LAND COVER CHANGE DETECTION USING POLSAR IMAGE

Heena Kaldane[1], DR. Varsha Turkar[2], Prof. Mandar Sohani[3], and Dr. Y. S. Rao[4]
[1]Dept. of Electronics and Telecommunication Engg, Vidyalankar Institute of Technology, Wadala. Mumbai, India,
Email: heenakaldane@gmail.com
[2,3]Dept. of Information Technology, Vidyalankar Institute of Technology, Wadala. Mumbai India,
Email: varshaturkar@gmail.com
Email: mandarsohani@vit.edu.in
[4]CSRE, Indian Institute of Technology-Bombay, Powai, Mumbai-400 076, India,
Email:ysrao@csre.iitb.ac.in

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ABSTRACT: In this paper, a change detection scheme for Polarimetric Synthetic Aperture Radar (PolSAR) images using Normalize Difference Ratio (NDR) is proposed. The NDR change map is compared with change maps obtained using traditional Difference Image (DI), Mean Ratio Detector (MRD) and Log Ratio Detector (LRD) operators. The amplitude information of (HH, HV) and the elements of the coherency matrix (T3) from both the dates are used to generate the change image. Supervised threshold segmentation is used to extract a binary mask for change detection. ALOS-1-PALSAR dual pol L-band images acquired on two different dates are used for this study. The proposed change detection technique is also compared with supervised post classification technique. The result demonstrates that the proposed NDR operator produce much higher detection rate than traditional difference, ratio operators and post classification technique.

1. INTRODUCTION

Land-cover and land-uses are dynamically changing over a period. This change depends on the natural disasters such as earthquakes, floods, forest fires, etc. and man-made structures such as construction of settlements, agriculture practices, industrialization. Collecting this change information by ground-based survey is more accurate than any other method, but it is impractical to do regularly and at short intervals in a rapidly growing large areas. Thus, remote sensing is the best available technique to monitor these changes (Bazi, et al., 2005). The utility of remotely sensed images in change detection has already been proved for urban change detection and disaster monitoring (Mishra et al., 2014, Qong 2004, Turkar et al., 2013). Among the various remote sensing data, Polarimetric Synthetic Aperture Radar (PolSAR) provides data independent of weather conditions and sun illumination. The PolSAR sensor has the capability to collect data over earth surface in various polarization and frequencies. Now high-resolution SAR data is available from Radarsat-2, TerraSAR-X, CosmoSkyMed, RISAT-1, ALOS-1 and ALOS-2 PALSAR, and UAVSAR. It is shown by many researchers that SAR technology can be effectively and accurately used to extract the information about the surface of the Earth.

Change detection methods could be categorized as either supervised or unsupervised according to the nature of data processing. Supervised methods requires ground truth to derive a suitable training set (Lu, D. et al., 2004) for classification. However, unsupervised methods extract information without any prior knowledge information (Bruzzone et al., 2000). These methods can be applied to either pixel or feature vectors, obtained from images. Several approaches have been proposed in the literature to deal with change detection. Most are based on “Difference image (DI)” which is obtained by taking the difference of pre- and post changes of land cover. The straightforward way to generate DI is by Change Vector Analysis (CVA), or a statistical modelling of changes detection (Bazi. et al., 2005), or image ratio (Oliver et al., 2004). Researchers have also used Multitemporal Coherency Analysis (Rignot et al., 1993), Fuzzy-Rule-based Analysis (Li et al., 2004), and Kernel C-means clustering techniques for change detection (Fazel et al., 2013). Some of the likelihood ratio tests have been used for classification and change detection such as maximum likelihood (Lombardo et al., 2002) and complex wishart distribution (Conradsen et al., 2003). Recently, a region based changed detection has been introduced for PolSAR images using Wishart Mixture Model (Yang et al., 2016). For unsupervised SAR change detection, generalized Gaussian model method and generalized minimum-error thresholding methods have been proposed by Moser et al., 2006. To find optimum change and unchanged classes, Markov Random Field (MRF) model is used in Kasetkasem, et al., 2002. Similarly, Support Vector Machines (SVM) is used for unsupervised change detection which uses binary classification of changed and no changed classes (Bovolo et al., 2008). Akbari et al. (2015) proposed a method for SAR change detection based on relaxed Wishart distribution.

In this paper, unsupervised NDR technique is analysed. The change maps are also produced by DI, MRD, LRD and NDR methods. These change map techniques are pixel based techniques. The mean-ratio detector (MRD) is based on the ratio of local intensity of pixel. The log-ratio detector (LRD) reduces the effect of multiplicative speckle noise by performing a logarithm operation on the ratio of local mean. These ratio operators are robust to speckle, but they are limited to the first-order statistics since the mean intensity of pixel is considered. Therefore, if the mean values of pixel remain the same, they are not able to detect changes and they by increasing miss detection rate.

2. **STUDY AREA AND DATA SET**

The two datasets from ALOS-1 PALSAR dual polarized (HH,HV) data acquired on June 16, 2007 and on June 24, 2010 with 24m ground resolution are used for effectiveness of the proposed. Study area is Mumbai city and surroundings and has several land-use and land-cover types including urban, forest, mangroves, water bodies, bare land wetland etc. Mumbai city lies at the mouth of the Ulhas River on the western coast of India, in the coastal region known as the Konkan. It is an island connected to the Thane district. The change is mostly related to settlement as population of Mumbai has more than doubled since 1991(Villaitramani, et.al 2014). As the population increases the wetlands and mangroves forest are under pressure. Wetlands cover 1.12% of total land area in the Mumbai metropolitan region and are declining day by day (Oren et al., 2006). Mumbai is experiencing disorganized growth with a high intensity of urban sprawl. This leads to increase in pressure on urban infrastructure and ecosystem. If this pattern of growth is continued, it will lead to unsustainable development. To prevent this, new effective management systems should be introduced on priority. PolSAR images will be useful to find out changes on land cover.

3. METHODOLOGY

The change detection using DI method is obtained by finding the difference between two POLSAR images acquired on two dates. However due to existing of speckle noise, the difference method does not provide accurate change for POLSAR data. Therefore, ratio of images HH/HV is preferred for generation of change detection. The proposed method is like (Mishra et al., 2013) but with different data set and the result of NDR is compared with Difference image and Log Ratio Operator.
SAR change detection involves four major basics steps:
1. Preprocessing: filtering and co-registration
2. Difference map extraction
3. Threshold segmentation
4. Accuracy Measurement

For change detection applications, ALOS-1 PALSAR images (two images) must be precisely co-registered. The proposed system is explained with the help of flow chart shown in Figure 1

3.1 Pre-processing

Speckle act as a barrier in the analysis of POLSAR data. It complicates the task of segmentation and classification. Pre-processing of SAR data is done using speckle reducing filters. To reduce the speckle noise present in the SAR image, enhanced Lee filter of window size 5 × 5 was implemented.

3.2 Change Map Generation

The SAR backscattering values at two date's t1 and t2 obtained from co-registered images is used to calculate Normalize difference ratio (NDR). The NDR method produces less error than the difference and ratio method which is proven below. Therefore, NDR operator has been adopted in this study. The NDR operator used for generating change map is given as

$$\text{NDR change}=\frac{a2-a1}{a2+a1} \tag{1}$$

where a2 and a1 are the SAR backscattered magnitude of coregistered data set t2 and t1 respectively. Now comparing the errors generated from NDR and simple ratio image. The NDR ratio (1) can be rewritten as follows:

$$c=\frac{a2-a1}{a2+a1} \tag{2}$$

where *c* is the change image generated from NDR operation.
According to the law of error propagation, the variance of NDR operator σ^2_c can be derived as follows:

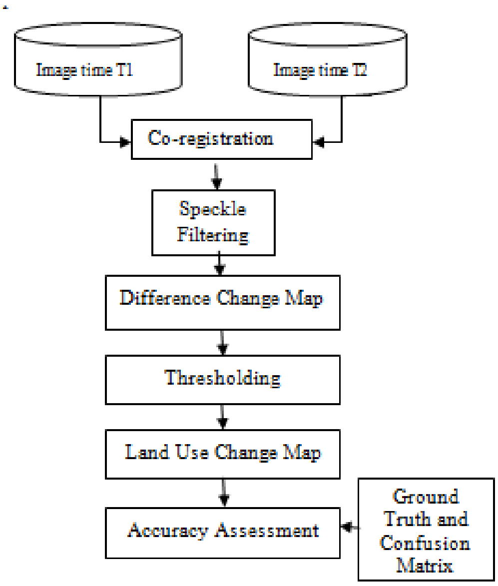


Figure1. Flow chart illustrating the methodology for change detection.

$$\sigma_c^2 = \left\{ \frac{d}{da1}\left(\frac{a2-a1}{a2+a1}\right)\right\}^2 \sigma_{a1}^2 + \left\{ \frac{d}{da2}\left(\frac{a2-a1}{a2+a1}\right)\right\}^2 \sigma_{a2}^2$$

$$\sigma_c^2 = \frac{4a2^2}{(a2+a1)^4}\sigma_{a1}^2 + \frac{4a1^2}{(a2+a1)^4}\sigma_{a2}^2.$$

Assuming that the variance of a1, (σ_{a1}^2) and a2, (σ_{a2}^2) are equal and substitute them by σ_a^2 we get

$$\frac{\sigma_c^2}{\sigma_a^2} = \frac{4(a2^2+a1^2)}{(a2+a1)^4} \tag{3}$$

Similarly, the ratio operator is defined as

$$r = \frac{a2}{a1} \tag{4}$$

where r is the image generated from ratio operator, a1 and a2 are the backscattering magnitude at two dates. According to the law of error propagation, the variance of ratio operator can be calculated as follows:

$$\sigma_r^2 = \left\{ \frac{d}{da1}\left(\frac{a2}{a1}\right)\right\}^2 \sigma_{a1}^2 + \left\{ \frac{d}{da2}\left(\frac{a2}{a1}\right)\right\}^2 \sigma_{a2}^2$$

$$\sigma_r^2 = \frac{a2^2\sigma_{a1}^2 + a1^2\sigma_{a2}^2}{a1^4}.$$

Similarly to the NDR operation, (σ_{a1}^2) and (σ_{a2}^2) are equal and substitute them by σ_a^2 we get

$$\frac{\sigma_r^2}{\sigma_a^2} = \frac{(a2^2+a1^2)}{a1^4}. \tag{5}$$

Dividing (3) by (5) gives

$$\frac{\sigma_c^2}{\sigma_r^2} = \frac{4a1^4}{(a2+a1)^4} \tag{6}$$

The right-hand side of (6) is less than 1 for all values of a2>0.414a1. This shows that the variance of ratio operator is smaller than the variance of NDR operator only if the backscattering intensity is decreased heavily, i.e., a2 < 0.414a1. The ratio operator is better than NDR in very limited combination of backscattered amplitude. For ratio operator, as the variance increases, the probability of error in detecting changes increases (Bhogendra M. et al., 2014). Thus, the proposed NDR operator produces less error than ratio method.

The difference map generation using NDR algorithm, along with the change map using simple difference, Log difference and log ratio image for the HH is shown in Figure 2. Bright areas indicate increase in backscattering intensity (positive change), whereas dark areas indicate decreased backscattering intensity (negative change) and the smooth area indicating no change in corresponding images. The mixed areas i.e. bright and dark composed of those pixels having value around 0. In POLSAR imagery the change obtained by backscattering values or backscattered intensity is always high for land cover (double bounce scattering) than the change in backscattered intensity due to volume and surface bounce scattering.

3.3 Thresholding

A manual thresholding is applied to obtain binary segmentation of difference map. The difference map after thresholding is classified into changed and unchanged classes. The Gaussian distribution range $\mu \pm 3\sigma$ covers almost all pixels around 99.85% and rest is assumed to be noise. In Figure 3 the change region indicated in black pixels.

3.4 Accuracy Measurement

The generated change image gives three classes: no change, increase intensity and decreased intensity. A binary confusion matrix is used to estimate the overall land cover change and accuracy for an allocation into change and no change classes. The kappa coefficient is one measure parameter to estimate the accuracy of proposed method. Accuracy of NDR operator for change detection is visually analysed with the help of Google Earth images which are acquired with approximately same dates as PALSAR images were acquired.

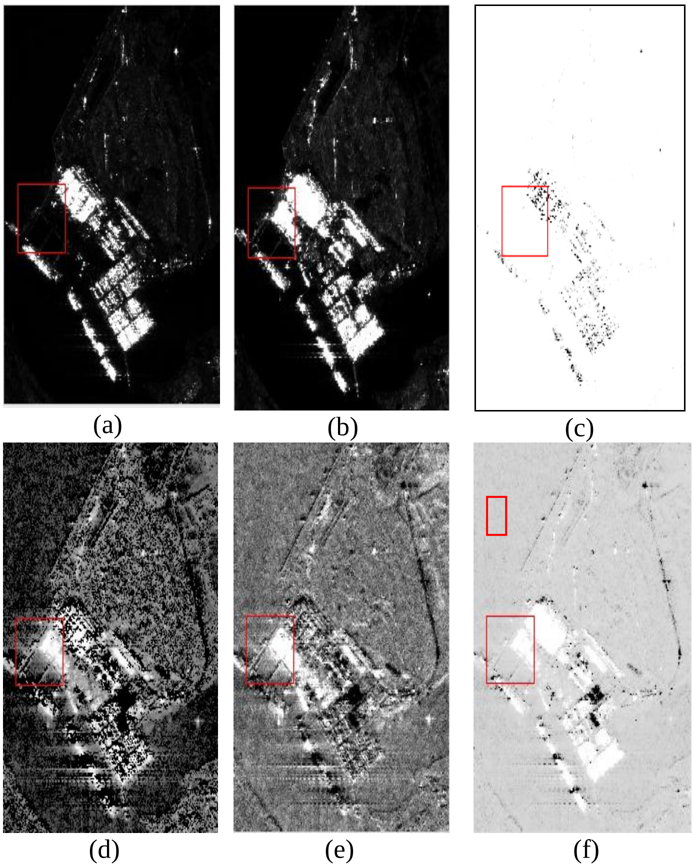
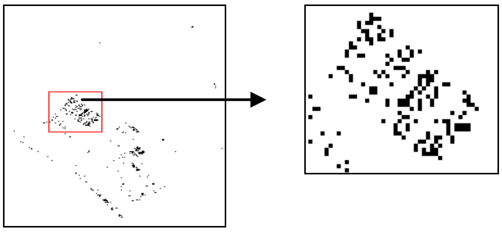
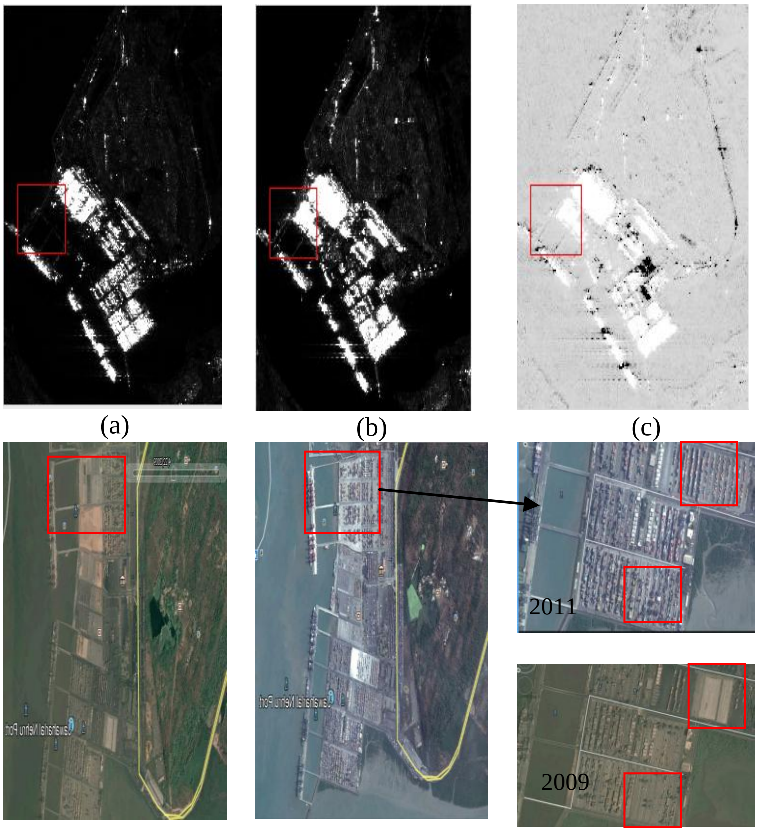


Figure 2. SAR intensity and change maps of a small part of Mumbai close to Jawaharlal Nehru Port Trust using various methods are shown. (a) SAR intensity image of 2007. (b) SAR intensity image of 2010. (c) Simple Difference image. (d) Log Difference (e) Log Ratio and (f) NDR Smooth Area Mixed Area



(a) (b)

Figure 3. Thresholding on NDR change image.



(a) (b) (c)

(d) (e)

Figure 4. Change obtained near Jawahar Nehru Port Trust area Mumbai: (a) SAR intensity image of 2007. (b) SAR intensity image of 2010. (c) NDR change image. (d) Corresponding Google Earth image acquired on June 2009. (e) Corresponding Google Earth image acquired on Jan. 2011.

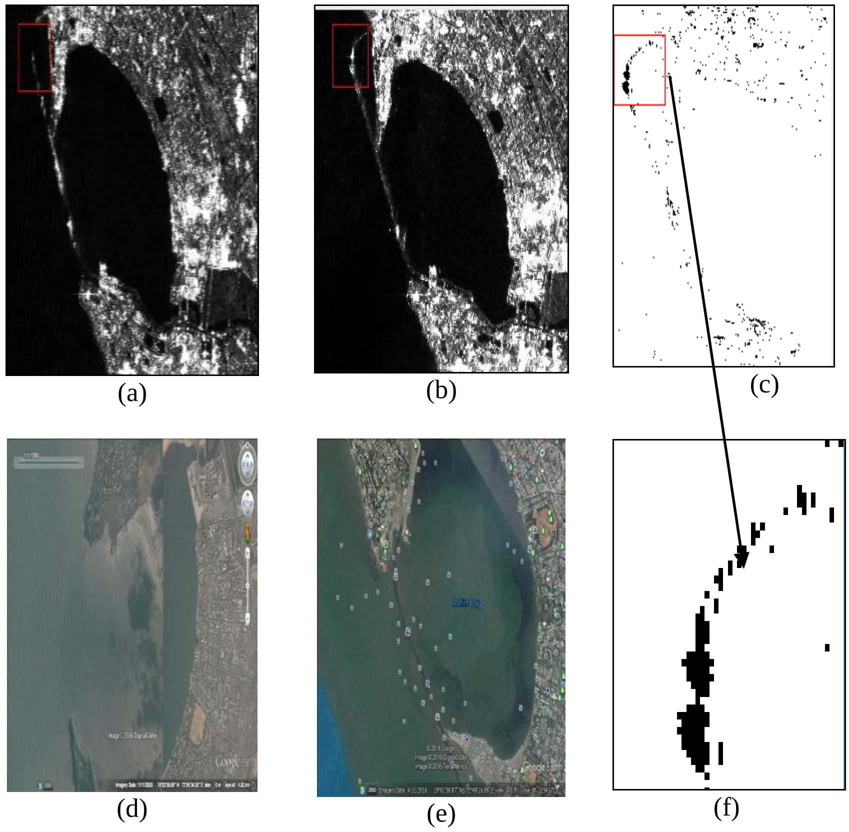


Figure 5. Accuracy measurement using Google Earth: (a) June 2007 PALSAR intensity image. (b) June 2010 PALSAR intensity image. (c) NDR change image. (d) Corresponding Google Earth image acquired on June 2000. (e) Corresponding Google Earth image acquired on May 2010.

The Worli sea link of Mumbai was under construction and it's not completed since June 2007. The change obtained after completion of bridge is clearly shown by NDR segmented image [Figure 5 (f)]. By visual inspection it is clear that proposed methodology for change detection provides better change information. The results are shown using HH component. Similarly, the same procedure is applied on HV.

4. RESULT AND DISCUSSION

In this paper, an unsupervised change detection approach for dual polarimetric SAR images has been presented. Figure 1 presents an overview of this paper. It starts with preprocessing step with co-registration and speckle filtering. In the second step, an unsupervised technique is adopted to generate difference map images using proposed NDR method. The proposed method is compared with traditional DI, MRD, and LRD methods. Then these change maps are subjected to represent in binary map by supervised threshold segmentation. The proposed unsupervised NDR technique is best suited for change detection compared to all the traditional difference methods, shown in figure 2. The last step is to analyze the accuracy of proposed method. The experimental PolSAR images have the positive (increased backscattering intensity) and negative changes (decreased backscattering intensity). The manual trial and error procedure (MTEP) thresholding technique is used for experiment. The kappa coefficient obtained by NDR for 255x286 ROI is 0.81 and overall accuracy is 95.18%. While the kappa coefficient obtained by MRD and LDR are 0.16 & 0.34 respectively for the same ROI, and the overall accuracy is 65.60% for MRD and 66.67% for LDR. Also, results are computed with and without speckle filter. The kappa coefficient is increased to 0.71 to 0.78 and accuracy to 88.75% by removing the speckle noise using Enhanced Lee filter with window size 5x5 for the full scene of HH. Similarly, the study area is classified using Minimum distance supervised classifier.

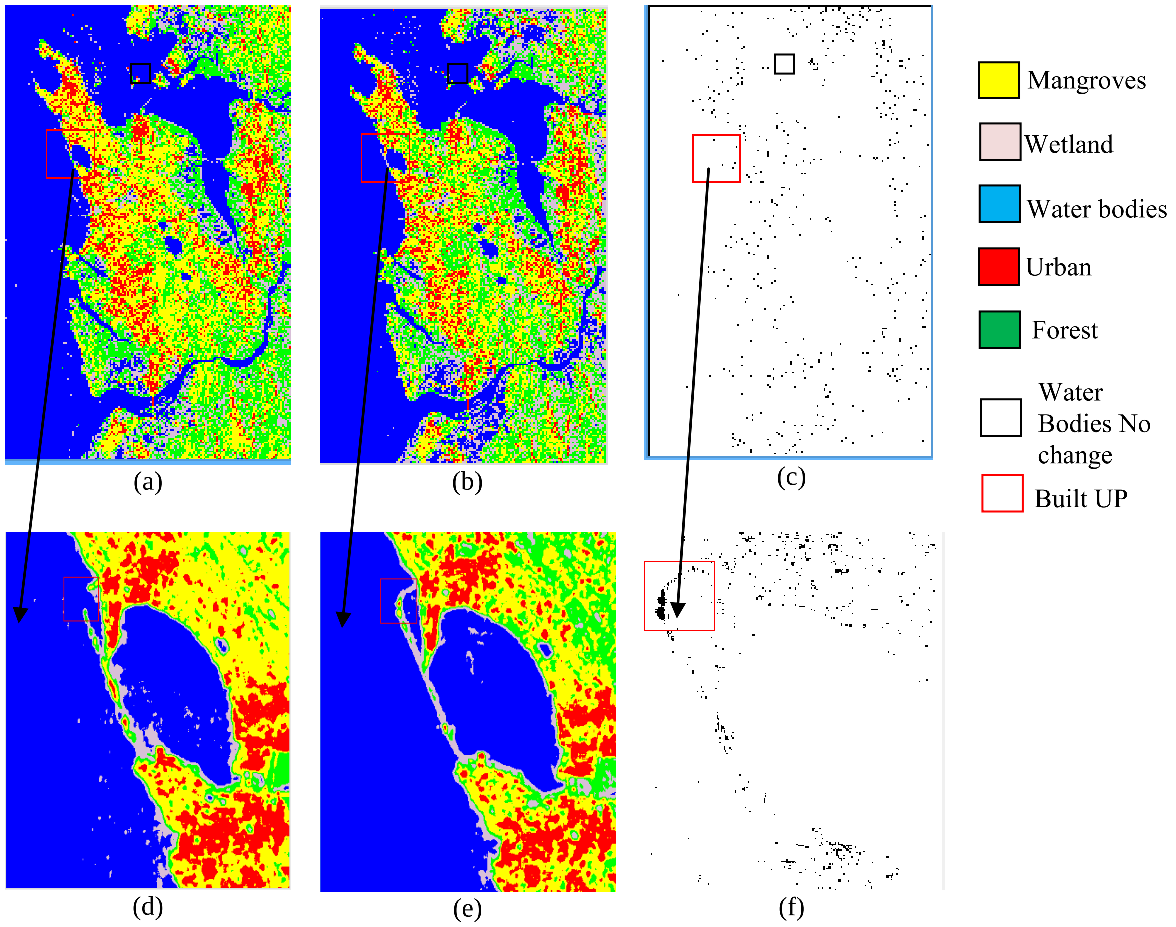


Figure 6. Computing proposed technique with post classification technique: Supervised classification of study areas taken (a) in June 2007 and (b) in June 2010. (c) Unsupervised change generated image using NDR operator. (d) ROI of Worli sea link under construction in 2007, (e) ROI of Worli sea link after completion in 2010, (f) Change obtained in ROI using NDR.

The accuracy of change is also analyzed with classified image, where land is classified into several classes including settlement, water, Forest, Mangroves and wetland. NDR change has accurate change information of Worli sea link as classified urban class near Worli in figure 6. The statistical change obtains from experimental data sets after post classification: for urban, positive change obtained is 18.88%, and for wetland are 23.16% changes. Up to 14.03% decrease in Forest areas and 8.83% decrease found in Mangroves for 255x286 ROI of HH taken from data set. The kappa coefficient obtained by supervised method is 0.67 which less than unsupervised NDR technology. Supervised classification has some misclassified pixels due to presence of speckle noise and due to improper selection of training sets. It is observed that unsupervised NDR gives exact change in whole target area independence of any training sets. Thus, the unsupervised technique for change detection is better suited than supervised technique.

5. CONCLUSION

The proposed NDR operator for change detection is providing more accurate change in land cover. The proposed algorithm can be suited to all kind of multitemporal spaceborne or airborne data. For Mumbai city, the change obtained in dual-pol data can be compared with full pol data to get more statistical information of land use and land cover.

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