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VARIATIONAL DATA ASSIMILATION OF SOIL MOISTURE USING 6 AND 10 GHZ PASSIVE MICROWAVE DATA

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1. INTRODUCTION

An observational operator and its adjoint has been created that is suitable for use within variational data assimilation using new 6 and 10 GHz passive microwave satellite observations. The new operator will allow soil moisture initialization to be performed using current and future satellite data sets (e.g., NASA AMSR, DoD WindSat, and the NPOESS CMIS). Five primary control variables are used within the operator, and explicitly includes surface soil moisture as one of the control variables. This operator and its adjoint will be used to perform Land Surface Model (LSM) data assimilation experiments to better determine important NWP surface characteristics. The operator is being incorporated into a 4DVAR system at CSU/CIRA. Current observational operator results and numerical simulations are presented.

2. MWLSM Observational Operator

The observational operator is based on the microwave land surface model (MWLSM) used in the NASA AMSR land surface algorithms (Njoku 1999; Njoku and Li, 1999). The model was initially created and validated using SMMR data and is currently under going extensive calibration and validation in several AMSR-related field experiments (NASA 2000; SMEX02 2002). Some extensions are made for improved calibration and experimental use within the 4DVAR data assimilation context. In particular, the land surface temperatures are decomposed into soil surface and vegetation canopy temperatures, and a frequency-dependent vegetation parameterization is used. A thorough perturbation scale-factor analysis of the observational operator was performed. This facilitated the numerical adjoint tests of the observational operator, since it uses a mix of complex and real number spaces. Those analysis details have been omitted from this paper.

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3. ADJOINT SENSITIVITY STUDIES

Of particular importance to the soil moisture retrieval problem, is the need for an understanding of which state variables are driving the particular solution. We hope to demonstrate the utility of the constructed adjoint and the variational approach for answering this question.

A traditional univariant sensitivity analysis is performed to create a reference frame for the reader. The univariant sensitivity analysis is performed with respect to a single variable, soil moisture. In Figure 1 results are presented from a) the forward model at the base state as a function of soil moisture, and b) the corresponding univariant soil moisture responses using nominal first guess errors. The results are as expected,

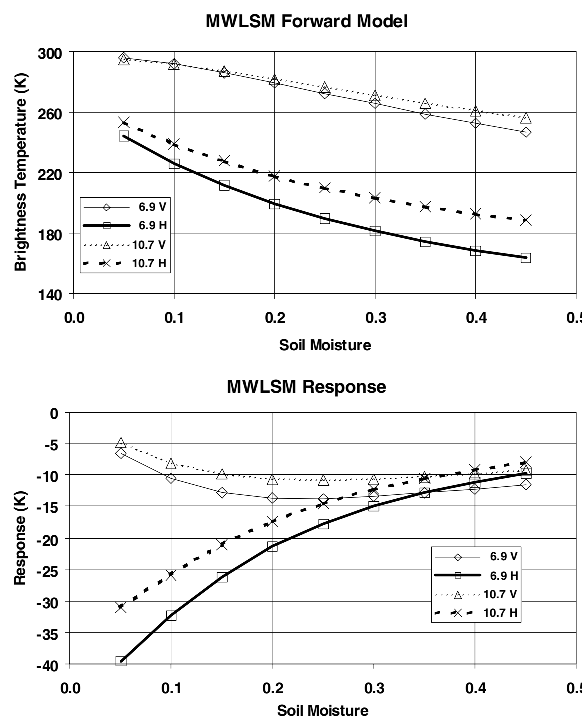

Figure 1. Univariate MWLSM a) forward model results, and b) responses with respect to nominal perturbations in the soil moisture control variable for base state conditions. The soil moisture variable is the only variable that is adjusted.

with the brightness temperatures decreasing with increasing soil moisture values (Figure 1a). The vertical polarization brightness temperatures are greater than the horizontal polarization values due to Fresnel reflection behaviors at the surface dielectric discontinuity. The 6.9 GHz results show lower brightness temperatures than at 10.7 GHz. This is due to the larger dielectric constant of water at lower frequencies. Imbedded within Figure 1 are also the vegetation and microwave surface roughness effects appropriate for conditions at the nominal base state. The MWLSM response as a function of soil moisture (Figure 1b) is simply the derivative of the brightness temperature results (Figure 1a) with respect to the soil moisture variable. These results more visibly demonstrate the relative strength of the soil moisture signal for each sensor channel.

Multivariate sensitivities are performed by adjusting the state vector across a wide range of conditions simultaneously. Many permutations of control variable combinations are now straightforward to analyze with the constructed observational operator. For the multivariate analysis example, a multidimensional state vector is used that incrementally progresses between the values ($\eta = 0.05$, $W_C = 0.0$ kg m^{-2}, $h = 0.0$, $T_{eff} = 273$ K, $T_C = 273$ K) and ($\eta = 0.45$, $W_C = 1.5$ kg m^{-2}, $h = 1.0$, $T_{eff} = 320$ K, $T_C = 320$ K) at uniformly spaced intervals (Figure 3), where η is the volumetric soil moisture, W_C is the vegetation canopy water content, h is the microwave surface roughness parameter, T_{eff} is the effective bare-soil temperature, and T_C is the vegetation canopy temperature. This multidimensional vector is simply a positive bias from the minimum state vector values along a multidimensional diagonal toward the maximum state vector values. This is one example out of numerous other possible multidimensional state traversals. This example was selected to demonstrate a broad range of conditions. It does not represent an expectation of system performance in the real world since the climatological probability distribution of the multidimensional state vector is poorly known at this time.

The forward model and its associated response (Figure 3) are calculated in the same manner as the univariate results (Figure 1). Since the abscissa is traversing a diagonal along the entire input range for all control variables and just projected onto the soil moisture variable dimension, the multivariate results are markedly different from the univariate results. Most notable is the increase of brightness temperature with increasing soil moisture. As will be shown, this is due to a complex interaction of various physical phenomena, but certainly most obvious would be the effect of increasing the effective soil temperature and vegetation canopy temperature as soil moisture is increased. It can also be seen that the horizontal polarization frequency differences can increase with increasing abscissa values, and then reverse behavior as the soil moisture signal weakens at wet soil conditions.

Similar to the previous univariate analysis (Figure 1b), the multivariate MWLSM response is of most interest in the context of the optimal estimation problem. Results (Figure 3b) show a complex interaction between radiometric channels. At dry soil conditions ($\eta = 0.05$) the response is similar to previous results at ($\eta = 0.05$) (Figure 1b), however, the response at horizontal polarization is slightly reduced due to enhanced vegetation water content effects for sparse vegetation conditions (this will be explicitly shown in the following analysis). Generally, however, the multivariate responses exhibit crossover conditions where the response switches from negative to positive. This introduces "balanced" conditions where the model produces no response due to the initial guess perturbation. This is due to counter-acting model variables. For example, the soil moisture and vegetation water content variables tend to act in an opposite manner. With increasing soil moisture, brightness temperatures decrease, while with increasing vegetation water content brightness temperatures increase. This is the nature of the physics of the system. This creates opposing or competing responses within the MWLSM system. In fact, each radiometric channel exhibits a cross-over condition for the particular multidimensional model state vector. This is certainly not always the case, but serves to elucidate the utility of the adjoint sensitivity analysis that follows.

One of the characteristics of the adjoint operator is its ability to transform the analysis space from radiometric space to model vector space. This is demonstrated by the relative component strengths shown in Figure 2. The relative component strength is given by

$$RCS = \frac{\left\langle \mathbf{L}^{\mathbf{T}}\mathbf{L}\,\mathbf{x}',\mathbf{x}' \right\rangle_i}{\left\langle \mathbf{L}^{\mathbf{T}}\mathbf{L}\,\mathbf{x}',\mathbf{x}' \right\rangle}, \tag{1}$$

where < >i denotes the inner product component of the ith model vector element (e.g., the i = 1 component would correspond to the soil moisture variable, where **L** is the model perturbation operator, and **x′** is the model state perturbation vector. This is then normalized to the full inner product. Thus, the relative magnitude of the model vector element to the other model vector elements can be calculated. It should be pointed out that a full adjoint sensitivity analysis would have to also include the background error covariance interactions as well as model and observation error covariances. Therefore, the results presented are a necessarily simplified form of a more complete analysis. Such future work is planned. However, the relative component strength results (Figure 2) are very useful. The *RCS* of the soil moisture variable is the largest system signal, with large positive contributions for dry soil conditions, and smaller, yet sizable, negative contributions at more moist soil moisture conditions. The remaining control variables act as masking phenomena and oppose the *RCS* of the soil moisture variable. Only for a small interval between

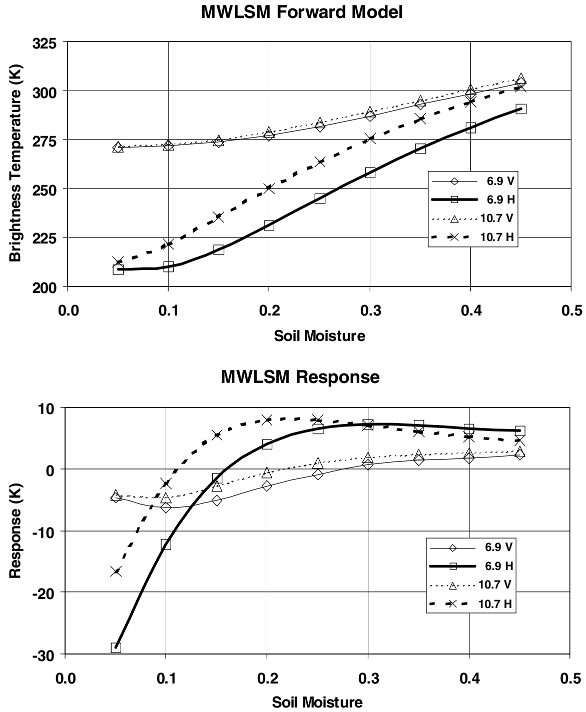

Figure 3. Multivariate MWLSM a) forward model results, and b) responses with respect to nominal perturbations in all control variables and presented as a projection onto the soil moisture dimension. All control variables are simultaneously adjusted through their entire variable range. Thus, the abscissa represents a multidimensional state vector incrementally progressing between the values (η = 0.05, W_C = 0.0 kg m-2, h = 0.0, T_{eff} = 273 K, T_C = 273 K) and (η = 0.45, W_C = 1.5 kg m-2, h = 1.0, T_{eff} = 320 K, T_C = 320 K) at uniformly spaced intervals.

$0.13 < \eta < 0.18$ do any of the other control variables assist the *RCS* of the soil moisture variable.

For this particular multidimensional vector traversal, the primary masking variables are vegetation water content and the microwave surface roughness parameter. However, the remaining control variables show *RCS* > 20 % at some point along the model state traversal, so their effects are not negligible for these conditions. This also supports the control variable selection, in that if a control variable were negligible it would exhibit small *RCS* values. Perhaps the most powerful aspect of such an analysis is that the discussion of model impacts are now moved from discussions in terms of radiometric vector space to the model vector space. It is much more natural to speak of quantities as related to the physical model phenomena than in radiometric space where cause and effect are much more difficult to assign. The adjoint sensitivity analysis is a quick and efficient approach and thus lends itself more easily to the optimal estimation problem.

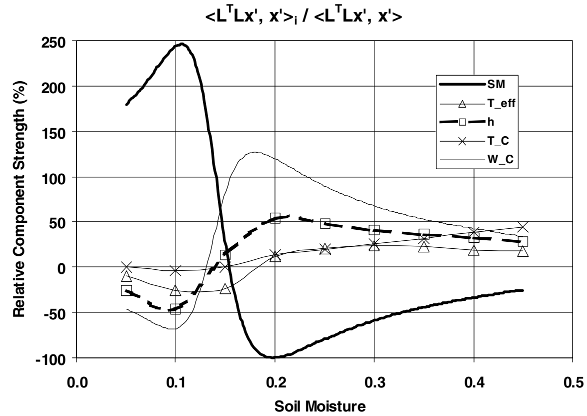

Figure 2. Same as Figure 3, except that results are for the relative component strength of the MWLSM operator due to a nominal perturbation of all control variables as computed using the adjoint operator.

4. CONCLUSIONS

The MWLSM observational operator is an extension of the AMSR land surface forward model made to be more suitable for NWP land surface model data assimilation use. Thru various perturbation studies and numerical tests, a valid MWLSM adjoint was constructed and numerically tested. This work demonstrates the use of the relative component strength as a measure of multidimensional influence on the minimization direction as diagnosed via the adjoint operator, $\mathbf{L}^T$.

It is also shown that certain masking conditions can obscure the soil moisture signal. The variational approach explicitly identifies the physical conditions in which the counter-acting phenomena are present and can predetermine the influence of such conditions using a straightforward multidimensional analysis. This capability is exploited within variational optimization methods.

Future work will employ the MWLSM OO within the CIRA RAMDAS 4DVAR system for experiments using observational data sets. Upon practical application to a bio-physical system (e.g., corn) the implicit temporal filtering of slowly changing control variables within a 4D data assimilation system should allow for an optimal estimate for some of the more elusive control variable quantities (e.g., *h*, W_C) in addition to the primary target variable, soil moisture. This will be the endeavor of future research activities.

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