, and the lack of suitable algorithm or method to conduct change detection based on fractional images. To date, there are no suitable algorithms to effectively use multitemporal sub-pixel images to produce 'from-to' change trajectories.

### 4.4 *Use of thematic information*

Since change detection based on spectral response (e.g., spectral bands and derived products) or textures is influenced by external factors such as different atmospheric conditions, soil moisture conditions, topography, sun elevation angle and vegetation/crop phenology (Jensen 2005), direct use of multitemporal spectral responses does not lead to satisfactory change detection results. In order to avoid these impacts, one solution is to conduct image classification for each date of imagery separately before conducting change detection. Many classification algorithms are available, as summarised by Lu and Weng (2007). The key is to develop accurate classification result for each image by properly designing a classification procedure (Lu *et al*. 2012). The classified images are then used to examine LULC change trajectories using the post-classification comparison approach (Lu *et al*. 2012). Depending on the needs of change detection results, design of a suitable LULC classification system is important.

### 4.5 *Development of biophysical attributes*

Majority of change detection techniques are based on the direct use of remote sensing data. It may be difficult to detect some specific changes, such as urban expansion due to the fact that changed areas cover less than one pixel (Lu *et al.* 2011b), and forest degradation due to the small difference in spectral response caused by complex forest structures (Lu *et al.* 2013b). Some biophysical attributes, such as impervious surface area in urban landscapes and LAI in forest ecosystems, can be derived from remotely sensed data. These variables may lead to better results for specific change detection purposes. For example, much research has gone into the examination of mapping impervious surface distribution from multi-spectral signatures using spectral mixture analysis (Wu and Murray 2003, Lu *et al.* 2011b). The analysis of multitemporal impervious surface data helps examine urban expansion (Lu *et al.* 2011b, Michishita *et al.* 2012). In another study in a moist tropical region, Lu and his colleagues found that entropy (calculated from probability distribution of tree heights within a sample plot) reflecting forest stand structure can be better used to separate different successional stages (Lu 2005). The use of entropy images may better reflect the change of forest stand structure due to disturbance, resulting in more accurate forest degradation or regrowth information. When using biophysical attributes for change detection, the key is to identify a suitable parameter that can better reflect the change of a specific LULC type, meanwhile, this parameter can be accurately extracted from remotely sensed data.

### 4.6 *Use of multi-source data*

Different variables from remote sensing or ancillary data (e.g., previously developed thematic maps) may be used in a change detection procedure (Petit and Lambin 2001, Li 2010). In particular, satellite images are not available before the 1970s, while aerial photographs and survey maps may be available in a longer history for some study areas. Cautions should be taken for quality evaluation of each selected data set. Different source of data have various format, quality and spatial resolution. Improper use of multi-source data may produce a large error due to the data quality problem among the data sources. Therefore, data preprocessing, including geometric rectification, conversion of data formats and resampling of data sets to have the same cell size, will be necessary before conducting change detection. Geographic information system (GIS) techniques will be valuable for integrating these data in a change detection procedure (Li 2010, Hussain *et al.* 2013).

## 5. A brief overview of change detection methods

Many change detection techniques are summarised in the literature (e.g., Singh 1989, Lu *et al*. 2004b, Bhagat 2012, Hussain *et al*. 2013). Lu *et al.* (2004b) summarised over 30 techniques and grouped them into seven categories: algebra, transformation, classification, advanced models, GIS approaches, visual analysis and other approaches. Bhagat (2012) summarised 29 techniques which were grouped into eight categories: spectral classification, multi-date radiometric change, support vector analysis approach, hybrid approach, artificial neural network approach, fusion approach, object comparison approach and triangle model approach. Hussain *et al.* (2013) summarised over 20 approaches which were grouped into 10 sub-classes, and provided a brief description of 15 per-pixel based change detection techniques and three object-based techniques. Advanced non-parametric algorithm such as neural network and support vector machine may provide better performance for change detection (Nemmour and Chibani 2006a, b, Huang *et al*. 2008, Hussain *et al*. 2013). More research is needed to combine different change detection techniques to meet the specific purpose. Some literature has explored the combination or fusion of different change detection methods for improving performance (Du *et al*. 2012, 2013). In this section, detailed descriptions of individual change detection techniques are not provided because previous publications have done. According to the algorithms and variables used, the techniques are grouped into six categories: per-pixel thresholding, per-pixel classification, sub-pixel, object-oriented, hybrid and indirect methods.

### 5.1 *Per-pixel thresholding-based methods*

Many change detection techniques, such as image differencing, vegetation index differencing, PCA and regression analysis (Im *et al*. 2007), are used for detecting change and non-change categories using thresholding methods based on the spectral responses (spectral bands, or derived images using vegetation indices and transform algorithms). In these methods, the critical steps are identifying suitable bands that can effectively reflect the change of interesting types, and determining suitable thresholds in both tails of the histogram representing the changed areas for separation of change and non-change categories (Lu *et al*. 2005, Im *et al.* 2008a, 2009). As described in the above section, different variables can be used, but it is valuable to identify one that best reflects the interest of the features, for example, drought-induced tree mortality or selective logging-induced biomass change.

Selection of thresholds can be based on (1) interactive procedure or manual trial-and-error procedure – an analyst interactively adjusts the thresholds and evaluates the resulting image until satisfied; and (2) statistical measures – selection of a suitable standard deviation from the mean (Lu *et al*. 2005). Im *et al.* (2009) further explored the methods to determine optimal thresholds using a moving threshold window approach. In practice, the determination of thresholds is highly subjective and scene-dependent, depending on the analyst's skills and familiarity with the study area (Lu *et al*. 2004b, 2005). Different external factors, such as phenology and soil moistures, can affect change detection results, especially those related to vegetation and agricultural land change. Although the per-pixel thresholding-based methods only provide the spatial patterns and magnitude of changed results without detailed LULC change trajectory information, they indeed provide valuable information for designing a proper procedure for further examining the detailed change trajectories.

### 5.2 *Per-pixel classification-based methods*

The per-pixel classification-based change detection methods may be the most commonly used ones in practice (Hussain *et al*. 2013) because they can avoid the impacts of external factors on change detection results (Lu *et al*. 2012). However, these methods are criticised for their incapability of solving mixed pixel problem in medium or coarse spatial resolution images and high spectral variation within the same land covers in high spatial resolution images. The quality of 'from-to' change detection results is mainly dependent on the classification accuracy for each date being analysed (Jensen 2005). That is, the classification errors from the individual-date images will affect the final change detection accuracy. Therefore, the development of accurate LULC classification becomes critical (Lu and Weng 2007). However, accurate LULC classification from historical remote sensing data is a challenging task because of lack of training samples and the complex landscapes (Lu *et al*. 2012). In particular, the per-pixel classification-based method is difficult to detect LULC modification, such as forest disturbance.

### 5.3 *Object-based methods*

In order to effectively employ rich spatial information-inherent high spatial resolution images, object-based change detection methods have recently gained increasing attention (Desclée *et al.* 2006, Im *et al.* 2008b, Chen *et al*. 2012a, Hussain *et al*. 2013). In general, the object-based change detection methods can be conducted in three ways: (1) direct comparison of segmentation images at different dates; (2) comparison of classified objects; and (3) image segmentation and classification based on stacked multitemporal images. Object-based methods can reduce the spectral variation within the same land covers. Therefore, these methods are more suitable for high spatial resolution images than for medium or coarse spatial resolution images (Lu *et al*. 2010). The key is to identify optimal parameters (e.g., minimum value distance, variance factor, minimum size of pixels in a segment) for producing suitable segmentation images.

### 5.4 *Sub-pixel based methods*

Since mixed pixels in medium and coarse spatial resolution images have been regarded as an important factor influencing the LULC change detection results (Lu *et al.* 2011c), sub-pixel-based methods have been proposed to solve this problem (Adams *et al*. 1995, Haertel *et al.* 2004, Zanotta and Haertel 2012). Different sub-pixel methods, such as fuzzy classification and spectral mixture analysis, may be used. A common method is to decompose the multi-spectral image into fractional images having biophysical meanings. The thresholding-based methods can be used to examine the changes in the fraction values. This method is valuable for some specific change detection studies such as forest disturbance (Lu *et al*. 2013b, Souza 2013) and urban expansion (Yang *et al*. 2003, Lu *et al*. 2011c, Michishita *et al.* 2012). Although sub-pixel-based methods are especially valuable when coarse spatial resolution images, such as MODIS, are used at national and global scales, there is still a lack of suitable sub-pixel based algorithms to detect detailed 'from-to' trajectories.

### 5.5 *Hybrid methods*

Previous studies mainly examined LULC change/non-change or detailed 'from-to' change trajectories using individual methods, but different methods have their own merits, thus a combination of them may provide better results or more detailed results than individual methods (Im and Jensen 2005, Liu *et al*. 2008, Chen *et al*. 2012b, Du *et al*. 2012, Cassidy *et al*. 2013). In general, hybrid methods may be conducted in two ways: (1) combination of different methods into one change detection procedure; and (2) combination of change detection results from different methods into a new result using certain rules or fusion methods such as feature or decision-level fusion. For example, Lu *et al.* (2008a) had explored the combination of binary change/non-change detection and a post-classification comparison approach to produce vegetation degradation or restoration in the Brazilian Amazon based on Landsat TM and SPOT data. They used PCA to integrate TM and SPOT panchromatic data, and then used image differencing method based on the fused image and original TM image to produce vegetation growth or degradation. A rule-based method was used to classify the Landsat TM and SPOT multi-spectral images into thematic images with three coarse land-cover classes – forest, non-forest vegetation, and non-vegetation lands, and then the post-classification comparison approach was used to detect major LULC change. This hybrid method can produce vegetation gain and loss, in addition to the traditional LULC conversion.

Data fusion-based change detection methods are categorised in three groups: (1) use of different sensor data at various dates such as Landsat at date 1 and panchromatic or radar data at date 2 (Lu *et al.* 2008a), (2) use of different sensor/resolution images in the same year to improve the LULC classification performance (Gungor and Akar 2010), and (3) use of remote sensing and GIS data (Li 2010). Different sensor data may result in the possibility to combine them in a change detection procedure (Zeng *et al*. 2010, Du *et al*. 2013). Different source data, including different remote sensing data and previous thematic or survey data, may be integrated too (Li 2010), especially when remote sensing data are not available in a study area because of the cloud cover problem or a long-term time period. Zeng *et al.* (2010) overviewed remote sensing image fusion methods and Li (2010) overviewed remote sensing and GIS data fusion for LULC change detection. Du *et al.* (2013) compared the change detection results based on pan-sharpened images and decision-level fusion and indicated the advantage of using fusion techniques in improving change detection performance.

### 5.6 *Indirect methods*

The complexity of landscapes and spectral confusion amongst different LULC types lead to poor results based on direct use of remote sensing features for change detection. Indirect methods identify some biophysical attributes that can effectively reflect the LULC change. These attributes can be derived from remote sensing data through modelling. Common attributes are, for example, impervious surface in urban landscapes and LAI in forest ecosystems (Lu *et al.* 2011b, 2013b). The key is to develop accurate biophysical attributes from remote sensing data while the attribute is suitable for use as a variable for change detection analysis. Indirect methods could be valuable for global LULC change detection using coarse spatial resolution images, especially for rapidly updating some specific change categories, such as deforestation and urbanisation. Another important application may be the detection of forest disturbance caused by natural or anthropogenic factors based on analysis of vegetation structure change such as LAI, biomass, or greenness abundance. However, cautions should be taken to ensure that the uncertainty or error of forest attribute estimates is sufficiently less than the change amount due to forest disturbance.

## 6. Consideration of landscape complexity and scales in change detection analysis

The extent and complexity of a study area is an important consideration for designing a change detection procedure for a specific study. The extent of a study area (local, regional and global scales) will affect the selection of remote sensing data, thus further affecting the application of a change detection algorithm. Different complexity of a landscape under investigation, such as forest-dominated or urban-dominated ecosystems, requires specific consideration for the use of remote sensing data and change detection algorithms.

### 6.1 *Consideration of landscape complexity*

Different ecosystems, such as vegetation, urban, agriculture and wetlands have different characteristics in land cover composition and spatial patterns, influencing the selection of remote sensing data and change detection techniques. In a vegetation-dominated ecosystem, common change detection applications are deforestation (e.g., conversion from forest to crop lands or impervious surface area) and regeneration/reforestation (e.g., conversion from crop lands to vegetation). Because of the significant differences in spectral signatures between vegetation and non-vegetation types, detection of vegetation conversion is relatively easy. The difficulty lies in detection of vegetation modification, such as forest degradation due to selective logging, diseases and drought, and vegetation growth or restoration, because forest is partially changed in density or vertical stand structure (Lu *et al.* 2013b). However, natural and anthropogenic-induced forest disturbances have been regarded as important factors resulting in high uncertainty in biomass/carbon estimation in the terrestrial ecosystem (Frolking *et al*. 2009); it is therefore an urgent task to develop suitable methods to accurately detect forest disturbance. Spectral feature is an important concern for the selection of remote sensing data. Change detection techniques should have the capability to effectively identify the best spectral variables for distinguishing small spectral difference due to forest disturbance. Vegetation indices and image transform are common methods to enhance vegetation information. Another important method is to identify suitable forest attributes, such as fractional greenness or non-photosynthetic vegetation, which can be developed using spectral mixture analysis (Lu *et al.* 2003) or LAI and biomass that can be estimated using empirical models (Lu 2006). Therefore, sub-pixel-based or indirect-based change detection methods could be a good choice for detection of forest disturbance.

In an urban-dominated ecosystem, urban expansion generally occurs in urban–rural frontiers, where the composition of different land-cover types is very complex. Spatial resolution is an important concern for the selection of remote sensing data (Lu *et al.* 2011c). Change detection technique should have the ability to handle mixed pixel problem when medium or coarse spatial resolution images are used. If very high spatial resolution images such as QuickBird are used, spatial information, such as textures or segments, is useful in reducing the spectral heterogeneity in an urban landscape (Lu *et al*. 2010). Fusion of LiDAR (LIght Detection And Ranging) and high spatial resolution optical image is another choice in improving urban change detection because of the capability of LiDAR in providing height information (Rottensteiner *et al*. 2005). Incorporation of height information for 3-D change detection is proven to be valuable, especially in urban landscapes (Chaabouni-Chouayakh *et al.* 2013). At the regional scale, data fusion of multi-resolution images, such as Landsat TM and SPOT panchromatic band, is another option to improve spatial resolution for improvement of change detection spatial patterns.

In agriculture-dominated ecosystem, crop rotation, growing stage and management are important concerns that significantly affect their spectral signatures. It is important to decide the change detection contents: crop change or agricultural land change. In the same location, different seasons or dates could have various crops, thus they have different spectral signatures. Because of this characteristic, detection of crop change or agricultural dynamics is very difficult. A combination of crop phenology knowledge and time series remote sensing data is critical for accurate detection of crop/agricultural change. Another concern in change detection is the patch size of agricultural lands. In some regions with dense population such as east China, agricultural lands, forest, residential areas and ponds are mosaicked into a complex landscape. While in north-east China, the patch size of agricultural lands can be very large, reaching a few hundred or thousand hectares. In a large area, time series MODIS data have become an important data source for examining agricultural expansion (Galford *et al*. 2008), but in a relatively small area, high or medium spatial resolution images are needed to accurately extract the agricultural land spatial patterns.

Wetlands play an important role in biodiversity, hydrology and climate change. It is necessary to monitor wetland dynamic change accurately (Baker *et al*. 2007, Nielsen *et al.* 2008, Hall *et al*. 2011), but different seasons, such as dry or rainy seasons, can considerably affect wetland detection results. A clear definition of wetland types is required. Use of multi-seasonal remote sensing data is valuable for better examining wetland change. Because radar data have different backscatter coefficients between water and other land covers, and are sensitive to water contents, use of multitemporal radar data or integration of optical and radar data is valuable for effectively detecting wetland dynamic change.

### 6.2 *Scale issues*

Scale such as local, regional and continental/global is an important concern in the selection of remote sensing variables and change detection algorithms. At the local scale, accurate change detection results with very detailed spatial patterns are required, especially in urban landscapes. The sub-meter spatial resolution satellite images provide new opportunities to develop change detection results (Zhou *et al.* 2008, Bruzzone and Bovolo 2013, Falco *et al*. 2013, Volpi *et al*. 2013), but produces new challenges in methods/techniques to solve such problems as (1) shadows caused by tall objects, (2) confusion of shadow, dark impervious surface areas, water and wetland, (3) high spectral variation of the same urban land cover due to different construction materials and colours, and (4) spectral confusion among impervious surfaces, bare soils and grass/crop residuals (Lu *et al*. 2010). Previous research has examined the application of textures and segmentation-based methods to reduce the spectral variation problem, but these methods cannot solve spectral confusion and shadow problems. Manual editing is valuable for solving the shadow problem (Lu *et al*. 2010).

Medium spatial resolution images, such as Landsat, are commonly used for LULC change detection at a regional scale (Vogelmann *et al.* 2009, Wang *et al*. 2009, Huang *et al*. 2010, Lu *et al.* 2011b, Sexton *et al*. 2013). The relatively low revisit time and atmospheric conditions (e.g., cloud cover problem) make the collection of the same sensor data difficult, especially in the moist tropical regions (Asner 2001). Use of different sensor data is necessary (Wulder *et al.* 2008). In the past two decades, many kinds of sensor data with medium spatial resolution became available, providing more choices to select different sensor data for change detection. However, the difference in spectral and spatial resolutions in different sensor data requires new techniques to conduct the change detection (Lu *et al.* 2008a), especially when optical and radar data are used together for change detection. Data fusion techniques at different levels, such as pixel, feature and decision, can be used to integrate different remote sensing data or combine change detection results from different algorithms to improve change detection performance (Zeng *et al*. 2010, Zhang 2010, Du *et al*. 2012, 2013, Reiche *et al*. 2013).

At the national scale, Landsat images were used to examine LULC dynamic changes in USA (Ahlqvist 2008, Xian *et al.* 2009, Jin *et al*. 2013). It takes much time and labour cost to finish this work. Coarse spatial resolution images become a primary data source at national and global LULC change detections (Hansen and DeFries 2004, Fraser *et al.* 2005, Le Hégarat-Mascle *et al.* 2005, Verbesselt *et al*. 2010b, Bontemps *et al.* 2012).

Time series MODIS or SPOT VGT data sets provide potentials to detect forest disturbance in a large area (Mildrexler *et al*. 2007, Spruce *et al*. 2011, Bontemps *et al.* 2012). In general, the changed areas are small and scattered, much smaller than the cell size of MODIS data. The complexity of land-cover composition in coarse spatial resolution image makes change detection a challenge. Integration of MODIS and Landsat images has been used to detect LULC change (Hansen *et al.* 2008b), and more research is needed to effectively integrate the multi-scale remote sensing data for conducting continental and global LULC change.

## 7. Summary

Change detection is a comprehensive procedure that requires careful consideration for each step: the nature of change detection problems, selection of remotely sensed data, image preprocessing including geometric and atmospheric correction, extraction of suitable variables from remote sensing and GIS data, selection of suitable change detection algorithms and evaluation of results. When the study area and the user's needs are defined, selection of suitable variables and corresponding algorithms has been an active research topic for a long time. New techniques continue to appear due to new needs for change detection contents and accuracy, and availability of new satellite images and other ancillary data. Overall, per-pixel-based methods are common, especially when high and medium spatial resolution images are used. Texture- and object-based methods become valuable for change detection using high spatial resolution images. Coarse spatial resolution satellite imagery such as MODIS provides the potential to detect LULC change at national and global scales, but generates challenges due to the mixed pixel problem. At a regional scale, different kinds of sensor data with medium spatial resolution images have provided new opportunities to integrate multi-sensor data to improve LULC change detection. Data fusion at pixel, feature and decision levels based on different resolution or sensor images has been proven to be promising in improving change detection performance. As multiple sources of data covering remote sensing and ancillary data are available, GIS-based techniques are valuable.

High-quality LULC change detection results at a local scale are required for management and planning purposes or for use as reference data. The availability of sub-meter spatial resolution satellite images provides a new platform to detect scattered and small changes at a local scale, but the displacement, high spectral variation and shadow problem produce a challenge for automatic change detection. Although use of texture- and segmentation-based methods have proven to be valuable for reducing the spectral variation problem, more research is needed to automatically identify optimal parameters for producing suitable textural and segment images. Alternately, integration of LiDAR and high spatial resolution optical data is valuable to improve urban LULC change detection at a local scale.

National and global LULC change data sets are required for many studies related to climate change, environmental, demographic and economic conditions. However, development of this data set using coarse spatial resolution images is a challenge and no suitable techniques are available to conduct change detection using the multitemporal MODIS or AVHRR data yet. More research is needed to develop the techniques to integrate multi-scale remote sensing data to improve LULC change detection results.

Most of previous change detection studies are at a regional scale using medium spatial resolution images such as Landsat, SPOT and radar. The same sensor data are usually used in a change detection procedure, but a combination of multi-sensor data is also needed when the same optical sensor is not available due to the cloud cover problem. Data fusion at feature and decision levels has been proven to be valuable in improving results. Since satellite images are only available for about 40 years, use of multi-source data, such as aerial photographs and GIS data can provide change detection results with a longer history in some study areas. Difference in data format, structure, quality and spatial resolution make change detection a challenge and GIS-based techniques provide important tools for integration of multi-source data for change detection.

Different change detection algorithms have their own merits in extracting LULC change information. Integration of the individual change detection results into a new one using certain expert rules or fusion techniques can improve the results. Meanwhile, most change detection techniques are used to detect LULC conversion, not for modification. For vegetation ecosystem, it is even more important to develop suitable techniques to detect vegetation modification to understand how human and nature-induced factors affect vegetation dynamic change and their interactions. In particular, more research is needed to examine changes of continuous variables at national and global scales using time series MODIS data and multi-scale remote sensing data.

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