LAND COVER CLASSIFICATION BASED ON SAR DATA IN SOUTHEAST CHINA

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ABSTRACT

Southeast China is a sub-tropical area where it is rainy or cloudy for most time of the year. Optical remote sensing data are often unavailable because of the meteorological conditions. SAR becomes the most effective and sometimes the only remote sensing instrument for earth observation in these areas due to its penetration to rain and cloud. This research study presented here focuses on the use of ERS and Envisat-1 SAR data for land cover/land use classification in Fujian province in southeast China. Both SAR backscatter intensity and interferometric coherence were investigated. To overcome the well-known speckle phenomenon, a parcel based approach to information extraction is used for classification by synergistic use of SAR and high spatial resolution optical data. The classification result was validated by field campaign and showed promising application of ESA SAR data in southeast China.

1 INTRODUCTION

The use of space-borne remote sensing for land use applications has been widely demonstrated as an important tool, particularly for land cover identification. Land use/land cover and crop classification are usually performed using high resolution optical data, such as Landsat TM or SPOT HRV data. For many regions in China with very diverse land use and crop types, and particularly in the southern China, the main limitation of optical data is cloud cover, which prevents multi-date acquisition during the growing season. This limitation has been alleviated by the use of Synthetic Aperture Radars (SAR) which is essentially all-weather systems. Hence, the potential of multi-temporal SAR data for producing land cover maps has become of increasing interest. It has been shown that a multi-temporal analysis of SAR data allows monitoring changes in land cover using the backscatter change intensity. Moreover, it has been demonstrated in [1-3] that the coherence component derived from an interferometric pair gives additional useful information for land cover classification. ERS-1, ERS-2 SAR data has been successfully used for land use applications. Their successor, ENVISAT ASAR, has more important new capabilities: beam steering for acquiring images with different incidence angles, dual polarization and wide swath coverage. Owing to the implementation of alternating polarization mode it is possible to obtain images in one of three available polarization configurations (VV&VH or HH&HV or HH&VV), which considerably increases the classification capability. With Image Mode ASAR can only obtain image in one polarization (VV or HH) but the data has better radiometric quality which is more suitable for INSAR processing.

In this paper, we present our research on land cover/land use classification application in Zhangzhou, Fujian province, China, which is part of work of Dragon ID 2563 project. To overcome the well-known speckle noise phenomenon, a parcel based approach to information extraction is used for classification by the synergistic use of high resolution optical data and radar information derived from SAR and INSAR data. First, we present the different steps to derive a series of parameters from both amplitude and complex data. In particular, we investigate the usefulness of the coherence image (both ERS tandem and ASAR IM long time interval pair) and the multi-temporality of ASAR backscatter images for crop mapping. Second, a description of the data-driven classification method is given, where the high spatial resolution optical data is used to create the vector parcels.

2 TEST SITE AND DATA

The test site is located in the Zhangzhou district in the south of Fujian province in southeast of China. A 1230km² area was selected for our analysis (Fig.1). Zhangzhou District lies between 116°53′-118°09′E and 23°32′-25°13′N, belonging to the subtropical regions. This site has a wide variety of land cover types ranging from forest, urban area and agriculture land including rice, water bamboo, potato and sugarcane.

The remote sensing data collected for this research include:

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1) ERS data. One pair of ERS-1/2 tandem SLC data from March 12, 1996 and March 13, 1996;
2) ENVISAT ASAR. IMS data from June 6, 2004, April 17, 2005, July 31, 2005 and September 4, 2005; IMP data for the same acquisitions from April 17, 2005 and July 31, 2005;
3) ASTER data. Band 1-3, spatial resolution 15m.

3 DATA PROCESSING

3.1 Amplitude processing

Amplitude images ASAR IMP and APP are processed to derived different parameters used in the classification process: (1) Backscatter coefficient $S^0$; (2) Backscatter intensity difference $D_s^0$; (3) Maximum of backscatter in two images $\text{Max}S^0$.

To derive these parameters from multi-temporal SAR data, the first step in the processing chain has been radiometric calibration using calibration constant given in the image file header and local incidence angle from auxiliary data as Eq.1[4]. The calibrated image was temporally stored in linear format for further processing. The calibration was performed with ESA freeware BEST.

$$\sigma^0 = \frac{I^2}{K} \cdot \sin(i) \quad (1)$$

Where, $\sigma^0$ is backscatter coefficient in linear scale; $I$ is a digital number of a pixel; $K$ is calibration constant, $i$ is incidence angle.

After calibration, the multi-temporal images were set to the same geometric projection of the data from April 17, 2005 by co-registration based on correlation matching.

To make the ERS and ASAR data with different incidence angles comparable to each other and to the existing maps, orthorectification was performed by using DEM. The data was finally transformed to sigma_nought values by log operator following the formula given by Eq.2.

$$s^0 = 10.0 \times \log_{10}(\sigma^0) \quad (2)$$

Where, $s^0$ is backscatter coefficient (dB), $\sigma^0$ is backscatter coefficient in linear scale.

The backscatter intensity difference $D_s^0$ is estimated as Eq.3.

$$D_s^0 = s_1^0 - s_2^0 \quad (3)$$

Where, $s_1^0$ is the backscatter image of date from July 31, 2005; $s_2^0$ is the backscatter image of date from April 17, 2005.

3.2 Interferometric processing

Two main components can be derived from an interferometric pair. The phase is normally used to derive terrain height. The interferometric coherence component can provide complementary information to the backscattered intensity for land cover classification. Then, for our purpose, only the coherence component is derived from the interferometric pair.

The degree of coherence for each pair $(s_1, s_2)$ of co-registered complex values $s_1, s_2$ is given by Eq.4.

$$\gamma = \frac{\langle s_1^* s_2 \rangle}{\sqrt{\langle |s_1|^2 \rangle \langle |s_2|^2 \rangle}} \quad (4)$$

Where $s_1$ and $s_2$ are the complex images; $\langle \ldots \rangle$ the spatial average operator, which is estimated by the spatial average over a finite-size window; $^*$ is the conjugate operator; and $\gamma$ is the estimated coherence.

In this paper, a pair of ERS-1/ERS-2 data with 1 day apart was processed for short-term coherence product as well as 4 ENVISAT ASAR IM mode data for long-term coherence.

4 DATA ANALYSIS

4.1 ASAR backscatter signatures

To assess whether the temporal behavior of land cover and crop types could be exploited in classification,
ASAR backscatter signatures were studied, taking published results into account. ASAR returns from different land cover types (urban, forest, rice, water bamboo and water surfaces) were measured on the two ASAR IMP images from 14 April, 31 July in 2005, as shown in Fig.2.

Many previous studies show that rice field and some other agricultural field exhibit large variability in their radar responses [5]. This is the basis of the approach to agricultural field mapping relying on temporal change measurement. Knowledge of crop calendar is very important to crop mapping by multi-temporal SAR data. In Zhangzhou, spring rice is transplanted in early April and harvested in middle or late July. At its early growing stage, rice field is flooded and exhibit extremely low radar backscatter due to specular reflection of the water surface. The backscatter coefficient of rice field increases gradually with rice plants’ development. It reaches a climax before harvesting. Fig.2 shows that the backscatter coefficient increases from -19~ -18dB at transplanting stage to -8~ -7dB before it’s harvesting. Water bamboo has a similar temporal radar backscatter response behavior as rice. It is planted in November and harvested in May and June the next year. After harvesting, the fields will be left unseeded as fallow farmlands and flooded for about one month. Water bamboo’s backscatter signatures in Fig.2 explain the phenomena too. The backscatter coefficient decreases from -5dB at its well developed stage to -17dB during its fallow farmland period.

Unlike rice and water bamboo, other land cover types exhibit lower temporal variability. Forests can be distinguished from other types of vegetation using their temporal stability in the radar images. But in those areas like Zhangzhou with great terrain variation forest is not easy to be distinguished from other types due to radar geometric errors such as radar shadow, layover and foreshortening. Fig.2 shows that urban and forest foreshortening have very close backscatter coefficients. Interferometric coherence from ERS-1/2 tandem mission has been successfully applied to forest mapping in many places of the world. A pair of tandem data in 1996 for Zhangzhou was used for forest class discrimination in this research. The urban class also has high temporal stability compared to most natural targets, but with a very wide range of backscattering values that overlaps significantly with other land cover types. Four ASAR IMS data was tested to create coherence images to separate urban areas from other land cover types in our research.

### 4.2 Coherence signatures

The coherence measures the changes between two image acquisitions. High coherence means no or small changes whereas no coherence indicates a high degree of change. Low coherence is expected for vegetated areas, as a high coherence value over non-vegetated areas like bare soils, grasslands and deforested areas.

By examining the backscatter responses of dense urban area and forest foreshortening area, we found that they both have high backscatter coefficients and a wide dynamic range, as shown in Fig.3. It is very difficult to make these two classes separated by only backscatter intensity. Fig.3 also shows that there is no overlay between the tandem coherence values of forest and those of urban area. It is potential to distinguish forest area from urban area by using the tandem coherence image.

### Table 1 Parameter for long-term coherence generation

<table>
<thead>
<tr>
<th>No.</th>
<th>Date 1</th>
<th>Date 2</th>
<th>Baseline(m)</th>
<th>Time apart(d)</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>20040606</td>
<td>20050904</td>
<td>60</td>
<td>455</td>
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<td>2</td>
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<td>20050904</td>
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<td>3</td>
<td>20050417</td>
<td>20050904</td>
<td>173</td>
<td>140</td>
</tr>
</tbody>
</table>

Three long-term coherence images were produced using different combinations (Table 1) of four ASAR IMS data. The first pair of data from June 6, 2004 and September 4, 2005 gives poor coherence image on which urban area is not very distinguishable. The potential reason is that the temporal baseline is too long (455 days). The coherence images produced from the other two combinations of data pair give very good visualization of urban area. Statistic analysis of urban and bare land is shown as Fig.4. The statistics in Fig.4 show that ASAR long-term
interferometric coherence is better than backscatter intensity in separating urban area from bare land.

Figure 3 Plot of $s_0$ as a function of coherence (Data: 20050731, ERS-1/2 tandem coherence)

**Figure 4** Plot of $s_0$ as a function of coherence (Data: 20050731, Coherence from ASAR pair)

5 Classification method
To overcome the well-known speckle noise phenomenon, a parcel based approach [6] to information extraction is used for classification by the synergistic use of high resolution optical data and radar information derived from SAR and INSAR data. The objected oriented classifier implemented in eCognition software [7] was used to perform the parcel based approach to information extraction from SAR and INSAR data. Firstly, the co-registered dataset were fed into the classifier, including ASTER data and SAR/INSAR data. With the data analysis in chapter 4, the input SAR/INSAR data include ERS tandem coherence image, ASAR long-term coherence, backscatter intensity images from 20050417 and 20050731 and the intensity difference between them. Secondly, the image objects were created by image segmentation using 3 ASTER bands. The land cover parcels in Zhangzhou area are in small sizes, particularly for the agricultural fields. The image objects from ASTER data can reflect land cover parcels better than the objects from SAR data due to its high spatial resolution. Lastly, image objects are assigned to classes using a fuzzy rule base. After segmentation, each image object has a set of SAR/INSAR statistic attributes, among which the mean layer value is the most important and commonly used one. Mean value is calculated by averaging the original pixel values within the object. SAR speckle noise phenomenon is greatly reduced after the averaging process. The fuzzy rule base is set using the SAR/INSAR layer attributes as Fig.5. Water surfaces also have variations in backscatter due to wind conditions. The misclassification was corrected by visual interpretation and manual editing to improve the accuracy.

**Figure 5 Chart of fuzzy rule base for classification**

6 Result and validation
The image objects were assigned to land cover classes (Fig. 6) based on the fuzzy rules in eCognition. The classification was validated with a SPOT-5 image from February 20, 2003 (2.5m resolution) and field survey data collected in 2005 and 2006. The discrimination between forest and urban is quite satisfactory. There is nearly no confusion between these two classes. Urban area is separated from bare land well too. Two agriculture crop types, rice and water bamboo, are classified with good accuracy using their temporal changes in backscatter intensity. But some small fields which are identified in SPOT-5 image have not been classified correctly. The classification accuracies for forest, urban (urban area and rural residential area), rice
and water bamboo are 92%, 90%, 85% and 76% separately.

Figure 6 Land cover classification map of Zhangzhou

7 Discussion and conclusion
Two agriculture types, rice and water bamboo, have been successfully mapped by using 2 key multi-temporal data at their different growth stages. But multi-temporal analysis is not sufficient for land cover classification over areas like Zhangzhou. Some land cover types cannot be discriminated, due to similar backscatter coefficient and geometric or radiometric errors caused by terrain variations. However, it has been demonstrated in this paper that multi-temporal study in combination with interferometric analysis can give useful information for land cover classification. ERS-1/2 tandem coherence image is quite appropriate for forest/ non-forest discrimination, while ASAR long-term coherence can be a new discriminator for urban area. Moreover, small baselines are required to avoid a degradation of the level of coherence.

For further study, many new features of ENVISAT ASAR are to be exploited to improve the land cover classification performance besides multi-temporal analysis, particularly for the dual polarization and multi-incidence capability. 35-day-apart coherence images both from ERS-1 or ERS-2 pair and ASAR IM mode pair will be used together for land cover/ land use change monitoring.

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