NEIGHBORHOOD CORRELATION IMAGE ANALYSIS TECHNIQUE FOR CHANGE DETECTION IN FOREST LANDSCAPE

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KEY WORDS: Change detection, Neighborhood Correlation Image, Decision tree classification

ABSTRACT:

The origin of the concept of using contextual information of Correlation in neighborhood of a pixel for change detection is the simple geo-statistical fact that the same geographical area (neighborhood window) on two dates of imagery will tend to be highly correlated if no or little change has occurred and uncorrelated when change occurs. The main objective of this study is to investigate the usability of this technique for change detection in forest landscape with the use of medium spatial resolution satellite data with decision tree classification approach. This research has came to the conclusion that the NCI analysis technique does provide change information and it requires larger windows (15 x 15 pixels) for NCI information to become useful when medium resolution imagery is used for change detection in forest.

1. INTRODUCTION

Forests of India are one of the most treasured repositories of biodiversity of the world but it is also under immense biotic pressure. This is causing qualitative and quantitative decrease in canopy density of forest. Forest policy makers always require detail and accurate assessment of changes in forest landscape to formulate appropriate initiatives for sustainable management of forest. Hence, need for developing newer change detection techniques is always felt which is accurate and precise as well as able to provide the knowledge of change dynamics.

Neighborhood Correlation Analysis technique (NCI) is a new technique which has been found to be a powerful tool in detecting changes in the urban area with high accuracy but by using very high resolution imagery of~1m spatial resolution (Jungho and Jensen, 2005).The study is based on the fact that the same geographical area (pixel window) on two dates of imagery will tend to be highly correlated when no change occurs and less correlated when change occurs. The contextual information of “correlation” between two datasets provides information about location and numeric value of change.

The problem of detecting change using this technique with high resolution images in forest landscape is the huge cost of high resolution imagery and uncertainty in availability of historical data for comparison. It is worth investigating whether this technique is able to detect change in forest landscape using medium resolution imagery with same high accuracy. If yes, than it can be established that this technique can be applied successfully for change detection using both medium as well as high resolution satellite data in forest landscape.

1.1. Change Detection

There are four important aspects of change detection for monitoring natural resources: (i) Detecting if a change has occurred, (ii) Identifying the nature of change, (iii) Measuring the aerial extent of change and (iv) Assessing the spatial pattern of change (Macleod and Congalton, 1998). In recent past many change detection techniques have been developed which attempted to focus on either or all of the above aspects with varying success. Different sensors with different change detection algorithm for different applications were used for this purpose but the question of best suitability of the technique for a specific study area remains unanswered which implies that no single method is suitable for all cases. Various remote sensing change detection algorithms which have been developed in the process of addressing above mentioned four aspects of change detection, can be grouped into two categories: (i) Binary change/no change or Image enhancement methods like Image differencing, Image ratioing, Vegetation index differencing and PCA. These algorithms provide information on the existence and magnitude of change but do not identify the nature of change. (ii) Information on the nature of change extraction method i.e. Post classification comparison, CVA and hybrid change detection method. These algorithms provide detailed information about the type of land cover change but it requires accurate thematic classification of the images. There is also an ample possibility of classification error propagation into final out put (Jungho and Jensen, 2005) (Chan et al., 2001; Lu et al., 2004). Most of the above traditional algorithms have been used to identify change using coarse to medium resolution images (Hayes and Sader, 2001; Lyon et al., 1998). They do not function successfully in high and very high resolution domain (Khudhairy et al., 2005). To overcome this problem, instead of pixel based change detection techniques, an object oriented image segmentation change detection approach has been adopted (Niemeyer and Canty, 2003)

1.2. Neighborhood Correlation Image

An entirely different approach to this problem of change detection for high resolution images is the NCI technique which is still pixel based but dependent on contextual information of a pixel on the first image and its associated neighboring pixels on the second image. In this approach a new three channel Neighborhood Correlation Image that contains three different types of information about (i) Correlation (ii) Slope and (iii) Intercept is generated to derive the information of change (Jungho and Jensen, 2005). The correlation image derived from a specific neighborhood of pixels (2x2, 3x3, 4x4,) contains valuable change information associated with the central pixel and its neighboring pixels of two images. The other two images “Slope” and ”Intercept” provide change related information which facilitates the process of accurate change detection through “Correlation” image. When combined with Decision Tree Classification technique the knowledge of correlation, slope and intercept can be used to produce detailed information on the nature of the change.

2. LOCATION OF STUDY AREA

The area of study chosen for the current research is Kannod Forest Subdivision of Dewas district which is located in the central Indian province of Madhya Pradesh. The boundary of the study area lies between the latitude of 22° 15’ N and 22° 50’ N and longitude of 76°00’E and 77°10’ E (Fig. 3.1). Narmada River, which is one of the most important rivers of central India, makes the southern boundary. As the study area is located in the catchment of Narmada River, the existence of forest cover has a very significant impact on the water recharge of Narmada. The area has a hot and dry summer climate and moderate warm winter with rainy monsoon season in between. Except monsoon season the general climatic condition throughout the year is dry.

2.1. Forest profile of study area

The Forest Types of Study area according to the classification of Champian and Seth, (1968) are:
1. Type 3B/C-1-c: South Indian Moist Deciduous Slightly Moist Teak Forests (about 5% of total forests)
2. Type 5A/C1-b: Southern tropical Dry Deciduous Teak Forests (about 85%)
3. Type 5A/C-3: Southern Tropical Dry Deciduous Mixed Forests (about 10%).

The main characteristic of forests of Kannod subdivision is that they are composed of a large number of dry species. They are usually predominated by the Tactona grandis, Boswelia serrata and Hardwickia binata. One of the major change processes, which have contributed to forest cover change in the study area during the period of 1999 to 2005, is the clear felling of 4000 hectare of dense or open forest coming under submergence of a multipurpose dam that is being constructed in Narmada River.

3. DATA

The study proposes to detect change in forest landscape of the study area between the years 1999 and 2005 using medium spatial resolution multi-spectral remotely sensed data. The spatial resolution of 23.5 meters of IRS-1D and IRS-P6 LISS-III (Linear Imaging Self Scanner) multi-spectral sensor is considered suitable for this study. The bands considered were B2 (0.52-0.59µm), B3 (0.62-0.68µm), and B4 (0.77-0.86µm), which are suitable for vegetation monitoring. For the purpose of this research it was required that bi-temporal data should be of near anniversary dates so that seasonal variation in phenological character of the vegetation under observation is kept at minimum. The remotely sensed data of the second week of November was considered suitable for this study. The details of RS data acquired and used in this study are given in Table 1

Satellite ID	IRS-ID (for 1999)	IRS-P6 (for 2005)
Sensor	LISS-III	LISS-III
Type	Multi-spectral	Multi-spectral
No. of Bands	3 VNIR	3 VNIR
Spectral-Range (micron)	0.52-0.59, 0.62-0.68, 0.77-0.86	0.52-0.59, 0.62-0.68, 0.77-0.86
Resolution	23.5 meters	23.5 meters
Swath Width	141 k.m.	141 k.m.
Revisit Time	25 Days	24 Days

Table 1 Characteristics of IRS series satellite

4. METHOD

The entire process of change detection using NCI analysis technique is explained by a conceptual flow chart given in Figure 1.The entire process of change detection based on Neighborhood Correlation Image analysis using Decision tree classification technique is phased out into five major stages. They are pre-processing of data, which includes geometric correction, image-to-image co-registration and radiometric normalization. Second stage is band wise Correlation, Intercept and Slope image generation. The third stage is generation of reference data for training and testing the knowledge based classifier and classifier generation. Next step is assessment of accuracy of classifier so developed and the final step is interpretation of result of classification and generation of change detection map. At every stage there is an utmost requirement of exactness of execution of processing and validation of result as any error at any stage may finally result into spurious change detection information.

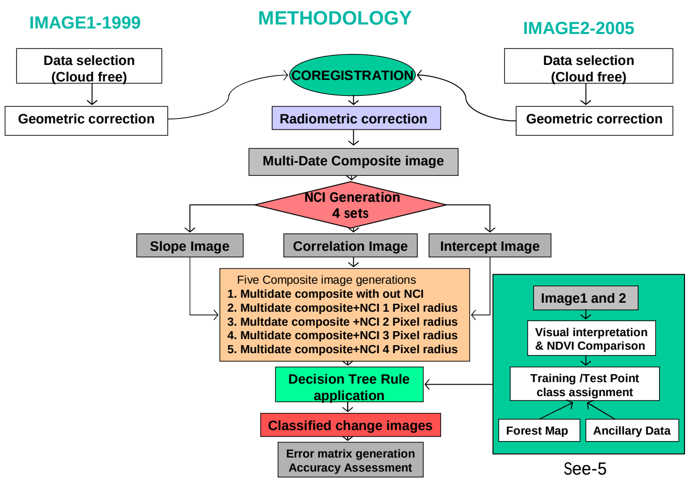

Figure 1. Flow chart showing steps involved in NCI change detection process

4.1. Classification Scheme for Change and No change

The basis of the classification of forest cover adopted by "Forest Survey of India" is crown density. A crown density of 1 signifies totally dense forest and density of 0 as non forest. Resulting cover classes can be seen in Table 2.

1. Dense forest	Density more than 0.4
(i) Very Dense forest	Density 0.7 to 1.0
(ii) Moderately Dense forest	Density 0.4 to 0.7
2. Open forest	Density 0.1 to 0.4
3. Non-forest/scrub	Density less than 0.1

Table 2 Forest cover classification according to crown density

The category Non-forest includes all lands without forest cover such as agricultural croplands, scrub, water bodies, riverbeds, and built up areas. For the purpose of this study three major forest cover classes namely dense forest (DF), open forest (OF) and non- forest (NF) are considered. The change classes associated with these classes are: "Forest to Non forest", "Forest to open forest", "Open forest to Dense forest", "Open forest to Non forest" and "Non-forest to Open forest". Change class from Non forest to Dense forest was excluded as it is most improbable for non forest area to change into dense forest in a period of six years. A separate class for water was also considered in the study because of its unique spectral distinctiveness. Thus there are four no change classes and five change classes which is of interest The notations used in this study for these classes are F-F, OF-OF, NF-NF and WW for no change classes of dense forest, open forest non-forest and water respectively. Similarly for change classes F-NF, F-OF, OF-F, OF-NF and NF-OF are used for dense forest to non-forest, dense forest to open forest, open forest to dense forest, open forest to non forest and non forest to open forest respectively.

4.2. Neighborhood configurations

For generation of contextual information between the two images in the form of Correlation, Slope and Intercept images, and for identification of most suitable NCI configuration appropriate for forests change detection, circular neighborhood (kernel) of sizes 1, 2, 3 and 4 pixel radius were considered.

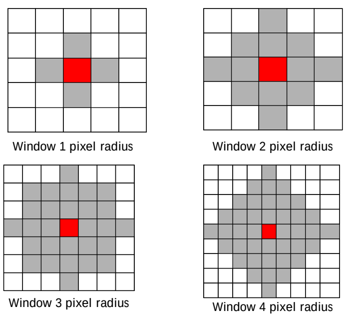

Figure 2 Circular windows considered

At spatial resolution of 23.5 meters, window size of radius 1 to 4 pixel will be equivalent to an area of 0.49 ha to 4.47 ha respectively on ground. In the stock mapping of forest, change in area only of greater than 5 ha is observed and recorded on a scale of 1:50000 and it is also the minimum observational area of interest. Since ground extent equivalent to maximum window size of four-pixel radius is less than 5 ha hence it is considered as maximum window size for observation. Standard algorithm of correlation was used for contextual image generation. For a given neighborhood configuration having ***n*** number of pixel around the central pixel, Correlation coefficient ***r***, slope ***a*** and intercept ***b*** is given by the following equation (Jungho and Jensen, 2005)

$$r = \frac{\mathrm{cov}_{12}}{s_1 s_2} \qquad (1)$$

$$\mathrm{cov}_{12} = \frac{\sum_{i=1}^{n}(BV_{i1}-\mu_1)(BV_{i2}-\mu_2)}{n-1} \qquad (2)$$

$$a = \frac{\mathrm{cov}_{12}}{s_1^{\,2}} \qquad (3)$$

$$b = \frac{\sum_{i=1}^{n} BV_{i2} - a\sum_{i=1}^{n} BV_{i1}}{n} \qquad (4)$$

Where, ***r*** = Pearson correlation coefficient., cov_{12}=covariance between brightness values found in all bands of the two date data sets in the neighborhood, s_1, s_2 = standard deviations of the brightness values found in all bands of two date datasets in the neighborhood, BV_{i1}, BV_{i2}=brightness value of i^{th} pixel in all bands of image 1and 2 respectively, ***n***= total number of pixels in the neighborhood, , $\mu_1$and μ_2 are the means of brightness values in the neighborhood in Image1 and Image2 respectively.

4.3. Decision tree classification approach

The decision tree classification approach is used for image classification because it is one of the most efficient forms of expert systems and suited for remotely sensed data sets with relatively small number of training samples. The advantage of using this approach is that it can handle non-categorical and categorical data equally well. (Jungho and Jensen, 2005; Quinlan, 2003).The advantages of decision tree classifier over traditional statistical classifier include its simplicity, ability to handle missing and noisy data, and its non- parametric nature.

4.4. Reference data generation

For training and testing of the Decision Tree Classifier, reference data is required in terms of pixel values of each layer for which change/no change class is known. Such a knowledge base should be generated for a sufficient number of points randomly distributed over the entire area of study. For this purpose 2043 random points were generated and "Change, No-Change" class was assigned to each of the random points based on visual inspection of two images. NDVI values associated with the pixel under consideration were also used to further facilitate this classification process. Out of the total 2043 random points whose class assignment had been done, 60% of points were used for training and 40% of points were kept aside for testing the accuracy of the classification. The number of points used for training and testing are given per class in Table 3

Class	Total points	Training Points	Testing Points
Forest to Forest	509	308	201
Forest to Non forest	21	11	10
Forest to Open forest	302	192	110
Non forest to Non forest	159	158	101
Non forest to Open forest	24	16	8
Open forest to Forest	120	75	45
Open forest to Non forest	274	166	108
Open forest to Open forest	504	304	200
Water	30	21	9
Total	2043	1251	792

Table 3 Reference data for training and testing

5. RESULT AND DISCUSSION

To test the decision tree classification, the knowledge base developed for training of the classifier is applied to a single date image of year 1999 to classify the image into dense forest, open forest and non forest. Overall classification accuracy was 95.5%, which is fairly high in comparison to other traditional classification models. For accuracy assessment of change detection classification, the 792 reference points were considered. The error matrices of classification applying the decision tree classifier from the knowledge base consisting only of six initial bands, three of each of the two date images (without NCI) is given in Table 4, and with NCIs derived from different neighborhood configurations of 1, 2, 3 and 4 pixel radius are given in Tables 5 to 8. From the analysis of all five error matrices it is found that overall accuracy, i.e. with and without NCI, is within a narrow range of 82 to 84 percent. When NCI-1, NCI-2 and NCI-3 are considered the overall accuracy goes down below the overall accuracy of classification without NCI. The decrease is most in the case of NCI-3. But in the case of NCI-4 overall accuracy is higher than overall accuracy of all cases either with or without NCI. This shows that decision tree classifier utilizing NCI-4 knowledge base is most efficient in this case though the difference is not significant. On the analysis of the Kappa coefficient a similar trend is observed as in overall accuracy. The Kappa coefficient in all the cases is found within a narrow range of 0.79 to 0.80. Kappa coefficients of NCI-1, NCI-2 and NCI-3 are below the Kappa coefficient of the case when no NCI is used. It is lowest in the case of NCI-3. Only in the case of NCI-4 it is higher than that of without NCI

Without NCI	**ACCURACCY ASSESMENT WITHOUT NCI**									**Row Total**	**User Acc.**
	F-F	FNF	FOF	NF-NF	NF-OF	OFF	OF-NF	OF-OF	WW		
F-F	180	0	4	0	0	9	0	0	0	193	0.933
F-NF	0	0	0	0	0	0	1	0	0	1	0
F-OF	15	3	98	0	0	1	0	10	0	127	0.772
NF-NF	0	0	0	86	3	0	9	0	4	102	0.843
NF-OF	0	0	0	3	1	0	0	1	0	5	0.2
OF-F	3	0	0	0	0	28	0	4	0	35	0.8
OF-NF	0	7	0	9	0	0	86	6	0	108	0.796
OF-OF	3	0	8	3	4	7	12	179	0	216	0.829
WW	0	0	0	0	0	0	0	0	5	5	1
Ref.Total	201	10	110	101	8	45	108	200	9	792	
Pro. Acc.	0.9	0	0.89	0.852	0.125	0.62	0.796	0.899	0.56		
OVERALL ACCURACY = 83.71 KHATT = 0.7987											

Table 4 Error matrix of change classification without NCI

NCI-1	**ACCURACCY ASSESMENT WITH NCI 1**									**Row Total**	**User Acc.**
	F-F	FNF	FOF	NF-NF	NF-OF	OFF	OF-NF	OF-OF	WW		
F-F	183	0	6	0	0	9	0	2	0	200	0.915
F-NF	0	2	0	0	0	0	0	0	0	2	1
F-OF	14	1	96	0	0	2	0	10	0	123	0.781
NF-NF	0	1	0	85	3	0	16	1	2	108	0.787
NF-OF	0	0	0	0	2	1	0	0	0	3	0.667
OF-F	3	0	0	0	1	25	0	3	0	32	0.781
OF-NF	0	6	1	10	0	0	82	8	0	107	0.766
OF-OF	1	0	7	3	2	8	9	176	0	206	0.854
WW	0	0	0	3	0	0	1	0	7	11	0.636
Ref.Total	201	10	110	101	8	45	108	200	9	792	
Pr Acc.	0.9	0.2	0.87	0.842	0.25	0.56	0.759	0.88	0.78		
OVERALL ACCURACY = 83.08 KHATT = 0.7912											

Table 5 Error matrix of classification with NC1-1

NCI-2	ACCURACCY ASSESMENT WITH NCI 2									Row Total	User Acc.
	F-F	F-NF	F-OF	NF-NF	NF-OF	OF-F	OF-NF	OF-OF	WW		
F-F	179	0	5	0	0	7	0	1	0	192	0.932
F-NF	0	1	0	0	0	0	0	0	0	1	1
F-OF	12	1	98	0	0	1	0	8	0	120	0.817
NF-NF	0	0	0	86	2	0	11	0	3	102	0.843
NF-OF	0	0	0	1	1	1	0	1	0	4	0.25
OF-F	8	0	1	0	0	30	0	9	0	48	0.625
OF-NF	0	8	1	11	0	0	84	5	0	109	0.771
OF-OF	2	0	5	3	5	6	13	176	0	210	0.838
WW	0	0	0	0	0	0	0	0	6	6	1
Ref.Total	201	10	110	101	8	45	108	200	9	792	
Prod.Acc	0.9	0.1	0.89	0.852	0.125	0.67	0.778	0.88	0.67		
OVERALL ACCURACY = 83.46 KHATT = 0.7962											

Table 6 Error matrix of classification with NC1-2

NCI-3	ACCURACCY ASSESMENT WITH NCI 3									Row Total	User Acc.
	F-F	FNF	FOF	NF-NF	NF-OF	OFF	OF-NF	OF-OF	WW		
F-F	189	0	10	0	0	11	0	4	0	214	0.883
F-NF	0	0	0	0	0	0	0	0	0	0	DIV/0
F-OF	8	2	92	0	0	1	0	11	0	114	0.807
NF-NF	0	0	0	81	0	0	15	1	3	100	0.81
NF-OF	0	0	0	1	4	0	0	1	0	6	0.667
OF-F	3	0	0	0	0	22	0	2	0	27	0.815
OF-NF	0	8	0	14	0	0	83	6	0	111	0.748
OF-OF	1	0	8	3	4	11	10	175	0	212	0.826
WW	0	0	0	2	0	0	0	0	6	8	0.75
Ref.Total	201	10	110	101	8	45	108	200	9	792	
Prod.Acc	0.9	0	0.84	0.802	0.5	0.49	0.769	0.875	0.67		
OVERALL ACCURACY = 82.32 KHATT = 0.7808											

Table 7 Error matrix of classification with NC1-3

NCI4	ACCURACCY ASSESMENT WITH NCI 4									Row Total	User Acc.
	F-F	F-NF	F-OF	NF-NF	NF-OF	OF-F	OF-NF	OF-OF	WW		
F-F	186	0	7	0	0	11	0	1	0	205	0.907
F-NF	0	3	0	0	0	0	0	0	0	3	1
F-OF	12	2	95	0	0	2	0	11	0	122	0.779
NF-NF	0	0	0	89	3	0	11	0	2	105	0.848
NF-OF	0	0	0	1	1	0	0	0	0	2	0.5
OF-F	1	0	0	0	1	24	0	4	0	30	0.8
OF-NF	0	4	1	9	0	0	88	8	0	110	0.8
OF-OF	2	1	7	2	3	8	9	176	0	208	0.846
WW	0	0	0	0	0	0	0	0	7	7	1
Ref.Total	201	10	110	101	8	45	108	200	9	792	
Prod.Acc	0.9	0.3	0.86	0.881	0.125	0.53	0.815	0.88	0.78		
OVERALL ACCURACY = 84.47 KHATT = 0.8078											

Table 8 Error matrix of with NC1-4

5.1. Map Output and Analysis of Area change

The various change detection maps derived with and without using NCI of different configuration are shown in Figure 3. From the change detection maps generated, total area of each change and no change class is evaluated which is given in Table 9. On the analysis of this table it is found that all the classifiers either with NCI or without NCI are giving an approximately similar area in no change classes (F-F, NF-NF, OF-OF and WW). Within change classes the area detected in OF-NF, OF-F classes are similar but there is too much variation in detection of F-NF and NF-OF classes. This may be due to a lesser number of training pixels in these classes. Considering the average area of all classes for all NCI configurations it is found that forest cover of 28962 ha has degraded (high crown density class to low density class) and 7932 ha is restocked in terms of density.

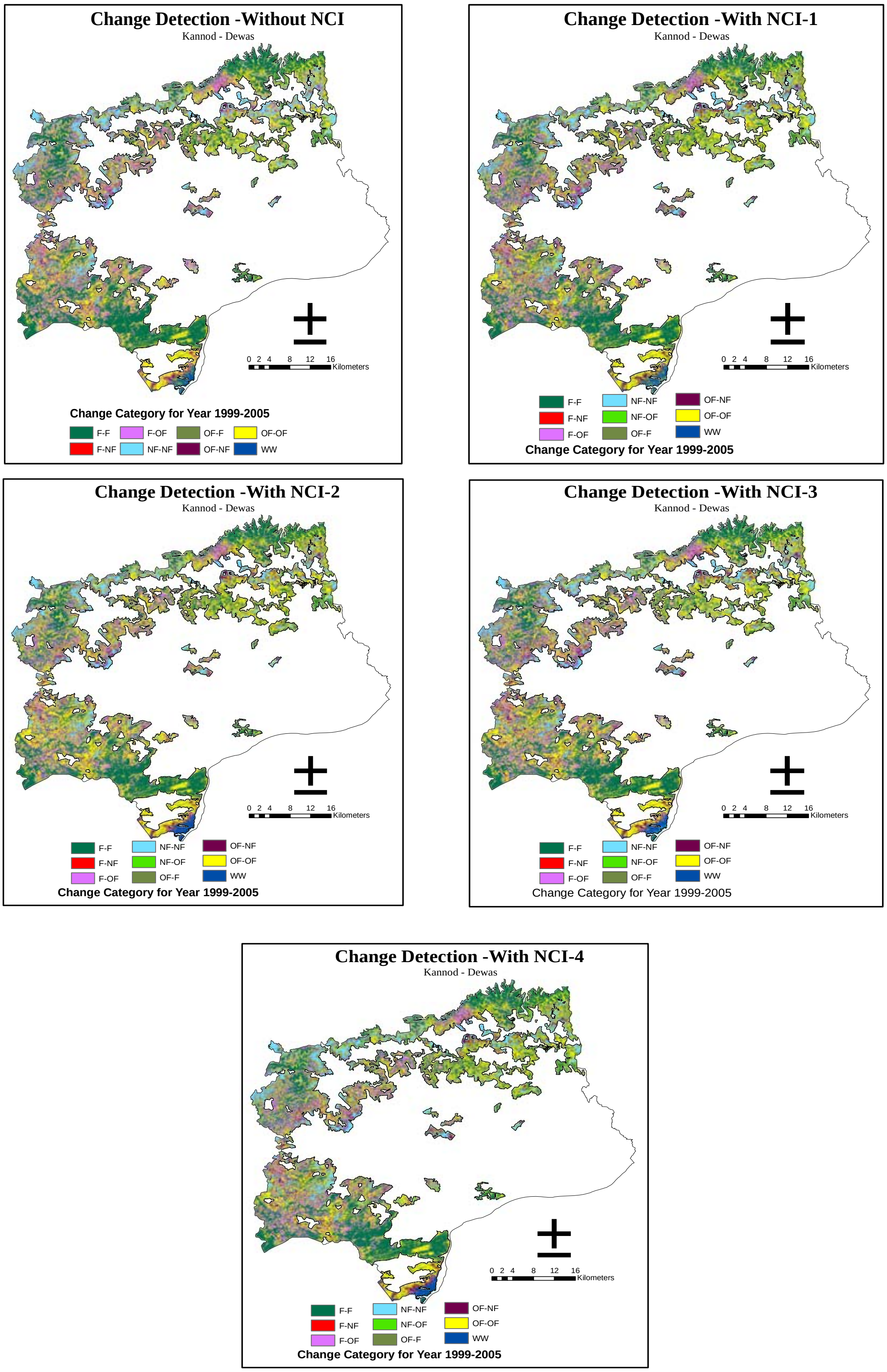

Figure 3 Change detection map with using NCI-4 information

CLASS	F-F	F-NF	F-OF	NF-NF	NF-OF	OF-F	OF-NF	OF-OF	W-W
NCI-O	31499.40	355.70	17956.08	15825.28	1583.96	5589.32	9710.38	27740.68	831.30
NCI-1	27572.41	10.49	16765.04	15185.22	4112.33	5382.89	12987.48	27992.56	1083.68
NCI-2	28861.58	480.62	15544.95	14875.41	2160.62	5307.56	11771.87	31099.74	989.74
NCI-3	28783.71	0.00	16030.71	16185.84	336.71	4883.16	13146.42	30850.78	874.76
NCI-4	28497.65	58.76	17127.21	15447.04	6523.01	3781.59	12865.00	25916.43	875.43

Table 9 Area in hectare under different classes

5.2. Conclusion and recommendation

It can be concluded that NCI information obtained with a smaller window sizes of one, two or three pixel radius does not provide much change information whereas NCI generated from a window of four pixel radius provides best change information and as a result the accuracy achieved by NCI-4 is higher than that of the other NCIs. However, the accuracy of NCI-4 was not significantly better than change detection without NCI. A test study done with much bigger window sizes has established that a bigger window may give more accurate results. Some of the other factors besides the window size which might have influenced the accuracy of change detection based on contextual information in forest landscape are: sub pixel level geo-correction of images, radiometric normalization, phenological characteristic of vegetation, climatic condition at the time of data capture, sensor characteristics and window size. In this study these parameters were kept under manageable limit by using anniversary date dataset from same type of sensor. The outcome of this research can be summarized by concluding that the NCI analysis technique does provide change information but it requires bigger windows for NCI information to become useful when medium resolution imagery is used for change detection in forest. The earlier study done by Jungho and Jensen (2005) using very high resolution imagery (0.7x0.7mts) in urban area has found that NCI size of 3 pixel radius is most suitable but the same is not found applicable in this study. Recommendations that emerge from this research work which can be taken for further study are:-

- On the basis of trial classification using bigger window sizes of 11x11, 15x15 and 17x17, it is found that 15x15 window shows promising result. It is recommended that detailed analysis is done using this window size. It would also be pertinent to analyze the ability of bigger size window in detecting small areas of change.
- One of the important aspects of this study was the use of contextual information in the form of Correlation, Slope and Intercept. Future study may incorporate other contextual information such as entropy.
- Another aspect of the study is selection of bands. The three bands selected for this study are most commonly used for vegetation monitoring but other information layer like DEM and soil type can also be considered for knowledge base creation as forests vegetation is dependent on these variables

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ACKNOWLEDGEMENTS

I am grateful to International Institute of Earth Observation and Geosciences (ITC), The Netherlands, Indian Institute of Remote Sensing (IIRS), Department of Space, GoI and Forest Department, Government of M.P. for giving opportunity and support to do this research work as a part of Masters Course of Geo-informatics. I wish to give special thanks to Mr. C. Jegannathan Course coordinator, IIRS for his active support for this work. This paper has been written as part of the M.Sc Geo-informatics course conducted jointly by IIRS and ITC, The Netherlands.