Joint Monitoring of Ground and Sky for Cereal Crops Based on Scatterometer Measurement and ASAR Images

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Abstract—The joint monitoring of the ground and sky for cereal crops based on microwave data has become a popular method for researches on earth surface objects. Focused on the sensitivity of backscatter from the scatterometer measurement and advanced synthetic aperture radar (ASAR) images to cereal parameters of rice, nine acquisitions, including rice parameters related eco-physiological variables and scattering coefficients, have been carried over the paddy field corresponding to rice growth stages. This paper analyzes the relationship between the corresponding backscatter to the cereal parameters based on the measurement at the interesting bands, polarizations, and incidence angels. Further, a modified water cloud model is built based on the ground measurement and advanced integrated equation model (AIEM), and then cereal parameters from ASAR images are retrieved and verified. The research results show that the sensitivity of backscatter to cereals from the sensor of the radar scatterometer could be helpful to build the retrieve model for synthetic aperture radar (SAR) images, which can achieve the scientific goals of the joint monitoring of ground and sky for cereal crops.

Index Terms—Backscatter, cereal, joint monitoring, scatterometer, synthetic aperture radar (SAR).

1. Introduction

The earth is a highly complex nonlinear system, changes in any composition will cause changes in the earth’s system[1]. Currently, the joint monitoring of the sky, air, earth, and sea for objects on the earth surface have been a popular method in remote sensing fields. Cereal crops (such as, corn, wheat, and rice) are paid more attention because it is critical for food security, society stability, and economic development. To monitor and estimate cereals growth status has been an active research spot in research institutes, companies, and governments. Since the electromagnetic wave plays a key role in measurement fields, optics and microwave methods have become a popular technology in remote sensing fields[2][3] including the ground measurement[2][3] and
joint monitoring of the sky and earth[7][8]. Further, the booming synthetic aperture radar (SAR) technology also attracts lots of researchers in the microwave remote sensing field[9][11].

Cereal scattering characteristics have been analyzed and modeled by collecting backscatter and cereal parameters[12][14]. The backscatter from the SAR system was also introduced for rice growth monitoring[15][16]. The temporal change corresponding to the high growth rate of cereal plants is crucial to study the scattering characteristics of cereal parameters, and the temporal behavior was effectively reported in several studies based on SAR data[17][18]. However, the empirical model was unable to represent universality and robustness, and the inversion precision needed to be improved[19][20]. So, the joint monitoring for cereal crops is still well worth considering. The research had acquired five years measured scattering data from the scatterometer system with multi-frequency bands (L, S, C, and X), full-polarization (HH, VV, HV, and VH, where H indicates horizontal and V denotes vertical), and different incidence angles (0 to 90°) in different regions, and then the cereal scattering characteristics could be analyzed at different frequencies and various incidence angles. Although the scattering data and SAR images are useful for assessing the sensitivity between the backscatter and cereals growth parameters[21], the simultaneous joint monitoring with ground-based sensors and space-borne sensors during the rice growth cycle still needs to be documented.

2. Measurement and Data

The cereal experiment site locates in Qianjin town, Qionglai, Chengdu (30°24′11″N, 103°32′24″E). The site area is 30000 m² and its topography is smooth with an elevation of 483 m as shown in Fig. 1. During the rice growth cycle, both the backscatter and advanced synthetic aperture radar (ASAR) images are acquired from the scatterometer and ENVISAT satellite, respectively.

2.1. Ground Experiment

The rice seedlings were transplanted in the measurement site on May 28, 2010 by using a transplanting machine. The measurement was taken from Jun. 11 to Sept. 20, 2010. The entire growth cycle was usually divided into eight growth stages (seedling, tillering, jointing, booting, heading, flowering, dough, and ripening) (Fig. 2). This paper selected nine measurement results at different stages and the last measurement was after the rice harvest.

The ground real data of the paddy were also collected during the rice growth cycle. The research collected rice canopy height, rice biomass, leaf area index (LAI), canopy structure, or geometric description. In each experiment, at least 20 sampling points were randomly selected in the paddy field; Table 1 reports the main parameters of eight rice growth stages, including rice canopy high, biomass, LAI and stem density, and rice moisture. More than 36 independent
samples are necessary to guarantee a 90% confidence level\cite{22}. As a result, the number of independent samples is from about 50 (incidence angle 10°) to 5000 (incidence angle 70°). The total number of independent samples was more than 220 resolution cells in the research. Assuming the calibration and statistical errors are independent, the overall system error of the measurement can be estimated as ±1 dB.

2.2. ASAR Data

Three scenes of ASAR images covering the study area were acquired (Table 2), which have a nominal spatial resolution of 30 m and a pixel size (the distance between neighbor pixels) of 12.5 m×12.5 m. The acquisition dates located in the rice growth cycle were Jun. 18, Sept. 20, and Sept. 28, 2010, respectively. The imaging modes were IS3, IS4, and IS5, and their incidence angles were 26.0° to 31.4°, 31.0° to 36.3°, and 35.8° to 39.4°, respectively.

Table 2 shows the dates of images belong to the following periods: Seedling stage or tillering stage, ripening stage, and post-harvest. The corresponding days after the transplant of rice of images are 18 days, 112 days, and 120 days, respectively, which are among the five major periods of the rice grown cycle.

3. Data Analysis for Sensitivity of Backscatter

The research successfully collected a wide range of data measured and information during an entire rice growth cycle. All the measured data included the full-polarization and the incidence angles from 0 to 90°. To show the temporal character of rice backscatter, the temporal variations of full polarization at four selected incidence angles (29°, 34°, 38°, and 43°) had been analyzed, which matched the incidence angle of the ASAR sensor. Since the backscatter at cross-polarizations (HV and VH) is equivalent for the same target in theory, data from both cross-polarizations were averaged.

Figs. 3 to 6 show these curves at four bands (L, S, C, and X). As can be seen from these figures, the backscattering coefficient ($\sigma_0$) of all bands was sensitive to the age changes in the early rice growth stage. The maximum backscatter values were different at different frequencies. The maximum backscatter values of L-, S-, C-, and X-bands appeared at the 90th day, 70th day, 25th day, and 20th day after transplant, respectively, so there should be different ways to analyze the sensitivity of different bands. The research demonstrated that L- and S-bands had a similar characteristic, while the character of C-band is like X-band.
For L- and S-bands (Figs. 3 and 4), the entire growth cycle was divided into two separate periods (sharply rising (from the 13th to the 40th days) and gentle change (from the 40th to the 112th days)), which showed a distinct behavior in the growth cycle.

At the first period, pretty large changes were shown for each polarization. The range of HH was larger than that of VV. The maximum range of backscatter for L- and S-bands was more than 10 dB at HH and cross-polarizations. The minimum range of VV backscatter reached 6 dB. The backscatter regularity showed that the temporal backscatter change was more dynamic at smaller incident angles, and the low frequency bands were suitable to monitor the rice growth for the spatial radar in the observation period.

In the second period, the backscatter changes were relative flat following the rice growth condition, and the backscatter range was less than 3 dB. L- and S-bands had different manifestations in the late rice growth period. The L-band backscatter had a slight rise, while S-band backscatter decreased. The possible reason is that S-band is more sensitive to the rice moisture change (Table 1), and unable to fully penetrate the rice canopy. In addition, the maximum difference between HH and VV at the booting stage was more than 5 dB, and the minimum difference between HH and VV was at least 3 dB after the 40th days. In short, the temporal change of the backscatter agreed well with the rice growth at the first period, but the difference between HH and VV was more distinctive for the rice paddy fields at the second period. Therefore, to estimate rice-planted areas and monitor rice growth effectively, we can select multi-temporal observation data at the first period and perform polarization observation at the second period.

For C- and X-bands (Figs. 5 and 6), the entire growth cycle is divided into three separate periods. The first period (the 13th to the 25th): From the stage seedling to tillering stage; the second period (the 25th to the 70th): From the jointing stage to heading stage; the third period (the 70th to the 112th): From the flowering stage to ripening stage.

Fig. 3. L-Band backscatter change trend at incidence angles: (a) 29°, (b) 34°, (c) 38°, and (d) 43°.
Fig. 4. S-Band backscatter change trend at incidence angles: (a) 29°, (b) 34°, (c) 38°, and (d) 43°.

Fig. 5. C-band backscatter change trend at incidence angles: (a) 29°, (b) 34°, (c) 38°, and (d) 43°.
In the first period, the backscatter was gradually increased with the rice growth; the change range of C- and X-bands was larger than that of L- and S-bands, which showed the short wave bands were more sensitive to rice growth when the biomass is small.

In the second period, the backscatter gradually decreased when the biomass reached more than 2.0 kg/m². The X-band backscatter reduced more than 10 dB, while the C-band backscatter reduced less than 5 dB. The possible reason is that the short wave is more attenuated by canopy for microwave backscatter energy, rather than scattered. In addition, the difference between HH and VV reached more than 5 dB for C- and X-bands, which was also similar with L- and S-bands.

In the third period, the C-band backscatter continued to drop, while that of the X-band started to rise. The possible reason is that the panicle emergence brought a special scattering phenomenon to X-band, but canopy attenuation still dominates for C-band. In short, different bands have different responses to the change of rice parameters. Therefore, multi-band observations are suitable to monitor rice growth.

The rice biomass had a strong positive correlation for L- and S-bands at most polarizations and their combination as shown in Fig. 7, where \( r \) is the correlation coefficient. However, the negative correlation between the backscatter and biomass for C-
band at HH and VV was presented. Furthermore, all the correlation coefficients were negative for X-band. The best correlation coefficients were different for each band: L-band was at HH and cross polarization ($r > 0.90$), S-band was at HH/VV ($r < 0.95$), C-band was at VV ($r < -0.75$), and X-band was at HH ($r < -0.70$). The results also show that multi-polarization data have great potential for estimating rice-planted areas and monitoring rice growth.

4. Biomass Retrieve Methods

Fig. 8 shows three layers of the water cloud model, including air, vegetation, and soil. The electromagnetic wave emitted, transmitted, and returned at the two interfaces between three layers. A semi-empirical model based on the water-cloud (WC) model was established in [22], and the modified water-cloud model can be expressed as

$$\sigma^0_{\text{total}} = \sigma^0_{\text{rice}} + 2 \sigma^0_{\text{soil}}$$

where, $\sigma^0_{\text{rice}}$ and $\sigma^0_{\text{soil}}$ are the backscattering coefficients for rice and soil, respectively; $\gamma^2(\theta)$ is the two-way attenuation through the canopy; $\theta$ is the incident angle; $A$ and $B$ are the constant coefficients depending on canopy types, which are determined by iterative optimization.

The soil underlying the cereals was assumed to be a random rough surface and the cereals could be taken as a layer over soil, and the total backscatter involves the responses from the cereals and soil.

For co-polarization, $W_{\text{Biomass}}$ could be input to connect the biomass with the backscatter, then the adaptation of the water-cloud model could be expressed as

$$\sigma^0_{\text{HH}} = A_{\text{HH}} W_{\text{Biomass}} \cos \theta [1 - \exp(-2B_{\text{HH}} W_{\text{Biomass}} \sec \theta)] + \exp(-2B_{\text{HH}} W_{\text{Biomass}} \sec \theta) \sigma^0_{\text{HH}}$$

(4a)

$$\sigma^0_{\text{VV}} = A_{\text{VV}} W_{\text{Biomass}} \cos \theta [1 - \exp(-2B_{\text{VV}} W_{\text{Biomass}} \sec \theta)] + \exp(-2B_{\text{VV}} W_{\text{Biomass}} \sec \theta) \sigma^0_{\text{VV}}$$

(4b)

where $W_{\text{Biomass}}$ is the biomass retrieved. Constants $A$ and $B$ are the empirical parameters of the model. Subscripts HH and VV represent horizontal and vertical polarizations, respectively. The parameters $\sigma^0_{\text{HH}}$ and $\sigma^0_{\text{VV}}$ listed in (4) above could be obtained by using the advanced integrated equation model (AIEM) [23].

The expression of input and output is given in (5):

$$W_{\text{Biomass}} = f \text{solve} (\sigma^0_{\text{HH}}, \sigma^0_{\text{VV}}).$$

(5)

The flow chart of the inversion procedure is illustrated in Fig. 9. In the flow chart, all data are presented as the parallelogram. The algorithms or processes are marked with rectangles. Two types of backscatter and multi-temporal SAR images are used in the process. The backscattering coefficients are measured and collected by using the scatterometer system and ASAR images. Two major steps to retrieve rice biomass are as follows: Establishing the retrieve model and achieving the biomass from ASAR images. After completing the estimation of semi-empirical model parameters, the retrieve model could be established.
5. Results and Discussion

Fig. 10 represents the extracted backscatter coefficients and the inverted biomass for the test area in Jun. 18, Sept. 20, and Sept. 28, respectively. Figs. 10 (a) and (d) are the processing results from the ASAR image in Jun.18. Fig. 10 (a) indicates the backscatter coefficients extracted, and Fig. 10 (d) shows the biomass inversion results. Based on the above analysis, Figs. 10 (b) and (e) and Figs. 10 (c) and (f) indicate the corresponding contents in Sept. 20 and Sept. 28, respectively. The ASAR image was processed with The Environment for Visualizing Images (ENVI) software, and the image of Jun. 18 was taken as the main image in the co-registration part. The backscatter obtained from the image obeyed the regularity of the surface object. The river, buildings, and cereal crops could distinguish from the image. After the rice harvest (as shown in Fig. 10 (c)), the backscatter reduces because the soil dominates in the total contribution, which can increase backscatter values.

The data were combined as the input arrays of the retrieve model, and then the biomass maps of different periods could be output. Figs. 10 (d) to (f) display the spatial application of the model at different periods according to three scenes of ASAR images. As can be seen from the color bar, the biomass maps show that the value of biomass is very uniform for each image. However, the other vegetations show higher biomass in the map compared with the rice after harvest in Fig. 10 (f). Further, compared with different maps, the values of biomass are different in each growth period. The main values are distributed at about 0.1 kg/m² to 0.4 kg/m², 3.5 kg/m² to 4.5 kg/m², and 0.3 kg/m² to 0.9 kg/m² for three maps, respectively. The corresponding true values were 0.26 kg/m² and 5.4 kg/m² for Jun. 18 and Sept. 20, respectively. The estimated biomass is about 0.5 kg/m² at the post-harvest period on Sept. 28 (Fig. 10 (f)). The results are consistent with the actual growth of the rice area at Jun. 18 and Sept. 20. However, the retrieve results were around 0.5 kg/m² larger than the true values on Sept. 28, because little biomass remained after the rice harvest. Further, the correlation coefficient between the backscatter and biomass is small at C-band, which makes the retrieve results inaccurate. Overall, the results show a good retrieval performance by using the modified WC model, the sensitivity of backscatter to cereals from the sensor of the
system could be helpful to build the retrieve model for ASAR images.

The histogram of biomass retrieved for three scenes of images is shown in Fig. 11. The biomass value range retrieved agrees well with the biomass collected.

Rice biomass measured over the paddy field and that retrieved from SAR images is shown in Fig. 12, where the parameter of the horizontal axis Age indicates the days after transplant. The root-mean-square error and correlation coefficient are 0.5781 kg/m² and 0.9615, respectively, which show that the values from the semi-empirical model can agree well with the data measured. Finally, the backscatter extracted from SAR images can be applied to estimate the biomass value based on the model.

6. Conclusions

Focused on the scattering principle of sky-ground joint monitoring for cereal crops, the paper analyzed temporal variations at four incidence angles (29°, 34°, 38°, and 43°) from the ground scatterometer corresponding to SAR images, and modified a semi-empirical model to retrieve the cereal growth
parameters from sky monitoring images. For the sensitivity analysis, L- and S-bands had similar characteristics, while the C-band character was similar to that of X-band. For L- and S-bands, the temporal change of the backscatter agreed well with the rice biomass in the early stage, but the difference between HH and VV was more distinctive in the middle and late rice growth stages. For C- and X-bands, the sensitivity to cereal parameters was different at different growth periods. The canopy attenuation and panicle emergence had essential impacts on the radar backscatter for short wave bands.

The empirical constants of the modified water-cloud model were obtained by the measurement results and AIEM. The biomass retrieved was related to the actual growth of the rice with small biomass error, while the biomass retrieved was underestimated at the ripening stage. In summary, multi-temporal observation data at the early rice growth stage and multi-polarization observation data at the middle and late rice growth stages could estimate rice-planted areas and monitor rice growth effectively. The research results showed the backscatter simultaneous obtained from ground-based sensor is helpful to build the semi-empirical model to retrieve cereal parameters from the space-borne sensor. Future researches should focus on the algorithm improvement by taking more variable into account.

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References


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