OPTICAL AND SAR DATA INTEGRATION FOR AUTOMATIC CHANGE PATTERN DETECTION

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Commission VII, WG VII/5, VII/6

KEY WORDS: Change type detection; data fusion; optical images; SAR images; NDVI; NDR;

ABSTRACT:

Automatic change pattern mapping in urban and sub-urban area is important but challenging due to the diversity of urban land use pattern. With multi-sensor imagery, it is possible to generate multidimensional unique information of Earth surface features that allow developing a relationship between a response of each feature to synthetic aperture radar (SAR) and optical sensors to track the change automatically. Thus, a SAR and optical data integration framework for change detection and a relationship for automatic change pattern detection were developed. It was carried out in three steps: (i) Computation of indicators from SAR and optical images, namely: normalized difference ratio (NDR) from multi-temporal SAR images and the normalized difference vegetation index difference (ΔNDVI) from multi-temporal optical images, (ii) computing the change magnitude image from NDR and ΔNDVI and delineating the change area and (iii) the development of an empirical relationship, for automatic change pattern detection. The experiment was carried out in an outskirts part of Ho Chi Minh City, one of the fastest growing cities in the world. The empirical relationship between the response of surface feature to optical and SAR imagery has successfully delineated six changed classes in a very complex urban sprawl area that was otherwise impossible with multi-spectral imagery. The improvement of the change detection results by making use of the unique information on both sensors, optical and SAR, is also noticeable with a visual inspection and the kappa index was increased by 0.13 (0.75 to 0.88) in comparison to only optical images.

1. INTRODUCTION

As hundreds of thousands of people are migrating from rural to urban area every year, land cover/use classes in urban and suburban areas are changing rapidly and this trend is likely to increase in future. In addition to that, several human interventions such as agricultural practice, deforestation, reforestation, dam construction etc. make a big changes in the Earth’s surface. Thus, continuous monitoring is very important in several aspects including infrastructure planning and development to environmental monitoring, etc. Change information detected from the multi-temporal remote sensing images is deemed to be extremely useful (Dierking and Skriver 2002; Hayes and Sader 2001; Liao et al. 2008; Mishra and Susaki 2013; Du et al. 2013). Mainly, optical and radar images have used for change detection independently as well as in a combination with each other or with ancillary dataset. In case of optical image, the normalized difference vegetation index (NDVI) is the major index while the change in vegetation is monitored by preserving spectral information (Du et al. 2013; Hong et al. 2009). In addition to that, SAR and optical image fusion is driven from better land cover classification or some specific structure detection. Tupin and Roux (2003) have used the SAR and optical data for building outline detection using feature based fusion approach in one of their studies. Their study showed that SAR images are capable to show the building presence and optical images are good for the shape delineation complementary information about building presence and proper shape extraction. They carried out it in two steps: first, extraction of partial potential building footprints on the SAR image and then shape detection in the optical one. Hong et al. (2009), proposed a fusion method based on wavelet-IHS transformation for SAR and optical multi-spectral (MS) images that was mainly motivated to preserve the spectral information of MS images and spatial detail of high resolution SAR image. (Hong et al. 2014), in another work for grassland and alfalfa segmentation, the same fusion technique was implemented. The fusion results gave spatial details of relatively high spatial resolution of SAR imagery and spectral detail was obtained from Moderate-resolution Imaging Spectroradiometer (MODIS) image. Major concern was again to improve the spatial resolution. As presented, several data fusion techniques are available, which allow better analysis and interpretation by making use of complementary information. Very few fusion works were inspired by the change detection (Du et al. 2012; Du et al. 2013; Hong et al. 2009), however none of them were motivated from automatic change pattern detection. Multi-class change detection based on IHS on SAR images are available (Malilla 1980; Johnson and Kasischke 1998) but the discriminated classes are very limited due to the lack of enough information in MS images. Even though,

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the number of discriminated classes are limited, the CVA is a good approach for making use of MS information. Consequently, it could be a very good approach for information fusion that is obtained from optical and SAR imagery. It is known that the unique signature of SAR and optical images for each land use/cover feature is stable and site independent, in the similar weather and light condition for optical imagery and same configuration in case of SAR images, it is possible to develop a relationship between them and can deploy for an automatic change pattern detection.

In this study, an empirical relationship is developed by using the unique response from major features in the Earth’s surface in SAR and optical imagery and deployed for automatic change pattern detection. Before that, a change area is segmented through CVA-based SAR and optical information fusion. The fusion is motivated to use the complementary information without losing the inherent information that comes either from SAR or from optical images for better change detection. Specifically, it is expected to improve the sharpness of the detected feature, or be able to detect the changed features that were otherwise not possible from a single data source.

The data used in this study are described in Section 2. Section 3 explains about statistical analysis. Section 4 reveals the methodology followed. The results and discussion is reported in Section 5. Finally the conclusions are presented in Section 6.

2. STUDY AREA AND DATA USED

2.1 Study area

For an experimental purpose, a section of approximately 19 × 20 km in an outskirts part of the Ho Chi Min City was selected. Figure 1 shows the study area. The major events occurred in the area were constructions, deforestation and smoothing of agricultural land that causes the changes on agricultural land to bare land (preparation for construction), forest to bare land, bare land or agricultural land to built-up area or under-construction area. These are believed to be the major changes while expanding the urban area all over the world; therefore, study poses a sufficient generality.

2.2 Data used

HH component of two fully Polarimetric Synthetic Aperture Radar (PolSAR) images acquired by the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) in April 2007 and April 2011 were used. Similarly, the Landsat-7 band 3 (Visible Red) and band 4 (Near InfraRed) acquired by the Enhanced Thematic Mapper Plus (ETM+) images nearly the same date as PALSAR images were considered. Table 1 shows the detail of all images used in this study.

Since all images used in this study were acquired on nearly the same time of year (April), all the changes due to agricultural practices were ignored. Additionally, the different intensity of precipitation may cause the various levels of vegetation growth even in the same season of the year, thus the years (2007 and 2011) with normal precipitation records were selected for the study. Hence, all the phenological changes were also ignored and focused solely on the change due to the human intervention. The results were evaluated based on Advanced Visible and Near Infrared Radiometer type-2 (AVNIR-2) optical data acquired nearly the same time with PALSAR images and a very high-resolution (less than 1 m) QuickBird images in Google Earth.

3. STATISTICAL ANALYSIS

The backscattering coefficients and NDVI value of five major features (water body, bare land, grassland, forest and building) in the area were calculated and saved for analysis. Table 1 shows the sample pixels used in the analysis from both optical and SAR imagery for each land use/cover feature type, the sample pixels were more than 1000, and assumed that this signature is site independent. Figure 2 (a) represents the NDVI for major five features, and Figure 2(b) represents the backscattering coefficients of HH polarimetric component for the same features.

While generalizing these five features, we considered grassland, forest and agricultural land (with crop plantation) as a vegetation area and identified the following possible change types. Inundation (vegetation, built-up or bare land to water bodies) and vice versa (water body to vegetation, built-up or bare land), bare land to vegetation and vice versa, bare-land to built-up and vice versa, vegetation to built-up and vice versa. Statistical analysis has been done for NDVI and SAR backscattering responses in earlier and later imagery for the above-mentioned possible change types and presented in Figure 3. Some change types are equally sensitive to the SAR and optical sensors e.g. vegetation to bare-land and vice versa, some have reverse effect such as: vegetation to built-up and vice versa and some are sensitive to one sensor whereas not in another, such as building construction in a bare land or building to bare land change. Similarly, some greenery appears in grassland or pastureland is not sensitive in some SAR sensor with relatively longer wavelength. Therefore, the complementary information available in multi-sensor images paves the way for further analysis.

4. METHOD

The process flow diagram for the optical and SAR image fusion for change detection and automatic pattern detection is presented.
4.1 Preprocessing

4.1.1 Calibration and gap filling for Landsat data: The Landsat L1T image has been used in this study. Atmospheric correction was done using ENVI 5.0 in which the raw digital number (DN) values were converted into surface reflectance. The calibrated images were then subjected for filling gaps (Scaramuzza et al. 2004). The image acquired in March 31, 2007 and April 11, 2011 were the main considered image and dated on May 2, 2007 was used for filling gaps in March 31, 2007 and image acquired on March 8, 2011 was used to fill the gap in the image acquired in April 11, 2011.

4.1.2 PALSAR images - geometric correction and coregistration: All images were geometrically corrected using 30 m ASTER Global Digital Elevation Model (GDEM) using ASF Map-Ready 3.2. The images were geo-coded with Universal Transverse Mercator (UTM) system and co-registered with Landsat imageries with 19 ground control points selected manually in ENVI 5.0, where the overall error was less than a single pixel. The nearest neighbors re-sampling was used at this stage.

4.2 Derivation of change from different sensor images

4.2.1 Normalized difference ratio from SAR images: A normalized form of ratio, normalized difference ratio (NDR), operator is used to generate the change image from multi-temporal SAR images. The NDR operator generates pixel value from -1 to +1. All no-change pixels are clustered around 0, while all the change pixels are deviated far from 0. The NDR operator (Mishra and Susaki 2013) is defined as Equation (1).

\[ NDR(t_1, t_2) = \frac{A_{t_2} - A_{t_1}}{A_{t_2} + A_{t_1}} \]  

where, \( A_{t_1} \) and \( A_{t_2} \) are amplitudes of co-registered images acquired on two dates \( t_1 \) and \( t_2 \), respectively.

4.2.2 NDVI difference (\( \Delta NDVI \)) image: The NDVI gives the vegetation greenness, and thus it is very useful to study the surface dynamics. NDVI at date \( t \) for Landsat TM/ETM+ is defined as Equation (2).

\[ NDVI(t) = \frac{\rho_{4,t} - \rho_{3,t}}{\rho_{4,t} + \rho_{3,t}} \]  

where \( \rho_{3} \) and \( \rho_{4} \) are reflectance of TM/ETM+ band 3 and 4, respectively. The difference of NDVI, \( \Delta NDVI \), is derived by Equation (3):

\[ \Delta NDVI = NDVI(t_2) - NDVI(t_1) \]
4.3 Fusion of NDR and \( \Delta \text{NDVI} \) for change detection

As discussed in Section 3 some changes are sensitive to both sensors however, others are sensitive in only one. Therefore, they have some complementary information, which are important for full dimensional change detection. We devise two different data fusion techniques in order to make use of complementary information that can capture all changes.

4.3.1 Decision level fusion: Decision level fusion is common for multi-sensor image fusion, specifically in SAR and optical imagery and motivated from classification. In this study, we have developed a change map through thresholding of both change images independently, namely NDR image, that was derived from two multi-temporal SAR amplitude images from Equation (1), and \( \Delta \text{NDVI} \) image, derived from two multi-temporal NDVI image generated from the Equation (3). Union of the detected changed area was carried out to get the final change map. The Figure 5. (a) represents the procedure for the change detection process using decision level fusion.

4.3.2 Change vector analysis (CVA): Change vector analysis is a well-established change detection method for multi-spectral images (Malila, 1980; Johnson and Kasischke, 1998). Even though the CVA is well-accepted methodology for multi-spectral images, it is new for optical and SAR integration.

For all land cover/use status, we assume that the quantity of land cover/use status in optical and SAR response, \( f \), can be expressed as follows:

\[
f = f(N, B)
\]

where \( N \) denotes \( \text{NDVI} \) obtained from optical sensor and \( B \) denotes backscatter from SAR, respectively. When we take a partial derivative of Equation (4), with respect to \( t \), Equation (5) is derived:

\[
\frac{df}{dt} = \frac{df}{dN} \frac{dN}{dt} + \frac{df}{dB} \frac{dB}{dt}
\]

Assuming \( N \) and \( B \) are independent to each other, amplitude of the change, \( A \), can be written as:

\[
A = \left| \frac{df}{dt} \right| = \sqrt{\left( \frac{df}{dN} \frac{dN}{dt} \right)^2 + \left( \frac{df}{dB} \frac{dB}{dt} \right)^2}
\]

Now, we assume \( f \) as a simple linear function in Equation (7)

\[
f = a_1 N + a_2 B + a_3
\]

Equation (6) can be rewritten as Equation (8):

\[
A \approx \sqrt{a_1^2 \left( \frac{\Delta N}{\Delta t} \right)^2 + a_2^2 \left( \frac{\Delta B}{\Delta t} \right)^2}
\]

By adding another assumption that \( \left| a_1 \right| = \left| a_2 \right| \), Equation (9) is derived:

\[
A \approx \sqrt{\left( \frac{\Delta N}{\Delta t} \right)^2 + \left( \frac{\Delta B}{\Delta t} \right)^2} \approx \sqrt{\Delta N^2 + \Delta B^2}
\]

Now, \( \Delta N = \text{NDVI}(t_2) - \text{NDVI}(t_1) \) and \( \Delta B = B(t_2) - B(t_1) \approx \text{NDR}(t_1, t_2) \) expressed by Equation (1). Then, Equation (9) can be rewritten in the form of \( \Delta \text{NDVI} \) and NDR as follows:

\[
A = \sqrt{\Delta \text{NDVI}^2 + \Delta \text{NDR}^2}
\]

Equation (10) represents a change magnitude from both optical and SAR images. A threshold value in this image was identified with manual trial and error procedure that can segment change and no-change area. The overall procedure is presented in Figure 5 (b).
that, the change detection map obtained from proposed methodology was evaluated with the change map obtained from the high-resolution AVNIR images and very high-resolution images from Google Earth interactively in selected areas.

In order to evaluate the results quantitatively, confusion matrix was used. This allocates the change and no change class and its expected value is derived using those in a corresponding ground reference data set. The confusion matrix allows deriving numerous summary measures of the accuracy of the allocated classes and amount of change that has occurred. The considered accuracy measures are user’s accuracy, producer’s accuracy, error of omission, error of commission, overall accuracy and kappa index (Foody 2010).

5. RESULTS AND DISCUSSION

5.1 Change detection

The change map was generated through the proposed fusion techniques. The obtained results were compared with the results obtained from ∆NDVI, NDR and widely used multi-spectral change vector analysis (CVA) for Landsat imagery (Malila 1980; Jhons and Kasischke 1998). Threshold values for each of the input change images was obtained with MTEP and implemented in an ENVI 5.0 that segmented the changed area from no-change area. For the visual analysis, a false color composite of Landsat imagery was used. Figure 7 represents the false color composite of Landsat imagers in (a) 2007 and (b) 2011 and (c) and (d) are the interested zoom-in sites corresponding to the images acquired on 2007 and 2011 respectively. These figures and interested zoom-in sites were considered as a ground truth and the results obtained from each input change image were compared with a simple visual inspection.

Figure 8 illustrates the change image, corresponding change map and zoom-in change map in interested sites corresponding to the interested sites in Figure 7 for all input datasets. Figure 8 (a) (c) represents the change vector magnitude (CVM) from tasseled cap transformation of Landsat-7 ETM+, corresponding change map and zoom-in map of the interested areas, similarly Figure 8 (d) (f) are for the NDVI, Figure 8 (g) (i) are for the NDR, Figure 8 (j) (l) for proposed CVM generated from ∆NDVI and NDR and Figure 8 (m) (n) are for the union of change map obtained from

ΔNDVI and NDR.

While comparing the grayscale change image in Figure 8 (a), (d), (g) and (j), some images are better than others even though all of them are in the same spatial resolution. ∆NDVI (Figure 8 (d)) and NDR (Figure 8 (g)) appear to be smoother than other two, however, NDR images are not as smooth to ∆NDVI. In these images, bright and dark colors represent the change areas whereas the moderately gray area is for no-change. Regarding the change images obtained from the CVM using Tasselled cap transformation (Figure 8 (a)) and CVM using ∆NDVI and NDR (Figure 8 (j)), both appear to be more contrast between change and no-change area. In these images, the bright color represents the change area and dark color represents no-change area.

As far as the change map results and their corresponding zoom-in areas are concerned, the change map obtained only from optical or SAR imageries have several errors of commission and omission. For example, using only optical imageries (Figure 8 (b), (c)) site (ii) has a big error of omission and site (iv) has big error of commission. However, while considering the NDR image (Figure 8 (e), (f)) site (iv) all are missing and almost all detected areas are not same to the actual shape in the field. Similarly, while comparing the results obtained from integrating the results from NDR and NDVI, in Figure 8 (m), (n) the resulting the consider-

<table>
<thead>
<tr>
<th>Observation</th>
<th>Zone</th>
<th>Change type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDR</td>
<td>NDVI</td>
<td>Increase</td>
<td>I</td>
</tr>
<tr>
<td>Increase</td>
<td>No change</td>
<td></td>
<td>II</td>
</tr>
<tr>
<td>Increase</td>
<td>Decrease</td>
<td></td>
<td>III</td>
</tr>
<tr>
<td>No change</td>
<td>Increase</td>
<td></td>
<td>VII</td>
</tr>
<tr>
<td>No change</td>
<td>No change</td>
<td></td>
<td>Center</td>
</tr>
<tr>
<td>No change</td>
<td>Decrease</td>
<td></td>
<td>IV</td>
</tr>
<tr>
<td>Decrease</td>
<td>Decrease</td>
<td></td>
<td>V</td>
</tr>
<tr>
<td>Decrease</td>
<td>No change</td>
<td></td>
<td>VI</td>
</tr>
<tr>
<td>Decrease</td>
<td>Increase</td>
<td></td>
<td>VII</td>
</tr>
</tbody>
</table>

Table 2: Relationship between NDR and ΔNDVI with land use/cover change type, and associated zones in ΔNDVI vs. NDR plane.

| Table 3: Change detection accuracy assessments for several approaches. |
|-------------------|------------------|----------------|
| Input data set    | Over all accuracy | Kappa coefficient |
| ΔNDVI             | 88.23            | 0.73            |
| NDR               | 89.13            | 0.74            |
| CVA - MS image    | 90.36            | 0.75            |
| NDVI ∪ NDR       | 85.69            | 0.69            |
| CVA - NDVI, NDR  | 94.7             | 0.88            |
Table 4: Generalized relationship between NDR and ∆NDVI with land use/cover change type.

<table>
<thead>
<tr>
<th>Class</th>
<th>Response</th>
<th>NDR</th>
<th>NDVI</th>
<th>Change type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>Increase</td>
<td>No change</td>
<td>Decrease</td>
<td>Increase</td>
</tr>
<tr>
<td>Class 2</td>
<td>Increase</td>
<td>No change</td>
<td>Decrease</td>
<td>Increase</td>
</tr>
<tr>
<td>Class 3</td>
<td>Increase</td>
<td>Decrease</td>
<td>Decrease</td>
<td>Vegetation to built-up</td>
</tr>
<tr>
<td>Class 4</td>
<td>No change</td>
<td>Decrease</td>
<td>Decrease</td>
<td>Vegetation to bare land</td>
</tr>
<tr>
<td>Class 5</td>
<td>Decrease</td>
<td>No change</td>
<td>Decrease</td>
<td>Built-up to bare land</td>
</tr>
<tr>
<td>Class 6</td>
<td>Decrease</td>
<td>Increase</td>
<td>Decrease</td>
<td>Built-up to vegetation</td>
</tr>
</tbody>
</table>

5.2 Automatic multi-class change labelling

The change map developed through the CVA based SAR and optical information fusion approach was subjected to automatic change labeling. The results obtained from the relationship presented in Table 2 suggested that the increase or decrease in NDVI without altering NDR is very rare. Those changes, which do not alter the surface roughness significantly, such as bare land to pasture land or grassland and vice versa, which are characterized as increased or decreased vegetation are shown in Figure 9; this includes the boundary line of the change areas, mainly due to the changes in vegetation. Here, two examples are presented, (i) site 1, that is decrease in NDVI smoothing of some agricultural area that is associated with decrease in vegetation area (Zone VIII in Figure 2) and (ii) increase NDVI area, growth of small vegetation/greenness, that is associated with increase vegetation area (Zone IV as in Figure 6). Thus, these zones were merged with associated zones i.e. (Zone VIII to Zone I and Zone IV to Zone V as in Figure 6). Now we have six change classes and one no-change class as with the generalized relationship presented in Table 4.

In order to compare the results of the proposed change labeling approach with optical and SAR information, an automatic labeling with optical imageries using tasseled cap transformation brightness and greenness index (Malila 1980; Johnson and Kasirschke 1998) was implemented. The Figure 10 (a) is the change labeling map using the proposed optical and SAR information fusion and Figure 10 (b) is the change labeling map obtained using the optical imagery only. While interpreting the resulted map visually, all the area classified as class 2, class 3 and class 4 (vegetation or bare land to built-up and decrease vegetation area according to the relationship in Table 4) were classified in a single class 3 (increase NDVI and increase brightness) in the optical imagery based on the brightness and greenness index obtained from the Tasseled cap transformation in Landsat 7 images. These are the major change classes in the urban extension; therefore, the change labeling using the optical information in an urban information is suffering from a poor performance. Such misclassification obtained while implementing the brightness and greenness
The CV A technique for information fusion proved its capability of fulfilling their requirement for change detection. Given a huge potential of multi-source data, continue expansion of the quantity of diverse sensor types of remote sensing data, CV A might provide a capability of fusion of increasing demand of multi-source information for full-fledged change detection and a relationship among the responses of the Earth surface feature’s to these sensors would provide a broader-dimension of change type detection. In addition to the change detection in a very complex urban sprawl area, an automatic multi-class change detection with an empirical relationship between the response of surface feature to optical and SAR imagery has shown to be effective. By further analyzing the response of each change feature to optical and SAR imagery or using ancillary dataset, this method can be further extended for disaster monitoring, crop monitoring, etc. In addition to that, an automatic adaptive thresholding would enhance the results by protecting from the human biases and error and make the system fully automatic.

ACKNOWLEDGEMENTS
This research was supported in part by a program of the 4th ALSO-2 research announcement of the Japan Aerospace Exploration Agency (JAXA).

REFERENCES

Table 5: Confusion matrix for automatic change labeling in CV A - NDR and ∆NDVI.

<table>
<thead>
<tr>
<th></th>
<th>Zone I or VIII</th>
<th>Zone II</th>
<th>Zone III</th>
<th>Zone IV or V</th>
<th>Zone VI</th>
<th>NO-change</th>
<th>Total</th>
<th>Producers accuracy (%)</th>
<th>Error of omission (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone I and VIII</td>
<td>1385.00</td>
<td>34.00</td>
<td>0.00</td>
<td>0.00</td>
<td>262.00</td>
<td>1681.00</td>
<td>82.39</td>
<td>17.61</td>
<td></td>
</tr>
<tr>
<td>Zone II</td>
<td>38.00</td>
<td>417.00</td>
<td>21.00</td>
<td>0.00</td>
<td>0.00</td>
<td>484.00</td>
<td>86.16</td>
<td>13.84</td>
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</tr>
<tr>
<td>Zone III</td>
<td>0.00</td>
<td>31.00</td>
<td>251.00</td>
<td>24.00</td>
<td>53.00</td>
<td>359.00</td>
<td>69.92</td>
<td>30.08</td>
<td></td>
</tr>
<tr>
<td>Zone IV or V</td>
<td>0.00</td>
<td>96.00</td>
<td>76.00</td>
<td>1325.00</td>
<td>49.00</td>
<td>193.00</td>
<td>76.19</td>
<td>23.81</td>
<td></td>
</tr>
<tr>
<td>Zone VI</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>67.00</td>
<td>123.00</td>
<td>0.00</td>
<td>190.00</td>
<td>64.74</td>
<td></td>
</tr>
<tr>
<td>No-change</td>
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<td>78.00</td>
<td>76.00</td>
<td>111.00</td>
<td>49.00</td>
<td>7008.00</td>
<td>1739.00</td>
<td>93.53</td>
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<tr>
<td>Total</td>
<td>1594.00</td>
<td>656.00</td>
<td>424.00</td>
<td>1535.00</td>
<td>221.00</td>
<td>7516.00</td>
<td>11946.00</td>
<td>6.47</td>
<td></td>
</tr>
</tbody>
</table>

| Users accuracy(%) | 86.89 | 63.57 | 59.20 | 86.32 | 55.66 | 93.24 |
| Error of commission (%) | 13.11 | 36.43 | 40.80 | 13.68 | 44.34 | 6.76 |

Figure 9: Change area with no-change in NDR, (a) reference image in 2007, (b) reference image in 2011 and (c) change map with the change that is not sensitive to SAR backscattering (NDR) and interested zoom-in sites.
Figure 10: Change map with change type labeling, (a) CV A with NDR and ∆NDVI, (b) CV A with brightness and greenness obtained from tasseled cap transformation in Landsat images.


