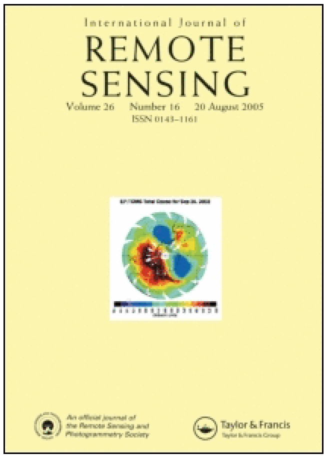

International Journal of Remote Sensing
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713722504

Regression and analytical models for estimating mangrove wetland biomass in South China using Radarsat images

X. Li [ab]; A. Gar-On Yeh [c]; S. Wang [a]; K. Liu [b]; X. Liu [a]; J. Qian [b]; X. Chen [c]
[a] School of Geography and Planning, Sun Yat-sen University, Guangzhou 510275, PR China
[b] Guangzhou Institute of Geography, Guangzhou 510070, PR China
[c] Centre of Urban Planning and Environmental Management, The University of Hong Kong, Hong Kong SAR, PR China

First Published on: 19 June 2007
To cite this Article: Li, X., Yeh, A. Gar-On, Wang, S., Liu, K., Liu, X., Qian, J. and Chen, X. (2007) 'Regression and analytical models for estimating mangrove wetland biomass in South China using Radarsat images', International Journal of Remote Sensing, 28:24, 5567 - 5582
To link to this article: DOI: 10.1080/01431160701227638
URL: http://dx.doi.org/10.1080/01431160701227638

International Journal of Remote Sensing
Vol. 28, No. 24, 20 December 2007, 5567–5582

Regression and analytical models for estimating mangrove wetland biomass in South China using Radarsat images

X. LI*†§, A. GAR-ON YEH‡, S. WANG†, K. LIU§, X. LIU†, J. QIAN§ and X. CHEN‡

†School of Geography and Planning, Sun Yat-sen University, 135 West Xingang Road, Guangzhou 510275, PR China

‡Centre of Urban Planning and Environmental Management, The University of Hong Kong, Pokfulam Road, Hong Kong SAR, PR China

§Guangzhou Institute of Geography, Guangzhou 510070, PR China

(*Received 15 February 2006; in final form 15 November 2006*)

Mangrove wetlands have been rapidly diminishing because of human pressures worldwide. The Guangdong Province in South China, which has the largest area of mangrove wetlands in the nation, is under severe threat as a result of rapid urbanization and economic development. In this paper, comparisons were made between optical Landsat TM images and Radarsat fine-mode images for estimating wetland biomass. Regression and analytical models were used to establish the relationships between remote sensing data and wetland biomass. The optimal parameter values for the analytical model were determined using genetic algorithms. Experiments indicate that the models using Radarsat fine-mode images have significant accuracy improvement in terms of Root Mean-Square Error (RMSE) whereas the use of the single Normalized Difference Vegetation Index (NDVI) may produce serious errors in biomass estimation. The Radarsat images can obtain more accurate trunk information about mangrove forests because of higher resolution and side-looking geometry. The use of genetic algorithms can help to decompose backscatter into vegetation and soil backscattering, which is very useful for ecological modelling.

1. Introduction

In many coastal areas of the Guangdong Province in South China, mangrove forests have been disappearing very rapidly because of reclamation projects in recent years. The rapid development of a lucrative shrimp industry along the coastal areas of the Province, especially in the Pearl River Delta, is also one of the major causes for the loss of mangrove forest. Protecting mangrove wetlands in the Guangdong Province has attracted the attention of international communities. Recently, the United Nations Environment Programme and Global Environment Facility (UNEP/GEF) has initiated a programme for rehabilitating the mangrove wetlands in the eastern coastal areas of the Guangdong Province.

Field investigations to obtain information about wetland biomass are very tedious and time-consuming. There is a lot of literature on the development of methodologies for vegetation studies using remote sensing (Richardson and Wiegand 1977, Clevers 1988, Huete 1988). Many methods have been proposed for

*Corresponding author. Email: lixia@mail.sysu.edu.cn

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online
http://www.tandf.co.uk/journals
DOI: 10.1080/01431160701227638

estimating and mapping forest biomass from remotely sensed data (Huete 1988, Li 1994, Mather 1999). Both optical and radar remote sensing data can be used for biomass mapping.

A variety of vegetation indices have been developed for retrieving vegetation information from optical remote sensing. The most common measurement is the Normalized Difference Vegetation Index (NDVI) (Mather 1999, Foody *et al.* 2001). The index is based on the characteristics that vegetation has noticeable absorption in the red and very strong reflectance in the near-infrared. Different types of vegetation often show distinctive variability from one another due to such parameters as leaf shape, spacing of the plants, water content, and soil background.

In tropical and subtropical areas, conventional optical remote sensing has difficulties in monitoring the growth cycle of wetland vegetation because of frequent cloud cover in summer months. Additionally, optical remote sensing may have drawbacks in biomass estimation. It has the problem of signal saturation because of using a shorter wavelength. Radar remote sensing, which can be used under cloudy conditions, has a great potential for wetland studies. Many studies indicate that synthetic aperture radar (SAR) images can be used for classifying land use types and estimating vegetation biomass (Dobson *et al.* 1996, Pierce *et al.* 1998, Magagi *et al.* 2002).

There is increasing literature on the application of SAR technologies for the quantitative investigation of vegetation biomass (Wigneron *et al.* 1999, Magagi *et al.* 2002). It is possible to measure the biophysical properties of forests, such as basal area and tree height (Le Toan *et al.* 1992, Dobson *et al.* 1995), tree diameter and density (Le Toan *et al.* 1992, Wang and Dong 1997) from radar remote sensing. The acquisition of remote sensing data during growing seasons allows better crop type determination and yield (productivity) estimation. Successful applications have been reported in the studies of crop biomass (Le Toan *et al.* 1997, Wigneron *et al.* 1999), forest structures in wetland (Townsend 2002), biomass of boreal forests (Pulliainen *et al.* 1996), biomass of mangrove forests (Mougin *et al.* 1999), and biomass of wetland forages (Moreau and Le Toan 2003).

These studies have found strong positive correlations between biomass and backscatters of SAR images. SAR backscatters increase linearly with increasing biomass until a saturation level is reached. Radar remote sensing can be applied to the quantitative analysis of wetland biomass (Mougin *et al.* 1999, Baghdadi *et al.* 2001, Townsend 2002, Moreau and Le Toan 2003).

For biomass estimation of forests, it is important to obtain the vertical information of vegetation because most biomass is held in trunks and large branches. Usually, trunk components may contain over 60% of the above-ground biomass (Bergen and Dobson 1999). The penetrability of radar remote sensing can help to obtain the trunk information of forests. Penetrability is different for various radar wavelengths. For example, L and P band radar penetrate deeper than K or X bands. Penetrability is rather weak for Radarsat images (C band) because of its shorter wavelength. However, the side-looking geometry of Radarsat images can greatly enhance the subtle topographic features that aid in the interpretation. It is expected that this feature can also help to obtain more trunk information for vegetation and improve the accuracy of biomass estimation.

The objective of this study is to compare the capabilities of radar remote sensing and optical remote sensing for estimating mangrove biomass. The comparison is useful for identifying the best method for biomass estimation. Regression and analytical models are compared based on the NDVI of Landsat TM images and the backscatter of Radarsat images. The analytical model should be useful for providing a clear structure of backscattering. However, the parameter values are difficult to define by traditional methods. In this study, genetic algorithms are used to find the optimal parameter values for the analytical model. Many studies have shown that the integration of images of different sensors can improve the accuracy of image analysis (Metternicht and Zinck 1998, Chena *et al.* 2003). The integration of optical remote sensing with SAR images is also tested to see if the accuracy of biomass estimation can be improved.

2. Study area and data collected

2.1 *Study area*

Half of the mangrove wetlands in China are situated in the Guangdong Province. The loss of wetlands in the Province is very fast because of rapid urbanization. According to field investigations, the area of mangrove forests had reduced from 8000 ha^2 in the 1950s to only 300 ha^2 recently in the eastern coast of the Province, and from 54,000 ha^2 in the 1950s to 12,000 ha^2 recently in the western coast of the Province (Wang and Chen 1998). However, accurate and updated information about the wetlands in the Guangdong Province is unavailable, especially the mangrove forests. Conventional field investigations have difficulties in collecting such information. Therefore, remote sensing should be a useful tool for monitoring mangrove forests in this region.

The methodology is tested on Qiao Island, Zhuhai City, the Pearl River Delta (figure 1). The island has an area of about 24 km^2. It is within the subtropical region, with an average temperature about 22–23°C and an annual precipitation of about 1700–2200 mm. The climate is very suitable for the growth of mangrove forests. However, conventional optical remote sensing has difficulties in monitoring the temporal vegetation conditions because the region is frequently covered by clouds.

China used to have three large sites of mangrove wetland, one of which was situated in Zhuhai City. However, the reclamation projects for the development of the shrimp industry have resulted in the rapid loss of mangrove forests in this region. For example, Qiao Island had lost about 1360 ha of mangrove forests before 1999 according to government reports. In 1999, there were only about 32 ha of mangrove forests left on the island. Since 1999, Zhuhai City has adopted the initiatives of rehabilitating the ecological system by planting mangrove trees on the island. The area of mangrove forests has increased from 32 ha to 533 ha since then.

The mangrove forests are mainly situated on the northwestern part of the island. The common mangrove types in the study area include: *Kandelia candel-Aegiceras corniculatum-Acanthus ilicifolius*, *Aegiceras corniculatum-Phragmites communi*, *Acanthus ilicifolius*, *Sonneratia apetala*, *Bruguiera gymnorrhiza-Heritiera littoralis*.

Sonneratia apetala, a fast-growing mangrove species, was first introduced from Bangladesh to Hainan Island, China in 1985. It was then transplanted from Hainan Island to the coastal areas of Guangdong in 1993. The growth rate of *S. apetala* is very high. The mean height is about 3.5 m for a 2-year tree, and about 11.5 m for a 3.5-year tree. The patch size is usually larger than $20\,m \times 20\,m$, which can be discerned from Radarsat images. The canopy is usually not completely close and with the presence of standing water on the ground. Therefore, the side-looking

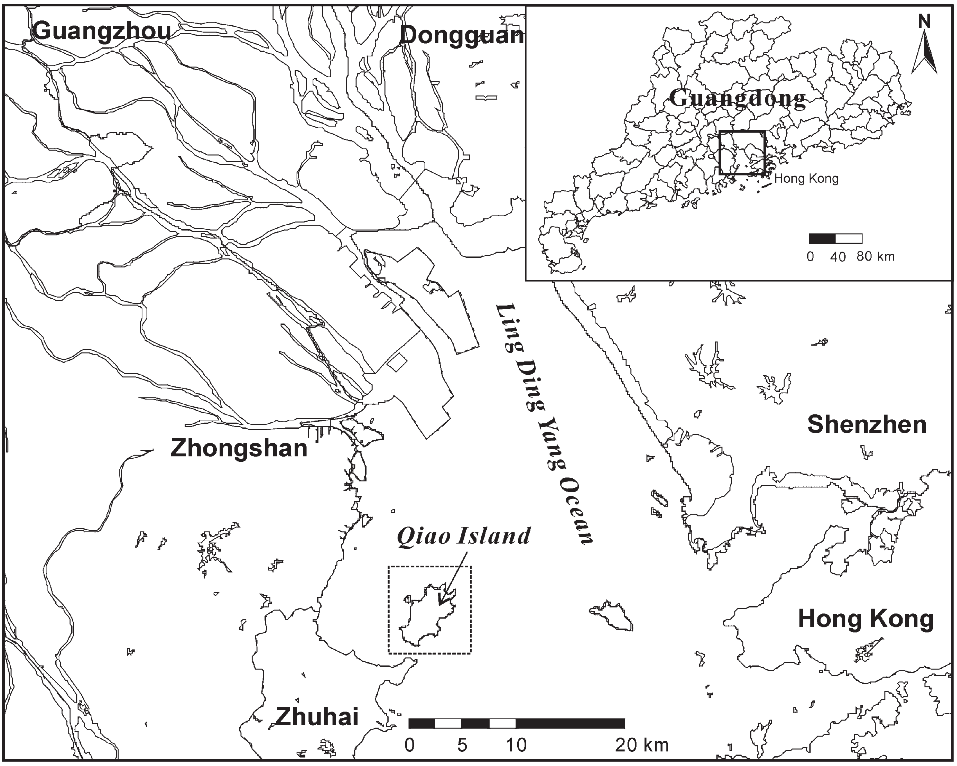

Figure 1. Location of the study area in the Pearl River Delta, Guangdong Province, South China.

geometry of Radarsat is useful for obtaining the trunk information for the mangrove forests.

Sonneratia apetala was planted to control the growth of *Spartina anglica*. *Spartina anglica*, an herbaceous species that flourishes in the region, originated from the south coast of Britain. In 1963, it was transplanted to the coast of Jiangsu province and later transplanted to the coasts of other provinces of China. The introduction of *S. anglica* was found to be a major mistake for wetland conservation because of its uncontrolled growth. Its invasion into the mangrove territory has caused the death of a large area of the mangrove forests. In the study area, *S. anglica* are situated in the frontier of the wetland, near the sea. In order to control the growth of *S. anglica* and protect the mangrove trees, local governments have transplanted a fast growing mangrove species, *S. apetala*. According to field observation, the introduction of *S. apetala* seems to have controlled the growth of *S. anglica*.

2.2 *Remote sensing data and image processing*

A Radarsat image taken on 15 May 2004 was acquired for estimating the mangrove biomass for the study area. The C-band SAR image is in the ascending orbit and with the fine-mode (F_2). It has a resolution of $8.3\,\text{m} \times 8.4\,\text{m}$ and a swath width of 50 km on the ground. The average incidence angle is within the range 37–41°. The weather was cloudy during the acquisition of the SAR image. An optical remote sensing image of Landsat 5 TM of similar acquisition time was also used for comparison. Table 1 lists these remote sensing data.

Image processing procedures were carried out before these data were used for the wetland analysis. The first step was to convert the original digital number (DN) of the SAR images into the backscatter coefficient using the PCI image processing software. The backscatter coefficient can represent the original signal amplitudes more accurately and thus produce more plausible results than the original digital number in many applications.

It is important to remove noise in the SAR images since they are affected by a kind of noise called speckle. The Frost adaptive filter was used to preserve edges while significantly reducing the noise in homogenous regions (Frost *et al.* 1982). A 3×3 filter was applied for the smoothing. Most of the noise was removed after the filtering using the Frost algorithm.

Co-registration was performed to register the SAR and Landsat TM satellite images to the survey maps by using control points. The geometry of the original Radarsat data was ground range. The map projection of the survey maps is Universal Transverse Mercator. The correction transformed the coordinates of these images into the Chinese Coordinate System (C80). Around 30 control points were selected on each image to carry out the polynomial transformation for the geometric correction. The control points were selected based on easy identification. For example, the intersections of roads or the corners of fishponds were usually selected as the control points. These control points were evenly distributed over the whole region to ensure accurate registration. The second order of the polynominal transformation was used for the correction. The co-registration error was 0.6 pixels on average.

2.3 *Training data*

Field investigation was carried out to collect the training data during the same period as acquiring the SAR image. The training data were used to establish the models for biomass estimation. Biomass is defined as dry weight, which is usually estimated by measuring tree diameter, or sometimes diameter and height. Empirical functions are frequently employed to calculate (estimate) biomass. Researchers studying tree volume have found very strong relationships between volume and the size of the bole at a relative height (Foody *et al.* 2001, Brown 1997). Breast height is a convention with a long history of use within forestry practice. In China, the breast height is 1.3 m for most of the applications.

In this study, the mangrove biomass measurement for the training data is based on the nondestructive double-sampling method (Bonham 1989). One hundred sampling sites were randomly selected in the study area. The diameter (perimeter) at the breast height for each tree was measured manually and the number of mangrove forests within a plot of $10\,\text{m} \times 10\,\text{m}$ was counted in each sampling site. The empirical

Table 1. Remote sensing data for the study area.

Remote sensing data	Acquisition date	Spatial resolution
Landsat TM	13 June 2004	About 30 m
Radarsat F_2 mode	15 May 2004	About 8 m

equation for each mangrove tree in this study area is as follows:

$$B_{\mathrm{a}} = 3.396 \times 10^{-2} \times D_{\mathrm{h}}^{2}, \tag{1}$$

where B_{a} is the dry biomass of a mangrove tree (kg), and D_{h} is the diameter (cm) at breast height (1.3 m). The biomass per square metre can be summed up by multiplying the biomass with the total number of trees within the area.

The biomass for the herbaceous species, such as *Spartina anglica*, was also measured at the field. A Global Positioning System (GPS) was used to record the coordinates of each measurement location so that the field investigation data can be associated with the remote sensing data for establishing the biomass estimation models.

Soil wetness was measured using the TDR 300 Soil Moisture Probe. The sampling sites are generally very saturated or completely covered by water. The wetness is usually greater than 90%. Radar signals can be more related to biomass because other influences of background can be minimized under such water conditions.

3. Methodology

3.1 *Regression models using NDVI and backscatters*

A simple way to estimate mangrove wetland biomass is based on the common NDVI index of optical remote sensing. The index is presented using the following formula (Mather 1999):

$$\mathrm{NDVI} = \frac{\text{near IR band} - \text{red band}}{\text{near IR band} + \text{red band}}. \tag{2}$$

Studies indicate that the index is effective for the monitoring of biophysical variables of temperate vegetation (Foody *et al.* 2001). It is highly related to net primary productivity (Goward *et al.* 1985). A simple linear regression model can be used to represent the relationship between vegetation biomass and reflectance values (Hansen and Schjoerring 2003):

$$V_{\mathrm{B}} = a_0 + a_1\ \mathrm{NDVI}, \tag{3}$$

where V_{B} is vegetation biomass, and a_i is the coefficient for each term.

A log/exponential transformation may be used before the regression analysis is carried out for correcting nonlinearity in the relationship (De Jong *et al.* 2003). The regression model is then revised as follows:

$$V_{\mathrm{B}} = a_0\ e^{\,a_1\ \mathrm{NDVI}}. \tag{4}$$

However, the log-transformation may not fit the nonlinear relationship in some situations. Polynomial models may be required to deal with complex nonlinearity. For example, the 2nd order polynomial equation is represented as follows:

$$V_{\mathrm{B}} = a_0 + a_1\ \mathrm{NDVI} + a_2 \mathrm{NDVI}^2. \tag{5}$$

A drawback with NDVI is that the index mainly reflects the crown information of vegetation. The vertical properties (e.g. tree height) cannot be retrieved by this index. It has frequently been applied less successfully to tropical forests since it loses sensitivity to biophysical properties at high biomass amounts for tall vegetation

(Sader *et al.* 1989, Foody *et al.* 1996). The lack of cloud-free data is another common problem in tropical and subtropical regions.

Radar remote sensing can overcome such limitations. When SAR images are used for biomass estimation, backscatter coefficients are frequently used to establish the relationship between biomass and remote sensing data (Ribbes and Le Toan 1999, Ranson and Sun 2000). The above simple linear, log/exponential and polynomial transformation can also be applied to the biomass estimation by using backscatter coefficients.

3.2 *An analytical model using genetic algorithms*

The above regression models require substantial empirical data to determine the coefficients for these variables. They cannot differentiate the influences of each component (e.g. soil background and vegetation). Analytical models may be more plausible because they can provide clear structures for understanding the mechanisms of backscattering interactions.

An analytical backscatter model may be defined based on the assumption that the backscattering coefficient (σ^0) for mangrove wetlands can be decomposed into two parts: (1) the backscattering component from the vegetation canopy; (2) the backscattering component from the ground (including the trunk-ground and surface vegetation). Backscatter can then be calculated using the following equation:

$$\sigma^0 = \sigma^0_{\text{veg}} + \tau^2 \sigma^0_{\text{gro}}, \tag{6}$$

where σ^0_{veg} is the backscattering coefficient from the vegetation canopy, τ is the vegetation transmissivity, and σ^0_{gro} is the backscattering coefficient from the ground.

Equation (6) can be further revised as follows (Fransson and Israelsson 1999, Kurvonen *et al.* 1999):

$$\sigma^0 = \gamma_{\text{veg}} \cos\alpha \left(1 - e^{-2\kappa V_{\text{B}}/\cos\alpha}\right) + \gamma_{\text{gro}} \cos\alpha\, e^{-2\kappa V_{\text{B}}/\cos\alpha}, \tag{7}$$

where γ_{veg} is a backscattering coefficient assumed to be independent of the incidence angle (α) and can be regarded as the saturated backscattering coefficient of a dense forest. γ_{gro} is the backscattering coefficient of the ground without vegetation cover. κ is the coefficient of attenuation, which determines the rate by which the sensitivity to stem volume change diminishes.

This analytical model provides a useful structure for understanding the backscattering mechanisms. Empirical data are required to obtain the parameter values of the analytical model. Conventional regression analysis can be applied under the conditions that this model cannot be too complex. It is difficult to determine the parameters for complex nonlinear equations. Genetic algorithms (GAs) should be a much better option for solving this complex analytical model.

In a GA program, there are two basic operations to the evolutionary approach—crossover and mutation (Goldberg 1989, Holland 1992). The 'crossover' operator exchanges genes between two parents to form two offspring that inherit the traits of both parents. The 'mutation' operator alters one or more genes of a single parent. Each individual (a solution) corresponds to a fitness value. The evolutionary process is mainly based on the assessment of each individual using the fitness functions. The 'survival of the fittest' regime is crucial for reaching an optimum or near-optimum solution. The search process is intelligent because of the use of the evolutionary approach.

The search procedure will stop when the improvement of the best fitness is insignificant. The optimal parameter values for equation (8) can be determined based on this evolutionary approach. The rules for terminating the program are:

IF $F(t+1)-F(t)<T$

THEN The search will be automatically terminated

where T is a small value.

4. Results

4.1 *Comparison of the use of NDVI and backscatters for biomass estimation*

The comparison was made between the NDVI and the backscatter method for calculating the biomass of mangrove forests. First, regression analysis was used to obtain the coefficients of the NDVI models based on the field investigation data (table 2). The correlation coefficient value (R) is 0.626 according to the regression analysis. The accuracy in terms of Root Mean-Square Error (RMSE) is 0.99 kg m^{-2}, compared to the field measured biomass ranging from 0.2 kg m^{-2} to 26.0 kg m^{-2}. The log/exponential transformation model was also tested as a comparison. However, this did not yield the regression results better than the simple linear model. The values of R and RMSE are 0.598 and 1.04 kg m^{-2}, respectively. It is because the transformation may not be the best model to fit the complex nonlinear relationship between NDVI and biomass. In fact, the 2nd order polynomial model has better performance in estimating mangrove biomass. The values of R and RMSE become 0.668 and 0.95 kg m^{-2}, respectively.

Secondly, the same method of regression analysis was applied to obtain the coefficients of the backscatter models (table 2). The values of R and RMSE are 0.726 and 0.868 kg m^{-2}, respectively for the linear model. The values of R and RMSE are 0.741 and 0.857 kg m^{-2}, respectively for the log/exponential model. The values of R and RMSE become 0.841 and 0.700 kg m^{-2}, respectively for the 2nd order polynomial model. This shows that the 2nd order model is also a better option for representing the nonlinear relationship between wetland biomass and the backscatter of SAR images.

The study indicates that Radarsat data can provide more accurate results than Landsat TM data for wetland biomass estimation. The backscatter model shows

Table 2. Regression models for estimating wetland biomass using NDVI and backscatter.

Regression models	R	RMSE (kg m^{-2})
(1) NDVI		
$V_B=-12.546+40.303$ NDVI	0.626	0.993
$V_B=0.037\ e^{8.918\mathrm{NDVI}}$	0.598	1.042
$V_B=11.460-68.821\mathrm{NDVI}+117.308\mathrm{NDVI}^2$	0.668	0.946
(2) Backscatter		
$V_B=20.878+1.801\sigma^0$	0.726	0.868
$V_B=49.949e^{0.361}\sigma^0$	0.741	0.857
$V_B=43.042+7.775\sigma^0+0.357\sigma^{0\ 2}$	0.841	0.700
(3) NDVI and backscatter		
$V_B=3.761-24.179$ NDVI $+52.710$ $\mathrm{NDVI}^2-0.084\sigma^0+0.001\sigma^{0\ 2}$	0. 769	0.738

much improvement in RMSE, compared to the NDVI model—14.1% for the simple linear, 21.4% for the exponential, and 35.7% for the 2nd order polynomial method. The analytical model has 16.4% improvement in RMSE, compared to the best NDVI model (the 2nd order model).

Figure 2 also shows that NDVI is saturated at a much lower amount of biomass than backscatter for estimating the wetland biomass. This indicates that the backscatter models should be more accurate than the NDVI models for estimating the biomass. The figure also suggests that the linear model should not be the best option for estimation.

A further study is to test whether the integration of Radarsat and Landsat TM images can produce better results for wetland biomass estimation. In this study, a 2nd order polynomial model is used to integrate the variables of NDVI and backscatter together. The regression analysis indicates that the integrated model has a correlation coefficient (R) of 0.769 and a RMSE of 0.738 $\mathrm{kg\,m^{-2}}$ (table 2). It produces better estimation results than the NDVI model alone. However, the integrated model cannot produce better results than the polynomial backscatter model because the errors from the NDVI method can cause the decrease of the accuracy.

Field investigation indicates that there are significant discrepancies when NDVI is applied to wetland biomass estimation. Higher values of NDVI should indicate higher amounts of biomass. It was found that the NDVI values are higher for some dense herbaceous species, such as *Spartina anglica*, than for the woody mangrove trees. This is because the NDVI mainly reflect canopy properties instead of trunk properties. This has caused serious errors in the estimation of wetland biomass without vertical information. For example, location m, which is *S. anglica*, has much higher NDVI values than location l, which is *Sonneratia apetala* (figure 3(a)). In fact, the front part of the wetland near the sea should have much lower amounts of wetland biomass according to field investigation. However, the section from A to B (figure 3(a)) indicates that a much higher amount of wetland biomass occurs in the front part. This contradicts the evidence from the field investigation. This problem can be solved when the SAR image is used (figure 3(b)). Moreover, the SAR image is able to provide more spatial information because of its higher resolution.

As an illustration, figure 4(a) and (b) presents the biomass maps of the study area, calculated by the NDVI and backscatter models, respectively. More spatial variations about the wetland biomass can be detected from the backscatter model because the SAR image has higher spatial resolution and side-looking features, which can help to obtain more trunk information (figure 4(b)). The detection results are consistent with the field investigation. However, much less spatial information is obtained from the NDVI model (figure 4(a)). It also has problems in the biomass estimation for *S. anglica* and *S. apetala*.

4.2 *Interpreting the backscatter response of mangrove wetlands using the analytical model*

The analytical model should be more useful for separating different terms of backscatter. However, the estimation of its parameter values is difficult by applying conventional regression analysis for solving the complex nonlinear equation. In this study, the parameter values of the analytical model were obtained by using the genetic algorithm (GA). The parameter values of the nonlinear equation were found

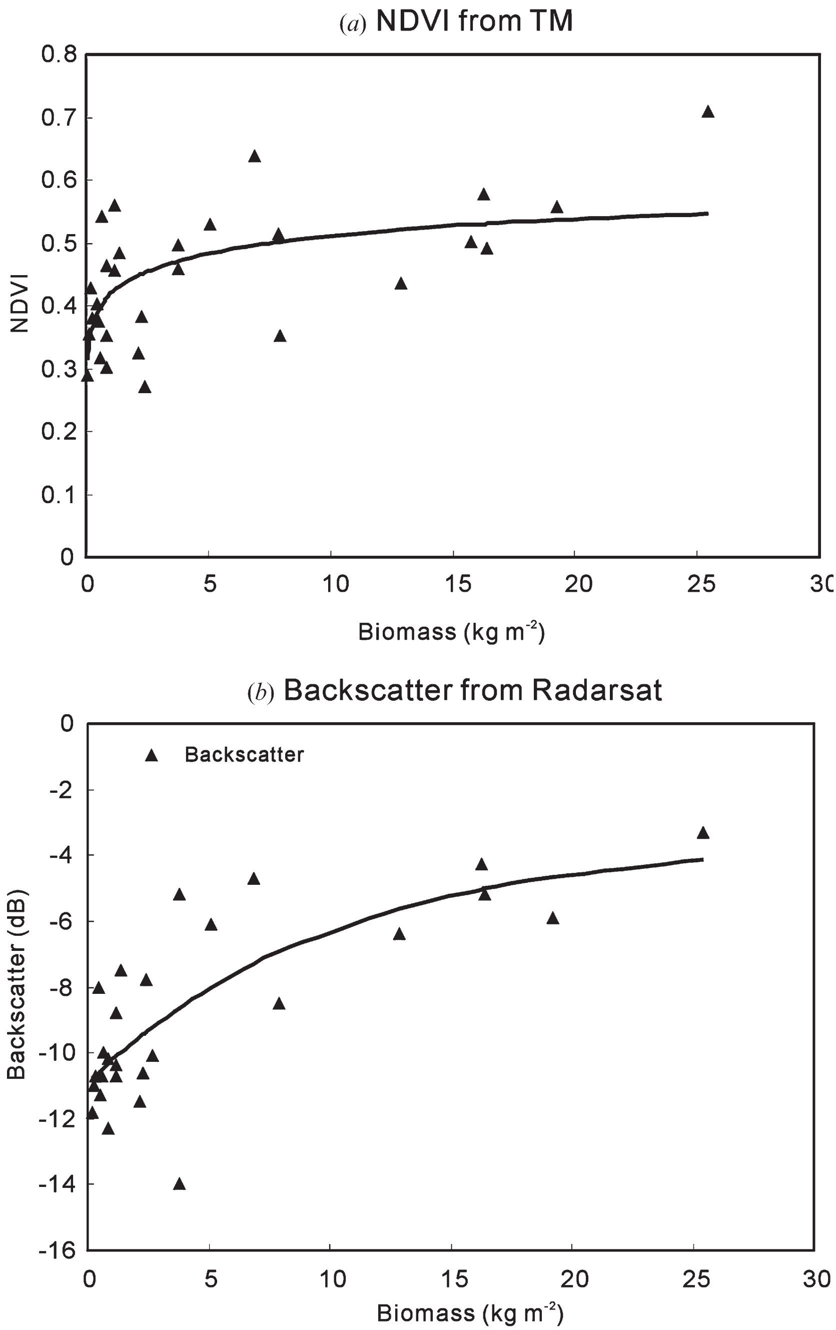

Figure 2. Scatter plot of remote sensing data and measured biomass.

by the evolutionary approach. A commercial genetic algorithm package, GeneHunter (Ward Systems Group, Inc., MD 21703, USA), was used to implement the evolutionary approach. In the GA programming, each of the individuals (chromosomes) of a population is a complete definition of a trial solution (e.g. the parameter values). The fitness function is defined by using the RMSE. The GA

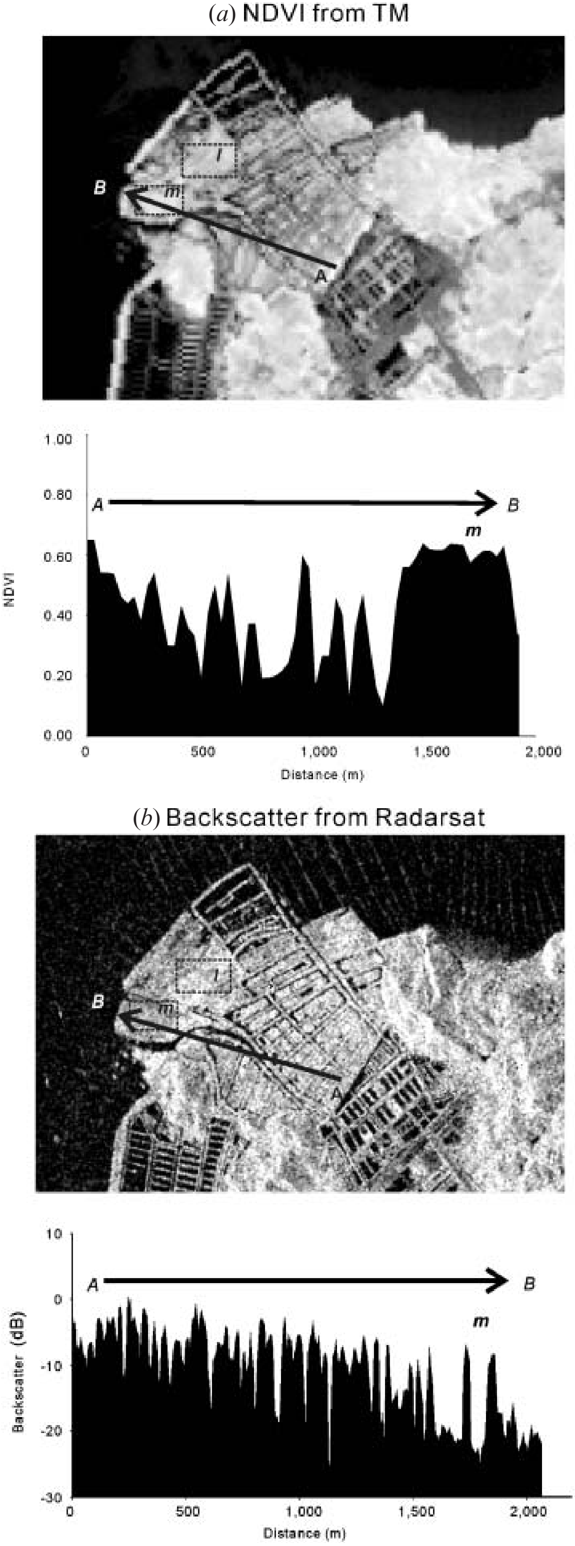

Figure 3. Profiles of NDVI and backscatter in the study area.

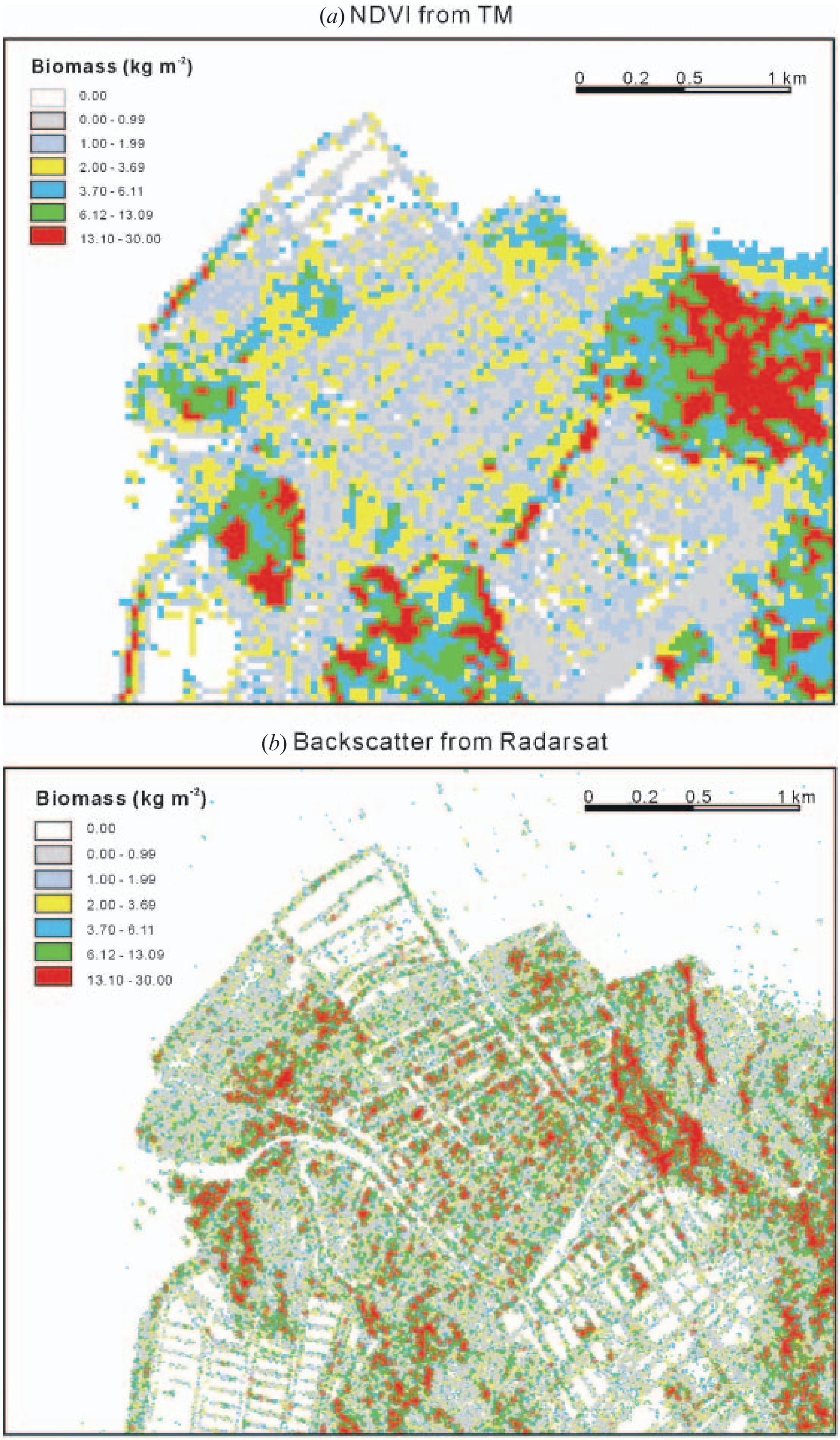

Figure 4. Biomass estimated from the NDVI and backscatter models.

program is able to find the parameter values so that the RMSE can be minimized. During the evolutionary approach, the improvement of RMSE (best fitness value) becomes stabilized after 50 generations (figure 2). The program stops and the optimal parameter values can then be determined. The final value of RMSE is $0.713\,\mathrm{kg\,m^{-2}}$.

It is important that the vegetation σ°_{v} and soil-vegetation interaction $T^2\sigma^{\circ}_{g}$ terms in equation (6) can be conveniently decomposed by the analytical model using the GA method (figure 5). This is very useful for ecological modelling because the decomposition can provide detailed information about vegetation and soil background at each location. The backscatter of the dense mangrove forest (γ_{veg}) is -4.567 and the backscatter of the ground without vegetation cover (γ_{gro}) is -14.061 in equation (7). The backscatter for the ground component is very low. The value is very close to that of water body. As the ground of mangrove wetlands is usually covered by water, this means that the analytical model can separate these two components of backscattering effectively. The use of genetic algorithms can conveniently retrieve the information about mangrove forests and background for the wetland system at each site. This type of information is important for ecological modelling. Regression models cannot be applied to the derivation of such information.

5. Conclusion

This study demonstrates that Radarsat data can provide useful information for wetland studies. It is able to produce more accurate biomass estimation for mangrove trees because of its high resolution and side-looking features. Many studies have shown that NDVI is highly correlated with vegetation parameters. However, this study indicates that NDVI may have significant confusions in estimating wetland biomass because NDVI can mainly obtain canopy information. According to our study, the NDVI significantly overestimates the biomass of some herbaceous species (e.g. *Spartina anglica*) and underestimates the biomass of some woody mangrove forests (e.g. *Sonneratia apetala*). The reason is that *S. anglica*

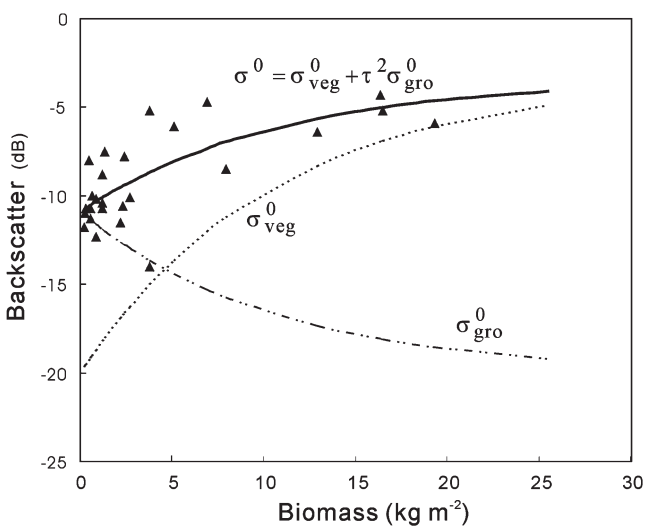

Figure 5. Decomposition of the analytical backscatter model into vegetation and soil components.

grows very densely in the region and its spectral reflectance is very high. The height information of mangrove trees, such as *S. apetala*, cannot be appropriately obtained by optical remote sensing. Therefore, *S. anglica* has much higher NDVI values than *S. apetala*.

The estimation models established from Radarsat data can improve the accuracy as much as 35.7% in terms of RMSE over the models from optical remote sensing. This is because the SAR data have higher resolution and side-looking features for obtaining more accurate trunk information for mangrove forests. The NDVI model may become saturated at a much lower amount of wetland biomass. Therefore, the use of the backscatter of SAR images can produce much more reasonable estimation results. The study also indicates that the integration of NDVI and backscatter can provide better estimation results than NDVI alone. However, it cannot produce better estimation results than the single backscatter model because of the errors from the NDVI itself.

Analytical backscatter models may be more plausible because they can provide much better modelling structures. However, the determination of the parameter values is difficult when nonlinear equations are used. Regression analysis is difficult to derive the parameter values for these complex equations. This study shows that the use of genetic algorithms can conveniently derive the optimal parameter values. The model derived from genetic algorithms also has much better performance than other models. It is more important that the two components, vegetation backscattering and soil backscattering, can be conveniently decomposed by this method. This can provide valuable information about the biophysical properties of mangrove wetlands.

Acknowledgment
This study is supported by funding from the Research Grants Council of Hong Kong (HKU 7301/04H), National Outstanding Youth Foundation of China (grant no. 40525002), the National Natural Science Foundation of China (NSFC) (project no. 40071060), and the Guangdong Natural Science Foundation (project no. 031647).

References

BAGHDADI, N., BERNIER, M., GAUTHIER, R. and NEESON, I., 2001, Evaluation of C-band SAR data for wetlands mapping. *International Journal of Remote Sensing*, **22**, pp. 71–88.

BERGEN, K.M. and DOBSON, M.C., 1999, Integration of remotely sensed radar imagery in modeling and mapping of forest biomass and net primary production. *Ecological Modeling*, **122**, pp. 257–274.

BONHAM, C.D., 1989, *Measurement for Terrestrial Vegetation* (New York: Wiley-Interscience).

BROWN, S., 1997, Estimating biomass and biomass change of tropical forests. *A Primer*, FAO Forestry Paper 134, FAO, Rome.

CHENA, C.M., HEPNERB, G.F. and FORSTER, R.R., 2003, Fusion of hyperspectral and radar data using the HIS transformation to enhance urban surface features. *Journal of Photogrammetry and Remote Sensing*, **58**, pp. 19–30.

CLEVERS, J.G.P.W., 1988, The derivation of a simplified reflectance model for the estimation of leaf area index. *Remote Sensing of Environment*, **35**, pp. 53–70.

DE JONG, S.M., PEBESMA, E.J. and LACAZE, B., 2003, Above-ground biomass assessment of Mediterranean forests using airborne imaging spectrometry: the DAIS Peyne experiment. *International Journal of Remote Sensing*, **24**, pp. 1505–1520.

DOBSON, M.C., ULABY, F.T., PIERCE, L.E., SHARIK, T.L., BERGEN, K.M., KELLNDORFER, J., et al., 1995, Estimation of forest biophysical characteristics in Northern Michigan with SIR-C/X-SAR. *IEEE Transactions on Geoscience and Remote Sensing*, **33**, pp. 877–895.

DOBSON, M.C., PIERCE, L.E. and ULABY, F.T., 1996, Knowledge-based land cover classification using ERS-1/JERS-1 SAR composites. *IEEE Transactions on Geoscience and Remote Sensing*, **34**, pp. 83–99.

FOODY, G.M., BOYD, D.S. and CURRAN, P.J., 1996, Relations between tropical forest biophysical properties and data acquired in AVHRR channels 1–5. *International Journal of Remote Sensing*, **17**, pp. 1341–1355.

FOODY, G.M., CUTLER, M.E., MCMORROW, J., PELZ, D., TANGKI, H., BOYD, D.S. and DOUGLAS, I., 2001, Mapping the biomass of Bornean tropical rain forest from remotely sensed data. *Global Ecology and Biogeography*, **10**, pp. 379–386.

FRANSSON, J.E.S. and ISRAELSSON, H., 1999, Estimation of stem volume in boreal forests using ERS-1 C- and JERS-1 L-band SAR data. *International Journal of Remote Sensing*, **20**, pp. 123–137.

FROST, V.S., STILES, J.A., SHANMUGAN, K.S. and HOLTZMAN, J.C., 1982, A model for radar images and its application to adaptive digital filtering of multiplicative noise. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **4**, pp. 157–166.

GOLDBERG, D.E., 1989, *Genetic Algorithms in Search, Optimisation and Machine Learning* (Reading, MA: Addison-Wesley).

GOWARD, S., TUCKER, C.J. and DYE, D., 1985, North American vegetation patterns observed with the NOAA-7 advanced very high resolution radiometer. *Vegetation*, **64**, pp. 3–14.

HANSEN, P.M. and SCHJOERRING, J.K., 2003, Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. *Remote Sensing of Environment*, **86**, pp. 542–553.

HOLLAND, J., 1992, *Adaptation in Natural and Artificial Systems: An introductory analysis with applications to biology, control, and artificial intelligence* (Cambridge, MA: MIT Press).

HUETE, A.R., 1988, A soil adjusted vegetation index (SAVI). *Remote Sensing of Environment*, **25**, pp. 295–309.

KURVONEN, L., PULLIAINEN, J. and HALLIKAINEN, M., 1999, Retrieval of biomass in boreal forests from multitemporal ERS-1 and JERS-1 SAR images. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 198–205.

LE TOAN, T., BEAUDOIN, A., RIOM, J. and GUYON, D., 1992, Relating forest biomass to SAR data. *IEEE Transactions on Geoscience and Remote Sensing*, **30**, pp. 403–411.

LE TOAN, T., RIBBES, F., WANG, L.F., FLOURY, N. and DING, K.H., 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. 41–55.

LI, X., 1994, A two-axis adjusted vegetation index (TWVI). *International Journal of Remote Sensing*, **15**, pp. 1447–1458.

MAGAGI, R., BERNIER, M. and UNG, C.H., 2002, Quantitative analysis of RADARSAT SAR data over a sparse forest canopy. *IEEE Transactions on Geoscience and Remote Sensing*, **40**, pp. 1301–1313.

MATHER, P.M., 1999, *Computer Processing of Remotely-sensed Images*, 2nd edn (Chichester: Wiley).

METTERNICHT, G.I. and ZINCK, J.A., 1998, Evaluating the information content of JERS-1 SAR and Landsat TM data for discrimination of soil erosion features. *Journal of Photogrammetry and Remote Sensing*, **53**, pp. 143–153.

MOREAU, S. and LE TOAN, T., 2003, Biomass quantification of Andean wetland forages using ERS satellite SAR data for optimizing livestock management. *Remote Sensing of Environment*, **84**, pp. 477–492.

MOUGIN, E., PROISY, C., MARTY, G., FROMARD, F., PUIG, H., BETOULLE, J.L. and RUDANT, J.P., 1999, Multifrequency and multipolarization radar backscattering from mangrove forests. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 94–102.

PIERCE, L.E., BERGEN, K.M., DOBSON, M.C. and ULABY, F.T., 1998, Multitemporal land-cover classification using SIR-C/X-SAR imagery. *Remote Sensing of Environment*, **64**, pp. 20–33.

PULLIAINEN, J., MIKKELÄ, P.J. and HALLIKAINEN, M.T., 1996, Seasonal dynamics of C-band backscatter of boreal forests with applications to biomass and soil moisture estimation. *IEEE Transactions on Geoscience and Remote Sensing*, **34**, pp. 758–770.

RANSON, K.J. and SUN, G., 2000, Effects of environmental conditions on boreal forest classification and biomass estimates with SAR. *IEEE Transactions on Geoscience and Remote Sensing*, **38**, pp. 1242–1252.

RIBBES, F. and LE TOAN, T., 1999, Rice field mapping and monitoring with RADARSAT data. *International Journal of Remote Sensing*, **20**, pp. 745–765.

RICHARDSON, A.J. and WIEGAND, C.L., 1977, Distinguishing vegetation from soil background information. *Photogrammetric Engineering and Remote Sensing*, **43**, pp. 1541–1552.

SADER, S.A., WAIDE, R.B., LAWRENCE, W.T. and JOYCE, A.T., 1989, Tropical forest biomass and successional age class relationships to a vegetation index derived from Landsat TM data. *Remote Sensing of Environment*, **28**, pp. 143–156.

TOWNSEND, P.A., 2002, Estimating forest structure in wetlands using multitemporal SAR. *Remote Sensing of Environment*, **79**, pp. 288–304.

WANG, S.G. and CHEN, X.G., 1998, The status of coastal wetlands and their protection in Guangdong province. *Environmental Sciences of Chongqing*, **20**, pp. 4–1 (in Chinese).

WANG, Y. and DONG, D., 1997, Retrieving forest stand parameters from SAR backscatter data using a neural network trained by a canopy backscatter model. *International Journal of Remote Sensing*, **18**, pp. 981–989.

WIGNERON, J., FERRAZZOLI, P., OLIOSO, A., BERTUZZI, P. and CHANZY, A., 1999, A simple approach to monitor crop biomass from C-band radar data. *Remote Sensing of Environment*, **69**, pp. 179–188.