SUITSABILITY OF DIFFERENT OBSERVABLES AND POLARIZATIONS FOR DINSAR-BASED SOIL MOISTURE ESTIMATION

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ABSTRACT

The mapping of soil moisture at field scales can potentially be achieved by the remote sensing technique differential interferometry, or DInSAR. Its signals have been shown to be sensitive to soil moisture changes. We analyse the suitability for this task of three DInSAR observables: the phase \( \phi \), the coherence \( |\gamma| \) and the phase triplets \( \Xi \). By inverting an electromagnetic scattering model, we obtain median correlations between the estimated and the in-situ measured soil moisture time series of 0.86 for the HH phase \( \phi_{HH} \), 0.85 for the coherence \( |\gamma_{HH}| \), and 0.78 for the phase triplets \( \Xi_{HH} \). The phase observable is also sensitive to deformations: these predominantly impact the phase in a way similar to soil moisture changes, thus rendering the separation difficult, e.g. for providing corrections for deformation studies. The other two observables are not affected by deformations, but turn out to be less robust and insensitive to certain temporal soil moisture variations. In the absence of deformations the phase is thus the most promising DInSAR observables for soil moisture retrieval.

1. INTRODUCTION

The remote sensing technique differential interferometry or DInSAR is commonly used to estimate deformations, but the measurements have also been shown to be sensitive to soil moisture [16, 14]. This dual sensitivity raises two important questions. Firstly, is it possible to estimate soil moisture changes using DInSAR? Secondly, to what extent can this be achieved in the presence of deformations?, i.e. whether one can separate the two influences. If this were possible, one could estimate deformations more reliably by controlling for the part of the signal due to soil moisture.

Among the DInSAR observables, the phase \( \phi \) is the most prominent one, as it can be used to estimate deformations [7]. The others – the coherence \( |\gamma| \) and the phase triplets \( \Xi \) – are insensitive to deformations [5], but also sensitive to soil moisture changes [2]. All three are thus potentially useful for estimating \( m_v \) (the first open question), whereas one needs to separate the impact of deformations and soil moisture for the phase (second question).

We propose to tackle these two problems by retrieving the soil moisture for each observable separately in the absence of deformations. The expected impact of hypothetical deformations on \( \phi \) will be compared to the one due to soil moisture: this will provide insight into the possibility of separating these two influences. The coherence \( |\gamma| \) and the phase triplets \( \Xi \) also contribute to this goal, as any soil moisture information derived from them can be used to apply corrections to the phase \( \phi \).

2. THEORETICAL CONSIDERATIONS

The three observables were modelled for a heterogeneous soil with varying soil moisture by [20]: the soil is described as a heterogeneous half space – the heterogeneities being expressed as fluctuations of the permittivity – with a rough interface. The phase contribution (related to the apparent distance) of these interface reflections hardly changes as the soil becomes wetter; however, the scattering from within the soil is affected in two ways. Firstly, the refractive index of the soil increases: the heterogeneities thus appear to be further away from the sensor as the wave takes more time to travel along the path. Secondly, the absorption increases (indicated by the thickness of the wavefronts): heterogeneities deeper within the soil contribute relatively less to the overall signal than for a dry soil. When applied to an interferometric pair of acquisitions, the first effect leads to a shift in the measured phase (the target appears to be further away when the soil is wet), and both of them combine to lead to decorrelation.

2.1. Model

The first-order solution to Maxwell’s equations of this scenario consists of the incoherent addition of the rough surface scattering (small perturbation model, SPM) and a ‘volumetric’ term due to the heterogeneities. The magnitude of the associated permittivity fluctuations is de-
scribed as a Laguerre polynomial $a(z')$ of degree $A$ in the non-dimensional depth $z'$ (normalized by a reference penetration depth). Assuming this magnitude to be constant with depth, $a(z') = 1$, one obtains the following covariance matrix of the volumetric term

$$C_{m,n}^w = \frac{1}{4W'}T_{m,n}(2i(k'_{b,m} \cdot \hat{z} - k'_{s,n} \cdot \hat{z}))$$

$$\left(k'_{b,m} \cdot \hat{z} - k'_{s,n} \cdot \hat{z}\right)^2$$

(1)

where $W'$ is a constant that drops out upon forming $\gamma$, $T_{m,n}$ is a matrix that contains Fresnel transmission coefficients, and $k'_{b,m} \cdot \hat{z}$ is the vertical component dimensionless wavenumber in the soil at acquisition $m$. As the soil moisture changes between two acquisitions, so does the background dielectric constant and with it the wavenumber: changes in its real part give rise to phase differences.

The combination of this 'volume term' with the one due to the surface yields the total scaled covariance matrix (the scaling drops out when forming the coherence)

$$C_{mn} = \frac{f}{f_{0,v}}C_{m,n}^w + \frac{1}{f_{0,s}}C_{m,n}^s$$

(2)

where $f_{0,v}$ and $f_{0,s}$ are normalization magnitudes (at a fixed value of $m_o$), and $f$ is the volume-to-surface ratio, which determines the relative importance of these two terms.

2.1.1. Parameterization

The volume-to-surface ratio plays a crucial role in the soil moisture sensitivity of the phase $\phi$. As illustrated in Fig. 1a, this sensitivity increases with increasing $f$, as it is the volume term that shows pronounced $m_o$ dependence. The nonlinearity of this dependence is evident in two ways: firstly, the predicted $\phi$ does not only depend on the soil moisture difference $\Delta m_o$ but also on the one of the 'master' acquisitions (red and blue lines). Secondly, the phase response saturates as $\Delta m_o$ increases. This saturation effect is more pronounced for the Peplinski mixing model than for the Hallikainen one, as shown in Fig. 1b. The former also shows stronger decorrelation for fixed $\Delta m_o$ (cf. Fig. 1c). The dissimilarities in the predictions are mainly related to the differences in the implied wave attenuation [20]. Owing to these differences in the predictions of the forward model, it is expected that they also carry over to the estimation of soil moisture from interferometry.

2.2. Inversion

The proposed inversion consists of two steps: In the first step, all the available images are combined to compute all available interferograms, from which the observables such as the phase $\phi$ are derived. Based on all these observables, the second step proceeds by computing a soil moisture time series. This soil moisture retrieval is referred to as inversion.

2.2.1. Optimization problems

The soil moisture retrieval is formulated as an optimization problem: the estimated values of $m_o$ are those that minimize the misfit between observed and predicted observables. The predictions are based on either the model (2) or a simplified variant thereof and the only unknowns are the soil moisture values; all other parameters are fixed. Using different parameterizations of the model, the inversion is done for each observable separately; each observable has its own associated misfit function.

The misfit between the simulated phase $\hat{\phi}$, which depends on the soil moisture time series, and the observed one $\phi$ is adapted from [20]

$$\mu_\phi^2 = \sum_{n>m} w_{m,n}(1 - \cos(\hat{\phi}_{m,n} - \phi_{m,n}))$$

(3)

where the weights $w_{m,n}$ are the reciprocals of the phase variances (based on the estimated coherence and the Gaussian speckle model, see [1]) and are normalized such that they sum to one. The $\cos$ term renders the expression insensitive to phase wrapping; to second order this misfit approximates the least-squares function

$$\mu_{\phi,LS}^2 = \frac{1}{2} \sum_{n>m} w_{m,n}(\hat{\phi}_{m,n} - \phi_{m,n})^2$$

(4)

An analogous formulation for the phase triplets $\Xi$ reads

$$\mu_\Xi^2 = \sum_{o>n} w_{m_o,n,o}(1 - \cos(\hat{\Xi}_{m_o,n,o} - \Xi_{m_o,n,o}))$$

(5)

where one acquisition $m_0$ is held fixed to avoid redundancy [12], and the normalized weights are also computed from the Gaussian speckle model.

The analogous misfit function for the coherences is taken to be [20]

$$\mu_\gamma^2 = \sum_{n>m} (|\hat{\gamma}_{m,n}| - |\gamma_{m,n}|)^2$$

(6)

2.2.2. Algorithms and initial values

The model of (2) relies on reference backscatter values to define the volume-to-surface ratio $f$. These are obtained using a reference soil moisture $m_v = 0.2 \text{m}^3\text{m}^{-3}$, the same value is also used to compute the penetration depth for obtaining the dimensionless form of (2). The expansion of the electric fluctuation is restricted to $A = 0$ and the unknown volume-ground-ratio is set to $\ln f = 10$, which corresponds to a dominant volume term and has been found to be a representative by [20].

The optimization problems of (3), (6) and (5) are nonlinear due to the form of the model (2) and the misfit functions. We propose to find solutions based on the downhill
simplex algorithm by [15], which does not require derivatives. We fix the soil moisture value at the first acquisition.

For the phase-based inversion, a simpler alternative to this approach can be found by linearizing the forward model:

$$\phi_{m,n} = \beta(m_m^o - m_n^o)$$

where the linear approximation has been found to i) explain more than 50% of the variation in \(\phi\) in the empirical study by [19], and ii) is expected to work well (relative errors <25%) for \(|m_m^o - m_n^o| < 0.1 \text{ m}^3\text{m}^{-3}\) based on Fig. 1. It does, however, predict zero phase triplets and its use is thus restricted to the phase. The latter optimization problem – based on (4) – is a standard linear least squares problem. It is parameterized by \(\beta\), which is assumed to be 5 \text{ rad m}^{-3}\text{m}^3, a value corresponding to the ones for the Hal model in Fig. 1b.

It is referred to as inversion model L, whereas the parameterizations of the non-linear model are denoted by P (Peplinski mixing model), and H (Hallikainen).

### 2.2.3. Assessment

The quantitative assessment of the quality of the inversion is hampered by the brevity of the soil moisture time series, see Sec. 3. It prevents us from calibrating the measured and estimated values with respect to each other, and thus renders the computation of RMS differences problematic. Such a calibration is generally deemed necessary because of differences in the spatial scale and uncertainties in the calibration of the remote sensing and in-situ data [6]. The in-situ data used in this study have been shown to exhibit large differences in both mean and dynamic range between the different fields [3, 19].

We thus restrict the assessment to the sample correlation coefficient \(\rho\), as it is insensitive to additive and multiplicative biases. Due to the limited number of samples, its standard error is expected to exceed 0.05 and it is also generally a biased estimator of the population correlation coefficient [17].

### 3. DATA AND STUDY AREA

The radar and in-situ data were acquired within the Canadian Experiment for Soil Moisture in 2010 [11] over the Kenaston, Saskatchewan, Canada, test site (51° 30’ N, 106° 18’ W). The area is characterized by rainfed agricultural fields, grassland, and pastures. The relief is flat, and at least 1.5% of the area is covered by open water surface. This percentage was higher during the campaign (June 2 - 14, 2010), as it had been preceded by wet weather conditions [3]. There are six UAVSAR L-band radar images taken in irregular intervals over the entire study area available [8]. These data comprise four polarizations (HH, HV, VH, and VV) and have a resolution of 1.7 m in range, and 0.8 m in azimuth [9]. All six images were taken from the same track (zero baselines); the deviations from this scenario are considered negligible for this data set and purpose [19].

The radar data were combined interferometrically to yield estimated covariance matrices \(C_{l,m}\) between acquisitions \(l\) and \(m\) [4]. These raw interferograms contain an unknown phase offsets and trends: the latter were removed by a third-order polynomial, the former by referencing with respect to a persistent scatterer [10] (see [19] for an analysis of the sensitivity with respect to the referencing).

Volumetric soil moisture \(m_m\) was measured hourly at ten permanent stations by Environment Canada (EC) using Stevens Hydraprobe probes in several depths, of which the 0-5 cm vertical sensor (using an improved factory calibration) will be considered [11, 19]. In addition, visual assessments of the tillage, vegetation cover and crop type are available for most fields [11]. The fields were all bare or partially covered with harvest residues.

### 4. RESULTS

The following comparisons will be based on the inversion methods outlined in Tab. 1.
<table>
<thead>
<tr>
<th>Observables</th>
<th>Polarizations</th>
<th>Model (equation)</th>
<th>Mixing model</th>
<th>log f</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \phi ), (</td>
<td>\gamma</td>
<td>), (\Xi)</td>
<td>HH, VV</td>
<td>Nonlinear (2)</td>
<td>Hallikainen</td>
</tr>
<tr>
<td>( \phi ), (</td>
<td>\gamma</td>
<td>), (\Xi)</td>
<td>HH, VV</td>
<td>Nonlinear (2)</td>
<td>Peplinski</td>
</tr>
<tr>
<td>( \phi )</td>
<td>HH, HV, VV</td>
<td>Linear (7)</td>
<td>–</td>
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<td>L</td>
</tr>
</tbody>
</table>

Table 1: The inversion methods used in this study.

![Figure 2](image1.png)

Figure 2: Estimated and measured values of \( m_v \) [\( m^3\ m^{-3} \)] for all the fields (number in upper left corner): the meaning of the symbols is given in the top legend. The numbers to the right of each panel give the correlations \( \rho \) between the estimates and the measured data.

### 4.1. Phase

The inverted soil moisture (based on the HH and VV phase) in Fig. 2 shows a similar temporal behaviour to the in-situ measured values for all three fields, as the wetting before the third acquisition and subsequent drying is present in all of them. The inverted time series are more closely related between all three fields than the in-situ measured ones; this similarity also concerns the magnitude of the variations in \( m_v \). The latter are always around 70% smaller for the inversion based on the Peplinski model (P) than for the Hallikainen one (H) or the linear model (L). There is no clear pattern regarding the temporal correlations \( \rho \): the two polarizations HH and VV and all three models achieve correlations between 0.6 and 1.0 for the three fields, and between 0.85 and 0.87 on average, i.e. for all 10 fields, cf. Fig. 3.

The linear model (L) was applied to the entire HH image, thus yielding a spatially continuous soil moisture time series, of which two instances are shown in Fig. 4 (cf. the supplementary video). They depict the wetting between the second (June 6) and the third acquisition (June 9), which is evident for almost all fields. The areas that do not follow this trend are mainly water bodies and fields for which correlation \(|\gamma| \ll 1\) are observed in Fig. 4.

The same linear model, when used to estimate \( m_v \) from the HV phase, yields soil moisture time series for all fields that are comparable to both HH and VV, with similar magnitudes, temporal patterns and correlations in Fig. 5 and 3.

### 4.2. Coherence

Estimated soil moisture from the coherence \(|\gamma|\) shows average correlations with in-situ \( m_v \) of around 0.85 for both the H and the P model. The spread of these \( \rho \) values is larger than for the phase, in particular in VV, where e.g. field 203 in Fig. 6 achieves \( \rho < 0.6 \).

### 4.3. Phase triplets

Similar average correlations 0.78 are also obtained when comparing the in-situ measurements with the inversions based on the phase triplets \( \Xi \), see Fig. 3. There are more outliers (fields with correlations <0.6), especially for the Peplinski model. Such low correlations are not obtained in the three test fields in Fig. 7, despite the presence of step-like patterns in the \( m_v \) time series of field 330: the soil moisture on June 9, 13, and 15 is considerably higher than on the remaining days.
Figure 3: Distributions (bar: median, error bars: first and third quartile) of achieved correlations between in-situ measured and inverted soil moisture

Figure 4: Inverted soil moisture [m³ m⁻³] based on the linearized model for $\phi_{HH}$ before (left, June 6) and after (middle, June 9) a rain event. The right panel gives the coherence $|\gamma_{HH}|$ between the first (June 5) and last (June 15) image.

Figure 5: Same as Fig. 2 but based on $\phi_{HV}$. 
5. DISCUSSION

5.1. Observables

5.1.1. Phase

The phase is found the be the most robust of the inversion methods, as evidenced by the lack of outlier fields with $\rho < 0.5$.

As displacements affect the phase, one is faced with the task of separating these two effects, each of which might be deemed confounding depending on the application. Approaching this task from the point of view of accountability, one notices that for $N$ SLC images, there are $\binom{N}{2}$ phases, from which one would like to estimate $N - 1$ displacements and $N - 1$ changes of $m_v$. For sufficiently large $N$, this will be possible if the $m_v$ changes affect the phases in a way that differs from the impact of the displacements. The latter do so in a linear way (the phase triplets $\Xi$ are zero); this is not the case for the soil moisture, but the success of the linear model $L$ at $m_v$ inversion demonstrates that the influence of $m_v$ is predominantly linear as well [13, 19, 20]. This dominance of the linear component in the soil moisture signal renders the separation from deformations difficult by comparison.

5.1.2. Phase triplets

The non-linear component of the phase is captured in the phase triplets $\Xi$. As they are not affected by deformations (or other phase offsets such as atmospheric influences or topography [5]), they would be ideally suited to estimating soil moisture as the impact of displacements would be
automatically controlled for, and the soil moisture signal could potentially be removed to estimate deformations.

The phase triplet observable contains less information than the phase, which might be related to the spurious patterns that is observed in the estimated time series of field 350 in Fig. 7, and lead to correlations \( \rho < 0.5 \) in several fields (see Fig. 3).

Overall, these results suggest that both objectives (estimation of \( m_v \), separation from displacements) can potentially be achieved with the \( \Xi \) observable, but that this will be exceedingly difficult unless additional influences (decoration, vegetation, etc.) are kept sufficiently small and adequate prior knowledge (e.g. from models) is available.

5.1.3. Coherence

The estimation of \( m_v \) from the coherence is feasible if the decorrelation is dominated by soil moisture effects, which appears to be the case for the monitored fields in the campaign (see Fig. 3). There are other fields visible in Fig. 4 that decorrelate either completely (in which case no observable will be reliable) or only partially. Such partial temporal decorrelation might be due to noise, the vegetation or the surface structure [18]. The widespread occurrence in less well-controlled situations (presence of vegetation, longer time gaps) [2] raises the question whether the coherence observable is well-suited to \( m_v \) estimation in most data sets.

5.2. Methods and parameterizations

The model-based inversion using all these observables is dependent on the parameterization of this model, such as the mixing model. This observation is consistent with the notion that differences in the absorptive properties of a soil (governed by the mixing model) exert a strong impact on the non-linearities of the phase and thus the phase triplets [20].

The linear part of the soil moisture dependence of \( \phi \) can be represented by the linearized model \( L \), whose inversion results, i.e. the correlations but also the temporal patterns and the magnitude, are similar to those of the non-linear models. In the data analysed in this study, the linear contribution dominates [19]. Pronounced non-linearities for changes in moisture \( \Delta m_v \) exceeding 0.15 m\(^3\)/m\(^{-3}\) are predicted for the for the Hallikainen mixing model according to Fig. 1b, whereas these non-linearities are expected to be more striking at smaller \( \Delta m_v \) for the Peplinski model. For such larger dynamic ranges of \( m_v \), it is thus expected that the linearized model will be less suitable and that the impact of the mixing model will become larger.

Besides the mixing model, the volume-to-surface scattering ratio \( f \) governs the predictions of the observables. Its impact on the correlations between inverted and prescribed \( m_v \) was generally less than 5 pp. This is consistent with the observation by [19] that in a first-order approximation, the impact of \( f \) and the observables (and also on the estimated \( m_v \)) is an overall scaling, which does not affect the correlations. The quality of this approximation is also expected to decrease as the dynamic range of the soil moisture becomes larger [19]. In these cases, it might be necessary to estimate \( f \) rather than prescribing it.

When the volume-to-surface scattering ratio \( f \) is fixed in the inversion, different surface roughnesses and sub-soil dielectric heterogeneities in the real-world will correspond to different dynamic ranges in the estimated soil moisture. The latter is thus only a relative measure. However, the observed similarity of the interferometric data between the fields could be (according to the forward model) due to comparable values of \( f \) and soil moisture dynamic ranges, or with different calibrations of the in-situ probes.

The areal comparison of Fig. 4 indicates that there are inter-field variations in the interferometric observables, which translate to differences in the estimated \( m_v \). According to the previous analysis, it is not possible to associate these differences with actual spatial soil moisture patterns, as they could also be caused by different roughnesses.

5.3. Polarimetric diversity

The inversion for all three observables yields results that do not show a conspicuous difference between those obtained with HH and those obtained with VV: the difference in median correlations is much smaller than either interquartile range. For the phase \( \phi \), the linearized HV results are also comparable to the ones at HH and VV. The model is known not to work in the HV polarization [20], but the HV data tend to compare favorably to the predictions at HH and VV. This similarity has now been shown to also extend to the inversion of soil moisture from the phase.

6. CONCLUSIONS

The feasibility of estimating soil moisture from three interferometric observables (phase \( \phi \), coherence \( |\gamma| \), and phase triplet \( \Xi \)) was studied using measured L-band data. The estimation was based on an electromagnetic scattering model. By computing the observables from all possible combinations (i.e. by forming all interferograms), one can estimate the entire soil moisture time series. For the 10 fields where in-situ measurements are available,
one obtains median correlations between these measurements and the inverted soil moisture of 0.8-0.85. These results were seen to be most robust for the phase, whereas both the coherence and the phase triplets are increasingly prone to gross errors as the noise level or model deviations (vegetation, decorrelation) increase. These errors are linked to deficiencies that are intrinsic to the respective observable, and thus expected to also occur in different data sets or when different models are applied.

Both these observables are unaffected by piston-like deformations – they can thus potentially be used to estimate soil moisture in the presence of deformations and thus separate these two influences on the observed signals. The phase, on the other hand, does not suffer from the mentioned lack of robustness to e.g. noise. However, as soil moisture changes and deformations were shown to impact this observable in a similar way, the phase is less suitable for estimating both soil moisture changes and displacements simultaneously.

Such combined retrieval thus poses a challenge for which additional data might be helpful in constraining the estimates. Possible examples include the incorporation of different techniques and observables to derive soil moisture, or restricting the deformations to certain temporal scales. In the absence of such deformations, differential interferometry turns out to be a promising technique for estimating soil moisture at the field scale.

REFERENCES


