Classification of Multitemporal InSAR Data for Land Cover Mapping in Selenga River Basin, Mongolia

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Abstract

The aim of this study is to evaluate different features extracted from the multitemporal spaceborne interferometric synthetic aperture radar (InSAR) data sets for a rural land cover mapping. For the actual land cover classification, the traditional statistical maximum likelihood classification and neural network method are performed and the results are compared. Overall, the research indicated that the multitemporal InSAR data sets have a valuable contribution to efficient land cover mapping.

Keywords: InSAR, Multitemporal, Classification, Accuracy

1. Introduction

At present, InSAR data sets are being widely used for land cover/use and other resources mapping. Unlike the traditional single frequency and single polarisation SAR, the InSAR uses both the amplitude and phase information from a pair of single look complex (SLC) SAR images. From this pair of SLC images, different SAR products such as amplitude and coherence images as well as a digital elevation model can be generated. These derived products or their enhanced features combined with other data sets can be successfully used for different classifications to increase the performance of the applied decision rules [2,4].

In the present study, we wanted to discriminate rural land cover types in Mongolia using the features derived from multitemporal InSAR data sets. As a test site, the Selenga River Basin, Northern Mongolia has been selected. The area represents a forest-steppe ecosystem and is characterized by fertile for agriculture chestnut soil. In the area, such classes as forest, agricultural fields, swampy area, natural vegetation, soil and water were available.

For the discrimination of the selected classes, the traditional statistical maximum likelihood (MLH) and neural network (NN) classifications have been applied and compared. The actual classifications have been performed using a) the original InSAR products, b) the SAR derivative features and c) the results of a principal component analysis (PCA), and the final results were compared. Overall, the research indicated that the multitemporal InSAR data sets have a valuable contribution to the efficient land cover mapping.

2. Data sources

As data sources, multitemporal interferometric ERS-1/2 SLC SAR data with a spatial resolution of 25m acquired with 1 day repeat pass interval on 16 and 17 October 1997, and 8 and 9 August 1998 were used. In addition, for ground truth checking topographic maps of 1984, scales 1:100,000 and 1:200,000 as well as soil and vegetation maps, scale 1:200,000 were available.

3. Derivation of the InSAR coherence and amplitude images

The coherence and amplitude images have been derived as follows [1,4]:

- Initially, 200 ground control points (GCP) regularly distributed over the images were automatically defined using the satellite orbit parameters and the two SLC images were co-registered with 0.1pixel accuracy. Then, a course registration followed by a fine registration was performed.
- Coherence has been calculated using 10x3 size window and the coherence image was generated.
- From the complex images, amplitude images were generated.
- The preliminary SLC images were converted from the slant range onto a flat ellipsoid surface.
- The true size (5800x5800) SAR images were generated using image undersampling applying 3x3 size low pass filter.

4. Derivation of the texture features

To derive texture features occurrence and co-occurrence measures were applied to the coherence and average amplitude images of the multitemporal ERS-1/2 data sets. The occurrence measures use the number of occurrences of each grey level within the processing window for the texture calculations, while the co-occurrence measures use a grey-tone spatial dependence matrix to calculate texture values [5]. By applying these measures, initially 36 features have been obtained, but after thorough checking of each individual feature only 12 features, including the results of the data range, mean and variance filters applied to the original SAR products were selected.

5. Principal component (PC) images

To reduce the dimensionality of the dataset, the PCA [7,8] has been performed to the extracted SAR features. For the PCA 16 features, including the multitemporal ERS-1/2 coherence and average amplitude images, and 12 texture features were used. As it was seen from the PCA, PC1 which contained 49.68% of the overall variance was dominated by the variance (loadings of 0.72) of the ERS amplitude image of 1997 looked very similar to the original variance dominating image and did not contain useful information, while PC2 which contained 21.82% of the overall variance was also dominated by the variance (loadings of 0.63) of the ERS amplitude image of 1997 and did not contain much information. Moreover, PC3 and PC4 which were dominated by the variances of the ERS coherence images of 1997 and 1998 also did not contain useful information. However, PC5, PC6 and PC7 which were dominated by the variances of the mean filtered coherence image of 1998, data range filtered coherence image of 1998 and data range filtered amplitude image of 1997, respectively, contained just 1.6% of the overall data variance, but contained very useful information. These PC images delineated clear spectral views of the selected classes of objects. Therefore, these PC images have been selected for further analysis and the other PCs were rejected.

6. Classification of the InSAR features

As it is known, before classification of SAR images, the speckle noise of the SAR images should be reduced, because, the reduction of the speckle increases the spatial homogeneity of the classes which in turn improves the classification accuracy. In this study, to reduce the speckle of the selected features a 5x5 size frost filter has been applied [5].

After the speckle suppression, from the features, 2-3 areas of interest (AOI) representing the six selected classes have been selected using a polygon-based approach. Then, training samples were selected on the basis of these AOIs. The separability of the training signatures was firstly checked on the feature space images and then evaluated using JM distance [8]. Then the samples which demonstrated the greatest separability were chosen to form the final signatures. For the classification, the following feature combinations have been used:

1. The coherence and amplitude images of InSAR products (4 bands),
2. 12 features selected from the occurrence and co-occurrence measures,
3. The PC5, PC6 and PC7 derived from the PCA.

For each of these feature combinations, the statistical MLH classification and NN method have been applied and the results were compared [7,8].

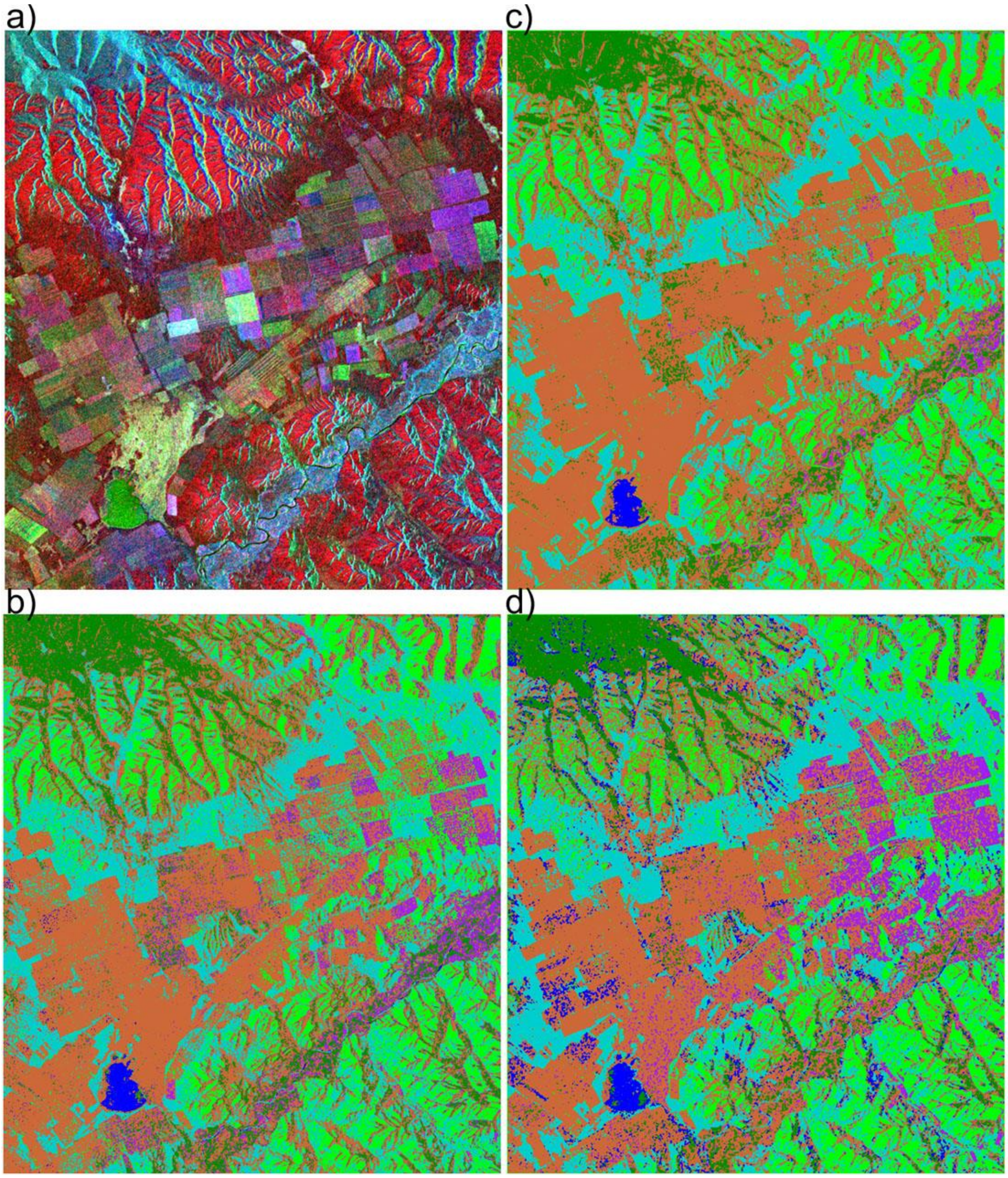

Figure 1. The original SAR image of the test area (a) and the results of the MLH classification ((b) original InSAR products, (c) 12 features, (d) PCs).

(dark green-forest, brown-agricultural fields, pink-swampy area,
green-natural vegetation, cyan-soil and blue-water).

For the accuracy assessment of the final classification results, the overall performance [4] has been used. As ground truth information, for each class several regions containing the purest pixels have been selected. In all cases, the performance of the MLH classification was better than the performance of the NN method. The overall classification accuracies of the selected classes in the selected features are shown in table 1. As seen from table 1, the performances of the classifications using the 12 features were higher than any other combinations. The original SAR image of the test area and the results of the MLH classification are shown in Figure 1.

Table 1. The overall classification accuracy of the classified features.

Feature combinations	Overall accuracy of MLH method (%)	Overall accuracy of NN method (%)
The original InSAR products	81.02	76.16
12 features	82.29	77.86
The PCs	78.54	71.47

7. Conclusions

The aim of this research was to evaluate different features extracted from the multitemporal spaceborne InSAR data sets for a rural land cover mapping. For the classification of the individual and extracted features, the statistical MLH and NN classifications were used and the results were compared by measuring the overall accuracy. In all cases, the performance of the MLH classification was better than the performance of the NN method. Overall, the study indicated that the multitemporal InSAR data sets could be efficiently used for a land cover mapping.

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