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Support Vector Regression for Retrieval of Soil Moisture Using Bistatic Scatterometer Data at X-Band

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Abstract**—**An approach was evaluated for the retrieval of soil moisture of bare soil surface using bistatic scatterometer data in the angular range of 20^0 to 70^0 at VV- and HH- polarization. The microwave data was acquired by specially designed X-band (10 GHz) bistatic scatterometer. The linear regression analysis was done between scattering coefficients and soil moisture content to select the suitable incidence angle for retrieval of soil moisture content. The 25^0 incidence angle was found more suitable. The support vector regression analysis was used to approximate the function described by the input output relationship between the scattering coefficient and corresponding measured values of the soil moisture content. The performance of support vector regression algorithm was evaluated by comparing the observed and the estimated soil moisture content by statistical performance indices %Bias, root mean squared error (RMSE) and Nash-Sutcliffe Efficiency (NSE). The values of %Bias, root mean squared error (RMSE) and Nash-Sutcliffe Efficiency (NSE) were found 2.9451, 1.0986 and 0.9214 respectively at HH-polarization. At VV- polarization, the values of %Bias, root mean squared error (RMSE) and Nash-Sutcliffe Efficiency (NSE) were found 3.6186, 0.9373 and 0.9428 respectively.

Keywords**—**Bistatic scatterometer, soil moisture, support vector regression, RMSE, %Bias, NSE.

I. Introduction

THE accurate estimation of soil moisture is one of the Essential Climate Variables (ECV) in the Global Climate Observing System (GCOS) for understanding the Earth's hydrological cycle and ecosystem services [1]. The global observations of the spatial and temporal changing in Earth's soil moisture is important to enhance climatic prediction skills, weather forecasting, assessment of water quantity and quality, agricultural irrigation management, crop productivity, mitigation of natural hazards such as flood prediction and drought monitoring, landslides, rainfall, runoff [2], [3].

The point based measurement of soil moisture is not a good technique to measure the global soil moisture continuously at a time. The point based measurement of soil moisture does not give exactly spatial distribution of soil moisture because soil moisture is highly spatial and temporal variable [4]-[6]. Recently, the active and passive microwave remote sensors are widely using than optical sensors for the estimation of soil moisture due to its weather independence capability. The microwave is very sensitive towards changing in dielectric constant, soil surface roughness and vegetation cover. At the microwave frequencies, the dielectric constant of water and dry soil is about ~80 and ~4 respectively. The dielectric constant of soil-water mixer varies about 4-40. The variation in dielectric constant of soil-water mixer due to changing in moisture content is detectable by microwave.

Several researchers have been conducted ground based [7]-[13] experiments using monostatic radar geometry for the modeling of backscattering coefficients to the estimation of soil surface moisture by active and passive microwave remote sensing. However, only limited number of bistatic experiments have been conducted [14], [15] for the modeling of bistatic scattering coefficients for the estimation of soil surface moisture. It will be great interest and worthy of pursuit to significantly increase the experience with the knowledge of bistatic microwave measurements. The support vector regression has been widely used for the modeling of real world problems [16], [17].

The foremost objectives of this paper is to analyze the angular microwave response of bare and rough soil surfaces and modeling of bistatic scattering coefficients for retrieval of soil moisture from rough and bare soil surfaces using bistatic scatterometer data at HH- and VV- polarization for X-band. For this purpose, the bistatic scatterometer measurements have been performed at incidence angle 20^0 to 70^0 steps of 5^0 at HH- and VV- polarization. The computational technique namely support vector regression (SVR) is used for the modeling of bistatic scattering coefficients. The performance of the model is evaluated by the statistical parameters like %Bias, root mean squared error (RMSE), Nash-Sutcliffe Efficiency (NSE) between experimentally observed and support vector regression model estimated soil moisture data.

II. Experimental Setup and Measurements

An outdoor test bed (4m × 4m) is specially prepared to carry out bistatic scatterometer measurements of bare soil surface at X-band beside the Department of Physics, Indian

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Institute Technology (B.H.U), Varanasi, India. Fig. 1 and Table I show the photograph and specifications of bistatic scatterometer system used respectively. The bistatic scatterometer system can be categorized into two sections. The first section is called transmitter and second section is called receiver. The transmitter sends the electromagnetic waves while the receiver receives the electromagnetic waves after interaction from scatter. In this study, the transmitter part consists of a pyramidal dual polarized X-band horn antenna, a waveguide to N-female coaxial adaptor and PSG high power signal generator (E8257D, 10MHz to 20 GHz). The receiver part consists of a pyramidal dual polarized X-band horn antenna, a waveguide to N-female coaxial adaptor, EPM- P series power meter (E4416A) and peak and average power sensor (E9327A, 50 MHz – 18 GHz). The gain of these antennas are approximately 20 dB, whereas, their half power beam width are found 18^0 and 20^0 for E and H plane respectively. The 90^0 E-H twisters are used to change the polarization HH- to VV- and vice versa.

The bistatic scatterometer system has facility to change the incidence angle from 0^0 to 90^0 but the observations are taken only for 20^0 to 70^0 steps of 5^0. The height and distance from the center of target can also vary to adjust the focus of both antennas at the center of the target. The antennas are placed in far field region from the center of the target to minimize the near field interactions. The system is calibrated by noting the signals returned from an aluminum plate placed on the top of the target. The calibration of system is done regularly during the experiment to ensure the integrity of the system.

The surface roughness is taken constant during entire observations to study the microwave response of soil moisture content only. Bare soil test bed is flooded with water for 20 to 24 hour to have large range of soil moisture constants before making observations. The gravimetric moisture content of soil is defined as ratio of weight of water present in soil to weight of dry soil. It is expressed as a percentage of soil moisture content. Five randomly soil samples are collected in aluminum soil container up to depths of 5 cm from the soil surface. These soil samples are dried in an oven at 100^0C for 24 hour. The samples are weighted before and after drying to compute the gravimetric moisture content. The average of gravimetric moisture content of all the five soil samples are taken to calculate the percentage of soil moisture content of the soil surface.

III. Support Vector Regression (SVR)

Support vector machine (SVMs) has been first introduced by Vapnik. SVMs are structured in two categories, SVMs for the classification and SVMs for the regression. The SVM for regression has been first anticipated by [18]. The support vector regression solves the estimation problem by mapping between an input and output data sets. In the SVR, minimizes that fuction $\frac{\|w\|^2}{2} + C\sum_{i=1}^{N} K\left(y_i - (\emptyset(x_i)^T w + b)\right)$ to solve the estimation problem by finding regressor w and b using least square approach to minimize the sum of the squared deviations of the data [19] where K is the kernel function, w and b are parameters, N is the number of training data, x_i and y_i are vectors used in the training process. The parameters w and b are derived by maximising their objective function[20].

In this study, *'ksvm'* package in R software based ε -SV regression approach is used [20]. The Gaussian Radial Basis kernel function is used. The deviation between the target value and the function describing the hypothesis found by the support vector machine is controlled by the ε parameter. The optimised values of cost function or SVR parameters are given in Table II.

Fig. 1 Photograph of bistatic scatterometer system at measurement site

TABLE I
SPECIFICATIONS OF BISTATIC SCATTEROMETER SYSTEM

Specification of instruments	
RF generator	E8257D, PSG High Power Signal Generator,10MHz to 20 GHz (Agilent Technologies)
Power meter	E4416A, EPM-P Series Power meter, 10MHz to 20 GHz (Agilent Technologies)
Power sensor	Peak and average power sensor (E9327A, 50 MHz – 18 GHz)
Frequency (GHz)	10 ± 0.05 (X - Band)
Beam Width E plane (^{0})	17.3118
Beam Width H plane (^{0})	19.5982
Antenna gain (dB)	20
Cross-polarization isolation(dB)	40
Polarization modes	HH- and VV-
Antenna type	Dual-polarized pyramidal horn
Calibration accuracy	1dB
Incidence angle (^{0})	20^0 (nadir) – 70^0

IV. Performance Indices

The performances indices like %Bias, Root Mean Squared Error (RMSE) and Nash-Sutcliffe Efficiency (NSE) are used for estimating the performance of support vector regression model for the estimation of soil moisture using bistatic scatterometer data. The percentage bias (% Bias) measures the average tendency of the estimated values to be larger or smaller than their observed values. The optimum value of %Bias is 0.0 and the smaller value of %Bias indicates that accurate model prediction.

$$\%Bias = 100 * \left[\frac{\sum(y_i - x_i)}{\sum x_i}\right] \qquad (1)$$

where x_i is the observed and y_i is the simulated variable.

Root-mean-square error (RMSE) is a frequently used to measure the differences between estimated values by a model or an estimator and the observed values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \qquad (2)$$

where n is the number of observations.

The Nash-Sutcliffe Efficiency (NSE) is based on the sum of absolute squared differences between the estimated and observed values normalized by the variance of the observed values during the study. The NSE was calculated using the given formula, the observed values during the study. The NSE was calculated using the given formula:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2} \qquad (3)$$

V. RESULT AND DISCUSSIONS

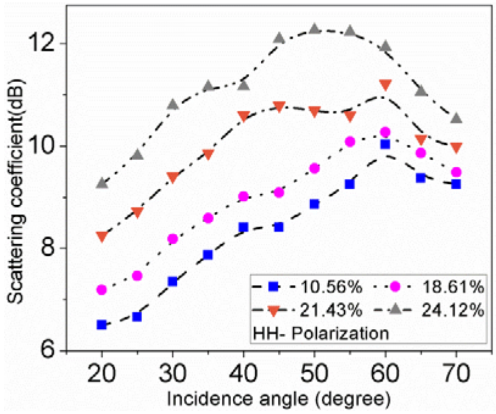
A. Angular Variation of Bistatic Scattering Coefficients

Figs. 2 (a) and (b) show the angular variation of bistatic scattering coefficients with soil moisture content of slightly rough and bare soil surface at HH- and VV- polarization. The bistatic scattering coefficients show the increasing trend as the soil moisture content increasing for all the incidence angles at HH- and VV-polarization. At HH- polarization, the angular variation of bistatic scattering coefficients shows the increasing trend as the angle of incidence increases up to a 60^0 incidence angle then decreases. In case of VV- polarization, the angular variation of scattering coefficients shows the decreasing trend as the incidence angle increases up to 60^0 incidence angle then increases. The bistatic scattering coefficients trend follows the Fresnel reflection theory. The separation between scattering coefficients are decreases at higher incidence angles. The soil surface seems smoother at higher incidence angle than lower incidence angle.

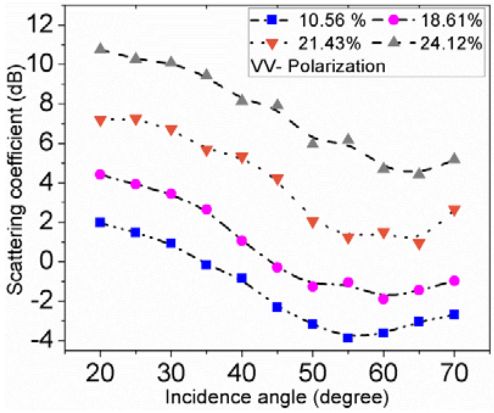
B. Estimation of Soil Moisture

The linear regression analysis has been made between bistatic scattering coefficients and soil moisture contents at all the incidence angle for selecting the suitable incidence angle to generate the calibration and validation data sets for support vector regression model. The higher value of coefficient of determination (R^2) is found at 25^0 incidence angle. The bistatic scattering coefficients at 25^0 incidence angle and soil moisture content are interpolated into 68 data sets for generating the large data set. The 51 data sets are selected for the calibration of support vector regression model and remaining is kept as validation data sets.

The R software based ‘ksvm’ package is used to generate the support vector regression model. The bistatic scattering coefficients are taken as the input variable while the corresponding soil moisture is taken as the output data sets at HH- and VV- polarization. The parameters are used during the calibration and validation of support vector regression model shown in Table II at HH- and VV- polarization. The Gaussian Radial Basis Kernel function is used for the calibration and validation of support vector regression model. Figs. 3 (a) & (b) show the scatter plot between support vector regression model retrieved soil moisture and experimentally observed soil moisture with 1:1 equi line at HH- and VV- polarization respectively for the validation of support vector regression model.

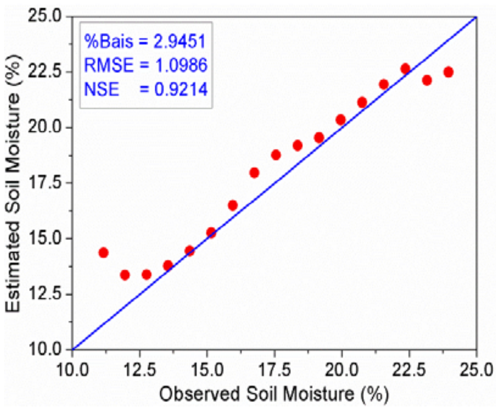


(a)

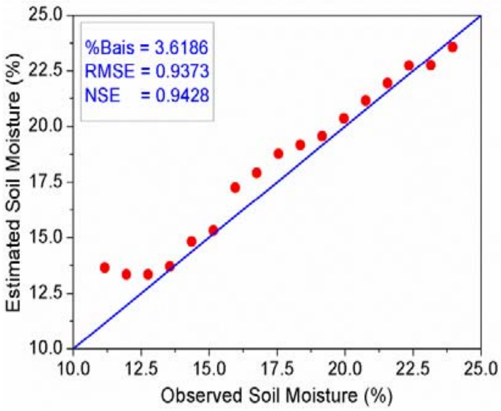


(b)

Fig. 2 Angular variation of scattering coefficients at various soil moisture contents (a) for HH- and (b) for VV- polarization at X-band



(a)



(b)

Fig. 3 Plot between observed and estimated values of soil moisture (a) at HH-polarization, (b) at VV-polarization

For the validation of support vector regression, the values of %Bias, RMSE and NSE is found 2.94, 1.09 and 0.92 respectively at HH- polarization while at VV- polarization, the values of %Bias, RMSE and NSE is found 3.61, 0.93 and 0.94 respectively. The values of experimentally observed soil moisture and support vector retrieved soil moisture are found very close at HH- and VV- polarization. It means, the support vector regression model may be suitable for the estimation of soil moisture from slightly rough surfaces using bistatic scatterometer data. The result is found more accurate at VV- polarization than HH- polarization.

TABLE II
PARAMETERS OF SVR USED DURING RETRIEVAL OF SOIL MOISTURE AT HH- AND VV-POLARIZATION

Support Vector Machine object of class "ksvm" SV type: eps-svr (regression) Gaussian Radial Basis kernel function						
epsilon	cost (C)	Hyperparameter (σ)	Number of Support Vectors	Objective Function Value	Training error	Pol.
0.1	5	65.20	40	-36.318	0.1436	HH
0.1	5	20.19	31	-35.654	0.1496	VV

VI. CONCLUSION

The bistatic scattering coefficients are found increasing trend as the soil moisture content increases. The angular variation of bistatic scattering coefficients are found increasing trend at HH- polarization while in case of VV- polarization, the bistatic scattering coefficients are found decreasing trend. The 25^0 incidence angle is found most suitable for estimation of soil moisture from slightly rough soil surface. The estimated values of soil moisture by support vector regression model are found close to the experimentally observed values of soil moisture at HH- and VV- polarization. The best result for the estimation of soil moisture by support vector regression using bistatic scatterometer data is found at 25^0 incidence angle for VV- polarization than HH- polarization.

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