Automatic Land-Cover Change Detection Using RADARSAT-2 Images

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Abstract

The present study proposes an effective means to detect land-cover changes using the polarimetric SAR (PolSAR) images from the same or different orbits. RADARSAT-2 images are adopted in this research. To examine the proposed algorithm, two experiments are designed. One involves images from the same orbit (both are from ascending orbits), and the other involves images from different orbit (one image is from ascending orbit and the other is from descending orbit).

Methodology

To minimize the speckle influence of PolSAR images, the proposed approach is implemented on object level. The algorithm is composed of three main parts: 1) hierarchical segmentation based label propagation, 2) change detection based probability estimation, 3) anomalous label detection.

1. Hierarchical Segmentation

The classification map of the first image is used as a constraint layer for the image segmentation of the second image (Figure 1). The segmented object will inherit the classification label from previous image. Errors will be introduced in this step due to land-cover conversion. The following steps are designed to correct the classification label.

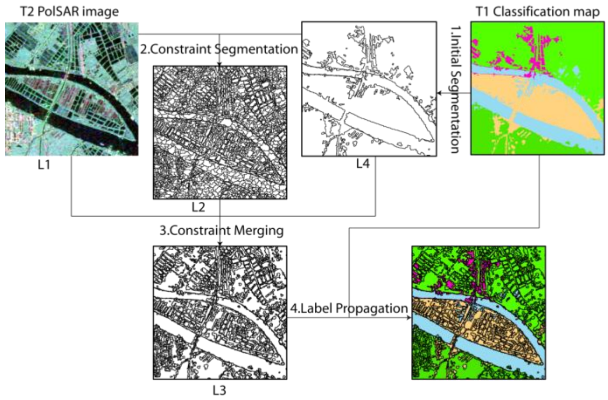

Figure 1. Hierarchical Segmentation based label propagation**.**

2. Probability Estimation

The non-change probability is calculated by a combination of two estimators: difference vector probability estimator (DVPE) and sum vector probability estimator (SVPE). Let $\Omega = \{\omega_1, \omega_2, \ldots, \omega_c\}$ be the set of possible land cover classes, and $\mathrm{I}_k = \{\boldsymbol{x}_1^k, \boldsymbol{x}_2^k, \ldots, \boldsymbol{x}_N^k\}$ be the set of objects in $\underline{k}$th (k=1 or 2) image where $\boldsymbol{x}_n^k$ (n=1~N) is a vector which descript the *n*th object.

1) DVPE: This estimator starts by calculating change vectors of image objects: $\mathbf{d}_n = \boldsymbol{x}_n^1 - \boldsymbol{x}_n^2$. The image objects are divided into several groups based on the number of land cover classes. The *i*th class group is represented as: $\mathrm{Gr}(\mathbf{d}_n, i) = \{\mathbf{d}_n | y_n = \omega_i\}$. Maximum-likelihood estimation (MLE) is then used to derive the probability of each object. After the estimation, the probability of the change vector of *n*th image object as

$$p_d(\mathbf{d}_n | y_n = \omega_i) = \frac{1}{\sqrt{|2\pi\hat{\boldsymbol{\Sigma}}_i|}} e^{-\frac{1}{2}(\boldsymbol{d}-\hat{\boldsymbol{\mu}}_i)^{\mathrm{T}}\hat{\boldsymbol{\Sigma}}_i^{-1}(\boldsymbol{d}-\hat{\boldsymbol{\mu}}_i)}$$

where $\hat{\boldsymbol{\mu}}_i$ is the estimated mean vector of *i*th group and $\hat{\boldsymbol{\Sigma}}_i$ is the estimated covariance matrix.

2) SVPE: SVPE follows similar procedures as DVPE except the first step: $\mathbf{S}_n = \boldsymbol{x}_n^1 - \boldsymbol{x}_n^2$.

After estimation of DVPE and SVPE, they are combined to express the non-change probability of each object: $p_{nc}(y_n = \omega_i) = w_d * p_d(\mathbf{d}_n | y_n = \omega_i) + w_s * p_s(\mathbf{s}_n | y_n = \omega_i)$. w_d and $w_s$are weights of each component.

3. Anomalous Label Detection

Anomalous label detection aims to identify the wrong class labels which are incorrectly assigned to the image object in the label propogation step. Based on the non-change probability, multivariate kernel density estimation is applied to to calculate the probability that image object belongs to a certain class.

Experimental results

In Figure 2, a strong correlation between band differences is also observed. The variance of each class varies from class to class which means we couldn’t use a single threshold for all the classes. The variances of Figure 2(b) (Barren) and (g) (Water) are larger than others because the number of objects in these two categories is less, and the changed objects would cause more influence. Therefore, if the change detection task is performed based on DVPs, each category must be processed independently.

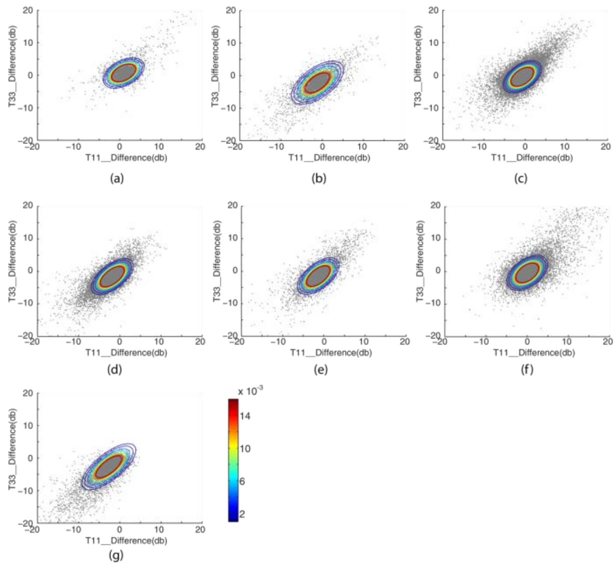

Figure 2. Difference vector probability estimation (DVPE) of 7 classes. (a), (b), (c), (d), (e), (f), and (g) represents *Musa, Barren, Vegetation, Lawn, Paddy, Urban and Water* respectively

In Figure 3(b), two distinct Gaussian distributions are mixed (two red circles). One is centered around (*-49,-33*) and the other is a bit weaker which is centered at about (*-30,-18*). This phenomenon is caused because lots of changes occurred in *Barren* lands between the two images. The distribution of *urban* class [Figure 3(f)] resembles a triangle. It can also be seen as a mixture of two multivariate Gaussian distributions.

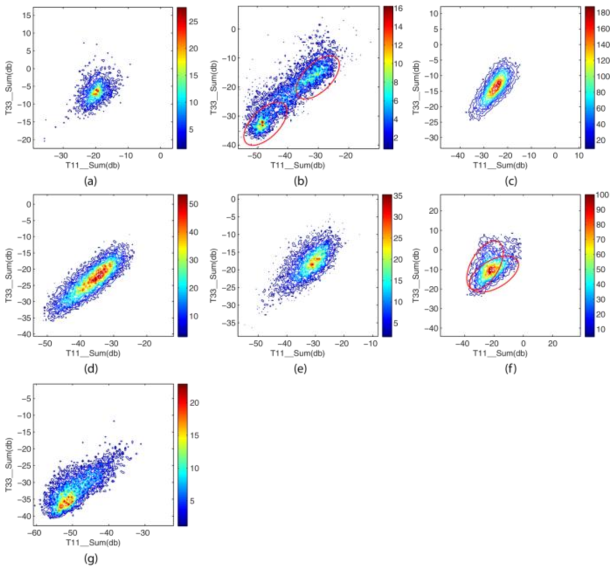

Figure 3. Distribution of sum vectors of different classes. (a), (b), (c), (d), (e), (f), and (g) represents *Musa, Barren, Vegetation, Lawn, Paddy, Urban and Water* respectively

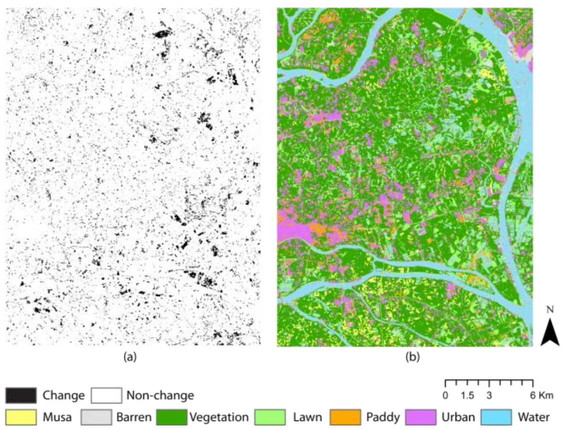

Figure 4. Experimental results of using RADARSAT-2 from the same orbit

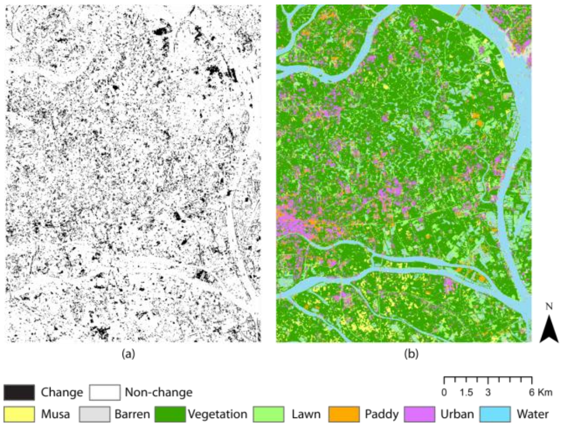

Figure 5. Experimental results of using RADATSAT-2 from different orbits

Conclusion

This study proposes a novel approach to automatically detect the land-cover changes using the PolSAR images. Experiments are conducted on two distinct sets. The change due to phenological cycle in which the land-cover class may not change is extracted and identified as non-change. In the final results of the first experiment, the detection rate of Paddy class is lowest because the second image is acquired near the end of the planting season. *Musa* and *barren* are also in low accuracy. *Musa* is wrongly classified as *vegetation* because the *vegetation* objects are more than *musa*. *Barren* is also easily mixed with *water* even for human experts. When it is sparsely vegetated, it can be classified as *lawn* or *vegetation*. In the second experiment, PolSAR images from different orbits are used. Final change detection results show changed areas are over-detected due to local deformation. Although the proposed approach doesn't solve the deformation problem directly, it could assign the new object with the right land-cover label.