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Research Article

Review of Change Detection Techniques from Remotely Sensed Images

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Abstract: The increasing need for real-time data on the various land surface form phenomena led to the rising research interest in the area. Among the applications making use of such data are national, regional and global monitoring systems resource monitoring platforms, changes in land use and land cover monitoring and various studies on environmental issues. One of the techniques used for affording such real-time data is remote sensing. Remote sensing satellite platforms capture environmental data at different resolutions, which are extensively utilized today for detecting changes occurring in the environment. The real-time detection of precise changes occurring on the surface of the earth constitutes a vital component in understanding the interrelation between the interactions of humans with nature, which is important for suitable decision-making. In real life scenarios, change detection is a complex phenomenon which includes different procedures such as identifying the specific change detection problem, image preprocessing and variables and algorithm selection for the computations. Over the years, quite a wide range of techniques have been developed for analyzing remote sensing data and yet newer methods are still being developed. As such, this study seeks to provide a comprehensive review of the fundamental processes required for change detection. The study also seeks to provide a concise summary of the main techniques of change detection and to discuss the need for development of new, enhanced change detection methods.

Keywords: Change detection analysis, classification, land use and land cover, object base method, remote sensing, sub pixel method

INTRODUCTION

In the study of Remote Sensing (RS), a change is associated with the alteration of a surface component of the earth at different rates. Information pertaining to the changes in the Land-Cover (LC) and Land-Use (LU) (also referred to as LULC) is quite useful given the numerous practical applications. These include deforestation, damage assessment, disaster monitoring, urban expansion monitoring, city planning, as well as the management of land resources. LULC has been identified as a significant factor that influences climate change and the environmental status quo (Grimm *et al*., 2008; Jones *et al*., 2008), population distribution and the prevailing economic situation (DeFries, 2012).

Given the fact that the LULC constitutes an important source of vital data for numerous investigations, it is necessary for the LULC data to be updated in real-time. Remote sensing technology proved to be a primary source of data for the periodic monitoring and estimation of LULC across a period of time (Xian *et al*., 2009; Hansen and Loveland, 2012). According, to Singh (1989), Change Detection (CD) is defined as ''the process of identifying differences in the state of an object or phenomenon by observing it at different times''. The framework of CD employs multi-temporal datasets for the qualitative analysis of the temporal impacts of a phenomenon as well as quantifying the changes. During the last half century, In the past four decades, research on LULC change detection has obtained great research attention, with a number of techniques already developed (Singh, 1989; Coppin *et al*., 2004; Lu *et al*., 2004; Chen *et al*., 2013). Change detection continue to be an area of active research (Demir *et al*., 2012; Volpi *et al*., 2013), with novel techniques being developed for enhanced detection results (Ardila *et al*., 2012; Chen *et al*., 2013; Kim *et al*., 2013).

Given the complex interactions between the different factors, different researchers often come up with different results and in some cases, controversial conclusions concerning the most optimal change detection model. For this reason, suitable algorithm selection, for a specific task, is often very difficult in

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practical projects. Therefore, a review of the various change detection models proposed by the various researchers and their respective applications is quite vital for the ascertaining the most suitable method for solving a specific research problem. Upon identifying the study site and the input image data, the production of high quality change detection results greatly depends on the selection of a suitable change detection model. Hence, this study seeks to provide a summary of the different change detection models proposed by the various authors, in a bid to provide recommendations for their suitability for specific change detection tasks.

MATERIALS AND METHODS

A General procedure for conducting a change detection analysis: In any study involving change detection, it is important to clearly specify the research problem, aims and objectives, project site as well as the scope of the study site (Jensen, 2005). In addition, suitable remote sensing data selection together with the corresponding algorithms is afforded based on the nature of the specific change detection problem at hand. Other important dimension include properly defining the change detection system, the scope and complexity of the project site, the requirements of the user in the change detection result, the availability of the relevant data as well as the period of the year. The change detection procedure is developed upon the clear comprehension of the needs of the user. The selection process of the required variables from remotely sensed data and the corresponding change detection algorithms is especially critical in a change detection procedure; both of which are still actively researched by numerous scholars. Remotely sensed data exhibit various characteristics in radiometric, spectral, spatial and temporal resolutions and polarization modes. A comprehensive understanding of the merits and demerits of the various types of sensor data is also a fundamental prerequisite in the selection of the required data for a specific investigation (Lefsky and Cohen, 2003); while the degree of site heterogeneity and the scope of the aerial view of the project site are critical for the remote sensing data selection (Lu and Weng, 2007).

Advanced spatial resolution images like the IKONOS, Quick Bird and Worldview proved to be highly utilized and accepted sources of data for detecting change at the local dimension (Lu *et al*., 2010). At the regional dimension, images of medium spatial resolutions such as those of the Lands at have, over the years, been consistently utilized for detecting changes concerning LULC owing to their longerputation of providing historic data onthe spectral and spatial resolution of images (Hansen and Loveland, 2012). Specifically, the AVHRR, MODIS and SPOT VGT have proven to be very successful for monitoring at the regional and global scales (Bergen *et al*., 2005; Hansen *et al*., 2008; Lippitt *et al*., 2008; Bontemps *et al*., 2012). However, even with the availability of the required data from such high-tech equipment, the extraction and processing of the changed parameters from the coarse spatial resolution data continues to be a major challenge in the field of environmental monitoring. Given the fact that radar systems are capable of providing information relating to land surface features information with no impact of the atmospheric conditions, they have also been used in studies involving change detection in LULCs (Wang and Allen, 2008; Whittle *et al*., 2012; Nascimento Jr *et al*., 2013), especially for scenarios where there is no optical sensor data due to cloud cover issues. In the ideal situation, change detection is afforded using multi-temporal images generated from a single sensor. Nevertheless, such data is sometimes unavailable owing to constraint conditions. For such situations, data from a number of sensors remain the only practical solution (Reiche *et al*., 2013); even though acquisition of such images on different dates is associated with design constraints. In such cases, precautions must be in place in order to minimize the influence of externalities such as the varying atmospheric conditions on the different dates of data retrieval, the status of soil moisture as well as the phenology of the vegetation. Studies have also reported cloud cover to be among the factors that need to be catered for before the detection procedure is carried out (Eckardt *et al*., 2013).
In general, the CD scheme in RS mainly includes:

- Extraction of the features
- The decision function. Similarly, the CD procedure may also be divided into:
- Pre-processing stage
- CD method selection
- Assessing the accuracy

Correction procedures related to radiometric, atmospheric and topographic irregularities are carried out in the pre-processing phase. Geometrical rectification and image registration are also carried out in this phase. Here, the use of data from the same sensor avoids problems associated with sun angle, seasonal variations and phonological differences (Song and Woodcock, 2003).

It must be noted that the preprocessing stage is indeed required before carrying out the change detection analysis. During this stage, accurate geometric registration among the multi-temporal images is crucial in that the lack of it may lead to spurious change detection result (Dai and Khorram, 1998; Stow and Chen, 2002; Shi and Hao, 2013), mainly due to the development of fake change detections. For this reason, geometrical registration of sub-pixels is a requirement in the majority CD-based research works (Jianya *et al*., 2008). The varying physical characteristics of the prevailing atmosphere on the different dates of data acquisition affect the spectral signatures even for a single object. Thus, an appropriate calibration procedure is required to convert the raw data to surface reflectance (Vicente-Serrano *et al*., 2008; Chander *et al*., 2009).

Over the year, a number of correction algorithms have been developed (Song *et al*., 2001). Among them is the dark-object subtraction technique, which is one of the most widely employed approaches mainly due to its ability to correct effects resulting from the zenith angle of the sun, solar radiance, as well as the scattering effect of the atmosphere (Chavez, 1996). For studies involving mountainous regions, it is necessary to carryout topographic correction in order to minimize the effect of the land form on the reflectance. Common topographic correction models include Minnaert and statistical-empirical techniques (Riaño *et al*., 2003). Prior to the collection of the RS data for the CD, it is vital to put into consideration the relationship between change and the temporal factors. In the data collection process, to rapid a collection of data within a short period of time may result to the omission the slower changes occurring over prolonged period of time, while too slow a data collection process may result to excessive omission errors, thereby resulting in incomplete CD (Lunetta *et al*., 2004).

Numerous techniques of CD have been developed and reported in a number of reviews in the literature (Jensen, 2005; Kennedy *et al*., 2009), however, analysis on the best method to be selected for a specific study has been largely ignored. Analysis of the best technique for a specific study is dependent on the skills and expertise of the analyst and the nature of the study site.

Accuracy assessment is another vital step for decision-making on the suitability a particular CD technique. Among the mainly utilized methods are overall accuracy, producer's accuracy, user's accuracy and Kappa coefficient. In CD, accuracy assessment is not an easy task because of the difficulty associated with the collection of reliable field based temporal data required for the assessment (Foody, 2010; Olofsson *et al*., 2013). However, with the availability of the required reliable data, techniques such as the traditional error matrix model may be employed for assessing the reliability as described by Congalton (1991), Foody (2002), Van Oort (2007) and Congalton and Green (2008). Various categories of change including binary change, non-change as 'from-to' change, requirevarying techniques of assessing accuracy, such as sampling technique, especially when the area of the study site is wide (Herold *et al*., 2008). In addition to the accuracy assessment, uncertainty analysis also enables the researcher to recognize the specific factors affecting change detection errors, thereby enhancing the detection procedure. However, this research direction is yet to attract enough research.

A brief overview of change detection methods: The literature, a number of change detection methods have been reported; these include Singh (1989), Lu *et al*. (2004) and Chen *et al*. (2013). For example, the study by Lu *et al*. (2004) provided a summary of over thirtydifferent models of change detection and categorized them under seven different headings, namely algebra, transformation, classification, advanced techniques, GIS models, visual analysis and other approaches. A similar study by Hussain *et al*. (2013) provided a summary of over twenty techniques of CD, which were categirized under ten broad headings. Techniques such as the advanced non-parametricalgorithmslike artificial neural networksas well as support vector machines, may be employed for enhancing the performance of CD (Nemmour and Chibani, 2006; Huang *et al*., 2008). Despite the fact that some works have attempted to fuse two or techniques in their napproaches, (Du *et al*., 2013); the combination of more than one CD approach for the attainment of the single objective continue to be largely an open research agenda. In this section, indepth description of the various CD models has been deliberately ommitted becauyse that was afforded in previous publications. Based on the model and vriables utilized, the various models are categorized into six groups, namely per-pixel thresholding, per pixel classification, sub-pixel, object-oriented, hybrid and indirect method.

Per-pixel thresholding-based methods: There are a number of CD techniques that can be considered as per-pixel thresho;ding based. These include image differenciation (Coppin and Bauer, 1996), image ratio technique (Howarth and Wickware, 1981), regression models (Singh, 1986), vegetation index differenciation (Wilson and Sader, 2002; Nordberg and Evertson, 2005), change vector analysis (Chen *et al*., 2003), Principal Component Analysis (PCA) (Deng *et al*. 2008) as well as tasselled cap Transformation (KT) (Jin and Sader, 2005). An important step in this type of CD technique is the identifiction of suitable bands which can typically reflect the specific change of interest and determine the suitable threshold values at both tails of the constructed histogram as the representation of the areas of the change and non-change categories (Lu *et al*., 2005; Im *et al*., 2009).

There are generally two methods of selecting the threshold: Interractive (manual trial and error) method or statistcal method. In the former, the the thrashold is interractively adjusted and the resultant image evaluated until the resultant image satisfies specific requirements. In the latter, a suiable standard deviation is selected from the mean (Lu *et al*., 2005). The study by Im *et al*. (2009) further investigated the techniques of identifying the optimal threshold by means of a moving threshold window. In particular, threshold identification is a largely subjective judgement depending mainly on the scene, the skills and expertise of the analyst ans well as the level of familiarity with the geographic area being studied (Lu *et al*., 2005).

Other externalities such as phenology and soil moisture, may also influence CD reults, especially for studies involving vegetative cover and agricultural lands. Despite the fact that the per-pixel thresholding-based techniques only explore the spatial patterns and the level of changed results without sufficient information about the change trajectort of the LULC, they can serve as vital prerequisites for indepth examination into the change trajectories.

Per-Pixel classification-based methods: In real life implimentations, per-pixel classification-based change detection techniques may be viewed as the most extenively employed; mainly due to their ability to avoid the influence of external factors on the results of the change detection (Rogan and Chen, 2004). Nevertheless, the primary demerit of these method is their inability to solve mixed pixel problemsassociated with images of medium and coarse spatial resolutions and high spectral variations within the same land covers in high spatial resolution images. For the 'from-to'CD techniques, the accuracy of the detections significantly depends on the classification accuracy of the individual dates under investigation (Jensen, 2005). This implies that any error assciated with any specific date's images directly affects the accuracy of the final CD. It therefore goes without saying that accurate LULC classification mechanism plays a pivotal role in the overall success of the CD scheme (Lu and Weng, 2007). But even with this in mind, complex topographies coupled with the lack of training samples, such as post classification comparison (Ghosh *et al*., 2011) anddecision tree (Lippitt *et al*., 2008), makes it quite difficult to afford accuracy in LULC classification through the mere use of remotely sensed data.

Object-based methods: In the recent years, object based CD techniques increasingly gained research attention (Desclée *et al*., 2006; Im *et al*., 2008). This new CD approach enables the effective use of high spatial resolution images for detecting changes. Generally, there are three main steps involved in the object-based change detection techniques, namely:

- Directly comparing the segmented images of the different dates (Zhou *et al*., 2008)
- Comparing the classified objects (Stow, 2010)
- Segmenting and classifying the images using tacked multitemporal images (Bontemps *et al*., 2008)

The use of object based techniques minimize the variations in the spectral dimensions within identical land covers. As such, the techniques are more suited for images with high spatial resolutions, compared to those with medium to low patial resolutions (Lu *et al*., 2010). Here, the primary procedure is to specify the optimal parameters (such as the minimum distance, variance factor, minimum pixel size etc) for the production of suitable segmentation images.

Sub-pixel based methods: Given the fact that the mixed pixelimages in medium and coarse spatial resolutions are considered to have sgnificant impact on the result of LULC change detection (Lu *et al*., 2011), subpixel based techniques have been identified to resolve this problem (Haertel *et al*., 2004; Zanotta and Haertel, 2012). Among them is the fuzzy classification as well as the spectral mixture analysis. Here, the multi-spectral image may be decomposed into fractional images with biophysical meanings, followed by the employment of the thresholding-based technique for examining the changes in the fraction values. Such a method of CD is most suitable for specific change detection investigations like forest disturbances (Souza *et al*., 2012) as well as studied pertaining to urban expansion (Yang *et al*., 2003; Michishita *et al*., 2012). Despite the suitability of sub-pixel-based techniques with coarse spatial resolution images, like the MODIS, at the local and regional dimensions, the detection of indepth from-to trajectories using a suitable sub-pixel based algorithm continues to be anopen research challenge.

Hybrid methods: The majority of the previous works focussed on change/non-change and 'from-to' change trajectories through the employment of individual techniques, however, each individual technique is associated with specific advantages. As such, combining more than one CD technique is likely to produce better performane compared to the individual methods employed (Im and Jensen, 2005; Chen *et al*., 2012; Cassidy *et al*., 2013). Generally, such hybrid techniques may be applied in one of two way:

- Combining of a number of techniqus into a single CD technique
- Combining CD results from a number of techniques into a new result by utilizing specific rules such as decision-level fusion (Lu *et al*., 2008)

Suhc a method was employed by Lu *et al*. (2008) which combined the binary change/non-change detection with the post-classification comparison technique for investigating the degradation/ restoration of vegetation across thhe Amazon in Brazil using data retrieved from the Landsat TM and SPOT. The authors employed the PCA for integrating TM and SPOT panchromatic data, followed by image differentiation technique based on the fused image and original TM image for prducing the growth/degradation in vegetation. Here, a rule-based procedure was applied of r classifying the Landsat TM and SPOT multi-spectral images into three classes of land covers, namely forest, non-forest vegetation and non-vegetation land, followed by the post-classification comparison technique for detecting the primary chages in LULC. With this hybrid approach, the loss or gain in the vegetation can be ascertained, apart from the attainment of the traditional LULC conversion. In general, data fusion-based CD schemes can be classified under three headings, namely:

- Those that utilize a different sensor data on the different dates of data retrieval (e.g., Landsat on the first date and radar on the seconddata (Lu *et al*., 2008)
- Those that employ different sensor/resolution images within the same year in a bid to optimize the performance of the LULC classification (Gungor and Akar, 2010)
- Those that utilize data from remote sensing and GIS (Li, 2010).

The use of data from different sensors avails the opportunity for combination in CD scenario (Zeng *et al*., 2010). Similarly, data from different sources such as those from remote sensors and those from previous srveys may be also be combined (Li, 2010), especially for scenarios where remote sensing data is not readily available due to cloud constraints. A survey of works using remote sensing data fusion is afforded by Zeng *et al*. (2010), while survey on the fusion of remote sensing with GIS data techniques for LULC CD is afforded by Li (2010). The study by Du *et al*. (2013), on the other hand, provided a comparison of CD results generated from pan-sharpened images and decision-level fusion and further dilated on the merts of using such a methods for enhancing the performance of CD.

Indirect methods: The heterogeniety of land cover coupled with the spectral confusion among the various types of LULC, may lead to undesirable results if only the remotely sensed data is employed for CD. Indirect techniques enable the identification of certain biophysical characteristics which may effectively mimic the LULC change. Such characteristic features may be generated through the modelling of remtely sensed data. These characteristic features may include impervious surface in the urban topography and LAI for forest zones (Lu *et al*., 2013). The funda,ental idea here is to ensure the development of suitable biophysical attributes using the remotly sensed data in way that its suitability is ensured as CD variable. Indirect techniques can proove to be very effective fr CD at the global scale with the utilization of coarse spatial resolution images, especially for generating rapid updates of specific change categories e.g. deforestation and urbanisation. Other prospective applications of indirect techniques may include the detection of forest disturbances due to the natural and anthropogenic causes using changes in the vegetation structure (e.g. LAI, biomass and the concentration of greenness. Nevertheless, for such analysis, the error level of the forest characteristic features must be significantly lower than the amount of change emanating from the forest disturbance.

RESULTS AND DISCUSSION

Change Detection (CD) is a comprehensive process which comprises of a number of steps, namely identification of the CD problem, remote sensing data selection, image preprocessing (which comprises of the data correction subphase), extraction of the reuired variabls from the remote;y sensed data, as well as the CD algorithm selection and analysis of the result.

Theoretically, the various types of LULC are associated with individual spectral signatures in such a way that a change in the LULC type results in a change in the corresponding spectral signatures. Therefore, by comparing these signatures at two unlike points with the aid of a suitable algorithm, the underlying LULC change can be detected accordingly. Despite the many differences associated with the different change detection algorithms, each and every change detection technique should avail the following:

- The area changed and the rate at which the change occurred
- The spatial distribution of the type of change which occurred
- The trajectories of change of the different types of land covers
- Assessment of the accuracy of results emanating from the change detection

Apart from these theoretical assertions, a number of other factors also influence the results of change detection. These include the topographic condition of the project site, the constitution of the remotely sensed data being used, image registration quality as well as the atmospheric correction among the multi-temporal images being used, the employed technique for detecting the change, as well as the skills and expertise of the researcher. Thus, change detection can be viewed as a comprehensive process in which all the aforementioned factors must be considered. Upon clearly outlining the needs of the user and the selecting the study site, the identification of the important variables and the change detection algorithm to be utilized, become crucial.In general however, the per-pixel based techniques appear to be widely employed, especially for cases with high and medium spatial resolution images. In addition, texture and object-based techniques are common for situations involving CDs for high spatial resolution images. Satellite imagery of the coarse spatial resolution feature, such as the MODIS, are suitable for national and global scale LULC change detection, but faces problems associated with mixed pixel phenomenon. At the reginal scale, the availability of various types of sensor data with medium spatial resolution images added a new dimension to the CD research-data fusion. Data fusion proved to enhance the CD performance, given its utilization of data from multiple sources such as remote sensing, accillary and GIS data.

CONCLUSION

In this study we have presented a review of the change detection methods and highlighted their functionalities and limitations. Change detection from remotely sensed data is a topic of ever-growing interest. Change detection from remotely sensed data is a complicated process, with no single approach optimal and applicable to all cases. Given the emergence of new CD contents and accuracy requirements coupled with the emergence of new satellite imagery, novel CD techniques are emerging as well.

Enhanced LULC change results are important for the management and planning of a number of environmental resources. Sub-meter spatial resolution satellite imagery enables the sprouting of detecton mechnisms for even smaller changes, however the problem of displacement, high spectral variation and shadow problems continue to be major challenges in CD. Despite the fact that the texture and segmentation-based techniques combat this problem to a great extent, further research is required for the robust identification of the optimal parameters for the generation of suitable textural and segment images. In the development of novel CD techniques, spcial focus must be placed on accuracy and ease of use; and the selection of a suitable CD technique requires the careful consideration of primary impact factors.

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