Quantitative Comparison of Unsupervised Change Detection Capability in Multiple Polarimetric SAR Data

Abstract: This paper addresses the change detection capabilities of fully polarimetric synthetic aperture radar (SAR) for the L-band frequency in comparison with single- and dual-polarization and fully polarimetric SAR data. All polarization combinations are investigated quantitatively for unsupervised change detection under different topographic characteristics. In particular, a highly urbanized area, a vegetated area, and a mixed topographic area were examined. This allows optimal selection of polarization combinations that provide the highest change detection accuracy. The unsupervised change detection method applied in this study was based on a closed-loop process. Firstly, adaptive iterative filtering was used to determine an optimal filter size such that the speckle noise was sufficiently reduced. Secondly, the log-ratio image was generated from the filtered SAR images and was modeled according to a Gaussian distribution. Thirdly, the modified Kittler–Ilingsworth minimum error thresholding (Kl) algorithm was applied under generalized Gaussian (G) assumption to select double threshold that discriminates the positively and negatively changed classes from the unchanged class. Experimental results reveal that the most suitable data used for the change detection was the combined cross-polarized (HV+VH) power image, because it can achieve high correct change detection rate for any topography. The selection of filter size affects the change detection accuracy, and was dependent on the topographic characteristics. In addition, the use of the combined polarized power data, which were generated after filtering the single-polarization data at each filter size, was found out to increase the change detection accuracy.

1. Introduction

Change detection applications are widely used in environmental monitoring, agricultural surveys, studies on land use/land cover dynamics, urban studies, and forest monitoring. More recently, remotely sensed imagery has shown great potential for providing and updating spatial information as well as manual tasks can be reduced. In particular, the Synthetic aperture radar (SAR) data can be obtained from the satellite-based microwave sensors. These data are expected to provide the information on various land surface characteristics.

Even the presence of speckle noise makes analysis of SAR data difficult, however utilizing SAR data for change detection has several advantages, for example, its quality is unaffected by atmospheric (e.g., rain and clouds) and sunlight conditions. In addition, SAR also provides a large amount of multi-temporal data with the short revisit time (e.g., TerraSAR, or PALSAR). Hence, regions can be monitored at a time defined according to end-user requirements for monitoring applications. Thus, analysis of multi-temporal SAR data for change detection is considered in the present study.

Change detection by remote sensing involves acquiring two co-registered images of the same geographical area at different times (Bazi et al., 2005). Several change detection techniques have been employed; the majority of these methods were
reviewed by (Lu et al., 2004). The change detection techniques are broadly categorized into two types: supervised and unsupervised techniques. Supervised change detection is based on supervised classification methods, which require a suitable training set for the learning process of the classifiers. Obtaining robust training samples for supervised techniques is typically difficult. On the other hand, the drawback of SAR-based change detection is addressed in unsupervised techniques without a priori knowledge of the scene. Unsupervised change detection merely discriminates between two opposing classes (e.g., the changed and unchanged classes). Hence, an unsupervised change detection technique is considered here.

Several aspects of unsupervised change detection using SAR image analysis must be focused on, including despeckling the SAR images, selecting a comparison method for the multi-temporal SAR images, and developing an optimal thresholding selection procedure. To fulfill all the above aspects, an unsupervised change detection approach based on a closed-loop process by Bazi et al. (2005) was proposed. This approach has the following three main steps: (1) a preprocessing based on controlled adaptive iterative filtering is applied to the SAR data to reduce speckle noise and to maximize discrimination between changed and unchanged pixels. The Kittler–Illingworth minimum error thresholding (KI) algorithm is applied to the filtered images for selecting the optimal thresholds. The optimal threshold is determined by selecting the lowest performance index value. The performance index values are computed by the KI predefined criterion function, which is directly related to error probability (Kittler and Illingworth, 1986). The lowest performance index values of the filtered images are considered again to find out the minimum value one. Then, the final optimal threshold is defined. Thus, the final change detection map is generated based on the filtered image that provides the lowest performance index value with the least change detection error; (2) the multi-temporal images are compared according to a standard log–ratio operator; and (3) an optimal thresholding selection procedure is performed, which is based on the reformulation of the KI algorithm. In regard to step (2), the robustness to calibration errors of the ratio operator has more effective than the difference operator when used to compare two SAR temporal images (Rignot et al., 1993). The simple ratio image can be used to generate the difference image, which it reflects the real difference image. However, because of the multiplicative nature of speckle in the SAR image, the use of log–ratio image is considered. The logarithm scale is used to compress the range of variation of the ratio image. Thus, the better balance of values below and above one can be obtained (Bazi et al., 2005). The logarithm scale is also characterized by enhancing the low–intensity pixels (Kuruoglu and Zerubia, 2004). The point of view for the cooperation of the log–ratio image with the KI algorithm is also considered. As Dekker (1998) studied, the distribution of the log–ratio image is closed to a Gaussian distribution which this model reveals a first simple and reasonable approximation (Bazi et al., 2005). The change detection task is carried out by a threshold of the cumulative histogram of the log–ratio image. Therefore, the use of the log–ratio image is more appropriate than the simple ratio image to analyze the change detection using SAR image.

Multi-temporal single polarimetric SAR data can be exploited for change detection, however obtaining the information is quite limited due to the scattering features under a certain polarized transmit and receive signals. Analyzing multi-polarimetric SAR data is interesting since each type of polarization (HH, HV, VH or VV) yields a different pattern of scattering from the ground. Xia (1996) found that the cross-polarized return is usually weaker than the co-polarized return, and the receiver channel for the cross-polarized return is usually set higher to compensate for the weaker signal return. While the energies received by the cross-polarized channels has are equivalent, the receiver noise in the radar
electronics is different between the HV and VH channels. Hence, the effects of such differences in single-polarization, dual-polarization (in particular the combined co-polarized and the combined cross-polarized data) and the polarimetric total power data should be investigated for the purposes of improving the accuracy of change detection applications. Therefore, the motivation for this paper is to compare the performance of an automatic unsupervised change detection method based on a closed-loop process between fully polarimetric SAR data for the L-band frequency and combinations of polarized power data: the combined co-polarized (HH + VV) power data, the combined cross-polarized (HV + VH) power data, and the total power (HH + HV + VH + VV) data. Unsupervised change detection in this experiment can distinguish between changed and unchanged classes, and both positive and negative changes can be detected. Unsupervised change detection is quantitatively assessed for the polarization combinations under different topographic characteristics, in particular, a highly urbanized area, a vegetated area, and a mixed topographic area. Thus, all of the combinations are used to select the optimal combination of polarizations that provide the highest change detection accuracy for various change detection applications or different topographic characteristics. The remainder of the paper is organized as follows. Section 2 introduces the characteristics of the study areas. Section 3 describes the preprocessing techniques. The unsupervised change detection framework is presented in Section 4, and the experimental results are reported in Section 5. The results are discussed and conclusions are drawn in Sections 6 and 7, respectively.

2. Study Area and Data Description

Test sites for this study were selected in Chiba, Kyoto, and Osaka in Japan. In the Chiba images (Figures 1(a1) and (a2)), the majority of the area was covered by vegetation; paddy fields were particu-

Figure 1  Location of three study areas (Chiba, Kyoto, and Osaka) in Japan. (a1, b1, c1) PALSAR images of specific test sites. (a2, b2, c2) Google Earth images of specific test sites.
larly widespread across the entire image, although some woodlands can also be seen. Images of the Kyoto site (Figures 1(b1) and (b2)) show the residential areas (the center of the image), agricultural areas (the left of the image), in particular, paddy fields and woodlands (the right of the image). The Osaka images (Figures 1(c1) and (c2)) show a highly urbanized area with a large number of adjacent high-rise buildings. As shown in Figure 1, the multi-temporal ALOS/PALSAR fine beam HH-polarization (L-band) data of the areas were used. Two PALSAR level 1.1 images with an ascending orbit of observation in fully polarimetric mode were taken of three test sites for experiments (Table 1). The range and azimuth pixel sizes were 9.37 m×26.54 m.

3. Preprocessing Techniques

The SAR images were orthorectified. Orthorectification is the rectification that incorporates a digital elevation model (DEM) to relief terrain effect for creating a planimetrically correct image. In this research, the orthorectification was done by using the MapReady software (AFS, 2010). This freeware currently supports geocoding and terrain correction. The geocoding step is performed by transforming the SAR image geometry into one of the standard map projections and is invoked by selecting the projection and the zone number; and the datum on the MapReady software tool. The Universal Transverse Mercator (UTM) projection at grid zones 53 north (for the Kyoto and the Osaka datasets) and 54 north (for the Chiba dataset); and the World Geodetic System 1984 (WGS84) geodetic datum surface were defined. For the terrain correction step, a 90 m Shuttle Radar Topography Mission (SRTM) was assumed to be used. Once a SRTM was defined, the correction of distortions caused by the SAR geometry (e.g., layover or shadow regions) was improved. The size of the image was 400×400 pixels at a 10 m spatial resolution.

3.1 Signal Polarizations of SAR Data

Seven signal polarizations were tested in the change detection experiments: the amplitudes of the single-polarization SAR (HH, HV, VH, and VV) images, the combined co-polarized (HH+VV) power image (referred to as CO), the combined cross-polarized (HV+VH) power image (referred to as CS), and the total power (HH+HV+VH+VV) image (referred to as TP). As PALSAR Level 1.1 produces complex data (i.e., numbers with real and imaginary parts), thus the amplitude is computed as the square root of the sum of the squares of the real and imaginary parts. The TP received by the four channels of a polarimetric radar system can then calculated as the sum of the squares of the amplitudes of all polarization data:

\[ TP = |HH|^2 + |HV|^2 + |VH|^2 + |VV|^2 . \]  

As the TP is the sum of all of the polarization powers, the TP image represents a combination of the characteristics of all four polarization images. In this regard, the CO and the CS images represent

<table>
<thead>
<tr>
<th>Study areas (Japan)</th>
<th>Chiba</th>
<th>Kyoto</th>
<th>Osaka</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topography characteristics</td>
<td>Vegetated areas (paddy fields and small woodlands)</td>
<td>Mixed topography (residential area, paddy fields)</td>
<td>Highly urbanized (high-rise buildings)</td>
</tr>
<tr>
<td>Image center Lat/Long</td>
<td>35.7373/140.3806</td>
<td>35.7328/140.4039</td>
<td>34.7412/135.8117</td>
</tr>
<tr>
<td>Size (sample×line)</td>
<td>1,280×18,432</td>
<td>1,280×18,432</td>
<td>1,088×18,432</td>
</tr>
<tr>
<td>Orbit/Off-nadir angle</td>
<td>Ascending/21.5°</td>
<td>Ascending/21.5°</td>
<td>Ascending/23.1°</td>
</tr>
</tbody>
</table>
the combination of characteristics of their polarization, and are defined as
\[
CO = |HH_{\text{mea}}|^2 + |VV_{\text{mea}}|^2. \tag{2}
\]
\[
CS = |HV_{\text{mea}}|^2 + |VH_{\text{mea}}|^2. \tag{3}
\]

4. Methodology

4.1 Unsupervised Change Detection Based on a Closed-Loop Process

The framework for the automatic unsupervised change detection based on a closed-loop process by Bazi et al. (2005) was proposed. The KI algorithm was used to select an appropriate decision threshold \(T \in [0, 1, ..., L-1]\) based on the optimization of a predefined criterion function \(J(T)\) that averages over the histogram of the log-ratio SAR image \(h(X)\) (Kittler et al., 1986). In this research, the modified double-thresholding KI algorithm implemented under the generalized Gaussian (GG) assumption by Bazi et al. (2006) was applied, as shown in Figure 2. It begins with two co-registered SAR images \(X_i = \{X_i(i, j), 1 \leq i \leq I, 1 \leq j \leq J\}\) and \(X_0 = \{X_0(i, j), 1 \leq i \leq I, 1 \leq j \leq J\}\) of the same area acquired at different times. The seven signal polarizations described in Section 3.1 were investigated. A selected controlled adaptive iterative filtering was an adaptive enhanced Lee filter. This filter was applied to the SAR images for effectively removing the speckle noise (Lopes et al., 1990). An iterative filtering loop was used to determine an optimal filter size in which the filtered SAR images \((X_{i,k} \text{ and } X_{0,k})\) were generated for \(k=3\) kernels. This process was repeated with \(k=k+2\) until the predefined maximum kernel \(k_{max} (=11)\) was reached. The log-ratio image \(X_{i,k}\) was obtained by applying \(\log([X_{i,k}(i, j)/X_{0,k}(i, j)]\). Then, the histogram of log-ratio image \(h(X_{i,k})\) was computed and modeled to Gaussian distribution. This histogram was the combination of three distributions; two of these distributions were associated with the changed classes \(\omega_c = \omega_c1 \cup \omega_c2\), while the final one was the unchanged class \(\omega_u\). The modified KI algorithm thus selects a double threshold value \((T_1, T_2)\) based on the optimization of a predefined criterion function \(J(T_1, T_2)\) that averages over the histogram \(h(X)\) (Bazi et al., 2006). At each filter iteration, the \(J(T_1, T_2)\) was calculated and evaluated as a performance index. The lowest performance value was determined for selecting an optimal filter size to generate a change detection map with the least overall error. The optimal double threshold that minimizes the criterion function is defined as:
\[
(T_1^*, T_2^*) = \arg\min J(T_1, T_2) \quad (T_1, T_2) = [0, 1, ..., L-1]^2
\]

The modified KI algorithm of the double thresholding selection under the implemented GG assumption is given by:
\[
J(T_1, T_2) = \sum_{X_{i,0}} h(X_i)[b_c(T_i)X_i - m_c(T_i)]^{b_c(T_2)} + \sum_{X_{i,1}} h(X_i)[b_c(T_i)X_i - m_c(T_i)]^{b_c(T_2)} + \sum_{X_{i,2}} h(X_i)[b_c(T_i)X_i - m_c(T_i)]^{b_c(T_2)} + H(T_1, T_2)
\]

The entropy \(H(T_1, T_2)\) is estimated according to \(H(T_1, T_2) = -P_c(T_1)\cdot[lnP_c(T_1)+lna_c(T_1)] - P_s(T_1, T_2)\cdot[lnP_s(T_1, T_2)+lna_s(T_1, T_2)] - P_c(T_2)\cdot[lnP_c(T_2)+lna_c(T_2)].\)
where \( L (=0\rightarrow 255) \) is the number of possible gray levels. Here, the prior probabilities \( P_\mathrm{a}(T_1, T_2), P_\mathrm{u}(T_1), \) and \( P_\mathrm{c}(T_2) \); the means \( m_\mathrm{a}(T_1, T_2), m_\mathrm{c}(T_1), \) and \( m_\mathrm{c}(T_2) \); and the variances \( \sigma_\mathrm{a}^2(T_1, T_2), \sigma_\mathrm{c}^2(T_1), \) and \( \sigma_\mathrm{c}^2(T_2) \) associated with the unchanged class \( \omega_\mathrm{u} \) and the changed classes \( \omega_\mathrm{c} \), respectively. These estimated parameters in the KI algorithm are given by

\[
P_\mathrm{a}(T_1, T_2) = \sum_{X_0} h(X_i),
\]

\[
m_\mathrm{a}(T_1, T_2) = \frac{1}{P_\mathrm{a}(T_1, T_2)} \sum_{X_0} X_i h(X_i),
\]

\[
\sigma_\mathrm{a}^2(T_1, T_2) = \frac{1}{P_\mathrm{a}(T_1, T_2)} \sum_{X_0} [X_i - m_\mathrm{a}(T_1, T_2)]^2 h(X_i).
\]

\[
P_\mathrm{c}(T_1) = \sum_{X_0} h(X_i),
\]

\[
m_\mathrm{c}(T_1) = \frac{1}{P_\mathrm{c}(T_1)} \sum_{X_0} X_i h(X_i),
\]

\[
\sigma_\mathrm{c}^2(T_1) = \frac{1}{P_\mathrm{c}(T_1)} \sum_{X_0} [X_i - m_\mathrm{c}(T_1)]^2 h(X_i).
\]

The positive constants \( a_\beta \) and \( b_\beta \), which \( \Omega = \{ \omega_\mathrm{a}(T_1, T_2), \omega_\mathrm{u}(T_1), \omega_\mathrm{c}(T_2) \} \), are estimated by using

\[
a_\beta = \frac{b_\beta a_\beta}{2 \Gamma \left( \frac{3}{\beta} \right)} , \quad b_\beta = \frac{1}{\sigma_\beta} \sqrt{\Gamma \left( \frac{3}{\beta} \right) \Gamma \left( \frac{1}{\beta} \right) \Gamma \left( \frac{2}{\beta} \right)}.
\]

where \( \Gamma(\cdot) \) is the Gamma function and \( \beta \) is the shape parameter of the distribution.

To compute \( \beta \), the estimation technique of Sharifi et al. (1995) was applied, as the following four steps.

1. Generate a lookup table by computing the GG ratio function \( r(\beta) \):

\[
r(\beta) = \frac{\Gamma \left( \frac{1}{\beta} \right) \Gamma \left( \frac{3}{\beta} \right)}{\Gamma \left( \frac{2}{\beta} \right)} , \quad \beta \geq 0.
\]

2. Estimate the modified mean of the absolute values:

\[
E[|X_i|]\Omega = \frac{1}{P(\Omega)} \sum_{X_0} h(X_i)\cdot|X_i - m_\beta|.
\]

3. Compute the ratio:

\[
\rho_\beta = \frac{\sigma_\beta^2}{E[|X_i|]\Omega].
\]

4. Identify the solution to the equation using the lookup table:

\[
\hat{\beta}_\beta = r^{-1}(\rho_\beta) \text{ or } r(\beta_\beta) = \rho_\beta.
\]

The change detection map can be generated by using the selected double threshold. The detected results consist of the unchanged class and a pair of changed classes corresponding to positive and negative changes. Positive changes that occur with an increase in backscatter were distinguished by applying optimal threshold \( T^*_\beta \), whereas the negative changes that occur with a decrease in backscatter were detected through \( T^*_\beta \). The final form of \( f(T_1, T_2) \) for double thresholding selection based on the GG assumption, as defined by Eq. (5), was applied in this research.

4.2 Accuracy Assessment

4.2.1 Automatic Region of Interest Generation

Test sets containing the three different classes—unchanged class, positive changes with backscatter increase, and negative changes with backscatter decrease—were selected for accuracy assessment. Since test pixels were unavailable for determining the accuracies, automatic region of interest (ROI) generation procedure was proposed. For the procedure of unchanged ROI class selection, a quantization phase was first conducted (i.e., all seven signal polarizations were converted into grayscale values, ranging from 0 to 255). The same grayscale values of image pair acquired at the same area were selected to assign the unchanged class. The unchanged ROI class was thus generated as the union of the unchanged classes of the seven signal polarizations. For the procedure of the change classes, the positive and the negative classes were generated based on the detected change results of the seven
signal polarizations with the lowest $J(T_i, T_j)$ values. Because Bazi et al. (2005) found that change detection error probability is directly related to the utilization of the cost function or a predefined criterion function, generating the change detection map with the least overall error is performed by using the minimum value of $J(T)$ as a performance index for selection of an optimal filter size. From an analysis of the behavioral similarities in the output of the seven signal polarizations, it can be categorized into three subgroups: HH–VV–CO data, HV–VH–CS data, and TP data. For each subgroup, the intersection in a particular area was used to ensure the accuracy. The intersected areas of the three subgroups were then combined to generate positive and negative change ROI classes. The test sets used to assess the classification accuracy, are listed in Table 2.

Several terms associated with accuracy assessments were used in the experiment and require definition: detected changes, changed pixels that are correctly classified as changed; false alarms, unchanged pixels that are incorrectly classified as changed; missed changes, changed pixels that are incorrectly classified as unchanged; and overall error, the total number of missed changes and false alarms.

4.2.2 ROI Manual Checking (Point by Point)

Automatic ROIs were generated based on Section 4.2.1 for the accuracy assessment. However, pixels in the unchanged class were found and included in the positive and negative change classes, particularly in the case of Osaka. To realize greater accuracy, point-by-point manual checking of ROIs was therefore necessary. Two ALOS/AVNIR-2 images acquired on similar dates to the SAR images, as well as high-resolution QuickBird images from Google Earth, were used in this step. Two optical AVNIR-2 images at level 1B2G (geometrically corrected data) with a descending orbit of the Osaka study area were acquired on 2 December 2008 and 18 May 2009. The sizes of the images were $8,523 \times 8,422$ and $8,491 \times 8,390$ pixels, respectively, at a 10 m spatial resolution. In the manual-checking procedure, small ROIs of 8 pixels or fewer that were misclassified as being in the positive or negative change class were moved to the unchanged class (Table 2, Osaka “manual” column). The accurate ROIs of the Osaka dataset were thus used for accuracy assessment.

5. Experimental Results

The framework (Figure 2) was applied to the study areas of Chiba, Kyoto and Osaka. The three datasets were analyzed, and the results are shown in Table 3 and Figures 3–10.

5.1 Results Obtained from the Chiba Dataset

The change detection results for the Chiba dataset are listed in the first column of Table 3. The positive changes (Pos), negative changes (Neg), overall error (OE), and overall accuracy (OA) are listed in the subcolumns. The cells highlighted in light gray denote the lowest values between the
## Table 3  Change detection results for the Chiba, the Kyoto and the Osaka datasets (reported in percentages) using different filter sizes obtained by using the modified KI algorithm under GG assumption

<table>
<thead>
<tr>
<th>Filter size</th>
<th>Chiba dataset (percentage)</th>
<th>Kyoto dataset (percentage)</th>
<th>Osaka dataset (percentage)—automatic</th>
<th>Osaka dataset (percentage)—manual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>*Pos b Neg OE OA</td>
<td>*Pos b Neg OE OA</td>
<td>*Pos b Neg OE OA</td>
<td>*Pos b Neg OE OA</td>
</tr>
<tr>
<td>Without filtering</td>
<td>Original log-ratio image</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH</td>
<td>39.39 53.35 8.27 90.52</td>
<td>40.56 35.61 12.23 87.43</td>
<td>42.13 40.26 3.74 94.24</td>
<td>41.85 39.50 3.38 94.56</td>
</tr>
<tr>
<td>HV</td>
<td>57.56 44.46 8.33 91.13</td>
<td>35.52 39.65 12.25 87.31</td>
<td>45.08 47.85 3.38 94.65</td>
<td>44.75 48.65 3.01 94.99</td>
</tr>
<tr>
<td>VH</td>
<td>59.91 43.16 8.36 91.11</td>
<td>34.70 39.53 12.26 87.26</td>
<td>44.26 47.65 3.41 94.49</td>
<td>44.02 47.29 3.07 94.78</td>
</tr>
<tr>
<td>VV</td>
<td>39.55 55.94 7.98 90.80</td>
<td>43.13 33.99 12.20 87.67</td>
<td>42.30 39.66 3.76 94.20</td>
<td>42.21 38.15 3.42 94.50</td>
</tr>
<tr>
<td>TP</td>
<td>54.27 64.41 6.40 92.46</td>
<td>50.45 44.73 10.54 89.52</td>
<td>54.75 55.74 2.84 95.27</td>
<td>54.71 54.40 2.59 95.48</td>
</tr>
<tr>
<td>CO</td>
<td>44.79 64.31 6.86 91.86</td>
<td>43.56 41.26 11.39 88.67</td>
<td>48.20 50.75 3.19 95.03</td>
<td>48.37 49.44 2.90 95.28</td>
</tr>
<tr>
<td>CS</td>
<td>63.66 49.14 7.57 91.88</td>
<td>37.27 41.55 11.84 87.95</td>
<td>47.38 55.84 3.02 94.83</td>
<td>46.74 56.43 2.70 95.11</td>
</tr>
<tr>
<td>Optimal filter size</td>
<td>(7×7)</td>
<td>(11×11)</td>
<td>(3×3)</td>
<td></td>
</tr>
<tr>
<td>HH</td>
<td>38.92 73.04 6.17 92.96</td>
<td>74.63 69.28 6.06 92.77</td>
<td>58.52 59.74 2.63 94.59</td>
<td>57.79 59.26 2.39 94.79</td>
</tr>
<tr>
<td>HV</td>
<td>73.30 67.36 5.18 93.73</td>
<td>81.69 84.34 3.60 95.61</td>
<td>72.79 76.02 1.63 96.20</td>
<td>74.09 77.88 1.37 96.42</td>
</tr>
<tr>
<td>VH</td>
<td>73.38 61.79 5.78 93.39</td>
<td>84.34 85.68 3.24 95.49</td>
<td>71.48 74.53 1.73 95.35</td>
<td>71.74 75.85 1.49 95.54</td>
</tr>
<tr>
<td>VV</td>
<td>5.64 78.25 7.03 83.11</td>
<td>76.29 67.55 6.12 92.91</td>
<td>59.84 55.54 2.76 94.35</td>
<td>59.96 54.74 2.49 94.57</td>
</tr>
<tr>
<td>TP</td>
<td>53.25 81.97 4.51 94.03</td>
<td>70.43 67.06 6.62 92.70</td>
<td>74.10 76.02 1.60 95.63</td>
<td>73.73 75.40 1.46 95.74</td>
</tr>
<tr>
<td>CO</td>
<td>48.55 80.48 4.92 93.25</td>
<td>66.58 62.01 7.50 91.87</td>
<td>64.75 65.93 2.23 95.28</td>
<td>65.04 64.67 2.03 95.44</td>
</tr>
<tr>
<td>CS</td>
<td>75.25 68.99 4.90 94.07</td>
<td>79.12 84.51 3.81 95.23</td>
<td>54.75 82.32 1.84 95.13</td>
<td>54.53 83.75 1.60 95.31</td>
</tr>
</tbody>
</table>

*Positive change, b Negative change, OE Overall error, and OA Overall accuracy.

Figure 3  Change detection results of $J(T_1, T_2)$ for the Chiba dataset (% overall accuracies) with filter size increases.

![Change detection results for Chiba dataset](image1)

(a) Single-polarization data

![Change detection results for combined data](image2)

(b) Co-polarized and cross-polarized data

original and the filtered images for each signal polarization, while the highest values are highlighted in the dark gray. The double threshold of the log-ratio images generated the change detection results in the highest overall errors (6.40%–8.36%), the lowest positive changes, the lowest negative changes, and the lowest overall accuracies (90.52%–92.46%) for all seven signal polarizations. This is because the three class distributions in the log-ratio images almost overlap. Consequently, identifying detected changes accurately was difficult. Conversely, by filtering the original log-ratio
images, the accuracies considerably improved. In particular, a $7 \times 7$ filter size attained the lowest overall errors ($4.51\% - 7.03\%$) and the highest overall accuracies ($92.64\% - 94.07\%$) for nearly all of the seven signal polarizations. As a result, the optimal change detection for the Chiba dataset (which is a vegetated area) was found after filtering the original log-ratio image using a $7 \times 7$ filter size.

Figure 3 shows the behavior of the overall accuracies (in percentage) for the Chiba dataset with filter size increases. Figure 3(a) compares the change detection results for the single-polarization (HH, HV, VH, and VV) data with the TP data. Figure 3(b) compares the change detection results for the CO data, the CS data, and the TP data. In Figure 3(a), the TP data generated the change detection rate with the highest accuracy for both the original image and the filtered images at all filter sizes. This is because the information of each single-polarization data was combined to produce the TP data. The complementary of different information leaded to an accurate detection. The TP data seems desirable; however it was found that the highest accuracy was obtained from the CS data after a $5 \times 5$ filter size, as shown in Figure 3(b). The CO data has low accuracy for the original image and the filtered images at all filter sizes.

5.2 Results Obtained from the Kyoto Dataset

The change detection results for the Kyoto dataset are listed in the second column of Table 3. For all seven signal polarizations, the majority of the highest overall errors ($10.54\% - 12.26\%$), the lowest positive changes, the lowest negative changes, and the lowest overall accuracies ($87.26\% - 89.52\%$) were obtained for the double threshold of the original log-ratio images. As a result, the highest improvement was found at an $11 \times 11$ filter size, where the majority of the highest positive and negative changes were obtained, as well as the lowest overall errors ($3.24\% - 7.50\%$), for all seven signal polarizations. Thus, the optimal change detection for the Kyoto dataset (which consists of a mixed topographic area) was found after filtering the original log-ratio image using an $11 \times 11$ filter size (which is the maximum size in this experiment).

Figure 4 shows the behavior of the overall accuracies (in percentage) for the Kyoto dataset with filter size increase. For Figure 4(a), for the original log-ratio image, the TP data has the change detection rate with the highest accuracy ($89.52\%$), whereas the single-polarization data had accuracy of less than $87.67\%$. However, when the original log-ratio image was filtered using different filter sizes, the behavior in the overall accuracy of each signal polarization data differs in terms of improved change detection rate. The cross-polarized (HV or VH) data have a higher accuracy than the TP data and the co-polarized (HH or VV) data.

![Figure 4](image-url)  
(a) Single-polarization data  
(b) Co-polarized and cross-polarized data  
Figure 4  
Change detection results of $J(T_1, T_2)$ for the Kyoto dataset (% overall accuracies) with filter size increases. (Case : The combined polarized power data were generated by using the original single-polarization data or before filtering the single-polarization data).
behaviors were found in the overall accuracies of the HH and the VV data, and likewise for the HV and the VH data. For the dual-polarization data in Figure 4(b), without filtering, the accuracies of the change detection rates for the CO data and the CS data were 88.67% and 87.95%, respectively. The dual-polarization data thus generated change detection results with higher accuracy than those of the single-polarization data, although the TP data attains the highest accuracy. When the original image was filtered, the CS data was found to have the highest accuracy, while the change detection of the TP data was better than the CO data.

In regard to the results in Figures 4(a) and (b), the reason of the TP data performed worse than the HV, the VH and the CS data, were figured out. As the enhanced Lee filter is related to a dependent parameter (i.e., the Equivalent Number of Looks (ENL), the combined polarized power data have different ENL values as the single-polarization data, so that the filter should be tuned differently. Thus, the combined polarized power data: the CO, the CS, and the TP data which were generated after filtering the single-polarization data at each filter size, were tested, as shown in Figure 5. Considering the change detection results of two cases, case of the combined polarized power data were generated before and after filtering the single-polarization data at each filter size (Figures 4 and 5, respectively), the similar accuracy trends were found. The TP data still performed worse than the HV, the VH and the CS data. However, the improvement was obtained from this experiment, the accuracies of the change detection rates of the CO, the CS, and the TP data from using the combined polarized power data which were generated after filtering the single-polarization data at each filter size, were significantly increased.

Turning to the calculation of the ENL, the ENL can be used to estimate the speckle reduction (Walella and Datcu, 2000), and is given by

$$\text{ENL} = \frac{\text{mean of the image}}{\text{standard deviation of the image}}^2.$$  \hspace{1cm} (15)

From the study of Walella and Datcu (2000), as a speckle being exponential distribution, the reduced speckle was detected by calculating the mean and the amount each pixel differs from another was detected by calculating the standard deviation. If the mean of the filtered image and the original image are the same, it means that the image is completely smooth and thus the standard deviation would be zero. Then, the ENL value will become infinite. Therefore, the higher ENL value indicates the better speckle reduction. The ENL index was computed to estimate the speckle reduction of the CO, the CS and the TP images at each filter size of the $X_i$ image ($X_i = \{X_i(i, j), 1 \leq i \leq I, 1 \leq j \leq J\}$). The comparison between the case of the combined polarized power data after filtering the single-polariza-

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![Graph](image1.png)  ![Graph](image2.png)

**Figure 5** Change detection results of $J(T_1, T_2)$ for the Kyoto dataset (% overall accuracies) with filter size increases. (Case: The combined polarized power data were generated after filtering the single-polarization data at each filter size).
tion data at each filter size; and the case of the combined polarized power data were generated by using the original single-polarization data, was investigated, as shown in Figure 6. As a result, the highest ENL value was generated for the CS data as shown in Figure 6(b). The ENL value of the TP data (Figure 6(c)) was higher than the ENL of the CO data (Figure 6(a)). As the ENL index is an indicator to estimate the speckle reduction, the speckle reduction of the CS data outperformed over the TP and the CO data. These results supported and were consistent to the change detection results in Figures 4 and 5.

5.3 Results Obtained from the Osaka Dataset (Automatic ROI Generation)

The change detection results for the Osaka dataset when only automatic ROI generation was employed are listed in the third column of Table 3. For all seven signal polarizations, the highest overall errors (2.84%–3.76%), the lowest positive changes, and the lowest negative changes were obtained for the double threshold of the original log ratio images. In contrast, by filtering the original images, the accuracies of the change detection considerably improve. A $3 \times 3$ filter size gave the highest overall accuracies (94.35%–96.20%) for the majority of the seven signal polarizations. As a result, optimal change detection for the Osaka dataset (which is an urbanized area) was found after filtering the original multi-temporal images using a $3 \times 3$ filter size.

Figure 7 shows the behavior of the overall accuracies (in percentage) for the Osaka dataset as a filter size was changed. Without filtering, the TP data had change detection rate with the highest accuracy of 95.27%, whereas single-polarization data have accuracies of less than 94.65% (Figure
7(a)). However, when the original image was filtered, the overall accuracies of the signal polarization data become even lower. From Figure 7(b), the CO data has the lowest accuracy for the original image and for filtered images at all filter sizes. The TP data generated the most accurate results both without filtering and with filtering up to a 3×3 filter size. After this, the change detection rates with highest accuracy were obtained from the CS data.

5.4 Results Obtained on the Osaka Dataset (ROI Manual Checking)

The change detection results for the Osaka dataset after ROI manual checking are listed in the final column of Table 3. Here, ROIs were selected as described in Section 4.2.2. The accuracies of the change detection rates increased slightly, but showed similar trends to the results in Section 5.3, as shown in Figure 8. This figure compares the change detection results (in particular, the overall accuracy) for the Osaka dataset between using only automatic ROI generation (Section 4.2.1) and after ROI manual checking. In each graph, data labels indicate the percentage of accuracy improvement after applying ROI manual checking.

Figure 9 illustrates an example of positive change

![Image](image-url)

**Figure 8** Change detection results (% overall accuracies) with filter size increases. Comparison for the Osaka dataset between using automatic ROI generation and after using manual checking for accuracy assessment. Data labels in the graphs indicate the percentage of accuracy improvement.

![Image](image-url)

**Figure 9** An example of positive change detection for the Osaka dataset. (a, b) 4× magnified AVNIR-2 true color composite image acquired on 2/12/2008 and 18/5/2009, respectively. Red crosshair indicates the positive change area. (c, d) QuickBird image from Google Earth. Yellow pin denotes the positive change area where backscatter increased.
detection for the Osaka dataset. Magnified optical ALOS/AVNIR-2 true color composite images (Figures 9(a) and (b)) acquired on similar dates to the SAR images and high-resolution QuickBird images (Figures 9(c) and (d)) taken from Google Earth are shown. The red crosshairs in the AVNIR-2 images show the position of a detected change, while the yellow pins in the QuickBird images mark the area of positive change together with its latitude and longitude. Figure 9(c) shows an area of bare soil, which has low backscatter in the SAR image, and Figure 9(d) shows the change of a new building in the same area, which has higher backscatter. Figure 10 illustrates an example of negative change detection for the Osaka dataset. Figure 10(c) shows buildings positioned along all four sides of a central rectangular parking lot. This area has high backscatter in the SAR imagery. Conversely, Figure 10(d) shows the same area after all the buildings and a parking lot were removed, leaving behind only bare soil. This change was seen as a negative change due to the backscatter decrease.

6. Discussion

By considering the effect of filtering the original log-ratio images on the performance of change detection in terms of overall accuracy, it was found that the topographic characteristics of the areas in the images influence accuracy. The original log-ratio images of the Chiba (a vegetated area) and the Kyoto (a mixed topography area) datasets were the most inaccurate. These accuracies were improved by employing filtering using larger filter sizes. Hence, an $11 \times 11$ filter size generated the highest accuracy for the Kyoto dataset. The performance trend for the Chiba dataset followed a bell curve such that a $7 \times 7$ filter size seemed to generate the highest accuracy. In contrast, the performance decreased with larger filter sizes for the Osaka dataset, which consists of high-rise buildings. In this case, filtering using an $11 \times 11$ filter size produced result with the lowest accuracy, whereas the most accurate result was obtained using a $3 \times 3$ filter size.

Let us consider the performance of the polarimetric data for all of the tested datasets. The change detection accuracies for the single-polarization data were, as expected, considerably lower than those for the dual-polarization or fully polarimetric SAR data. The cross-polarized (HV or VH) data generated higher change detection accuracies than the co-polarized (HH or VV) data. The TP data generated the highest change detection accuracies. Since the TP image is a fusion of the single-polarization data, each single-polarization data has a different capability for distinguishing surface characteristics between the classes, and thus the fully polarimetric power image is more detailed and has stronger contrast. However, the TP data generated a more accurate change detection rate using small filter size while lower accuracy was attained when large filter size was used. Considering the
results after filtering between the single-polarization data with the TP data of the Kyoto (most of residential area and small of paddy field), the Osaka (an urbanized area) and the Chiba (a vegetated area) datasets, the TP data performed worse than the HV and VH data for the Osaka (i.e., it was similar to the Kyoto dataset), while the TP data outperformed over other data for the Chiba dataset. It can be seen that the topography was another factor to affect the accuracy. On the other hand, the CS data may enhance the accuracy after filtering. This was followed by the result of the ENL for the CS and the CO data, which has the highest ENL at any filter sizes. In general, the ENL of the TP data is higher than those of the CS data and the CO data when the ENL is calculated with the selected homogeneous area. However, the ENL in the present study was computed using an entire image mixed with the heterogeneous area. In change detection applications, the different topographic characteristics are considered. Thus, it might be possible to generate lower ENL from the TP data than ENL from the CS data when the heterogeneous area is considered. Moreover, the different approaches for calculating the ENL may affect the computed ENL from different polarization data. In this regard, to select the data used for change detection, the topographic characteristics and filter size should be considered. Thus, it was found that the combined cross-polarized (HV + VH) power image (or the CS data) was the most suitable data for a change detection application because the high correct change detection rate can be obtained for any topography.

Each polarizing channel has a different sensitivity to the various surface characteristics. An equal amount of energy is received by the cross-polarized channels (the backscattering coefficients of HV\_\phi and VH\_\phi); however, the receiver noise in the radar electronics is different between the HV and VH channels. As shown in the results of the unfiltered images under the seven signal polarizations, the change detection rates of all tested sites were similar for each single- and dual-polarization. In particular, the accuracies for the co-polarized data were approximately equal across the test sites, and a similar trend was also found for the cross-polarized data. When a fully polarization data was thus not provided, HH-polarized imagery, for example, can commonly be used for change detection of a variety of different topographies. Furthermore, the VV data was the least desirable for change detection analysis of any topography.

As a result, change detection of vegetated areas in the Chiba dataset was improved by using the cross-polarized SAR data and their combinations. Since the vegetated area in the current study was covered by paddy fields and woodland, two reasons for this improvement were considered. In woodland areas, the geometry of the vegetation (i.e., the leaves, branches, trunks, and groundcover) causes volume scattering, which enhances the cross-polarization returns. In fact, volume scatter can be said to be the major influence on the signal return for cross-polarized imagery, whereas surface scatter dominates the signal return for co-polarized imagery. Let us now consider the change detection for the paddy fields. The penetration of the signal through a plant canopy was reduced when using vertically polarized microwaves. Thus, VV images provide high change detection for different canopy structures (i.e., changes resulting from the vegetation growth stages). Horizontally polarized microwaves penetrate greater than vertically polarized waves. Thus, HH images can provide more information about the underlying soil condition. However, in paddy fields, both soil and vegetation information were combined, and hence extracting paddy field information by using only HH or VV backscatter was difficult. Cross-polarized radar returns result from multiple reflections within the vegetation volume. Thus, HV and VH images were sensitive to crop structure within the total canopy volume and can provide information that was complementary to HH and VV imagery.

From the study of an urbanized area in the Osaka dataset, the cross-polarized SAR data, and their
combination, were found to improve change detection. The urbanized areas in the SAR image usually consist of the strong backscattering (e.g., buildings, wall or ground corners, and the ground surface). Such features correspond to dihedral and trihedral effects. A dihedral reflector is a corner reflector formed from two intersecting flat surfaces that are perpendicular to each other. A trihedral reflector is a passive radar calibration device constructed from three flat surfaces arranged to form a corner with the sides intersecting at 90°. The cross-polarized data is susceptible to the specular return from dihedral and trihedral reflectors. In addition, the volume scattering always occur in urban environment, which is the major influence on signal return of the cross-polarized data. Therefore, the cross-polarization SAR data were preferred when analyzing urban or residential areas. The change detection results for the mixed topographic area (the Kyoto dataset) reveal that cross-polarized SAR data, or their combination, were desirable. The results in this case were consistent with the two other cases (i.e., the vegetated and urbanized areas), because this study area consists of residential areas, paddy fields, and woodlands. These topographic characteristic were therefore combined, and improvements in change detection from cross-polarized SAR imagery were as discussed above for the vegetated area in the Chiba dataset and the urbanized area in the Osaka dataset.

Turning our attention to the results in Figure 8 (the improvement in accuracy of change detection for the Osaka dataset by applying ROI manual checking), the change detection rates of all seven signal polarizations were found to increase after ROI manual checking. Since the Osaka dataset is for a highly urbanized area with a large number of adjacent high-rise buildings, shadows and foreshortening effects may occur. These effects can be especially pronounced in densely built-up areas. Pixels in the unchanged class were included in the positive and negative change classes during automatic ROI generation. Therefore, point-by-point manual checking of ROIs was used to remove misclassified pixels, as described in Section 4.2.2. After ROI manual checking, 95 out of 133 ROIs were verified as belonging to the negative change class, and 44 out of 60 ROIs were verified as belonging to the positive change class. The remaining ROIs were defined as being misclassified due to the influence of shadows and foreshortening effects during automatic ROI generation. These misclassifications lowered the change detection accuracy. Hence, by removing the small number of pixels forming the misclassified ROIs—28 ROIs (115 pixels) from the negative class and 13 ROIs (88 pixels) from the positive class—the change detection maps were reanalyzed. Finally, the accuracies were improved. Hence, the analysis results have shown that the unsupervised change detection based on a closed-loop process with SAR imagery was effective for discriminating among positive change, negative change, and unchanged classes.

7. Conclusion

The effectiveness of an unsupervised change detection method based on a closed-loop process for quantitatively evaluating the change detection capabilities of fully polarimetric, dual-polarization, and single-polarization SAR were investigated. A quantitative comparison was made between a highly urbanized area (Osaka), a vegetated area (Chiba), and a mixed topographic area (Kyoto) in Japan. The change detection method was applied under the GG assumption for the log-ratio image based on the modified KI algorithm to discriminate positively changed, negatively changed, and unchanged classes. The optimal double threshold was obtained from the lowest performance index $J(T_1, T_2)$ value, and it showed high potential for generating accurate change detection. From a comparison of the change detection performance for various topographic features, the most suitable data used was the combined cross-polarized (HV+VH) power image. The TP image did the best with the original log-ratio image,
while the combined cross-polarized power image generated the best change detection accuracy after a $3 \times 3$ filter size. The VV image was the least desirable in any different topography. It can be concluded that the multi-polarized data can supply and complement the different information on the surface characteristics, it led to provide better accuracy than the single-polarization data. However, filtering the original log-ratio image had a strong influence on the change detection. The selection of the filter size affected the change detection accuracy and was dependent on the topographic characteristics. The suitable filter sizes for each topographic characteristic (the TP data, single- and dual-polarization data were considered) are as follows: (1) a $3 \times 3$ filter size was preferred for urbanized area; (2) a $7 \times 7$ filter size was preferred for vegetated area; and (3) an $11 \times 11$ filter size was preferred for mixture of topography area. In addition, the accuracies of the change detection rates of the combined polarized power data, which were generated after filtering the single-polarization data at each filter size, were significantly increased.

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