Development of the Flux-Adjusting Surface Data Assimilation System for Mesoscale Models

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ABSTRACT

The flux-adjusting surface data assimilation system (FASDAS) is developed to provide continuous adjustments for initial soil moisture and temperature and for surface air temperature and water vapor mixing ratio for mesoscale models. In the FASDAS approach, surface air temperature and water vapor mixing ratio are directly assimilated by using the analyzed surface observations. Then, the difference between the analyzed surface observations and model predictions of surface layer temperature and water vapor mixing ratio are converted into respective heat fluxes, referred to as adjustment heat fluxes of sensible and latent heat. These adjustment heat fluxes are then used in the prognostic equations for soil temperature and moisture via indirect assimilation in the form of several new adjustment evaporative fluxes. Thus, simulated surface fluxes for the subsequent model time step are affected such that the predicted surface air temperature and water vapor mixing ratio conform more closely to observations. The simultaneous application of indirect and direct data assimilation maintains greater consistency between the soil temperature–moisture and the surface layer mass-field variables. The FASDAS is coupled to a land surface submodel in a three-dimensional mesoscale model and tests are performed for a 10-day period with three one-way nested domains. The FASDAS is applied in the analysis nudging mode for two coarse-resolution nested domains and in the observational nudging mode for a fine-resolution nested domain. Further, the effects of FASDAS on two different initial specifications of a three-dimensional soil moisture field are also studied. Results indicate that the FASDAS consistently improved the accuracy of the model simulations.

1. Introduction

In recent years, much of the research designed to improve atmospheric boundary layer (ABL) simulations has focused on the surface boundary conditions used in atmospheric models. For a given synoptic con-
perhaps the most crucial for ABL modeling; it influences not only weather simulations but also climate simulations (Mitchell et al. 2004).

To alleviate modeling errors, surface measurements have been used in data assimilation methods to improve the accuracy of the simulated ABL in meteorological models. Since direct ground-based soil moisture measurements are not routinely available, assimilation methods have often been developed to use surrogates for soil moisture, such as rainfall, near-surface (~2 m AGL) air temperature and moisture, or remotely sensed radiances from which soil moisture may be estimated. Considerable progress has been made recently with such stand-alone approaches for hydrological balance and flux simulation using land data assimilation systems such as the North American land data assimilation system (NLDAS) and the high-resolution land data assimilation system (HRLDAS; Mitchell et al. 2004; Chen et al. 2007). These multiagency efforts have resulted in routine operational and research applications of the Noah land surface model (Ek et al. 2003; Hogue et al. 2005). However, an emerging need exists for coupling techniques or ad hoc assimilation systems in the atmospheric models to account for error adjustment while soil information is assimilated and thermodynamic and hydrological consistency is still maintained (Kumar 1999; Reichle et al. 2002).

Toward this requirement, both direct and indirect surface data assimilation methods for coupled land surface–atmosphere models are available. In direct assimilation methods, surface measurements (i.e., measurements available at ~2 m AGL) are used to directly assimilate air temperature and moisture without assimilating the soil moisture or soil temperature. For example, Ruggiero et al. (1996) studied the improvements in a mesoscale model simulation using intermittent assimilation of analyzed surface measurements. In their attempt to perform a direct and continuous assimilation of surface temperature measurements, Stauffer et al. (1991) found that serious errors arose in the ABL structure because the sign of the surface buoyancy flux changed unrealistically as new data were assimilated, even in midday conditions. Thus, while the approach adopted in these techniques is physically correct, the thermodynamic feedbacks resulting from these corrections need to be coherently considered in developing robust assimilation techniques.

In indirect assimilation methods, surface air measurements of temperature and moisture are used to assimilate soil moisture. Mahlfouf (1991) and Boultier et al. (1993) used the evolving surface layer temperature and humidity to estimate the soil moisture in numerical model predictions. Pleim and Xiu (2003) corrected some undesired features in this indirect soil moisture assimilation method by using a more realistic nudging methodology to produce better results in long-term simulations. McNider et al. (1994, 2005) and Lakshmi (2000) took a similar approach, but assimilated satellite-observed surface skin temperature tendencies to estimate the soil moisture. These indirect assimilation methods have been found useful for improving ABL simulations. In each the central assumption is that the largest errors present in the simulated surface energy budget are due to errors in the soil moisture parameter.

Many indirect assimilation methods assume that errors in the surface air temperature and moisture are only due to errors in the surface fluxes. However, in some cases these errors may be due to uncertainties in surface and boundary layer formulations or errors in the prediction of dynamical features (spurious advection, cloud-radiation errors, and other errors related to various model physical formulations). In such cases, errors in air temperature and moisture are not directly related to errors in soil moisture specification. Hence, when using air temperature or moisture as an assimilation input, adjustments related only to soil moisture specification may produce misleading results. Omitting such considerations can cause cumulative adjustments of soil moisture to drift from reality, leading to spurious model solutions, particularly in medium-range (and long-term) simulations. Additionally, the surface layer measurements may be sparse in certain portions of a modeling domain, so use of a single nudging strategy for the entire modeling domain may lead to errors in the assimilated soil moisture over data-sparse/void regions. Furthermore, the magnitude of nudging coefficients used in many direct and indirect methods is based on heuristic arguments and/or trial–error methods rather than a physically based methodology. Therefore, an alternative methodology over the data-sparse regions is necessary.

A robust surface data assimilation methodology is necessary for mesoscale models that can address the issues described above and perform direct as well as indirect assimilation of surface data to reduce modeling errors. The objective of this study is to develop, test, and evaluate such a surface data assimilation technique to reduce errors in retrospective modeling studies.

2. Description of the technique

Using a 1D model, Alapaty et al. (2001c) developed and tested a technique that allows continuous assimilation of surface observations to improve atmospheric surface and boundary layer simulations. This technique addressed problems associated with surface data noted
by Stauffer et al. (1991) in their observation nudging scheme applied in the fifth-generation Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model (MM5; Grell et al. 1994), directly assimilating surface temperature and water vapor mixing ratio observations in the model’s lowest layer (assumed to be the surface layer, at least for convectively unstable boundary layers). Then, the differences between the observations and model predictions of surface layer temperature and water vapor mixing ratio were converted into respective heat fluxes, referred to as adjustment heat fluxes of sensible and latent heat. These adjustment heat fluxes were then used as new terms in the prognostic equation for the ground temperature, thereby affecting the predicted surface fluxes on the subsequent time step. This indirect data assimilation was applied simultaneously with the direct assimilation of surface data in the model’s lowest layer, thereby maintaining greater consistency between the ground temperature and the surface layer mass-field variables in the 1D model. This approach has been found to eliminate the spurious changes in the sign of the surface buoyancy flux noted by Stauffer et al. (1991). Alapaty et al. (2001b) showed that the simulation errors in the ABL were reduced without the disruption of the model’s physical processes within the ABL.

In this study, we have extended our 1D modeling work (Alapaty et al. 2001c) into a 3D mesoscale model. Extension of the original 1D version of flux-adjusting surface data assimilation system (FASDAS) to 3D was straightforward because its implementation in MM5 is in the form of a column parameterization, requiring no structural changes to the 1D code. Our objective is to obtain not only the correct ABL structure as was demonstrated in our earlier studies, but also to develop improved surface and subsurface parameters such as soil temperature and moisture. Thus, we have further extended the surface data assimilation technique to include an indirect soil moisture assimilation to improve the accuracy of simulated soil temperature and moistures. In this soil moisture assimilation procedure, the adjustment latent heat flux is partitioned into several new adjustment evaporative fluxes, and these new adjustment terms are then introduced into the prognostic equations of soil moisture for each soil layer. This continuous data assimilation methodology is referred to as FASDAS. It is composed of continuous and direct surface layer assimilation as well as the indirect assimilation of soil temperature and moistures.

Following Stauffer et al. (1991) and Alapaty et al. (2001b,c) for analysis nudging, the surface data assimilation equation for a variable $\alpha$ for the model’s lowest layer can be written as

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

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 other physical and dynamical processes affecting $\alpha$ in the model’s lowest layer; $x$ and $y$ are the horizontal spatial coordinates; $G_\alpha$ is a nudging factor for $\alpha$; $W_\alpha$ is a weighting function that determines the horizontal, vertical, and time weighting applied to the analysis; $\varepsilon_\alpha$ is an analysis quality factor ranging between 0 and 1 (generally a function of data density); and $\hat{\alpha}$ is the analyzed (gridded) value obtained from observations for $\alpha$. Substituting the temperature ($T_a$) and water vapor mixing ratio ($q_a$) from the model’s lowest layer for $\alpha$ in the above equation, respective equations for the surface data assimilation can be written as

$$\frac{\partial p^*T_a}{\partial t} = F(T_L, x, y, t) + G_T W_T \varepsilon_T p^*(\hat{T} - T_a) \tag{2}$$

and

$$\frac{\partial p^*q_a}{\partial t} = F(q_L, x, y, t) + G_q W_q \varepsilon_q p^*(\hat{q} - q_a). \tag{3}$$

The parameter $G_\alpha = G_T = G_q = 9.0 \times 10^{-4} \text{s}^{-1}$ is the nudging factor that determines the magnitude of the data assimilation term in the above equations. In general terms, the inverse of the nudging factor gives a characteristic assimilation time scale (Stauffer and Seaman 1990). In our technique, $G_\alpha$ for the surface data has been chosen to be 3 times greater than that used for upper-air sounding data (see Alapaty et al. 2001c) because the adjustment rate of surface fluxes to changes in external forcing is quite rapid compared to the time scale of the inertia–gravity waves typically responsible for adjustments in the free atmosphere. Thus, in our methodology the nudging factor (also referred to in the literature as nudging coefficient; Alapaty et al. 2001a) is scaled to the time scale of the largest turbulent eddies of the convective boundary layer [i.e., $1/G_\alpha \approx 15–20$ min based on analysis of the First International Satellite Land Surface Climatology Project (ISLSCP) Field Experiment (FIFE) observations and simulations using a coupled 1D PBL model]. This procedure is referred to as direct assimilation, which completes the first phase of the FASDAS. Next, we deal with the assimilation of soil temperature and moistures that constitutes the indirect assimilation phase of the FASDAS.
The last term in Eq. (2) can be rewritten as \( \partial T_s^F/\partial t \), the rate of change of the surface layer temperature due to the direct nudging (after dividing by \( \rho^s \)). Since we have chosen to let the effect of errors in all processes be corrected through the data assimilation occurring at the surface, the adjustment turbulent sensible heat flux, \( H_s^F \) (W m \(^{-2}\)), can be written as

\[
H_s^F = \rho C_p (\partial T_s^F/\partial t) \Delta z, \tag{4}
\]

where \( \rho \) is air density, \( C_p \) is specific heat for air at constant pressure, and \( \Delta z \) is the thickness of the lowest layer. Similarly, if \( \partial q_a^F/\partial t \) represents the rate of change of the surface layer water vapor mixing ratio due to direct nudging, then the adjustment turbulent latent heat flux, \( H_l^F \) (W m \(^{-2}\)), can be written as

\[
H_l^F = \rho L (\partial q_a^F/\partial t) \Delta z, \tag{5}
\]

where \( L \) is the latent heat due to condensation.

The FASDAS is a generic technique; that is, it can be used in any land surface model. As an example, we consider a multilayer land surface model that includes detailed vegetation–atmosphere interactions, the Noah land surface model in MM5 (Grell et al. 1994), which includes prognostic equations for four soil layers along with a canopy storage equation (see section 3).

For use in soil moisture and temperature assimilation, we scale \( H_l^F \) such that errors in specification of soil moisture only are accounted for (to avoid the overcorrections discussed earlier). Since such types of errors may not be directly related to errors in soil moisture, we include corrections only relevant for soil moisture errors in the assimilation given below.

At any time, let the change in the water vapor mixing ratio \( (q_a) \) for the model’s surface layer (first model atmospheric layer above ground surface) due to surface turbulent fluxes and boundary layer mixing processes be denoted as \( \Delta q \). Then, the normalized weighting factor \( (\psi_q) \) for soil moisture adjustment can be written as \( \psi_q = \Delta q / q_a \). Thus, the product of \( \psi_q \) and \( H_l^F \) represents the process-weighted adjustment latent heat flux for use in soil moisture assimilation. Now, we will describe the methodology for adding new terms into the Noah land surface model to enable us to perform soil moisture assimilation.

The total kinematic evaporation flux in the Noah land surface model, \( E \) (kg kg \(^{-1}\) m s \(^{-1}\)), is given by

\[
E = E_{dir} + E_{t1} + E_{t2} + E_{t3} + E_c, \tag{6}
\]

where \( E_{dir} \) represents the direct evaporation flux from the ground surface; \( E_{t1}, E_{t2}, \) and \( E_{t3} \) are transpiration from vegetation; and \( E_c \) is evaporation flux from the precipitation intercepted by vegetation or dew formed on the canopy. Similar to these five evaporation fluxes, we now introduce new adjustment fluxes that arise because of surface data assimilation and relate them to the \( H_l^F \). These new adjustment evaporation fluxes for use in prognostic equations of soil moisture can be written as

\[
E_{dir} = \left( \frac{E_{dir}}{E} \right) \psi_q \left( \frac{H_l^F}{\rho L} \right), \tag{7a}
\]

\[
E_{t1} = \left( \frac{E_{t1}}{E} \right) \psi_q \left( \frac{H_l^F}{\rho L} \right), \tag{7b}
\]

\[
E_{t2} = \left( \frac{E_{t2}}{E} \right) \psi_q \left( \frac{H_l^F}{\rho L} \right), \tag{7c}
\]

\[
E_{t3} = \left( \frac{E_{t3}}{E} \right) \psi_q \left( \frac{H_l^F}{\rho L} \right), \tag{7d}
\]

\[
E_c = \left( \frac{E_c}{E} \right) \psi_q \left( \frac{H_l^F}{\rho L} \right), \tag{7e}
\]

where \( \rho_L \) is the density of water. Note that the partition of \( H_l^F \) in the above equations is based on the relative contribution of each of the terms \( E_{dir}, E_{t1}, E_{t2}, E_{t3}, \) and \( E_c \) compared to the total evaporation flux, \( E \). For example, if \( E_{t2} \) is the dominating component of the total evaporation flux, then it is adjusted to a greater degree compared to other evaporation fluxes. Thus, adjustments are done to these variables to preserve the roles played (i.e., the magnitude) by the physical fluxes.

The modified prognostic equations that include the newly adjusted terms (underlined) for volumetric soil moisture (\( \Theta \)) of the four soil layers and the equation for the canopy storage can be written as

\[
d_{z1} \left( \frac{\partial \Theta_1}{\partial t} \right) = -D \left( \frac{\partial \Theta_1}{\partial z} \right)_{z1} - K_{z1} + P_d - R - E_{dir} - E_{t1} \nonumber + E_{dir}^F + E_{t1}^F, \tag{8a}
\]

\[
d_{z2} \left( \frac{\partial \Theta_2}{\partial t} \right) = D \left( \frac{\partial \Theta_2}{\partial z} \right)_{z2} - D \left( \frac{\partial \Theta_2}{\partial z} \right)_{z2} - K_{z2} - K_{z2} - E_{t2} \nonumber + E_{t2}^F, \tag{8b}
\]

\[
d_{z3} \left( \frac{\partial \Theta_3}{\partial t} \right) = D \left( \frac{\partial \Theta_3}{\partial z} \right)_{z3} - D \left( \frac{\partial \Theta_3}{\partial z} \right)_{z3} + K_{z2} - K_{z3} - E_{t3} \nonumber + E_{t3}^F, \tag{8c}
\]

\[
d_{z4} \left( \frac{\partial \Theta_4}{\partial t} \right) = D \left( \frac{\partial \Theta_4}{\partial z} \right)_{z3} + K_{z3} - K_{z4}, \tag{8d}
\]

\[
\frac{\partial W}{\partial t} = \sigma_P - D - E_c + E_c^F. \tag{9}
\]
In the above, \(d_{si}\) is thickness of the \(i\)th soil layer, \(P_{ij}\) is the precipitation not intercepted by the canopy, and \(E_{si}\) is the contribution to canopy transpiration by the root system in the \(i\)th layer within the root zone layers [the root zone has three layers in the coupled MM5–land surface model (LSM)]. The total soil depth of the Noah model is \(2\) m with the root zone, represented by the top three soil layers, constituting the upper \(1\) m. The lowest \(1\)-m soil layer (fourth layer) acts like a reservoir with gravity drainage. Thus, at the bottom of the soil model, hydraulic diffusivity is assumed to be \(0\), so that the soil water flux is due only to the “gravitational” percolation term \(K_{sdt}\) (also called subsurface runoff or drainage). Descriptions of all other terms can be found in Chen and Dudhia (2001).

The adjusted ground/skin temperature can be written as

\[
T_{g}^{F} = T_{g}^{a} + \left( \frac{H_{s}^{F} - \psi_{q} H_{F}^{E}}{C_{g}} \right) \Delta t, \tag{10}
\]

where \(T_{g}\) is the predicted ground temperature and \(T_{g}^{F}\) is updated–assimilated \(T_{g}\), and \(C_{g}\) is the thermal capacity slab per unit area of the uppermost soil.

It is important to note that we do not assume that all errors in \(T_{a}\) and \(q_{a}\) result only from errors in the surface fluxes. Typically, direct assimilation is applied such that it accounts for all modeling errors in assimilating \(T_{a}\) and \(q_{a}\). However, we alter soil temperature and moisture through a weighted adjustment to the surface fluxes based on known errors in \(T_{a}\) and \(q_{a}\) yielding an indirect, but physically plausible, way to correct for errors in soil temperature and moisture. In FASDAS, we adjust surface heat fluxes so that the model’s near-surface air temperature and humidity converge to the observed values. Thus, surface layer corrections are based on the magnitude and sign of the simulation errors. In the event that the model predictions are in perfect agreement with the analyzed observations, all adjustment terms drop out naturally from the various equations. The magnitudes of the new terms in Eqs. (5)–(10) are scaled by the turbulence time scale (i.e., \(1/G_{\kappa}\)) for the surface boundary layer eddies. Note that when weights are set to \(0\) over data-sparse regions, the FASDAS can behave like an observational nudging scheme in which the radius of influence is limited to one grid cell. Additionally, in the FASDAS, we have provided a constraint that the indirectly assimilated soil moisture is not added to the grid-averaged values when soil moisture exceeds its field capacity.

To summarize, FASDAS is composed of two components: 1) the direct assimilation using atmospheric surface layer assimilation measurements and 2) the indirect assimilation via soil temperature and soil moisture. FASDAS smoothly corrects and adjusts both the land surface and atmospheric variables at each model time step. The surface layer assimilation includes three specific steps: (i) develop a quality controlled surface analysis for the model’s lowest layer and assign smaller weights (by \(90\%\)) to data-sparse regions such that assimilation effects are minimal for those regions; (ii) directly assimilate the temperature and moisture analysis in the model’s lowest layer using a nudging coefficient based on the time scale of turbulence in the ABL; and (iii) estimate adjustment sensible and latent heat fluxes.

The indirect assimilation is composed of five steps: 1) calculate a normalized weighting factor—a ratio of change in the water vapor mixing ratio (due to surface latent heat flux) to the water vapor mixing ratio for the surface layer; 2) weight the adjustment latent heat fluxes with the normalized weighting factor to reflect soil moisture error adjustments only; 3) partition the weighted adjustment latent heat flux into new components of adjusted evaporation fluxes according to relative magnitudes of physical evaporation and transpiration fluxes in the Noah land surface model; 4) introduce the new adjustment evaporation flux term in the prognostic equations for soil moisture (fourth step), thereby affecting soil moisture predictions at the next time step; and 5) add the sensible and latent heat flux adjustment terms to the predicted ground temperature to provide the updated physical heat fluxes at the next time step.

3. Brief description of mesoscale model and configuration

MM5 is one of the most widely used three-dimensional prognostic meteorological models (Grell et al. 1994). MM5 is a limited-area, nonhydrostatic model primarily designed to simulate or predict mesoscale and regional-scale weather. MM5 uses a terrain-following nondimensional pressure, or \(\sigma-P\), vertical coordinate similar to that used in many operational and research weather models. Several options can be chosen to represent various atmospheric physical processes either implicitly or explicitly. MM5 uses an efficient split–semi-implicit temporal integration scheme and has a nested-grid capability that can support up to \(10\) different domains of arbitrary horizontal resolution. This allows MM5 to simulate local details with resolution as fine as \(~1\) km while accounting for influences over great distances, with horizontal resolutions on coarser outer domains ranging up to about \(200\) km. Initial and lateral boundary conditions on the outermost grid mesh can be specified from mesoscale 3D analyses or predictions. MM5 also has the option of specifying 2D surface
meteorological fields over the variable terrain. The lateral boundary data are introduced using a relaxation technique applied in the outermost five rows and columns of the coarsest grid domain. The horizontal grid has an Arakawa–Lamb B-staggering of the velocity variables with respect to the scalars.

Description of Noah LSM

The Noah LSM, as implemented in MM5 and the Weather Research and Forecasting system (WRF), is based on coupling the diurnally dependent Penman potential evaporation approach of Mahrt and Ek (1984) to the multilayer soil model of Mahrt and Pan (1984), Pan and Mahrt (1987), Chen et al. (1996), Chen and Dudhia (2001), and Ek et al. (2003). It has one canopy layer and the following prognostic variables: soil moisture, soil ice, soil temperature, water stored on the canopy, and snow stored on the ground. We used four soil layers so the soil model could capture the daily, weekly, and seasonal evolution of the soil moisture and also mitigate possible truncation errors in discretization. The thicknesses of each layer downward from the ground surface are 0.1, 0.3, 0.6, and 1.0 m, respectively. The total soil depth is 2 m, with the maximum depth of the root zone confined to the upper 1.0 m of soil. The local depth of the vegetation roots can be specified as a function of vegetation type. Surface skin temperature is determined following Mahrt and Ek (1984) with a single linearized surface energy balance equation dependent on the surface radiation, turbulent heat, and ground heat fluxes, thus representing the combined ground–vegetation surface flux conditions.

The Noah land surface model was coupled to the National Centers for Environmental Prediction (NCEP) operational Eta Model in February 1996 and has significantly enhanced skill in the prediction of precipitation and near-surface weather variables (Chen et al. 2007). It was coupled to MM5 and more recently to the WRF Model. Chen and Dudhia (2001) have verified 48-h simulations of surface heat fluxes, near-surface temperature, PBL development, and precipitation in the coupled MM5–LSM system against observations obtained from the FIFE field experiments.

4. FASDAS tests with Noah–MM5

The purpose for developing the FASDAS are two-fold: 1) to develop improved surface meteorological fields for use in retrospective modeling studies geared to drive air quality models and 2) to alleviate errors related to specification of 3D soil moisture in regional climate modeling studies. As a starting point, we conducted coupled tests involving the FASDAS implemented within the 3D Noah–MM5 configuration. Numerical simulations were produced on three nested domains for a 10-day period (1200 UTC 22 August–1 September 2000) that included both clear sky conditions and rain events. Note that this configuration is designed from the weather forecasting perspective where the land surface model is coupled to the meso-scale model. Future tests could be performed with an offline version of Noah as well as coupled seasonal simulations for much longer periods (section 6).
Since the soil moisture of the top few centimeters of soil exhibits a strong diurnal variation, uncertainty in the specification of the top-layer soil moisture can rapidly fade away during the course of model simulations. More problematic, however, are the deep soil layers whose moisture values are difficult to specify accurately. Also, these are the layers that influence the evapotranspiration over vegetated regions, another complicating factor. To test the soil moisture feedback, we conducted additional sensitivity studies by varying initial soil moistures with and without FASDAS.

**Fig. 3.** Spatial distribution of near-surface (a) air temperature differences (K), and (b) water vapor mixing ratio differences (g kg⁻¹) for (Fasdas – Base) at 2100 UTC 24 Aug.
a. Model setup

The Noah–MM5 was configured with horizontal grids of 36 km for the outermost domain (D1) and 12 and 4 km (D2 and D3) for the one-way nested domains, both to perform a base case simulation (without FASDAS) and tests with FASDAS coupling. Additionally, four sensitivity tests were performed with the 36-km grids (D1) to examine the FASDAS–MM5 response to different initial soil moisture conditions. Time series and spatial plots of various model outputs are examined, focusing on precipitation events simulated in the central United States and around Houston, Texas, on the 36- and 4-km domains (Fig. 1). We will not present any results obtained from the second domain D2 (12-km grid) as it is primarily used to provide lateral boundary conditions to the 4-km grid (D3). In all of the MM5 simulations, we used 28 vertical layers to discretize the atmosphere between the surface and 100 hPa, with about 8 layers in the lowest 1.5 km of the model atmosphere. The thickness of the lowest layer is about 18 m. For these simulations we used the Medium-Range Forecast (MRF) scheme (Pan and Mahrt 1987) to represent the turbulent mixing process in the ABL and the Grell cumulus scheme (Grell 1993) to represent subgrid-scale deep convective clouds.

In all of the FASDAS–Noah–MM5 coupled simulations, we have used the archived National Oceanic and Atmospheric Administration (NOAA) surface observations (which are used to produce analyses data), which are typically available at 3- and 6-h intervals. For statistical evaluation of the model simulations, we have obtained hourly surface measurements from the NOAA Techniques Development Laboratory (TDL), now known as the Meteorological Development Laboratory (MDL). The TDL data contain all of the 3- and 6-h surface data. The geographical locations of these stations are shown in Fig. 1. After performing quality control, the total number of TDL surface observations used to perform model evaluations for the D1 and D3 domains are between 750 and 850 and between 10 and 16, respectively. (Some stations did not report during the nighttime.) Simulated temperatures at the lowest model level (~18 m AGL) are used to estimate temperatures at 2 m AGL based on similarity relationships. These 2-m estimated values are then directly compared with TDL surface measurements at 2 m AGL. For the water vapor mixing ratio, we used simulated values available at about ~18 m AGL along with the observed values at 2 m AGL to generate statistical evaluations. This was done to avoid confounding with the similarity theory-based interpolation. For every observation site, a corresponding grid cell in the modeled domain was paired to generate the statistical measures (e.g., RMS error).

b. Synoptic overview

The study period 22 August–2 September 2000 represented a typical summertime pattern with the upper-level jet stream displaced to the northern United States and weak, warm, moist, southerly flow across the south. A persistent stationary frontal boundary was draped over the northern sections of domain 1 (Nebraska, southern Iowa, and Illinois) for most of the study period (not shown). This frontal boundary struggled to push further south, leaving a moist air mass across most of the southern regions of the domain. On 25–26 August, an upper-level trough was present over the northern sections of domain 1 and the eastern United States, thus impelling the eastern portion of the stationary frontal boundary further south during this time period. A second upper-level trough also propagated through the eastern United States on 27–28 August. Both of these events caused an increase in precipitation across the eastern sections of domain 1.
The second half of the study period was more synoptically active. On 28 August, a surface low pressure system was developing in southern Canada with a trailing cold front that was moving southeastward through the Great Plains region. The cold front swept through the midwestern United States on 29 August. On 30 August, a potent surface low pressure of 996 hPa was centered over South Dakota. This low pressure also...
produced a cold frontal event in the Great Plains region on 30 and 31 August. Both fronts struggled to make it to the southern United States, slowing into a quasi-stationary frontal boundary across the central regions of domain 1.

Specific to the innermost domain centered over Houston, Texas, 7 days out of the 10-day study period were influenced by a high pressure system, thus leading to fair to partly cloudy skies. The remaining days were under the influence of strong daytime heating and surface trough boundaries. Toward the end of simulation period, an east–west oriented surface trough was present over the northern Gulf of Mexico causing an increase in shower activity over the Houston region.

5. Results and discussion

In the following, MM5 simulations with the FASDAS–MM5 coupling are referred to as “Fasdas,” and those without coupling are referred to as the “Base.” In both cases, that is, Base and Fasdas, four-dimensional data assimilation suggested by Stauffer et al. (1991) was used in the free atmosphere. Thus, the main difference between Base and Fasdas simulations is that surface temperature and water vapor mixing ratio data (i.e., from analysis) are assimilated in Fasdas and not assimilated in Base.

a. Results for the 36-km grids

First, we present the results obtained from the 36-km (D1) domain. Figure 2 presents the domain-averaged (at observation sites over land) 10-day time series results for the air temperature (K) at 2 m AGL for the observations (Obs), Base, and Fasdas. Overall, results from the Fasdas are closer to the Obs particularly for the daytime. During the first five days when several precipitation events were present, the Fasdas showed some minor domain-averaged improvements over the Base (approximately 0.5–1.0 K higher daytime temperature maxima and lower nighttime minima, respectively). However, during the latter five days of simulation (a mostly dry period), Fasdas showed significant improvements over the Base and closely followed the Obs. Note that the domain-averaged rise in daytime temperatures produced with the Fasdas in Fig. 2 is not indicative of a higher temperatures at all grid points. A spatial plot (Fig. 3a) of 2-m air temperature differences (Fasdas – Base) at 2100 UTC 24 August (midafternoon) reveals that Fasdas has cooled or warmed the model atmosphere based on the local sign and magnitude of the temperature errors and corresponding adjustments by the data assimilation. Since the Fasdas is not applied over water-covered grid cells, the temperature differences over bodies of water are only due to changes in advection in Fasdas compared to that in Base.

Figure 3b shows the spatial distribution of water vapor mixing ratio differences (Fasdas – Base) at 18 m AGL for 2100 UTC 24 August. Responding to the sign and magnitudes of mixing ratio errors, the Fasdas moistened the region across southeast Texas, southern Louisiana, and the mid-Mississippi River valley and dried the regions across Mississippi and Alabama, as well as portions of the Carolinas and the northeast corridor. Figures 4a and 4b show time series plots of domain-averaged 2-m temperature and 18-m mixing ratio (g kg⁻¹) RMS errors from the Base and Fasdas. The figure clearly shows Fasdas consistently had much lower RMS errors for temperature and moderately lower RMS errors for mixing ratio, especially during afternoons.

Next, the geographical distribution of surface sensible and latent heat flux differences (Fasdas – Base) at
1900 UTC 26 August is shown in Figs. 5a and 5b. The distribution of these flux differences across the domain appears to depend on the sign and size of the simulated errors in the surface temperature and mixing ratio. The Fasdas boosted the early afternoon latent heat fluxes by about 100–200 Wm$^{-2}$ across much of the southeast United States including the region of interest near Houston, Texas, on the 4-km domain (D3; section 5b). Locally, larger values of sensible heat flux (by approximately 50–100 Wm$^{-2}$) were produced by the Fasdas over parts of the Great Plains. The temporal variation of domain-averaged surface sensible and latent heat flux for the Base and Fasdas are shown in Figs. 6a and 6b. During the first five days of simulation, the Fasdas resulted in weak changes (approximately 0–10 Wm$^{-2}$) in the surface sensible heat flux as compared to the Base, while during the rest of the simulation Fasdas produced peak sensible heat fluxes, which were ~100 W m$^{-2}$ higher than the Base. A somewhat qualitatively similar impact, but opposite in nature, can be seen in the surface latent heat fluxes (Fig. 6b). The differences between the first and second halves of the period reflect their comparatively greater and lesser amounts of precipitation and clouds, respectively. In general, Fasdas resulted in an overall daytime warming in the surface layer during the entire simulation period with a moistening during the first five days and a drying for the rest of the period.

Fig. 7. Spatial distribution of cloud cover from GOES imagery at (a) 1200 UTC 26 Aug, (b) 0000 UTC 27 Aug, (c) 1200 UTC 27 Aug, and accumulated 24-h precipitation ending at 1200 UTC 27 Aug for (d) CPC analysis, (e) Base, and (f) Fasdas cases. Negative values for precipitation are used for graphical display convenience allowing plotting of trace precipitation (i.e., 0.01 in.) contours.
Nudging of the surface temperature and mixing ratio values toward measurements and the resulting surface heat flux adjustments has a feedback on other model variables. Also, updating soil temperature and moisture additionally impacts surface air temperature and its dewpoint \( T_d \) in the coupled model. Fasdas alters surface air temperature and moisture leading to higher (lower) \( T_d \), which tends to produce higher (lower) boundary layer depths, lifting condensation level values, and thus results in higher (lower) available convective potential energy, which is important in the initiation and maintenance of mesoscale convection and associated convective precipitation. Thus, these variations provide the boundary layer feedback for convection development as well as possible convection inhibition. We analyzed these different feedbacks throughout the simulation period to determine the impact of FASDAS on the simulated convective precipitation processes, discussed below.

Figures 7a–c show Geostationary Operational Environmental Satellite (GOES)-retrieved infrared images at 1200 UTC 26 August, 0000 UTC 27 August, and 1200 UTC 27 August 2000. The presence of clouds over the eastern United States, north-central United States, and Atlantic Ocean indicates the presence of convective systems in these regions. Figure 7d shows the 24-h accumulated (observed) precipitation analysis obtained from the Climate Prediction Center (CPC) ending 1200 UTC 27 August 2000. This dataset is derived from three sources: daily cooperative stations from NOAA’s National Climatic Data Center, the CPC dataset including data from the River Forecast Centers, and daily accumulations from the hourly precipitation dataset. Approximately 13 000 station reports are received each day. Note that precipitation amounts and their distribution over coastal and oceanic regions were uncertain because of a lack of data, and interpolation–advection artifacts. Figures 7e and 7f show modeled accumulated total precipitation for the same period as in the CPC analysis for the Base and Fasdas cases, respectively, and they reveal some interesting features. Over the northwestern regions of the domain (i.e., over Colorado and Wyoming), and along the central regions of South and North Carolina and eastern Virginia, the simulated precipitation in Fasdas was generally in better agreement with the analysis as compared to the Base. Another interesting feature present in the Fasdas simulations is the suppression of spurious precipitation over southern Texas, particularly west of the Houston area, which was incorrectly simulated in the Base. In general, the Base and Fasdas appeared to replicate the CPC analysis, but both also overestimated the heavy precipitation over the Midwest. The analysis suggests that three heavy precipitation regions occurred from Michigan to Tennessee. The Fasdas appears to have produced somewhat heavier rainfall over Michigan, where the Base case underpredicted the precipitation, but Fasdas also led to erroneous expansion of rainfall into western Louisiana. A time series of land domain-averaged precipitation rates for the Base and Fasdas simulations (Fig. 8) indicate significant differences in the precipitation evolution as a result of modifications in the surface and soil moisture and temperature fields. Overall, this brief visual inspection suggests that the addition of Fasdas may have led to small improvements in the simulated precipitation via feedback in the surface soil moisture–temperature. However, more careful statistical evaluations using many more cases would be required to determine whether this preliminary assessment is significant or not.

Differences in the precipitation and surface evaporation rates by adopting Fasdas resulted in further modification of surface and subsurface soil fields. We next examine the differences (Fasdas – Base) in soil moisture distribution across the four soil layers at 1200 UTC 27 August (Fig. 9) at the end of the fifth day of simulation. Major differences exist for the top soil layer, which is strongly influenced by direct evaporation, and diffusion of water to and from the second soil layer and especially by occurrences of precipitation. As seen in the Fig. 9, the majority of soil moisture corrections are associated with the mesoscale convective precipitation. Wherever precipitation is fairly heavy, soil moisture fields are expected to require little to no adjustments since the upper soil layers would rapidly become saturated. It is noteworthy that Fasdas does not seem to
show a persistent wet or dry bias across the different soil layers.

Further, even though differences between the Fasdas and Base case soil moistures are not widespread, these are still significant enough to cause thermodynamical changes in the deeper coupled model environment. For example, several observed temperature profiles (not shown) indicated a deeper and well-mixed boundary layer capped by clearly visible inversion. Concurrently, simulated profiles for Base underpredicted the surface temperatures, but Fasdas is able to introduce surface warming of approximately 1–2 K. Consistently, the ABL depth in the Fasdas is deeper, closer to the observations. Similar results can also be seen in the dew-point temperature profiles, but differences in the horizontal winds between Base and Fasdas are insignificant.

b. Results for the 4-km grids over Houston, Texas

High-resolution domains such as the 4-km domain (D3) traditionally have small area and thus contain a limited number of observation sites. Therefore, the usual practice is not to perform analysis nudging for such small domains. However, a viable option is to perform observational nudging for grid cells at and near the observation sites (Stauffer and Seaman 1994). For this reason, the FASDAS is employed as an “observational” nudging technique on the 4-km grid. In this re-

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**Fig. 9.** Spatial distribution of soil moisture differences (m$^3$ m$^{-3}$) for (Fasdas – Base) at 1200 UTC 27 Aug for (a) layer 1, (b) layer 2, (c) layer 3, and (d) layer 4.
gard, surface data assimilation is allowed to dominate only for three grid points in all directions surrounding each observational site. Here, a damping coefficient is applied that has the value 0.9 for all the grids within the three grid points around the observational site, while for other points the damping coefficient is assumed to be 0.1. This feature allows us to test and evaluate FASDAS for a higher-resolution domain without extensive recoding. For domain D3, there were approximately $10^{16}$ observation sites, depending on the time of day, so the overall impact of FASDAS is expected to be limited.

Figures 10a and 10b show the RMS errors for the 2-m air temperature and mixing ratio on the 4-km domain for the Base and Fasdas cases. These trends are consistent with those obtained on the coarse grid, with Fasdas resulting in lower RMS errors for the 10-day period. Particularly, temperature errors in the Fasdas are smaller during the second five days of the simulation (period with little precipitation), which again is consistent with results obtained on the 36-km grid. Similarly, small improvements in mixing ratio RMS errors can also be seen in the Fasdas.

Accumulated model precipitation for the 24-h period ending 1200 UTC 24 August for domain D3 is shown in Fig. 11 along with GOES cloud imagery and CPC rain analysis. Because of the convective nature of this rain event, the observed precipitation will again have high uncertainty. The precipitation analysis shows a maximum over Galveston Bay with a total accumulated precipitation amount of approximately 0.5 in. The Fasdas and the Base simulations show many spatially isolated convective rain cells up to 1–2 in. that appear generally consistent with the GOES imagery. The Fasdas simulation resulted in heavier precipitation over the Galveston Bay region than that in the observations and in the Base. However, if averaged to the coarser scale of the analysis, the Fasdas-generated rainfall is fairly similar with that of the observations. Consistent with the analysis of other meteorological variables, the results indicate that FASDAS was able to improve the model performance by modulating the surface variables for the 4-km grids as well. Another interesting feature was the expected difference between the Base and the Fasdas offshore precipitation as a result of the dynamical response of the surface temperature and land–sea breeze circulation changes.

c. Sensitivity simulations

To test the impact of uncertainty in initial soil moisture fields on the ability of FASDAS to adjust soil fields, we performed four additional simulations using the 36-km grids. In the first set of sensitivity simulations, both the Base and Fasdas runs are repeated, but with a 25% reduction, and then with a 25% increase in the initial soil moisture for all soil layers and at all points across the domain. In so doing, we constrained the soil moisture values such that they never go below wilting point or above soil saturation level. The model simulations for the Base and Fasdas with a 25% decrease in the initial soil moisture are referred to as SM075B and SM075F, respectively, while the simulations with a 25% increased soil moisture are referred to as SM125B and SM125F, respectively. We recognize the fact that errors in the specification of 3D soil moisture are not uniformly distributed as chosen here. However, for the sake of simplicity and to facilitate a convenient testing of the FASDAS, we have chosen this simple modeling strategy.

Figure 12 shows the surface air temperature bias versus observations for experiments SM075B and SM075F. The Fasdas case has a lower bias for surface temperature (and humidity fields, not shown), consistent with our earlier results. This improvement is expected as a result of the changes in the initial soil moisture due to
Fig. 11. Spatial distribution of (a) cloud cover from GOES imagery at 1200 UTC 24 Aug, and accumulated 24-h precipitation ending at 1200 UTC 24 Aug for (b) CPC analysis, (c) Base, and (d) Fasdas cases.
FASDAS. Figure 13 shows the temporal variation of land domain-averaged soil moisture for four soil layers. In all of the time series, a clear diurnal signal is evident with a decreasing trend present for the deeper soil layers 3 and 4. In general, soil moisture decreases during the daytime in all soil layers because of dominant evaporation losses, while during the nighttime, soil moisture for layers 1 and 2 increases because of vertical diffusion from the layers below. The differences between soil moisture for SM075B and SM075F for layers 3 and 4 are evident after about 36 h of simulation. The step function type diurnal variations present in the soil moisture for layers 3 and 4 are due to the strong diurnal variation in the evapotranspiration fluxes, while for layer 4 (the storage layer), the variation is mostly due to a loss of water to layer 3 resulting from vertical diffusion. In general, the FASDAS has successfully increased in domain-averaged soil moisture in a complex feedback between the surface and the atmosphere. Figure 14 shows the difference between the Base and the Fasdas accumulated land domain-averaged rainfall for the SM075B and SM075F case. Fasdas has resulted in a small increase in overall precipitation that is due to the increased soil moisture in a complex combination of dynamic feedbacks.

The impacts of the 25% increase in the initial soil moisture for the Base and the Fasdas cases (SM125B and SM125F) on the temporal variation of land domain-averaged soil moisture for the four layers are
shown in Fig. 15. As expected, the soil moisture for SM125B and SM125F decreases for all soil layers during the model integration, primarily because of daytime evapotranspiration. The differences between SM125B and SM125F soil moistures are relatively large for the top soil layers. The resulting differences in the accumulated land precipitation shown in Fig. 16 are consistent with the soil moisture variations shown in Fig. 15. Again, temperature and moisture biases for the SM125F (not shown) are found to be lower than those in the SM125B.

The intent of the sensitivity studies is to show that for known “errors” in the initial soil moisture, FASDAS is able to bring the surface fields closer to the “observations.” Thus, for the SM075 case, FASDAS seeks to add soil moisture to bring it closer to the optimal; for the SM125, the overall soil moisture is adjusted across the soil column to maintain consistency with the surface–subsurface and the surface–atmosphere interactions.

To examine the soil moisture variations, we present in Fig. 17 a temporal variation of land domain-averaged soil moisture differences in the four soil layers for the Base, Fasdas, and the two sets of sensitivity experiments. These are labeled Fasdas-Base, SM075F-SM075B, and SM125F-SM125B. During the first 60 h, simulated precipitation rates were essentially similar in all of these experiments; therefore simulated differ-
ences in soil moisture for all four soil layers were primarily due to FASDAS. Also, for the top three soil layers, the soil moisture differences in the Fasdas-Base were again to some extent sandwiched between the SM075F-SM075B and SM125F-SM125B differences. Note that the absolute differences are small and are not important from the perspective of a short-term weather forecast. During the 61–120-h period of the simulations, increased precipitation rates in addition to the FASDAS adjustments led to a sharp rise in the variation among the experiments. Also, soil moisture differences for the thicker third and fourth soil layers were nearly an order of magnitude smaller than those for soil layers 1 and 2. The important issue is that, although soil moisture measurements are lacking, the curves represent different adjustments to the soil moisture that are as physically realistic as can be expected for dry to moist versus moist to more moist conditions. This successful concurrence is important for the robustness of the technique.

6. Conclusions

We have developed a new flux-adjusting surface data assimilation system for mesoscale models. FASDAS can account for the biases in the surface air temperature and humidity and make a thermodynamical adjustment of soil temperature and moisture within the constraints imposed by the prognostic changes in soil temperature, moisture, and surface layer variables. The biases are not completely assigned to correct the soil fields, but are assigned instead according to the relative contributions to surface latent heat fluxes and energy

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**Fig. 16.** As in Fig. 15, but for SM125B and SM125F cases.

**Fig. 17.** Temporal variation of land domain-averaged soil moisture differences (m³ m⁻³) for all simulations of the 36-km domain.
balance. The scheme is simple enough to be applied for mesoscale models either in analysis nudging or observational nudging modes. It does not require specification of arbitrary nudging coefficients for soil temperature and soil moisture assimilation. The nudging coefficients for surface air temperature and moisture are representative of the time scales associated with boundary layer turbulent eddies. Thus, FASDAS is thermodynamically different in its procedure than other surface data assimilation schemes (e.g., Bouttier et al. 1993; Mahfouf 1991; McNider et al. 1994; Lakshmi 2000) because of its explicit and thermodynamically consistent adjustments to both soil moisture and soil temperature simultaneously.

The FASDAS approach was implemented in a mesoscale model and tested for a 10-day continuous simulation, which encompassed a period of heavy rains across the continental United States followed by a period that had little rain and synoptically weak anticyclonic conditions. The approach was tested for a nesting configuration with 36-, 12-, and 4-km grids. Implementation of FASDAS did not cause any spurious model drifts or thermodynamic imbalances that had to be damped artificially in the short-term experimental runs performed in this study. The performance was modest for the wet periods because precipitation resulted in more dramatic and rapid changes to the soil moisture values than the adjustments because of FASDAS calculations. For the contrasting dry period, the impact of FASDAS is much more apparent, with surface soil moisture and temperature fields showing realistic changes over the diurnal cycles. In both wet and dry periods, however, the seemingly modest changes in the soil moisture and temperature fields lead to small but appropriate changes in the surface fluxes, surface air temperature, and humidity. These effects are reflected in feedbacks to the amounts and distribution of precipitation as well as boundary layer evolution.

In summary, our results include the following main points:

(i) The 3D FASDAS was successfully implemented in a mesoscale model coupled with a land surface model. The coupled system is able to simulate realistic surface fields and their associated boundary layers, mesoscale convection, and precipitation feedbacks.

(ii) The model performance was consistently improved by adopting FASDAS for the 10-day simulation period. Improvements were seen in the surface air temperature and humidity fields as well as in the resulting boundary layer profiles and slightly in the simulation of precipitation patterns and amounts.

(iii) Nested-grid modeling studies showed that the FASDAS can also be applied to high-resolution domains even with limited number of surface observations, and the coupled model results were again in good agreement with observations.

(iv) Sequential assimilation approaches such as FASDAS were sensitive to the initial soil moisture fields. Thus, the results are subject to the errors in the “cold start” soil states, but the model rapidly approached the “control” soil moisture values with the indirect soil moisture assimilation approach.

(v) Comparison of the model fields with and without FASDAS showed small but consistent and significant differences in the average precipitation values across the domain. This indicates that relatively small changes in surface moisture and temperature can lead to significant feedbacks in the mesoscale convection and boundary layer response that ultimately affect precipitation patterns. It also suggests efforts to improve the soil moisture and soil temperature fields using assimilation approaches should continue to improve our ability to reduce biases in surface temperature and humidity fields and also enhance precipitation scores in the long term.

(vi) The FASDAS approach is inherently simple and can be applied for reanalysis of experimental data. It is expected to lead to thermodynamically consistent model results which can be used to study the mesoscale processes in more detail. Studies involving simulations for seasonal climate as well as offline models, which will extend the capabilities of the approach, are anticipated and will be presented in a future study.

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REFERENCES


