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Assessment of different CVA based change detection techniques using MODIS dataset

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सार – परिवर्तन सदिश विश्लेषण (CVA) यानि परिवर्तन संसूचन तकनीक में दो अलग-अलग कालिक उपग्रह चित्रों से प्राप्त परिवर्तन परिमाण और परिवर्तन दिशा संबंधी भू आवरण परिवर्तनों को बताने और उनकी पहचान करने की उपयोगी क्षमताएँ हैं। CVA में विद्यमान बाधाओं को दूर करने के लिए पिछले दो-तीन दशकों से कई प्रभावी CVA आधारित परिवर्तन संसूचन तकनीक अर्थात् उन्नत परिवर्तन सदिश विश्लेषण (ICVA), संशोधित परिवर्तन सदिश विश्लेषण (MCVA) और परिवर्तन सदिश विश्लेषण उत्तरकालीन संभाव्यता स्पेस (CVAPS) का विकास किया गया। किंतु किसी क्षेत्र विशेष के लिए बेहतर उचित CVA तकनीक का चयन करने की प्रक्रिया बहुत ही कठिन है क्योंकि अलग-अलग CVA तकनीकों की अपनी-अपनी विशेषताएँ होती हैं और कोई भी एकल तकनीक सभी मामलों के अध्ययनों पर लागू नहीं होती है। उपर्युक्त CVA तकनीकों की प्रभावोत्पादकता की जाँच ऊबड़-खाबड़ मैदानी भागों के हिम आच्छादित क्षेत्र में नहीं की गई है। इसके अतिरिक्त, छाया जैसी स्थलाकृतिक विकृतियां परिवर्तन संसूचन विश्लेषण के निष्पादन को प्रभावित करती हैं क्योंकि सूर्य की विपरीत दिशा के ढलान की तुलना में सूर्य की तरफ के पर्वतीय सतही ढलान में अधिक परावर्तकता के मान प्राप्त होते हैं। यह महत्वपूर्ण सूचना को नष्ट कर देती हैं जिसके कारण गलत परिणाम प्राप्त होते हैं। अत: इस पर आगे ओर विचार करने से पहले उपग्रह आँकड़ा सेट को लागू करने के लिए स्थलाकृतिक सुधारों की भी आवश्यकता है। इस शोध पत्र में बेहतर संभव तकनीक का पता लगाने के लिए स्थलाकृतिक सही MODIS डाटासेट का उपयोग करते हुए ऊबड़-खाबड़ मैदानी क्षेत्रों के हिम आच्छादित क्षेत्र में अलग-अलग CVA तकनीकों की जाँच की गई जिससे परिवर्तन और परिवर्तन नहीं पिक्सलों की सटीकता का पता लगाने और ´से-तक´ परिवर्तन संसूचन का भी सही निष्पादन किया जा सकेगा। इस शोध पत्र में किए गए सीमित अध्ययन के आधार पर यह पाया गया है कि ऊबड़-खाबड़ मैदानी क्षेत्रों के हिम आच्छादित क्षेत्र में कुल संप्रेषित आँकड़ों का मूल्यांकन करने की CVAPS तकनीक में MCVA और ICVA तकनीकों की अपेक्षा अधिक क्षमता है। इस अध्ययन के परिणामों में ऊबड़-खाबड़ मैदानी क्षेत्र में LULC परिवर्तनों के बेहतर सही विश्लेषण करने के लिए उपयोगी क्षमताएं होने की संभावना है जिससे विभिन्न उपयोगकर्त्ताओं द्वारा ऐसे अनुप्रयोगों के लिए MODIS आँकड़ा सेट की उपयोगिता को उन्नत किया जा सकेगा।

ABSTRACT. Change Vector Analysis (CVA) as change detection technique has useful capabilities of extracting and identifying land cover changes in terms of change-magnitude and change-direction from two different temporal satellite imageries. Since past two-three decade, 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 CVA. But the choice of best suitable CVA technique for particular area is a very difficult process because different CVA techniques have their own features and no single technique is applicable to all case studies. An efficacy of aforementioned CVA techniques has not been examined on snow cover area of rugged terrain. On the other hand, topographic distortions such as shadow, affects the performance of change detection analysis because hilly surface slope towards the sun receiving more reflectance value as compared to slope opposite direction from the sun. It suppresses the vital information that leads to the inaccurate consequences. So topographic corrections are also necessary to be executed on satellite dataset before further considerations. In the present paper, different CVA techniques have been investigated over snow covered area of rugged terrain using topographic corrected MODIS dataset to find out the best possible technique which could distinguish more accurately changed and no-changed pixels, and also accurately perform "from-to" change detection. Based on limited study done in this paper, it is formed that CVAPS technique has greater potential than MCVA and ICVA techniques to evaluate the overall transformed data over snow covered area of rugged terrain. Results of this study are expected to be potentially useful for more accurate analysis of LULC changes over rugged terrain which will, in turn, improve the utilization of MODIS dataset for such applications by various users.

Key words – Topographic correction, Improved change vector analysis (ICVA), Modified change vector analysis (MCVA), Change vector analysis posterior-probability space (CVAPS), Moderate resolution imaging spectroradiometer (MODIS).

1. Introduction

Remote sensing offers a rapid way to obtain up-to-date information about regional climate monitoring (Haefner *et al*., 1997), natural resources management (Flores and Yool 2007), and early warning for snow avalanches (Mohan 1985; Sharma and Ganju 2000) that occurs due to air temperature anomalies. The detection of multi-temporal environmental change is a major application of remote sensing (Lu *et al*., 2004). Change detection is a phenomenon to find out the difference in sequence of events that occurred at two different time instances (Singh 1986). A number of change detection approaches have been proposed since past few decades.

Change detection techniques can be grouped into two categories; (a) post classification techniques; (b) enhancement techniques (Nelson 1983). The post classification techniques comprise the spectral classification comparison of satellite dataset that acquired at two different time instances of same study area (Pilon *et al*., 1988). Enhancement techniques involve the algebraically grouping of multi-temporal satellite imageries to provide a composite imagery that signifies the changes in distinguishing colors (Mas 1999). Enhancement categories are; (a) band differencing or ratioing (Weismiller *et al*., 1977; Howarth and Wickware 1981); (b) regression analysis (Singh 1989), (c) Principal Component Analysis (PCA) (Byrne *et al*., 1980; Gong *et al*., 1992), (d) Change Vector Analysis (CVA) (Malila 1980). The CVA technique is an effective tool to do research on change dynamics of LULC region that delivers spectral change information in terms of change-magnitude and change-direction (category). Numerous features and potential of CVA techniques have been extensively explored in different case studies (Lu *et al*., 2004; Michalek *et al*., 1993; Lambin and Strahler 1994a; Lambin and Strahler 1994b; Sohl 1999). On the other side, research activities on topographic correction helps in extraction maximum information from rugged terrain satellite imagery. Topographic correction must be applied to MODIS dataset to remove the variations that occurs due to shadow effects, *i.e*., sun-facing illuminated slopes show more reflectance values whereas shaded area which shows less reflectance values (Yongnian and Wanchang 2009; Mishra *et al*., 2009a; Raino *et al*., 2003). Different studies on topographic correction have shown that multi-spectral and multi-temporal image classification of rugged terrain can significantly improve to retrieve maximum information (Mishra *et al*., 2009a; Colby 1991; Meyer *et al*., 1993).

In the present study, a few recently developed different CVA techniques, *e.g*., Improved Change Vector Analysis (ICVA) (Chen *et al*., 2003), Modified Change Vector Analysis (MCVA) (Nackaerts *et al*., 2005) and Change Vector Analysis Posterior-probability Space (CVAPS) (Chen *et al*., 2011), have been evaluated from the point of view of their efficacy in data processing on rugged terrain using topographically corrected MODIS dataset. The ICVA (Chen *et al*., 2003) technique includes two stages; (a) Double-window Flexible Pace Search (DFPS) algorithm to generate binary image; (b) Direction cosines approach to attain the change classified imagery. Similarly, MCVA (Nackaerts *et al*., 2005) technique is based on an enhanced 2n-dimensional feature space comprising change information in its change-magnitude and change-direction. Moreover, CVAPS (Chen *et al*., 2011) technique integrates the potentials of Post Classification Comparison (PCC) into CVA to relieve the strict requirement of radiometric corrected satellite imagery. It has been analyzed that each CVA technique has its own unique features and no single technique is applicable to all case studies. Therefore, it is necessary to investigate the efficacy of different CVA techniques over snow covered area of rugged terrain using topographically corrected MODIS dataset and evaluate a technique which could more accurately distinguish the "change" and "no-change" pixels, and also accurately perform "from-to" change detection.

In order to assess the effectiveness of all CVA techniques on rugged terrain, each technique been experimented on same study area using topographically corrected MODIS dataset. This paper is divided into five major sections. Following the introduction part, the study area and required pre-processing steps have been described in section two. All CVA techniques are implemented in third section, followed by the results and discussions of prior studies on different CVA techniques in fourth section. The general conclusion has been drawn in last section.

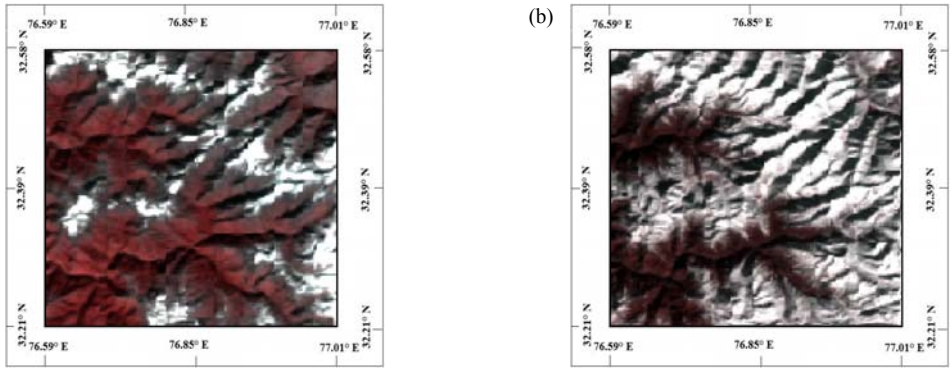
2. Pre-processing of study site

The dataset for study site have been acquired from MODIS (Moderate Resolution Imaging Spectroradiometer) sensor satellite, over western Himalayan region (India). Two multi-temporal imageries (6 November, 2010 and 8 February, 2011) covering the area located between latitude 32.21° N to 32.58° N and longitude 76.59° E to 77.01° E, have been used in this research work [Figs. 1(a&b)]. The MODIS dataset is well suited for change detection studies because of its appropriate repeativity (1-2 days) over the area of interest.

2.1. *Geometric correction*

All imageries were geometrically corrected using 25 Ground Control Points (GCPs) to define images in a

(a) (b)



Figs. 1(a&b). MODIS dataset of study site (comprises of Soil, Snow, Vegetation and Shadow) (a) 6th November, 2010 at 0530 UTC and (b) 8th February 2011 at 0530 UTC

common geographic coordinate system. A first order polynomial transformation has been used to maintain the Root Mean Square Error (RMSE) less than one (Mather 2004). The RMSE represents a measure of the accuracy of GCPs points in the dataset. The Nearest Neighbor (NN) method has been selected for resampling the satellite imagery. In NN, each incorporated pixel allocated to the value of the nearest distance point in the input imagery. It occupies less space and fast to compute the process. This step reduces arbitrary and residual distortion which results a 'map-coordinated' dataset.

2.2. *Radiometric correction*

Radiometric correction overcomes the errors that affect the illumination value due to irregular atmospheric conditions, *e.g.*, different scattering and absorption, and different viewing geometry, *e.g.*, variation in Sun and Earth distance, solar azimuth angle or solar zenith angle. The radiometric correction converts the illumination values in reflectance values. The Digital Numbers (DN) of the images were transformed to reflectance "R" based on the following equation (Song *et al*., 2001; Pandya *et al*., 2002).

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

where, "E_0" and "$L_{sat\lambda}$" represents the exo-atmospheric spectral irradiance and sensor radiance of MODIS (Mishra *et al*., 2009b), respectively. The solar zenith angle is represented by "θ_z" that is calculated for all different pixels (Kasten 1962), "d" represents the distance between Earth and Sun (Vander Meer, 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" (Chavez 1996).

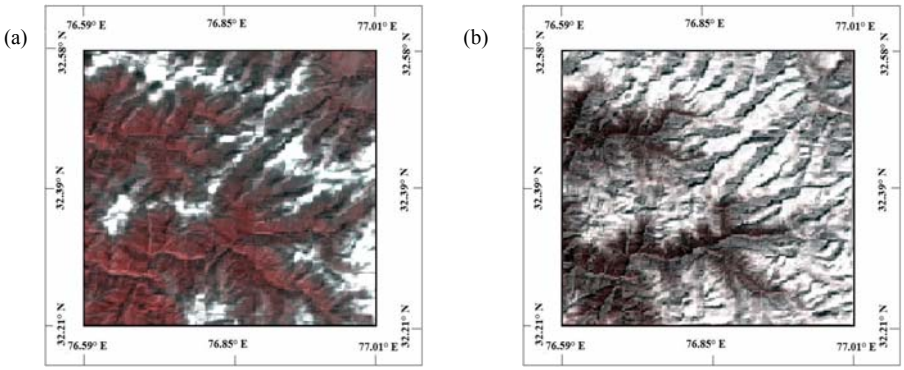
2.3. *Topographic corrections*

Topographic corrections refer to the compensation of the different solar illuminations that occur due to irregular shape of the terrain. This effect causes a high variation in the reflectance value of satellite imagery in which shaded areas shows low reflectance and bright areas shows the high reflectance (Raino *et al*., 2003). The topographic is an important factor that affects quantitative and qualitatively analysis of satellite dataset when remotely sensed data are acquired over mountainous regions (Mishra *et al*., 2009a). In this paper, slope match technique as topographic correction has been used to remove the shadow effects (Nichol *et al*., 2006). The following Equation gives the slope match topographically corrected imagery.

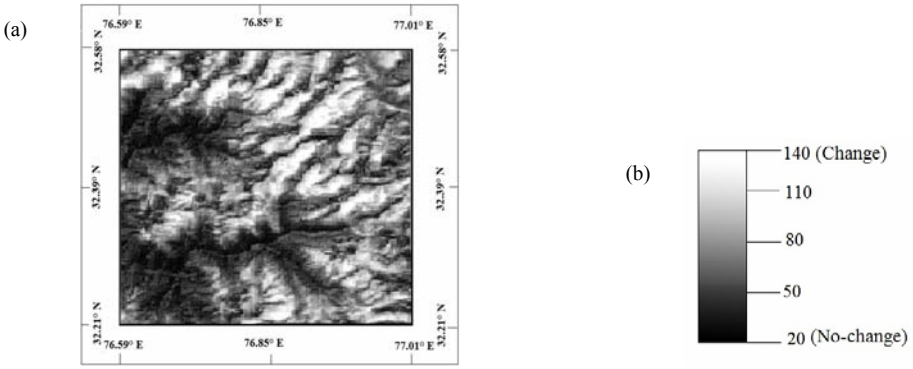
$$L_N^s = R + \left(L_{\max} - L_{\min}\right) \times \left[\left(\frac{\cos_s(i) - \cos i}{\cos_s(i)}\right)\right] C_s \qquad (2)$$

$$C_s = \left[\frac{\left(S_a^1 - N_a\right)}{\left(N_a^1 - N_a\right)}\right] \qquad (3)$$

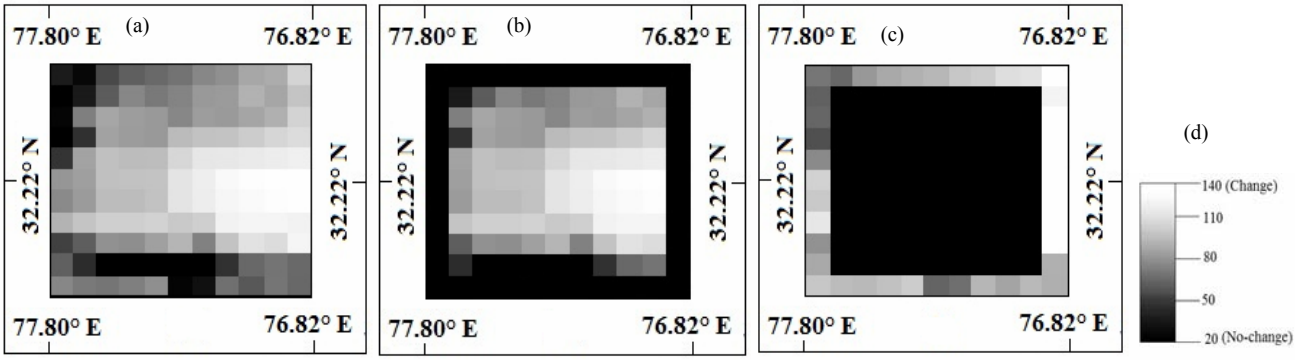
In Equation (2), cos i and $\cos_s$ (i) represent illumination (IL) and slope of illumination, respectively; The parameters L_{max} and L_{min} represents maximum and minimum reflectance, respectively; In Equation (3), the parameter C_s is normalization coefficient of slope match technique for different satellite bands; S_a^1 represents mean reflectance on sunlit slopes after first stage normalization, N_a represents mean reflectance on shady slopes in uncorrected reflectance imagery and N_a^1 is the mean reflectance value on shady slope after first stage normalization. The slope match topographically corrected imageries of both dates (6th November, 2010 and 8th February, 2011) have been shown in Fig. 2.



Figs. 2(a&b). Slope match topographically corrected MODIS dataset of study site (a) 6th November, 2010 at 0530 UTC and (b) 8th February, 2011 at 0530 UTC



Figs. 3(a&b). (a) Change magnitude image and (b) Change magnitude "change" and "no-change" scale (140-20)



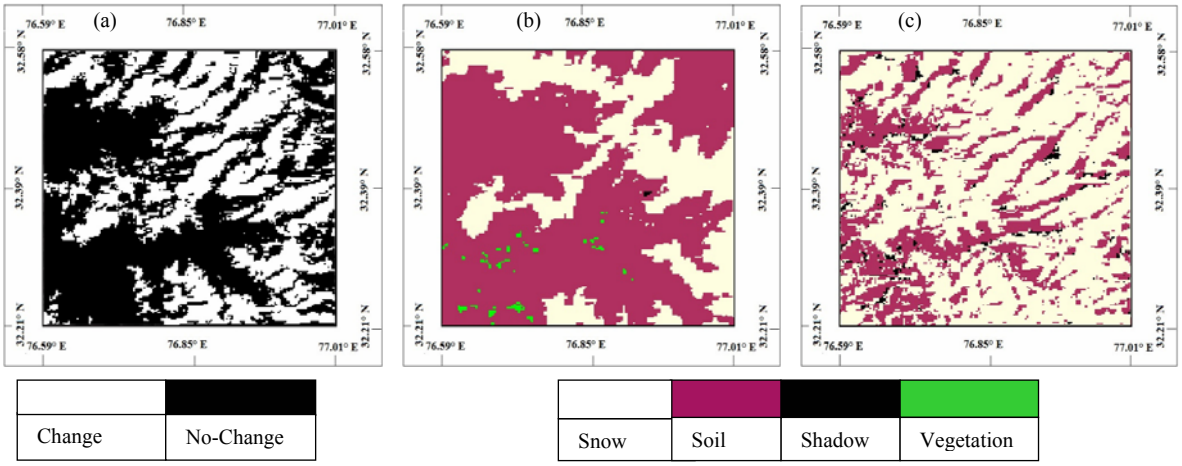
Figs. 4(a-d). Training sample of change magnitude image (a) Sample, (b) Inner boundary of sample, (c) Outer boundary of sample and (d) Change magnitude "change" and "no-change" scale (20-140)

3. Change vector analysis (CVA) techniques

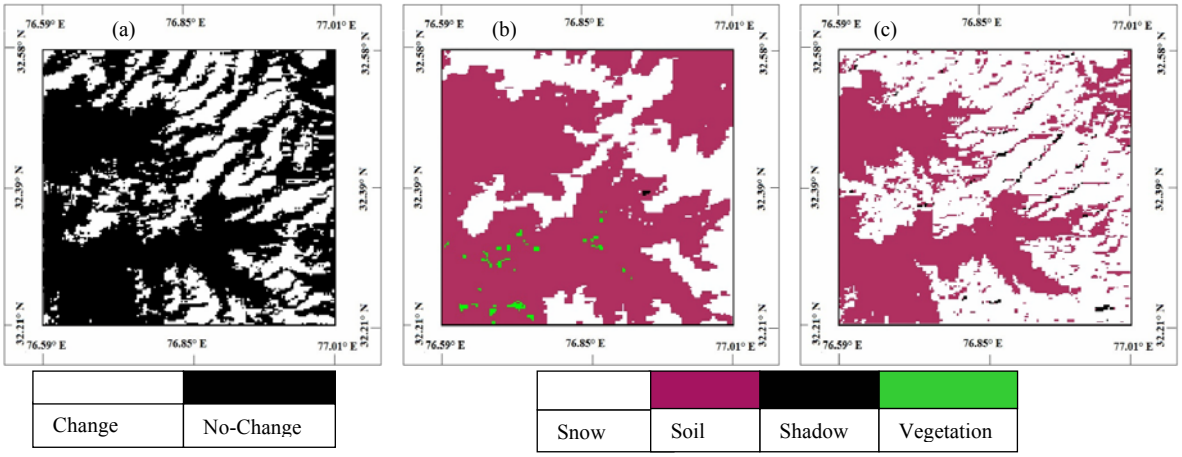
The core concept of CVA comprises computation of spectral change vectors based on multi-temporal pairs of spectral measurements and compares their magnitude based on specific threshold approach (Chen *et al*., 2003; Nackaerts *et al*., 2005). The CVA can overcome the disadvantages of "type-one" approaches, *e.g*., cumulative errors in image classification of an individual date and processing any numbers of spectral bands simultaneously to retrieve maximum change-type information (Malila 1980). It has also been concluded (Sohl 1999) that CVA is better than all other change detection techniques because of its graphically rich content and its ability to detect LULC changes with good locational information. The change vector magnitude imagery is calculated according to Euclidian distance as following Equation (Malila 1980, Chen *et al.,* 2003).

$$|\Delta G| = \sqrt{(m_1 - n_1)^2 + \ldots + (m_i - n_i^2)} \qquad (4)$$

"ΔG" represents that transformed data lies between the two multi-temporal imageries captured at different



Figs. 5(a-c). Improved change vector analysis (ICVA) technique (a) Binary image with color codes; (b) change discriminated on 6th November, 2010 and (c) change discriminated on 8th February, 2011 with color codes



Figs. 6(a-c). Modified change vector analysis (MCVA) technique (a) Binary image with color codes; (b) change discriminated on 6th November, 2010 and (c) change discriminated on 8th February, 2011 with color codes

time periods, time "T_1" (6th November, 2010) and time "T_2" (8th February, 2011) for a given pixel defined by $M=(m_1,m_2,...,m_i)^{T_1}$ and $N=(n_1,n_2,...,n_i)^{T_2}$, respectively and "$i$" represents number of bands in imagery. In Fig. 3, the change magnitude imagery that calculated according to Euclidian distance represents the change (bright area) and no-change (dark area) pixels.

3.1. *Improved change vector analysis (ICVA) technique*

The Improved Change Vector Analysis (ICVA) (Chen *et al*., 2003) technique consists of two stages; (a) Double-window Flexible Pace Search (DFPS) approach to semi-automatically predict a threshold value for change magnitude to generate "change and no-change" imagery; (b) direction cosines to determine the change direction based on a minimum-distance classification method. In this paper, DFPS technique has been executed on training dataset sample containing all possible kinds of changes to select a threshold value. The selected training sample is shown in Fig. 4(a). A succession rate of change detection analysis 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 according to the following equation to select the most optimal threshold value for change magnitude imagery.

$$S_r = \frac{I_c - O_c}{I_r}\% \tag{5}$$

In Equation (5), "I_c" represents number of transformed pixels inside an inner window sample that has been shown in Fig. 4(b), "O_c" represents number of

TABLE 1

Succession rate results for DFPS threshold determination (ICVA) technique

Search range = 160-20		Search range = 110-80		Search range = 110-90		Search range = 100-90		Search range = 97-93	
Pace difference = 20		Pace difference = 10		Pace difference = 5		Pace difference = 2-3		Pace difference = 1	
Threshold value	Success percentage	Threshold value	Success percentage	Threshold value	Success percentage	Threshold value	Success percentage	Threshold value	Success percentage
160	4.9%	110	48.14 %	110	48.14 %	100	56.79 %	97	57.85 %
140	4.9%	100	56.79 %	105	52.68 %	98	57.85 %	96	58.76 %
120	39.5 %	90	55.55 %	100	56.79 %	95	59.25 %	95	59.25 %
100	56.79 %	80	51.85 %	95	59.25 %	92	56.87 %	94	56.87 %
80	51.85 %			90	55.55 %	90	55.55 %	93	56.87 %
60	50.61 %								
40	48.14 %								
20	48.14 %								

transformed pixels in an outer window sample that has been shown in Fig. 4(c) and "I_c" is the total number of pixels in inner training window sample. The Double-Window Flexible Pace Search method was used to determine the threshold of change magnitude. The search range of DFPS can be set from highest to lowest value (160-20) based on sample magnitude with pace (step) difference from maximum to minimum (20-1) value. The threshold search process iterated until the success rate difference between the maximum and the minimum value was less than 1 per cent that is calculated according to Equation (5). As a result, the threshold of change magnitude was obtained as 95 with a maximum success rate of 59.25 per cent. The search process has been noted in Table 1, and the search range changed five times with the paces (steps) of 20, 10, 5, 2-3, and 1. The number of thresholds verified totaled 18. The change and no-change pixels in the study site at threshold 95 were extracted and shown in Fig. 5(a).

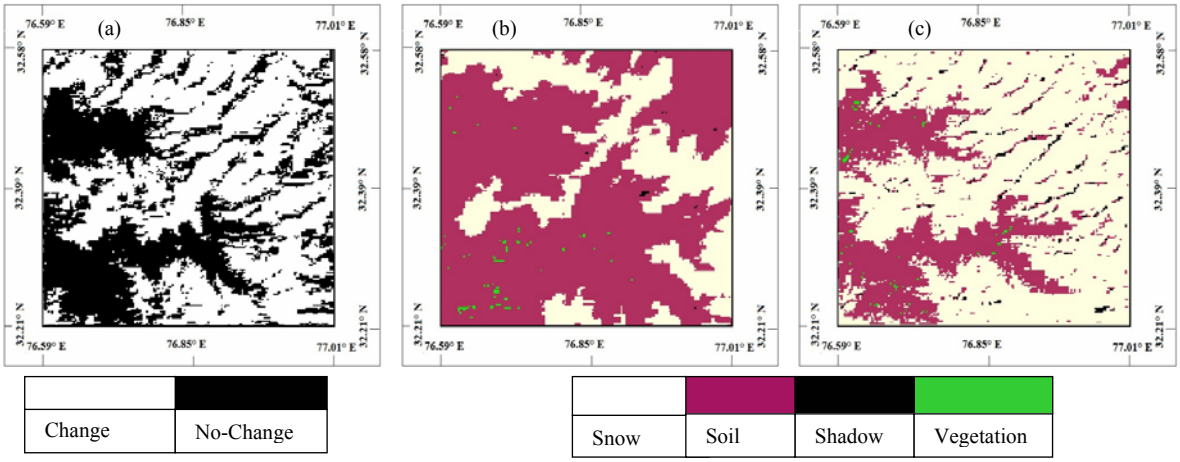
In ICVA (Chen *et al*., 2003), change type discrimination can be obtained using change vector's direction cosines (Hoffmann 1975). The change vector's direction can be defined by a sequence of cosine functions according to subsequent equation in which $X(x_1, x_2, \ldots, x_i)$ represents vector, "i" is the number of bands.

$$\mathrm{Cos}\,\theta_1 = \frac{x_1}{|\Delta G|}, \mathrm{Cos}\,\theta_2 = \frac{x_2}{|\Delta G|}, \mathrm{Cos}\,\theta_i = \frac{x_i}{|\Delta G|}, \qquad (6)$$

Change type information is calculated according minimum distance classifier in which an unknown pixel is assigned to a certain class or unclassified class based on a minimum distance to means of all candidate classes when the distance is within a certain threshold (Richards and Jia, 1999). The change type discriminated imageries of respective dates which are calculated through ICVA technique, are shown in Figs. 5(b&c). All land classes in the study site have been categorized into four classes (with respective color coding) : snow covered land (white), soil land (red), vegetation (green) land and shadow (black).

3.2. *Modified change vector analysis (MCVA) technique*

Modified Change Vector Analysis (MCVA) (Nackaerts *et al*., 2005) stores the change information in change-vector's magnitude and direction as change-type data. In MCVA, each change vector is described by Cartesian coordinates in a continuous domain. Moreover, requirement of reference is data only for feature extraction and it enhances the applications of MCVA. In Fig. 6(a), binary image generated through MCVA represents the "change" pixels in white color and "no-change" pixels in black color. The important advantages of this technique are (Nackaerts *et al*., 2005); (a) change discrimination (categorization) is in the continuous domain which allows change descriptors to be used in classification approaches such as supervised or unsupervised classifiers, (b) the computational simplicity, (c) feature space multidimensionality (two or more number of change descriptor input bands). In this paper, Maximum Likelihood Classifier (MLC) has been used to categorize change type information in the continuous domain. The change type discriminated imageries using MCVA technique, have been shown in Figs. 6(b&c).



Figs. 7(a-c). Change vector analysis posterior-probability Space (CVAPS) technique (a) Binary image with color codes; (b) change discriminated on 6th November 2010 and (c) change discriminated on 8th February 2011 with color codes

3.3. *Change vector analysis posterior-probability space (CVAPS) technique*

Change Vector Analysis Posterior-probability Space (CVAPS) (Chen *et al*., 2011) integrates the merits of Post Classification Comparison (PCC) (Castellana *et al*., 2007) into CVA to enhance its capability. CVAPS identifies LULC changes by pixel-wise radiometric comparison (Chen *et al*., 2011) instead of comparison as in PCC (Castellana *et al*., 2007). This process reduces the occurrence of error in individual classified imageries. In CVAPS approach, the posterior probability is implemented by Maximum Likelihood Classifier (MLC). Generally, change-type (category) information can be obtained based on the change vector's direction "ΔP". A pixel transformed from one class "*a*" to another class "*b*" is represented by change base vector. 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 "ΔP_{ab} " can be defined as

$$\Delta P_{ab} = P_b - P_a \tag{7}$$

"P" denotes the posterior probability vector belonging to class from 1 to *m*, where *m* is the number of classes. Here, "P_{zi}" represents the pure pixel posterior probabilities that belongs form a class i to a class z in the following Equations.

$$P = (P_1, \ldots, P_m) \tag{8}$$

$$P_{zi} = \begin{cases} P_{zi} = 1, & if\ i = z \\ P_{zi} = 0 & if\ i \neq z \end{cases} \tag{9}$$

In order to determine change information, DFPS (Chen *et al*., 2003) threshold determination technique has been employed in CVAPS. Fig. 7(a) represents binary image generated through CVAPS in which the "change" pixels donated as white color and "no-change" pixels as black color. The change vector's direction in a posterior-probability space has an effective particular mean in change-type identification. The change type discriminated imageries of respective dates have shown in Figs. 7(b&c).

4. Results and discussion

Accuracy assessment of each change detection technique is an essential part of remote sensing data processing for evaluations the effectiveness of different CVA based change detection techniques. The most common accuracy assessment elements to generate error matrix include overall accuracy (accuracy of a map), 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) (Green 1994; Biging *et al*., 1999). The result of an accuracy assessment typically provides us with an overall accuracy of the map and the accuracy for each class in the map. In order to access the accuracy, binary output ("Change" and "no-change" imagery) of each CVA technique is compared with reference image to generate the error matrix, kappa coefficient and commission error. With experimental outcomes, it is evaluated that ICVA technique achieved 0.76 kappa coefficient and 88% accuracy assessment as shown in Table 2, MCVA technique achieved 0.56 kappa coefficient and 78% accuracy assessment as shown in Table 3, and CVAPS technique achieved 0.80 kappa coefficient and 90% accuracy assessment as shown in Table 4. It has been analyzed that both ICVA and CVAPS techniques achieved nearly high accuracy in terms of kappa coefficient and accuracy assessment. On the other hand, MCVA overestimates the change and thus, achieved lower kappa coefficient as well as accuracy assessment.

TABLE 2

Error matrix for ICVA technique using 50 samples

Reference change		Un-change Pixels	Change Pixels	Sum	Commission error
Classified change	Un-change pixels	21	4	25	16%
	Change Pixels	2	23	25	8%
	Sum	23	27	50	
	Commission error	8.6%	5.5%		
Accuracy assessment = 88%					
kappa coefficient = 0.7600					

TABLE 3

Error matrix for MCVA technique using 50 samples

Reference change		Un-change pixels	Change pixels	Sum	Commission error
Classified change	Un-change Pixels	20	5	25	20%
	Change Pixels	6	19	25	24%
	Sum	26	24	50	
	Commission Error	23.07 %	20.83%		
Accuracy assessment = 78%					
Kappa coefficient = 0.56					

TABLE 4

Error matrix for CVAPS technique using 50 samples

Reference Change		Un-change Pixels	Change Pixels	Sum	Commission Error
Classified Change	Un-change Pixels	22	3	25	12%
	Change Pixels	2	23	25	8%
	Sum	24	26	50	
	Commission Error	8.33%	11.53%		
Accuracy assessment = 90%					
Kappa Coefficient = 0.80					

TABLE 5

"From-to" accuracy assessment for ICVA technique using 50 samples

Reference change		Snow	Soil	Vegetation	Shadow	Row total
Classified change	Snow	-	15	-	-	15
	Soil	24	10	-	1	35
	Vegetation	-	-	-	-	-
	Shadow	-	-	-	-	-
	Column Total	24	25	-	1	50
Overall Accuracy = 78%,						
Kappa Coefficient = 0.6808						

TABLE 6

"From-to" accuracy assessment for MCVA Technique using 50 samples

Reference change		Snow	Soil	Vegetation	Shadow	Row total
Classified change	Snow	13	2	-	-	15
	Soil	16	19	-	-	35
	Vegetation	-	-	-	-	-
	Shadow	-	-	-	-	-
	Column Total	29	21	-	-	50
Overall accuracy = 88%,						
Kappa coefficient = 0.8244						

TABLE 7

"From-to" accuracy assessment for CVAPS technique using 50 samples

Reference change		Snow	Soil	Vegetation	Shadow	Row total
Classified Change	Snow	13	1	-	1	15
	Soil	22	13	-	-	35
	Vegetation	-	-	-	-	-
	Shadow	-	-	-	-	-
	Column Total	35	14	-	1	50
Overall Accuracy = 92%,						
Kappa Coefficient = 0.8814						

The commission errors were less in ICVA and CVAPS as compared to MCVA. These results have been evaluated on same study area of rugged terrain for evaluation of different CVA techniques for change detection.

The "From-to" (one class to another class) change accuracy assessment of ICVA, MCVA and CVAPS techniques have shown in Table 5, Table 6 and Table 7, respectively. ICVA achieved a kappa coefficient of 0.6808 and accuracy assessment of 78%, MCVA achieved 0.8244 kappa coefficients and 88% accuracy assessment and CVAPS achieved 0.8814 kappa coefficient and 92% accuracy assessment. Both CVAPS and MCVA achieved equal accuracy but kappa coefficient of CVAPS is much better than MCVA. On the other side, ICVA achieved low accuracy and low kappa coefficient as compared to CVAPS and MCVA.

5. Conclusions

This paper summarizes different Change Vector Analysis (CVA) based change detection techniques, *e.g.*, ICVA, MCVA and CVAPS, and evaluated their impact on snow covered rugged terrain. MODIS sensor satellite dataset has been used in this research work to experiment

the effects of different CVA based change detection techniques for retrieving more accurate change map between two different time instances imageries. Furthermore, necessary pre-processing steps such as geometric correction, radiometric correction and topographic correction for rugged mountain terrain, have been implemented to correct the estimated spectral reflectance value.

In this investigational report, it has been concluded that Double-window Flexible Pace Search (DFPS) technique plays a vital role in Improved Change Vector Analysis (ICVA) and Change Vector Analysis Posterior-probability Space (CVAPS) to detect more accurately the LULC changes in western Himalaya. Based on the results of this limited study, ICVA has achieved 88% overall accuracy (0.76 kappa coefficient), and CVAPS has achieved 90% overall accuracy (0.80 kappa coefficient) for change imagery. Moreover, ICVA and CVAPS can control commission errors up to a great extent using DFPS approach. All ICVA, MCVA and CVAPS change detection have capability to access multiple satellite imagery bands simultaneously in contrast to traditional CVA technique that can apply only to single satellite imagery band.

In ICVA technique, change type information is extracted by direction cosine of the change vectors because the spectral feature difference between any two kinds of LULC types on either date are similar to their spectral change features from time t_1 (6^{th} November, 2010) to time t_2 (8^{th} February, 2011). This process overcomes the requirement of ancillary data from another date to obtain change type information. However, ICVA technique has achieved 78% overall accuracy (0.6808 kappa coefficient) for "from-to" change. On the other hand, MCVA required training samples for extraction of feature descriptors, which is based on MLC. This technique has achieved 88% overall accuracy (0.8244 kappa coefficient) for "from-to" change. In CVAPS, the direction of the change vector in a posterior probability space has a specific physical meaning, and such information is easy to be used in change-type identification. CVAPS has achieved maximum (92% overall accuracy with 0.8814 kappa coefficient) accuracy as compared to other two techniques, *i.e*., ICVA and MCVA. Only drawback of CVAPS is that it relies on analyst skills in proper selection of training samples required for classification of image and threshold value. The CVAPS technique provides number of features such as less sensitive to topographic effects, describes the output in term of overall magnitude of change, direction of change, simultaneously processing of multiple satellite imagery bands, semi/automatic threshold finding process (DFPS), and makes a perfect choice of CVAPS as change detection technique for regional climatic change and snow avalanche hazard analysis over rugged terrain. It is expected that further developments in CVA will provides more integrated techniques and robust algorithms for the processing of satellite dataset in the area related to LULC change detection.

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