A REVIEW OF LAND CHANGE MODELLING TECHNIQUES USING REMOTE SENSING AND GIS

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KEY WORDS: change detection; LULC; time-series

ABSTRACT: Land Use and/or Land Cover Change (LULCC) is characterized as dynamic, widespread, and accelerating process. Due to the significance of such changes, modeling changes in land cover is a high priority area for research thus, monitoring and analyzing LULCC has become one of the most critical studied issues. In effect, maps and datasets which quantify biophysical variables, including LULC, are essential for understanding and modeling complex interactions and impacts between the natural and human environments, from regional to global scales. Furthermore, multi-temporal analyses of LULC provide important insights into long-term trends which serve to identify drivers and determinants of change and prediction of future changes. Remote sensing (RS) is continuously providing valuable data for the earth's surface since 1972, while the power of the Geographic Information System (GIS) in modeling the change provides the suitable platform for handling the digital spatial data necessary for characterizing and predicting these changes and associated impacts. This review deals with the most frequent, up to date methods for modelling the LULCC such as data types, pre-processing of RS data and time-series imagery, and analysing the LULCC using conventional as well as the most developed and cutting-edge algorithms and techniques. The generic flow of the LULCC modeling, challenges, and limitations faced by the researchers over the past five decades were presented and discussed. Indeed, in regions where there is a lack of sufficiently detailed cartographic information, land change modelling using geospatial technologies can be pivotal in providing a basis for planning, management, and conservation initiatives.

1. INTRODUCTION

Human developments and natural activities on land through time, causing irreversible conversion from one Land Use and/or Land Cover (LULC) class to another, resulting in serious modification of and threat to our environment is known as LULC Change (LULCC). The changes on lands can be generally distinguished into; (1) conversion, i.e. the complete change from one Land Use and/or Land Cover (LULC) class to another; and (2) modification, i.e. subtle changes that affect the character of the LULC class without changing its overall classification (like expanding, shrinking, altering shape, shifting position, fragmenting, and coalescing) (Coppin *et al.*, 2004). LULC classes are in a state of permanent and continuous change, spatially and temporally. Causes of these changes can be related to human developments (e.g. agricultural expansion) or natural activities (e.g. flooding), or may be a combination of both (Coppin *et al.,* 2004). The accurate detection of LULC change (LULCC) is needed for better understanding of the change dynamics, the relationships and interactions between human and natural phenomena, and their impacts in different countries (Lu *et al.*, 2004). The vast majority of LULCC occurring due to the rapid development are not very well documented or planned (Choudhury *et al.,* 2019). This leads to chaotic, unplanned, and mostly permanent changes in land classes. Quantifying the processes of LULCC and its causes and drivers are necessary to ensure a sustainable management of natural resources, undertake suitable actions for efficient uses of these resources (Kleemann *et al.,* 2017; Nelson *et al.,* 2006; Petit et al., 2001). LULCC plays a critical role in any regional socio-economic development (Xiuwan, 2002). Many sectors, such as land use planning, food security, and natural resource management, critically require timely and accurate land cover maps (Saah et al., 2019). The call for studying of LULCC was raised by the scientific research community during the 1972 Stockholm Conference on the Human Environment, and again 20 years later, at the 1992 United Nations Conference on Environment and Development (UNCED) (Attri et al., 2015). Singh, 1989 defined change detection as "the process of identifying differences in the state of an object or phenomenon by observing it at different times". This definition implies the capability to quantify the temporal effects and using time-series sets (Lu et al., 2004; Singh, 1989). Multi-temporal analyses of LULCC provide important insights into trends which serve to identify drivers and determinants of change and prediction of future changes. One LULC class can be changed due to various potential drivers. For example, vegetation cover class change can be caused by succession, pollution stress, global warming, insect infestation, fire, flooding, resource exploitation, and others (Coppin et al., 2004). To run a change detection task, there is a definite need for a change detector which will automatically correlate and compare two sets of imagery, at least, taken of the same area at different times and display only the changes rather than all of the information in both images (Singh, 1989). Furthermore, the LULCC detection process using remote sensing can be affected by environmental factors including atmospheric conditions (humidity), soil moisture, sun angle, and phonological characteristics (Chughtai et al., 2021;

Lu et al., 2004). Under these circumstances, the change detection task becomes more complex than just comparing in time the spatial representation of two point, at least, and includes controlling the variances caused by variables that are not directly related to the LULCC process (Green et al., 1994).

Change detection is useful in a wide spectrum of applications. For example, it is used extensively in forest change (e.g. deforestation, logging, fire), landscape change, urban change, environmental change (e.g. drought, flood, desertification), crop monitoring, planning, land management, and many other applications (Attri et al., 2015; Lu et al., 2004; Singh, 1989). Although visual change detection of aerial photographs can produce accurate results and a high degree of precision, it is difficult to repeat and is significantly expensive in terms of data acquisition (Coppin et al., 2004; Edwards, 1990). Besides, it includes visual interpretation of a time-series of image composites and on-screen digitizing of changed areas. This method makes full use of an analyst's experience and knowledge (Lu et al., 2004); although, different visual interpreters of images produce different results (Coppin et al., 2004). In addition, visual change detection methods are time consuming over large areas, difficult to apply for timely update of change detection results, and do not usually provide detailed change trajectories (Lu et al., 2004). On the other hand, remotely sensed data have become the major data source for different change detection applications because of the advantages of repetitive data acquisition, its synoptic view, and digital format suitable for computer processing, (Lu et al., 2004).

This review is organized into six sections as follows: §1 gives a brief introduction about LULCC; §2 demonstrates the work methodology of the review; §3 highlights the use of remote sensing in digital change detection analysis; §4 reviews the considerations and pre-processing tasks for digital change detection §5 summarizes and reviews the most frequently used methods and techniques for LULCC; §6 discusses the new trends in change detection techniques such as integrated GIS with remote sensing approach and machine deep learning; and §7 provides summary and conclusion of the study.

2. METHODOLOGY

In the current review, we used search terms that would provide an overview of the use of geospatial technologies (RS and GIS) in conducting change detection. The search terms used in the literature review were: "land change", "land change and remote sensing", and "land change and GIS". A textual search on two search engines: Google Scholar and Science Direct were conducted to find a statistically meaningful temporal trend. To highlight the development of research in the subject under review over five decades and the increase in the use of geospatial technologies (RS/GIS) in change detection studies, the search was customized to group results by ten-year intervals starting in 1972 (Figure 1). Results have shown that more than half (52%) of change detection studies were conducted during the last two decades highlighting the increased interest in conducting change detection studies among the scientific community, mainly because of increasing availability of remotely sensed data (Figure 1, blue pie). For change detection studies using remote sensing, the results have shown that around 80% of the studies were conducted during the last two decades (Figure 1, green pie). For change detection studies using GIS, the percentages of the studies have increased dramatically from 0%, 1%, 5%, 47%, and 47% over the last five decades, respectively (Figure 1, orange pie). Following, a systematic review was conducted in two databases other the mentioned search engines (Google Scholar and Science Direct). The databases were last accessed in 19th Sept, 2021. The search was applied to articles that were published in peer-reviewed journals only. The results were pared down by applying two criteria: (1) the results were NOT "review papers" OR "conference proceeding" papers and only restricted to research articles; and (2) the study is not a duplicate from a previous search. All articles were downloaded and stored using the reference management software (ZOTERO).

3. CHANGE DETECTION AND REMOTE SENSING

It has long been established that remote sensing data, provides the capability to monitor, map, and detect the changes of LULC (Coppin et al., 2004). Satellite remote sensing has been used extensively to capture and quantify the extent and types of LULC in numerous environments around the world (Coppin et al., 2004; Lu et al., 2004). The repetitive coverage, cost effectiveness and accessibility of remote sensing data offer great potential in terms of identifying and modelling long-term LULCC (Bhatta, 2009; Ramachandra et al., 2012; Song et al., 2016). In order to model LULCC, a full assessment of past changes, their spatial extent and driving forces need to be undertaken. Remote sensing data which have consistently been available since the seventies constitute a unique tool that provides information about past changes and their spatial distribution. In particular, Landsat imagery, one of the most used sources for LULCC studies. The successive missions of Landsat satellites have allowed the acquisition of consistent data covering all areas around the globe since 1972. After the enactment of the free and open data policy for all Landsat data in 2008, more than one million images were downloaded during the first full year of 2009 (Zhu et al., 2019). This gave a wide range of scientists and researchers the opportunity to utilize these data particularly, for applications relying on time series analysis benefited from the freely available extensive archive of Landsat multispectral imagery acquired globally at regular intervals. This archive allowed scientists to characterize changes over large areas around the world by using historical data for almost the past 50 years (Zhu et al., 2019). On the other hand, Geographic Information

Systems (GIS), with their ability to integrate both spatial and non-spatial data and to mathematically model changes, help understand the driving forces and run various scenarios to predict future behaviour.

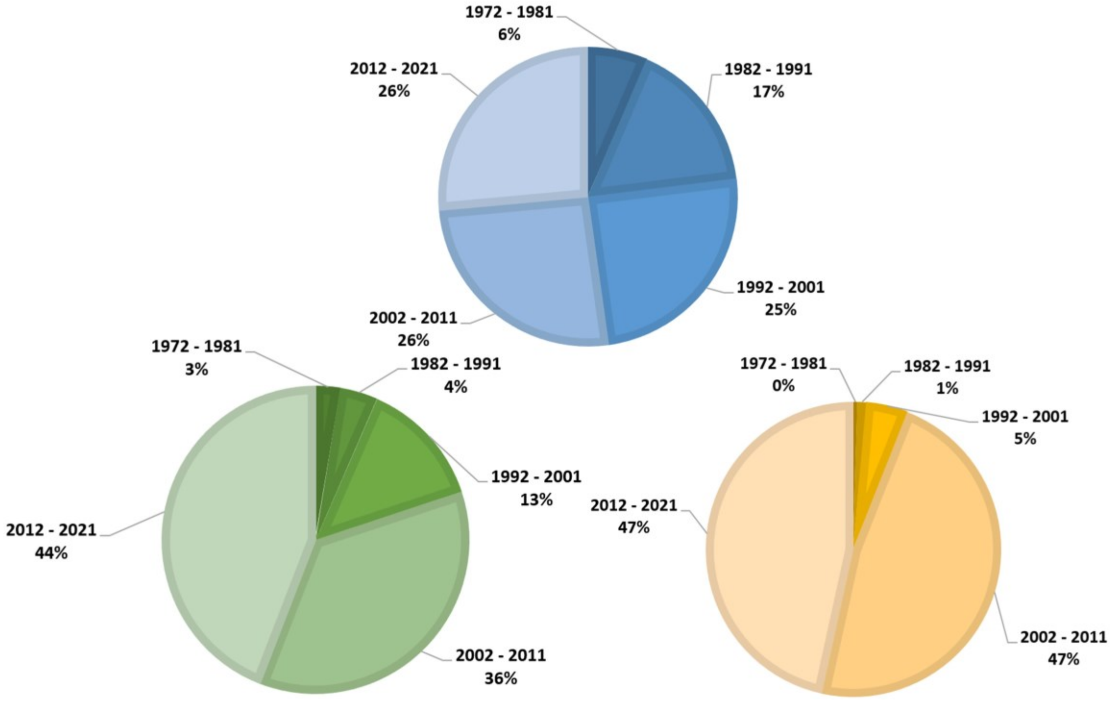

Figure 1. Textual analysis of terms: land change (blue pies); land change AND remote sensing (green pies); land change AND GIS (orange pies) using (a) Google Scholar and (b) Science Direct (accessed on 19th Sept, 2021 at 19:00 PM Abu Dhabi) over five decades by ten-years intervals starting in 1972.

The basic premise in using remotely sensed data for change detection is that changes in the LULC class will result in changes in reflectance values or local textures that are separable from changes caused by other factors (Deer, 1995; Lu et al., 2004). Therefore, the target of change detection task is the difference in radiance values between two dates, at least, that come from the actual change in LULC (signal) not the differences in illumination, atmospheric conditions, sensor calibration, ground moisture conditions, the registration among images (Singh, 1989).

4. CONSIDERATIONS FOR TIME-SERIES IMAGES CHANGE DETECTION

Digital change detection is a difficult task and requires cautious considerations (Coppin et al., 2004). These considerations can be categorized into three groups (1) environmental characteristics; (2) remote sensing data; and (3) image pre-processing ((Jensen, 2005; Lu et al., 2004; Weber, 2001). One of the main issues for accurate change detection using remote sensing is the maximization of the signal-to-noise ratio. The inherent noise can produce illusory change phenomena which can be caused by atmospheric conditions (e.g. differences in absorption, scattering, and water vapour and aerosol concentrations), soil moisture conditions, phonological characteristics, variation in the sun angle, and inconsistences in remote sensing images calibration (Coppin et al., 2004; Jensen, 2005; Lu et al., 2004; Weber, 2001).

The resolution of remote sensing data (temporal, spatial, spectral and radiometric) have a vital influence on the success of a change detection task (Lu et al., 2004). Selecting the appropriate remote sensor depends on the objectives of the change detection project and on the availability of the remote sensing data for the study area. Moderate spatial resolution sensors (e.g. Landsat and SPOT) are often used for a local area, while coarse spatial resolution sensors (e.g. MODIS and AVHRR) are more suitable regionally and globally. The advantage of coarse spatial resolution sensors includes the frequent coverage of large areas (high temporal resolution). While high spatial resolution sensors can provide reliable LULCC at a local level, they present a great challenge to analyse for large areas due to the huge volume of data that require increased processing loads, time, and cost. The relationship between change and the temporal factors must be considered prior the acquisition of remote sensing data that will be used for change detection. A short time interval may result in the omission of slower changes occurring over prolonged period of time (Lunetta et al., 2004). The determination of time interval depends on the nature of the class and the change being assessed. For example, a one-year interval is suggested to detect the successional herbs, a three-to five-year interval to monitor non-forest to successional shrubs stage, and five-to ten-year interval to detect the consecutive establishment of a forest cover (Singh, 1989). To eliminate the effects of external factors such as sun angle and environmental characteristics (e.g. seasonal and phonological differences), it is important to use the same sensor, same radiometric and spatial resolution data with anniversary or very near anniversary acquisition dates. Practically, it is difficult to acquire the same sensors in time series-series format due to the effects of clouds (i.e. tropical zones) or lack of availability (e.g. Landsat-8 OLI images are not available before 2013 and SPOT images are not available before 1986). Therefore, the integration of different sensor data (multi-sensor) becomes more pressing in change detection studies and requires the use of more advanced and adapted change detection techniques.

Image pre-processing is a very important step to ensure that undesired distortions or noise in the data are suppressed for further processing and analysis (Miljkovic, 2009). The main goal of pre-processing of remote sensing data before conducting the change detection task is to establish a direct linkage between the remote sensing data and the LULC classes under study. This can be done through removal of data error and noise, and masking of contaminated and/or irrelevant features (e.g. clouds) (Coppin et al., 2004). The most important requirements of pre-processing for change detection are images registration, radiometric corrections and calibration, atmospheric corrections or normalization (Lu et al., 2004). Misregistration of time series imagery will produce largely incorrect results of change detection (Stow and Chen, 2002). Prior to conducting change detection analysis, geometric rectification of imagery used in the process must be applied (Singh, 1989). For many change detection applications, absolute radiometric correction is unnecessary, but variations in solar illumination conditions, in atmospheric scattering and absorption, and in detector performance need to be normalized (Coppin et al., 2004). Conversion of digital numbers to radiance or surface reflectance is a requirement for quantitative analyses of time-series images. For some change detection algorithm, atmospheric correction is a necessary step in the image pre-processing step to remove any atmospheric effects from the satellite images. A variety of methods have been developed for radiometric and atmospheric normalization or correction (Lu et al., 2004).

Four major steps are involved when implementing a change detection project to build LULCC (Figure 2): (1) image pre-processing; (2) selection of suitable techniques; (3) accuracy assessment; and (4) building the models. Next section summarizes and reviews the most frequent and related method and techniques for LULCC.

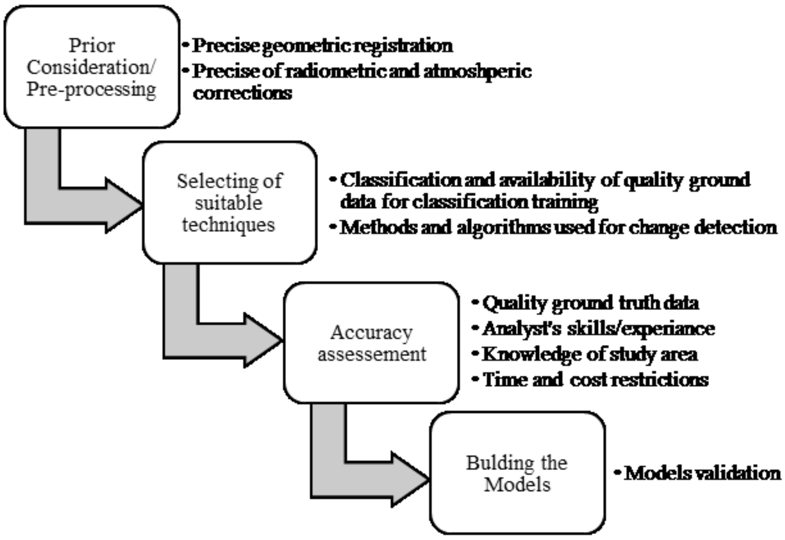

Figure 2. The LULCC modeling procedure and the factors that affect the accuracies of the results.

5. LULCC TECHNIQUES

Lu et al., 2004 stated that “Good” change detection research should provide the following: (1) changed areas and change rate; (2) spatial distribution of changed classes; (3) change trajectories of LULC classes; and (4) accuracy assessment of change detection results. These characteristics make the selection of a suitable change detection algorithms an important and tricky issue. Change detection poses a number of methodological challenges (Singh, 1989). Most authors report success of using specific change detection techniques rather than shortcomings and limitations of their approaches which make the choice of the suitable change detection techniques more pragmatic (driven more by the application itself) not scientifically based (Coppin et al., 2004). Research on change detection techniques is still considered as an active topic and new techniques are constantly being developed. In general, the change detection techniques can be categorized into two types: (1) techniques that provide “change/non change” information; and (2) techniques that provide complete matrix of change direction and detailed “from-to” change information (the temporal trajectories). Deer, 1995 suggested three levels of image processing that differentiate these methods by introducing the notion of: pixel level (i.e. refers to numerical values of each image band, or simple calculations between corresponding bands); feature level (i.e. involves transforming the spectral or spatial properties of the image); and object level (i.e. involves symbolic identification in addition to pixel or feature change detection).

On the other hand, Lu et al., 2004 generalized the change detection methods into six types, namely: arithmetic operations, transformation, classification comparison, advanced models, GIS integration, and visual analysis. They introduced an additional type named "some other methods" to host methods that do not fall in any of the six main categories. Singh, 1989 concluded that even in the same environment, various techniques may yield different results. In this study, some of the most frequently used change detection techniques were reviewed. Their characteristic, advantages, and disadvantages are summarized in Table 1.

5.1 Image Differencing

Image differencing technique is a simple method and conducted at pixel level using arithmetic operations (algebra). It consists of subtracting registered images acquired at different times, pixel by pixel and band by band (Coppin et al., 2004; Lu et al., 2004; Singh, 1989). The produced image represents the change between the two times where "no-change" results in pixel values of 0 (distributed around the mean) while "change" occurred when values are positive or negative (distributed in the tails of the distribution curve). Image differencing technique is widely used in a variety of geographical environments and characterized by its simplicity which perform better than much more sophisticated techniques (Singh, 1989). However, the change information obtained using image differencing technique can be in the form of simple binary change ("change" vs. "no-change"). Another limitation of this technique is its sensitivity to misregistration and the existence of mixed pixels (Im et al., 2008; Riordan, 1980; Singh, 1989). Additionally, this technique requires a judicious choice of the threshold boundaries between "change" and "no-change" pixels. The overall accuracy of the methods depends on the proper choice of this threshold. Higher threshold values can lead to missing detection of change, and lower threshold value can cause false change detection (Mishra et al., 2017; Xu et al., 2009).

5.2 Image Ratioing

Image ratioing technique conducted at pixel level using arithmetic operations (algebra). It calculates the ratio of registered images acquired on different dates with one or more bands, band by band. In the areas of "change", the ratio value will be greater or less than 1 (depending upon the nature of the "change"). The advantages of image ratioing technique including its ability to eliminate or reduce the influences of topography (e.g. slope and aspect), shadow, sun angle, radiation change (caused by seasonal variations), and noise (Attri et al., 2015; Singh, 1989). The image ratioing technique is limited by selecting appropriate threshold values which differentiate "change"/"no-change" and cannot provide complete matrices of change information (Lu et al., 2004). It is worth mentioning that ratioing multi-sensor and time-series images can produce higher change detection accuracy and considered useful as LULCC enhancement technique (Lu et al., 2004; Stow et al., 1990).

5.3 Image Regression

Image regression technique conducted at pixel level using arithmetic operation (algebra). This approach assumes that band values of pixels acquired on time 1 and time 2 are related by a linear function and that their spectral properties do not change significantly over the time interval. Hence, the dimension of the residuals is an indicator of where change occurs (Attri et al., 2015; Singh, 1989; Vogelmann, 1988). The image regression technique accounts for differences in the mean and variance of pixel values acquired at different dates. One advantage of image regression technique is reducing the adverse effects from differences in atmospheric conditions or sun angles (Jensen, 1981). Several change detection studies reported marginally better in accuracy by using image regression technique for LULCC of two main classes; forest and urban (Ridd and Liu, 1998; Singh, 1986). A threshold value is required to detect areas of "change" and "non-change". One disadvantage of this technique is its requirement for developing an accurate regression function for the selected bands before implementing change detection (Lu et al., 2004).

5.4 Vegetation Index Differencing

Vegetation index differencing technique is conducted at feature level using arithmetic operations (algebra). This technique starts by producing the vegetation index for the time-series images separately, then subtracts the second-date vegetation index from the first-date vegetation index (Nordberg and Evertson, 2005; Pettorelli et al., 2005; Unsalan, 2007). The difference in vegetation indices (e.g. NDVI, RVI, DVI, and SAVI) can provide an avenue for deciding whether or not a vegetation canopy, for example, has been significantly altered (Singh, 1989). The vegetation index differencing technique has the ability to reduce considerably the data volume for processing and analysis, the impacts of topographic effects and illumination, and can provide more information related to changes than from a single band (Coppin et al., 2004; Lu et al., 2004). However, no single vegetation index can be expected to summarize all the information in the multidimensional spectral data space. The indices derived for one analysis may be inappropriate in another context (Wallace and Campbell, 1990). Lu et al., 2004 stated that vegetation index differencing technique used for change detection can enhance random noise or coherence noise.

Technique	Level	Type	Advantage	Disadvantage
Image Differencing	Pixel	Arithmetic operation	*Simple method *Widely used	*Binary change only *Sensitive to mis-registration *Require thresholds
Image Ratioing	Pixel	Arithmetic operation	*Eliminate influence of topography, shadow, and radiation changing *High change detection accuracy	*Binary change only *Require thresholds
Image Regression	Pixel	Arithmetic operation	*Eliminate influence of atmospheric conditions *High change detection accuracy	*Binary change only *Require thresholds *Need developing of regression functions
Vegetation Index Differencing	Feature	Arithmetic operation	*Reduce the data volume *Reduce the impacts of topography and elimination *Gather more “change” info than a single band	*Identify suitable vegetation index *Require thresholds
Change Vector Analysis	Feature	Arithmetic operation	*Produce detailed change detection information *High overall accuracy	*Difficult to identify “change” trajectories
Principal Component Analysis	Feature	Transformation	*Reduce data redundancy *High overall accuracy	*Difficult to interpret and label the change” *Cannot provide details matrix *Require thresholds
Tasselled Cap Transformation	Feature	Transformation	*Reduce data redundancy *High overall accuracy	*Difficult to interpret and label the change” *Need an accurate atmospheric calibration *Cannot provide details matrix *Require thresholds
Post-Classification Comparison	Pixel	Classification methods	*Produce a matrix of changes *Bypass the needs for accurate registration *Widely used and easy to understand *Compensate the variations in atmospheric conditions, sensor and environmental differences	*Require a great amount of time *Require expertise to create classification products *Depends on the quality of the classified image *Rely on the sufficient of training samples

Table 1. The most frequent used techniques in LULC change detection.

5.5 Change Vector Analysis

Change vector analysis technique is conducted at feature level using arithmetic operations (algebra). The procedure can be summarized by computing a change vector in a multi-temporal feature space rather than in a multi-spectral feature space (Coppin et al., 2004). It was proposed to detect the change and the direction of change (Chughtai et al., 2021; Xiaolu and Bo, 2011). The decision that a “change” has occurred is made if the magnitude of the computed spectral change vector exceeds a specified threshold criterion (Singh, 1989). Berberoglu and Akin, 2009 compared four different change detection techniques and found that change vector analysis technique resulted in high overall accuracy compared with others. This technique has the ability to process any number of spectral bands and to produce detailed change detection information (Lu et al., 2004). Unlike with other techniques that use arithmetic operations (e.g. image differencing, rationing, and regression), the change vector analysis technique can provide matrices of change information (LULCC trajectories), with some difficulty though (Lu et al., 2004; Singh, 1989).

5.6 Principal Component Analysis

Principal component analysis technique is conducted at the feature level using linear transformation. It is considered as the most important linear transformation technique for change detection (Coppin et al., 2004). This technique is used to reduce the number of spectral components to fewer principal components. It assumes that multi-temporal images are highly correlated and the “change” information can be highlighted in the new components (Lu et al., 2004; Singh, 1989). It can be applied for change detection in two ways: (1) putting the two dates (or more) of the dataset into a single file, then preform the principal component analysis (the minor component images) for change information; or (2) performing principal component analysis separately (for different dates), then subtracting the time 2 principal component from the time 1. The main advantage of this technique is reducing the data redundancy between bands and highlight only the different information (derived components). Deng et al., 2008 compared between post-classification change detection technique (subsection 5.8) and principal component analysis-based on the classified images They concluded that principal component analysis-based post-classification resulted in more accuracy compared with the traditional post-classification method alone.

5.7 Tasseled Cap Transformation

Tasselled cap transformation technique is conducted at feature level using transformation. The concept is similar to principal component analysis (subsection 5.6). A tasseled cap transformation to produce the three components: brightness, greenness and wetness is applied to images from both dates and subsequently used in the change analysis (Jin and Sader, 2005; Lu et al., 2004). As with principal component analysis, the tasseled cap transformation reduces data redundancy between bands and emphasizes different information in the derived component (Lu et al., 2004) leading to better interpretation of imagery. For example, the tasselled cap transformation enhances land surface information before running a classification process (Haijiang et al., 2008). Minu and Shetty, 2015 conducted a comparative analysis of different change detection techniques to detect changes in agricultural land areas. The results showed that the tasselled cap transformation technique achieved good overall accuracy and kappa value. The disadvantages of tasselled cap transformation based change detection include: the difficulty to interpret and label “change” information; its inability to provide a complete change matrix; the requirement of determining thresholds to identify the changed areas; and the need for an accurate atmospheric correction for each date of image (Lu et al., 2004).

5.8 Post-Classification Comparison

Post-classification comparison technique is conducted at the pixel level using usual classification methods. The time-series images are classified into thematic maps that are in turn compared pixel by pixel (Lu et al., 2004). By properly coding the classification results for time-series images, the analyst can produce change maps which show a complete matrix of changes (Singh, 1989). One of the advantages of the post-classification method is bypassing the problem of getting accurate co-registration of the original time-series images (Singh, 1989). Post-classification comparison technique is widely used and easy to understand. It provides more information related to the type of change (“from-to”) and compensates for variations in the atmospheric conditions, sensor, and environmental differences (e.g. vegetation phenology) (Butt et al., 2015; Lu et al., 2004; Yuan et al., 2005). The post-classification comparison technique requires a great amount of time and expertise to create classification products. The final accuracy depends on the quality of the classified image of each date which depends on the size and quality of training samples. To avoid pixel miss-classification, a precise classification approach, such as hybrid classification, decision rule-based classification, fuzzy classification, and object-based classification may be needed to extract LULC complete information and detect changes (Chen and Wang, 2010; Hegazy and Kaloop, 2015; Kusimi, 2008; Munthali and Murayama, 2011; Samal and Gedam, 2015; Singh and Singh, 2018).

6. NEW TRENDS IN CHANGE DETECTION TECHNIQUES

In recent years, the use of machine-learning algorithms, among which artificial neural networks and decision tree classifiers, has gained considerable attention as an alternative to conventional approaches of change detection (Coppin et al., 2004). Increased classification accuracy is often cited as the primary reason for developing and applying these techniques. However, machine-learning algorithms can also be computationally very complex and require a considerable number of training samples. Due to its effective applications, deep learning has also been introduced for automatic change detection and achieved great success. Specifically, these deep learning-based methods were classified into three groups; fully supervised learning-based methods, fully unsupervised learning-based methods, and transfer learning-based techniques (Khelifi and Mignotte, 2020). Deep learning based methods can automatically learn complex features of remote sensing images on the basis of a huge number of hierarchical layers, in contrast to traditional hand-crafted feature-based methods (Khelifi and Mignotte, 2020).

In addition, using GIS provides a base for data integration, visualization, analysis and map production. GIS also has proved to be a useful tool in many change detection applications, in particular when multi-source data are used (Butt et al., 2015; Halimi et al., 2018; Haque and Basak, 2017; Hegazy and Kaloop, 2015; Lu et al., 2004; Meshesha et al., 2016). Today, most image processing systems are integrated with, or at least compatible with, GIS systems, and classifications of remotely sensed data are commonly viewed as inputs to GIS. GIS also allows integrating past and current maps for comparison and change detection and has the ability to directly update LULC information (Attri et al., 2015; Lu et al., 2004). However, different source data associated with different data accuracies (e.g. geometric accuracy), classification system, and formats often affect the change detection results (Lu, 2006).

7. CONCLUSION

Before implementing a change detection study, it is crucial to consider carefully selecting the suitable acquisition dates, sensor, and change detection technique. It is important to use the same sensor, same radiometric and spatial resolution data with anniversary or very near anniversary acquisition dates. However, in some cases, it is difficult to acquire the same sensors in time series-series, therefore, integration of different sensor data (multi-sensor) become more important in change detection studies which require more advanced and appropriate change detection techniques. A “good” change detection technique is one that can distinguish between LULC change and the change that arising due to external factors (e.g. atmospheric conditions, moisture conditions, sun angle differences and in sensor calibration differences). Pre-processing and image corrections are required to perform change detection task including geometric rectification, radiometric calibration and atmospheric normalization. The review shows that different techniques of change detection can produce different “change” maps since the results vary depending on the environmental settings of the area under study and the remote sensing images. Each change detection technique has its own advantages and disadvantages. Although change detection techniques that use arithmetic operations are simple and easy to apply (image differencing, image ratioing, image regression, vegetation index differencing, and change vector analysis), they can provide only binary change information and highly rely on the determination of the thresholds to differentiate between “change”/”no-change” (except for change vector analysis technique which can identify change trajectories with some difficulty). Principal component analysis and tasselled cap analysis techniques can reduce data redundancy, however, they are still, like the change detection techniques used arithmetic operations, cannot provide detailed change matrix (“from-to”) and require selection of thresholds to identify changed areas. Post-classification comparison technique can avoid the problem of selecting the thresholds while provide more information related to the type of change (trajectories) and compensates for variations in the environmental conditions. The successful application of post-classification comparison technique depends on the quality of the classified image which can be solved by implementing precise classification methods such as hybrid classification and object-oriented classification methods. Introducing machine learning algorithms for automatic change detection can achieve great success. Besides, integrating GIS approach has proved to be a useful tool in many change detection applications, in particular when multi-source data are used.

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