Soil Moisture Retrieval using Sliced Regression Inversion Technique

A Project Report

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THESIS CERTIFICATE

This is to certify that the thesis titled **Soil Moisture Retrieval using Sliced Regression Inversion Technique**, submitted by **Sakees Veerappa Chidambaram**, to the Indian Institute of Technology, Madras, for the award of the degree of **Master of Technology**, is a bona fide record of the research work done by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

KEYWORDS: Soil Moisture Retrieval ; Synthetic Aperture Radar .

Soil moisture is an important parameter of study for various applications across multiple disciplines.

In this thesis, a robust algorithm is proposed to retrieve for soil moisture, for the case of bare soil surface, from Synthetic Aperture Radar data. The proposed technique is aimed to be modular in format, in order to facilitate the choice of an appropriate module depending on the need. The proposed technique is compared against a similar widely accepted algorithm, and better retrieval results are observed from the proposed algorithm. In context of soil moisture retrieval from bare soil surface out of NISAR mission, studies are conducted and the results are reported. Finally, the proposed soil moisture retrieval technique is applied over real data collected out of RISAT-1. In all the cases, the soil moisture retrieval accuracy is around the acceptable level and performance of the proposed algorithm is satisfactory.

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ABBREVIATIONS

SAR	Synthetic Aperture Radar
dc	Datacube
LUT	Look-up table
IEM	Integral equation model
SR inversion	Sliced regression inversion
s.d.	Standard deviation
SM	Soil moisture
BS	Backscatter coefficient

NOTATION

λ_{op}	Radar operating wavelength, cm
θ_{inc}	Radar angle of incidence in degrees
M_v	Volumetric soil moisture content, cm^3/cm^3
h	r.m.s surface height, cm
l	Correlation length, cm
ϵ_r	Real part of complex dielectric constant
ϵ_{im}	Imaginary part of complex dielectric constant

CHAPTER 1

Introduction

Soil moisture (SM) is an important parameter in various environmental studies, such as, in building climate models in meteorology; crop yield forecasting, irrigation scheduling in agriculture; to predict early warnings of drought/ flooding in disaster management, to name a few. Hence it is important to measure SM on a large scale, cost-effective and routine basis.

SM, here, refers to water content in the surface soil corresponding to top few centimeters (5 cm in general) (Petropoulos *et al.*, 2015). SM is commonly expressed in gravimetric units, M_g (g/cm^3) or in volumetric units, M_v (cm^3/cm^3). The latter is usually preferred, and is used in this thesis throughout. This is mainly due to the fact that M_g is independent of the bulk density (b.d.) of soil, which can often result in inaccurate SM quantification. (M_v = b.d. $\times$ M_g)

Remote sensing from air/ space is a promising method to measure SM on a large scale and routine basis. In particular, microwave remote sensing offers various advantages over optical/ IR remote sensing; such as, the former offers all-weather and round-the-clock monitoring capability and is less affected by the presence of vegetation (longer the wavelength implies higher the penetration depth). Remote sensing by a typical side-looking radar system is depicted in fig 1.1 (credits: (van Zyl, 2011)).

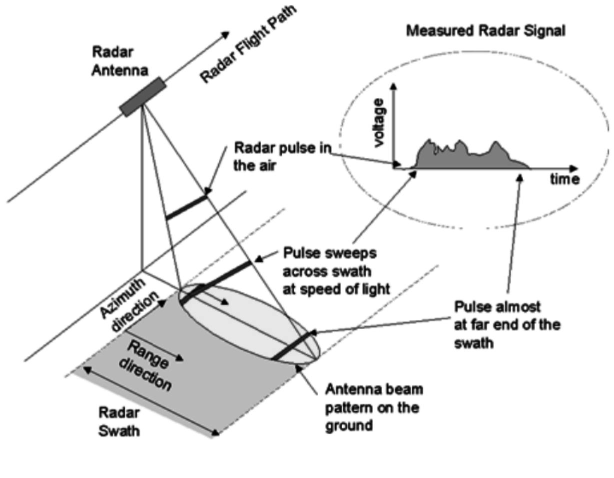


Figure 1.1: Remote sensing using side-looking airborne radar

Microwave remote sensing instruments can be broadly classified into active and passive (known as radars and radiometers, respectively). In addition to a receiver that a radiometer has, radar has a transmitter as well, that is, the later has its own signal source. Usually, active microwave sensors have high spatial resolution, whereas passive microwave sensors have high temporal resolution. However, the latter has its own drawbacks such as coarse spatial resolution (≈ 25-50 km) and radio frequency interference influence on brightness temperature at low frequencies (Petropoulos *et al.*, 2015) . Whereas active microwave sensors can be custom-made to image various sections of earth surface cover, ranging from top of canopy cover to several cm into soil surface through canopy cover. As mentioned earlier, longer the operation wavelength, higher will be the penetration depth and deeper the imaging section (as shown in fig 1.2). Microwave sensors operating at L-band (18 cm to 30 cm) are commonly and increasingly employed in SM monitoring as part of various global missions.

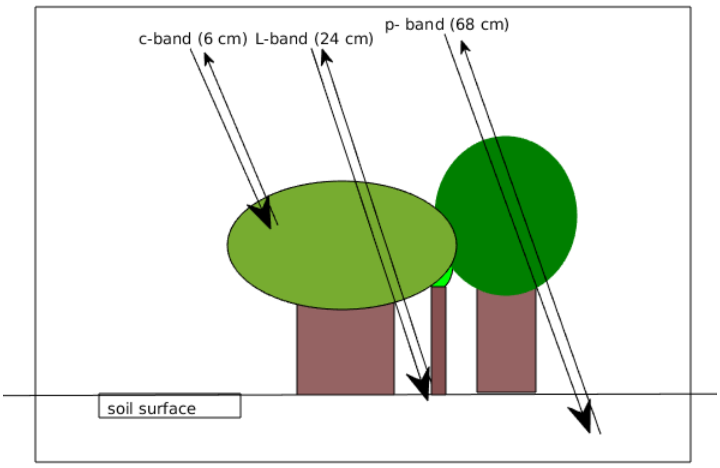


Figure 1.2: Illustration on selective scanning of earth surface

Active microwave radar sensors are further classified into imaging and non-imaging sensors; synthetic aperture radar belonging to the former class and the later class being further sub-classified to scatterometers and altimeters. Synthetic-aperture radar (SAR) is one of the widely used active microwave sensor for remote sensing purposes. SAR utilizes the flight path of the platform to electronically simulate an extremely large antenna/ aperture, to generate high resolution images. Spatial resolution of SAR is determined by the beam width from the transmitter, and hence the antenna size (Longer the antenna, narrower the beam width, higher the resolution of the image captured). Theoretical spatial resolution limit of SAR in the azimuth direction (along the flight path direction) equals one-half the length of actual antenna. This limit is independent on the flight altitude of SAR.

1.1 Problem statement

The core purpose of this thesis is to develop a robust retrieval algorithm for the case of base soil surface, provided the information from synthetic aperture radar that flew over that location (as illustrated in fig 1.3).

Backscatter coefficient (BS), which is a way to quantify the ratio of power between the emitted and received electromagnetic radiation by SAR, is dependent on the complex dielectric constant ($\epsilon_{surface}$) of the bare soil surface. SM is directly related to the complex dielectric constant owing to the high dielectric constant contrast between dry soil ($\approx$ 2-3) (Dubois *et al.*, 1995) and water ($\approx$ 80) in the microwave frequencies. This way, one can retrieve for SM once the information on BS is known. But the backscatter is also dependent on statistical nature of the surface in consideration, and also on a lower level, on various other factors; which makes the accurate estimation of SM a difficult task. Nevertheless, various techniques have been developed in the past, fairly succeeding in SM retrieval, but many times with a price to pay.

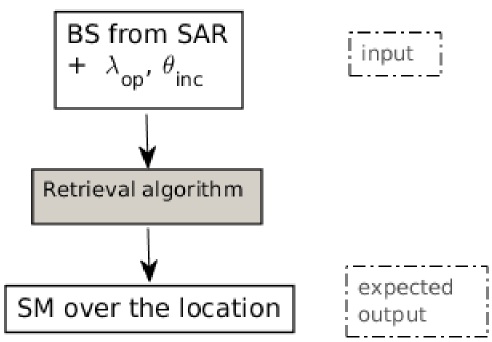


Figure 1.3: Problem Statement

Due to the importance and requirement of global SM mapping on a regular basis, various space missions by different organisations have been launched in the past (such as the Soil Moisture Active Passive mission, or SMAP (2015)) primarily for this purpose and several missions are yet to be launched in the near-future (such as the NISAR mission) owing to better resolved and more accurate SM mapping. This demands for a robust SM retrieval algorithm for the same, which at present is either computationally intensive or less accurate. This forms to be the core motivation for the study conducted through this thesis.

1.2 Literature review

Over the past few decades, several studies have proposed various algorithms/ methods/ models for surface SM retrieval from the SAR backscatter data. These can be broadly classified into three groups namely, *physically-based/ theoretical* models, *semi-empirical* models, and *empirical* models (Petropoulos *et al.*, 2015) .

Empirical models are based on specific datasets and implementation conditions (such as the sensor parameters). They do suffer from severe drawbacks such as site-specific applicability, lack of physical basis for the model and on.

Semi-empirical models are built based on experimental/ simulated datasets, but guided by trends based on theoretical models. In this way, they serve to be a simplistic model compared to theoretical models and site independent as opposed to empirical models. Some of the widely used semi-empirical models include Oh *et al.* (1992), (Dubois *et al.*, 1995), Shi *et al.* (1997). Numerous studies have used one of the above methods and reported to obtain satisfactory results.

Physically-based models have a strong physical basis often resulting in more accurate SM retrieval; but have the downsides of being a complex and challenging model to work with. Several methods have been proposed to invert for physically-based backscatter model, such as IEM (developed by Fung *et al.* (1992)) or its improved version- Improved IEM (Fung *et al.*, 2002), using optimization or regression techniques which include, Look-Up Table (LUT) approach, neural networks or by least-squares method. Yet another challenge for the same lies in calibration of the forward model employed with respect to the BS data from SAR, that may result in retrieval inaccuracies.

1.3 Technical background

Radar backscatter coefficient (σ^0) from a random rough surface primarily depends on the surface geometrical properties, quantified by

a). surface roughness (h), which is the r.m.s. surface height,

b). correlation length (l), which quantifies the typical length scale over which the roughness deviation stop being similar,
and on the surface electrical properties, quantified by

c). complex dielectric constant (ϵ) of soil surface.

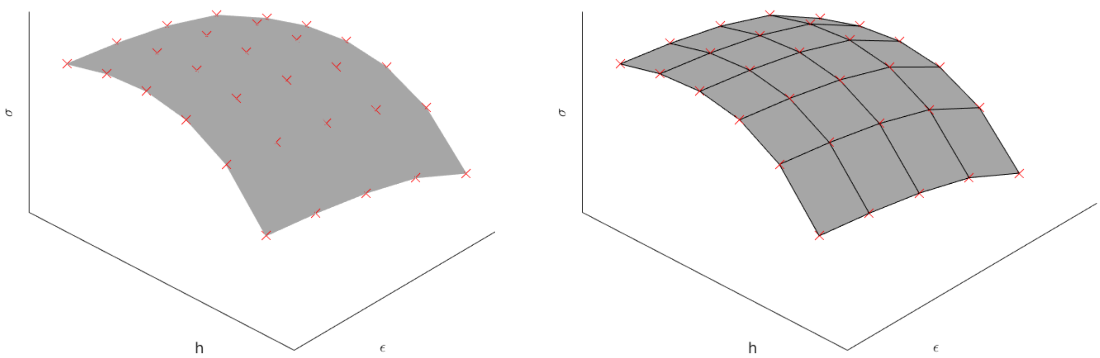
Since most of the earth surface is non-magnetic in nature, backscatter can be considered to be independent of surface magnetic properties. Backscatter can be modelled as a function of the above quantities, along with the information on radar parameters such as operating wavelength and look angle of the radar (which is equal to the signal incidence angle, θ_{inc}) on which BS heavily depends on. This refers to a Forward model, inverting of which, for ϵ remains the core challenge of SM retrieval. Once ϵ value is retrieved over a soil surface, corresponding M_v value can be obtained by inverting for any of the microwave dielectric models available in literature.
Forward models are employed to synthetically generate σ^0 values for all possible combinations of physically possible discrete surface parameter values (h, l, ϵ). Such a construct of dataset is generally referred to a 'datacube'(because it seems like a cube of data). SAR sensor operation can be classified into more than one operation configurations, depending on the nature of the signal polarization the sensor emits or records. Depending on the sensor on-board SAR, the collected data can be co-polarized backscatter data (either σ_{hh}, σ_{vv} or both) or cross-polarized backscatter data (σ_{hv} / σ_{vh}, both being the same in case of a mono-static radar). Notation-wise, in case of σ_{hv}, h refers to transmitted signal polarization and v refers to received signal polarization, and similar notation will be used through the thesis.

CHAPTER 2

Proposed Technique

σ being a non-linear function of h, l and ϵ, makes inversion for ϵ from the non-linear function involving several parameters, both a challenging and computationally intensive task. In this section, a physically-based inversion technique, which we call, Sliced Regression Inversion, is proposed for ϵ (and further, SM) retrieval from information on σ.

In this technique, σ which is a non-linear function of the parameters (h, l and ϵ), is expressed as a collection of independent functions of the parameters; such that in each of the *sub-functions*, σ can be approximated as a linear function of h, l and ϵ, for the defined range of the parameter values (as illustrated in).



(a) (b)

Figure 2.1: a non-linear function in 2.1a represented as a collection of independent linear functions in 2.1b

The proposed technique aims to be modular in format, such that there exists feasibility of replacing any of the modules with an alternative method depending on the retrieval scenario.

The proposed algorithm broadly consists of 2 parts; a). to solve for forward problem (to populate the datacube) & b). to solve for inverse problem, to retrieve soil moisture by inverting datacube from (a). Steps involved in the proposed technique are detailed as follows-

input : backscatter data from SAR (σ_{hh} / σ_{vv} / σ_{hv}) + information on radar parameters : (λ_{op} & θ_{inc}) + (other information, if any)

1) *Preprocessing*:

step 1a) Choose an appropriate Forward model (depending on input data);
Populate datacube for all possible combinations of discrete, physically possible values of soil surface parameters (for all input backscatter configurations: σ_{hh} / σ_{vv} / σ_{hv}) as illustrated in fig. 2.2

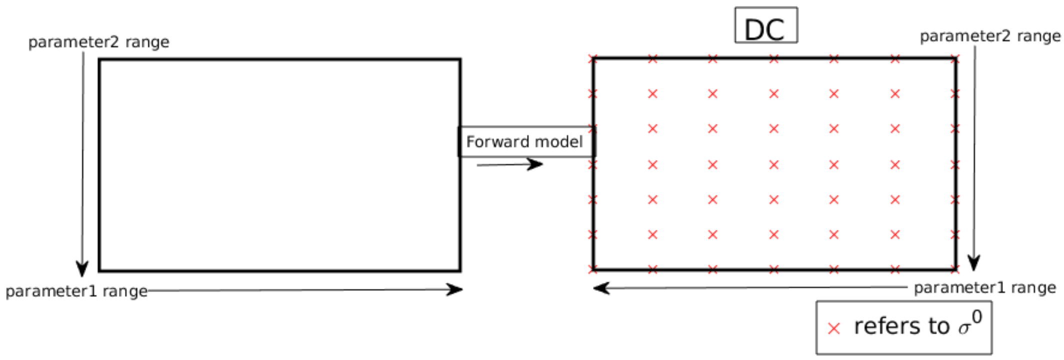


Figure 2.2: two parameter populating of datacube

note: In 2.2, parameter1 could be h and parameter2 could be ϵ

Remark: Calibration of the above, synthetically generated, datacube to be done, if necessary
(against few of the given radar measurements & the corresponding surface parameter ground truth values)

step 1b) Slice the datacube (dc) into sub-dc's (as illustrated in fig. 2.3)

Choice of slicing (among various possibilities) :

(i) Perform all of slicing combinations.
(ii) find the fitting error, $\Sigma^{sub-dc's}\Sigma^{i}(|\sigma^0_{true,i}$ - $\sigma^0_{fit,i}|)$ for each of the combination. (i refers to different backscatter data)
(iii) Choose the slicing combination that has the least fitting error.

step 1c) Each of the sub-dc can be approximately represented by the relation,

$$\sigma^0_{fit,i} = \beta_{0i} + \beta_{1i}.x_{1i} + \beta_{2i}.x_{2i} + \ldots + \beta_{ni}.x_{ni}$$

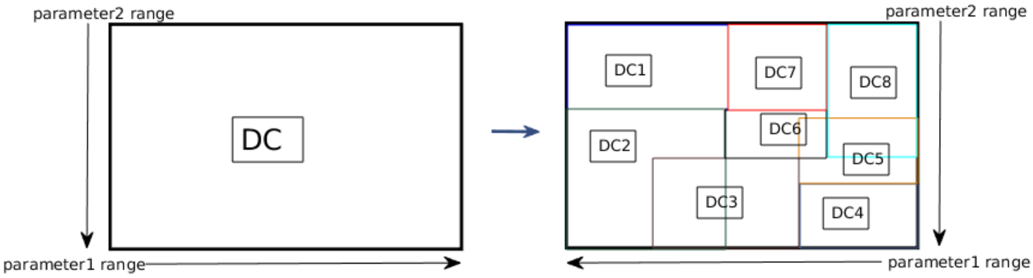


Figure 2.3: two parameter datacube slicing

(x refers to surface parameter variables involved in the model; n refers to total number of such variables; $\beta's$ represent regression coefficients)
Perform multiple linear regression for each of the sliced sub-dc s.

$$\underbrace{\begin{bmatrix} 1 & x_{1_1} & x_{2_1} \dots & x_{n_1} \\ 1 & x_{1_1} & x_{2_1} \dots & x_{n_2} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{1_2} & x_{2_2} \dots & x_{n_2} \end{bmatrix}}_{\mathbf{X}} \underbrace{\begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{n+1} \end{bmatrix}}_{\beta} = \underbrace{\begin{bmatrix} \sigma_1^0 \\ \sigma_2^0 \\ \vdots \\ \sigma_{2^n}^0 \end{bmatrix}}_{\hat{\mathbf{Y}}}$$

$$\mathrm{X}\beta = \hat{Y}$$

obtain

$$\beta = (X'X)^{-1}X'\hat{Y}, \qquad \text{for all sub-dc s}$$

Repeat the above operations and obtain corresponding regression coefficients for all of i backscatter data.

step 1d) Store the corresponding regression coefficients ($\beta_{i,m}$'s) & independent variable bounds (lower bound($x_{n,m}$), upper bound($x_{n,m}$)), for i^{th} backscatter type, n^{th} surface parameter variable and m^{th} sub-dc.

Preprocessing result : Regression coefficients & surface variable bound matrices for all sub-dc's

2) *Inversion*:

step 2a) Find linear least-square solution, subject to bound constraints, for each of the sub-dc s,

$$\min ||\beta x - \hat{Y}||_2^2 \quad provided, \quad x_{LB} \leq x \leq x_{UB}$$

step 2b) Find the sub-dc that returns the more accurate retrieval values, with the help of a suitable error metric;
Return the retrieved ϵ_r for that sub-dc.

step 2c) Find the corresponding M_v value from the retrieved ϵ_r by inverting for a suitable microwave dielectric model.

Output : Retrieved values of volumetric soil moisture ($M_v's$) for the given set of SAR backscatter data

2.1 Generalised "best slicing" candidate

In order to generalise a best method to often, if not always, slice the dc into sub-dc s; several possible 'best slicing' candidates were chosen and their corresponding retrieval results were compared. It is found, slicing the dc into smallest possible sub-dc s always resulted in better retrieval results.
This motivated to follow up similar way of slicing for the studies conducted through this thesis.

2.2 Comparison of error metrics

In order to find out the sub-dc that returns the more accurate retrieval result, two of the error metrics were identified, their retrieval accuracies were studied and compared, and the better one is chosen for incorporating into the proposed model.

i) *sum-of-residuals error metric*
By this metric, for each of the sub-dc s, sum of the residual (or, the difference in the computed backscatter and the sub-dc backscatter) values for all of the i different backscatter readings is found. Mathematically speaking, it is found,

$$\Sigma_i(|\sigma^0_{sub-dc,i} - \sigma^0_{computed,i}|) \quad \forall \quad sub-dc$$

Sub-dc associated with the least sum of the residual value returned to be the sub-dc corresponding to the more accurate retrieval values.

ii) *ranking error metric*
By this metric, for a particular (i^{th}) backscatter configuration (i.e., σ_{hh}/ σ_{vv}/ σ_{hv}),

- rank all of sub-dc (in ascending order) depending on the corresponding value of, $(|\sigma^0_{sub-dc,i} - \sigma^0_{computed,i}|)$ (in the same order).

- Repeat the same for all of the i backscatter configurations

- Sum the rank for all i configurations for each of the sub-dc.

- Return the sub-dc associated with the least rank among all sub-dc s; retrieved values corresponding to which is chosen to be the more accurate parameter retrieval values.

For $i \leq 2$; both the metrics return similar results. But for $i > 2$; sum-of-residuals metric often returns more accurate results compared to ranking metric. Hence the former metric is chosen to be the default metric for studies conducted through this thesis.

CHAPTER 3

Validation of Proposed Technique

In order to test the accuracy of the retrieval values from the proposed model, comparison of the retrieval results from the proposed model, which is physically-based, is done against the retrieval results (for the same BS data and radar parameter values) from a widely employed semi-empirical model, SMART Inversion algorithm (which is developed out of Dubois *et al.* (1995)). Further, the degree of improvement in the retrieval accuracy upon having information on dual band backscatter, as opposed to single band backscatter information is studied. Finally, considering the challenge in meeting the required SM retrieval accuracy, for given information on dual-band, co-polarised backscatter (σ_{hh} & σ_{vv}), the proposed inversion technique has been applied to datacube populated by all of primary influencers on BS from rough soil surface (i.e., h, l, ϵ_r, ϵ_{im}), and corresponding retrieval results are presented. Backscatter (σ^0's) from SAR are typically noise-affected (with noise standard deviation on the order of $\pm$ 0.5 dB). This makes it important to validate the proposed technique for backscatter coefficients affected by various noise levels (or say, for various degrees of added Gaussian/ random noise). The same has been implemented for each of the study results presented in this section. Since the noise added to the backscatter is random, that may return different retrieval result for each retrieval instance, several retrieval instances were performed and the mean retrieval value along with standard deviation is reported for each study. (Here the number of retrieval instance were chosen to be 10. This is owing to the observation from the simulation; upon performing retrieval for unity to 100 instances in random steps, retrieval instances to be 10 were fixed.)

Also, throughout this thesis, microwave dielectric model discussed in Hallikainen *et al.* (1985) is employed to invert for the volumetric SM from the retrieved dielectric constant of soil. Soil texture is chosen, by default, to be sandy loam (corresponding to sand content = 51 %; silt content = 13 %); and frequency is chosen to be 1.4 GHz for the same.

3.1 Comparison with SMART inversion algorithm

Soil Moisture Assessment Radar Technique (or SMART) Inversion is a semi-empirical soil moisture inversion model. Due to simplistic nature of the model and good retrieval accuracies, it has been applied at numerous sites to map the soil moisture from multi-polarised radar data.

To compare the retrieval results from SMART inversion algorithm and the proposed Sliced Regression Inversion algorithm, BS coefficients were synthetically generated from SMART Forward model, whose corresponding soil surface parameter values (here, h & ϵ_r) being already known (also , $\lambda_{op} = 24cm$ in single-band operation, $\theta_{inc} = 40^0$), are used to find the retrieval accuracies for the models to be compared.

Retrieval values using Sliced Regression Inversion technique are obtained by populating datacube using SMART Forward model, covering physically possible values of soil surface parameters (and by setting $\lambda_{op} = 24cm$, $\theta_{inc} = 40^0$).

Obtained retrieval results from both the methods, for various noise added BS data, are as follows :

1) Without any added noise -

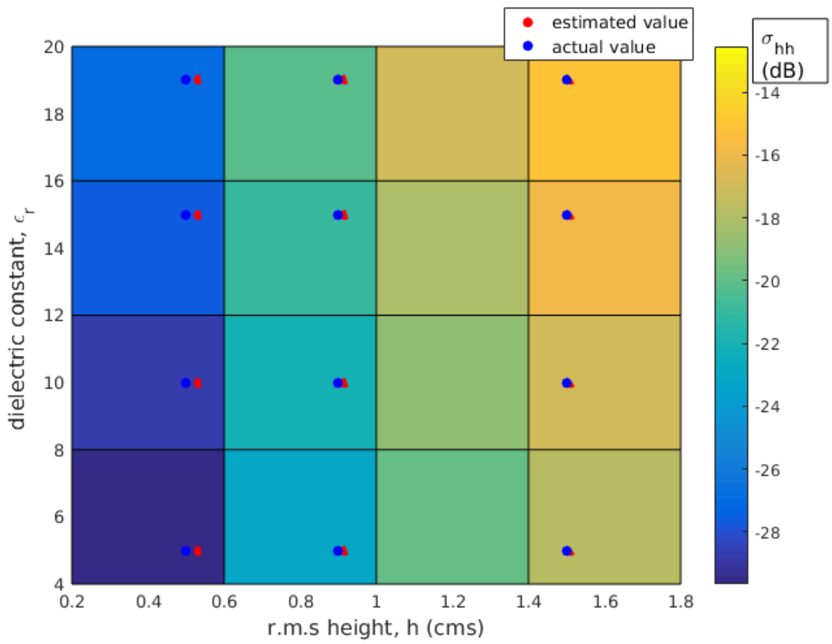


Figure 3.1: comparison result (1)

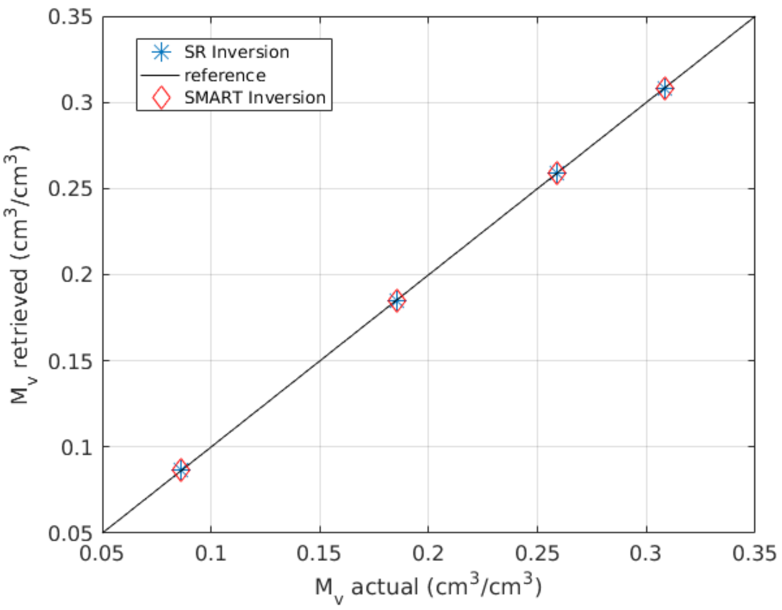


Figure 3.2: comparison result (2)

2) For added noise of 0.3 dB (on an average) -

mean rms error (s.d.) in,	h (cm)	ϵ_r	M_v (cm^3/cm^3)
SR inversion algorithm	0.11 (0.03)	1.60 (0.36)	0.026 (0.007)
SMART inversion algorithm	0.13 (0.04)	1.86 (0.39)	0.035 (0.008)

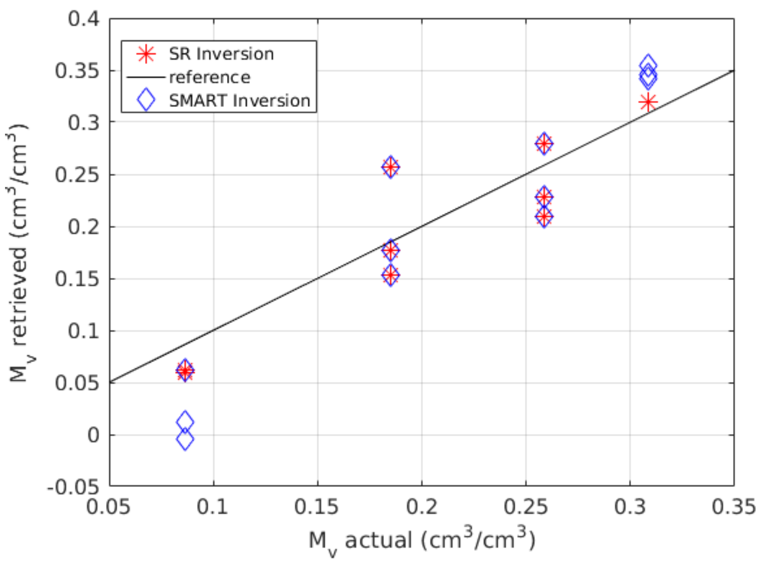


Figure 3.3: comparison result (3)

3) For added noise of 0.6 dB (on an average) -

mean rms error (s.d.) in,	h (cm)	ϵ_r	M_v (cm^3/cm^3)
SR inversion algorithm	0.20 (0.04)	3.24 (0.66)	0.053 (0.012)
SMART inversion algorithm	0.25 (0.07)	3.95 (0.80)	0.073 (0.019)

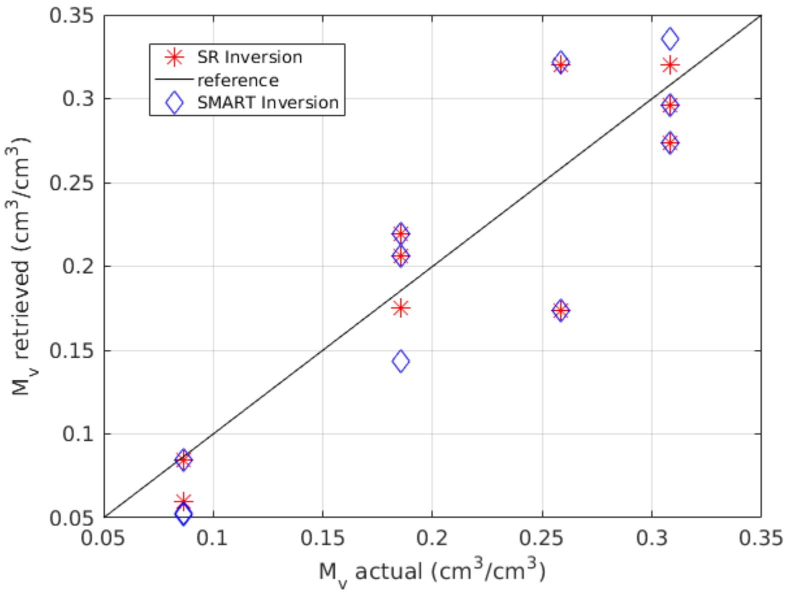


Figure 3.4: comparison result (4)

4) For added noise of 1 dB (on an average) -

mean rms error (s.d.) in,	h (cm)	ϵ_r	M_v (cm^3/cm^3)
SR inversion algorithm	0.25 (0.06)	4.02 (1.17)	0.065 (0.017)
SMART inversion algorithm	0.36 (0.09)	5.85 (1.60)	0.115 (0.033)

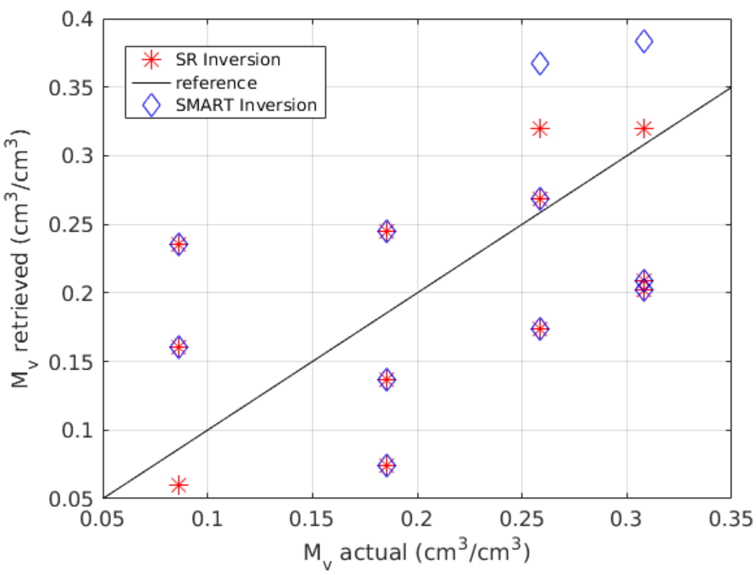


Figure 3.5: comparison result (5)

3.2 Single-band vs dual-band retrieval results

As mentioned earlier, microwave remote sensors can be employed to map specific sections of a geographical location over earth surface, by using suitable operating wavelength for the sensors. Backscatter information for different operating wavelengths are, to a larger extent, independent of each other.

The significance of this study lies in context of the NISAR mission (an upcoming mission), which will employ a dual-band SAR to monitor earth surface as opposed to all the previous missions which employs or employed single-band SAR. Operating SAR at two different frequencies is expected to provide more information about the location being monitored compared to the information that can be collected with single frequency SAR operation.

The following study is conducted to figure out the degree to which retrieval accuracy could be improved upon using backscatter information for additional wavelength of operation. As in the previous section, SMART Forward model is employed here to populate the datacube. Datacubes are populated for $L-$band in case of single-band study and for both $L-$band & $S-$band in case of dual-band study, as are the bands to be employed in NISAR mission. Upon employing the proposed technique for the two cases, retrieval results for the same are presented below :

1) For added mean noise standard deviation of 0.3 dB -

mean rms error (s.d.) in,	h (cm)	ϵ_r	M_v (cm^3/cm^3)
single-band results	0.12 (0.02)	1.81 (0.37)	0.030 (0.007)
dual-band results	0.09 (0.02)	1.21 (0.27)	0.020 (0.005)

2) For added mean noise standard deviation of 0.6 dB -

mean rms error (s.d.) in,	h (cm)	ϵ_r	M_v (cm^3/cm^3)
single-band results	0.19 (0.05)	3.28 (0.88)	0.053 (0.015)
dual-band results	0.14 (0.03)	2.21 (0.49)	0.037 (0.010)

3) For added mean noise standard deviation of 1 dB -

mean rms error (s.d.) in,	h (cm)	ϵ_r	M_v (cm^3/cm^3)
single-band results	0.26 (0.04)	4.45 (1.29)	0.071 (0.021)
dual-band results	0.19 (0.04)	3.17 (0.88)	0.051 (0.014)

3.3 Further retrieval results

3.3.1 IEM as the forward model

It is important to have access to a fairly accurate forward model, so as to expect good retrieval accuracy from inversion of the same. Integral equation model (IEM) is a physically-based forward model that computes the back-scattering of a random surface with any specified surface electrical/ geometrical condition (to an extent) for any of the receive/ transmit wave polarization combinations.The simulation results from IEM is reported to be in close agreement with the experimental data for many of the comparison studies done in the past. In this section, the backscatter coefficients were synthetically generated using IEM forward model to test the degree of its applicability for the real world data.

For bare surface SM retrieval, it is important to incorporate all the primary influencing parameters on radar BS to the model, which are - h, l, ϵ_r, and ϵ_{im}. In this section, retrieval accuracies for the above mentioned parameters along with SM are studied for a given dual band ($L-$ band & $S-$ band) co-polarized BS information (+ radar parameters), as a measure of noise added to the generated BS data.

Using the dielectric model Hallikainen *et al.* (1985), real part (ϵ_r) and complex part (ϵ_{im}) of the the complex dielectric constant can be expressed as independent functions of M_v. Hence, it is possible to invert for M_v from either of the two functions. Since the typical range of ϵ_{im} values considered is much lower than that of ϵ_r, retrieval error in ϵ_{im} highly amplifies the retrieval error in M_v compared to the retrieval error in ϵ_r. Same observation is noted from the retrieval results as well. Hence we retrieve for M_v from its relation with ϵ_r and present the same here. Retrieval results, upon building datacube using IEM model and further applying sliced regression inversion algorithm, are as follows:

1) For no noise added case

	h (cm)	l (cm)	ϵ_r	ϵ_{im}	M_v (cm^3/cm^3)
rms error	0.95	30.79	0.52	0.82	0.008

2) For 0.3 dB (on an average) noise added case

	h (cm)	l (cm)	ϵ_r	ϵ_{im}	M_v (cm^3/cm^3)
mean rms error (s.d.)	0.94 (0.02)	29.00 (1.69)	3.38 (0.52)	0.88 (0.07)	0.053 (0.006)

3) For 0.6 dB (on an average) noise added case

	h (cm)	l (cm)	ϵ_r	ϵ_{im}	M_v (cm^3/cm^3)
mean rms error (s.d.)	0.94 (0.05)	28.52 (2.26)	5.32 (0.60)	0.94 (0.04)	0.082 (0.009)

4) For 1 dB (on an average) noise added case

	h (cm)	l (cm)	ϵ_r	ϵ_{im}	M_v (cm^3/cm^3)
mean rms error (s.d.)	0.95 (0.04)	29.40 (1.80)	6.13 (0.31)	0.95 (0.03)	0.093 (0.005)

3.3.2 Retrieval results from RISAT-1 dataset

Radar satellite-1 (RISAT-1) is a microwave remote sensing satellite with a SAR payload operating in c-band (5.35 GHz), launched in the year 2012.

For the dataset from RISAT-1, on the backscattering coefficient (σ_{hh}), recorded over a few specific region (within the range of latitude (22.5-23.4); longitude (72.3-72.6)) across a few specific time of the year (2015), soil moisture (SM) levels are retrieved, within certain accuracy level, employing the proposed technique. IEM is used as the forward model to populate datacube, with the motivation of fairly accurate retrieval of the surface parameters h, l & ϵ from a single observation information on σ_{hh}. Furthermore to obtain M_v from the retrieved ϵ value, a widely popular model (Topp *et al.*, 1980) is employed. The employed dielectric model is a third order polynomial relating ϵ and M_v without considering the nature of soil texture or the frequency of operation of radar employed to collect the data. The results on the same are presented below.

information provided :

(which also serves to be *input to the inversion model*)

1) backscatter information (σ_{hh}); *2)* look angle (same as the incidence angle) = 36.8 degrees; *3)* frequency of radar operation = 5.35 GHz (corresponding to c-band wavelength)

Retrieval results from the information provided :

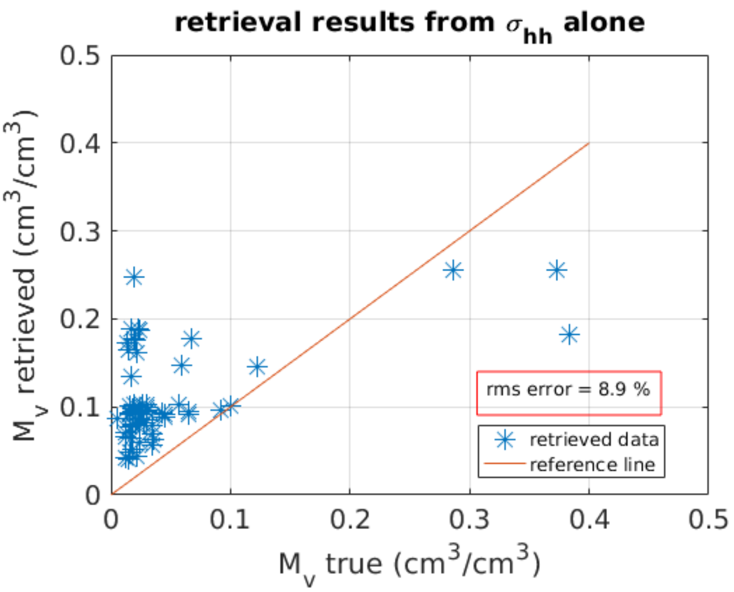


Figure 3.6: RISAT-1 retrieval result

rms error in,	
h (in cm)	0.31
ϵ	3.81

Retrieval results for the dataset provided from the developed inversion method looks satisfactory, if not excellent. The accuracy of model prediction is expected to improve significantly on having σ_{vv} information, in addition. Moreover, simultaneous backscatter information on more than one wavelength is observed to return highly accurate retrieved surface parameter values. It is tested and observed for dual-band backscatter information against single band backscatter information, which is visible from the previous section.

The forward method employed in the proposed retrieval algorithm is not calibrated in retrieving for the surface parameters for the time/ site specific dataset provided. This is believed to be the primary reason for the observed retrieval error.

CHAPTER 4

Conclusion

4.1 Summary

A physically-based soil moisture retrieval algorithm is proposed and validated with good retrieval accuracy . The proposed technique is aimed at having a modular design such that any of the algorithm module can be replaced by another suitable one, depending on the need; without affecting any other module in the algorithm. The proposed algorithm is compared against a widely employed semi-empirical inversion algorithm, and it is observed, better results are returned from the former. Performance of the proposed retrieval algorithm on single band retrieval and dual band retrieval is studied; and it is found dual band retrieval almost always returns better retrieval results for SM, along with other soil surface parameters. The proposed algorithm is employed to synthetically generated datasets in consideration to a more practical bare surface SM retrieval scenario considering all the primary influencers on BS into the model, and employing an advanced Forward model. Finally, the proposed technique is applied to real data from RISAT-1 to retrieve for soil moisture corresponding to the recorded backscattered coefficients. The retrieval results for all the cases are found satisfactory.

4.2 Future work

The proposed algorithm is developed for a simplistic case of bare surface soil moisture retrieval, whose application is limited to the real world scenario. Most of the earth surface is covered by vegetation and to some extent by artificial structures, which makes soil moisture retrieval beneath its surface difficult, if not impossible. Hence it is important to develop exclusive models depending on the geographical conditions of the location or in general, a commonly applicable model that can give a fairly accurate retrieval results for majority of the earth surface locations. A simple up gradation that can be made to the current model is to incorporate another quantity (say, vegetation water content) that represents the effect of a layer of vegetation on top of soil surface. There is also a huge scope for development of better inversion algorithm that returns more accurate retrieval values for any dataset. Furthermore the proposed algorithm is yet to be applied to dataset obtained from air-borne/ space-borne SAR, and corresponding retrieval result accuracies yet to be found.

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