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Review Article

Remote Sensing & GIS based Approaches for LULC Change Detection – A Review

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Abstract

Economic development and population growth have triggered rapid changes to Earth's land cover over the last two centuries, and there is every indication that the pace of these changes will accelerate in future. Land use and land cover (LULC) change has become a central component in current strategies for managing natural resources and monitoring environmental changes. The Remote Sensing and Geographic Information System have proved to be very important in assessing and analyzing land use and land cover changes. Recent progress in remote sensing and associated digital image processing offers unprecedented opportunities to detect changes in land cover more accurately over increasingly large areas, with diminishing costs and processing time. The present reviews have assorted the detection approaches and drawn many useful conclusions. Based on the former classification methods, this article classifies change detection methods into three groups, based on pixel, feature and object level image processing.

Keywords: *Remote Sensing, LULC change detection, GIS, Pixel-based, Feature space, Object-based change detection, soft computing, accuracy assessment*

1. Introduction

Land use/land cover change is widely recognized as an important aspect of global environmental change, which plays a pivotal role in regional socio-economic development (Chen, 2002). To ensure a sustainable management of natural resources, it is necessary to understand and quantify the processes of landscape change (Petit *et al*, 2001). It is also necessary to develop a better understanding of the causes of land use change so that efficient counter-measures can be undertaken. Scientific research community called for substantive study of land use changes 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). Land use and land cover (LULC) changes play a very important role on regional to global scales, with impacts over ecosystem functioning, ecosystem services, and biophysical and human variables such as climate and government policies (Meyer and Turner 1994). Human induced changes in land cover for instance, influence the global carbon cycle, and contribute to the increase in atmospheric CO (Alves and Skole, 1996). It is therefore indispensable to examine the changes in land use/cover, so that its effect on terrestrial ecosystem can be discerned, and sustainable land use planning can be formulated (Muttitanon and Tripathi, 2005).

Land use and land cover changes, apart from changing the physical dimension of the spatial extent of the land use and land cover classes, also influence many of the secondary processes which lead to the eventual degradation of the ecosystems of the earth (Dregne and Chow, 1992). First and foremost, the impact of land use and land cover changes is the reduction of vegetation cover that leads to many other deleterious effects on the environment, namely, loss of biodiversity, climate change, changes in radiative forcing, pollution of other natural ecosystems with a reduction in their quality, changes in hydrological regimes, and the list continues (Niyogi, *et al*, 2009). The secondary impact of land use and land cover changes initiates a cascade of effects on the environment and this works in a loop to further influence land use and land cover changes.

Land-cover and land-use change information imparts practical uses in various applications, including deforestation, damage assessment, disasters monitoring, urban expansion, planning, and land management. The change detection frameworks use multi-temporal datasets to qualitatively analyze the

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temporal effects of phenomena and quantify the changes. It provides the spatial distribution of features and qualitative and quantitative information of features changes.

Inventory and monitoring of land-use/land-cover changes are indispensable aspects for further understanding of change mechanism and modeling the impact of change on the environment and associated ecosystems at different scales (Turner *et al,* 1995; William *et al,* 1994). Change detection can be defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh A., 1989). The goal of change detection is to discern those areas on digital images that depict change features of interest (e.g., forest clearing or land-covert land-use change) between two or more image dates. One of the major applications of remotely-sensed data obtained from Earth-orbiting satellites is change detection because of repetitive coverage at short intervals and consistent image quality (Anderson 1977, Ingram *et al.* 1981, Nelson 1983, Singh 1984). Land use land cover change studies provides information for better understanding of previous practices, current land use pattern and future land use trajectory (Sharma *et al,* 2008).

2. Remote sensing & GIS techniques for land use and land cover change

The Remote Sensing and Geographic Information System have proved to be very important in assessing and analyzing land use and land cover changes. Satellite-based Remote Sensing, by virtue of its ability to provide synoptic information of land use and land cover at a particular time and location, has revolutionized the study of land use and land cover change. The temporal information on land use and land cover helps identify the areas of change in a region. Geoinformatics allow to assign spatial connotations to land use land cover changes, namely, population pressure, climate, terrain, etc which drive these changes (Roy & Roy, 2010). The quantitative analysis and identifying the characteristics and processes of surface changes can be analyzed from the different periods of remote sensing data. It involves the type, distribution and quantity of changes, that is the ground surface types, boundary changes and trends before and after the changes. The remote sensing data has become a major source for change detection studies because of its high temporal frequency, digital format suitable for computation, synoptic view, and wider selection of spatial and spectral resolutions (Chen *et al,* 2012; Coops *et al,* 2006; Lunetta *et al,* 2004).

In mathematical terms general change detection algorithm analysis an input image sequence {IM1, IM2,...IMn}

where n is the number of images, and generates a difference image D, where: $\mathrm{D(i)} = \begin{cases}1,\\0,\end{cases}0$ if Ith pixel if changed in IMn otherwise Here each pixel I has an intensity I(i) € Rj, where j depends on type of image, e.g. 1 for grayscale images, 3 for RGB images or more for hyperspectral or SAR images.

Digital change detection is affected by spatial, spectral, radiometric resolution, temporal constraints, atmospheric conditions, and soil moisture conditions (Jensen, 2005) therefore before implementing change detection analysis, some conditions must be satisfied like precise registration of multi-temporal images; precise radiometric and atmospheric calibration or normalization between multi-temporal images and selection of the same spatial and spectral resolution images if possible.

Good change detection research should provide the information like area change and change rate, spatial distribution of changed types, change trajectories of land-cover types and accuracy assessment of change detection results. Arrays of techniques are available to detect land use/ cover changes from multi-temporal remote sensing data sets which can be broadly grouped into two general types (Singh, 1989; Jensen, 1996; Coppin and Bauer, 1996; Ding *et al,* 1998; Johnson and Kasischke, 1998): (1) those based on spectral classification of the input data such as post-classification comparison (e.g., Mas, 1999) and direct two-date classification (e.g., Li and Yeh, 1998); and (2) those based on radiometric change between different acquisition dates, including (a) image algebra methods such as band differencing (Weismiller *et al,* 1977), ratioing (Howarth and Wickware, 1981), and vegetation indices (Nelson, 1983); (b) regression analysis (Singh, 1986); (c) principal component analysis (Byrne *et al*., 1980; Gong, 1993); and (d) change-vector analysis (CVA) (Malila, 1980). Based on a mixture of categorical and radiometric change information, hybrid approaches have also been proposed and evaluated (Colwell and Weber, 1981). Deer (1998) suggested a three level categorization system that differentiates these methods by introducing the notion of pixel, feature and object level image processing.

Lu *et al,* (2004) generalized the change detection methods into seven types, namely, arithmetic operation, transformation, classification comparison, advanced models, GIS integration, visual analysis and some other methods. Change information obtained may be either in the form of simple binary change (i.e. change vs. no change as in the case of image differencing, image rationing etc) or detailed from-to change as in the case of using post-classification comparison (Im *et al,* 2007). In this present study change detection techniques are categorized according to Deer's categorization system in three levels based on pixel, feature and object level image processing and also presents a classification based on learning techniques used in soft-computing methods for change detection. Pixel refers to numerical values of each image band, or simple calculations between corresponding bands such as image differencing or rationing. The feature level is a more advanced level of

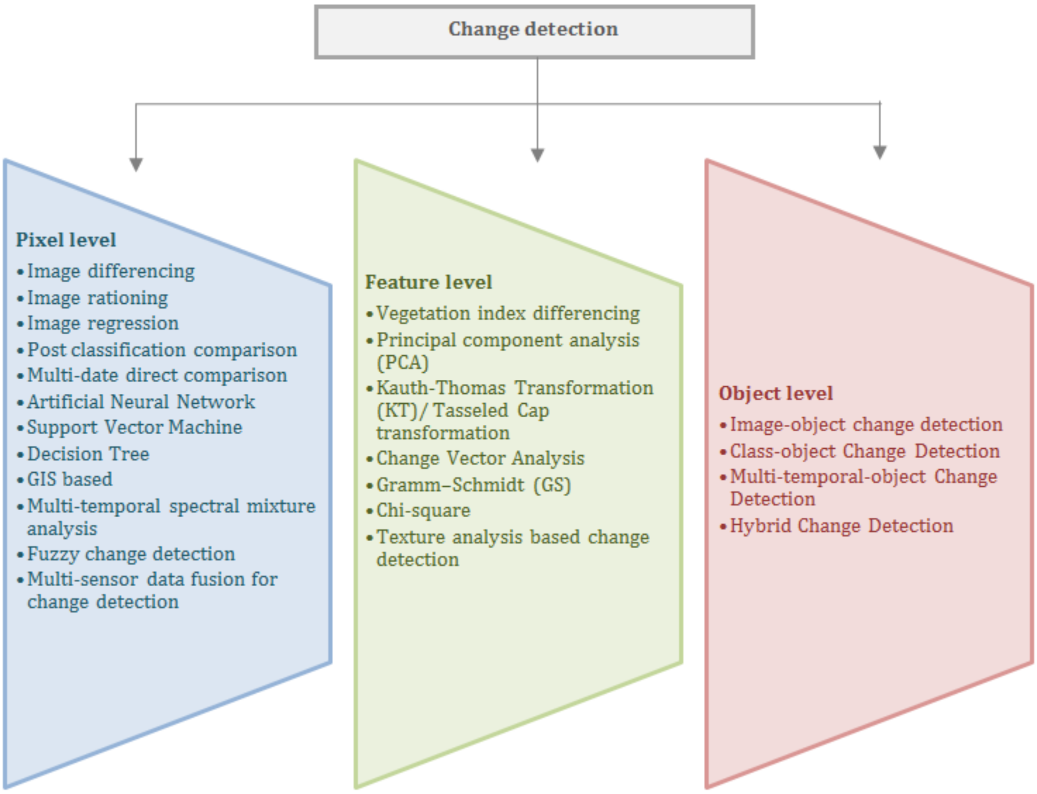

Fig.1 Classification concept of change detection algorithms

processing, which involves transforming the spectral or spatial properties of the image (e.g. principal components analysis (PCA), texture analysis, or vegetation indices), thus the enhanced feature may have real-world meaning (e.g. vegetation indices in the radiometric domain). The object is the most advanced level of processing. All levels involve symbolic identification in addition to pixel or feature change detection.

3. Pixel level change detection techniques

Image pixel is the fundamental unit of analysis and is exploited to detect and measure changes without taking into considering the spatial context. The results of pixel-based change detection strategies are often limited when applied to very-high-resolution (VHR) imagery. Using VHR image data for change raises a number of challenges: (a) geo- referencing accuracy, (b) larger reflectance variability in each class, and (c) different acquisition characteristics (e.g. sensor viewing geometry, shadow effect, and illumination angle) (Wulder *et al,* 2008). Afiify (2011) applied four of the most commonly used change detection techniques i.e. post-classification, image differencing, image ratioing and principal component analysis to detect the nature and extent of the land-cover changes in New Burg El-Arab city using Landsat multispectral images.

Cao (2014) studied a method for change detection in high-resolution remote sensing images by means of Multi-resolution level set (MLS) evolution and support vector machine (SVM) classification, which combined both the pixel level method and the object-level method.

1) Image Differencing

This simple method is widely used and consists of subtracting registered images acquired at different times, pixel by pixel and band by band where $Dx^k ij$ is the difference between pixel value x located at row *i* and column *j*, for band *k*, between acquisition date 1 (t_1) and date 2 (t_2) (Singh, 1989).

$Dx^k ij = x^k ij (t_2)-x^k ij (t_1)$,

No changes between times result in pixel values of 0, but if changes occurred, these values should be positive or negative. Optimal threshold values based on standard deviations from the mean can be used on the new image to determine the changed from unchanged pixels. An accuracy assessment on the no-change from change pixels was performed to determine the threshold value with the highest accuracy. Pixels with change in radiance are distributed in the tails of the distribution curve (Singh, 1989) whereas pixels with no change are distributed around the mean (Lu *et al,* 2005. As changes seem to occur in both directions, the analysts have to decide the order of the image to subtracted (Gao, 2009). Dependence on the accuracy of the threshold values is a major drawback, because higher threshold values can cause information and lower threshold value can cause void inspecting (Shaoqing and Lu, 2008).

2) Image Rationing

In ratioing two registered images from different dates with one or more bands in an image are rationed, band by band. The data are compared on a pixel by pixel basis. One computes where,

$R\, x^{k}_{ij} = x^{k}_{ij}(t_1) / x^{k}_{ij}(t_2)$

$x^{k}_{ij}(t_2)$ is the pixel value of band k for pixel x at row i and column j at time t_2. If the intensity of reflected energy is nearly the same in each image then $R\, x^{k}_{ij} = 1$, this indicates no change (Singh, 1989)

The image ratio method is useful for the extraction of vegetation and texture. The influence of the slope and aspect, the shadow or sun angle, radiation changing caused of strong seasonal variations and multiplicative noise can be eliminated or reduced. It can highlight different slope features between the bands. It has higher accuracy and can be applied to estimate change detection in cities. A drawback of this method is also that the type of feature changes can't be analyzed and the choice of threshold value is difficult.

3) Image Regression

This approach assumes that there is a linear relationship between pixel values of the same area at two different times. This implies that a majority of the pixels did not encounter changes between the two dates. When using least-squares regression analysis gains and offsets are identified by radiometrically normalizing the subject image to match the reference image (Lunetta, 1999) and the change denoted by Id can be obtained by subtracting regressed image from the first-date image.

$Id_1(x,y)=aI_d(x,y)+b$
$I_d(x,y)=I_d(x,y)-I_{d1}(x,y)$

The regression technique accounts for differences in the mean and variance between pixel values for different dates so that adverse effects from differences in atmospheric conditions or Sun angles are reduced (Jenson, 1983).

4) Post-Classification Comparison

It is widely used and easy to understand. Two images acquired at different times are independently classified and then compared. Ideally, similar thematic classes are produced for each classification. Changes between the two dates can be visualized using a change matrix indicating, for both dates, the number of pixels in each class.

5) Multi-date direct comparison

Multi-date images are combined into a single dataset on which a classification is performed. The areas of changes are expected to present different statistics (i.e., distinct classes) compared to the areas with no changes. The approach can be unsupervised or supervised and necessitates only one classification procedure. However, this method usually produces numerous classes corresponding to spectral changes within each single image but also to temporal changes between images. The interpretation of results is often complex and requires a good knowledge of the study area.

6) Artificial Neural Network

ANN is non-parametric supervised algorithm. It estimates data properties based on training data. The input used to train the neural network is the spectral data of the period of change. A Back propagation algorithm is often used to train the multi-layer perceptron neural network model. The main issues with ANN include: (a) the hidden layer in ANN is not known properly; (b) the amount of training data is important in teaching the network; and (c) ANN functionalities are not common in image processing software (Hussain *et al,* 2013).

7) Support Vector Machine

It is Non-Parametric and there is no assumption on data distribution. It is able to handle small training data sets and often produces higher classification accuracy than the traditional methods (Mantero *et al,* 2005). Theoretically can handle larger data sets with higher dimensionality and is particularly used for hyper spectral image classification (Melgani and Bruzzone, 2004).

8) Decision Tree

The decision tree classification algorithms are non-parametric with no assumption about data distribution and independency. These algorithms build a flowchart-like tree (hierarchical) structure in which each node represents a test on a number of attribute values, each branch represents an outcome of the test, and tree leaves represent classes or class distribution (Han *et al,* 2011; Larose, 2005). The classification rules at the node of the decision tree are based on the analysis of attribute values. Change vs. no-change can be treated as a binary-classification problem or a post-classification comparison can be performed to measure changes. Some other machine learning algorithms used for classification and change monitoring include; genetic programming (Makkeasorn *et al,* 2009), random forest (Pal, 2005; Sesnie *et al,* 2008; Smith, 2010), and Cellular automata (Yang *et al,* 2008).

9) GIS based

Geographic Information Systems (GIS) provides a base for data integrating, visualizing, analyzing and map producing. The flow of the data can be bidirectional, as GIS data can be used to overlay onto an image; alternatively, the results from image analysis and can be used to update the GIS data. For example, the parcel layers stored in a GIS database are used to assist classification and change detection from an image (e.g. Smith, 2008). GIS also allows integrating past and current maps for comparison and change detection. In such cases, image overlaying and binary masking may help reveal quantitatively the change dynamic in each class.

GIS data and methods such as spatial association, spatial clustering, spatial relation, spatial distribution, spatial evolvement and spatial feature, plays important role for change detection by integrating the land cover maps derived from image data (Li, 2010; Petit *et al*, 2001). The spatial and aspatial information about objects stored in the GIS database can play an important role when linked to the objects extracted from RS image for change detection along with other image analysis (Bouziani *et al*, 2010). Walter (2004) presented an object-based technique for change detection where the training data is extracted from the GIS database to classify the image. The classified objects from the images were then compared against the objects stored in GIS to measure changes.

10) Multi-temporal spectral mixture analysis

Spectral mixture analysis addresses the increased dimensionality (more than one target class in one pixel) because of high spectral resolution. Spectral mixture analysis assumes that multispectral image pixels can be defined in terms of their sub-pixel proportions of pure spectral components which may then be related to surface constituents in a scene. In linear mixture model, each end-member is linearly combined with the end-member spectra that are weighted by the percent ground cover (Versluis and Rogan, 2009). A linear spectral mixture model is given as:

$$r_i = \sum_{j=1}^{n} a_{ij} f_j + e_i$$

r_i = measured reflectance of a given pixel in spectral band

i, n is the number of mixture components,

f_j is the a real proportion, or fraction, of end member j in r_i ,

aij is the reflectance of end member j in spectral band i, and

e_i is the residual, the difference between the observed (r_i) and modeled pixel values (Versluis and Rogan, 2009). It is important to select the number and spectrum of the end members for an accurate application of spectral mixture analysis techniques which can be based on the image itself or use field-spectra measures in-situ or in labs (Solans Vila and Barbosa, 2010).

11) Fuzzy change detection

Fuzziness implies that the boundaries between different classes and phenomena are fuzzy and that there is heterogeneity within a class perhaps due to the physical differences (Lizarazo and Joana, 2010). The results of fuzzy reasoning are not discrete and crisp, but are, rather, expressed in terms of probabilities' (Metternicht, 1999). It can contain elements with only a partial degree of membership. Fuzzy membership differs from probabilistic interpretation as fuzzy set is defined by a membership function and the class with highest probability is interpreted as actual class. Post-classification comparisons are applied to measure the change (Eklund *et al,* 2000; Fisher *et al*, 2006; Fisher and Pathirana, 1993; Foody and Boyd, 1999). This method is useful when selecting a threshold value to distinguish change from no-change is difficult.

12) Multi-sensor data fusion for change detection

In multi-temporal spectral mixture analysis the multispectral image pixels is assumed to be defined in terms of sub-pixel proportions of pure spectral components that is related to surface constituents in a scene. Due to high spectral resolution it addresses the increased dimensionality. In linear mixture model, each end-member is linearly combined with the end-member spectra that are weighted by the percent ground cover (Versluis and Rogan, 2009). For accuracy in applying this technique that is based on image or field-spectra measures in situ or in labs Solans Vila and Barbosa (2010) argue to give importance in selecting the number and spectrum of the end members.

4. Feature level change detection techniques

The feature level is a more advanced level of processing, which involves transforming the spectral or spatial properties of the image (e.g. principal components analysis (PCA), texture analysis, or vegetation indices etc). The following techniques are included under this category of change detection.

1) Vegetation index differencing

Vegetation indices have been developed for the enhancement of spectral differences on the basis of strong vegetation absorbance in the red and strong reflectance in the near-infrared part of the spectrum. It has been shown that a ratio of near-infrared Multispectral Scanner (MSS) band 4 and red MSS band 2 is significantly correlated with the amount of green leaf biomass (Tucker, 1979).

The Normalized Difference Vegetation Index (NDVI) is calculated by NDVI = (NIR- RED) / (NIR + RED) where NIR is the near-infrared band response for a given pixel and RED is the red band response. After computing the vegetation index for two date's standard pixel based approaches (e.g. differencing or rationing) are applied to determine the change (Nelson 1983, Singh 1989). Other vegetation indices developed include (a) Ratio Vegetation Index (RVI) (b) orthogonal indices, including Perpendicular Vegetation Index (PVI) and Difference Vegetation Index (DVI), and (c) Soil Adjusted Vegetation Index (SAVI) and modified soil adjusted vegetation index (MSAVI) (Chen *et al*., 1999).

$$\mathrm{RVI} = \frac{\mathrm{n}}{\mathrm{r}}$$

$$\mathrm{NDVI} = \frac{\mathrm{n}-\mathrm{r}}{\mathrm{n}+\mathrm{r}}$$

$$\mathrm{TVI} = \sqrt{\frac{\mathrm{n}-\mathrm{r}}{\mathrm{n}+\mathrm{r}}} + 0.5$$

$$SAVI = \frac{\mathrm{n}-\mathrm{r}}{\mathrm{n}-\mathrm{r}+\mathrm{L}}(1+\mathrm{L})$$

$$\mathrm{MSVI} = \frac{2\mathrm{n}+1-\sqrt{(2\mathrm{n}+1)^2-8(\mathrm{n}-\mathrm{r})}}{2}$$

Where n is near infrared band and r is there d band. The L in SAVI confirms the same bound between NDVI and SAVI. Unsalan (2007) modifying RVI and NDVI by calculating angle vegetation index (Unsalan and Boyer, 2004) and developed bi-temporal vegetation Time-Dependent Vegetation Indices (TDVI).

2) Principal component analysis (PCA)

PCA, mathematically based on ''Principal Axis Transformation'', is a transformation of the multivariate data to a new set of components, reducing data redundancy (Lillesand *et al,* 2008). PCA uses either the covariance matrix or the correlation matrix to transfer data to an uncorrelated set. The eigen vectors of the resulting matrices are sorted in decreasing order where first principal component expresses most of the data variation.

This allows the dataset to be uncorrelated variables representing the most important information from the original (Jensen, 2005). The calculation of the variance-covariance matrix (C) of multiband images is expressed as:

$$\mathrm{C} = \frac{\sum_{\mathrm{j}=1}^{\mathrm{n}}(\mathrm{X_j}-\mathrm{M})(\mathrm{X_j}-\mathrm{M})^{\mathrm{T}}}{\mathrm{n}-1}$$

where M and X are the multiband image mean and individual pixel value vectors respectively, and n is the number of pixels.

3) Kauth-Thomas Transformation (KT)/ Tasseled Cap transformation

The principle of this method is similar to PCA. The only difference from PCA is that PCA depends on the image scene, and KT transformation is independent of the scene. The change detection is implemented based on the three components: brightness, greenness and wetness. It cannot provide detailed change matrices and require selection of thresholds to identify changed areas.

4) Change Vector Analysis

Change Vector Analysis is a technique where multiple image bands can be analyzed simultaneously. The concept of the traditional change vector analysis involves the calculation of spectral change based on multi-temporal pairs of spectral measurements, and relates their magnitudes to a stated thresh old criterion (Malila, 1980). In change vector analysis pixel values are vectors of spectral bands. Change vectors are calculated by subtracting vectors pixel wise as in image differencing. The magnitude and direction of the change vectors are used for change analysis. The total change magnitude per pixel pixel can be computed by determining the Euclidean distance between end points through n-dimensional change space (J.L. Michalek, *et al*, 1993).

$$\mathrm{CM_{pixel}} = \sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{X_2} - \mathrm{X_1})^2$$

where X_1 and X_2 are date one and date two pixel values in i band. Change vector analysis can also be applied to transformed data such as Kauth-Thomas Transformation (KTT) rather than to raw data. The two important reasons that make change vector analysis a more level headed change detection technique than other techniques are: (a) it relies on entirely contiguous pixels; (b) it relaxes the requirement of training and ground truth data.

5) Gramm–Schmidt (GS)

Gram-Schmidt (GS) is developed by modifying KT to handle multi-temporal data which produce stable components corresponding to multi-temporal analogs of KT brightness, greenness and wetness, and a change component (Collins & Woodcock, 1994).

6) Chi-square

Chi-square transformation uses multi-bands together to produce a single change image. The original chi-square test, also referred to as Pearson's chi-square, was presented by Karl Pearson in early 1990s. Ridd and Liu (1998) introduced the chi-square formula:

$$\mathrm{Y} = (\mathrm{X}-\mathrm{M})^{\mathrm{T}}\sum\nolimits_{-}^{-1}(\mathrm{X}-\mathrm{M})$$

where Y is the digital value of the changed image; X is the vector of the difference of the six digital values between the two dates; M is the vector of the mean residuals of each band; T is the transverse of the matrix; and is the inverse covariance matrix of the bands (D. Lu, *et al,* 2004).

7) Texture analysis based change detection

Change is measured by comparing the textural values from images. Texture provides information about the structural arrangement of objects and their relationship with respect to their local neighborhoods (Caridade *et al*, 2008). Comparing the textural values from images is used to measure changes. Grey level co-occurrence matrix is one among the texture measuring algorithms is a second order statistics that examine the spectral as well as spatial distribution of grey values. Here initially the image is divided into smaller windows instead of per-pixel comparison then the texture is computed and comparison is performed at window level (Sali and Wolfson, 1992). He and Wang (1991) highlighted to use texture information only in conjunction with spectral data.

5. Object-Based Change Detection Techniques

The unit for analysis in the object-based image analysis is an image object which gets richer information including texture, shape, and spatial relationships with neighboring objects and ancillary spatial data for different spatial resolution (Aguirre-Gutiérrez *et al*, 2012; Bock *et al*, 2005) allowing the exploitation of the spatial context. Object-based procedures can employ change measures and also exploit the changes of shape values, such as border length or size, or changes of object relations. Hence, thematic, geometric and topographic changes of objects could be analysed. Niemeyer and Nussbaum (2006) used a combination of pixel-and object-based approaches by firstly pinpointing the significant change pixels by statistical change detection, object extraction and subsequently post-classifying the changes based on a semantic model of object features. Im *et al* (2007) introduced change detection based on object/ neighbourhood correlation image analysis and image segmentation techniques. Gamanya *et al* (2007) adopted a hierarchical image segmentation approach and applied a standardized, object-oriented automatic classification method. Zhou (2008) used object-based land cover classification and change analysis in the Baltimore metropolitan area using multi-temporal high resolution remote sensing data and it provides an effective way to incorporate spatial information and expert knowledge into the change detection process. Object-Based Change Detection algorithms are classified in four categories – image-object, class-object, multi-temporal-object and hybrid change detection.

1) Image-object change detection

Multi-temporal images are segmented separately with changes analyzed based on an object's spectral information (e.g. averaged, mean band values), extracted features (e.g. texture) and/or other features extracted from the original objects (e.g. image-texture and geometry) (Lefebvre *et al*, 2008). Miller *et al* (2005) studied algorithms to detect the change of significant objects between a pair of grey-level images. Connectivity analysis is used to extract the objects from the master image and each of these objects was searched for a corresponding object in the second image. A matching method to identify the relationship between two object boundary pixels was used to detect the change. Lefebvre *et al*. (2008) preferred texture features and object contour to detect changes in very high-resolution airborne or space-borne images at the sub-metre level. The major advantage is that since objects are extracted using segmentation the algorithms are easy to implement and involves the direct comparison of objects to detect the change.

2) Class-object Change Detection

Class-object change detection algorithm detects landscape changes by comparing the independently classified objects from multitemporal images. The classification algorithms incorporate both texture and spectral information. The GIS layers or existing maps are updated using this approach. Decision-tree, maximum likelihood, nearest neighbor classifier (Im and Jensen, 2005), fuzzy classification (Durieux *et al,* 2008) and maximum likelihood classification (MLC) techniques are used for classification.

3) Multi-temporal-object Change Detection

Multi-temporal images are segmented separately with changes analyzed based on an object's spectral information (e.g. averaged band values) or other features extracted from the original objects (e.g. image-texture and geometry). Mahalanobis distance calculation and thresholding method can also be integrated to detect change (Bontemps *et al*., 2008). Nearest-neighbor supervised classification approach and reference data was used by Conchedda *et al*. (2008) to quantify changes. Incremental segmentation procedure by Li *et al* (2009) for radar imagery first segmented the first-date image then treated the result as a thematic layer and finally segmented the derived layer together with the second-date image. The major advantage of image-object change detection is the straightforward comparison of objects.

4) Hybrid Change Detection

Hybrid change detection algorithms involve the use of both object and pixel paradigms. Niemeyer and Nussbaum (2006) used combination of pixel- and object-based approaches where initially statistical change detection and object extraction pinpointing change pixels and semantic model of object features subsequently post-classified the changes. Region-merging segmentation was applied on Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Matter (ETM) and then fuzzy-logic model classification was performed before comparing them to compute the change (Gamanya *et al* (2009)). Yu *et al* (2010) used support vector machine to perform an object based classification and then compared land use vector data with these objects to detect change. Carvalho *et al*. (2001) studied that wavelet inter-scale correlation computed from pixel-based difference images (e.g. differencing, rationing, PCA, CVA) were effective to identify all land-cover changes over a study area. Region-growing segmentation was then performed to extract objects solely where changes occurred.

6. Soft Computing Approaches for Change Detection

Soft computing is a fusion of methodologies designed to model and enable solutions to real life problems, which are not modeled or too difficult to model mathematically. The basic methodologies of soft computing incorporate fuzzy logic, evolutionary computing and neural networks. These techniques are not isolated but mutually cooperative (Yasuhiko & Seppo, 2001).

1) Fuzzy Logic Approach

In soft computing a fuzzy logic scheme integrates numeric as well as linguistic data. It maps crisp vector input to a crisp scalar output. By the usage of fuzzy logic and fuzzy sets, various engineering and mathematical problems can be approximated closer to actual solutions (Jerry, 1995). Gong & Ma (2012) adopted fuzzy clustering and image fusion for change detection in SAR images.

2) Neural Network Approach

A neural network refers to a set of identical processing units, each having some internal factors known as weights. Non linear controller problems can be efficiently solved using such systems. It mimics the working of human brain and nervous system (Derrick & Bernard, 1999). The multiple layers can be used for learning from complex data. Using neural networks for any application requires us to define the architecture of neural network, the activation functions for neurons and the learning algorithm. Prominent architectures are Multi layer perceptron model, self organizing maps, competitive networks, Hopfield. Santos, Castaneda & Yanez (2012) utilized aggregated Pulse Coupled and Hopfield networks for detecting changes in remotely sensed images.

3) Genetic Algorithms (GA) based methods

Genetic algorithms belong to evolutionary computing paradigm. This technique is widely used in optimization problems, where we need to optimize some objective function, which is highly non-linear. The probable solutions to a problem are coded as chromosomes (representation of solution as strings). Mostly the chromosomes are coded as strings of 0's and 1's.

4) Evolutionary Computing Approach

Evolutionary computing uses principal of natural selection and evolution. It uses a population of individual elements that performs optimization using certain objective functions that help select the best individuals which are carried forward for the further computation. This mechanism helps search large and complex solution spaces which would otherwise be difficult to search using traditional algorithms. The major techniques in this category include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Bee Colony Optimization (BCO). Tang, Huang, Muramatsu & Zhang (2010) studied Genetic Algorithm based Change Detection on High Resolution Images in an Object-Oriented approach.

7. Accuracy assessment of change detection

Accuracy of change detection depends on many factors, including precise geometric registration and calibration or normalization, availability and quality of ground reference data, the complexity of landscape and environment, methods and algorithms used, the analyst's skills and experience, and time and cost restrictions (Lu *et al,* 2004). Shao (2006) summarized the main errors in change detection including errors in data (e.g. image resolution, accuracy of location and image quality), errors caused by pre-processing (the accuracy of geometric correction and radiometric correction), errors caused by change detection methods and processes (e.g. classification and data extraction errors), errors in field survey (e.g. accuracy of ground reference) and errors caused by post processing (e.g. change identification, removal of the small map patches, and vectorization).

Among various assessment techniques, the most efficient and widely used is the error matrix (i.e. confusion table) of classification. Based on this matrix, Biging *et al* (2000); Gong & Mu (2000) proposed the error matrix for the accuracy assessment of change detection. Some alternative methods are also used in analyzing and evaluating change detection of land cover. Nemour & Chibani (2006) proposed the fuzzy error matrix (FEM) and receiver operating characteristics (ROC). Morisette & Khorram (2000) used accuracy assessment curves to analyse satellite-based change detection. Lowell (2001) developed an area based accuracy assessment method for analysis of change maps. Liu & Zhou (2004) proposed an accuracy analysis of time series of remote sensing change detection by rule-based rationality evaluation with post-classification comparison.

8. Probable Future in change detection

In the past decades availability of remotely sensed data has increased constantly with the launch of numerous satellite sensors as well as the reduction of product costs. The early remote sensing data had limited spatial, spectral and temporal resolutions which were the major cause of the limitation in remote sensing based change detection methodologies (Boyd & Foody, 2011). The increased use of remote sensing data in past decades is mainly due to the lower cost and the launch of advanced sensors, in private sector, capable of acquiring data at much finer scales. Artificial intelligence systems as well as knowledge-based expert systems and machine learning algorithms represent new alternatives in change detection studies (Coppin *et al,* 2004). Ghosh *et al* (2009) proposed an unsupervised and context-sensitive technique for change-detection in multi-temporal remote sensing images. Here semi-supervised learning is integrated with an unsupervised context-sensitive change detection technique. The technique discriminates the changed and unchanged regions in the difference image by using a modified self-organizing feature map network (SOFM) network implemented according to a specific architecture. The number of input neurons was equal to the dimension of the input patterns and the number of output neurons was equal to the number of pixels in the difference image, i.e. one neuron is assigned to each pixel of the difference image.

With the increasing availability of multi-sensor images more systematic tests on the sensitivity of different pixel-based change detection approaches should be done using multiple sensor data. More advanced change detection technology focusing on multi-scale statistical, textural, and pattern changes will be needed to overcome the limitations of pixel-based statistical approaches when multiple sensor data are used. Complex techniques will evolve over time with the advanced technologies emerging and the availability of finer resolution data sets and higher computational power in the future. Currently, OBIA based change detection techniques are more frequently used because of their advantages over the traditional techniques in the analysis of high-resolution images (Hussain *et al,* 2013).

Developments in this area will allow automation in feature extraction and change detection more reliably and accurately in near future. Advanced computational and data processing algorithms such as Artificial Intelligence, knowledge-based expert system, agent-based models and machine learning algorithms represent new directions in change detection studies. The increased use of algorithms decision tree, support vector machine in the remote sensing based change detection studies can be seen in the literature. One can expect the integration of more machine learning algorithms in the image processing packages for classification and change detection (Vieira *et al*., 2012; Chen *et al*., 2012a, b; Hamedianfar and Shafri, 2013). More developments are expected in the future which will provide new tools for integrating multisource data more easily (e.g., digital imagery, hard maps, historical information, vector data).

Conclusions

Changes of the objects on the Earth's surface have their time-space evolvement processes. Better understanding of these change processes can assist in the retrieval of objects and changes and improve change detection accuracy. Multi-source data especially with different characteristics are often needed for change detection. GIS based analysis of the remote sensing derived temporal data of the land use and land cover of a region can identify the potentially vulnerable areas to change as a result of the different driving forces. Developing change detection methods in remote sensing is an ever-growing research agenda. Change detection is a complicated process with no single optimal approach applicable to all cases. It is imperative that the changes in land use and land cover be assessed for spatial extent as well as intensity and magnitude to understand the cause behind this irreversible change. The change detection technique should provide a flexible framework to integrate multi-source data, processing procedures, intelligent method and existing geographical knowledge. Digital change detection is affected by spatial, spectral, radiometric and temporal constraints therefore the selection of a suitable change detection method or algorithm for a given research project is important to get accurate results. No one technique of change detection is suitable for all cases. Selection of an appropriate method for detecting change in an object or a phenomenon on the earth's surface depends on a number of elements, including the characteristics of the study area, the spatial resolution of the sensor, atmospheric effects and sun angle, which should be taken into account before applying a suitable technique for the detector.

In this paper three, pixel, feature and object level change detection techniques are briefly discussed. The binary change/no-change threshold techniques all have difficulties in distinguishing true changed areas from the detected change areas. Single band image differencing and PCA are the recommended methods. Classification-based change detection methods can avoid such problems, but requires more effort to implement. Post-classification comparison is a suitable method when sufficient training data is available. When multi-source data is available, GIS techniques can be helpful. Advanced techniques such as ANN, or a combination of change detection methods can produce higher quality change detection results. The object-oriented change detection approaches reduce effects of slight miss registration between the two images, reduce the 'salt and pepper' noise, include context relationships and object shape information, reduce effects of shadows from trees, reduce effects of differences in sensor viewing geometry and thus provide better results than the pixel-based methods. Soft computing techniques provides new horizon in this field by fusion methodologies. The technological advancements over the last few decades has allowed the applications to exceed the traditional limits and endeavor new ventures which in turn fed back to the remote sensing technologies for further developments (Blaschke *et al,* 2011). The launch of new satellites represent challenges to develop effective and efficient change detection methodologies and frameworks capable of searching through huge achieve of remote sensing data with different spatial/ spectral/temporal resolutions and enable change analysis (Vieira *et al,* 2012).

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