# MODELING THE ERRORS OF A TIME SERIES ALGORITHM FOR RETRIEVING SOIL MOISTURE IN THE NISAR MISSION

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## ABSTRACT

The National Aeronautics and Space Administration (NASA) - Indian Space Research Organization (ISRO) Synthetic Aperture Radar (NISAR) mission plan to launch a SAR operating at L- and S-band with a 12-day repeat frequency. A global soil moisture product at 200 m spatial resolution derived from 200 m NISAR radar measurements is currently under development. Although several retrieval algorithms are being investigated, this paper focuses on a "time series ratio" retrieval approach. In order to understand and assess the performance of this algorithm, an error model has been developed and is reported in this paper. The model is applied to examine errors as a function of the instrument characteristics and for a given location. Initial progress in including vegetation effects and in predicting errors as a function of spatial location is also described.

***Index Terms***— NISAR, Soil Moisture, Error Model

## 1. INTRODUCTION

Soil moisture information is important for many land surface applications. For the past decade, the monitoring of global soil moisture has been successfully demonstrated using L-Band radiometer measurements [1]-[2]. Although L-Band radiometry allows for global coverage and frequent revisits, the soil moisture maps produced have a spatial resolution of ~ 40 km, which is not sufficient for agriculture monitoring. Research has also been pursued to develop techniques that use Synthetic Aperture Radar (SAR) for soil moisture retrievals that achieve a finer spatial resolution [3]-[4]. The launch of the National Aeronautics and Space Administration (NASA) - Indian Space Research Organization (ISRO) Synthetic Aperture Radar (NISAR) [5] (expected in 2024) opens new opportunities for performing soil moisture monitoring at 200 m spatial resolution using SAR measurements.

NISAR is being developed as a joint effort between NASA and ISRO and will operate a 1.26 GHz SAR system utilizing a SweepSAR technique that will provide 12-day exact repeat sampling. The expected spatial resolution will vary from 3 to 10 meters depending on the radar mode utilized, and the incidence angle will range from 34 to 48 degrees over the swath. For soil moisture applications, NISAR's L-band frequency is particularly of interest as it provides significant penetration into vegetated regions, allowing continued measurements of soil moisture even for mature crop regions. The development of a global soil moisture product at 200 m with a 12 day revisit time is currently in process. Although several retrieval algorithms are being investigated, this paper focuses on a "time series ratio" approach [6]-[10]. In order to understand and assess the performance of this algorithm, an error model was developed. Expected algorithm errors are examined in this paper as a function of instrument characteristics (number of looks, measurement noise) and for a given location.

The following section describes the time series ratio algorithm in more detail, and Section 3 formulates the error model considering multiple sources of uncertainty. Section 4 then presents preliminary results of the error model obtained from simulations, and Section 5 describes extensions of the model that are currently under development.

## 2. TIME SERIES RATIO ALGORITM

The time series ratio retrieval algorithm is based on the observation that roughness and vegetation impacts on the backscattered signal from land surfaces can be eliminated if a ratio of two consecutive observations is considered. The algorithm begins by expressing the backscattered normalized radar cross section (NRCS) for a vegetation-covered soil layer as a sum of three components:

$$\sigma_{pq}^{t} = \sigma_{pq}^{s} e^{-\tau_{pq}} + \sigma_{pq}^{SV} + \sigma_{pq}^{V} \tag{1}$$

where $\sigma_{pq}^{t}$ represents the total NRCS in polarization combination $pq$, $\sigma_{pq}^{s}$ represents the NRCS of the soil surface that is also multiplied by the two-way vegetation attenuation $\tau_{pq}$, $\sigma_{pq}^{V}$ is the NRCS of the vegetation volume, and $\sigma_{pq}^{SV}$

represents scattering interactions between the soil and vegetation.

The time series ratio approach assumes that vegetation and roughness effects can be considered negligible between two consecutive observations. The approach also nominally assumes that the vegetation attenuated surface backscatter is the dominant term between consecutive overpasses, and that this term can be written as a product of a function of soil moisture only $\alpha_{pq}$, a function of surface roughness only $\sigma_{pq}^{S\,r}$, and the vegetation attenuation $e^{-\tau_{pq}}$:

$$\sigma_{pq}^{s}\, e^{-\tau_{pq}} = \alpha_{pq}\, \sigma_{pq}^{S\,r}\, e^{-\tau_{pq}} \tag{2}$$

It is noted that this assumption can remain valid even in cases in which the surface-volume interaction term dominates the observed backscatter.

Because surface roughness and vegetation properties are assumed to remain almost constant over two consecutive measurements, the ratio of NRCS values measured at times $t_1$ and $t_2$ can be expressed as:

$$\frac{\sigma_{pq}^{t2}}{\sigma_{pq}^{t1}} = \frac{\alpha_{pq}^{t2}}{\alpha_{pq}^{t1}} \tag{3}$$

where $\alpha_{pq}$ is a known function of the surface permittivity and incidence angle. In this study, $\alpha_{pq}$ is estimated from the first-order scattering amplitude of the small-perturbation model (SPM). Given a time series of N measurements, successive ratios can be combined into a matrix equation having N-1 ratios for N unknown $\alpha_{pq}$ values. To solve this undetermined system, ancillary minimum and maximum bounds are provided for $\alpha_{pq}$ over the time series duration. The $\alpha_{pq}$ coefficients are then determined by solving the system using a bounded least mean square method, and the obtained $\alpha_{pq}$ are inverted into soil moisture using ancillary soil texture information.

## 3. ERROR MODEL

The performance of this retrieval algorithm versus *in-situ* measurements has been assessed on specific datasets as shown in [11]. Here a more general error model for the expected algorithm performance is developed. In this development, it is assumed that the minimum bound for $\alpha_{pq}$ is applied in the matrix equation solution in order to simplify the formulation.

The successive ratios of a time series of N measurements (as in Eqn (3)) can be combined to show that the $\alpha_{pq}$ value at time t is related to that at an earlier time "zero" through

$$\alpha_{pq}^{t} = \alpha_{pq}^{0}\, \frac{\sigma_{pq}^{t}}{\sigma_{pq}^{0}} \tag{5}$$

To apply the minimum bound in the time series solution, we assume in what follows that time "zero" is labeled as the time with the minimum NRCS value, for which it is assumed that the minimum bound $\alpha_{pq}^{0}$ is applicable. Note that this time zero may then occur at any point in the time series, with the solution at all other time series points then determined from Eqn (5).

As previously discussed, the $\alpha_{pq}$ coefficients obtained from (5) are then inverted into soil moisture $s_m$:

$$s_m = f_{inverse}(\alpha_{pq}^{t}) \tag{6}$$

where $f_{inverse}$ is the inverse of the function relating $\alpha_{pq}$ to soil moisture for a specified soil texture. Errors $\Delta\, \alpha_{pq}^{t}$ in the measured value of $\alpha_{pq}^{t}$ then map to errors in soil moisture $\Delta\, s_m$ through

$$s_m + \Delta\, s_m = f_{inverse}(\alpha_{pq}^{t} + \Delta\, \alpha_{pq}^{t}) \tag{7}$$

which for small errors can be expanded as

$$s_m + \Delta\, s_m = f_{inverse}\left(\alpha_{pq}^{t}\right) + df_{inverse}\left(\alpha_{pq}^{t}\right) \Delta\, \alpha_{pq}^{t} \tag{8}$$

so that

$$\Delta\, s_m = df_{inverse}\left(\alpha_{pq}^{t}\right) \Delta\, \alpha_{pq}^{t} \tag{9}$$

From Eqn (5),

$$\Delta\, \alpha_{pq}^{t} = \Delta\left(\alpha_{pq}^{0}\, \frac{\sigma_{pq}^{t}}{\sigma_{pq}^{0}}\right) = \alpha_{pq}^{0}\, \Delta\left(\frac{\sigma_{pq}^{t}}{\sigma_{pq}^{0}}\right) \tag{10}$$

in terms of speckle errors in the radar measurements; additional potential errors in $\alpha_{pq}^{0}$ will be discussed subsequently. Eqn (10) now involves the standard deviation of the ratio of the NRCS at times t and zero. Modeling the NRCS $\sigma_{pq}^{t}$ and $\sigma_{pq}^{0}$ as uncorrelated Gaussian random variables (due to the extensive multi-look integration used to create the 200 m NRCS values of interest), the standard deviation of the ratio is:

$$std_{ratio} = \sqrt{\frac{m_t^2}{m_0^2}\left(\frac{s_t^2}{m_t^2} + \frac{s_0^2}{m_0^2}\right)} \tag{11}$$

where $m_t$, $s_t$, $m_0$ and $s_0$ are the mean and standard deviation of the random variables $\sigma_{pq}^{t}$ and $\sigma_{pq}^{0}$ respectively.

The standard deviation of the NRCS can be expressed as function of the number of looks in the multi-look average:

$$s_t = \frac{m_t}{\sqrt{N_{looks}}} \tag{12}$$

so that Eqn (11) becomes:

$$std_{ratio} = \sqrt{\frac{m_t^2}{m_0^2}\left(\frac{2}{N_{looks}}\right)} \tag{13}$$

Finally, the error in soil moisture due to speckle contributions is

$$\Delta\, s_m = df_{inverse}\left(\alpha_{pq}^{t}\right) \alpha_{pq}^{0} \sqrt{\frac{m_t^2}{m_0^2}\left(\frac{2}{N_{looks}}\right)} \tag{14}$$

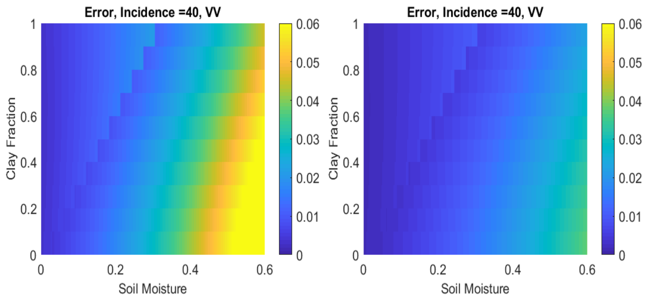


Figure 1: Modeled error in retrieved soil moisture as a function of soil moisture and clay fraction for $\boldsymbol{N_{looks}}$=400 (left) or 1600 (right) for incidence angle = 40º and frequency = 1.26 GHz. Uncertainty in $\boldsymbol{\alpha_{pq}^0}$ is neglected**.**

Eqn (14) shows that the error obtained depends on the soil texture and soil moisture values at time t, the minimum bound $\alpha_{pq}^0$, as well as the number of looks in the 200 m product. It is noted that the term $\frac{m_t}{m_0}$ in Eqn (14) is equivalent to $\frac{\alpha_{pq}^t}{\alpha_{pq}^0}$, so that equation (14) could be further simplified. However this simplification is avoided at this point in order to enable an inclusion of additional errors that account for uncertainties in the minimum bound applied. These errors in the minimum bound are modeled by describing $\alpha_{pq}^0$ in Eqn (5) as its mean value multiplied by a Gaussian random variable with mean equal to 1 and a specified standard deviation. This results in additional error contributions in Eqn (14) that are included in what follows.

## 4. RESULTS

### 4.1. Results for a single measurement

Errors were computed for incidence angle 40º, frequency 1.26 GHz, $m_0$ and $\alpha_{pq}^0$ corresponding to 1% soil moisture and varying truth soil moistures (which determine $\alpha_{pq}^t$). The number of looks is defined using

$$N_{looks} = \left(\frac{Cell\ Size}{Original\ Resolution}\right)^2 \qquad (15)$$

in which a 200 m cell size (spatial resolution) is assumed, and the original resolution is set to either 5 m (i.e. $N_{looks} =$ 1600) or 10 m ($N_{looks} = 400$).

The Mironov model [12] is applied for the soil permittivity; this model describes the dielectric constant as a function of the clay fraction, the soil moisture, and the radar frequency. Predicted soil moisture retrieval errors are then presented for various clay fractions and soil moisture conditions.

Figure 1 illustrates predicted speckle induced errors (i.e. uncertainty in $\alpha_{pq}^0$ is neglected) for VV polarized NRCS measurements using 400 (left plot) or 1600 (right) looks. As expected, the error decreases when the number of looks increases. Errors also increase with soil moisture (due to the decreased sensitivity of $\alpha_{pq}$ to soil moisture for higher soil moisture values). Errors also increase for lower clay fractions. In both plots, the speckle-induced errors are predicted to remain less than a targeted performance value of 6% uncertainty in most cases.

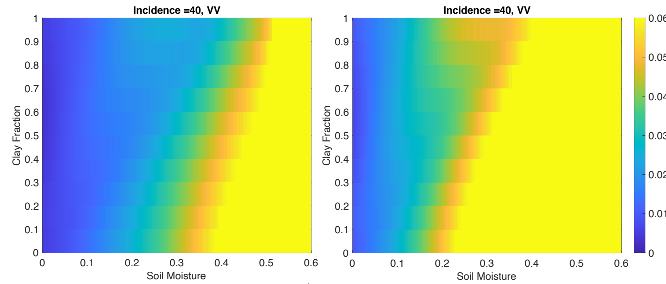


Figure 2: Modeled error in retrieved soil moisture as a function of soil moisture and clay fraction for $\boldsymbol{N_{looks}}$= 1600 including uncertainties of 10% (left) and 20% (right) in $\boldsymbol{\alpha_{pq}^0}$.

Figure 2 considers the same case as in Figure 1 using $N_{looks}$=1600 but further incorporates uncertainties in the minimum bound $\alpha_{pq}^0$ of 10% (left) and 20 % (right). Including these uncertainties further increases errors especially for lower clay fractions and higher soil moisture. Given that errors in $\alpha_{pq}^0$ are expected to remain below approximately 10%, the results again show that the performance target of 6% accuracy can be met in most situations.

## 5. EXTENSIONS

### 5.1. Predicting performance over larger regions

The error model results of Figures 1 and 2 can be extended over larger regions by incorporating maps of soil texture and applying a climatology of expected soil moisture values. Such information has been previously compiled for the Soil Moisture Active/Passive (SMAP) mission, and can be used to develop a larger scale error simulation. The required climatology (initially at 40 km spatial scale) has been developed using 6 years of SMAP soil moisture products to determine bi-monthly minimum, maximum and average soil moisture maps. Errors predicting over large spatial and temporal scales based on this information will be presented.

### 5.2. Adding vegetation effects

The proposed error model has neglected vegetation contributions; extension to incorporate vegetation effects are currently under development. As a first step toward including vegetation effects, Eqn (10) can be rewritten as:

$$\Delta\, \alpha_{pq}^t = \Delta \left(\alpha_{pq}^0\, \frac{\sigma_{pq}^t + \sigma_{veg}^t}{\sigma_{pq}^0 + \sigma_{veg}^0}\right) = \alpha_{pq}^0\, \Delta \left(\frac{\sigma_{pq}^t + \sigma_{veg}^t}{\sigma_{pq}^0 + \sigma_{veg}^0}\right) \qquad (16)$$

in which $\sigma_{veg}^{t}$ and $\sigma_{veg}^{0}$ correspond to additive vegetation scattering contributions that bias measured NRCS returns. It is proposed to describe these quantities as a function of the NDVI and terrain class at a given location. The incorporation of a model for uncertainties in these quantities is also under consideration. Both an NDVI climatology and terrain class information are available from the MODIS mission for use in these efforts. Results from these studies will also be presented.

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