AN INVERSE TECHNIQUE FOR ASSIMILATING/ADJUSTING SOIL MOISTURE IN THE MM5

Kiran Alapaty[1]*, Devdutta Niyogi[2], and Madhavi Alapaty[3]

[1]*MCNC–Environmental Programs, Research Triangle Park, North Carolina*
[2]*North Carolina State University, Raleigh, North Carolina*
[3]*M.A.S.C., Apex, North Carolina*

1. INTRODUCTION

In recent years, much attention has been given to improving ABL predictions by addressing the surface boundary conditions used in atmospheric models. For a given synoptic condition, the ABL structure and evolution are controlled mostly by the entrainment fluxes at the top of the ABL and by surface fluxes, especially the latter. Thus, multilevel soil models, some with vegetative canopy submodels (e.g., Noilhan and Planton, 1989), have become more common and have been coupled with rainfall estimates to provide case-specific soil-moisture profiles (e.g., Chen et al. 1996, 1997; Chen and Dudhia, 2001). However, this approach relies heavily on the accuracy of the land-surface models and rain estimates, which are often taken from prior forecast-model runs. Mahfouf (1991) and Bouttier et al. (1993) used the evolving surface-layer temperature and humidity to estimate the soil moisture in numerical model predictions. McNider et al. (1994) took a similar approach, but assimilated satellite-observed surface skin temperature tendencies to estimate soil moisture. In these techniques, the largest errors are present in the simulated surface-energy budget and are due to errors in the soil moisture parameter.

Alapaty et al. (2001a,b) developed a new technique that allows continuous assimilation of surface observations to improve surface-layer predictions. In this technique, they first directly assimilated surface-layer temperature and water vapor mixing ratio by using the analyzed surface data. Then they used the difference between the observations and model predictions to calculate adjustments to the surface fluxes of sensible and latent heat. These adjustments were used to calculate a new estimate of the ground temperature, thereby affecting the predicted surface fluxes in the subsequent time step. Here, we extend that work further by assimilating/adjusting the soil moisture availability using an inverse technique. This indirect data assimilation/adjustment of soil moisture and temperature is applied simultaneously with the direct assimilation of surface data in the model's lowest layer, thereby maintaining greater consistency between the soil temperature and moisture, and the surface layer mass-field variables.

The objectives of our research are to develop and evaluate an inverse technique for adjusting soil moisture such that it (1) helps reduce errors in the surface layer simulation, and (2) varies noticeably only at weekly to monthly time scales. Note that the latter objective is of interest to many modelers because that type of observed temporal variability is missing in many meteorological models. We first present descriptions of how each of three land surface models (LSMs) are modified using our inverse technique, followed by some preliminary results obtained using the mesoscale model MM5V3.4. Our ultimate goal is to perform a seasonal simulation to study the ability of this technique to replicate seasonal variability in the soil moisture that exists during a drought or a moist period.

2. DESCRIPTION OF INVERSE TECHNIQUE

First, we start with the work of Alapaty et al. (2001a,b) and Stauffer et al. (1991). From their work, the surface data assimilation (SDA) equation for a surface variable, α (e.g., temperature, T_L, of a model's lowest layer close to the surface) can be written as:

$$\frac{\partial p^*\alpha}{\partial t} = F(\alpha, x, y, t) + G_\alpha W_\alpha \varepsilon_\alpha p^*(\hat{\alpha} - \alpha) \qquad (1)$$

where p^* is the difference between base state pressures at the surface and model top; t is time; F is a forcing term representing all physical processes affecting α in the model; x and y are the horizontal spatial coordinates; $G_\alpha = 9.0 \times 10^{-4}\ s^{-1}$ is nudging factor for α; W_α is a weighting function that determines the horizontal, vertical, and time weighting applied to the analysis; ε_α is an analysis quality factor ranging between 0 and 1; and $\hat{\alpha}$ is the analyzed (gridded) value obtained from observations for α. When the last term in Eq. (1) was rewritten for the air temperature of the model's lowest layer as $\partial T_L^F / \partial t$, the change in the surface-layer temperature in the time interval Δt due to the direct nudging was used to compute the nudging adjustment to the turbulent sensible heat flux, H_S^F (Wm^{-2}), and it was written as

$$H_S^F = \rho C_p (\partial T_L^F / \partial t \bullet \Delta t)\frac{\Delta z}{\Delta t} = \rho C_p (\partial T_L^F / \partial t)\Delta z$$

***Corresponding author address:** *Dr. Kiran Alapaty, MCNC–Environmental Programs, P.O. Box 12889, 3021 Cornwallis Road, RTP, NC 27709-2889. E-mail: alapaty@ncsc.org; phone: 919-248-9253; fax: 919-248-9245.*

where ρ is near-surface air density, and C_p is specific heat of air at constant pressure. Similarly, if $\partial q_L^F / \partial t$ is the rate of change of the surface-layer water vapor mixing ratio due to direct nudging, then the adjustment to the turbulent latent heat flux, H_l^F (Wm^{-2}), was written as

$$H_l^F = \rho L(\partial q_L^F / \partial t \bullet \Delta t)\frac{\Delta z}{\Delta t} = \rho L(\partial q_L^F / \partial t)\Delta z$$

where L is the latent heat due to condensation. Thus, the adjustment to the ground/skin temperature due to indirect assimilation of surface-layer temperature and moisture data over the interval Δt, ΔT_g^F, was written in the form of the surface energy budget equation as

$$\Delta T_g^F = (\frac{\partial T_g^F}{\partial t})\Delta t = (H_S^F - H_l^F)\frac{\Delta t}{C_g}$$

where C_g is the thermal capacity of the uppermost soil slab per unit area.

We now discuss the main focus of the current work, the assimilation/adjustment of soil moisture using an inverse technique, for each of three LSMs: (1) the Carlson and Boland scheme; (2) the Noilhan and Planton scheme; and (3) the Chen and Dudhia scheme. The first LSM is a simple scheme that has been used over a decade by many users. The second and third LSMs are more sophisticated, dealing in detail with many soil and vegetation parameters.

Carlson and Boland Scheme: The surface kinematic latent heat flux estimated using the formulation by Carlson and Boland (1978) in the MM5 is written as

$$H_\ell = \frac{M_a k u_* \left(q_{vs}(T_g) - q_{va}\right)}{\ell n\left(\frac{k u_* z_a}{K_a} + \frac{z_a}{z_\ell}\right) - \Phi_h} \qquad (2)$$

where M_a is the soil moisture availability, k the von Karman constant, u_* the friction velocity, q_{vs} the saturated water vapor mixing ratio at temperature T_g, q_{va} the water vapor mixing ratio of air in the lowest layer of the model, z_a the altitude of the lowest model level, K_a the background molecular diffusivity, z_ℓ the depth of the molecular layer, and Φ_h the nondimen–sional stability parameter for heat. In the Carlson and Boland formulation, M_a is generally specified as a constant during a season, and is a function of land use. Since we already estimated the nonphysical latent heat fluxes that arise due to surface data assimilation (H_ℓ^F), we adopt an inverse methodology using Eq. (2) to estimate nonphysical soil moisture availability due to surface data assimilation. It can be written as

$$M_a^F = \frac{H_\ell^F \left\{\ell n\left(\frac{k u_* z_a}{K_a} + \frac{z_a}{z_\ell}\right) - \Phi_h\right\}}{k u_* \left(q_{vs}(T_g) - q_{va}\right)}$$

Then, the updated soil moisture availability ($\hat{M}_a$) can be written as

$$\hat{M}_a = M_a + M_a^F \qquad (3)$$

An equation for assimilation of soil moisture availability analogous to Eq. (1) can be written as:

$$\frac{\partial M_a}{\partial t} = F(\vec{R}, t) + G_{Ma}(\hat{M}_a - M_a) \qquad (4)$$

In the above equation, the first term on the right side, ($\vec{R}$), represents variations in soil moisture availability due to rainfall rate, runoff, vegetation interception, and soil characteristics; its estimation will be addressed in a future paper. Substituting Eq. (3) into Eq. (4), we get

$$\frac{\partial M_a}{\partial t} = F(\vec{R}, t) + G_{Ma} M_a^F \qquad (5)$$

The nudging coefficient, G_{Ma}, is taken to be 1.286 x 10^{-7}, the reciprocal of the number of seconds in a 90-day period. This small value ensures that the diurnal variation in M_a is insignificant. It also implies that in the presence of a persistent error, it will take at least 90 days for M_a to converge into $\hat{M}_a$. Note that we restricted the range of variability in M_a^F such that

$$M_a^F \in \{-M_a, +M_a\}$$

allowing an adjustment of –100% to +100% in the soil moisture availability in a long-term time frame. The forward time integration method is used to solve the prediction equation (5) for every advection time step. Since the magnitude of the forcing term on the right-hand side of Eq. (5) is very small, our numerical solver is absolutely stable even for a large advection time step (appropriate for mesoscale modeling).

Noilhan and Planton Scheme: The second LSM is a more detailed formulation to estimate surface latent heat fluxes suggested by Noilhan and Planton (1989). This formulation uses prognostic equations for the soil moisture of the two soil layers and a prognostic equation for canopy storage. The total kinematic latent heat flux (H_ℓ) into the atmosphere's surface layer is the sum of bare-ground evaporation, transpiration from plant canopies, and evaporation from wet parts of the canopy (due to dew formation and/or rainfall interception). This can be written as

$$H_\ell = (E_g + E_{tr} + E_r)/\rho_a$$

where E_g , E_{tr} , and E_r are physical fluxes and ρ_a is the air density at the surface. Now we consider three nonphysical evaporation fluxes (similar to the above physical fluxes) denoted E_g^F , E_{tr}^F , and E_r^F . These three fluxes arise due to surface data assimilation of the surface water vapor mixing ratio. To estimate these nonphysical fluxes, we use the already known H_ℓ^F flux due to surface data assimilation. The problem here is to link H_ℓ^F with E_g^F , E_{tr}^F , and E_r^F . A simple solution to this problem is as follows. If E is the total evaporative flux, then

$$E = (E_g + E_{tr} + E_r)$$

Now, H_ℓ^F can be partitioned according to the relative magnitudes of the fluxes E_g , E_{tr} , and E_r . The nonphysical evaporation fluxes arising due to surface data assimilation of water vapor mixing ratio can then be written as

$$E_g^F = \left(\frac{E_g}{E}\right) H_\ell^F \rho_a \; ; \; E_{tr}^F = \left(\frac{E_{tr}}{E}\right) H_\ell^F \rho_a$$

$$E_r^F = \left(\frac{E_r}{E}\right) H_\ell^F \rho_a$$

Finally, introducing the above terms into the original set of equations results in a new set of equations:

$$\frac{\partial W_{g1}}{\partial t} = \frac{C_1}{\rho_w d_1}(P_g - E_g + \underline{E_g^F}) - \frac{C_2}{\tau}(W_{g1} - W_{geq})$$

$$\frac{\partial W_{g2}}{\partial t} = \frac{(P_g - E_g - E_{tr} + \underline{E_g^F} + \underline{E_{tr}^F})}{\rho_w d_2}$$

$$\frac{\partial W_r}{\partial t} = (V_c P_r) - E_r + \underline{E_r^F}$$

This way, all terms interact very smoothly with the soil moisture for layers 1 and 2. Note that the new terms are underlined in the above equations. Descriptions of all terms can be found in Pleim and Xiu (200x) and Alapaty et al. (1997).

Chen and Dudhia Scheme: We now consider the third LSM, which also includes detailed vegetation-atmosphere interactions. This scheme uses prognostic equations for three soil layers along with the canopy storage equation. The total kinematic evaporation flux is given by

$$E = (E_{dir} + E_{t1} + E_{t2} + E_{t3} + E_c)$$

where E_{dir} is direct evaporation flux from the ground surface; E_{t1} , E_{t2} , and E_{t3} are evaporation fluxes via canopy and roots; and E_c is evaporation flux from the precipitation intercepted by the canopy. As we did with the Noilhan and Planton scheme, we introduce nonphysical fluxes similar to these evaporation fluxes using the H_ℓ^F flux arising due to surface data assimilation. These can be rewritten as

$$E_{dir}^F = \left(\frac{E_{dir}}{E}\right) H_\ell^F \; ; \; E_{t1}^F = \left(\frac{E_{t1}}{E}\right) H_\ell^F$$

$$E_{t2}^F = \left(\frac{E_{t2}}{E}\right) H_\ell^F \; ; \; E_{t3}^F = \left(\frac{E_{t3}}{E}\right) H_\ell^F$$

$$E_c^F = \left(\frac{E_c}{E}\right) H_\ell^F$$

The modified prognostic equations that include adjustment terms for volumetric soil moisture of the three soil layers and the equation for the canopy storage can be written as

$$d_{z1}\frac{\partial \Theta_1}{\partial t} = -D\left(\frac{\partial \Theta}{\partial z}\right)_{z1} - K_{z1} + P_d - R - E_{dir} - E_{t1} + \underline{E_{dir}^F} + \underline{E_{t1}^F}$$

$$d_{z2}\frac{\partial \Theta_2}{\partial t} = D\left(\frac{\partial \Theta}{\partial z}\right)_{z1} - D\left(\frac{\partial \Theta}{\partial z}\right)_{z2} + K_{z1} - K_{z2} - E_{t2} + \underline{E_{t2}^F}$$

$$d_{z3}\frac{\partial \Theta_3}{\partial t} = D\left(\frac{\partial \Theta}{\partial z}\right)_{z2} - D\left(\frac{\partial \Theta}{\partial z}\right)_{z3} + K_{z2} - K_{z3} - E_{t3} + \underline{E_{t3}^F}$$

$$\frac{\partial W_c}{\partial t} = \sigma_f P - D - E_c + \underline{E_c^F}$$

Note that the new terms in the above equations are underlined. Descriptions of all terms can be found in Chen and Dudhia (2001).

3. MM5 SIMULATIONS AND RESULTS

First, we tested the Carlson and Boland method and the Noilhan and Planton method in our 1-D model using the FIFE observations; these results are documented in Alapaty et al. (2001c). We then implemented our inverse technique in all three LSMs using the MM5V3.4 for initial testing. For each LSM, two sets of numerical simulations were performed for three days starting from July 10, 1997. In the first set, only the SDA technique was used (no soil moisture adjustment), while in the second set the inverse technique and the SDA technique were used. Note that the objectives of this work are to improve surface layer simulations and to introduce seasonal variation into the soil moisture availability. Because the results presented in this paper are from simulations of just three days, one should anticipate only minor differences between the simulations without and with soil moisture adjustment. After completing evaluation of our preliminary results, we will perform a seasonal simulation. The work described here serves as confirmation that the inverse technique does truly make small adjustments in the soil moisture. Figure 1 shows the temporal variation in spatially averaged soil moisture availability (SMA) obtained using the Carlson and Boland scheme with and without the inverse technique. Without using the inverse technique, SMA stays constant (during an entire season). When the inverse technique is used, spatially averaged SMA, in general, increases over time but only by a small amount. Over certain regions, spatially averaged SMA showed a decrease over time, again by a small amount. In general, the modeled lowest-layer mixing ratio was underpredicted; as a result, more moisture is added by the SDA technique and by the inverse technique to reduce the simulation errors in the surface layer. Other results obtained using the Noilhan and Planton scheme and the Chen and Dudhia scheme are being analyzed and compared with observations.

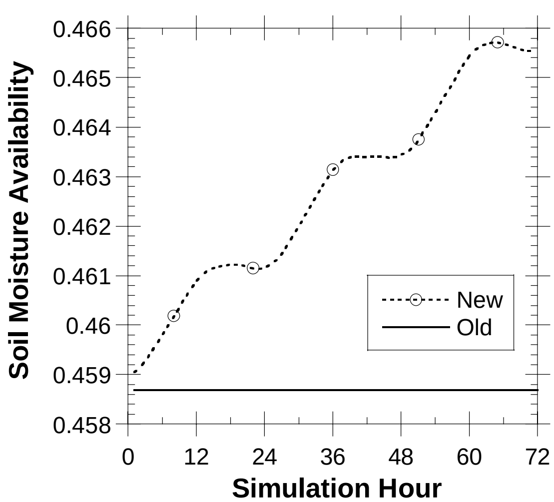

Figure 1. Temporal distribution of domain-averaged soil moisture availability, with the inverse technique ("New") and without it ("Old").

REFERENCES

Alapaty, K., N. Seaman, D. Niyogi, and A. Hanna, 2001a: Assimilating surface data to improve the accuracy of atmospheric boundary layer simulations, *J. Appl. Meteorol.*, in press.

Alapaty, K., N. Seaman, D. S. Niyogi, M. Alapaty, G. Hunter, and D. Stauffer, 2001b: Evaluation of surface data assimilation technique using the MM5. This preprint volume.

Alapaty, K., D.S. Niyogi, and M. Alapaty, 2001c: Adjusting soil temperature and moisture using sur–face observations: Initial results from a single column model. Ninth Conference on Mesoscale Processes, 30 July-2 August, 2001, Ft. Lauderdale, Florida.

Alapaty, K., J.E. Pleim, S. Raman, D.S. Niyogi, and D.W. Byun, 1997: Simulation of atmospheric boundary layer processes using local- and nonlocal-closure schemes. *J. Appl. Meteorol.*, **36**, 214-233.

Bouttier, F., J.-F. Mahfouf and J. Noilhan, 1993: Sequential assimilation of soil moisture from atmospheric low-level parameters. Part I: Sensitivity and calibration studies. *J. Appl. Meteor.*, **32**, 1335-1351.

Carlson, T.N., and F.E. Boland, 1978: Analysis of urban-rural canopy using a surface heat flux/temperature model. *J. Appl. Meteor*., **17**, 998-1013.

Chen, F., and J. Dudhia, 2001: Coupling an advanced land-surface/hydrology model with the Penn State/NCAR MM5 modeling system. Part I: Model implementation and sensitivity. *Mon. Wea. Rev*., **129,** 569-585.

Chen, F., K. Mitchell, J. Schaake, Y. Xue, H.L. Pan, V. Koren, Q.Y. Duan, K. Ek, and A. Betts, 1996: Modeling of land-surface evaporation by four schemes and comparison with FIFE observations. *J. Geophys. Res*., **101**, 7251-7268.

Chen, F., Z. Janjic and K. Mitchell, 1997: Impact of atmospheric surface layer parameterization in the new land-surface scheme of the NCEP mesoscale Eta numerical model. *Bound.-Layer Meteor.*, **85**, 391-421.

Mahfouf, J.F., 1991: Analysis of soil moisture from near-surface parameters: A feasibility study. *J. Appl. Meteor*., **30**, 1534-1547.

McNider, R.T., A.J. Song, D.M. Casey, P.J. Wetzel, W.L. Crosson and R.M. Rabin, 1994: Toward a dynamic-thermodynamic assimilation of satellite surface temperature in numerical atmospheric models. *Mon. Wea. Rev.*, 122, 2784-2803.

Noilhan, J., and S. Planton, 1989: A simple parameter–ization of land surface processes for meteorological models. *Mon. Wea. Rev.*, **117**, 536-549.

Stauffer, D.R., N.L. Seaman, and F.S. Binkowski, 1991: Use of four-dimensional data assimilation in a limited-area mesoscale model. Part II: Effects of data assimilation within the planetary boundary layer. *Mon. Wea. Rev*., **119**, 734-754.

Xiu, A., and J. Pleim, 2001: Development of a land surface model. Part1: Application in a mesoscale meteorological model. *J. Appl. Meteor*., **40**, 192-209.