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A comparative study on change vector analysis based change detection techniques

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Abstract. Detection of Earth surface changes are essential to monitor regional climatic, snow avalanche hazard analysis and energy balance studies that occur due to air temperature irregularities. Geographic Information System (GIS) enables such research activities to be carried out through change detection analysis. From this viewpoint, different change detection algorithms have been developed for land-use land-cover (LULC) region. Among the different change detection algorithms, change vector analysis (CVA) has level headed capability of extracting maximum information in terms of overall magnitude of change and the direction of change between multispectral bands from multi-temporal satellite data sets. Since past two–three decades, many effective CVA based change detection techniques e.g., improved change vector analysis (ICVA), modified change vector analysis (MCVA) and change vector analysis posterior-probability space (CVAPS), have been developed to overcome the difficulty that exists in traditional change vector analysis (CVA). Moreover, many integrated techniques such as cross correlogram spectral matching (CCSM) based CVA. CVA uses enhanced principal component analysis (PCA) and inverse triangular (IT) function, hyper-spherical direction cosine (HSDC), and median CVA (m-CVA), as an effective LULC change detection tools. This paper comprises a comparative analysis on CVA based change detection techniques such as CVA, MCVA, ICVA and CVAPS. This paper also summarizes the necessary integrated CVA techniques along with their characteristics, features and shortcomings. Based on experiment outcomes, it has been evaluated that CVAPS technique has greater potential than other CVA techniques to evaluate the overall transformed information over three different MODerate resolution Imaging Spectroradiometer (MODIS) satellite data sets of different regions. Results of this study are expected to be potentially useful for more accurate analysis of LULC changes which will, in turn, improve the utilization of CVA based change detection techniques for such applications.

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Keywords. Change vector analysis (CVA); improved change vector analysis (ICVA); modified change vector analysis (MCVA); change vector analysis posterior-probability space (CVAPS).

1. Introduction

It has already been proven that remote sensing is only the practical means for detection of changes occurring over land-use land-cover (LULC) thousands of square kilometer area. Change detection analysis includes the use of multi-spectral bands of multi-temporal satellite data sets to discriminate the LULC changes (Gautam & Chennaiah 1985). Lu *et al* (2003) represent different classes of change detection techniques such as algebraic techniques, transformation, classification, progressive techniques, geographical information system (GIS) techniques, visual analysis and other techniques. As compared to all change detection techniques, algebraic techniques such as band differencing (Weismiller *et al* 1977), ratioing (Howarth & Wickware 1981), vegetation indices (Nelson 1983), regression analysis (Singh 1986), and change vector analysis (CVA) (Malila 1980), are easy to process. Among all algebraic techniques, change vector analysis (CVA) (Malila 1980) provides level headed capability of delivering spectral change information in terms of change-magnitude and change-direction (category) (Collins & Woodcock 1994; Johnson & Kasischke 1998; Houhoulis & Michener 2000; Civco *et al* 2002; Allen & Kupfer 2000; Hame *et al* 1998). Also, CVA has the capability of avoiding commission errors (including a pixel in a class when it should have been excluded) and Kappa coefficient (accuracy statistic that permits two or more contingency matrices to be compared) in retrieving maximum 'change and no-change' information.

Malila (1980) first implemented CVA for forest change detection which was implemented later on multi-spectral monitoring of coastal environment (Michalek *et al* 1993), high temporal dimensionality satellite data set (Lambin & Strahler 1994), multi-spectral monitoring of land cover (Houhoulis & Michener 2000), monitoring of selective logging activities (Silva *et al* 2003). Sohl (1999) discovered that CVA is the best among different change detection techniques because of its graphically rich content. Allen & Kupfer (2000) developed an extended CVA technique using the information preserved in the vector's spherical statistics in the change extraction procedure but it contained some of its inherent drawbacks. Aiming to overcome the shortcomings in threshold value selection (Johnson & Kasischke 1998; Smits & Alessandro 2000; Ding *et al* 1998), a semi-automatic double-window flexible pace search (DFPS) threshold determination technique, has been proposed for LULC in improved change vector analysis (ICVA) (Chen *et al* 2003). ICVA also has the capability of decisive change-type information based on direction cosine (Hoffmann 1975) of change vectors. Modified change vector analysis (MCVA) (Nackaerts *et al* 2005) and change vector analysis in posterior probability space (CVAPS) (Chen *et al* 2011) techniques have been proposed to deliver output in continuous nature and to overcome radiometric errors, respectively.

Moreover, different integrated CVA techniques have also been designed to incorporate the features of other change detection techniques in CVA such as CVA by means of principal component analysis (PCA) and inverse triangular (IT) function (Baisantry *et al* 2012) for threshold selection, CVA uses tasseled cap (TC) to discriminate change in terms of brightness, greenness and wetness (Allen & Kupfer 2000), cross correlogram spectral matching (CCSM) CVA (Chunyang *et al* 2013) to extract the degree of shape similarity between vegetation index (VI) profiles, and also CVA uses distance and similarity measures based on spectral angle mapper (SAM) and spectral correlation mapper (SCM) to the formulation of spectral direction change, and Euclidean distance to calculate magnitude (Osmar *et al* 2011), etc. Each CVA technique has its own capabilities and no one technique is suitable for every task (Johnson & Kasischke 1998), so it is vital to evaluate a CVA technique on global basis that will constitute all the features.

In this paper, traditional CVA, MCVA, ICVA and CVAPS change detection techniques have been evaluated using three different MODIS satellite data sets. Apart from this, pre-processing of multi-temporal satellite dataset is a critical task because overall accuracy of each change detection technique depends upon the geometric correction, radiometric correction and atmospheric correction (Singh 1989; Markham & Barker 1987; Gilabert *et al* 1994; Chavez 1996; Stefan & Itten 1997; Vermote *et al* 1997; Tokola *et al* 1999; Yang & Lo 2000; Mcgovern *et al* 2002; Mishra *et al* 2009a). The task of CVA based change detection technique will be initiated after all the necessary corrections, and selection of CVA technique depends on the required information, ground truth data availability, time and money constraints, knowledge and familiarity of the study area, complexity of landscape, and analyst's proficiency and experience (Lu *et al* 2003; Johnson & Kasischke 1998). The aim of this paper is to investigate all the major CVA based change detection techniques.

This paper is organized in five sections. Following this introduction, a brief summary of essential pre-processing steps of satellite data is presented in section 2. The comparative analysis of different CVA based change detection techniques are represented in third section, followed by results and discussion of prior studies along with their characteristics, features and limitations in fourth section. In section 5, general conclusion is provided.

2. Pre-processing of satellite dataset

In this paper, three different data sets from three different study areas have been acquired on 6^{th} November, 2010 and 8^{th} February, 2011 using MODIS (Moderate Resolution Imaging Spectroradiometer) sensor satellite over western Himalayan, India. First MODIS satellite dataset lies between 32.70°N to 33.05°N and 76.21°E to 76.92°E (figures 1a and b). Second MODIS satellite dataset lies between 32.70°N to 33.05°N and 76.57°E to 76.88°E (figures 1c and d). Third MODIS satellite dataset lies between 32.22°N to 32.57°N and 76.57°E to 76.88°E (figures 1e and f). Pre-processing of each satellite dataset is an important task for accurate analysis of change detection technique. Digital number (DN) or raw satellite imagery represents the energy reflected by Earth that depends on fraction of incoming solar radiation value, surface of slope and its orientation, surface anisotropy, and atmospheric constituents (Srinivasulu & Kulkarni 2004). The approximation of spectral reflectance imagery includes different corrections such as geometric correction, radiometric correction, and topographic correction. The comprehensive study on satellite image interpretation can be referred to different studies (Singh 1989; Markham & Barker 1987; Gilabert *et al* 1994; Chavez 1996; Stefan & Itten 1997; Vermote *et al* 1997; Tokola *et al* 1999; Yang & Lo 2000; Mcgovern *et al* 2002; Mishra *et al* 2009a). The radiometric correction converts the illumination values into reflectance values. The digital number (DN) imagery has transformed into reflectance $'R'$ imagery according to the following equation (Song *et al* 2001; Pandya *et al* 2002).

$$R = \frac{\pi\left(L_{sat\lambda} - L_p\right)d^2}{\left(E_0 \cos\theta_z + E_d\right)}, \tag{1}$$

where $'E_0'$ and $'L_{sat\lambda}'$ represent the exo-atmospheric spectral irradiance and sensor radiance of MODIS (Mishra *et al* 2009b), respectively. The solar zenith angle is represented by $'\theta_z'$ which is calculated for all different pixels (Kasten 1989), $'d'$ represents the distance between Earth and Sun (Van 1989), $'E_d'$ is the down-welling diffused radiation which can be represented as 'zero' (Chavez 1984). The path radiance is represented by $'L_p'$ (Gilabert *et al* 1994).

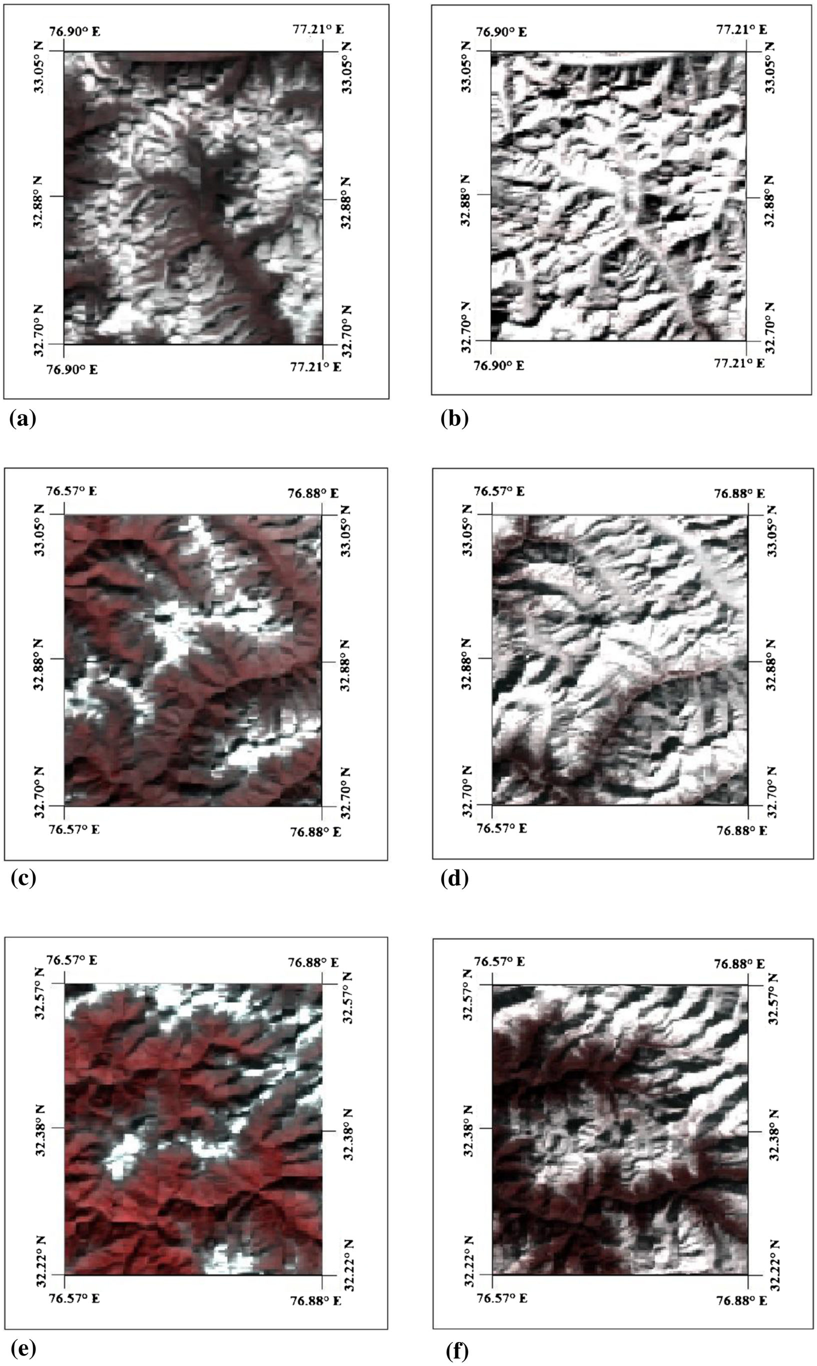


Figure 1. MODIS satellite datasets: (**a**) Pre-date (6^{th} November, 2010) imagery of dataset 1, (**b**) Post-date (8^{th} February, 2011) imagery of dataset 1, (**c**) Pre-date (6^{th} November, 2010) imagery of dataset 2, (**d**) Post-date (8^{th} February, 2011) imagery of dataset 2, (**e**) Pre-date (6^{th} November, 2010) imagery of dataset 3, (**f**) Post-date (8^{th} February, 2011) imagery of dataset 3.

3. Change vector analysis (CVA)

Change vector analysis (CVA) is a change detection tool that characterizes dynamic changes in multi-spectral space by a change vector over multi-temporal imageries (Malila 1980). The basic concept of CVA is derived from image differencing technique (Lu *et al* 2003). The CVA can overcome the disadvantages of 'type-one' approaches e.g., cumulative errors in image classification of an individual date and processing any number of spectral bands simultaneously to retrieve maximum change-type information (Malila 1980). A number of CVA based change detection techniques have been developed to make change detection more accurate for identifying changed area. In this paper, we have implemented all major CVA based change detection techniques on three different data sets to investigate the accuracy of each technique on global basis. The comparative analysis of different CVA algorithms have been shown in figures 2 and 3.

3.1 *Traditional change vector analysis (CVA)*

The concept of the traditional change vector analysis (CVA) involves the calculation of spectral change based on multi-temporal pairs of spectral measurements, and relate their magnitudes to a stated threshold criterion (Malila 1980). The computed change vectors comprise essential information in magnitude and direction (figure 2). The two important reasons that make CVA 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. In figure 4, the change vector magnitude imageries for three different MODIS satellite data sets of different regions have been calculated according to following Equation (Malila 1980; Chen *et al* 2003) in which transformed data is represented by 'ΔH' that lies between the two multi-temporal imageries (T_1: 06th November 2010 and T_2: 08th November 2011) captured for a given pixel defined by $Y = (y_1, y_2, \ldots . y_i)^{T_1}$ and $X = (x_1, x_2, \ldots . x_1)^{T_2}$, respectively and *'i'* represents number of bands in imagery.

$$|\Delta H| = \sqrt{(x_1 - y_1)^2 + \cdots + (x_i - y_i)^2}. \quad (2)$$

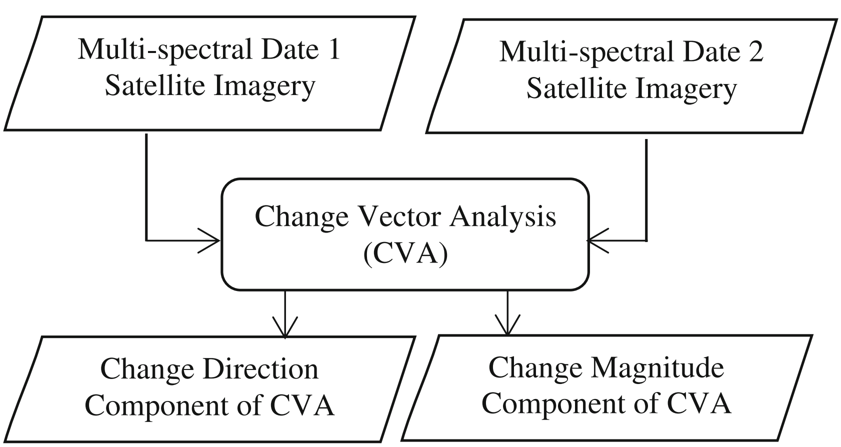


Figure 2. Basic algorithm of CVA in multi-dimensional space.

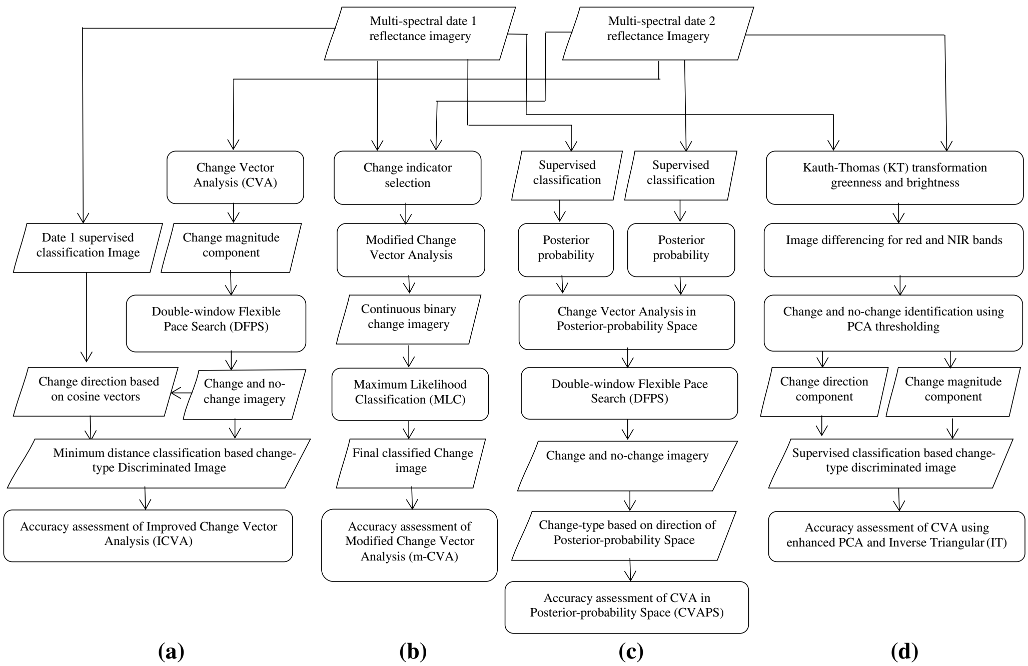


Figure 3. Comparative study on different Change Vector Analysis (CVA) based change detection algorithms: (**a**) ICVA, (**b**) m-CVA, (**c**) CVAPS, (**d**) CVA using PCA and IT.

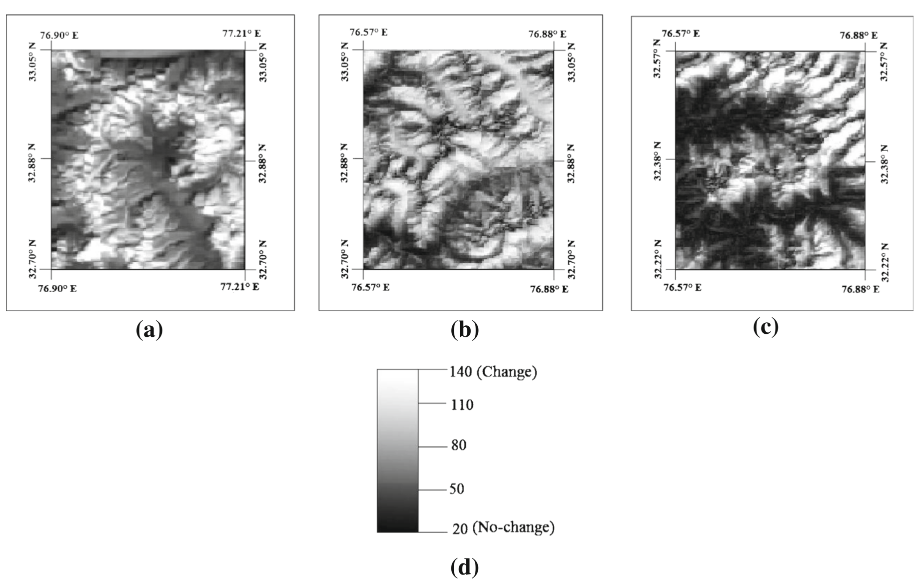
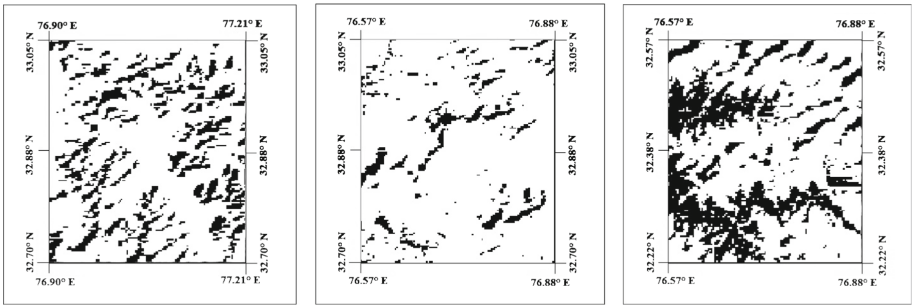


Figure 4. Change magnitude imageries: (**a**) Dataset 1, (**b**) Dataset 2, (**c**) Dataset 3 and, (**d**) Change magnitude 'change' and 'no-change' scale (140–20 represent maximum to minimum values of change magnitude imagery).



(a) (b) (c)

Figure 5. Binary imageries generated using CVA: (**a**) Dataset 1, (**b**) Dataset 2 and, (**c**) Dataset 3.

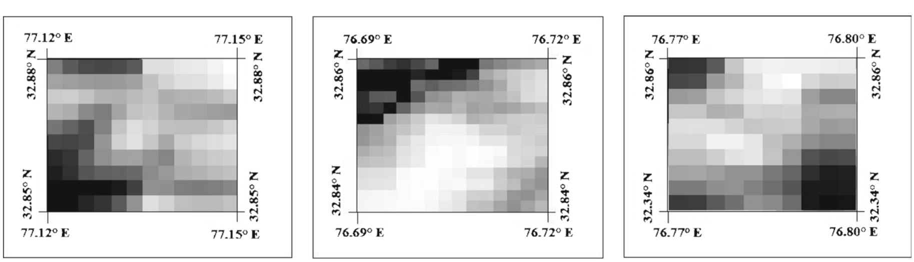
The main drawback of CVA technique is manual selection of threshold value to discriminate 'change' and 'no-change' pixels. In figure 5, binary image generated through CVA for three different data sets represented the 'change' pixels in white colour and 'no-change' pixels in black colour.

3.2 *Improved change vector analysis (ICVA)*

A semiautomatic threshold determination technique, called double-window flexible pace search (DFPS) has been proposed in improved change vector analysis (ICVA) (Chen *et al* 2003). The DFPS technique effectively determines the threshold value from change magnitude imagery (Allen & Kupfer 2000) as shown in figure 3a. The succession rate criteria of DFPS has been used to evaluate the performance of each potential threshold value during one search process for identifying 'change' and 'no-change' pixels. In semi-automatic DFPS process, success rate (S_r) criteria is calculated from training sample of three different respective satellite data sets (figure 6), according to the following equation to select the most optimal threshold value for change magnitude imagery.

$$Sr = \frac{(I_c - O_c)}{I_t}\%. \tag{3}$$

In Eq. (3), $'I_c'$ represents number of transformed pixels inside an inner window sample, $'O_c'$ represents number of transformed pixels in an outer window sample and $'I_t'$ is the total number of pixels in inner training window sample. Table 1 represents the results of succession rate for



(a) (b) (c)

Figure 6. Training sample subset for threshold value selection: (**a**) Dataset 1, (**b**) Dataset 2 and, (**c**) Dataset 3.

Table 1. Succession rate results of DFPS threshold determination (ICVA) technique for dataset 1.

Range = 30–150 Pace = 20		Range = 40–70 Pace = 10		Range = 50–70 Pace = 5		Range = 60–70 Pace = 2–3		Range = 62–68 Pace = 1	
Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage
30	50.00%	40	50.00%	50	51.25%	60	51.25%	62	52.50%
50	**51.00%**	50	51.00%	55	51.25%	62	52.50%	63	52.50%
70	48.75%	**60**	**51.25%**	60	51.25%	**65**	**53.75%**	64	52.50%
90	38.75%	70	48.75%	**65**	**53.75%**	68	52.50%	**65**	**53.75%**
110	16.07%			70	48.75%	70	48.75%	66	52.50%
130	5.35%							67	52.50%
150	5.35%							68	48.75%

dataset 1, table 2 represents the results of succession rate for dataset 2, and table 3 represents the results of succession rate for dataset 3. In figure 7, binary image generated through ICVA for three different data sets represented the ‘change’ pixels in white colour and ‘no-change’ pixels in black colour.

3.3 *Modified change vector analysis (MCVA)*

Additional development in change vector analysis, has been made by modified change vector analysis (MCVA) (Nackaerts *et al* 2005) technique which preserves the change information in the magnitude and direction of change vector as continuous data and provided the capability to execute ‘*n*’ change indicator input bands, simultaneously. The overall result of MCVA is a feature space where Cartesian coordinates in a continuous domain are used to describe each change vector. A significant advantage of this technique is that change classification is now entirely on the continuous data domain which permits change descriptors to be used in common change categorization methods. The MCVA technique is simple to execute as compared to ICVA (Chen *et al* 2003) as shown in figure 3b, because empirical technique has been used for the determination of threshold value instead of any semi/automatic procedure. The manual threshold determination technique depends on analyst’s skill and effects the accuracy assessment. In

Table 2. Succession rate results of DFPS threshold determination (ICVA) technique for dataset 2.

Range = 20–140 Pace = 20		Range = 40–80 Pace = 10		Range = 50–70 Pace = 5		Range = 60–70 Pace = 2–3		Range = 62–68 Pace = 1	
Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage
20	39.05%	40	48.12%	50	59.02%	60	60.40%	62	60.40%
40	48.12%	50	59.02%	55	59.02%	62	60.40%	63	60.40%
60	**60.40%**	**60**	**60.40%**	60	60.40%	**65**	**61.11%**	64	60.40%
80	57.63%	70	59.02%	**65**	**61.11%**	68	59.02%	**65**	**61.11%**
100	53.47%	80	57.63%	70	59.02%	70	59.02%	66	60.40%
120	39.58%							67	59.02%
140	20.83%							68	59.02%

Table 3. Succession rate results for DFPS threshold determination (ICVA) technique for dataset 3.

Range = 20–140 Pace = 20		Range = 40–80 Pace = 10		Range = 50–70 Pace = 5		Range = 60–70 Pace = 2–3		Range = 61–65 Pace = 1	
Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage	Cut-off value	Success percentage
20	45.31%	40	45.31%	50	50.00%	60	51.56%	61	51.56%
40	45.31%	50	50.00%	55	50.00%	**62**	**52.56%**	**62**	**52.56%**
60	**51.56%**	**60**	**51.56%**	**60**	**51.56%**	65	51.56%	63	51.56%
80	48.43%	70	51.55%	65	51.56%	68	51.56%	64	51.56%
100	31.25%	80	48.43%	70	51.56%	70	51.56%	65	51.56%
120	15.62%								
140	10.30%								

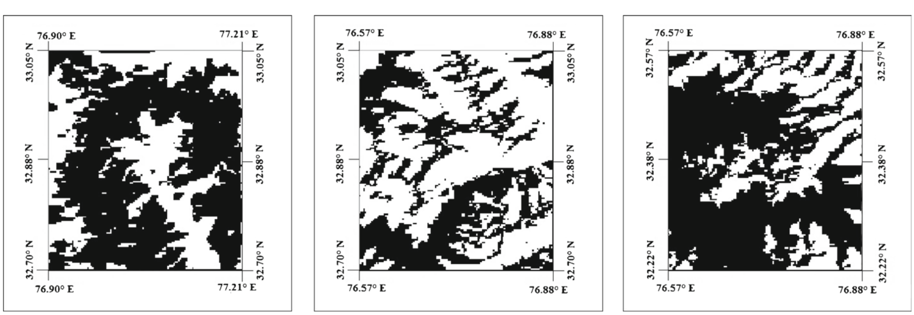
figure 8 binary image generated through MCVA for three different data sets represented the 'change' pixels in white colour and 'no-change' pixels in black colour.

3.4 *Change vector analysis in posterior probability space (CVAPS)*

All CVA based change detection techniques necessitate a consistent radiometric imagery because CVA is based on pixel-wise radiometric resolution. The requirement of reliable radiometric for image processing limits the application of CVA (Chen *et al* 2003). Change vector analysis in posterior-probability space (CVAPS) (Chen *et al* 2011) relaxes the strict requirement of radiometric consistency in remotely sensed data while this requirement is a bottleneck of CVA. In CVAPS approach, the posterior probability is implemented by maximum likelihood classifier (MLC) (Castellana *et al* 2007). Assuming that the posterior probability vectors of one pixel in time 1 and time 2 are $'P'_a$ and $'P'_b$, respectively. The change vector in a posterior probability space $'\Delta P'_{ab}$ can be defined as

$$\Delta P_{ab} = P_b - P_a. \tag{4}$$

CVAPS technique follows the semiautomatic DFPS (Chen *et al* 2003) approach for the selection of threshold value. In CVAPS algorithm (figure 3c), direction of the change vector in a posterior probability space is determined by applying supervised classification. In figure 9, the binary



(a) (b) (c)

Figure 7. Binary imageries generated using ICVA: (**a**) Dataset 1, (**b**) Dataset 2 and, (**c**) Dataset 3.

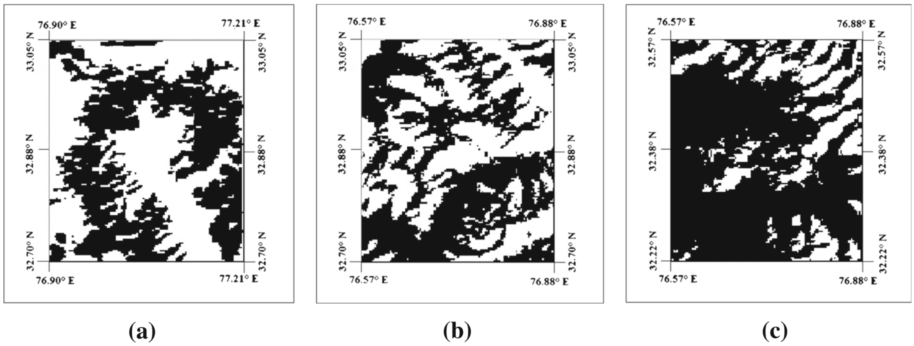


Figure 8. Binary imageries generated using MCVA: (**a**) Dataset 1, (**b**) Dataset 2 and, (**c**) Dataset 3.

image generated through CVAPS for three different data sets represented the 'change' pixels in white colour and 'no-change' pixels in black colour.

3.5 *Other integrated CVA techniques*

3.5a *Improved traditional CVA using cross-correlogram spectral matching (CCSM)* (Chunyang *et al* 2013): Cross-correlogram spectral matching (CCSM) technique has been proposed to overcome the difficulties of traditional change vector analysis (TCVA). The basic concept of CCSM is to recognize and exclude areas with no land-cover modification (no changes) from the total changes detected by it. CCSM technique tells the degree of shape similarity between vegetation index profiles to detect land-cover conversion.

3.5b *CVA using enhanced PCA and inverse triangular function* (Baisantry *et al* 2012): Another improvement in threshold value selection has been proposed by integrating principal component analysis (PCA) and inverse triangular (IT) function in CVA. In this algorithm (figure 3d), Kauth–Thomas tasseled cap transformation has been used to extract greenness-brightness coefficients.

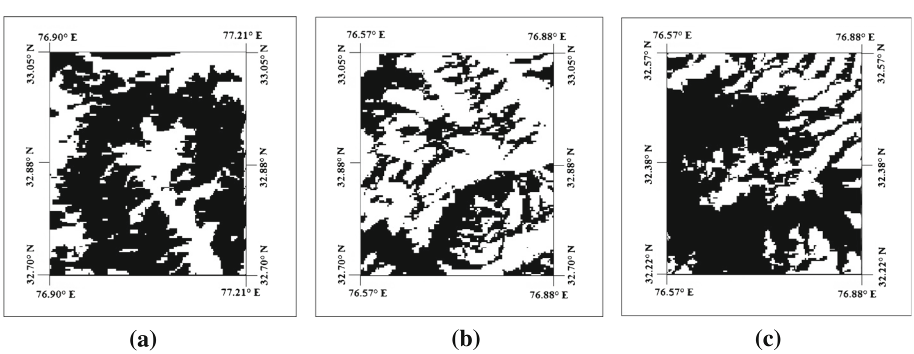


Figure 9. Binary imageries generated using CVAPS: (**a**) Dataset 1, (**b**) Dataset 2 and, (**c**) Dataset 3.

3.5c *Change vector analysis using distance and similarity measures* (Osmar *et al* 2011): In this technique, spectral angle mapper (SAM) and spectral correlation mapper (SCM) are used to compute spectral change direction. The information is processed in one band only in which the scale value represents degree of change and insensitivity to illumination variation.

3.5d *Median change vector analysis* (Varshney *et al* 2012): In this algorithm, enhanced 2n-dimensional feature space, integrates the change vector and median vector in direction cosine. This execution gives more accurate results than ICVA proposed by Chen Jin *et al* (2003).

3.5e *CVA using tasselled cap transformation* (Rene & Barbara 2008): In this technique, dissimilarities in the time-trajectory of the Tasseled Cap greenness and brightness were computed and then applied to change vector analysis. It also reduced the multi-dimensional bands and at the same time emphasized change categories of the land cover.

4. Results and discussion

In order to evaluate each CVA technique, accuracy assessment has been computed using three different MODIS satellite data sets for decision making process. The important accuracy assessment terms involve overall accuracy, commission errors and Kappa coefficient (Gautam & Chennaiah 1985; Congalton 1991; Congalton & Green 1998; Congalton & Plourde 2002; Congalton *et al* 1983). With experimental outcomes, it is observed that CVA technique achieved 0.40 kappa coefficient and 70% accuracy assessment for dataset 1 (table 4), 0.48 kappa coefficient and 74% accuracy assessment for dataset 2 (table 5) and 0.48 kappa coefficient and 74% accuracy assessment for dataset 3 (table 6). MCVA technique has achieved 0.64 kappa coefficient and 82% accuracy assessment for dataset 1 (table 7), 0.64 kappa coefficient and 82% accuracy assessment for dataset 2 (table 8) and 0.64 kappa coefficient and 82% accuracy assessment for dataset 3 (table 9). ICVA technique has achieved 0.68 kappa coefficient and 84% accuracy assessment for dataset 1 (table 10), 0.72 kappa coefficient and 86% accuracy assessment for dataset 2 (table 11) and 0.72 kappa coefficient and 86% accuracy assessment for dataset 3 (table 12). CVAPS technique has achieved 0.84 kappa coefficient and 92% accuracy assessment for dataset 1 (table 13),

Table 4. Accuracy assessment of CVA technique using 50 samples for dataset 1.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	18	7	25	28%
	Change pixels	8	17	25	32%
	Sum	26	24	50	
	Commission error	30.76%	29.16%		

Accuracy assessment = 70%
Kappa coefficient = 0.40

Table 5. Accuracy assessment of CVA technique using 50 samples for dataset 2.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	21	4	25	16%
	Change pixels	9	16	25	36%
	Sum	30	20	50	
	Commission error	30%	20%		
Accuracy assessment = 74%					
Kappa coefficient = 0.48					

Table 6. Accuracy assessment of CVA technique using 50 samples for dataset 3.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	21	4	25	16%
	Change pixels	9	16	25	36%
	Sum	30	20	50	
	Commission error	30%	20%		
Accuracy assessment = 74%					
Kappa coefficient = 0.48					

Table 7. Accuracy assessment of MCVA technique using 50 samples for dataset 1.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	21	4	25	16%
	Change pixels	5	20	25	20%
	Sum	26	24	50	
	Commission error	19.23%	16.66%		
Accuracy assessment = 82%					
Kappa coefficient = 0.64					

Table 8. Accuracy assessment of MCVA technique using 50 samples for dataset 2.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	19	6	25	24%
	Change pixels	3	22	25	12%
	Sum	22	28	50	
	Commission error	13.63%	21.42%		
Accuracy assessment = 82%					
Kappa coefficient = 0.64					

Table 9. Accuracy assessment of MCVA technique using 50 samples for dataset 3.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	22	3	25	12%
	Change pixels	6	19	25	24%
	Sum	28	22	50	
	Commission error	21.42%	13.63%		
Accuracy assessment = 82%					
Kappa coefficient = 0.64					

Table 10. Accuracy assessment of ICVA technique using 50 samples for dataset 1.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	22	3	25	12%
	Change pixels	5	20	25	20%
	Sum	27	23	50	
	Commission error	18.51%	13.04%		
Accuracy assessment = 84%					
Kappa coefficient = 0.68					

Table 11. Accuracy assessment of ICVA technique using 50 samples for dataset 2.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	21	4	25	16%
	Change pixels	3	22	25	12%
	Sum	24	26	50	
	Commission error	12.50%	15.38%		
Accuracy assessment = 86%					
Kappa coefficient = 0.72					

Table 12. Accuracy assessment of ICVA technique using 50 samples for dataset 3.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	22	3	25	12%
	Change pixels	4	21	25	16%
	Sum	26	24	50	
	Commission error	15.38%	12.5%		
Accuracy assessment = 86%					
Kappa coefficient = 0.72					

Table 13. Accuracy assessment of CVAPS technique using 50 samples for dataset 1.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	23	2	25	8%
	Change pixels	2	23	25	8%
	Sum	25	25	50	
	Commission error	8%	8%		
Accuracy assessment = 92%					
Kappa coefficient = 0.84					

Table 14. Accuracy assessment of CVAPS technique using 50 samples for dataset 2.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	23	2	25	8%
	Change pixels	2	23	25	8%
	Sum	25	25	50	
	Commission error	8%	8%		
Accuracy assessment = 92%					
Kappa coefficient = 0.84					

0.84 kappa coefficient and 92% accuracy assessment for dataset 2 (table 14) and 0.84 kappa coefficient and 92% accuracy assessment for dataset 3 (table 15).

It has been analysed that CVA analysis can be a useful tool for assessing continuous change. CVA technique was initially designed for interpretation of two spectral bands or dimensions and later extended to the unlimited number of bands using MCVA technique. ICVA presented first semi-automatic DFPS algorithm for threshold value determination, and change vector determination based on cosine functions in a multi-dimensional space. CVAPS eliminates the strict requirement of reliable image radiometry by incorporating the merits of post-classification comparison (PCC) into CVA. All CVA based change detection techniques are compared on the basis of their characteristics, advantages, disadvantages and their examples are given in table 16. The CVA technique provides number of features such as less sensitive to atmospheric effects, describes the output in terms of overall magnitude of change and direction of change, simultaneously processing of multiple bands, semi/automatic threshold finding process, etc. these factors make the perfect choice of CVA as change detection technique.

Table 15. Accuracy assessment of CVAPS technique using 50 samples for dataset 3.

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change pixels	24	1	25	4%
	Change pixels	3	22	25	12%
	Sum	27	23	50	
	Commission error	11.11%	4.34%		
Accuracy assessment = 92%					
Kappa coefficient = 0.84					

Table 16. Summary of change vector analysis (CVA) based change detection techniques.

Sl. no.	Technique	Characteristics	Merits	Demerits	Examples
1.	*Change Vector Analysis (CVA)*	1. The Change Vector Analysis (CVA) defines the changes in term of their direction and magnitude from two different time instances. 2. The change magnitude includes the calculation of the Euclidean distance between n-dimensional spectral changes.	1. More complete use of imagery information. 2. It can be applied to multi-spectral data. 3. Interpretation of change direction and magnitude.	1. Problematic in selection of threshold to identify land cover changes. 2. Requirement of ground truth data for change vector computation. 3. Difficulty in identification of land cover change classes.	Forest Changes with Landsat data (Malila 1980), multi-spectral monitoring of coastal environment with TM[1] data (Michalek *et al* 1993), high temporal dimensionality MODIS[2]data set (Lambin & Strahler 1994), multi-spectral monitoring of land cover with MSS[3] (Johnson and Kasischke 1998), monitor selective logging activities with ETM+[4] (Silva *et al* 2003).
2.	*Improved CVA (ICVA)*	1. Proposed semi-auto Double-window Flexible Pace Search (DFPS) threshold determination method. 2. Presented change type discrimination based on direction cosines of change vectors.	1. DFPS threshold determination method is capable to generate more accurate binary imagery comprises change and no-change pixels. 2. More accuracy with interpretation of change direction using cosine vectors.	1. Required reference data for change- type discrimination. 2. Strict requirement of radiometric corrected satellite imagery.	Land use/cover with Landsat TM[1]data (Chen Jin *et al* 2003), Snow Cover land with AWiFS[5] data (Sharma *et al* 2013).
3.	*Modified CVA (MCVA)*	1. Each change vector is described by Cartesian coordinates in a continuous domain. 2. Change indicators can be assembled into independent categories.	1. Change-type categorization is in the continuous data domain. 2. The computational simplicity of the algorithm. 3. Reference data is required only for feature extraction.	1. Simple (manual) threshold method for selection reduces the accuracy assessment. 2. It is difficult to decide changed categories.	Forest/ vegetation change with Landsat TM[1]data (Pandya *et al* 2002), Land use Land cover with SPOT[6] data (Nackaerts *et al* 2005)

Table 16. (continued)

Sl. no.	Technique	Characteristics	Merits	Demerits	Examples
4.	*CVA in Posterior Probability Space (CVAPS)*	1. Incorporate the features of Post Classification Comparison (PCC) in Change Vector Analysis (CVA). 2. Presented concept of posterior probability space in CVA.	1. Relieve the strict require ment of radiometric corrected satellite imagery by using PCC. 2. The posterior probability can avoid classification error cumulation. 3. A semi-automatic DFPS used for threshold selection.	1. The semi-supervised CVAPS which is independent of training samples, still need of better accuracy. 2. This algorithm is much more complex than others CVA algorithms.	Land cover with Landsat TM[1] data (Chen Jin *et al* 2011).
5.	*CVA using cross-correlogram spectral matching (CCSM)*	1. Cross-correlogram Spectral Matching (CCSM) can tell the degree of shape similarity. 2. CVA can effectively measure the change magnitude of VI[7].	1. More accurate land cover conversion maps.	1. Analyst's skill is required for determination of threshold value.	Land use with MODIS[2] data (Chunyang *et al* 2013)
6.	*CVA using enhanced PCA and Inverse Triangular Function*	1. This technique incorporates the Principal Component Analysis (PCA) and Triangular Function (TI) into CVA to determine the threshold value.	1. PCA can maximize the change information only in high variance components.	1. Difficult to interpret change type.	Land use with MSS[3] data (Baisantry *et al* 2012)
7.	*CVA using Distance and Similarity Measures*	1. Spectral direction of change, using the Spectral Angle Mapper (SAM) and Spectral Correlation Mapper (SCM) spectral-similarity measures. 2. Similarity based on standard Euclidean distance and Mahalanobis distance.	1. The change image information insensitive to illumination variability. 2. The information can be processed in only one band. 3. The degree of change is represented by resultant imagery scale value.	1. The empirical threshold determination technique depends on the analyst's skills. 2. More complexity due to implementation of SAM and SCM.	Land use with Landsat TM[1] data (Osmar *et al* 2011)

Table 16. (continued)

Sl. no.	Technique	Characteristics	Merits	Demerits	Examples
8.	*Hyper-spherical Direction Cosine (HSDC) CVA*	1. It is an extension of traditional two spectral band CVA to n-dimensional bands.	1. Automatic threshold determination method has been introduced in this technique.	1. Requirement of Training samples to identify threshold value for change and no-change pixels in satellite imagery.	Land use with Landsat MSS[3] data (Warner 2005)
9.	*Median Change Vector Analysis* (MCVA)	1. An enhanced 2n-dimensional feature space that incorporates the change vector and median vector in direction cosine.	1. More accuracy can be gained in categories detection as compare to ICVA.	1. Difficult to interpretation of change type discrimination.	Land cover with ETM+[4] (Varshney *et al* 2012)
10.	*CVA using Tasselled Cap transformation*	1. Tasselled Cap can highlight vegetation properties of the landscape.	1. Ability to monitor Land cover changes within and between categories.	1. Low accuracy.	Land cover with TM[1] and ETM[8] (Rene *et al* 2008)

[1]TM = Thematic Mapper
[2]MODIS = Moderate Resolution Imaging Spectroradiometer
[3]MSS = Multi-Spectral Scanner
[4]ETM+ = Enhanced Thematic Mapper Plus
[5]AWiFS = Advanced Wide Field Sensor
[6]SPOT = Satellite Pour l'Observation de la Terre (System for Earth Observation)
[7]VI = Vegetation Index
[8]ETM = Enhanced Thematic Mapper

5. Conclusion

It has been concluded that CVA technique has achieved 70 to 74% overall accuracy assessment and MCVA technique has achieved 82% overall accuracy assessment. On the other hand, ICVA technique achieved 84% to 86% overall accuracy assessment and CVAPS technique achieved 92% overall accuracy assessment. The double-window flexible pace search (DFPS) technique plays a significant role in ICVA and CVAPS to detect more accurately the LULC changes. Whereas CVA and MCVA have achieved less accuracy because of empirical threshold determination techniques. It has been also noted that commission errors have also been improved in ICVA and CVAPS as compared to CVA and MCVA. Furthermore, this paper also has summarized the well-defined change vector analysis (CVA) based change detection techniques with their comparative analysis and has provided recommendations for algorithms designers to experiment CVA on global basis and discovering new techniques that efficiently use the diverse and complex remotely sensed data for flat as well as undulating surface.

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