1. INTRODUCTION

China’s urban population continues to grow and the standard of living is rising. These two factors combine to exert increasing pressure on the agricultural land surrounding cities. As diet improves, shifting away from the national staple of rice, farmers are adapting by switching to more lucrative crops like fruit and vegetables. At the same time, the ever-advancing urban fringe is consuming these agriculture areas, placing greater demand on the remaining land. These changes need to be carefully monitored to ensure that future growth is sustainable. This research is intended to develop the methodologies for monitoring the land use/land cover changes by the synergistic use of ALOS PALSAR and archived JERS-1 SAR data, with emphasis on the monitoring of urban expansion and land use changes of agriculture fields.

2. PROJECT INFORMATION

1.1 Research objective

The objectives of the project are to develop and validate methodology using ALOS PALSAR data on two main issues: (1) Land use/land cover classification, with emphasis on urban and agriculture; (2) Land use/land cover changes using historical and/or archived JERS-1 SAR data. Two application projects will be carried out on (1) urban expansion monitoring of Fuzhou city and (2) rice field mapping and change monitoring.

1.2 Summary of the research work

Urban growth is a great thread to the vegetated areas like forest and agricultural regions. Thus, during the four years’ research, we focused on the classification method development using ALOS PALSAR data for urban detection and vegetation (rice and forest) mapping. With L band SAR like ALOS PALSAR, the usual rice mapping method based on temporal change cannot always be used to achieve high accuracy. We made analysis on the Bragg resonance scattering of L band SAR (PALSAR HH polarization) in machine planted rice fields and proposed a solution of how to use ALOS PALSAR data for rice mapping. The forest/non-forest mapping by ALOS was also investigated using both FBD and PLR data. Urban change mapping was carried out using SAR interferometry techniques. All the mentioned research results are to be discussed in the following chapters.

3. URBAN AREAS MAPPING USING COHERENCE

3.1 Test site and data

This study focus on the urban areas located in Fuzhou district, which in the east of Fujian province in the southeast of China. Fuzhou district lies between 118°08′-120°31′E and 25°15′-26°39′N. Data processing consists of calibration, image co-registration, coherence estimation and geocoding. The major steps of interferometer processing include two SLC images were co-registered at sub-pixel accuracy. Then, multilooking was performed to improve the estimates of the interferometric phase and coherence. The degree of coherence for each pair (g₁, g₂) of co-registered complex values g₁, g₂ is given by:

\[
\gamma = \frac{\langle g_1 \times g_2^* \rangle}{\sqrt{\langle |g_1|^2 \rangle \langle |g_2|^2 \rangle}}
\]  

Where g₁ and g₂ are the complex images; angular bracket represents averaging over the ensemble of speckle realizations; * is the conjugate operator.

3.2 Classification of urban using coherence

Coherence is first an indicator of the quality of the InSAR phase. It can also be used as a feature for land cover classification. Coherence is a measurement of the mechanical stability of the observed scatters. For example, the water and vegetation are very unstable even subject to winds, which give low coherence. The urban, however, consists of stable scatters, eg. buildings and other manmade structures, which give high coherence even with long-time interval. Based on this physics, we use coherence only for urban area mapping [1].
4. RICE FIELDS MAPPING USING PALSAR

The objective of this part of research is to assess the use of FBD mode (Fine Beam Double Polarization) data of the Phased Array type L-band Synthetic Aperture Radar (PALSAR) onboard ALOS satellite to map rice growing areas. While past studies have demonstrated the use of C-band Synthetic Aperture Radar (SAR) data (ERS-1/2, RADARSAT-1) to map rice areas, L-band SAR data (JERS-1) have been regarded ineffective due to the Bragg resonance scattering phenomena observed in some mechanically planted rice fields. PALSAR provides higher performance than its predecessor JERS-1 SAR. In this paper, we examined the temporal backscattering behaviors of rice fields in Haian, Jiangsu province at PALSAR HH and HV Polarization data. Image enhancement in backscattering intensity as a result of Bragg resonance scattering was found only at HH Polarization since double-bounce scattering is a prerequisite to Bragg resonance scattering for radar backscatter from bunches of rice plants. A classification method for rice growing areas mapping was developed and applied to the multi-temporal PALSAR HV data at Haian test site. Validation by the field work showed that rice areas mapping using L-band SAR is promising when cross-polarized data are available to cope with the Bragg resonance scattering effects.

4.1 Bragg resonance scattering of rice fields

The first condition for the Bragg resonance scattering to occur is defined as formula (2) in terms of the structure parameters of the rice fields [3]

$$\Delta y = \frac{\lambda}{2 \sin \theta \cos \gamma}$$

(2)

Where \(\Delta y\) is the bunch spacing in range direction; \(\gamma\) is the off-range angle of planting direction; \(\lambda\) and \(\theta\) are the wavelength of the microwave and incidence angle. Enhanced radar backscatter was observed and confirmed by field work measurements in some machine-planted rice fields in Haian test site as shown in the center of Fig.1 (a). The measured \(\Delta y\) is about 20.1 cm. The angle between north and planting direction is 12° off north to east. Considering the orbit inclination 98.16°, \(\gamma = 20.16°\). These measurements satisfy well the first condition.

The second condition for the Bragg resonance scattering to occur requires well defined phase difference between neighboring scattering elements. The enhanced backscattering was only found in HH polarization images as indicated by the bright white area in the center of Fig.1 (a). The dominant scattering mechanism in HV polarization is due to the multiple scattering from the quasi-randomly distributed elements within the bunch of rice, etc. leaves, stems. The phases of the received signals are also randomly distributed and the resonance condition does not hold. Fig.1 (b) shows there is no enhance backscatter in HV images.

4.2 Rice fields mapping method

The above analysis on the ALOS PALSAR backscatter of rice fields show that HV polarization is more promising for rice growing areas mapping. Our proposed rice areas mapping method is based on the temporal change threshold algorithm. Firstly we calculated the PALSAR HV intensity ratio of the data acquired on June 30 and August 30. The following two threshold rules were then applied to the ratio image and one HV image:

1. 6dB was set as a threshold to ratio image to separate rice and mulberry fields (> 6dB) from other land covers;
2. -15dB was set as a threshold to the August 30 HV image to separate rice fields from mulberry fields (> -15dB).

The derived rice maps are shown in Figure 2. The rice fields subject to the Bragg resonance scattering were not mapped as rice with HH polarization data. However, with HV the result is more accurate which can be seen by merely visual comparison. In addition, mulberry plantation was also mapped well with two temporal HV images using the proposed rice mapping method.
good results because of no Bragg resonance effects. Secondly, the mapping accuracy was investigated in areas without Bragg resonance effects. Both of the two polarization modes offered good rice mapping results with the overall accuracy 88.4% and 86.0%, Kappa index 0.767 and 0.719 separately. Considering the performance in Bragg resonance areas, HV polarization performs better than HH polarization for rice mapping at L band. Conclusion can be drawn that the cross-polarization (HV) should be used for rice areas mapping with L-band ALOS PALSAR [2].

5. FOREST MAPPING USING ALOS PALSAR

5.1 Forest/non-forest mapping with PALSAR FBD data

With the analysis of the PALSAR intensity of HH and HV images and the 46-day time interval InSAR coherence, a rule-based classification method was developed for the subtropical forest cover mapping in the regions as Fujian, China. This method uses the ratio of HH to HV and the coherence image as two primary features for the rule setting. Fig.3 shows a color composite image using coherence, intensity and ratio. From Fig.3, we can see that it is very promising to separate forest from non-forest area with these features. Fig.4 shows the developed rule-based classification procedure.

Figure3. Color overlay of coherence (R), average HV intensity (G) and polarimetric intensity ratio (B)

Fig.4. Forest mapping using combination of backscatter, polarimetric intensity ratio and coherence
The method was applied to the forest area in Zhangpu country in the south of Fujian province. Fig.5 shows the mapping result. Validated by a forest inventory map and a high resolution Spot-5 image, we found that the coastal forest was mapped with high accuracy of 92%. The overall classification accuracy is about 70%. Considering the very heterogeneous land surface, the accuracy can be satisfactory [4].

Fig.5. Forest map from PALSAR data (1: Coastal forest; 2: Hilly forest)

4.2 Forest mapping using ALOS PALSAR RVI

Radar vegetation index (RVI) derived from ALOS PALSAR full polarimetric data was tested for forest area mapping and compared with NDVI of Landsat TM data. The 3x3 complex Coherency $[T3]$ matrix being hermitian, semi-definite positive, its eigenvectors are orthogonal and its eigenvalues are real positive. The eigenvector decomposition of a distributed target coherency matrix is considered as a simple statistical model consisting in the expansion of the 3x3 complex Coherency matrix into a weighted sum of three coherency matrices

$$
\langle [T3]\rangle = \sum_{i=1}^{N} \lambda_i v_i v_i^\dagger = \lambda_1[T3]_1 + \lambda_2[T3]_2 + \lambda_3[T3]_3
$$

The average radar return of a distributed target is, in general, partially polarized. The natural target randomness can be measured by the range of the eigenvalues of the associated averaged coherency T3 or covariance C3 matrix. Van Zyl (2006) analyzed scattering from vegetated areas using a model of randomly oriented dielectric cylinders and showed that the second and third eigenvalues are equal for this type of model [5]. The radar vegetation index (RVI) is thus defined as

$$
RVI = \frac{4\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3} \quad 0 \leq RVI \leq \frac{4}{3}
$$

RVI is equal to 4/3 for thin cylinders and monotonically decreases to 0 for thick cylinders.

Based on formula (4), we calculated the RVI for a frame of ALOS PALSAR PLR data for Northeast China and compared RVI with NDVI from Landsat TM image. Fig.6 shows the two index images and Fig.7 shows their histograms.

From Fig.6, we can see that both RVI from SAR and NDVI from optical image can characterize forest area to some extent. They function differently though they can fulfill the same purpose. RVI is a measurement of the target randomness in respect of scattering mechanism, while NDVI is a measurement of the amount of vegetation due to different reflectivity of green vegetation component to NIR and VIR. The forest area can be better separated from other land cover types by RVI than NDVI which can be seen from Fig.6 from visualization. It can be further confirmed by comparing the histograms of these two index images (Fig.7). The histogram of RVI has two separated peaks near image value of 50 and 200, while that of NDVI has only one sharp peak near 190. The RVI histogram peak of the lower value 50 represents the dark areas in the image of Fig.6 (a). These are homogeneous agriculture regions where the scattering mechanism is pure – surface scattering. The second peak of higher value 200 represents the bright areas in the image of Fig.6 (b). These areas are covered with forest. As for the Fig.7 (b), all the NDVI values are around a single histogram peak value 190. The green vegetation, including forest and agriculture, shows bright color in Fig.6 (b). Comparing the two histograms, conclusion can be drawn that it is more promising to use RVI for forest area mapping than NDVI. It is difficult for NDVI to separate different vegetation types, forest and agriculture in this case for example.

Unsupervised classification was applied to both the RVI and NDVI. The result from RVI is much better than that from NDVI, which can be explained as follows: 1) The scattering mechanisms of forest and other non-forest vegetation, eg. agriculture, are usually quite different; 2) The crops present the similar greenness (NDVI) during its growing season to that of evergreen forest. Forest
mapping using optical remote sensing depends strongly on the acquisition time of the data. Conclusion can be drawn that polarimetric SAR data are more practical for forest monitoring due to better mapping results and its all-time/all-weather data acquisition capability [6].

6. URBAN DYNAMIC CHANGE MONITORING IN FUZHOU

6.1 Urban change detection

Two approaches for urban change detection were utilized in this paper. One is post-classification comparison, the other is multitemporal image ratioing. Post-classification comparison involves independent classification results from each end of the time interval, followed by a pixel-by-pixel or segment-by-segment comparison to detect changes in land-cover categories. The second approach is based on image ratio, which is one of the simplest and quickest change detection methods. Ratio was computed on a pixel-by-pixel basis. A pixel with no change will yield a ratio value 1. Areas of change will have values either higher or lower than one. According to the dynamics of $I$, if $I < 0$, it means urban growth, if $I > 0$, it means urban decrease or urban constant when $I \to 0$. Based on this theory, we computed two multitemporal SAR images for the urban areas change detection. The discrimination factor is defined as Eq. (5):

$$I = 1 - \frac{\sigma_2}{\sigma_1}$$  \hspace{1cm} (5)

Where $\sigma_1$ and $\sigma_2$ correspond to the two superimposed means of pixels computed on a small neighborhood of the two SAR images on dates 1 and 2 respectively.

6.1.1 Urban area detection

![Fig.8. Classification map of 1996(a), 2000(b) and 2007(c)](image)

Fig.8 shows the MLC classification maps from the ERS/ENVISAT ASAR coherence images in 1996, 2000 and 2007. The validation of the land cover maps were based on confusion matrix referred to TM image, Spot-5 image and field survey for 1996, 2000 and 2007 accordingly. The classification accuracies for urban area are all above 90% in the three temporal periods. The classification accuracies of water and forest are 92%, 88% and 87%, 90% in 1996 and 2000, respectively. For the assessment of the classification result of 2007, five 1km samples were selected as test sites for our attempt about areal samples validation. The classification accuracies for urban, forest and water are 90%, 93%, 86% respectively.

6.1.2 Urban change detection

The urban dynamics change maps, which time from 1995 to 2000 and 1995 to 2007, were exhibited in Fig. 9 by the post-classification. The primary urban growth direction is towards east and southeast of the old city. From 2000 to 2007, the urban expansion is primary to the west. These are caused by the new building of Fuzhou university town [1].

![Fig.9. Urban change map from 1996 to 2000 (a) and from 1996 to 2007(b)](image)

6.2 Land cover changes within agricultural fields

To get a better understanding of the current situation of the land cover types in this area and how the rice fields have been changed, a more detailed classification was performed using the three scenes of the HH Polarization PALSAR and JERS SAR. The multi-date data were classified using an objects based classifier, which was developed by DEFiNiENS and implemented in eCognition software. The processing consists of two main steps, multi-resolution segmentation and objects based classification. Image objects are assigned to classes using a fuzzy rule base. The multitemporal stability of the urban area and the multitemporal variation of the agriculture crops in SAR backscatter are the basic characteristics for the construction of the fuzzy rules. The distortions in the mountainous area, e.g. foreshortening, layover and shadow, can result in obvious misclassification. DEM was used before classification to reduce the effect of those distortions by masking the forest area out. The multitemporal color composite image and the derived land cover map are shown in Fig.7.
A land cover change map (Fig.10) was produced from the land cover map in 2007 and the rice map in 1998 from PALSAR and JERS-1 SAR separately to examine the changes that occurred within the rice fields after 9 years. Although it is indicated in Fig.8 that great changes have occurred, the lost of rice field to urban in this area is not intensive. The land use changes between different agriculture crops are quite obvious which can be seen from Fig.10 as well. The reason is that as diet improves with people’s living standard, shifting away from the national staple of rice, farmers are adapting by switching to more lucrative crops like fruit and vegetables.

7. CONCLUSIONS

In summary, our work during the four years’ cooperation with JAXA made 4 scientific achievements by the following conclusions:

1) Urban area detection method using long time interval InSAR coherence and the change detection based on it are proved to be very effective;

2) The Bragg resonance scattering makes rice mapping with L-band SAR difficult. But the solution was found by using HV polarization image for this application.

3) The research area – Fuzhou city has experienced a great urban growth since the last decades of 20th century, which is proved by the application of ALOS PALSAR and other satellite SAR data.

8. REFERENCES


