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Article

A Probability Model-based Method for Land Cover Change Detection Using Multi-Spectral Remotely Sensed Images

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Keywords: Change Detection, Chi-square Distribution, Remote Sensing, Image Differencing, Tasseled Cap Transformation

Summary: Change detection is one of the main research areas in remotely sensed image processing. Image differencing methods have been widely used to quantify changed pixels by labeling such pixels with differencing images. There is room, however, to further develop the approach by enhancing the change detection reliability method by reducing the index sensitivity to seasonal variations. Using the information provided by image differencing results, a probability model-based change detection method is proposed in this study. A Chi-square distribution model is built using multiple index images based on the assumption that the pixels in the differencing image follow a normal distribution. By means of Chi-square distribution percentiles, different probability contours can be found to differentiate the changed pixels from all pixels in the feature space. The pixels located outside the probability contour will then, be identified as the changed pixels with a certain probability level. Tasseled Cap transformation components can be utilized to construct the Chi-square distribution, thus obtaining a higher accuracy of change detection. Due to the availability of multiple index images such as NDVI and Tasseled Cap transformation components, ETM+ images of Hong Kong on Aug. 20, 1999 and Sep. 17, 2002 were used as experimental data to test the performance of the proposed method. The experiments showed that the combination of NDVI and Brightness indices produced the highest overall accuracy and Kappa coefficient values.

Zusammenfassung: *Ein wahrscheinlichkeits- und modellbasiertes Verfahren zur Veränderungsanalyse der Landnutzung durch Nutzung multi-spektraler Fernerkundungsdaten.* Die Veränderungsanalyse (Change Detection) ist ein sehr wichtiges Forschungsfeld in der fernerkundlichen Bildverarbeitung. Zwar sind Change Detection Methoden in der Vergangenheit schon häufig benutzt worden, um Veränderungen kenntlich zu machen, allerdings gibt es immer noch Potential zur Verbesserung der Methoden insbesondere zu deren Zuverlässigkeit gegenüber saisonalen Schwankungen der Landnutzung. In diesem Artikel wird ein wahrscheinlichkeits- und modellbasiertes Verfahren zur Veränderungsanalyse vorgestellt. Hierzu wird ein Chi-Quadrat-Verteilungsmodell durch die Nutzung multipler Indexbilder erstellt mit der grundsätzlichen Annahme, dass die Pixel in den zu untersuchenden Bildern der Normalverteilung folgen. Durch die Nutzung des Perzentilwertes der Chi-Quadrat-Verteilung können unterschiedliche Wahrscheinlichkeitskonturen gefunden werden, um die veränderten Pixel von allen anderen Pixeln mit einer bestimmten Wahrscheinlichkeit im Merkmalsraum zu unterscheiden. Die Tasseled Cap Transformation sollte verwendet werden, um die Chi-Quadrat-Verteilung zu konstruieren, so dass man eine höhere Genauigkeit zur Erkennung von Änderungen erhält. Die Leistungsfähigkeit der vorgestellten Methode wurde durch eine Vielzahl von verschiedenen Index-Bildern, wie z. B. den NDVI und die Tasseled Cap Transformation, und ETM-Bildern von Hongkong vom 20. August 1999 und 17. September 2002 getestet. Die Analysen zeigen, dass die Kombination von NDVI- und Brightness-Indizes die höchste Gesamtgenauigkeit und den besten Kappa Koeffizient ergeben.

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1 Introduction

Remotely sensed images have been extensively utilized to monitor and analyze Earth surface changes over time (Hansen et al. 2008, Hilker et al. 2009, Kaufmann & Seto 2001, Bayarsaikhan et al. 2009, Phua et al. 2008). Change detection is a commonly used method for providing change information. Normally detected are (a) the geographic locations of changes, (b) the types of changes, and (c) the number of changes, by analyzing two co-registered remote sensed images taken at different time. These images relate to a particular geographical area on two different occasions (Castellana et al. 2007, Im & Jensen 2005, Cakir et al. 2006, Gao & Liu 2010, Ouma et al. 2008). Change detection has been widely used for mapping land cover modification, deforestation assessment, damage assessment, disaster monitoring and urban expansion (Yuan et al. 2005, Dewan & Yamaguchi 2009, Wulder et al. 2008).

Over the past three decades, many change detection methods, using remotely sensed images have been proposed and reported in the literature (Hansen et al. 2008, Walter 2004, Phua et al. 2009, Xian et al. 2009, Deng et al. 2009, Galford et al. 2008, Hilker et al. 2009). Generally, these change detection methods can be grouped into two classes: supervised classification-based methods and unsupervised classification-based methods.

Supervised classification-based change detection methods utilize field samples as "true" ground for training the classifier, which will be used to label all other elements in the image. By comparing the classification results at different time, the changed pixels can be identified and quantified. Im and Jensen (Im & Jensen 2005) introduced a Neighborhood Correlation Image method, a method, which combined with the decision trees change detection method, can detect change with high accuracy. One of the supervised classification algorithms, support vector machines (SVMs) have been successfully applied to remote sensing image classification (Melgani & Bruzzone 2002). Nemmour & Chibani (2006) proposed an integration of SVMs and Fuzzy Integrals for change detection. This integration proved to have greater efficiency than the neural networks based method. Knorn et al. (2009) applied the SVMs algorithm to classify radiometrically uncorrected data to test a proposed chain classification method.

Unsupervised methods have been used for change detection when "true" ground is lacking because only old remote sensing images are available. By comparing the brightness difference between pre- and post-index images using methods such as image differencing, image rationing and change vector analysis, areas of changed pixels can be quantified (Castellana et al. 2007). Image differencing can be used to identify changed pixels from those pixels with a given threshold value. For instances, Normalized Difference Vegetation Index (NDVI) has commonly been used as the index image for image differencing purposes. Values of difference of NDVI are assumed to be normally distributed with a zero mean and standard deviation, and pixels with absolute values of difference of NDVI greater than the threshold value are identified as changed pixels (Teng et al. 2008). Other indices have also been used in image differencing, for example Tasseled Cap transformation components. Usually, an index image is selected for its sensitivity to a surface property. Using one single index image for image differencing, therefore, will not sufficiently represent land cover change, based on multi-temporal satellite images.

In this paper a probability image differencing model using multiple feature images is proposed. Components of a Tasseled Cap transformation at different time are used as feature images for constructing the probability model. Specifically, in this paper (a) a new change detection method is presented based on the Chi-square distribution probability model; and (b) the performance of a proposed method for change detection is assessed, based on remotely sensed images.

The outline of this paper is as follows. An introduction and a review and analysis of the methods of change detection are given briefly in this section. The study area and the remote sensed images used for this research are presented in Section 2. Section 3 is devoted to introducing the proposed probability model for change detection using image differencing results. The results of several numerical experiments are presented and discussed in Section 4. Finally, conclusions concerning the effectiveness of the newly proposed change detection model and algorithm are presented in Section 5.

2 Study Area and Data

Hong Kong, an international financial metropolis which has experienced quick economic growth and urban expansion over the past three decades, was selected as the study area. Hong Kong had reportedly, 6.41 million people and a 122.9 billion GDP (gross domestic product) in 1996. These numbers had increased to 6.70 million people and 129.9 billion GDP by 2001. In 2006, there were 6.86 million people with a 147.5 billion GDP. The population increases and economic growth resulted in expansion of the urban area and a corresponding conversion of land cover type. The study area is illustrated in Fig. 1.

ETM+ images have been extensively used for change detection research over the past two decades, primarily because they are free-of-charge and easy to process. In this research, ETM+ images obtained on Aug. 20, 1999 and Sep. 17, 2002 were used as the experimental source data. Radio calibration should be performed to convert the DN value to the reflectance value. Image registration was then performed using a registration model for which the earlier image was used as the base image. However, for the historical remote sensing

Fig. 1: The study area – Hong Kong. R: band 5; G: band 4; B: band 3 (Date of data captured: Feb. 17, 2002).

data, it is difficult to obtain the ground truth parameters such as visibility and aerosol scale height, which are needed by the radiance transfer algorithm. The quality of image after atmospheric calibration may be degraded due to the uncertainty in these parameters. Therefore, to compare the two images taken at different times, normalization was made to convert the digital number of the images into the range zero to one to reduce the brightness difference among these images. Sub-images of the same region were clipped to be used, here, for assessing the performance of the proposed algorithm. A SPOT image, with a higher spatial resolution, taken in 2003, provided the reference data.

3 Probability Model-based Change Detection Methods

3.1 *Probability Model*

The image differencing results derived from multi-temporal index images represent the spatial distribution of both the changed and unchanged pixels. A single index image, such as NDVI, can provide partial change information over the study area However, if more index images could be used in the image differencing method: greater change detection accuracy can potentially be obtained.

For multiple index images, the probability distribution of pixels in each image differencing result can be assumed to follow a normal distribution. This can easily be verified by numerical experiments. If the difference value for each different index pixel is represented by a random vector $x = [x_1,x_2,...,x_l]^T$ in which x_i is the difference value derived from the pre- and post- index images, the probability density function of the random vector x can then be expressed as

$$p(x) = \frac{1}{2\pi|\Sigma|^{1/2}} e^{-\frac{1}{2}[(x-\mu)^T\Sigma^{-1}(x-\mu)]}\sqrt{2} \tag{1}$$

where $\mu = [E(x_1),E(x_2),\ldots,E(x_l)]^T$ is the expectation of the random vector, and l is the number of index images; Σ is the covariance matrix of the random vector. The covariance matrix Σ reflects the correlation relationships between different index images. This function was used by Teng et al. (2008) to express the joint distribution of random variables, where x_1 and x_2 were used to represent the corresponding values of pre- and post-images. The covariance matrix Σ can be factorized as

$$\Sigma = Q^T \Lambda Q \tag{2}$$

where Q is the orthogonal matrix which is composed using the orthogonal vectors of $\Sigma^T\Sigma$ and Λ is a diagonal matrix composed of the eigenvalues of $\Sigma^T\Sigma$. The probability contour of the x^2 variable can be rewritten as

$$(Qx - Q\mu)^T \Lambda^{-1} (Qx - Q\mu) = c \tag{3}$$

Letting $x' = Qx$, the formula has the following expression

$$\frac{(x_1' - \mu_1')^2}{\lambda_1} + \frac{(x_2' - \mu_2')^2}{\lambda_2} + \cdots + \frac{(x_l' - \mu_l')^2}{\lambda_l} = c \tag{4}$$

where λ_i is the diagonal elements of matrix Λ. It is found that two random variables correspond to an oval on plan while three random variables correspond to an ellipsoid in three-dimensional space. When there is only one index image, the normal distribution can be used to delineate the spatial distribution of each pixel in the differencing image.

The parameter c represents the range of the probability contour. Those pixels inside the contour can be seen as unchanged pixels. The pixels with substantial change can be identified with a pre-determined probability α. The unchanged pixels can therefore be labeled using the significance level 100(1-α)%, i.e.,

$$p\left\{(x-\mu)^T \Sigma^{-1} (x-\mu) < \chi^2_\alpha\right\} = 1 - \alpha \tag{5}$$

Teng et al. (2008) assumed that the distributions of pixels in the pre- and post- index images were normal distribution. It was pointed out that the expectation and covariance matrix parameters used in the bivariate joint normal distribution function must be estimated from those unchanged pixels derived from the post-classification comparison method. The logic flow of the proposed method is given in Fig. 2 below.

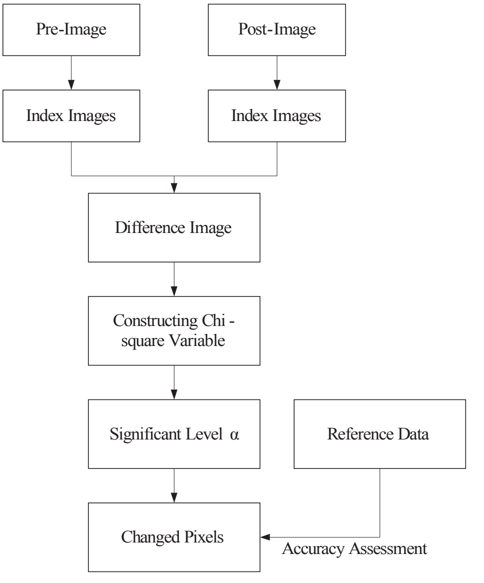


Fig. 2: The logic flow of the newly proposed algorithm.

This newly proposed algorithm has several advantages over the method provided by Teng et al. (2008). Firstly, the probability contour is constructed using differencing results derived from multi-temporal index images which boost the grey value contrast between changed pixels and unchanged pixels. Secondly, multiple index images rather than a single index image are used in the probability model for change detection. Therefore, more data sources, such as soil brightness, area of vegetation cover, water content of vegetation can all be used to reflect land cover changes. Thirdly, many possible combinations of the index images can be tested leading to much more accurate change detection results.

3.2 *Index Images*

The normalized difference vegetation index (NDVI) has been extensively used for extracting areas of vegetation cover and also for change detection. In addition to NDVI, Tasseled Cap transformation components can also be utilized to detect land cover changes, as discussed briefly immediately below.

The first three Tasseled Cap transformation indices of Brightness Index (BI), Greenness Index (GI) and Wetness Index (WI), have successively been used for change detection after these indices were first proposed. They were further modified over the past two decades (Crist & Cicone 1984, Huang et al. 2002). The BGW bands are directly associated with physical attributes reflecting land surface properties (Seto et al. 2002). Skakun et al. (2003) utilized the enhanced wetness TCT difference index to interpret spectral patterns with confirmed red-attack damage. Karnieli et al. (2008) found that BI proved to be the best spectral transformation for enhancing the contrast between the bright-degraded areas and the darker surrounding areas. Due to its excellent performance in change detection, the TCT indices proposed by Huang et al. (2002) were used here as index images for change detection. The TCT are given as follows. The RGB false color images using BI, GI, and WI are shown in Fig. 3.

$$BI = 0.3561 \cdot b1 + 0.3972 \cdot b2 + 0.3904 \cdot b3 + 0.6966 \cdot b4 + 0.2286 \cdot b5 + 0.1596 \cdot b7 \tag{6a}$$

$$GI = -0.3344 \cdot b1 - 0.3544 \cdot b2 - 0.4556 \cdot b3 + 0.6966 \cdot b4 - 0.0242 \cdot b5 - 0.2630 \cdot b7 \tag{6b}$$

$$WI = 0.2626 \cdot b1 + 0.2141 \cdot b2 + 0.0926 \cdot b3 + 0.0656 \cdot b4 - 0.7629 \cdot b5 - 0.5388 \cdot b7 \tag{6c}$$

4 Results and Discussion

From the visually interpreted results of the false color images applied at different times, 1695 changed pixels and 3122 unchanged pixels were selected from the original image as the samples to be used to assess the performance of the proposed algorithm. Results from the image differencing method and Teng's bivariate joint distribution method were used to make comparisons with the proposed method. In the first experiment, change detection results were provided using different single index images for both methods. In the second experiment and based on the results of the first experiment, two-index and three-index models demonstrated the advantages of the newly proposed method.

4.1 *Single Index Image-based Change Detection*

In the first experiment, an image differencing method using NDVI and the Tasseled Cap

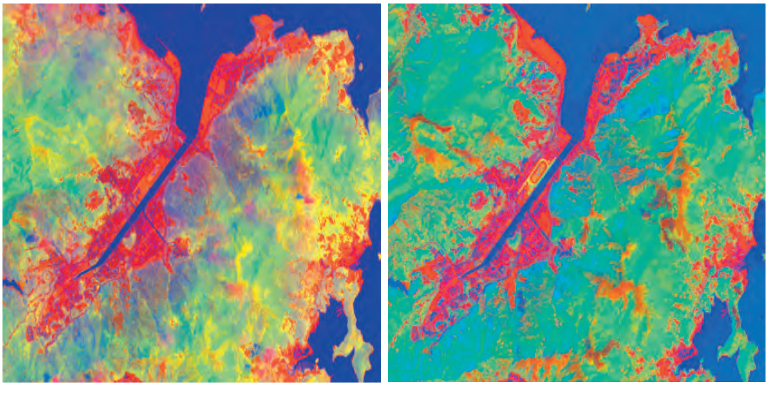


Fig. 3: False color image using Tasseled Cap Transformation (R: Brightness; G: Greenness; B: Wetness. Left: Aug. 20, 1999, Right: Feb. 17, 2002).

transformation index was applied to detect changed pixels. The results were generated when the threshold value was set as 1.96 which corresponds to significance level 0.05. We found that NDVI and the Greenness index successfully reflect the changes in vegetation cover over different seasons, but fail to detect the changes to buildings and impervious surfaces near the seaside. The latter can in fact, be detected by the brightness index and the wetness index. However, the brightness and wetness indices failed to detect vegetation cover changes.

To give a quantitative picture of the above change detection results, statistical data are given in Tab. 1 for three different threshold values. The best result appears when NDVI is used as the index image with a threshold value of 1.645. The overall accuracy is 83.37 and the Kappa coefficient, 0.6124. The Brightness index leads to less overall accuracy due to its failure to detect most of the vegetation cover changes. The Greenness index and the wetness index lead to worse change detection results and lower accuracy and Kappa coefficients.

Teng's bivariate joint distribution method was applied to change detection using NDVI and different index images derived from TCT, and the detection results with significance level 0.05 was generated. The statistical results are given in Tab. 2. When NDVI is used as an image index not only vegetation pixels but also most seawater pixels were identified as changed pixels. The TCT Wetness index also identified seawater pixels as changed pixels, but failed to find any vegetation cover region changes. According to Tab. 2, the Brightness index leads to greater overall change detection accuracy than the other three index images. The Brightness index, however fails to detect the changes in vegetation cover which are detected using the NDVI and Greenness index images.

4.2 *Change Detection Results of the Proposed Method Using Combination of Index Images*

Use of the single index image can reflect one type of land cover change such as vegetation cover, as verified by the experiment in Section 4.1. In contrast to the single index-based method, in the following experiments, the use of combinations of two different index images: NDVI and Brightness were used in the proposed probability model for change detection.

Tab. 1: Statistical results of image difference method using different index images.

	2.575 (α = 0.01)		1.96 (α = 0.05)		1.645 (α = 0.1)	
	Kappa	Over. Acc(%)	Kappa	Over. Acc(%)	Kappa	Over. Acc(%)
NDVI	0.4209	77.45	0.5734	82.52	***0.6124***	***83.37***
Brightness	0.2539	71.53	0.3268	73.67	0.4057	76.16
Greenness	-0.0193	63.83	-0.0363	62.83	-0.0421	62.09
Wetness	0.1961	70.20	0.1946	69.91	0.1959	69.87

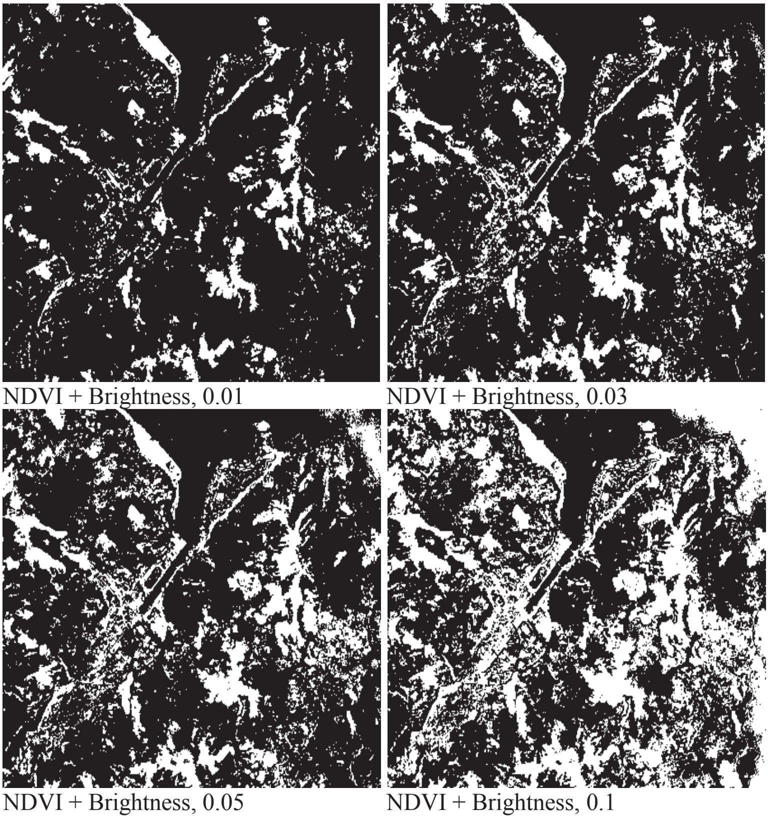
Tab. 2: Statistical results from Teng's bivariate joint distribution method which uses different index images with different significant levels.

	α = 0.01		α = 0.05		α = 0.1	
	Kappa	Over. Acc(%)	Kappa	Over. Acc(%)	Kappa	Over. Acc(%)
NDVI	0.3508	70.23	0.3729	69.52	0.3549	67.32
Brightness	0.3331	73.61	***0.4172***	***76.04***	0.3488	71.47
Greenness	-0.0450	61.67	-0.0216	60.88	-0.0157	60.51
Wetness	-0.0611	55.67	-0.0611	55.67	-0.0611	55.67

The change detection results at different significance levels are shown in Fig. 4 and the accuracy assessment is listed in Tab. 3.

It is found that the change detection results are sensitive to significance level: more and more changed pixels can be detected by increasing the level of α. However, the overall accuracy and Kappa coefficients decrease quickly with an increase of α. When the significance level is 0.01, among all the experiments, the change detection results have the highest overall accuracy of 92.60% and the highest Kappa coefficient of 0.8326.

By combining NDVI, Brightness and Wetness indexes, the change detection results at different significance levels are shown in Fig. 5 and the statistical results are shown in Tab. 3. It is found that with increase of significance level α, more and more seawater pixels are identified as changed pixels, which in fact, is



NDVI + Brightness, 0.01
NDVI + Brightness, 0.03
NDVI + Brightness, 0.05
NDVI + Brightness, 0.1

Fig. 4: Change Detection Results Using NDVI and Brightness indexes by using the probability model at different probability level.

Tab. 3: Statistical results of change detection using the combinations of two index images at different significant level.

	α = 0.01		α = 0.03		α = 0.05		α = 0.1	
	Kappa	Over. Acc(%)	Kappa	Over. Acc(%)	Kappa	Over. Acc(%)	Kappa	Over. Acc(%)
NDVI + Brightness	***0.8362***	***92.60***	***0.8175***	***91.53***	***0.7710***	***89.16***	0.6129	80.61
NDVI + Brightness +Wetness	0.7392	87.83	0.5929	79.65	0.5241	75.52	0.4196	68.90

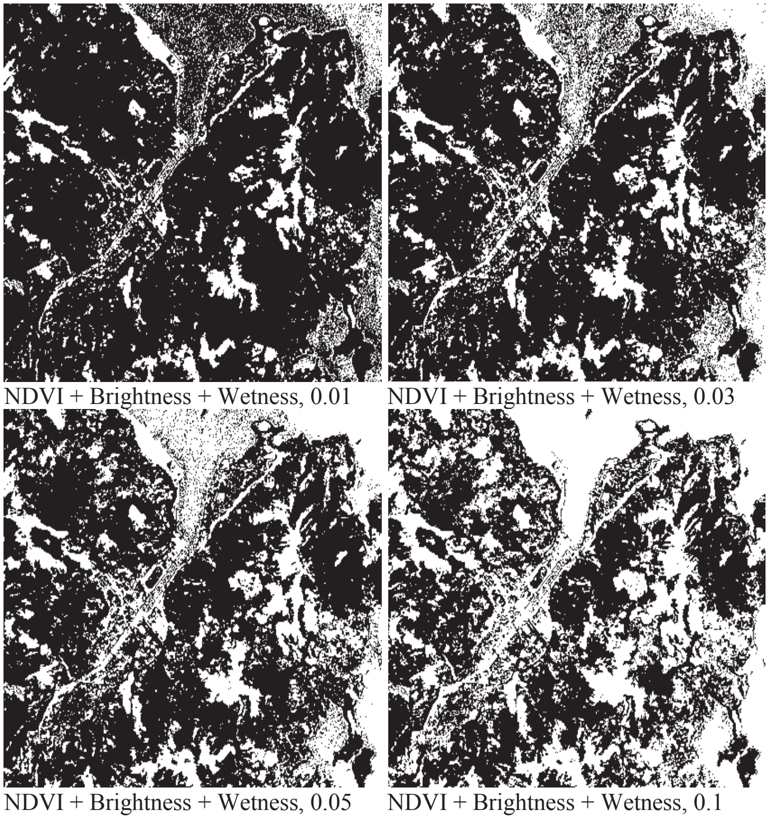


Fig. 5: Change Detection Results Using NDVI, Brightness and Wetness indexes by using the probability model at different probability level.

wrong. When $\alpha = 0.01$ the overall accuracy has the value of 87.83 and the Kappa coefficient has the value of 0.7392. However, the overall accuracy and Kappa coefficients decrease with increases in the significance level.

5 Conclusions

A new change detection method, i.e., a probability model based on the Chi-square distribution and using multiple index images, has been proposed. The newly proposed method was tested using Landsat ETM+ multi-temporal images. Image differencing method, based on a selected single index image, has been used extensively to quantify how areas change over time using remotely sensed images. The index image is usually sensitive to land surface properties such as vegetation cover and soil moisture, which make it difficult to precisely identify changed pixels. In addition, some indices are sensitive to the change of seasons; such changes also reduced the robustness of the image differencing method.

Based on the assumption that the distribution of pixels in an image differencing result conforms to a normal distribution, as has been observed in most cases, the authors have proposed the probability model based change detection method which utilizes multiple index images, derived using the image differencing method. Changed pixels displayed distinctive gray differences between the pre- and post-images enabling their identification with a particular probability. Multi-variables joint chi-square distributions derived from the difference images using multiple indexes remarkably boosted the contrast between changed pixels and unchanged pixels.

Compared with the image difference method and TENG's bivariate joint distribution method, the newly proposed method has the advantages of: (a) providing more accurate change detection results, (b) providing possible different index image combination options leading to optimal change detection results, and (c) providing different models for different types of land cover change detection purposes.

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