Abstract—The objective of this paper is to investigate potential of satellite C-band synthetic aperture radar (SAR) radar in monitoring sugarcane growth in southern China. This paper proposes a method to map sugarcane growing area and retrieve sugarcane leaf area index (LAI) in different growth stages using ENVISAT Advanced SAR (ASAR) alternating polarization HH/HV data. The temporal response of ASAR alternating polarization HH/HV data to sugarcane fields and sugarcane LAI was first analyzed in the study area. The analysis shows that sugarcane fields have increasing temporal radar response trend with sugarcane growth and ratio of ASAR HH to HV data has a better correlation with the increase of sugarcane LAI. A theoretical radiative transfer model was adopted to interpret the trend. Based on the temporal variation of the radar response of sugarcane fields, a method for mapping sugarcane planting area was developed using ASAR HH and HV polarization data at two acquisition dates with a certain classification accuracy. The empirical models were also established to estimate LAI of sugarcane using the HV/HH polarization ratio. The results suggest that C-band ASAR data appear promising in the development of an operational system for monitoring sugarcane growth in southern China.

Index Terms—ENVISAT Advanced Synthetic Aperture Radar (ASAR), leaf area index (LAI), sugarcane, synthetic aperture radar (SAR).

I. INTRODUCTION

SUCCULENT is an important perennial crop planted in tropical regions of many countries like Brazil, India, and China. Sugarcane is a crop that can be grown on about 80% of the total sugar production in China, and about 90% of China’s sugarcane crop grows in Southern and Southwest regions in Guangxi, Guangdong, and Yunnan provinces. Increasing attention has been paid to sugarcane plantation in recent years not only for strained sugar supply due to rapid global population increase but also for a growing demand for biomass energy. Considering the global environment, sugarcane is an important resource of alcohol which can be processed into biofuels for motor vehicles and generation of electricity. For the aforementioned economic and environmental aspects, there is a strong demand on effective methods for providing timely and accurate information on sugarcane growing areas and growth conditions at regional and global scales.

Remote sensing techniques have been widely used in agriculture surveys in past decades because of its unique capability of monitoring crop growth and estimating crop yield with certain accuracy. Optical remote sensing data like from sensors such as the Landsat-7 Enhanced Thematic Mapper Plus (ETM+), Advanced Spaceborn Thermal Emission and Reflection Radiometer (ASTER), and the Moderate Resolution Imaging Spectroradiometer (MODIS) have been used to discriminate sugarcane varieties and estimate sugarcane yield [1]–[3]. Research has shown that close relationships exist between the physical parameters of sugarcane crops such as leaf area index (LAI), phytomass, soil cover and vegetative growth, and their spectral features, and the growth situation and fresh biomass of sugarcane are closely correlated to its LAI [4]. LAI, an important structural variable descriptive of vegetation, is directly related to evapotranspiration, photosynthesis, and yield of crop. The knowledge of the LAI variation during the whole crop cycle is essential to the modeling of the plant growth and development. Optical remote sensing data in visible and near-infrared bands have been used often to estimate crop LAI by relational functions between vegetation indices such as the normalized difference vegetation index and LAI during the growing season [5]–[7].

Nonetheless, methods based on optical remote sensing have some limitations in application because the use of optical remote sensing data is often hampered by frequent rain and cloud cover at regional scale in tropical regions of southern China where most sugarcane crops grow. Synthetic aperture radar (SAR) can acquire remote sensing information with a high temporal resolution on a regular basis in tropical regions due to its all-weather capability. Many experimental activities have been carried out to map crop area and retrieve crop biophysical parameters by using satellite SAR sensors [8]–[12]. The results showed that the backscattering from crops is a complex combination of different mechanisms, and the intensity of backscattering from the crop fields depends on how strongly the incoming signal interacts with the crop; and the strength of interaction/coupling also depends on the sensor parameters (wavelength, polarization, incident angle) and crop biophysical features (texture, geometry, moisture content, and roughness). The microwave backscattering coefficient is sensitive to crop and crop field soil parameters, such as plant water content, LAI, soil moisture, and soil roughness. In order to a better understanding of the interaction between microwave radiation with ground targets and soil, various physical models based
on radiative transfer theory such as the Water–Cloud model and the Michigan Microwave Canopy Scattering (MIMICS) model have been developed over the past decades and been adapted to explain the backscattering behaviors of different crops like wheat, corn, canola, and alfalfa in Europe and the U.S., and rice in Asian countries like India, Japan, Indonesia, and Burma using polarimetric and multitemporal SAR data [13]–[17]. To reduce the mathematical complexities due to large numbers of variables associated with physical models for short crops like wheat, cotton, and rice, some semiempirical retrieval algorithms have also been developed based on the relationships between crop parameters, such as biomass and LAI, to monitor crop conditions [18]–[20]. However, these simplified models still need some crop and soil parameters like water content, LAI, height, and soil roughness, and the complexity of the distribution of crop geometry components often makes it difficult to use the models for wide area application. There still exits a strong demand for effective and practical operational systems to monitor crop growth on a large scale.

ENVISAT Advanced SAR (ASAR), operating at C-band, ensures continuity with the image mode and the wave mode of the European Remote Sensing 1/2 (ERS-1/2) satellite. It features enhanced capability in terms of coverage, range of incidence angles, polarization, and modes of operation compared to the ERS-1/2. In particular, it can provide dual-polarization data like HH/HV and HH/VV; particularly HV polarization and may be more sensitive to the change of biomass of crops and vegetation. Experiments have shown that the ENVISAT ASAR HH/VV polarization ratio is sensitive to forest LAI [21]. However, so far, SAR data are seldom used to monitor sugarcane growth. The objective of this paper is to examine the application of ASAR alternating polarization precision (APP) HH/HV data in mapping sugarcane growth area and retrieve LAI of sugarcane crop using the polarization ratio of ASAR HV/HH data.

This paper is divided in four main sections. In Section II, information on sugarcane crop test site and experiment data will be given. In Section III, the temporal variations of ASAR APP HH/HV data at various sugarcane growth stages are analyzed, and the method for mapping sugarcane growth area is proposed. In Section IV, the relationship of the polarization ratio of temporal ASAR HV/HH data with the LAI increase of sugarcane is analyzed, and empirical functions are established to retrieve LAI at different sugarcane growth stages. The comparison of the result with field measurements is also made.

II. EXPERIMENTAL DESCRIPTION AND RESULTS

A. Study Area and Sugarcane Growth Stages

The study area is located in the Nansha agricultural development area centered at 22°36’ N and 113°30’ E in the southeast part of Guangdong Province. The dominating ground types include mangrove wet land, buildings, cropland, and forest. With the rapid economic development of the area, a large amount of wet land has been transformed into cropland where economic crops like sugarcane, banana, and lotus are planted. The growth area of each crop changes frequently to adapt to market demand. At present, the growth area of sugarcane is approximately 4000 odd acres. Sugarcane is an annual irrigated crop with five major growth periods in the life cycle.

1) Germination period: New buds begin to put forth. The sprout date depends on the weather, particularly on the air temperature.
2) Seedling developing period: In this period, leaves begin to grow until 50% or more seedlings get five leaves.
3) Tillering period.
4) Grand growth period: The sugarcane plants elongate and grow up.
5) Mature period: The sugarcane plants mature and are ready to be harvested.

Temporally, these five periods for sugarcane in the study area are February 1 to March 1, March 5 to April 26, May 1 to May 20, May 25 to August 20, and August 25 to October 20, respectively. Fig. 1 shows the shapes of sugarcane in different growth stages. Climatically, the annual precipitation is about 900–1300 mm, the annual mean temperature is about 25.6 °C, and the average annual humidity is 70%–85%.

B. ENVISAT ASAR Data and Ground Measurements

Understanding the backscattering behavior of sugarcane over its life cycle and its relationships with sugarcane growth-related parameters is prerequisite for developing effective methods to map sugarcane plantation area and monitor sugarcane growth using ASAR data. In this paper, ASAR APP HH/HV intensity precision images with nominal spatial resolution of 25 m, nominal pixel spacing of 12.5 m × 12.5 m were selected from March to November 2006 over the sugarcane fields in the study area. The imaging modes of the data are IS4 and IS5 with incidence angle ranging from 31.0° to 39.4°. The dates of acquisition of these ASAR data are March 10, May 8, July 10, September 14, October 19, and November 23, 2006. The dates fall within the five major periods of sugarcane growth, corresponding to 36 days, 95 days, 167 days, 220 days, 255 days, and 290 days, respectively, following planting of the sugarcane. The ASAR intensity images were also calibrated to σ0 images using calibration factor given by raw data [22], and registered to the land use/cover map of 30-m resolution delivered by the China National Land Survey Department using ground control points and cubic resampling method.

Forty-five 150 m × 150 m plots evenly distributed over sugarcane fields in the test site were selected, and biophysical
TABLE I
AVERAGE VALUES AND STANDARD DEVIATION OF BACKSCATTERING COEFFICIENT OF SUGARCANE FIELDS AND RELATED FIELD MEASURED PARAMETERS

<table>
<thead>
<tr>
<th>Date</th>
<th>Mar.10</th>
<th>May 8</th>
<th>July 10,</th>
<th>Sept.14</th>
<th>Oct.19</th>
<th>Nov.23</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH/HV</td>
<td>IS4</td>
<td>IS5</td>
<td>IS5</td>
<td>IS4</td>
<td>IS4</td>
<td>IS4</td>
</tr>
<tr>
<td>Backscattering coefficient (dB)</td>
<td>-8.2±15.2</td>
<td>-6.8±12.6</td>
<td>-5.5±10.1</td>
<td>-4.8±8.8</td>
<td>-4.6±7.9</td>
<td>-4.6±7.8</td>
</tr>
<tr>
<td>LAI (cm²/cm³)</td>
<td>1.1±0.12</td>
<td>2.5±0.14</td>
<td>3.7±0.12</td>
<td>5.8±0.15</td>
<td>5.9±0.16</td>
<td>5.7±0.11</td>
</tr>
<tr>
<td>Leaf thickness (cm)</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Leaf length (cm)</td>
<td>13.3±1.3</td>
<td>24.1±1.6</td>
<td>48.5±1.4</td>
<td>54.1±1.9</td>
<td>56.7±1.8</td>
<td>46.1±1.5</td>
</tr>
<tr>
<td>Leaf water content (%)</td>
<td>64±3</td>
<td>72±7</td>
<td>77±4</td>
<td>78±6</td>
<td>68±5</td>
<td>69±6</td>
</tr>
<tr>
<td>Leaf PDF</td>
<td>uniform</td>
<td>uniform</td>
<td>uniform</td>
<td>uniform</td>
<td>uniform</td>
<td>uniform</td>
</tr>
<tr>
<td>Stem radius (cm)</td>
<td>0.21</td>
<td>0.65</td>
<td>1.1</td>
<td>1.4</td>
<td>1.6</td>
<td>1.6</td>
</tr>
<tr>
<td>Stems per bunch</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Stem gravimetric water content (%)</td>
<td>0.56±0.11</td>
<td>0.73±0.12</td>
<td>0.74±0.18</td>
<td>0.78±0.13</td>
<td>0.77±0.12</td>
<td>0.72±0.16</td>
</tr>
<tr>
<td>Stem height (cm)</td>
<td>46.3±3.2</td>
<td>112±2.3</td>
<td>183±2.1</td>
<td>221±1.9</td>
<td>283±2.0</td>
<td>296±1.8</td>
</tr>
<tr>
<td>Soil volumetric water content (%)</td>
<td>23±0.8</td>
<td>21±1.1</td>
<td>24±0.7</td>
<td>25±0.9</td>
<td>23±1.1</td>
<td>19±1.0</td>
</tr>
<tr>
<td>Soil RMS height (cm)</td>
<td>1.7</td>
<td>1.9</td>
<td>2.2</td>
<td>1.8</td>
<td>2.6</td>
<td>2.7</td>
</tr>
<tr>
<td>Soil correlation length (cm)</td>
<td>5.8</td>
<td>5.3</td>
<td>6.2</td>
<td>6.8</td>
<td>5.6</td>
<td>6.3</td>
</tr>
</tbody>
</table>

TABLE II
AVERAGE VALUES OF BACKSCATTERING COEFFICIENT OF OTHER CROPS IN THE STUDY AREA

<table>
<thead>
<tr>
<th>Date</th>
<th>Banana</th>
<th>Sea</th>
<th>Lotus</th>
<th>Fishpond</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH (dB)</td>
<td>-5.5</td>
<td>-10.8</td>
<td>-18.9</td>
<td>-23.3</td>
</tr>
<tr>
<td>HV (dB)</td>
<td>-10.9</td>
<td>-19.8</td>
<td>-21.9</td>
<td>-22.3</td>
</tr>
<tr>
<td>HH (dB)</td>
<td>-9.1</td>
<td>-18.5</td>
<td>-22.3</td>
<td>-11.8</td>
</tr>
<tr>
<td>HV (dB)</td>
<td>-9.6</td>
<td>-17.9</td>
<td>-21.2</td>
<td>-12.3</td>
</tr>
<tr>
<td>HH (dB)</td>
<td>-6.1</td>
<td>-18.1</td>
<td>-22.4</td>
<td>-11.9</td>
</tr>
<tr>
<td>HV (dB)</td>
<td>-8.9</td>
<td>-18.3</td>
<td>-21.5</td>
<td>-12.7</td>
</tr>
</tbody>
</table>

III. TEMPORAL BACKSCATTERING BEHAVIOR OF SUGARCANE AND THEORETICAL MODEL ANALYSIS

A. Temporal Backscatter Behavior of Sugarcane

The average backscatter of sugarcane fields and growth-related parameters on each acquisition date of ASAR are shown in Table I. Fig. 2 shows an increasing linear relationship of the LAI and height measured in the study site. Figs. 3–5 show the sugarcane’s temporal variation of the backscattering coefficient $\sigma_0$ of ASAR HH, HV data, and the variation of HH, HV data, and intensity ratio of HV to HH data as a function of LAI. The intensity ratio of HV to HH data is expressed in decibels by taking ten times the logarithm in base ten of the ratio of the intensity HV to intensity HH. The figures confirm a general trend of increasing $\sigma_0^H$ and $\sigma_0^V$ with LAI. As the crop grows, its height, number of leaves, and stems increase, resulting in a corresponding increase of LAI. This
entails an increase of volume backscattering intensity as well as attenuation due to the increase of canopy constituents of sugarcane. The increasing trend of \( \sigma_{HH}^0 \) and \( \sigma_{HV}^0 \) mean that volume scattering is the dominant effect with sugarcane growth. However, the increase and decrease of backscatter caused by volume scattering and attenuation at the same time make \( \sigma_{HH}^0 \) and \( \sigma_{HV}^0 \) reach saturation when LAI is larger than 4.1. Fig. 5 shows a correlation of ratio of HV to HH intensity data with LAI with linear regression coefficient 0.93. This ratio increases with LAI because both HV and HH increase with LAI, but the dynamic range of HV is greater than HH. The improved correlation may be partly because that ASAR co-pol HH data have a different backscattering mechanism and sensitivity to sugarcane LAI with cross-pol HV data. The advantages of using a ratio is that factors that might affect the absolute backscatter will not impact the relationship with the biophysical variables as long as these factors are affecting HH and HV to the same magnitude. More experiments need to be carried out in future to explain it better.

**B. Theoretical Modeling**

To understand better the temporal backscattering behavior of sugarcane fields, the MIMICS was employed to analyze the temporal variation of ASAR HH/HV of sugarcane. Many backscattering models have been developed to interpret the backscattering mechanism of vegetation in the literature. The MIMICS backscattering model is designed to use radiative transfer theory to analyze the backscattering behavior of forest [13]. The model is suitable for vegetation where scatters have discrete distribution and dielectric constants much larger than that of air. The major difference between the MIMICS model and the other models is that several different kinds of scatters are considered in the vegetation cover. The model has been adapted to simulated backscattering at L- and C-band from agricultural crops such as wheat and canola [18], and the simulation results was compared with field measurements. In the model, a vegetation layer has usually been represented as an ensemble of sparsely distributed elements (randomly oriented disks and almost vertical cylinders) with permittivity embedded in a medium with permittivity (air) upon a homogeneous dielectric half-space of permittivity and with a rough surface [15]. The radiative transfer equation was solved by iteration and the first-order backscattering coefficients and for co- and cross-polarized terms were computed as follows:

\[
\sigma_{pq}^0 = \sigma_{pq1}^0 + \sigma_{pq2}^0 + \sigma_{pq3}^0 + \sigma_{pq4}^0. 
\]

The total backscattering \( \sigma_{pq}^0 \) includes the following terms:
1) direct backscattering from soil \( \sigma_{pq1}^0 \);
2) direct backscattering from the vegetation layer (leaves and stems) \( \sigma_{pq2}^0 \);
3) soil–vegetation and vegetation–soil interaction (double scattering) \( \sigma_{pq3}^0 \);
4) soil–vegetation–soil interaction \( \sigma_{pq4}^0 \).

The backscattering from the soil contributes significantly to the total backscattering. This is particularly true in the early growing stage of crop. In this paper, the single-scattering integral equation model (IEM) was adopted to compute the direct backscattering from soil [21]. The other backscattering components in (3) were computed using field measured
Fig. 6. Theoretical model estimated LAI and ASAR observation.

parameters shown in Table I according to the description of the MIMICS mode at 5.3-GHz, HH/HV and average incidence angle of 35.0° (IS4-IS5). Fig. 6 shows the theoretical model simulation results of temporal variation of C-band SAR HH/HV backscattering coefficient of sugarcane field in growth stages. Fig. 7 shows the change of HH backscattering components in different sugarcane growth stages. The result demonstrates the theoretical simulated trend of C-band ASAR observations with the growth of sugarcane fields. The reasons for the difference of the theoretical results with ASAR observations may be: 1) the values of the parameters used in the model is the mean value; 2) the complicated leaf orientation distribution was assumed uniform; 3) the roughness of soil is not always suitable for IEM soil models; and 4) complicated multiple-scattering effect between the sugarcane and soil is not considered by MIMICS. The simulation results suggest that the backscattering coefficient of a sugarcane field depend on the mutual interaction between soil and crop stem and leaves in terms of scattering and absorption. The backscatter of C-band HH and HV polarization is sensitive to sugarcane vertical and horizontal components such as stem and leaves. The result confirms the general increasing trend of HV/HH ratio with sugarcane growth as observed in the aforementioned section. This might expected because HV is very low for the early stages of the phonological cycle and increases when more leaves appear. When sugarcane grows, the vertical and horizontal structure varies with LAI increase, which leads to variation of the HH and HV polarization backscatter of sugarcane field, and HV polarization backscatter increases more than HH polarization, which may be caused by the increase of volume scattering. However, volume scattering as well as attenuation due to sugarcane vertical and horizontal components increase competitively. The increase of HH and HV backscatter due to volume scattering and reduction due to attenuation continues to play until a mature period is reached. The HH/HV ratio can reflect the variation of sugarcane components simultaneously, and avoid the problem of calibration, data processing, and soil backscattering effects.

IV. MAPPING SUGARCANE GROWTH AREA AND ESTIMATING LAI OF SUGARCANE

For effectively monitoring sugarcane growth, sugarcane acreage and yield are the most important information. Based on the aforementioned analysis of backscattering characteristics of sugarcane field, methods for mapping sugarcane growth area and estimating LAI are proposed in this paper.

A. Mapping Sugarcane Growth Area

The backscattering behavior of sugarcane fields and theoretical results in Section III indicate that sugarcane fields show a relatively larger variation of temporal radar response over the whole life cycle than that of the other major ground types in Table II, which suggests that the difference of the variation can be used as a classifier. In previous experiments, some methods for mapping crop growth area have been proposed in [12]. These methods take advantage of the different variation of radar temporal response to a certain crop with others objects to select the proper data set of multitemporal single HH or VV polarization SAR data of different acquisition dates to discriminate the crop from other land cover types. The key to improve the accuracy of mapping crop field is to find proper data acquisition dates to maximize the temporal variation of other land cover types with the crop to be distinguished. The analysis results in Fig. 3 imply that important radar data acquisition time for sugarcane monitoring is at the end of the seedling period and mature period in March and October, respectively. The data set of the two dates can give the biggest difference of radar response between sugarcane and other targets. Distance factor

<table>
<thead>
<tr>
<th>Band combination</th>
<th>Sugarcane-Banana</th>
<th>Sugarcane-lotus</th>
<th>Sugarcane-fishpond</th>
</tr>
</thead>
<tbody>
<tr>
<td>March HH + October HH</td>
<td>1.87</td>
<td>1.95</td>
<td>1.89</td>
</tr>
<tr>
<td>March HV + October HV</td>
<td>1.86</td>
<td>1.95</td>
<td>1.93</td>
</tr>
<tr>
<td>March HV + October HH</td>
<td>1.94</td>
<td>1.97</td>
<td>1.95</td>
</tr>
</tbody>
</table>

TABLE III DISTANCE FACTOR OF SUGARCANE WITH OTHER GROUND CATEGORIES
was often used in many experiments to measure the separation of different objects using remote sensing data. According to the concept of feature separation [23], classes are supposed to be well separated if the distance between the different class mean values is large compared to the standard deviations

\[ d_{ij} = \frac{|\mu_i - \mu_j|}{\sigma_i + \sigma_j} \]  

(2)

where \( \mu \) and \( \sigma \) are mean values and standard deviations of class \( i \) and class \( j \). Class \( i \) and class \( j \) represents different ground objects. For values of \( d_{ij} \) between 0.8 and 1.5, the quality of the separation between classes \( i \) and \( j \) is average. Values of \( d_{ij} \) above 2.0 provide almost complete separation of class pairs. Table III shows that the separability between sugarcane fields and other main ground categories using a different data set of the two dates is reasonably good, and the data set of the March 10 HV image and October 19 HH images makes the best separability. Figs. 8 and 9 show the two images. In the two images, the change of backscattering response of sugarcane field ranges from 7 to 11 dB while other main ground types are less than 4 dB. Differencing and ratioing are often-used methods for change detection. Ratioing of the multiday radar intensities is found to be better adapted to the statistical features of SAR data, and it is very robust to radiometric errors [24].

The speckle noise in SAR data may affect the accuracy of the ratioing method. The research shows that to detect changes in radar intensity less than 2 dB with a confidence level better than 90% [24], the number of SAR image looks must be greater than 64 looks. Therefore, a filter could be used to drastically reduce speckle effect before the application of ASAR data with three looks. Therefore, based on the previous research results and above analysis [12], a method for mapping sugarcane growth area is proposed. The main procedure is the following.

1) First, HV image on March 10 and HH intensity image on October 19 are selected to be filtered twice using a Gamma MAP spatial filter with a 7 × 7 window and a texture filter with a 3 × 3 window to increase the number of looks to 100. It is then possible to detect changes in ASAR data less than 1 dB with a high confidence interval better than 80% [24].

2) Ratioing is applied to the above filtered images, and the ratio image is expressed in decibels. The aim of the ratioing is to highlight the backscatter temporal change of the sugarcane field. The ratioing was defined in

\[ \text{Image}_{\text{Ratio}} = 10^* \log_{10} \left( \frac{\text{image} (\text{HH})}{\text{image} (\text{HV})} \right) \]  

(3)

where image (HH) and image (HV) are the selected HH polarization intensity ASAR image on October 19 and HV polarization intensity ASAR image on March 10. Fig. 10 is the ratio image. In the image, the area corresponding to the sugarcane field is the brighter section which has a positive change segmented by a threshold of 5 dB to highlight the sugarcane field. The threshold is based on the analysis of the temporal variation of backscattering from sugarcane fields in the test site.

3) The data set of the HV image on March 10, HH image on October 19, and the ratio image or segmented image are used to map the sugarcane field.

Fig. 10 shows a ratio image between HH data in October and HV data in March. The figure can indicate the classification result of the proposed data set. The figure shows that sugarcane can be distinguished well from other crops by the data set, but speckle and spatial resolution also affect the accuracy of classification, particularly at the field edge and hedges. The mapping result was surveyed using the land cover/use map with random sampling with 45 samples, and classification accuracy was evaluated using the error matrix in this paper. The results showed that the mapping results of the three data set have a promising high accuracy of 79% for HH-HV and ratio image data set. The classification accuracy of the data set of col-polarization HH data in March and October and HV data in March and October are
0.76 and 0.71, respectively. In a practical application, the classification accuracy should be above 75%. Therefore, the data set of the HV image on March 10 and the HH image on October 19 can meet the requirement of application.

B. Empirical Model for LAI Estimation

LAI is a key parameter in process-based models to quantify the exchange of matter and energy flow between vegetation and the atmosphere. Research has shown that sugarcane LAI is closely related to growth conditions and biomass [9]. Optical remote sensing is an effective tool for LAI estimation at regional and global scales. However, the regular acquisition of optical data is often restricted by the unfavorable weather conditions in southern China. Many experiments have been carried out to analyze the relationship of radar response with crop LAI, and theoretical and semiempirical models to estimate LAI with certain accuracy [5]–[7]. However, the theoretical models need many input parameters and field measurements, which is sometime labor intensive and difficult to measure, and semiempirical models are often applied for short crops like rice, wheat, and cotton based on the water–cloud model [18]. In Section II, the ratio of ASAR HV to HH intensity data shows a good correlation with LAI, and the relationship was also analyzed, which suggests that the ratio of ASAR HV to HH intensity data be used to estimate LAI for an operational system for wide area application. Fig. 4 showed that when LAI ranges from 1.1 to 4.1, the ratio of ASAR HV to HH intensity data has a relatively good relationship with the increase of LAI, while the ratio changes less when LAI is greater than 4.1. To reduce the effect of saturation and improve the accuracy of LAI estimation, two empirical relationships were proposed to develop between the range of LAI from 1.8 to 4.1 and 4.1 to 5.8, respectively. Based on the field measurements and ASAR images, the following two empirical models are proposed:

\[
\text{LAI} = -3.87 + 0.11 \exp\left(\frac{\text{Ratio}_{HV/HH}}{1.64}\right) \quad (4)
\]

when LAI < 4.1:

\[
\text{LAI} = -2.99 + 0.08 \text{Ratio}_{HV/HH}. \quad (5)
\]

The correlation coefficients are 0.93 for (4) and 0.88 for (5). Figs. 11 and 12 show the variation of the ratio of ASAR HV to HH as a function of LAI when LAI ranges from 1.1 to 4.1 and 3.6 to 5.6, respectively. Based on the field measurements and ASAR images, the following two empirical models are proposed:

The difference of inverted LAI by the two empirical models from field-measured LAI values can be estimated using the parameters of \(E_{\text{sys}}\) (systematic error), \(E_{\text{res}}\) (residual error), and \(E_{\text{tot}}\) (total error). These parameters are defined in [16], and the relationship of these parameters is the following:

\[
E_{\text{tot}} = \sqrt{E_{\text{sys}}^2 + E_{\text{res}}^2}. \quad (6)
\]
The three parameters were calculated using field-measured and model-inverted LAI. The results show that when LAI ranges from 1.1 to 4.1, the total error of the models equation (4) is 0.15. The error of the model equation (5) is 0.23 for LAI greater than 4.1.

V. CONCLUSION

This paper showed preliminary results obtained using ENVISAT ASAR alternating polarization HH/HV data to monitor sugarcane growth in southern China in 2006. Temporal variation of the backscattering coefficient of ASAR HH and HV data as a function of sugarcane LAI was analyzed, and the results showed a general increasing backscattering trend of ENVISAT ASAR data with sugarcane growth. The theoretical model analysis suggests that SAR backscattering is sensitive to the change of the biophysical parameters of sugarcane. Based on the analysis of the temporal variation of ASAR data response to sugarcane fields, a method for mapping sugarcane fields was proposed using the data set of an ASAR HV polarization image in March and an HH polarization image in October at the end of sugarcane growth and their ratio image with an accuracy of 78%. Mapping accuracy is still needed to be improved and validated in other sugarcane fields. To monitor the growth conditions of sugarcane, a ratio of HV to HH intensity data is proposed to be used to establish a better empirical relationship with LAI. The LAIs obtained from proposed empirical models were compared with field measurements. The better correlation was found when LAI varies from 1.1 to 4.1 with an error of 0.15, while the error is 0.23 when LAI is greater than 4.1. The results confirm that C-band SAR data appear a very promising alternative to optical remote sensing data in developing an operational system for monitoring sugarcane crop growth in cloudy and rainy areas. In the future, applications of ASAR alternating polarization HH/HV data for monitoring sugarcane growth will be studied, and a more robust model needs to be developed for improving the accuracy of LAI estimation, particularly when LAI is greater than 4.1.

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REFERENCES

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