

## Soil moisture estimation of drained peat area using TOPSAR data

MAZLAN HASHIM, PETER SIM HOCK SENG, WAN HAZLI WAN KADIR and <sup>2</sup>NGAP DOLLAH SALAM

<sup>1</sup>Department of Remote Sensing,  
Universiti Teknologi Malaysia  
81310 Skudai, Johor Bahru, Malaysia

<sup>2</sup>Soil Branch, Department of Agriculture,  
Kuching, Sarawak, Malaysia

**Abstract.** Three empirical and theoretical radar backscatter models were examined in this study to characterise radar backscatter of TOPSAR data over coastal lowland of Sadong Simunjan River Basin, Sarawak, Malaysia. The main objective of this paper is to analyse the relationship between radar backscatter of TOPSAR data to degree of wetness of drained peat-land. The analysis of these models were examined using varying terrain-and-sensor related parameters namely surface roughness, dielectric constant, incidence angle, polarization and frequency, respectively. The results of this study indicate good relationship between moisture content and radar backscatter (RMSE < 5.0) in empirical model. However, this relationship is found rather restricted in the theoretical models due to its sensitivity to very moist to wet nature of the study area.

### I. Introduction

Peatland can be defined as an area where peat accumulates over time (hundreds or thousands of years) and where their formation varies at depths ranging between few cm to 12 m. Peat is an organic matter formed from roots, decaying plant residue and dead plants. The peat decomposition is very much dependent on the moisture content and the decomposition period varies with the rate of organic oxidation and reduction processes.

Completely decomposed peat will form peat substrate and in its natural condition consists of organic-rich materials (parts of plants) and water which is very favourable for selected hardy-crops such as oil palm and pineapple. Peatland with its organic soil content is known for its importance to wetland ecology and therefore need to be preserved.

There have been significant research efforts in the past two decades to develop remote sensing techniques to observe soil characterization from radar backscatter. Advances in active microwave remote sensing have demonstrated the ability to estimate soil moisture from radar backscatter in the surface layer under a variety of topographic and land cover conditions.

Radar backscatter particularly Synthetic Aperture Radar (SAR) data are dependent on several natural surface parameters such as dielectric constant (Dubois *et al.* 1995) and surface roughness (Evans *et al.* 1992). The large difference in dielectric constant between dry soil (typical dielectric constants of 2-3) and water ( $\approx 80$ ), formed the basis for inferring soil moisture from radar data. In fact, several studies have demonstrated the relationship between the radar backscattering coefficient  $\sigma^0$  and the surface soil moisture content under varying terrain condition (Ulaby *et al.* 1982, Benallegue *et al.* 1995, Weimann *et al.* 1998 and Sano *et al.* 1998).

Conventionally, in-situ soil moisture measurement techniques provide point measurements that do not account for the spatial variability of soil moisture profiles (Jackson and Schmugge 1986). The measurements are generally expensive, often problematic and not available at large-scale (Li *et al.* 1997). Remote sensing of soil moisture may resolve these problems since it naturally provides global views of soil moisture data at high spatial and temporal resolutions that are impractical to achieve with in-situ methods.

From the hydrological point of view soil moisture is a very important parameter in the semi and arid zones for many applications (Engman 1991). This might be one of the reasons for the many studies on estimating soil moisture using SAR in these regions. However, such studies have not been undertaken in the humid tropical regions such as Malaysia at least during the last decade. The all-weather penetration capability in SAR system offers an advantage for applications in tropical regions like Malaysia (lies at parallel 0° -5° N along the Equator) which has an average of more than 75% cloud cover throughout the year (Malaysian Meteorological service 2000).

One of the aims of this study is to examine whether there is a relationship between radar backscatter with degree of wetness of drained peatland in Malaysia.

## 2. Radar backscattering models

Three backscattering models used in this study are: (a) model developed by Dubois *et al.* (1995) hereafter referred to as Dubois model, (b) Integrated Equation Model (IEM) Fung *et al.* (1992), and (c) Oh model developed by Oh *et al.* (1992) hereafter referred to as Oh model. Brief descriptions of these models are given below.

1) *Dubois Model*: An empirical model describing the co-polarized backscatter coefficients of bare surface as a function of surface roughness, dielectric constant, incidence angle and frequency. The dielectric constant is the parameter sensitive to volumetric soil moisture. The HH and VV polarized backscattering cross-section  $\sigma_{hh}^o$  (power) and  $\sigma_{vv}^o$  (power) were empirically found by Dubois *et al.* (1995) to follow these two relationships:

$$\sigma_{hh}^o = 10^{-2.75} \frac{\cos^{1.5}\theta}{\sin\theta^5} 10^{0.028\varepsilon \tan\theta} (ks\sin^{1.4}\theta)\lambda^{0.7} \quad (1)$$

$$\sigma_{vv}^o = 10^{-2.35} \frac{\cos^3\theta}{\sin\theta} 10^{0.046\varepsilon \tan\theta} (ks\sin^3\theta)^{1.1} \lambda^{0.7} \quad (2)$$

where,  $\theta$  is the incidence angle (radian),  $\varepsilon$  is the real part of the dielectric constant,  $s$  is the root mean square (RMS) height (in cm),  $k$  is the wave number ( $k = 2\pi/\lambda$ ) and  $\lambda$  is the wavelength (in cm). These two relations are valid for frequencies varying between 1.5 and 11 GHz for surfaces with roughness ranging from 0.3 to 3 cm RMS height and for incidence angle between 30° and 60°. We calculated the backscatter coefficient ( $\sigma^o$ ) in units of decibel (dB), and can be converted to power using:

$$\text{Power} = 10^{\text{dB}/10} \quad (3)$$

2) *IEM Model*: This is a theoretical model which describes the co-polarized backscatter coefficients of bare surface as a function of surface roughness, dielectric constant, incidence angle and frequency and this model is expressed by the following relationship (Fung *et al.* 1992):

$$\sigma_{pp}^o = \frac{k^2}{2} \exp(-2k_z^2 s^2) \sum_{n=1}^{\infty} s^{2n} \frac{|I_{pp}^n|^2}{n!} W^{(n)}(-2k_x, 0) \quad (4)$$

*Soil moisture estimation of drained peat area using TOPSAR data*

where,

$$I_{pp}^n = (2k_z)^n f_{pp} \exp(-s^2 k_z^2) + \frac{(k_z)^n}{2} F_{pp} \quad (5)$$

$$f_{hh} = -\frac{2R_{\perp}}{\cos \theta} \quad \text{and,} \quad f_{vv} = \frac{2R_{\parallel}}{\cos \theta}$$

$$F_{vv} = \frac{2 \sin^2 \theta}{\cos \theta} \left[ \begin{array}{l} \left( 1 - \frac{\varepsilon \cos^2 \theta}{\varepsilon - \sin^2 \theta} \right) (1 - R_{\parallel})^2 \\ + \left( 1 - \frac{1}{\varepsilon} \right) (1 + R_{\parallel})^2 \end{array} \right] \quad (6)$$

$$F_{hh} = \frac{2 \sin^2 \theta}{\cos \theta} \left[ 4R_{\perp} - \left( 1 - \frac{1}{\varepsilon} \right) (1 + R_{\perp})^2 \right] \quad (7)$$

$$R_{\parallel} = \frac{\varepsilon \cos \theta - \sqrt{\varepsilon - \sin^2 \theta}}{\varepsilon \cos \theta + \sqrt{\varepsilon - \sin^2 \theta}} \quad (8)$$

$$R_{\perp} = \frac{\cos \theta - \sqrt{\varepsilon - \sin^2 \theta}}{\cos \theta + \sqrt{\varepsilon - \sin^2 \theta}} \quad (9)$$

where,

pp = hh or vv polarization

$\theta$  = incidence angle

$k_z$  =  $k \cos \theta$

$k_x$  =  $k \sin \theta$

$s$  = surface roughness (RMS)

$\varepsilon$  = dielectric constants

$R_{\parallel}$  = Fresnel *Reflectivity* constant for vertical polarization.

$R_{\perp}$  = Fresnel *Reflectivity* constant for horizontal polarization

$W^{(n)}(k_x, k_y)$  = surface roughness due to power of correlation for  $\rho(\zeta, \xi)$  by Fourier transformation.

3) Oh Model : This is an empirical model, the radar backscatters are expressed in two components q and p as below.

$$q = \frac{\sigma_{hv}^o}{\sigma_{vv}^o} = 0.23 \Gamma_o^{1/2} [1 - \exp(-ks)] \quad (10)$$

$$p = \frac{\sigma_{hh}^o}{\sigma_{vv}^o} = \left[ 1 - \left( \frac{2\theta}{\pi} \right)^{1/3\Gamma_o} \cdot \exp(-ks) \right]^2 \quad (11)$$

where,

s is surface roughness,  $\epsilon$  is dielectric constant,

$\Gamma_o$  is Fresnel Reflectivity for surface at nadir point (see equations (10) and (11), and

$\theta$  is incidence angle (radians).

### **3. Materials and methods**

#### **3.1. Study area**

The study area is located at Sadong Simunjan River Basin, Kota Samarahan of Sarawak, Malaysia covering an area of 170<sup>2</sup> km (5 km x 34 km), comprising partially-drained peatland, intended for large- scale agricultural plantation (Figure 1). The original vegetation found here are scarce, stunted and dwindling trees due to high water table and soil acidity (Lim 1992). It is also situated in one of the largest contiguous peatland remain in Malaysia with an approximate area of 1.6 million hectares.

#### **3.2. SAR data**

The TOPSAR data (L-band) used in this study were acquired as part of the PACRIM I campaign, a collaborative work between Southeast Asia, Australia and New Zealand with Jet Propulsion Laboratory (JPL) /NASA of USA. The data have already been corrected for slant-to-ground range and geometrically corrected to local mapping datum – the Timbilai Datum of the Borneo Rectified Skew Orthomorphic Projection System. The unsystematic errors that have not been taken into account were corrected in this study by image-to-map registration technique. A brief technical specification of the data is given in Table 1.

#### **3.3. Ancillary information**

Remote sensing is only capable of measuring the amount of radiance within the instantaneous field of view. This radiance is a mixture of different signals, one of which may be related to soil moisture. Therefore, in-situ ground measurements are necessary for establishing some relationship between soil moisture and observed radiance.

The ancillary information used in the study include the topographic map of the corresponding area (scale 1:50,000) and in-situ measurements carried out during the flight mission. Field surveys were conducted to gather samples for deriving information on the surface roughness, soil particle size, soil bulk density and soil moisture. In addition, the depth of water table was also determined.

Figure 2 shows the location of sample points collected in the study area. Two mutual sets of samples were generated, each meant for model calibration and accuracy assessments. They are designated as red and yellow ticks respectively in Figure 2.

*Soil moisture estimation of drained peat area using TOPSAR data*

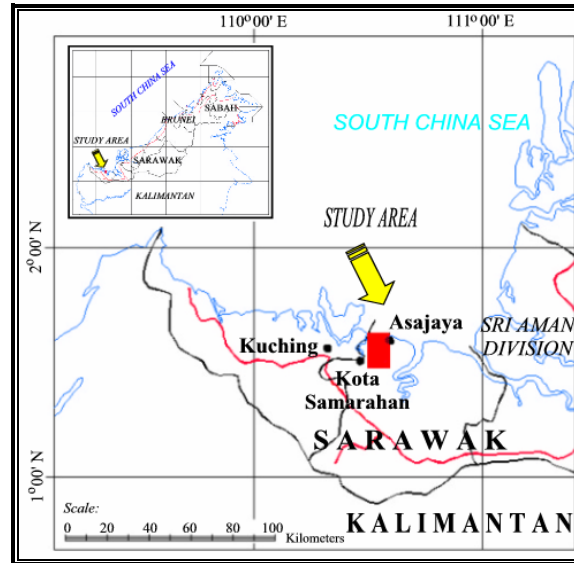


Figure 1. The study area.

Table 1. Specification of AIRSAR data.

Parameter	AIRSAR
Band	L (1.26 GHz, 23.0 cm)
Mode	TOPSAR
Altitude	8.382 km
Incidence angle	20° - 60°
Polarization	HH, VV and HV
Resolution	10 m x 10 m
Date of acquisition	25 Nov. 1996

### 3.3.1 Gravimetric observations

The oven-drying soil moisture technique is the standard for calibration of all other methods. The method involves obtaining a wet soil sample weight,  $W_w$  drying the sample at 100°C for 24 hours and then obtaining the dry sample weight  $W_d$ . Then, with a measurement of the bulk density,  $Y_d$  and the density of water,  $Y_w$  the volumetric water content can be found:

$$M_v = \frac{W_w Y_d}{W_d Y_w} 100\% \quad (12)$$

### 3.3.2 Soil roughness measurements

The height profiles of the soil surface were measured by a 1.5 m long row of 100 pins, spaced 1 cm for 1 meter and 100 pins spaced 0.5 cm for 0.5 m. The relative pin elevations were recorded photographically, after which they were digitized manually with AutoCAD software and analyzed to obtain surface profiles. From these measurements, three parameters can be calculated: standard deviation of surface height; correlation length and standard deviation of surface height slope (Tables 2 and 3).

### 3.3.3 Dielectric Constant

For the selected models examined, the critical input is the dielectric constant ( $\epsilon$ ). In this study, the approach by (Hallikainen *et al.* 1985) was adopted, where dielectric constant measurements for five different soil types at frequencies between 1.4 and 18 GHz were established. Based on these measurements, polynomial expressions can be derived relating the real and imaginary part of  $\epsilon$  to the volumetric moisture content,  $M_v$ , and the percentage of sand and clay. These polynomial expressions are of the following form:

$$\epsilon = (a_0 + a_1S + a_2C) + (b_0 + b_1S + b_2C)m_v + (c_0 + c_1S + c_2C)m_v^2 \quad (13)$$

where, S is the percentage (by weight) of sand, C is percentage of clay, and  $a_i$ ,  $b_i$ ,  $c_i$  are coefficients, which dependent on frequency.

## 4. Data processing

### 4.1 Speckle Reduction

Speckles found in SAR data due to random multiplicative noise can be recognised by the random pattern and the noise levels that increase with average grey level of specified window area in an image (Lee 1986). Minimisation of speckle effects in SAR data were carried out using adaptive radar filters (Lopes *et al.* 1990). In this study, several radar adaptive filters and convolution filters were used, namely Lee, Frost, Gamma, Kuan, Local-Sigma, Low-Pass, Laplacian, Gaussian and Median. The results in this study indicate that Gaussian  $7 \times 7$  filter is the best for this area, giving the best coefficient of variance test (Paudyal and Aschbacher 1993).

### 4.2 Extraction of Surface Roughness and Soil Moisture

The main processing carried out in this study was to extract surface roughness and soil moisture from radar backscatter of the TOPSAR data. In the first task, the surface roughness  $s$  or the RMS heights were computed using all the three backscatter models employing equations (1) and (2) for Dubois model and equations (10) and (11) for Oh model. In the case of IEM model which involves rigorous computations, a computer program developed by Fung *et al.* (1992) were used.

Apart from computed surface roughness ( $s$ ), the same parameter was computed directly using TOPSAR data after it was pre-processed and converted into dB image. This is then known as  $s$  computation directly from the image.

In the second processing task, the soil moisture estimation was performed using the regression analysis approach with main input derived from radar backscatter parameters obtained in the first task rather than using image directly.

## 5. Results, analysis and discussion

The derived surface roughness ( $s$ ) from the respective models were compared with  $M_v$  obtained from in-situ measurements by regression analysis and their respective relationship (based on  $r^2$ ) are summarized in Table 4.

With regard to the  $M_v$  versus backscattering coefficients, the best relationship was obtained with Dubois model with  $r^2 = 0.8$  and  $0.9$  in HH and VV polarizations, respectively. Figures 3 and 4 exhibit these relationships and the best-fit models are given by equations (13) and (14). The other models ie Oh and IEM however, do not show any significance when compared to original backscatter derived directly from the image. This is evident with relatively the same  $r^2$  shown by these models compared with the image.

*Soil moisture estimation of drained peat area using TOPSAR data*

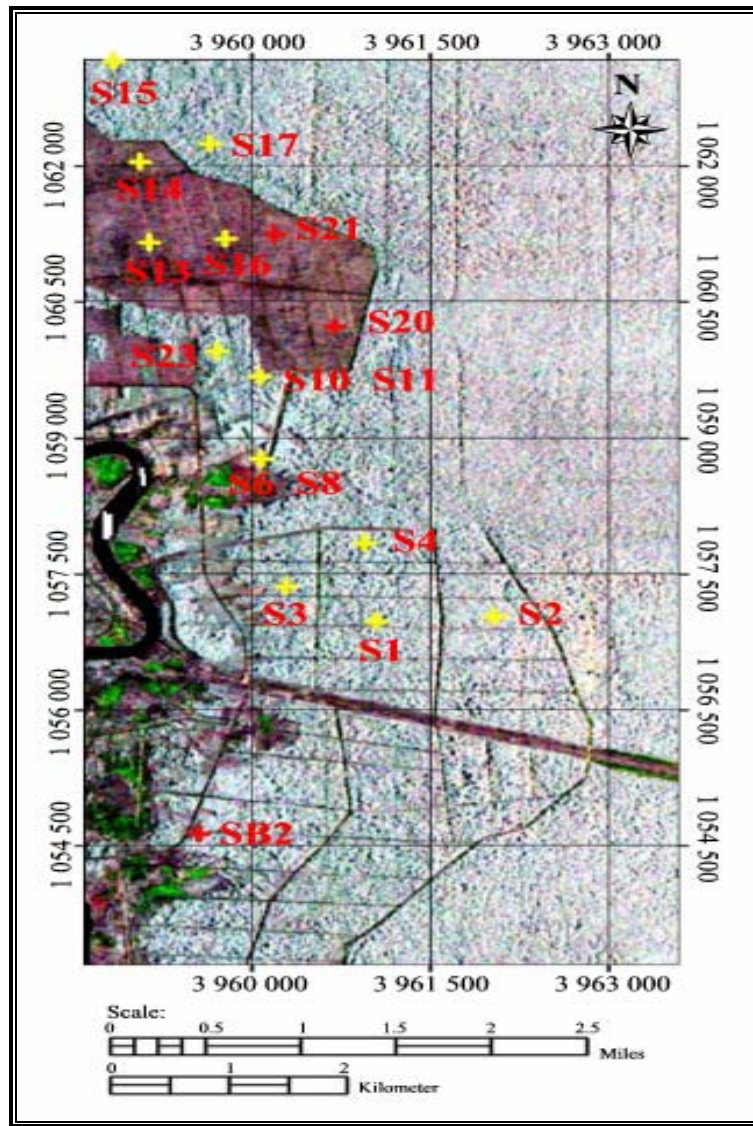


Figure 2. Location of sampling points collected in northern portion of the TOPSAR data strip.

Table 2. Volumetric soil moisture and soil roughness for the test points.

Sample Site	Surface Roughness (s, cm)	Correlation Length ( $\ell$ , cm)	Soil moisture ( $M_v$ , vol)
S8	0.333	31.589	0.53
S14	1.037	28.980	0.62
S16	1.580	31.946	0.63
S11	2.000	31.208	0.64
S13	0.445	28.496	0.68
S4	1.463	7.690	0.69
S15	1.746	23.754	0.70
S1	3.080	11.864	0.71
S10	1.511	33.166	0.72
S17	2.327	24.377	0.75
S3	0.935	2.696	0.76
S23	2.310	27.039	0.78
S2	2.994	13.845	0.87

Table 3. Volumetric soil moisture and soil roughness for the check points.

Sample Site	Surface Roughness (s, cm)	Correlation Length ( $\ell$ , cm)	Soil moisture ( $M_v$ , vol)
SB2	2.317	12.137	0.61
S6	0.706	29.875	0.63
S20	2.318	32.067	0.80
S21	2.283	27.105	0.70
S22	2.338	27.229	0.80

HH-Polarization:  $M_v = 0.610\sigma_{hh} + 45.99$

(14)

VV-Polarization:  $M_v = 0.765\sigma_{vv} - 49.93$

(15)

Table 4. Summary of the results of regression analysis.

Relationship analysed	Image Directly <sup>ψ</sup>		Dubois Model		IEM Model		Oh Model	
	$L_{hh}$	$L_{vv}$	$L_{hh}$	$L_{vv}$	$L_{hh}$	$L_{vv}$	$L_{hh}$	$L_{vv}$
Mv vs $\sigma^\circ$	0.5	0.3	0.7	0.8	0.5	0.5	0.5	0.3
	3	8	6	9	4	4	7	4
s vs $\sigma^\circ$	0.3	0.4	0.8	0.6	0.7	0.7	0.4	0.9
	7	6	2	9	5	0	9	7
$\theta$ vs $\sigma^\circ$	0.2	0.4	0.2	0.2	0.3	0.4	0.2	0.1
	1	2	1	8	9	5	2	4

Note: <sup>ψ</sup> Refer to TOPSAR data



## Soil moisture estimation of drained peat area using TOPSAR data

The best relationship of  $s$  and radar backscatter ( $\sigma^\circ$ ) was obtained with Dubois model ( $r^2 = 0.8$ ) followed by IEM model ( $r^2 = 0.7$ ) both in the HH polarizations. This shows that most other models have a weak relationship between incidence angle and backscatter. This is also exhibited by the  $r^2$  in the range of 0.1 to 0.4.

Of all the models analysed, Oh model was found to be the most inferior whilst, Dubois model exhibits the best correlation between  $s$  and  $M_v$ . IEM model fits has a moderate correlation. Next, the  $M_v$  and  $s$  derived from the respective models were also analysed for RMS. This was achieved by comparing the respective values with the corresponding in-situ measurements (mutual test set), and the results obtained are summarized in Table 5. Again, Dubois model shows the best result with the best  $M_v$  determined from  $L_{hh}$  whilst, the best  $s$  is obtained from  $L_{vv}$ . The RMSE obtained here are comparable to the results obtained by (Dubois *et al.* 1995), around 4.2 %.

Table 5. Summary of RMSE of models examined.

	Image Direct <sup>ψ</sup>		Dubois Model		IEM Model		Oh Model <sup>τ</sup>	
	L <sub>hh</sub>	L <sub>vv</sub>	L <sub>hh</sub>	L <sub>vv</sub>	L <sub>hh</sub>	L <sub>vv</sub>	L <sub>h</sub> <sub>h</sub>	L <sub>v</sub> <sub>v</sub>
M <sub>v</sub>	7.9	9.7	4.4	3.2	8.2	8.5	-	-
s	0.8	1.2	0.3	0.4	0.4	0.5	-	-
	0	7	7	8	3	0	-	-

Note: <sup>ψ</sup> Refer to TOPSAR data and <sup>τ</sup> most inferior to count

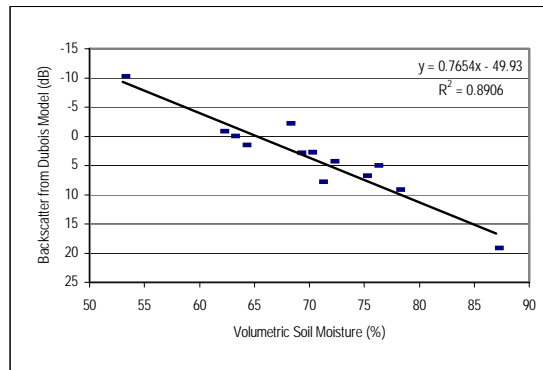
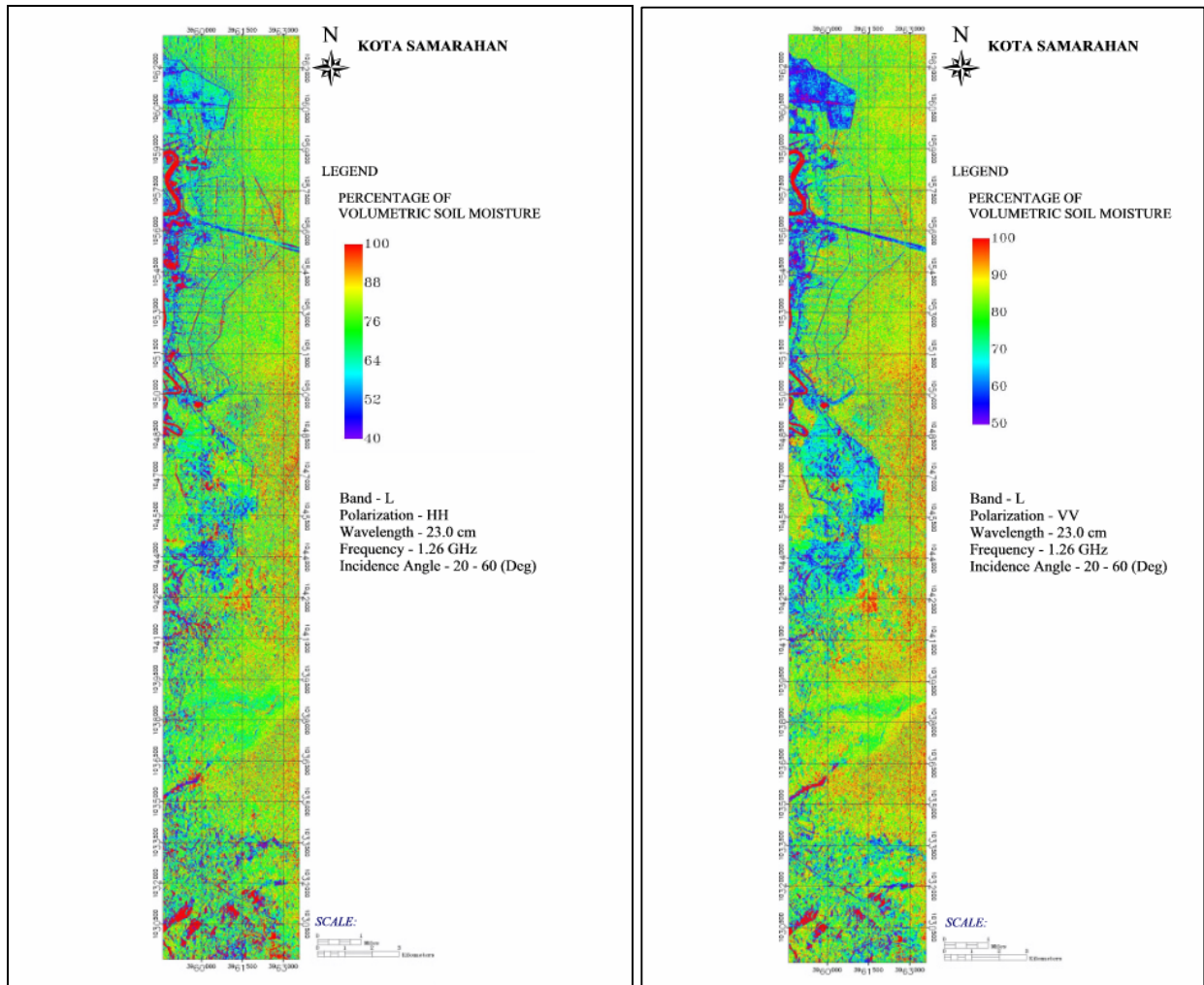


Figure 3. Estimated  $\sigma^\circ_{vv}$ , calculated from Dubois model

## 6. Conclusions

The results presented in this paper demonstrate that soil moisture can be estimated from SAR data, even in estimation of degree of wetness in the case of drained peatland in the humid tropics. This study also shows that there are restrictions in deriving the moisture content using the backscatter which is much dependent on the surface roughness by using the backscatter models. Of all the radar backscattering models (theoretical and empirical) examined, Dubois model is the best for TOPSAR data in this study. With TOPSAR data, soil moisture and surface roughness can best be estimated using  $L_{hh}$  and  $L_{vv}$  co-polarized SAR which is more sensitive to degree of wetness in the tropical regions.



(a)

(b)

Figure 4 (a). Mv map derived from TOPSAR L<sub>hh</sub> using Dubois model (1996) (extremely wet day) and (b) Mv map derived from TOPSAR L<sub>vv</sub> using Dubois model (1996).

## References

- BENALLEGUE, M., TACONET, O., VIDAL-MADJAR, D., and NORMAND, M., 1995, The use of radar backscattering signals for measuring soil moisture and surface roughness, *Remote Sensing of Environment*, **53**, 61-68.
- DUBOIS, P. C., ZYL, J. V. and ENGMAN, E. T., 1995, Measuring soil moisture with imaging radars, *IEEE Transactions on Geoscience and Remote Sensing*, GE-33(4), 915-926.
- ENGMAN, E. T., 1991, Applications of microwave remote sensing of Soil Moisture for Water Resources and Agriculture, *Remote Sensing of Environment*, **35**, 213-226, 1991.
- EVANS, D. L., FARR, T. G., VOGT, M., BRUEGGE, C., CONEL, J., ARVIDSON, R. E., PETROY, S., PLAUT, J. J., DALE-BANNISTER, M., GUINNESS, E., GREELEY, R., LANCASTER, N., GADDIS, L., GARVIN, J., DEERING, D., IRONS, J. R., KRUSE F., and HARDING, D. J., 1992, The Geologic Remote Sensing Field Experiment, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. **30**. pp.382-389.

*Soil moisture estimation of drained peat area using TOPSAR data*

- FUNG, A. K., LI, Z., and CHAN, K. S., 1992, Backscattering from a randomly rough dielectric surface, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-30(2). 356-369.
- HALLIKAINEN, M. T., ULABY, F. T., DOBSON, M. C., EL-RAYES, M. A., and WU, L. K., 1985, Microwave dielectric behaviour of wet soil – Part1: Empirical models and experimental observations, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-23(1). 25-34.
- JACKSON, T. J., and SCHMUGGE, T. J., 1986, Passive microwave remote sensing of soil moisture, In: *Advances in Hydrosience*, edited by V. T., Chow (London: Academic Press Inc. Ltd.), pp. 123-157.
- LEE, J. S., 1986, Speckle suppression and analysis for Synthetic Aperture Radar images, *Optical Engineering*, Vol. 25(5). 636-643.
- LI, K. Y., JONG, R. D., and BOISVERT, J. B., 1997, Estimating soil moisture profiles in the root zone using intermittent remotely sensed surface moisture contents, *International Symposium Geomatics In The Era of Radarsat, GER '97*. 2<sup>nd</sup> Edition. Ottawa, Canada. [CD-ROM]
- LIM, E. T., 1992, Peat soil of Sarawak, Chemistry Division Agriculture Research Centre, Department of Agriculture, Sarawak.
- LOPES, A., TOUZI, R., and NEZRY, E., 1990, Adaptive filters and scene heterogeneity, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-28(6). 992-1000.
- MALAYSIAN METEOROLOGICAL SERVICE, 2000, Climate of Malaysia, Malaysia Meteorological Service Report.
- OH, Y., SARABANDI, K., and ULABY, F. T., An empirical model and an inversion technique for radar scattering from bare soil surfaces, 1992, *IEEE Transactions on Geoscience and Remote Sensing*. Vol. GE-30(2). 370-381.
- PAUDYAL, D. R., and ASCHBACTER, J., 1993, Evaluation and performance test of selected SAR speckle filter, The International Symposium Operationalisation Org. Remote Sensing, ITC Enschede, Netherland.
- SANO, E. E., MORAN, M. S., HUETE, A. R., AND MIURA, T., 1998, C-and Multiangle Ku-band Synthetic Aperture Radar data for bare soil moisture estimation in agricultural areas, *Remote Sensing of Environment*, **64**, 77-90.
- ULABY, F. T., ASLAM, A., and DOBSON, M. C., 1982a, Effects of vegetation cover on the radar sensitivity to soil moisture, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-20(4). 476-481. 1982a.
- WEIMANN, A., SCHONERMARK, M. V., SCHUMANN, A., JORN, P. and GUNTHER R., Soil moisture estimation with ERS-1 SAR data n the East-German, 1998, *International Journal of Remote Sensing*, **19**(2). 237-243, 1998.