An NPOESS Feasibility Study to Retrieve Deep Soil Moisture using WindSat Data and a Temporal Variational Satellite Data Assimilation Method

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INTRODUCTION

We have developed a four–dimensional coupled atmospheric/land data assimilation system using the Regional Atmospheric Mesoscale Data Assimilation System (RAMDAS) to retrieve deep soil moisture profiles. Passive microwave data from CORIOLIS WindSat is used as a surrogate for future National Polar-orbiting Operational Environmental Satellite System (NPOESS) microwave sensors.

Current efforts are focused on the use of the system for a case study occurring in September 2003. New adjoint sensitivity results using this system are presented, and implications for deep soil moisture retrievals using 4D variational (4DVAR) data assimilation systems are discussed. Using a variety of observational radiative transfer studies and spatial correlation analysis methods, we've also determined the statistical behaviors of the soil moisture field and microwave radiative transfer model performance that are necessary for performing the 4DVAR soil moisture data assimilation experiments. We conclude that additional radiative transfer model debiasing will be beneficial; however, polarization ratio results show a strong temporal soil moisture signal from the observational WindSat data sets that are able to be propagated by the adjoint sensitivities to soil depths greater than 1 m. Therefore deep soil moisture retrievals are shown to be feasible. We expect that advanced microwave emissivity analysis studies would provide more realistic constraints on behaviors of the surface microwave radiative transfer model parameters.

APPLICATIONS

This work contributes to several areas of interest:

1. More accurate probability estimates of mobility and trafficability
2. Improved hydrologic forecasting capabilities
3. Improved NWP land surface initialization
4. Better understanding of atmospheric/land interactions
5. More accurate agricultural assessments

4DDA DEEP SOIL MOISTURE ESTIMATES

Direct remote sensing: Only Surface Soil Moisture
4DDA methods: Soil Moisture Profiles (up to 1m depths)

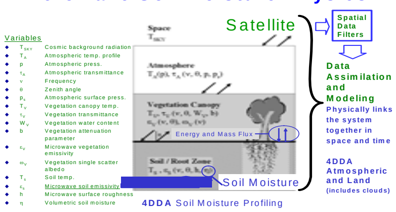
What makes this possible?
1. Diurnal soil moisture signal in land/atmos. physics
2. Use of temporal nature of the satellite data sets
3. Availability of good land surface models that can characterize the diurnal effects as a function of soil moisture

How long does it take to get results using the 4DDA method? Our results indicate that 7-14 days of integration time is necessary to reach 1 m soil depths, however shallower depths are reached in ~3 days of integration time or less. Some aspects of the 4DDA method is more immediate (for example, near the surface, new data impacts would be nearly immediate).

How is the WindSat data used? WindSat is sensitive to surface soil moisture variations. By matching those variations to the atmospheric/land surface model system, the soil moisture information in deeper levels can be inferred through its impact on the diurnal land/atmos. physics.

SOIL MOISTURE PHYSICS

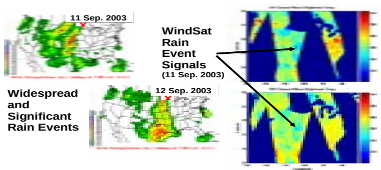
Microwave Soil Moisture Physics



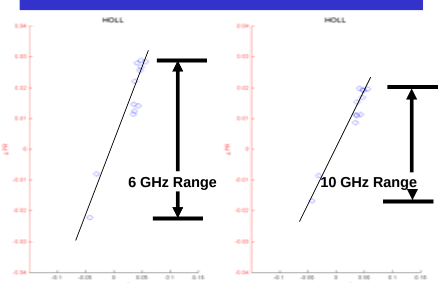
4DDA SOIL MOISTURE EXPERIMENT

Our case study is selected for the month of September 2003. This month had good WindSat data coverage, availability of in situ soil moisture data sets, and wide-spread rain events which were easily observed by WindSat.

Main Rain Event on Sep. 11-12 2003



6 GHz vs. 10 GHz



Frequency Polarization Ratio Perturbations (ΔPR) vs. AGRMET Soil Moisture Perturbations (Δm_v): (left) 6 GHz, (right) 10 GHz.

WindSat observational results show that the 6 GHz channels are approximately 30% more sensitive to soil moisture than the 10 GHz channels.

This result was obtained by comparing temporal perturbations of the normalized polarization ratios (PR) to AGRMET model soil moisture values for the HOLL site location (one of the RFI-free sites in OK). The AGRMET soil moisture temporal perturbation range for HOLL was ~10% in absolute SM units, or ~25% of the expected dynamic soil moisture range for the site. Larger rainfall events may have different frequency-dependent soil moisture responses due to soil saturation and surface flooding effects, etc.

WHAT ARE DEEP SOIL MOISTURE ADJOINT SENSITIVITIES?

Adjoints are used within variational data assimilation techniques to determine how to best adjust the model initial conditions to accommodate the observational sensor data information. Quantitatively a "cost function", *J*, is used to measure the distance that the model state is from the observational data. The adjoints are used to compute the gradients of the cost function. The gradient of the cost function is used to find the cost function minimum, so that the probability of the model state is maximized with respect to the observational data. Restated this is the most-likely model state given the data, and is our retrieval objective.

In time-dependent variational techniques such as 4DVAR, the cost function can be determined as a function of the temporally-integrated adjoint sensitivities. In our case, the control variables are the soil moisture at various soil depths. The adjoint sensitivities are computed with respect to these control variables. $\mathbf{L}$ $(t, t_0)^T$, where $\mathbf{L}$ is the tangent linear operator of the forward model, $\mathbf{M}$ (see Eq. (3)). This information is combined with the model background and observational error covariance fields ($\mathbf{B}$ and $\mathbf{R}$, respectively) and the observational operator, $\mathbf{H}$, to determine the cost function gradient with respect to the model state initial conditions, $\mathbf{x}$ (t_0). The model background error covariance is estimated relative to "truth", as are the observational error covariance fields which are estimated instrument noise errors relative to "truth". The observational operator, $\mathbf{H}$, transforms the model state information into the observational state (e.g., soil moisture and surface temperature model state information are transformed into passive microwave brightness temperatures).

The cost function gradient (Eq. 1) is the key factor which determines the new initial model state estimate. Thus, significant sensitivity within the adjoint integration demonstrates deep soil moisture retrieval feasibility given sufficient observational signal strength from the data (which WindSat already has already demonstrated for the surface soil moisture layers). For example, if the data indicate the model is off by amount "a" at time t_1, out of *N* data points, how much does the cost function (through its adjoint integration) indicate that the initial model conditions need to be adjusted to match this condition? It is interesting to note that the adjoints are integrated backwards in time. This is because we are interested in the propagation of data analysis increments, $[H(\mathbf{x}_i) - \mathbf{y}_i]$ back to the initial model time, t_0.

$$\frac{\partial J}{\partial \mathbf{x}(t_0)} = \mathbf{B}^{-1}[\mathbf{x}(t_0) - \mathbf{x}_b(t_0)] + \sum_{i=0}^{N} \mathbf{L}(t_i, t_0)^T \mathbf{H}_i^T \mathbf{R}_i^{-1}[H(\mathbf{x}_i) - \mathbf{y}_i] \quad (1)$$

$$\mathbf{H}_i = \frac{\partial H}{\partial \mathbf{x}_i} \quad (2)$$

$$\mathbf{L}_i = \frac{\partial M}{\partial \mathbf{x}_i} \quad (3)$$

$$\mathbf{x}(t_0) \quad (4)$$

ADJOINT SENSITIVITY RESULTS

The single-observation adjoint sensitivities, $\mathbf{L}^T$, are shown in Fig. 1. For this 21-day experiment, 13 additional WindSat data observations were available for multitemporal analysis. Thus, the single-observation results are conservative indicators of the ability of WindSat to detect deep soil moisture, as the additional data points would increase the deep soil moisture signal strength through repeated views of the scene. Here we show the single observation adjoint results as they are simpler to interpret and discuss. The adjoints are integrated backwards in time from day 21 to the initial condition time, $t = 0$. The results are normalized adjoint sensitivities, determined by dividing the temporal adjoint sensitivity result by the largest soil layer sensitivity. This means that at any one time, one soil layer will have 100% relative adjoint sensitivity strength relative to the other soil layers. What is most important about these results is which layer is the most sensitive. As we follow the backwards integration, the leadership of the adjoint sensitivity strength changes from the top soil layer to the deepest soil layer (1.2 m – 0.6 m) (see Fig. 1). This transition occurs within a period of 7-14 days. By the initial conditions, the bottom three layers at 1.2 m, 0.6 m, and 0.3 m, contribute 100%, 65%, and 35% of the signal strength respectively. The surface layers all contribute less than 20% at the model initial time. This means that surface information from earlier time periods are much more important to the determination of the deep soil moisture values, as expected.

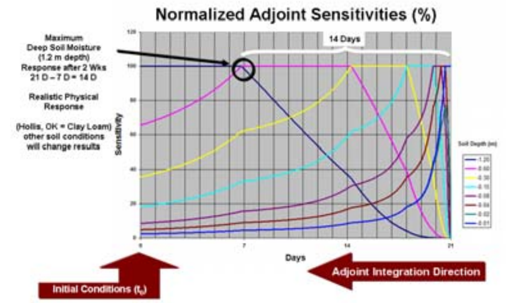


Figure 1: Normalized adjoint sensitivity results for Hollis, OK for the Sep. 2003 case study. Deep soil moisture at a depth of approximately 1 m has the largest sensitivity in the integration time period of 0-7 days. This indicates the strong deep soil moisture sensitivity as a function of soil depth with time.

CONCLUSIONS

Our conclusions are:

1) Deep soil moisture retrievals using temporal variational techniques are feasible given the very strong adjoint sensitivity results from the 21-day integration experiments using the off-line LSM adjoint 4DVAR system components.

2) The adjoint soil moisture sensitivity to the initial soil moisture conditions show a variety of time scales according to soil depth and as a function of soil type.

3) The RAMDAS 4DVAR data assimilation results were successful at creating the components necessary for full 4DVAR WindSat data assimilation capabilities for deep soil moisture retrievals. A full 21-day adjoint integration study was successfully performed for a single point observation to determine depth profile feasibility issues. Results from those experiments were very positive. Therefore, we can state that WindSat and future NPOESS surface soil moisture retrievals can be extended to lower depths using this technique.

4) We recommend that future data assimilation work focus on 14-21 day experiments using a computationally efficient 2DVAR method for operational use. Future 4DVAR integration studies using operational 4DVAR systems under development would also consume the 2DVAR components. The 2DVAR method would also be more flexible, also allowing for use in a decentralized computational environment.

5) Observational MWLSM parameter sensitivity studies and radiometric bias estimation indicate that the model bias is 5-8 K, which is higher than the instrument noise. Thus microwave radiative transfer model improvements are needed. This should be done by observationally retrieving microwave surface emissivities to improve the various model parameterizations. In particular, the optimized value of the microwave roughness parameter appears to be higher than expected. We believe this may be due to the use of untuned model results in the current analysis. If the model bias offsets were computed and used in the analysis, the model parameter values would exhibit reduced error variances.

ACKNOWLEDGEMENTS

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