Progress In Electromagnetics Research, PIER 77, 121–136, 2007

AN EFFICIENT MODELING WITH GA APPROACH TO RETRIEVE SOIL TEXTURE, MOISTURE AND ROUGHNESS FROM ERS-2 SAR DATA

D. Singh and A. Kathpalia

Department of Electronics and Computer Engineering
Indian Institute of Technology Roorkee
Roorkee-247667, (U.A), India

Abstract—One of the most important functions of radar remote sensing is to retrieve the soil moisture and surface parameters where surface parameters generally includes soil surface roughness and texture of soil (i.e., % of coarse sand, silt and clay). Variation of soil moisture and surface parameters changes the soil permittivity, and affects the observation of the radar wave scattering (σ^0). How to invert the moisture and surface parameters from radar data has been one of the most interesting problems to be resolved. Still, very few reported work is available to retrieve the soil textures with radar data. Therefore, in present paper an attempt has been made to retrieve the soil textures with soil moisture and surface roughness from Synthetic Aperture Radar (SAR) data. In this case number of variables are more and it is difficult to invert and retrieve the various parameters. To overcome this difficulty, an approach based on Genetic Algorithm (GA) with inclusion of empirical modeling has been proposed to retrieve the soil moisture, roughness and soil texture with ERS-2 (European Remote Sensing) SAR (Synthetic Aperture Radar) data of Haridwar region of India. The retrieved surface parameters and moisture content with proposed approach show quite good agreement with observed values of soil moisture and surface parameters. This study infers that modeling with GA has great potential to retrieve several variables simultaneously with good results.

1. INTRODUCTION

Knowledge of soil texture is important for the study of soil erosion and soil strength. According to United States Soil Department (USDA) soil can be classified according to the percentage of Coarse Sand, Silt and Clay. Coarse Sand, silt and clay are classified in terms of their size (i.e., coarse sand has particle size between 2–0.25 mm, fine sand has particle size 0.25–0.05 mm, silt has particle size 0.05–0.002 mm and clay has particle size less than 0.002 mm [1]. The relative percentage of these size categories, determines the soil's textural class (i.e., loamy, silty loamy etc.). Change in the soil textural class determines the soil erosion process because of soil erosion is very much dependence on the strength of the soil and soil texture is one of the factors to calculate the soil strength. Mathematically, soil erosion can be directly related to the soil texture by Universal Soil Loss Equation (USLE) [2]. On the other hand soil moisture content plays an important role in predicting, estimating and modeling major ecological processes such as evaporation, surface run-off and ground water replenishment. The soil water movement indirectly influences even the contamination of river and ground water with undesirable water pollutants. Thus, knowledge of soil water content is relevant to a wide spectrum of applications.

Soil moisture and surface parameters especially soil texture are often somewhat difficult to measure accurately in both time and space, especially large spatial scales, because it varies greatly from one location to another from one time to another. Single measurements have limited meaning. Hence, it is difficult and time consuming to conduct ground based measurements of soil moisture and surface parameter on a consistent and wide spread basis.

Remote sensing has the prospect of long term monitoring over large areas and offer such an opportunity both for science and operational application, ranging from precision farming to land and water resource management [1, 3, 11, 35]. Especially, radar remote sensing, which has the advantages over optical remote sensing is that to penetrate clouds, to be independent of the sun as a source of illumination, and to be able to penetrate deeper into vegetation and soil, and thus it is possible to have radar data from the target at user specified times and can acquire the information of vegetation and underlying soil. The application of active and passive microwave techniques from air borne and space borne platforms to infer soil moisture and roughness has been subject of study over the last three decades [1, 3–7, 33, 34] derive physically consistent soil moisture and roughness fields from radar data, the observations must be processed through adequate transformation model (retrieval algorithm) that is the inverse problem that must be solved. One challenge that lies ahead of the establishment of operational global soil moisture and surface parameter monitoring from space is the need to establish a framework to address the inverse problem at the macro scale. Several studies were conducted over the past few decades to study the relations between scattering coefficient with roughness and soil moisture [1, 12–15, 26–31]. The basis for the estimation of soil moisture with the use of microwave instruments is the sensitivity of the dielectric constant to water content for instance, the real part of the dielectric constant (ε) of a dry soil is about 2.5 where as it is about 80 for a free water surface. For a moist soil, the dielectric constant can range from 2.5 for very dry soil to 25 for very moist soil, as a function of both the composition of the soil and the microwave frequency [1]. The underlying principle that permits the use of remotely sensed radar scattering to estimate soil moisture is based on the increase in dielectric constant of soil as its moisture content increases. A change in dielectric constant causes a corresponding change in radar scattering coefficient. In addition to soil moisture, the soil texture, soil compaction and dense soil layer also affect its dielectric constant. All this makes the retrieval of soil moisture from radar reflectance/scattering error prone. It is difficult to identify whether moisture, roughness, soil texture or all, causes variation of scattering coefficient (σ^0). How to invert the moisture, soil texture and roughness from remote sensing data has been one of the most interesting problems to be resolved. A lot of theoretical and empirical models [1, 5, 10, 12, 14, 16, 17, 26, 30] were developed to retrieve the moisture content and roughness but limitations of these models are that they can invert a few parameters only depending upon the number of the datasets. With the need of the retrieval of more parameters with the less number of datasets, search of the optimization techniques started. Nowadays, commonly used optimization techniques are Artificial Neural Networks (ANN) [18] and Genetic Algorithms (GA) [19]. A mesh graph method to retrieve the surface roughness and soil moisture has been proposed by [20]. These methods have been proved applicability to retrieve moisture and roughness. The mesh graph method needs to know the soil structure to simulate and draw many mesh lines. The ANN method always takes large amount of data and long time to train the network.

In recent years, the genetic algorithm (GA), which is based on the principle of optimal selection in a natural evolutionary process, has been widely applied to the optimal problems in engineering, such as automatic design, pattern recognition, robotics control and synthesis of neural network, etc. The gene is the basic genetic building block. A set of genes is a chromosome, which represent a kind of organism. A certain number of chromosome combinations compose a population. Only organism adapted to environment can survive, mate, and develop so that optimal descendants are produced. The population undergoes genetic operation such as natural selection; cloning, mutation and mating to eventually arrive at the most optimal status [19, 21, 32].

A lot of work has been done for the retrieval of the moisture contents and the surface roughness. But still very few reported work are available for estimation of soil texture with radar approach. The soil texture is the field in which advancement and more research is required. For the retrieval of percentage of components of soil, we have to relate these components to the dielectric constant of the soil. Therefore, in this paper, an attempt has been made to propose a method by which surface roughness; soil moisture and especially soil texture can retrieve simultaneously with radar data. For this purpose, an optimization technique such as genetic algorithm with inclusion of semi-empirical model has been tested to retrieve the moisture, roughness and soil texture with European Remote Sensing (ERS) Synthetic Aperture Radar data of Haridwar region of India.

2. STUDY AREA AND DATA COLLECTION

Solani river catchment around Roorkee [(30.397°N, 78.713°E), (30.58°N, 77.692°E), (29.675°N, 77.478°E), (29.492°N, 78.488°E)] town has been taken as the study area in the newly formed state, Uttaranchal of India. The area is relatively flat. Two images of ERS-2 SAR (C-band; 5.3 GHz frequency, Vertical-Vertical; VV polarization) were taken first in July 2001 and second in March 2004. The full scene covered an area of 100.0 km × 102.5 km. The first image has been acquired at the start of the autumn season. At this time the area comprises of mixed vegetation that consists of five classes namely, barren land, grassland, sugarcane, cheery and rice. Second image is acquired at the beginning of the summer season. At this time area comprises of barren land, grassland, sugarcane, wheat classes. More than hundred ground soil samples over various land cover were collected. These samples were analyzed for soil moisture (gravimetric) and soil texture (i.e., % of coarse sand, silt, and clay) with standard techniques. Soil texture map published by the Survey of India has also been considered. Soil surface roughness was observed in the field with roughness profiler [1].

3. METHODOLOGY FOR RETRIEVAL OF MOISTURE AND SURFACE PARAMETERS

The flow chart of proposed method is shown in Fig. 1. The geo-referencing has been done on the raw image with more that 100 ground control points after that backscattering coefficient has been computed as the algorithm provided by the European Space Agency (ESA). The speckle noise has been removed by using Lee-Sigma filtering of ERDAS

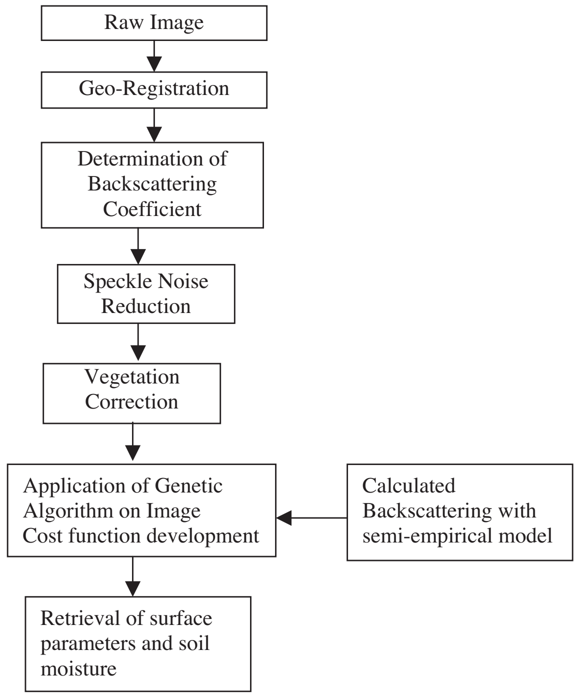

Figure 1. Retrieval flow chart for radar image.

8.6 after that vegetation correction has been applied, which is discussed in the following section.

3.1. Vegetation Correction

A semi empirical model term as the *Radiative Transfer Model* has been implemented for minimizing the effects of vegetation on backscatter coefficient from soil. The radar backscatter from a canopy can be expressed as a sum of contributions due to volume scattering in the canopy and surface scattering by underlying ground surfaces. Thus, the total backscatter coefficient recorded by the sensor over the vegetation is represented by the incoherent sum of the contributions of vegetation and soil. The Radiative Transfer Model, which is represented by water-cloud model [22] as following:

$$\sigma^0_{canopy} = \sigma^0_{veg} + \gamma^2\sigma^0_{soil} \tag{1}$$

$$\sigma^0_{veg} = AV_1\cos\theta(1-\gamma^2) \tag{2}$$

$$\gamma^2 = \exp(-2V_2B/\cos\theta) \tag{3}$$

γ^2 is the canopy two-way transmitting factor. V_1 and V_2 is the canopy descriptors, A and B are coefficient that depends on canopy type and obtained by the regression analysis [23]. We have considered canopy descriptors as LAI for V_1 and V_2 both. With the help of equation (1), σ^0_{soil} was calculated for different crop cover. This σ^0_{soil} has been used for further calculations.

3.2. Application of Genetic Algorithm (GA) for the Retrieval of Surface Parameters and Moisture Content

GA is used to retrieve moisture content, surface roughness, and percentage of coarse sand, silt and clay of the study area. The genetic algorithm is based on the concept of the optimal selection of the natural evolutionary process. GA is a globally iterative, numerical optimization method. Due to the rapid development of computer technology in recent decades, the GA has been widely applied in many engineering areas for optimized selection and simulation. In the GA, each parameter is encoded into a gene, which is simply a binary representation. A trial solution of a set of genes composes a chromosome. A number of different chromosomes form a population. The initial population is generated randomly. Then the population undergoes natural selection, i.e., the chromosomes are tested for their fitness to the cost function. A key element in GA is the selection of the fitness or cost function that accurately quantifies the desired solutions. All of the chromosomes with higher fitness survive as the parent for the next generation, while all of the chromosomes with lower fitness survive is discarded. Cloning of the surviving parents improves the population quality. Mating parent produce new offspring, which inherit their parents' fitness. During this operation, the size of the population remains constant. The binary encoded parent can mate with each other by swapping their binary bits with partner. To maintain population diversity and avoid the algorithm being trapped at a local minimum, a random operation of mutation or new blood is introduced into the population. To keep the parents fitness, the ratio of mutation and new blood should be too large; otherwise it would damage the good chromosomes, and even cause the algorithm to undertake random searching. The mutation operation to make a small change is very important for optimization when parameters are continuous. A good mutation operator will speed up the convergence [19, 21].

As a new population is obtained, the process above is iterated through natural selection, cloning, mating, mutation and introducing new blood, and the most suitable population is acquired eventually. In comparison with traditional optimization technique based on the gradient calculation, the GA is superior for global optimization, without complicated calculations and it is especially effective when the parameter number is very large. These parameters are encoded into genes. The most important thing is to develop the cost function for optimization or retrieval the parameters, because fitness, good or not the retrieval is measured by the cost function. Seeing the importance of cost function for retrieval of soil moisture and several surface parameters, we have considered Dubois et al. [5] model with small correction for this purpose. Because, this model is less complex in comparison to other models and also needs only one polarization data to relate the scattering coefficient with soil moisture and surface roughness, because it is the limitation of the ERS-2 data that we have only Vertical-Vertical polarization data. The other model like IEM [7, 14] is more complex and need more polarization data (i.e., Horizontal-Horizontal and cross polarization).

3.3. Modified Empirical Model Used for Developing the Cost Function for GA

The retrieval algorithm is quite dependent on cost function. For this purpose, we have selected Dubois et al. [5] model by proposing minor modification. Using the Scatterometer data and ground measurements, the empirically determined co-polarized backscatter coefficients, σ^0_{VV} for vertical polarization was expressed as a function of the system parameters, the local incidence angle and frequency, and soil parameters, such as dielectric constant and surface roughness by [5]. The resulting expressions are given by [5]

$$\sigma^0_{VV} = 10^{-2.35}\frac{\cos^3\theta}{\sin\theta}10^{0.046\varepsilon\tan\theta}(kh\sin^3\theta)^{1.1}\lambda^{0.07} \tag{4}$$

Where θ is the local incidence angle, ε is the real part of the dielectric constant, kh the normalized surface roughness and λ is the wavelength.

From equation (4), it can be interpreted that the scattering coefficient is a function of the incidence angle, permittivity and surface roughness and can be expressed as

$$\sigma^0 = f(\varepsilon, \theta, h_{rms}) \tag{5}$$

and the dielectric constant can be related to the moisture content, percentage of coarse sand, silt and clay as following [24]

$$\begin{aligned}\varepsilon \;=\; &(a_0 + a_1S + a_2Si + a_3C) + (b_0 + b_1S + b_2Si + b_3C) * m\\ &+(c_0 + c_1S + b_2Si + c_3C) * n\end{aligned} \tag{6}$$

where a, b and c are empirical coefficient [24] and m is soil moisture content. Putting equation (6) in eq. (4), it can be proposed that scattering coefficient can be expressed as

$$\sigma^0 = f(S, Si, C, \theta, h_{rms}) \tag{7}$$

Where S is the percentage coarse, Si is the percentage silt and C is the percentage Clay. So this modified scattering coefficient can be used to form a cost function, which is used in GA for the retrieval of various parameters.

3.4. Cost Function for GA

Five parameters, percentage of coarse sand, silt, clay, moisture and hrms are encoded into genes to be optimized. Co-vertically polarized σ^0_{VV} are used to retrieve the parameters. The empirical model eq. (7) is used as the training model and the observed data is used to form a cost function C as following,

$$C = \sum_N \left| \sigma^C_{VV}(\theta) - \sigma^O_{VV}(\theta) \right|^2 \tag{8}$$

Summation is over number of neighboring pixels N and σ^C_{VV} is the scattering coefficient calculated by the Dubois model eq. (7) and σ^O_{VV} is the observed data (after vegetation correction) from Radar image.

Genetic algorithm is applied on the observed data and with help of this cost function, surface parameters (percentage coarse, percentage silt, percentage clay and roughness) and moisture content were retrieved.

4. RESULTS AND DISCUSSION

The proposed algorithm has been applied on ERS-2 SAR data. Ground samples were collected from different types of land cover (i.e., barren land, grassland, sugarcane, cheery and rice) for July 2001 and barren land, grassland, sugarcane, wheat land covers for March 2004. The vegetation correction has been done for individual crops. The results, which are presented here, are the overall result of the whole study area. Approximately 60% of the data for which the ground samples were collected for July 2001 used for training and testing of the algorithm and rest 40% of the data has been used for validation of the developed algorithm for July 2001. The algorithm is also validated for the year 2004 ERS-2 data and results are shown in Figs. 2a–2h for July 2001 and March 2004. The R^2 and Standard Error (SE) for

Table 1. Values of R^2 and Standard Error (SE) for observed and retrieved results of various parameter.

Year	For Moisture		For hrms		For Coarse Sand		For Silt		For Clay	
	R^2	SE	R^2	SE	R^2	SE	R^2	SE	R^2	SE
July 2001	0.992	0.020	0.692	0.168	0.67	0.184	0.83	0.072	0.85	0.07
March 2004	0.998	0.009	0.878	0.062	0.859	0.073	0.86	0.069	0.82	0.08

observed and estimated value of each parameter is shown in Table 1. It is observed that retrieved results with proposed algorithm are quite satisfactory with observed values for each parameter, because R^2 is always approximately more than 0.70.

The slope of the studied area is less than 4 degree, therefore, approximately same retrieved results for soil texture has been obtained for year 2001 and 2004 (i.e., the range of coarse sand is 24–40%, range for silt is 42–62% and range of clay is 8–20% approximately). Due to the rainfall, which occurs three days before of observation in July 2001, moisture content is more in comparison to March 2004 (Fig. 2h). The dominance of moisture effect is clearly observed, if we compare

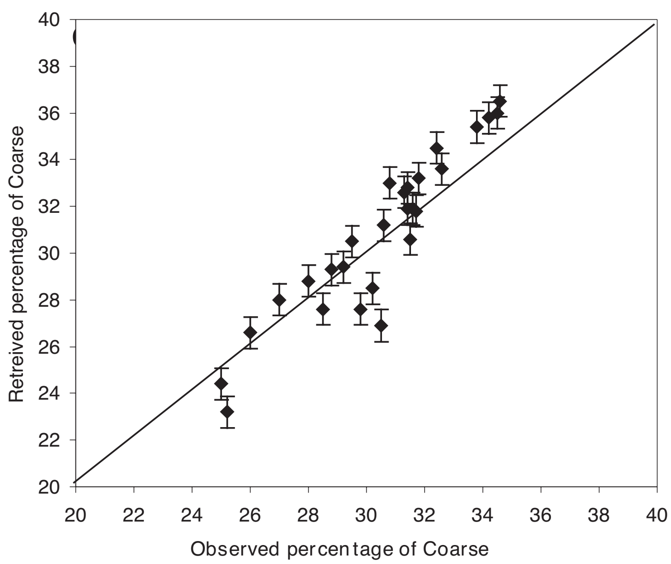

Figure 2a. Observed vs. retrieved percentage of coarse sand for March 2004.

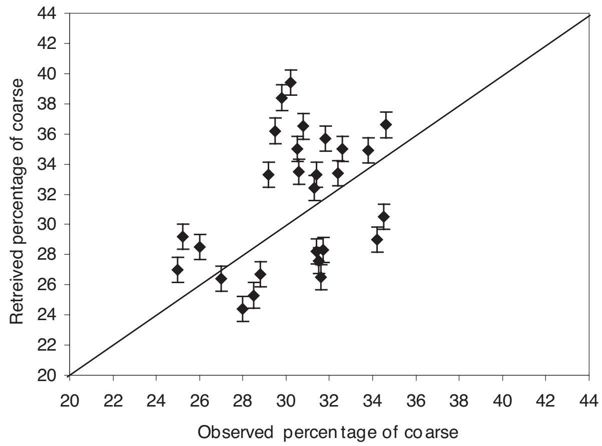

Figure 2b. Observed vs. retrieved percentage coarse sand for July 2001.

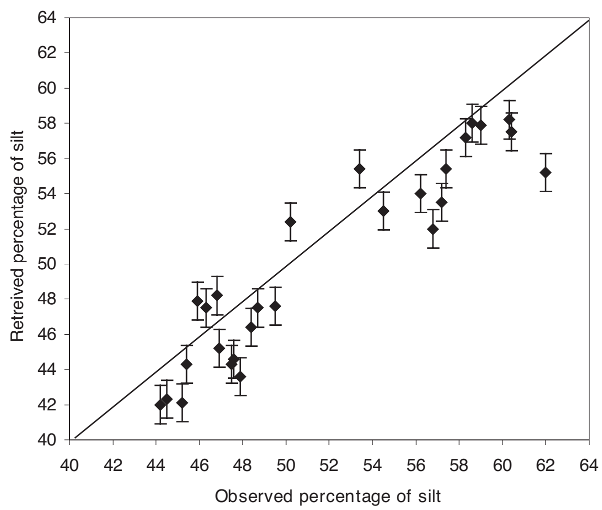

Figure 2c. Observed vs. retrieved percentage of silt for March 2004.

the results of 2001 and 2004. In 2001, due to high moisture the other parameter retrieval (i.e., surface roughness, soil texture) is quite affected. It can be infers from the table 1 with comparing the values of R^2 and SE for July 2001 and March 2004.

It represents that SAR data has great potential with the application of GA and electromagnetic modeling to retrieve various surface parameters and soil moisture together.

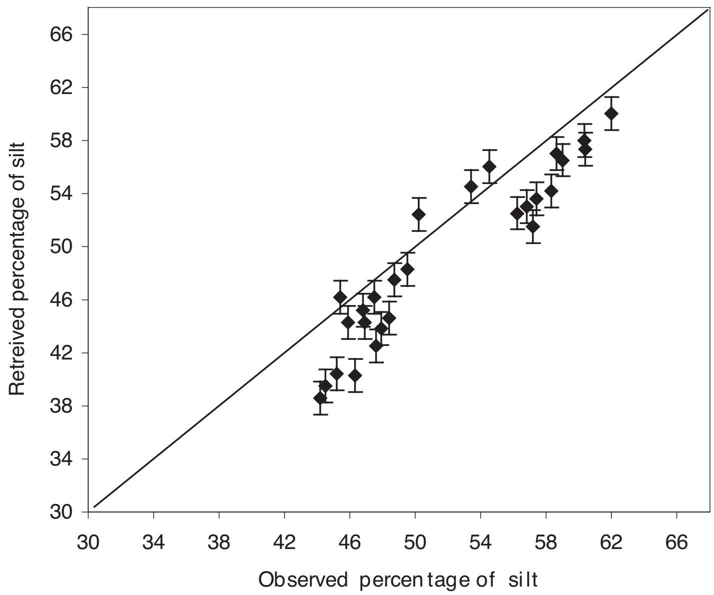

Figure 2d. Observed vs. retrieved percentage of silt for July 2001.

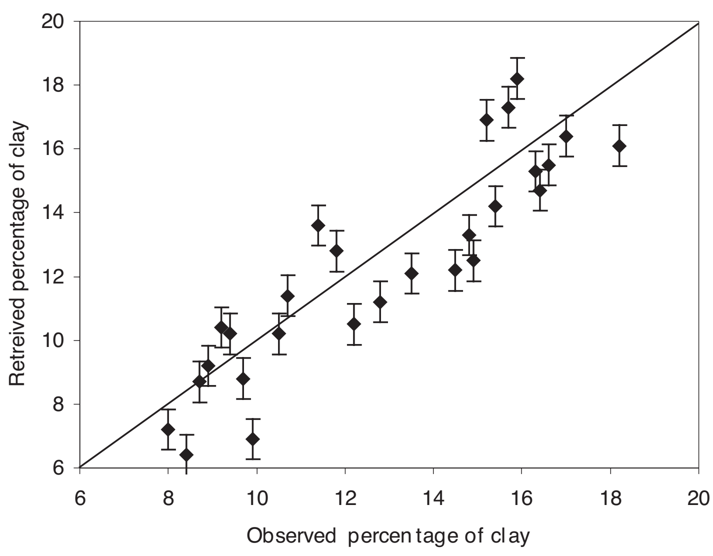

Figure 2e. Observed vs. retrieved percentage of clay for March 2004.

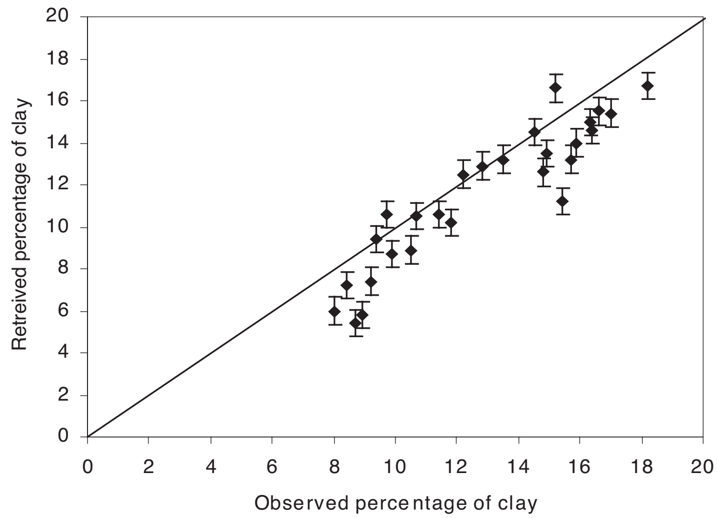

Figure 2f. Observed vs. retrieved percentage of clay for July 2001.

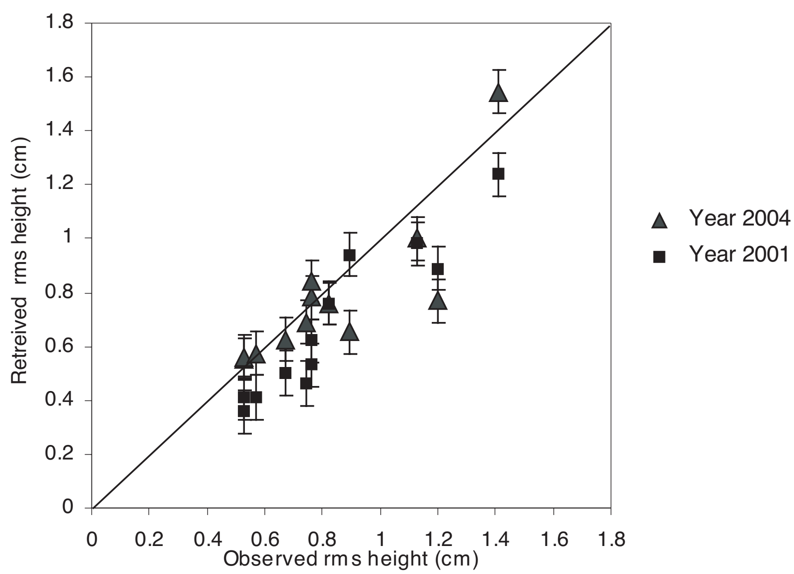

Figure 2g. Observed vs. retrieved rms height for July 2001 and March 2004.

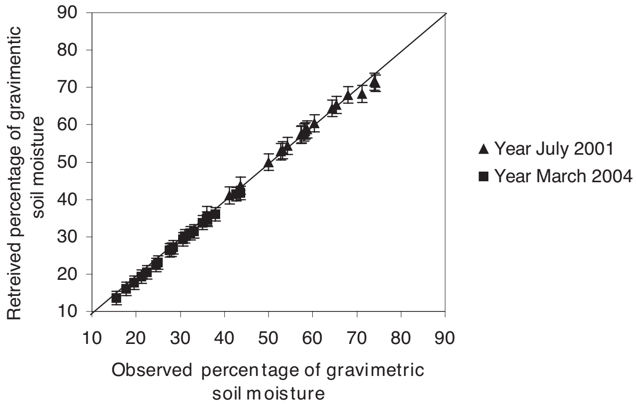

Figure 2h. Observed vs. retrieved percentage of soil moisture (gravimetric) for July 2001 and March 2004.

5. CONCLUSIONS

Two SAR images of different date and year were analyzed for retrieval of soil moisture, surface roughness, and especially soil textures. It is a problem of a lot of variable retrieval; therefore GA has been proposed to apply for retrieval. For developing the cost function in GA for various variables, a semi-empirical model based on Dubois et al, 1995 model is modified and proposed. The retrieved results are in good agreement with the observed results, but the high moisture effect can be seen while retrieving the surface roughness and soil texture. The retrieval of percentage of coarse sand, silt and clay is quite encouraging and this may be quite helpful information for landscape planning and management people. This type of analysis and results also show that GA may be a good tool to retrieve the physical parameters with satellite or airborne radar data.

ACKNOWLEDGMENT

Authors are thankful to Ministry of Human Resources and Development (MHRD) of India for their support to carry out this study.

REFERENCES

1. Ulaby, F. T., R. K. Moore, and A. K. Fung, *Microwave Remote Sensing—Active and Passive*, Addison Wesley, Vol. 2 and Vol. 3,

1982.
2. Formaggio, A. R., M. G. Gameiro, and J. C. N. Epiphanio, "Soil erosion modeling using "USLE": two approaches for evaluating the parameters "L" and "S"," *Symposium of Geoscience and Remote Sensing*, Vol. 2, 856–858, 1998.
3. Oh, Y. and C. V. Kay, "Conditions for precise measurement of soil surface roughness," *IEEE Trans. on Geo. Sci. and Rem. Sens.*, Vol. 36, No. 2, 691–695, 1998.
4. Wegmuller, U., C. Matzler, R. Huppi, and E. Schanda, "Active and passvie microwave signature catalog en bare soil (2–12 GHz)," *IEEE Trans. on Geosic. and Rem. Sens.*, Vol. 13, No. 3, 698–702, 1994.
5. Dubois, P. J., V. Zyl, and T. Engman, "Measuring soil moisture with imaging radar," *IEEE Trans. on Geo. and Rem. Sens.*, Vol. 33, No. 4, 915–926, 1995.
6. Bolten, J. D., V. Lakshmi, and E. G. Njoku, "Soil moisture retrieval using the passive/active l- and s-band radar/radiometer," *IEEE Trans. Geosc. Rem. Sens.*, Vol. 41, No. 12, 2792–280, 2003.
7. Fung, A. K., *Microwave Scattering and Emission Models and their Applications*, 573, Artech House, 1994.
8. Singh, D., Y. Yamaguchi, H. Yamada, and K. P. Singh, "Response of microwave on bare soil moisture and surface roughness by X-band scatterometer," *IEICE Trans. Commun. E*, Vol. 83-B, No. 9, 2038–2043, 2000.
9. Singh, D., K. P. Singh, I. Herlin, and S. K. Sharma, "Ground based Scatterometer measurements of periodic surface roughness and correlation length for remote sensing," *Advances in Space Research*, Vol. 32, No. 11, 2281–2286, 2003.
10. Singh, D., "A simplistic incidence angle approach to retrieve the soil moisture and surface roughness at X-band," *IEEE Trans. on Geo. and Rems.*, Vol. 43, No. 11, 2606–2611, 2005.
11. Singh, D., "Polarization discrimination ratio approach to retrieve bare soil moisture at X-band," *Proc. of IEEE, IGARSS*, 408–411, 2005.
12. Fung, A. K., U. Li, and K. S. Chen, "Backscattering from a randomly rough dielectric surface," *IEEE Trans. on Geo. and Rem. Sens.*, Vol. 30, 356–369, 1992.
13. Chanzy, B., B. Molineaux, and M. Zribi, "Influence of surface roughness frequency components on radar backscattering: Consequences on roughness sampling," *Proc. of IEEE, IGARSS*, 1414–1416, 2003.

14. Oh, Y., K. Sarabandi, and F. T. Ulaby, "An empirical model an inversion technique for radar scattering from bare soil surfaces," *IEEE Trans. on Geo. and Rem. Sens.*, Vol. 30, No. 2, 370–381, 1992.
15. Paloscia, S., G. Macelloni, E. Santi, and T. Koike, "A multifrequency algorithm for the retrieval of soil moisture on a large scale using microwave data from SMMR and SSM/I satellites," *IEEE Trans. on Geo. and Rem. Sens.*, Vol. 39, No. 8, 1655–1661, 2001.
16. Oho, Y., "Quantitative retrieval of soil moisture content and surface roughness from multipolarized radar observations of bare soil surfaces," *IEEE Trans. on Geo. and Rem. Sens.*, Vol. 42, No. 3, 596–601, 2004.
17. Satalino, G., F. Mattia, G. Pasquariello, and L. Dente, "Soil moisture retrieval from ASAR measurements over natural surfaces with a large roughness variability," *Proc. of IEEE, IGARSS*, 396–399, 2005.
18. Zhao, K. G., J. C. Shi, L. X. Zhang, L. M. Jiang, Z. J. Zhang, J. Qin, Y. J. Yao, and J. C. Hu, "Retrieval of bare soil surface parameters from simulated data using neural networks combined with IEM," *Proc. of IEEE, IGARSS*, 3881–3883, 2003.
19. Jin, Y. Q. and Y. Wang, "A novel genetic algorithm to retrieve surface roughness and wetness from angular back-scattering," *Proc. IGARSS IEEE*, 2000.
20. Huang, X. and Y. Q. Jin, "A simple method to estimate the soil wetness and surface roughness by using active/passive microwave data," *Remote Sensing of Environment*, Vol. 53, 212–214, 1995.
21. Haupt, R. L., "An introduction to genetic algorithms for electromagnetic," *Antenna and Propagation Magazine*, Vol. 37, No. 2, 7–15, 1995.
22. Attema, E. and F. T. Ulaby, "Vegetation model as water cloud," *Radio Sci.*, Vol. 13, 357–364, 1978.
23. Susan, M., A. Vidal, D. Troufleau, Y. Ionue, and T. A. Mitchell, "Ku- and C-band SAR for discriminating agricultural crop and soil conditions," *IEEE Trans Geosci Remote Sensing*, Vol. 36, No. 1, 265–272, 1998.
24. Hallikainen, M. T., F. T., Ulaby, M. C. Dobson, M. A. El-Rayes, and L.-K. Wu, "Microwave dielectric behavior of wet soil — part 1; Empirical models and experimental observations," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 23, No. 1, 25–34, 1985.

25. Engman, E. T. and N. Chauhan, "Status of microwave soil moisture measurements with remote sensing," *Rem. Sens. of Environ.*, Vol. 51, 189–198, 1995.
26. Ho, M., "Scattering of electromagnetic waves from vibrating perfect surface: simulation using relativistic boundary conditions," *J. of Electromagn. Waves and Appl.*, Vol. 20, No. 4, 425–433, 2006.
27. Storvold, R., E. Malnes, Y. Larsen, and K. A. Hogda, "SAR remote sensing of snow parameter in NORWEGIAN areas — current status and future perspective," *J. of Electromagn. Waves and Appl.*, Vol. 20, No. 13, 1751–1759, 2006.
28. Wang, C. J., B. Y. Wen,, Z. G. Ma, W. D. Yan, and X. J. Huang, "Measurement of river surface currents with UHF FMCW Radar systems," *J. of Electromagn. Waves and Appl.*, Vol. 21, No. 3, 375–386, 2007.
29. Arslan, A. N., J. Pulliainen, and M. Hallikainen, "Observations of L- and C-band backscatter and a semi-empirical model approach from forest-snow-ground system," *Progress In Electromagnetics Research*, PIER 56, 263–281, 2006.
30. Cocheril, Y. and R. Vauzelle, "A new ray-tracing based wave propagation model including rough surfaces scattering," *Progress In Electromagnetics Research*, PIER 75, 357–381, 2007.
31. Lim, K.-S., C.-P. Tan, J.-Y. Koay, V.-C. Koo, H.-T. Ewe, Y.-C. Lo, and A. Ali, "Multitemporal C-band radar measurement on rice fields," *Progress In Electromagnetics Research Symposium*, 36–40, Beijing, China, March 26–30, 2007.
32. Tian, Y. B., "Ultra conveniently finding multiple solutions of complex transcendental equations based on genetic algorithm," *J. of Electromagn. Waves and Appl.*, Vol. 20, No. 4, 475–488, 2006.
33. Fabbro, V., C. Bourlier, and P. F. Combes, "Forward propagation modeling above Gaussian rough surfaces by the parabolic wave equation: Introduction of the shadowing effect," *Progress In Electromagnetics Research*, PIER 58, 243–269, 2006.
34. Chen, K. S., A. K. Fung, J. C. Shi, and H. W. Lee, "Interaction of backscattering mechanismds from non Gaussian correlated random rough surfaces," *J. of Electromagn. Waves and Appl.*, Vol. 20, No. 1, 105–118, 2006.
35. Li, Z.-X., "Modelling the passive microwave remote sensing of wet snow," *Progress In Electromagnetics Research*, PIER 62, 143–164, 2006.