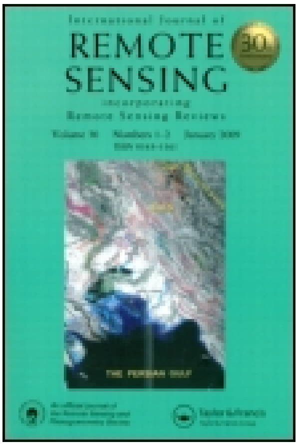

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Crop classification using multi-configuration SAR data in the North China Plain

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Crop classification using multi-configuration SAR data in the North China Plain

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Crop classification is a key issue for agricultural monitoring using remote-sensing techniques. Synthetic aperture radar (SAR) data are attractive for crop classification because of their all-weather, all-day imaging capability. The objective of this study is to investigate the capability of SAR data for crop classification in the North China Plain. Multi-temporal Envisat advanced synthetic aperture radar (ASAR) and TerraSAR data were acquired. A support vector machine (SVM) classifier was selected for the classification using different combinations of these SAR data and texture features. The results indicated that multi-configuration SAR data achieved satisfactory classification accuracy (best overall accuracy of 91.83%) in the North China Plain. ASAR performed slightly better than TerraSAR data acquired in the same time span for crop classification, while the combination of two frequencies of SAR data (C- and X-band) was better than the multi-temporal C-band data. Two temporal ASAR data acquired in late jointing and flowering periods achieved sufficient classification accuracy, and adding data to the early jointing period had little effect on improving classification accuracy. In addition, texture features of SAR data were also useful for improving classification accuracy. SAR data have considerable potential for agricultural monitoring and can become a suitable complementary data source to optical data.

1. Introduction

Remote-sensing techniques have long been an important means for agricultural monitoring, with their ability to quickly and efficiently collect information about spatial variability occurring in the field (Benedetti and Rossini 1993, González-Sanpedro *et al*. 2008, Wang *et al*. 2010). Crop type identification is a key issue for monitoring agriculture, and is the basis for crop acreage and yield estimations, which are critical to many applications in the domain of agricultural monitoring using remote-sensing techniques (Wu 2000, Blaes *et al*. 2005). Generally, crop maps are required to be updated at frequent intervals for proper agricultural management and yield forecasting (Foody *et al*. 1994). Out of the range of available remote-sensing systems, synthetic aperture radar (SAR) data is a particularly attractive data source for crop classification applications

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because of its characteristics of all-weather, all-day imaging capability, particularly in regions where cloud cover is a problem (Foody *et al*. 1994, Shao *et al*. 2001, Del Frate *et al*. 2003).

However, classification using a single SAR system with one single configuration, that is one image at a given frequency, polarization and incidence angle, is often inadequate to attain the required accuracy of classification (Del Frate *et al*. 2003). Considering the dependence of the scattering mechanisms in vegetation canopies on frequency, polarization and incidence angle, improvements of classification accuracy can be expected by using multi-frequency, multi-polarization or multi-angle measurements (Foody *et al*. 1994, Freeman *et al*. 1994, Del Frate *et al*. 2003, Jia *et al*. 2009). Alternatively, multi-temporal SAR data collected by repeated overpasses can also improve the classification accuracy, since they are affected by the peculiar variations induced in backscattering by the growth cycle of a given plant (Le Toan *et al*. 1997, Tso and Mather 1999, Shao *et al*. 2001, Wang *et al*. 2010). Thus, crop classification using multi-configuration SAR data has the potential for improving accuracy and is the trend for SAR data applications in the domain of agriculture. However, an important question is whether increasing different configurations of SAR data is really better for crop classification, since more configurations of SAR data can bring the problem of data redundancy, as well as the increase in processing and data acquisition costs.

SAR images are granular in appearance due to a phenomenon known as speckle which results in inter-class confusion and leads to isolated misclassified pixels and small misclassified spots being introduced into thematic maps (Li *et al*. 1998). Texture features, which are robust to speckle perturbation, are important aspects for improving SAR image classification accuracy and are widely used for classification of SAR data (Li *et al*. 1998, Haack and Bechdol 2000, Rajesh *et al*. 2001, Herold *et al*. 2004). Co-occurrence matrix features are always used to obtain texture features of images (He and Wang 1992, Berberoglu *et al*. 2007), such as contrast, correlation, energy, entropy, homogeneity, angular second moment (ASM), dissimilarity and so on. Clausi (2002) pointed out that a group of statistical factors consisting of contrast, correlation, and entropy performed better than any single one in the group or in other groups. Gong *et al*. (1992) found out that window sizes of 3×3 and 5×5 were better than other larger windows. ASM has been shown to improve classification performance of supervised classification in the urban fringes and change detection in cities (Jensen and Toll 1982). In this article, texture features for improving crop classification accuracy using SAR data were also investigated.

Currently, rice or irrigated crop monitoring has become the main subject of research of SAR data in the domain of agriculture (Shao *et al*. 2001, Li *et al*. 2008). However, SAR data have rarely been used for classifying upland field crops, which are soil background against the wetland crop like rice. In this article, multi-temporal C-band advanced synthetic aperture radar (ASAR) data and an X-band TerraSAR data are investigated for crop classification in the North China Plain. The specific objectives of this study are to investigate (1) the capability of SAR data for crop classification in the North China Plain, where the cropland is mainly occupied by winter wheat; (2) whether multi-frequency SAR data are more effective than multi-temporal SAR data for improving crop classification accuracy; and (3) the influence of texture features for improving crop classification accuracy.

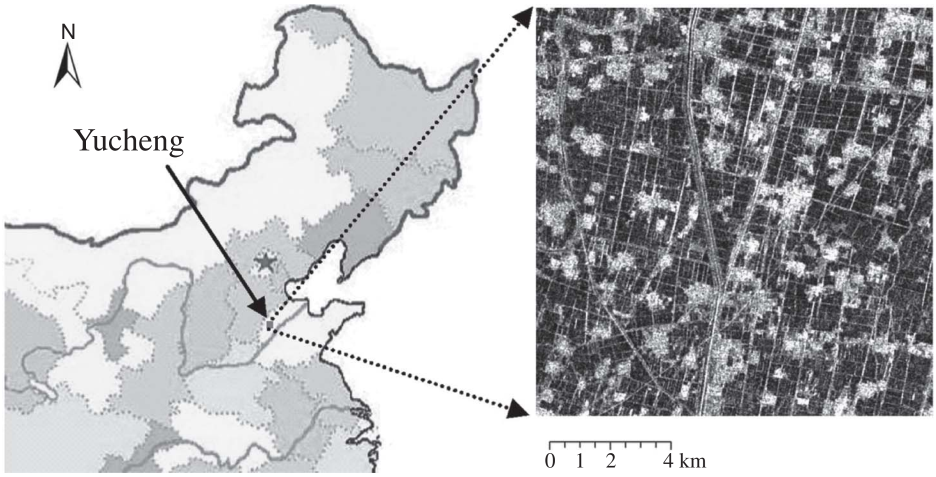

Figure 1. (*a*) Square region in the image shows the geo-location of the Yucheng study area in Shandong Province, China. (*b*) This image is the subset of the advanced synthetic aperture radar (ASAR) image received on 8 May 2009.

2. Study area

The study area is located in Yucheng (centred at 36° 47′ N, 116°33′ E), Shandong Province of China (see figure 1). This region belongs to the temperate climate zone and is a typical upland field agriculture area in the North China Plain. It is relatively flat farmland with an average altitude of about 20 m above sea level, so that uncertainty of classification accuracy caused by topographical facts will be reduced to a minimum. The annual precipitation is approximately 582 mm and the average temperature is about 13.1°C. The study area selected in this study is about 15 km $\times$ 15 km. Although it is not a big region, it has the representative characteristics of crop type distribution in the North China Plain. The cropland is mainly occupied by winter wheat and a small quantity of cotton. The wheat season begins in early October and is harvested in June the following year. Cotton is planted in April and harvested in September.

3. Data and processing

The ASAR on board Envisat, which is operated by the European Space Agency (ESA), is a C-band SAR. Under the framework of the Dragon 2 project, three ASAR image mode precision (IMP) images were received from ESA during the growing period of wheat in the year of 2009 (see table 1). The ASAR images were VV (radio waves transmitted and received in vertical polarization) polarization with 30 m spatial resolution, and acquired with an IS2 swath. The image acquisition dates were arranged for the same satellite orbit with a 35-day cycle on the following dates: 27 February 2009, 3 April 2009 and 8 May 2009. Wheat was after tillering and in the early jointing period in late February, it is called the early jointing period in this study. When ASAR data were acquired in April and May, wheat was in late jointing and flowering periods, respectively, in this study (see table 1).

Table 1. Main characteristics of the SAR data sets used in this study.

SAR type	Date	Incidence angle (°)	Polarization	Pixel size (m)	Period	Simple code in this study	Wheat average backscatter (dB)	Cotton average backscatter (dB)
ASAR	27 February 2009	19.2–26.2	VV		Early jointing	A1	−7.10	−7.49
ASAR	3 April 2009	19.2–26.2	VV	12.5 × 12.5	Late jointing	A2	−8.95	−5.44
ASAR	8 May 2009	19.2–26.2	VV	12.5 × 12.5	Flowering	A3	−14.57	−4.86
TerraSAR-X	10 May 2009	40.0–41.2	HH	12.5 × 12.5	Flowering	T	−18.74	−14.01

Note: SAR, synthetic aperture radar; ASAR, advanced synthetic aperture radar; VV, vertical polarization; HH, horizontal polarization.

The received 1B level ASAR data processing, which included radiance calibration, registration of the three ASAR data, geo-correction and speckle reduction, was carried out using the NEST 3A software (ESA, Paris, France). The radiance calibration converted the digital number at each pixel in the raw image to a calibrated linear backscattering coefficient. Because further steps such as speckle suppression have to be processed, the linear scale was taken as the calibration result instead of the dB scale. The calibration formula is given as

$$\sigma^0 = A^2 \frac{\sin\alpha}{K}, \tag{1}$$

where σ^0 is the backscattering coefficient; A is the digital number of the raw image; α is the local incident angle; and K is the absolute calibration constant, which is contained in the header files. After radiance calibration, the function automatic co-registration in NEST 3A was used to register the three ASAR data. Then geo-correction of the ASAR data was done using the satellite orbit parameters and the pixel size was resampled to 12.5 m. Since speckle in the SAR image would affect the image interpretation, the ASAR images were smoothed with a 5 × 5 window gamma adaptive filter to reduce image speckle.

TerraSAR-X is a side-looking X-band (9.65 GHz) SAR based on an active phased array antenna technology. It operates at several polarizations, incidence angles and spatial resolution configurations. A stripmap mode TerraSAR data were acquired over the study area under the Programme of TerraSAR-X Science Plan on 10 May 2009 (see table 1). The original range and azimuth spatial resolution of these TerraSAR data were 0.9 and 6.6 m, respectively, and in order to combine with ASAR data, the pixel size of the TerraSAR data was resampled to 12.5 m. TerraSAR data preprocessing included absolute radiance calibration, geo-correction and speckle reduction. Absolute calibration allowed the taking into account of all the contributions in the radiometric values that were not due to the target characteristics (German Aerospace Centre (DLR) 2008). This permits one to minimize the differences in the image radiometry and to make the SAR images obtained from different configurations compatible with acquisitions made by other radar sensors. The calibration formula is shown in the following equations:

$$\sigma^0 = \left[K_s(\mathrm{DN})^2 - (\mathrm{NEBN})\right]\sin\theta, \tag{2}$$

$$\mathrm{NEBN} = K_s \sum_{i=0}^{\deg} c_i(\tau - \tau_{\mathrm{ref}})^i, \tau \in [\tau_{\min}, \tau_{\max}], \tag{3}$$

where K_s is the calibration and processor scaling factor; DN is the pixel digital value; NEBN is the noise equivalent beta naught, which represents the influence of different noise contributions to the signal; θ is the local incidence angle; deg is the polynomial degree; c_i is the coefficient exponent equal to 'i'; τ_{ref} is the reference point; $\tau_{\min}$ and $\tau_{\max}$ are minimum validity range and maximum validity range, respectively. These parameters could be found in the header files of the TerraSAR-X data. Speckle suppression was done using a 5 × 5 window gamma adaptive filter.

In order to obtain exactly the co-registration of ASAR and TerraSAR-X data, the precise geometrical correction of these images, also known as the image to image registration method, was conducted using a quadratic polynomial method and the error was controlled within 0.5 pixels.

4. Method

4.1 *Texture features extraction*

In this study, the main approach to texture analysis was based on the grey level co-occurrence matrix (GLCM) method proposed by Haralick *et al*. (1973). The GLCM assessed the configuration of grey scales in an image and was used to quantify textural variation in images. Because the texture measure in SAR data was not scientifically justified, it was better to use the texture feature when the SAR data corresponded to the full growth stage of wheat, having little or no soil exposure. Therefore, the texture measurement was only applied on ASAR and TerraSAR data acquired in the flowering period of wheat to derive texture features on a per-pixel basis. The texture images were added to the original backscattering images for crop classification for further analysis. The co-occurrence matrix values were calculated using a 5×5 window size, and the grey level value was 64 to produce the average value for each texture measure. Four texture measures were used in this study:

$$\text{Homogeneity:} \quad \text{HOM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2}, \tag{4}$$

$$\text{Contrast:} \quad \text{CON} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P(i,j) \times (i-j)^2, \tag{5}$$

$$\text{Entropy:} \quad \text{ENT} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} -P(i,j) \times \log_N(P(i,j)), \tag{6}$$

$$\text{Angular second moment:} \quad \text{ASM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P(i,j)^2, \tag{7}$$

where N is the number of grey levels; and $P(i,j)$ is the normalized co-occurrence matrix of dimension $N \times N$.

4.2 *Classification method*

The support vector machine (SVM) classifier, which has been widely used for classification of remote-sensing data (Pal and Mather 2005, Kavzoglu and Colkesen 2009), was selected in this study. Modern SVM was introduced by Cortes and Vapnik (1995), and a detailed description of SVM can be found in Burges (1998). The SVM training algorithm promises to obtain the optimal separating hyperplane for a training data set in terms of a generalization error.

Field observation synchronous to the satellite pass is of great importance to assist SAR data in classification. Corresponding to ASAR data acquired in late jointing

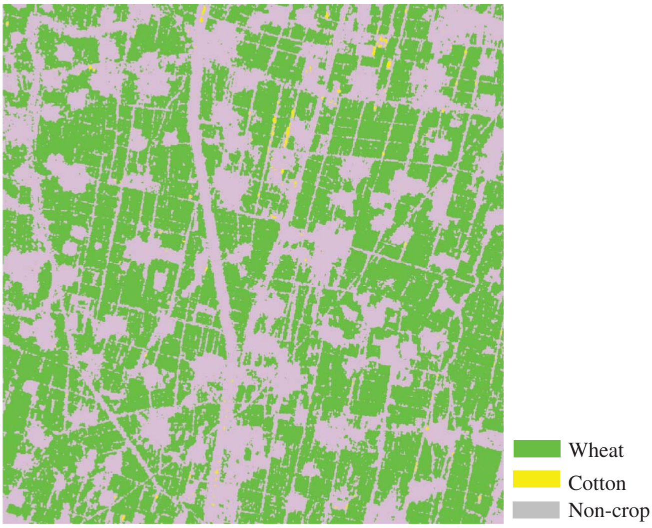

Figure 2. Classification results using SVM classifier based on combinations of the three ASAR data, TerraSAR data and texture features extracted from the SAR data acquired in flowering period of wheat.

Note: SVM, support vector machine; ASAR, advanced synthetic aperture radar; SAR, synthetic aperture radar.

and flowering periods, field observations about crop physiological parameters and soil conditions were conducted on 2–4 April and 8–10 May, 2009. The mainly measured contents included crop height, leaf area index (LAI), per cent crop cover, soil moisture and so on. In order to know the exact crop distribution characteristics of the study area, another special field survey to identify the main crop distribution in the study area was carried out on 19 May 2009. Based on the field survey, wheat, cotton and non-crop classes were identified as the final classification types. Non-crop areas include residential area, road, water body, trees and bare land. Randomly selected sample pixels based on the ground survey were used to select training and validation samples. For each cover class, sample pixels per class in the SAR image were obtained: 1812 pixels for non-crop area, 1800 pixels for wheat and 330 pixels for cotton. Then half of the samples were randomly selected as training samples and the remaining half were used as validation samples. The training and validation samples had no overlap. The average backscattering values of wheat and cotton can be seen in table 1.

4.3 *Accuracy validation*

Accuracy validation of the classified maps was based on the independent validation samples as presented above. For each class, validation samples were easily identified and located within the study area from the remote sensing images and ground survey. The overall classification accuracy and kappa statistics estimated from the confusion matrix using the validation samples (Congalton and Green 1999) were selected for evaluating the classification results derived from different combinations of the SAR data. For further validation, these samples were visited during another period of field data collection.

Table 2. Overall accuracy and kappa value of classification results using different combinations of SAR data and texture feature.

Backscatter data	Accuracy (%)	Kappa coefficient	Backscatter + texture	Accuracy (%)	Kappa coefficient
A3*	65.19	0.38	A3 + texture	70.42	0.47
T	61.74	0.32	T + texture	65.90	0.39
A1 + A2	59.31	0.25			
A1 + A3	82.19	0.67			
A2 + A3	82.39	0.68			
A1 + A2 + A3	84.12	0.71	A1 + A2 + A3 + texture	88.62	0.80
T + A1	71.74	0.48			
T + A2	71.63	0.48			
T + A3	86.55	0.76			
T + A1 + A2	71.23	0.47			
T + A1 + A3	86.91	0.76			
T + A2 + A3	87.72	0.78			
T + A1 + A2 + A3	88.48	0.79	T + A1 + A2 + A3 + texture	91.83	0.86

Notes: SAR, synthetic aperture radar; ASAR, advanced synthetic aperture radar.
*The sample code explanations are given in table 1 (e.g. A means ASAR data. A1 + A2 means the classification was done using A1 and A2 data).

5. Results and discussion

Classification was conducted using different combinations of ASAR, TerraSAR and texture features extracted from the SAR data acquired in the flowering period of wheat. Classification results using combinations of the three ASAR data, TerraSAR data and texture features extracted from the SAR data acquired in flowering period of wheat are shown in figure 2 as an example, and the classification accuracy of different data combinations can be seen in table 2. Classification using only a single SAR data set with just one single configuration was often inadequate to attain the required accuracy of classification (Del Frate *et al*. 2003). Therefore, classification using only one single SAR data set is only discussed using ASAR and TerraSAR data acquired in the flowering period in this study.

Almost all of the wheat fields have been discriminated in the different combinations of these SAR data except for the combination of A1 + A2 (meaning of the notation A1, A2, A3 and T can be seen in table 1), since the wheat plant height and coverage rate were lower and easily misclassified to other classes. In addition, there were misclassification pixels between wheat and other two classes at many edges of wheat fields, which might be caused by mixed pixels in the edges of the planted area. However, the classification accuracy of cotton fields was variable in different combinations and commonly lower than wheat fields identification. Taking the best achieved classification result as an example (T + A1 + A2 + A3 + Texture), it was clear that the user's and producer's accuracies of cotton were lower than wheat estimated from the confusion matrix (see table 3). The cotton fields were easily mixed with non-crop, because cotton fields were nearly bare soil before early April, the coverage rate came as 30–50% in May based on the field observation, and just after this period, cotton plants could have a sensible influence on backscattering characteristics and be separated from non-crop. Therefore, the SAR data acquired in the later period were more important for cotton field identification.

In principle, the accuracy of classification of crop types by SAR data depends mainly on the sensitivity of the radar backscattering coefficient to the difference in the biophysical characteristics of the plant structure, that is, the different interaction behaviour between radar backscatter and the structure of the canopy (Del Frate *et al*. 2003, Wang *et al*. 2010). In addition, soil conditions for plants in the early crop growth stages influence the backscattering characteristics of the SAR signal. As plants grow,

Table 3. Confusion matrix of classification results using combinations of the three ASAR data, TerraSAR data and texture features extracted from the SAR data acquired in the flowering period of wheat.

Mapped class (pixels)	Ground-truth result (pixels) Non-crop	Cotton	Wheat	Total	User's accuracy(%)
Non-crop	824	26	48	898	91.76
Cotton	14	139	5	158	87.97
Wheat	68	0	847	915	92.57
Total	906	165	900	1971	
Producer's accuracy (%)	90.95	84.24	94.11		

Note: ASAR, advanced synthetic aperture radar; SAR, synthetic aperture radar.

their radar backscattering characteristics also change with the variety of canopy structure and the influence of soil conditions is weakened. Thus, multi-temporal data can add useful information for improving crop classification accuracy (Chen *et al*. 2007). Likewise, the radar backscattering characteristics of crops change with the different frequency and polarization based on different scattering mechanisms. Therefore, multi-frequency and multi-polarized SAR data can increase the classification accuracy (Freeman *et al*. 1994, Del Frate *et al*. 2003). These phenomena were also observed in this study.

As the temporal frequency of ASAR data increases, the classification accuracy also increases clearly (e.g. A1 + A3 vs. A3 and A1 + A2 + A3 vs. A1 + A2). Furthermore, when the TerraSAR data were added to the ASAR data for classification, the accuracy also increased (e.g. T + A1 + A3 vs. A1 + A3). When all the SAR data sets acquired in this study were used for classification (T + A1 + A2 + A3), the overall accuracy and kappa coefficient reached 88.48% and 0.79, which was a satisfactory performance for crop mapping and cultivation acreage estimation. When the texture features extracted from the SAR data acquired in the flowering period of wheat were also added to the classification, the classification performance was even higher (T + A1 + A2 + A3 + Texture), with the overall accuracy and kappa coefficient reaching 91.83% and 0.86, respectively. The results indicate that the SAR data show satisfactory performance for upland field crop classification in the North China Plain if multi-configuration SAR data were available. There is another reason for achieving such high classification accuracy compared with previous research results (Del Frate *et al*. 2003, Wang *et al*. 2010); that is because wheat was the only dominating crop type and there was only a small quantity of cotton in the study area.

Although the performance of SAR data in classifying upland field crops may still not be as good as those obtained by optical data and has a much higher cost for acquiring appropriate data sets, it is a suitable substitution for or complement to optical data for agricultural monitoring using remote sensing techniques, especially in cloud-prone areas.

Considering the classification performance using only the C-band multi-temporal ASAR data, the combination of all the three temporal ASAR data sets achieved the highest classification accuracy (84.12%), which indicates that using more temporal ASAR data sets can provide more useful information for crop classification. When considering only two temporal ASAR data sets for classification, the combination of ASAR in early jointing and late jointing periods of wheat achieved much lower accuracy (59.31%) and many wheat fields were not identified. When the ASAR data set obtained in the flowering period of wheat was added for classification, the accuracy improved markedly. The classification accuracy using the data combination of A1 + A3 and A2 + A3 achieved 82.19% and 82.39%, respectively, which had a more than 20% improvement in accuracy compared with that using A1 + A2. The reason might be that the wheat had a much lower height and coverage rate during the early jointing and late jointing periods, and cotton in this period was not yet seeded or was only present as small seedlings, which resulted in the similar backscattering characteristics of wheat and cotton fields on the ASAR image, and also similar to bare land and unsurfaced roads. However, in the flowering period, the wheat was much taller (about 70 cm) and had almost 100% surface coverage according to the field observation, which would greatly influence the microwave signal of SAR and resulted in different backscattering characteristics between wheat and cotton and other objects. Moreover, it was found that, based on the field observation, soil under wheat plants had a higher moisture content than cotton fields, which leads to different influence on the SAR signal and enlarged separability between wheat and cotton. The classification results indicated that the flowering period was most important for crop classification using SAR data in the three growing periods of wheat in the North China Plain. The combination of ASAR in late jointing and flowering periods of wheat achieved comparable accuracy with that of early jointing and flowering periods (A2 + A3 vs. A1 + A3), which indicated that SAR data acquired in early jointing and late jointing periods had a similar contribution for crop classification and were inferior to those acquired during the flowering period.

When comparing the classification results using three and two temporal ASAR data sets, the accuracy using three temporal ASAR data achieved a smaller improvement (about 1%) compared with using only two temporal ASAR data sets when the flowering period ASAR data were used as one of the inputs (A1 + A2 + A3 vs. A1 + A3 and A1 + A2 + A3 vs. A2 + A3), which indicated that only two periods of ASAR data were enough for crop classification, if at least one of the two SAR data sets was acquired during the flowering period in this study. Adding another temporal data set in early jointing and late jointing periods of wheat had little effect for improving classification accuracy. These results could also be observed by comparing the classification accuracy of T + A1 + A2 + A3 versus T + A1 + A3, and so on. That is to say, the information contained in two temporal SAR data sets acquired in late jointing and flowering periods is enough for crop classification. Adding SAR data acquired in the early jointing period only brings information redundancy, which has little effect on improving classification accuracy. This phenomenon was also observed by Shao *et al.* (2001) when she investigated rice monitoring using multi-temporal Radarsat data in the Zhaoqing area. She also found that only three temporal radar data sets acquired at the end of the transplanting and seedling development period, during the ear differentiation period and at the beginning of the harvest period of rice were enough for rice production estimation.

The classification accuracy were all low if using only one data set acquired in the flowering period of wheat (65.19% of A3 and 61.74% of T), but the combination of A3 and T had a very much better classification performance, the overall classification accuracy came to 86.55%. That is to say, a crop had different scattering mechanisms on C- and X-band SAR and had complementary information for crop classification. When two temporal ASAR data were available, the classification accuracy showed a significant improvement when the ASAR in the flowering period of wheat was used, about 4–5% increased (T + A1 + A3 vs. A1 + A3 and T + A2 + A3 vs. A2 + A3). When ASAR data in the flowering period were not available, the TerraSAR data had a much higher effect on the classification accuracy improvement, more than 20% increased (T + A1 vs. A1 + A2 and T + A2 vs. A1 + A2). In addition, the classification accuracy using the combination of ASAR and TerraSAR data in the flowering period was better than any other combination of only using ASAR data, even when all the three temporal ASAR data sets were used (T + A3 vs. A2 + A3, T + A3 vs. A1 + A2 + A3 and so on). It is indicated that a combination of two frequencies SAR data (X- and C-band) is better than multi-temporal C-band ASAR data for crop classification in this study. In other words, crops in different growing periods influence the SAR signal less than that of different frequency SAR signals in only one growing period.

However, the performance for crop classification using TerraSAR data was slightly inferior to the ASAR data during the flowering period of wheat in this study

(T vs. A3, T + A1 vs. A1 + A3 and T + A2 vs. A2 + A3). It may be that C-band SAR data are more suitable for crop classification than X-band SAR data acquired during the same time period. Brown *et al*. (1992) also found that C-band data were slightly better than X-band data for crop classification when he analysed the correlations between X-, C- and L-band imagery in an agricultural environment. But, there is another possibility, which may be caused by the different spatial resolution and polarization of ASAR and TerraSAR data. TerraSAR data have a much higher spatial resolution than ASAR data and are resampled to a lower resolution to fit the ASAR data in this study. The high-resolution SAR signal is sensitive to the variety of crop states and generate speckles in the homogeneous crop fields, which lead to isolated misclassified pixels and small misclassified spots in the classification results and lower the classification accuracy. TerraSAR has HH (radio waves transmitted and received in horizontal polarization) polarization and the ASAR has VV polarization. Different polarizations may also influence the classification accuracy. Incident angle also influences the backscattering characteristics. ASAR data with a steep incident angle in this study are more sensitive to soil conditions than TerraSAR data, and soil conditions are quite different among the three class types based on the field observation. Whether the poor classification performance of the TerraSAR data is caused by the downscaling of the spatial resolution, the different polarization modes or different incident angles needs to be investigated in future work, when more SAR data with variational configurations become available.

The use of texture features was also important for improving the classification accuracy using SAR data. Only the texture feature extracted from ASAR and TerraSAR data acquired in the flowering period, having little or no soil exposure, was used for classification. A clear improvement in the classification accuracy was observed in this study when these texture features were added (see table 2). For all of the combinations of different SAR data sets in this study, there was a 3–5% classification accuracy improvement (e.g. T + Texture vs. T, A3 + Texture vs. A3) compared with use of backscattering data only. The texture features were robust to speckle perturbation and could remove part of the salt–pepper appearance in the classification results, and then improved the performance of SAR data for crop classification.

6. Conclusion

In this study, multi-temporal C-band Envisat ASAR data and an X-band TerraSAR data set, together with texture features extracted from the SAR data acquired in the flowering period of wheat, were investigated for crop classification in the North China Plain. Conclusions from this research show that (1) multi-temporal and multi-frequency SAR data can achieve satisfactory classification accuracy for upland crop classification in the North China Plain; (2) a combination of two frequencies of SAR data (X- and C-band) is better than multi-temporal C-band ASAR data for crop classification in this study; (3) two temporal SAR data acquired in late jointing and flowering periods have been shown to be sufficient for classification accuracy, and adding the data acquired in early jointing period has almost no effect on improving classification accuracy; and (4) texture features of SAR data acquired in the flowering period of wheat are useful for crop classification and improved the classification accuracy.

In this study, only multi-temporal and frequency SAR data were investigated for crop classification. Multi-polarization and multi-angle SAR data are also an important aspect of crop classification using SAR data and will be investigated in future work. SAR data is an attractive data source and has considerable potential for agriculture monitoring. It could become a suitable substitute for or a complementary data set to the use of optical data in the future.

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References

Benedetti, R. and Rossini, P., 1993, On the use of NDVI profile as a tool for agricultural statistics: the case study of wheat yield estimate and forecast in Emilia Romagna. *Remote Sensing of Environment*, **45**, pp. 311–326.

Berberoglu, S., Curran, P.J., Lloyd, C.D. and Atkinson, P.M., 2007, Texture classification of Mediterranean land cover. *International Journal of Applied Earth Observation and Geoinformation*, **9**, pp. 322–334.

Blaes, X., Vanhalle, L. and Defourny, P., 2005, Efficiency of crop identification based on optical and SAR image time series. *Remote Sensing of Environment*, **96**, pp. 352–365.

Brown, R.J., Manore, M.J. and Poirier, S., 1992, Correlations between X-, C-, and L-band imagery within an agricultural environment. *International Journal of Remote Sensing*, **13**, pp. 1645–1661.

Burges, C.J.C., 1998, A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, **2**, pp. 121–167.

Chen, J.S., Lin, H. and Pei, Z.Y., 2007, Application of ENVISAT ASAR data in mapping rice crop growth in southern China. *IEEE Transactions of Geoscience and Remote Sensing*, **4**, pp. 431–435.

Clausi, D.A., 2002, An analysis of co-occurrence texture statistics as a function of grey level quantization. *Canadian Journal of Remote Sensing*, **28**, pp. 45–62.

Congalton, R.G. and Green, K., 1999, *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices* (Boca Raton, FL: Lewis Publishers).

Cortes, C. and Vapnik, V., 1995, Support-vector networks. *Machine Learning*, **20**, pp. 273–297.

Del Frate, F., Schiavon, G., Solimini, D., Borgeaud, M., Hoekman, D.H. and Vissers, M.A.M., 2003, Crop classification using multiconfiguration C-band SAR data. *IEEE Transactions on Geoscience and Remote Sensing*, **41**, pp. 1611–1619.

Foody, G.M., Mcculloch, M.B. and Yates, W.B., 1994, Crop classification from C-band polarimetric radar data. *International Journal of Remote Sensing*, **15**, pp. 2871–2885.

Freeman, A., Villasenor, J., Klein, J.D., Hoogeboom, P. and Groot, J., 1994, On the use of multi-frequency and polarimetric radar backscatter features for classification of agricultural crops. *International Journal of Remote Sensing*, **15**, pp. 1799–1812.

German Aerospace Centre (DLR), 2008, *Radiometric Calibration of TerraSAR-X Data* (Wessling: German Aerospace Centre).

Gong, P., Marceau, D.J. and Howarth, P.J., 1992, A comparison of spatial feature extraction algorithms for land-use classification with SPOT HRV data. *Remote Sensing of Environment*, **40**, pp. 137–151.

González-Sanpedro, M.C., Le Toan, T., Moreno, J., Kergoat, L. and Rubio, E., 2008, Seasonal variations of leaf area index of agricultural fields retrieved from Landsat data. *Remote Sensing of Environment*, **112**, pp. 810–824.

Haack, B. and Bechdol, M., 2000, Integrating multisensor data and RADAR texture measures for land cover mapping. *Computers & Geosciences*, **26**, pp. 411–421.

Haralick, R.M., Shanmugam, K. and Dinstein, I., 1973, Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, **3**, pp. 610–621.

He, D.C. and Wang, L., 1992, Unsupervised textural classification of images using the texture spectrum. *Pattern Recognition*, **25**, pp. 247–255.

Herold, N.D., Haack, B.N. and Solomon, E., 2004, An evaluation of radar texture for land use/cover extraction in varied landscapes. *International Journal of Applied Earth Observation and Geoinformation*, **5**, pp. 113–118.

Jensen, J.R. and Toll, D.L., 1982, Detecting residential land-use developments at the urban fringe. *Photogrammetric Engineering and Remote Sensing*, **48**, pp. 629–643.

Jia, K., Wu, B.F., Li, Q.Z. and Tian, Y.C., 2009, Improvement of classification accuracy integrating C- and X-band synthetic aperture radar data. In *3rd IEEE International Symposium on Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications*, 27–29 October 2009, Beijing, China (Piscataway, NJ: IEEE Press), pp. 350–355.

Kavzoglu, T. and Colkesen, I., 2009, A kernel functions analysis for support vector machines for land cover classification. *International Journal of Applied Earth Observation and Geoinformation*, **11**, pp. 352–359.

Le Toan, T., Ribbes, F., Wang, L.-F., Floury, N., Ding, K.-H., Kong, J.A., Fujita, M. and Kurosu, T., 1997, Rice crop mapping and monitoring using ERS-1 data based on experiment and modeling results. *IEEE Transactions on Geoscience and Remote Sensing*, **35**, pp. 41–56.

Li, B., Yang, S., Le Toan, T., Tan, B. and He, W., 2008, Rice mapping and monitoring using Envisat ASAR data. In *Proceedings of Dragon 1 programme final results 2004–2007*, 21–25 April 2008, Beijing, China (Noordwijk: ESA Communication Production Office, SP-655).

Li, W., Bénié, G.B., He, D.-C., Wang, S., Ziou, D. and Gwyn, Q.H.J., 1998, Classification of SAR images using morphological texture features. *International Journal of Remote Sensing*, **19**, pp. 3399–3410.

Pal, M. and Mather, P.M., 2005, Support vector machines for classification in remote sensing. *International Journal of Remote Sensing*, **26**, pp. 1007–1011.

Rajesh, K., Jawahar, C.V., Sengupta, S. and Sinha, S., 2001, Performance analysis of textural features for characterization and classification of SAR images. *International Journal of Remote Sensing*, **22**, pp. 1555–1569.

Shao, Y., Fan, X.T., Liu, H., Xiao, J.H., Ross, S., Brisco, B., Brown, R. and Staples, G., 2001, Rice monitoring and production estimation using multitemporal RADARSAT. *Remote Sensing of Environment*, **76**, pp. 310–325.

Tso, B. and Mather, P.M., 1999, Crop discrimination using multi-temporal SAR imagery. *International Journal of Remote Sensing*, **20**, pp. 2443–2460.

Wang, D., Lin, H., Chen, J., Zhang, Y. and Zeng, Q., 2010, Application of multitemporal ENVISAT ASAR data to agricultural area mapping in the Pearl River Delta. *International Journal of Remote Sensing*, **31**, pp. 1555–1572.

Wu, B.F., 2000, Operational remote sensing methods for agriculture statistics. *Acta Geographica Sinica*, **55**, pp. 23–55 [in Chinese].