An Indirect Data Assimilation Scheme for Deep Soil Temperature in the Pleim-Xiu Land Surface Model

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(Manuscript received 10 June 2008, in final form 2 December 2008)

ABSTRACT

The Pleim-Xiu land surface model (PX LSM) has been improved by the addition of a second indirect data assimilation scheme. The first, which was described previously, is a technique in which soil moisture is nudged according to the biases in 2-m air temperature and relative humidity between the model- and observationbased analyses. The new technique involves nudging the deep soil temperature in the soil temperature forcerestore (FR) model according to model bias in 2-m air temperature only during nighttime. While the FR technique is computationally efficient and very accurate for the special conditions for which it was derived, it is very dependent on the deep soil temperature that drives the restoration term of the surface soil temperature equation. Thus, adjustment of the deep soil temperature to optimize the 2-m air temperature during the night, when surface forcing is minimal, provides significant advantages over other methods of deep soil moisture initialization. Simulations of the Weather Research and Forecasting Model (WRF) using the PX LSM with and without the new deep soil temperature nudging scheme demonstrate substantial benefits of the new scheme for reducing error and bias of the 2-m air temperature. The effects of the new nudging scheme are most pronounced in the winter (January 2006) during which the model's cold bias is greatly reduced. Air temperature error and bias are also reduced in a summer simulation (August 2006) with the greatest benefits in less vegetated and more arid regions. Thus, the deep temperature nudging scheme complements the soil moisture nudging scheme because it is most effective for conditions in which the soil moisture scheme is least effective, that is, when evapotranspiration is not important (winter and arid climates).

1. Introduction

The land surface components of meteorology modeling systems are responsible for the realistic representation of surface heat and moisture exchange processes and their dependence on vegetation and soil temperature and moisture. The surface fluxes of heat and moisture drive the near-surface air temperature and humidity and the evolution of the planetary boundary layer (PBL). The diurnal evolution of the PBL is of particular importance to air quality modeling applications. Thus, the continued development and improvement of land surface and PBL models are crucial for realistic meteorology and air quality model simulations. However, given the great variability of soil and vegetation types within mesoscale model grid cells (~1–20-km gridcell sizes), increasing detailed model complexity may not yield improved results. Thus, much of the recent model developmental research has focused more on data assimilation techniques than on developing more detailed physical parameterizations. For example, McNider et al. (2005) recently developed a technique to assimilate satellite retrievals of surface heat capacity. Alapaty et al. (2008) have developed a technique for adjustment of surface heat and moisture fluxes by means of indirect assimilation of surface analyses of air temperature and humidity. Several other groups have developed similar assimilation techniques using model biases compared to surface analyses to adjust soil moisture (e.g., Mahfouf 1991; Bouttier et al. 1993a,b; Giard and Bazile 2000; Douville et al. 2000; Pleim and Xiu 2003).

The Pleim–Xiu land surface model (PX LSM; Pleim and Xiu 1995; Xiu and Pleim 2001) was developed and improved over the years to provide realistic ground temperature, soil moisture, and surface sensible and latent heat fluxes in mesoscale meteorological models. The

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PX LSM was originally based on the Interactions between Soil, Biosphere, and Atmosphere (ISBA) model as described by Noilhan and Planton (1989). While the vegetation components of the model, such as the stomatal resistance functions and the land use-related parameterizations, have been extensively modified, the soil temperature and moisture components are essentially the same as the original ISBA model. Specifically, the PX LSM uses a two-layer force-restore (FR) mechanism for both soil temperature and soil moisture. Although this two-layer approach is less detailed than the multilayer (ML) soil models used in some other LSMs [e.g., Noah uses four soil layers (Chen and Dudhia 2001) and the Rapid Update Cycle (RUC) LSM uses six layers (Smirnova et al. 1997)], it is more computationally efficient and more suitable for simple data assimilation schemes.

When applied in mesoscale models, such as the fifthgeneration Pennsylvania State University-National Center for Atmospheric Research Mesoscale Model (MM5) and Weather Research and Forecasting Model (WRF), land surface models perform well only when provided with some source of realistic initialization for soil moisture. Operational systems often use a Land Data Assimilation System (LDAS), which is essentially an offline version of the LSM, forced with observed precipitation, radiation, and analyzed meteorology, so that the forecast starts with optimal soil moisture fields (e.g., Mitchell et al. 2004). Another way to initialize soil moisture, which is used with the PX LSM within the MM5 and WRF systems, is through dynamic adjustment within the mesoscale model simulation where soil moisture is nudged according to differences between modeled and analyzed observations of 2-m temperature and relative humidity as described by Pleim and Xiu (2003). Soil moisture, particularly root zone soil moisture, is a strong factor controlling surface evaporation and evapotranspiration and, thereby, the partitioning of available surface energy into latent and sensible heat flux. Thus, to the extent that soil moisture is either optimally initialized or dynamically adjusted, model errors in 2-m temperature and humidity are minimized. However, the influence of soil moisture is strongest in heavily vegetated areas (e.g., eastern North America) during the growing season. In more arid and sparsely vegetated areas (e.g., most of western North America) and in temperate climates during the winter, optimal initialization or dynamic adjustment of soil moisture is not an effective means of error control. Therefore, another means of reducing model error in these conditions is proposed where deep soil temperature is also dynamically adjusted.

Before developing a dynamic adjustment scheme for the deep soil layer of the thermal force–restore mechanism, it is important to understand the characteristics of the force–restore model. Therefore in section 2 the force– restore model is compared with a high-resolution multilayer thermal diffusion model to identify the limitations and inherent errors in the FR approach. It is also important to understand how to balance accurate diurnal response with the ability to track seasonal changes. The soil temperature nudging scheme is described in section 3 along with a comparison of WRF simulations with and without the soil temperature nudging scheme for both summer and winter conditions. Discussion, conclusions, and future work are included in section 4.

2. Force–restore versus thermal diffusion

The FR mechanism for ground temperature, developed independently by Bhumralkar (1975) and Blackadar (1976), results from the analytical integration of the thermal heat diffusion equation with sinusoidal surface forcing. The general force–restore equation is given as

$$\frac{\partial T_g}{\partial t} = C_1 G(t) - C_2 (T_g - T_2), \tag{1}$$

where G(t) is the surface energy forcing, T_g represents the soil temperature at the soil surface integrated over a depth δ , T_2 is the deep reservoir temperature,

$$C_1 = \frac{2}{cd\alpha}$$
, and
 $C_2 = \frac{\omega}{\alpha}$, (2)

where c is the volumetric heat capacity, ω is the diurnal frequency ($\omega = 2\pi/\tau$, where $\tau = 1$ day) and d is the damping depth of the diurnal temperature wave:

$$d = \left(\frac{2\lambda}{c\omega}\right)^{1/2},\tag{3}$$

where λ is the heat conductivity. There are several definitions of the coefficient α in Eq. (2) depending on the approximate relationship between T_g and $T(\delta, t)$. Using the limiting case for the surface slab thickness $\delta \rightarrow 0$, as suggested by Deardorff (1978), results in $\alpha = 1$. However, Hu and Islam (1995) showed that the assumption of Lin (1980) that $T_g = 0.5[T(\delta, t) + T(0, t)]$, which leads to $\alpha = 1 + \delta/d$, gives less error than a high-resolution thermal diffusion model as long as $\delta \ll d$. Thus, for the testing shown here the Lin (1980) definition of α is used.

For a test case with sinusoidal forcing, the forcerestore model gives nearly identical results for ground temperature compared to a multilayer thermal diffusion model as shown in Fig. 1. The ground temperature in



FIG. 1. Soil temperature from the FR model for surface 1-cm slab $(T_g - FR)$ and deep 1-m slab $(T_2 - FR)$ compared with the top 1-cm layer $(T_g - ML)$ and 100th 1-cm layer $(T_{g100} - ML)$ from the ML model with sinusoidal surface forcing.

Fig. 1 is the average temperature for a 1-cm slab at the soil surface for both the force–restore model and a 100-layer thermal diffusion model where all layers are 1 cm thick. The multilayer model is the numerical solution of the thermal diffusion equation

$$\frac{\partial T}{\partial z} = \left(\frac{\lambda}{c}\right) \frac{\partial^2 T}{\partial z^2},\tag{4}$$

with the boundary condition at the soil surface

$$\left(-\frac{\lambda}{c}\frac{\partial T}{\partial z}\right)_{z=0} = \frac{G(t)}{c}.$$
 (5)

The surface forcing for the experiment shown in Fig. 1 is

$$G(t) = G_{\max} \cos[\omega(t - t_{\max})], \qquad (6)$$

where $G_{\text{max}} = G(t_{\text{max}})$, where t_{max} is solar noon. Note that the deep soil temperature for the FR model (T_2) is about 0.75 K cooler than the temperature of layer 100 in the multilayer model (T_{g100}) .

a. Effects of vegetation

The derivation of the force–restore mechanism includes several assumptions that limit its accuracy for more realistic application in meteorological models. Among these assumptions is that Eq. (1) is derived with sinusoidal surface energy forcing, vertically homogeneous thermal diffusivity, conductivity, and heat capacity values, and bare soil surface. The effects of several of these assumptions are investigated via comparison with the 100-layer thermal diffusion model. First, the heat capacity effects of vegetation cover are considered by modifying Eq. (2) such that

$$C_1 = \left(\frac{1 - \operatorname{veg}}{C_{1g}} + \frac{\operatorname{veg}}{C_{1\nu}}\right)^{-1},$$
 (7)

where veg is the areal fraction of vegetation coverage, C_{1g} is C_1 for bare soil as defined in Eq. (2), and C_{1v} is for vegetation (Noilhan and Planton 1989). While the value of C_{1g} is determined by the FR derivation, C_{1v} is entirely empirical so appropriate values are quite uncertain. McNider et al. (2005) reviewed the progression of suggested values from 3×10^{-3} (Noilhan and Planton 1989) to 2×10^{-5} K m² J⁻¹ (Manzi and Planton 1994; Mahfouf et al. 1995) and finally to 8×10^{-6} K m² J⁻¹ (Giard and Bazile 2000). Since the last value is the only one that results in greater effective heat capacity than bare soil (note that C_1 is inversely related to effective heat capacity) it is the most reasonable of the published choices. Thus, using $C_{1\nu} = 8 \times 10^{-6} \text{ Km}^2 \text{ J}^{-1}$ gives an increasingly damped response as vegetation fraction increases as expected (Argentini et al. 1992) and as shown in Fig. 2. For comparison, the multilayer model is modified such that the heat capacity used to define the surface boundary condition [G/c in Eq. (5)] is the weighted average of the heat capacity for soil and vegetation such that

$$c = (1 - \operatorname{veg})c_s + \operatorname{veg}c_v, \tag{8}$$

where both soil (c_s) and vegetation (c_v) heat capacities are estimated according to their water content,

$$c_s = (1 - w_{sat})c_i + wc_w \text{ and } c_v = b_m c_w,$$
(9)



FIG. 2. Comparison of surface 1-cm slab soil temperature from the FR model and the ML model for three vegetation coverages.

where c_i is the volumetric heat capacity of the solid part of the soil, w is the volumetric soil water content, w_{sat} is the saturation volumetric soil water content, b_m is the vegetation water content, and c_w is the volumetric heat capacity of water. For these calculations $c_i = 1.13 \times 10^6$ J m⁻³ K⁻¹, $c_w = 4.18 \times 10^6$ J m⁻³ K⁻¹, $w_{sat} = 0.451$, and w = 0.3. The best agreement between the FR model and the multilayer model for 0%, 50%, and 95% vegetation coverage is obtained when b_m is set to 0.5. This is interesting because it gives some guidance to the meaning of values chosen for $C_{1\nu}$, and thereby the possibility of more sophisticated parameterizations that account for the amount of biomass and water content of various types of vegetation. However, this finding also demonstrates the ambiguity of the FR parameterization because if the value of c as defined in Eqs. (8) and (9) is substituted into Eqs. (2) and (3) to compute C_1 as a function of veg the result does not agree with Eq. (7) and does not give the good agreement between the FR and multilayer models seen in Fig. 2.

b. Realistic forcing

Another question concerning the force–restore approach: given that it was derived assuming sinusoidal surface forcing, how well does it respond to more realistic forcing? To answer this question both the FR and multilayer models were forced with realistic surface energy forcing as

$$G(t) = R_{\sigma} + \varepsilon (L - \sigma T_{g}^{4}) - H - LE, \qquad (10)$$

where R_g is solar radiation absorbed by the ground, ε is the emissivity of the ground, L is the downward longwave radiation at the ground, σ is the Stefan–Boltzmann constant, and H and LE are the upward sensible and latent heat flux at the surface. For testing purposes R_g is specified by a diurnal cosine function as shown by Eq. (6) but not allowing negative values. For simplicity, Hand LE are scaled from R_g as $H = 0.7 R_g - 20.0 \text{ W m}^{-2}$ and LE = 0.07 R_g . Both models were run cyclically for 50 days to allow the soil temperatures to come into equilibrium with the surface forcing. Note that the deep soil temperature, T_2 , is allowed to vary slowly for this test so that the model can adjust over time toward equilibrium. The results shown in Fig. 3 are for the last of the 50 days.

The comparison of the ground temperature (T_g) between the FR and multilayer models for realistic forcing is not as close as for sinusoidal forcing (Fig. 1). The ground temperature from the FR model exhibits a small time lag in the morning and a relative cold bias for most of the night, but with a slightly warmer minimum. These nighttime errors seem to result from more curvature in the nocturnal temperature time series (between about 50 000 and 80 000 s) relative to the more linear temperature time series exhibited by the multilayer model. These characteristic errors are often noticeable in the WRF results when 2-m air temperature is compared with observations as shown below (section 3).

c. Deep soil temperature time scale

The force-restore derivation assumes that the deep soil temperature T_2 is deeper than the diurnal temperature wave and therefore should be a diurnal constant. However, T_2 must be allowed to change on longer time scales to account for seasonal- and synoptic-scale changes. Both Blackadar (1976) and Bhumralkar (1975) suggested that T_2 be specified daily by the 24-h average of the surface temperature over the previous day, which would involve a daily discontinuity. Deardorff (1978)



FIG. 3. Soil temperature from FR model for surface 1-cm slab and deep 1-m slab compared with the top 1-cm layer and 100th 1-cm layer from the ML model with realistic surface forcing.

suggested allowing T_2 to be forced by the surface energy flux but at an annual time scale. The PX LSM allows T_2 to vary according to the temperature difference with the surface slab following Noilhan and Planton (1989) as

$$\frac{\partial T_2}{\partial t} = \frac{1}{\tau_2} (T_g - T_2). \tag{11}$$

The time scale for deep soil temperature variation, τ_2 , was originally set to 1 day as suggested by Noilhan and Planton (1989), whereas for many model applications of the PX LSM in the MM5 and WRF systems, $\tau_2 = 10$ days was used. Timescales of 3 and 5 days have also been tested in MM5. This time scale controls how quickly the model will respond to changes in the surface forcing. Setting the time scale to 1 day allows rapid dayby-day adjustment so that the model is always close to equilibrium with the surface energy forcing while longer time scales are intended to allow seasonal adjustments without necessarily maintaining equilibrium with the surface forcing.

There are two questions about the magnitude of the time scale for deep soil temperature: 1) how does a variable T_2 affect the performance of the FR model? 2) Is it desirable to either allow or require that the value of T_2 be close to the equilibrium value? To answer the first question the sinusoidally forced test case is revisited using various deep soil temperature time scales (Fig. 4). The T_2 = constant result ($\tau_2 = \infty$) is identical to Fig. 1. Shortening the time scale to 10, 3, and 1 days gives T_2 a diurnal periodicity of increasing amplitude while T_g exhibits some reduction in the afternoon cooling rate resulting in a small increase in the minimum temperature. While the 10-day time scale is almost identical to

the T_2 = constant result, the run using the 1-day time scale gives an increase of 1.33 K in the minimum T_g with a slight time lag and the greatest departure from the correct solution (the ML result in Fig. 1).

Figure 5 shows the effect of the deep soil temperature time scale for the test case with realistic forcing. Compared to the 10-day time-scale test, the decreased afternoon cooling of the 1-day time-scale test leads to better agreement with the multilayer model during the early part of the night (between 55 000 and 75 000 s) without changing the minimum temperature. Therefore, the answer to the first question posed above is that allowing periodic diurnal variation in T_2 may actually improve results by decreasing the cool bias during the early part of the night for realistic forcing even though it adds error to the sinusoidally forced test case.

The second question, however, cannot be easily answered using these "offline" tests since it involves whether or not there is a net heat flux to or from deep soil layers during different seasons and different conditions. Full meteorological model simulations suggest that such deep soil heat fluxes may be very important especially in the winter and in the transitional seasons. If so, the short deep temperature time scales (e.g., 1–3 days) may not be desirable since they allow T_2 to quickly adjust toward equilibrium. Conversely, if a net deep soil heat source or sink is important, it is crucial to set the T_2 to the optimal temperature and not let it adjust to the surface forcing too quickly.

To understand how quickly the FR model adjusts to changing conditions the model was run with three different values of the deep soil temperature time scale ($\tau_2 = 10, 3, \text{ and } 1 \text{ days}$) for 50 days with cyclic realistic surface forcing. The deep soil temperature (T_2) was



FIG. 4. Soil temperature from FR model for surface 1-cm slab (T_g) and deep 1-m slab (T_2) with sinusoidal surface forcing for three values of the deep soil temperature time scale.

initialized at 280 K, which is about 4.5 K cooler than the equilibrium temperature. After 50 days the run with the 10-day time scale for the deep soil temperature was close to but still slowly approaching the equilibrium temperature (Fig. 6). The $\tau_2 = 3$ days run achieves equilibrium after about 27 days while the $\tau_2 = 1$ day run achieves equilibrium in about 9 days. Thus, the average T_2 tendency for this experiment is about $(0.5 \text{ K})/\tau_2$. Therefore, any technique to nudge the deep soil temperature toward the optimal value should be coupled with a long deep soil temperature time scale that allows for seasonal trends but will not quickly revert toward the equilibrium state.

3. Deep soil temperature nudging

Indirect soil *moisture* nudging has been shown to be a very effective method for reducing bias and error in modeled temperature and humidity during the growing season in heavily vegetated areas (Pleim and Xiu 2003). In the nongrowing seasons or in areas of sparse vegetation, however, this method is not effective because evapotranspiration, which is modulated by deep soil moisture, is not a major part of the surface energy budget in these conditions. Thus, a complementary assimilation technique that is most effective when the soil moisture nudging technique is least effective seems to



FIG. 5. Soil temperature from FR model for surface 1-cm slab (T_g) and deep 1-m slab (T_2) with realistic surface forcing for values of the deep soil temperature time scale of 1 day and 10 days compared with the surface 1-cm slab (T_g) and layer 100 (T_{g100}) from the ML model.



FIG. 6. Deep 1-m slab temperature with realistic surface forcing for three values of the deep soil temperature time scale for 50 days.

be necessary to improve land surface simulations. Criteria for candidate parameters for dynamic adjustment include a long (multiday) time scale, substantial uncertainty due to the lack of routine measurement, and strong influence on the important model parameters, which in the case of land surface modeling are primarily near-surface temperature and humidity. Clearly, deep soil *moisture* fits these criteria quite well when evapotranspiration is important. Similarly, the deep soil *temperature* also fits these criteria for the complementary conditions where vegetative activity is more limited. For LSMs using a force-restore model, the deep soil temperature exerts a strong influence on the ground surface temperature, especially at night.

Many techniques have been used to initialize the deep soil temperature. The force-restore model implemented in MM5 (Grell et al. 1995) used a constant deep soil temperature for each run segment that was set to the diurnal average of the 2-m air temperature on the first day. Others, such as Deardorff (1978) and Dickinson (1988), allow T_2 to vary slowly according to the annual temperature wave. The PX LSM implementation in MM5 follows the Blackadar initialization but allows T₂ to vary according to Eq. (11). As discussed in section 2, the choice of τ_2 in Eq. (11) represents a trade-off between slightly less cold bias in the early night when using a short time scale ($\tau_2 = 1$ day), as shown in Fig. 5, and allowing for multiday persistence that may be important if the equilibrium with the surface energy forcing does not give the best result. The short time scale ($\tau_2 = 1$ day) seems to work well in the summer when surface forcing is at its strongest; however, during winter conditions the deep soil temperature is often considerably warmer than the equilibrium temperature. Thus, using the 1-day time scale in Eq. (11), or initializing T_2 according to the diurnal average air temperature, results in widespread persistent cold biases as shown by Gilliam et al. (2006) for MM5 runs using the PX LSM. Ren and Xue (2004) addressed this issue by adding a term to Eq. (11) that includes the lapse rate of the seasonal mean soil temperature that essentially accounts for seasonal heat flux from very deep layers. They showed improved results for their soil temperature forecasts for different seasons. However, because the modeling described here is intended primarily for retrospective simulations, nudging techniques can be developed to dynamically adjust T_2 to give optimal results.

To improve temperature performance of the PX LSM in the new WRF implementation, τ_2 is set to 10 days to allow more persistence and a new deep temperature nudging scheme analogous to the soil moisture nudging scheme described by Pleim and Xiu (2003) is implemented. As for soil moisture, T_2 is nudged according to the bias in 2-m air temperature (T_{2m}) relative to an analysis temperature (T_{obs}). The nudging strength is a very simple function of solar radiation absorbed by the ground (R_g):

$$N_{\rm T2} = G\left(1 - 5\frac{R_g}{1370}\right) \quad \text{with the requirement that}$$
$$N_{\rm T2} \ge 0.0, \tag{12}$$

and where $G = 1.0 \times 10^{-5} \text{ s}^{-1}$. The deep soil temperature tendency due to nudging is

$$\frac{\partial T_2}{dt} = -N_{\rm T2}(T_{\rm 2m} - T_{\rm obs}).$$
 (13)

Equation (12) is designed to nudge T_2 at a constant strength during the night ramping down linearly to zero



FIG. 7. Average 2-m temperature bias relative to analysis for January 2006 (left) with and (right) without deep soil temperature nudging.

as R_g increases to 274 W m⁻². The idea is that nighttime ground temperature and near surface air temperature are both greatly influenced by the deep soil temperature because surface forcing is much less at night, thus, the restore term [the second term on the rhs of Eq. (1)] dominates.

To test this simple scheme, the Advanced Research Weather Research and Forecasting Model, version 3.0 (ARW-WRFv3.0; Skamarock et al. 2008), was run for January and August 2006 at 12-km horizontal gridcell size with and without deep soil temperature nudging. The PX LSM was used with the soil moisture nudging scheme as described by Pleim and Xiu (2003) as well as analysis nudging for temperature and humidity above the boundary layer and winds at all levels (Stauffer et al. 1991). Other physics options include the Asymmetric Convective Model, version 2 (ACM2), for PBL processes (Pleim 2007a,b), the PX surface layer scheme (Pleim 2006), the WRF Single-Moment 6-class (WSM6)

microphysics scheme (Hong et al. 2004), the rapid radiation transfer model (RRTM) for longwave radiation (Mlawer et al. 1997), simple shortwave (Dudhia 1989), and version 2 of the Kain-Fritsch (KF2) cumulus parameterization (Kain 2004). Initial and lateral boundary conditions were derived from North American Mesoscale (NAM) model analyses at 6-h intervals with 3-h NAM forecasts between that were developed by the National Centers for Environmental Prediction (NCEP) and provided by the National Climatic Data Center. The WRF was run in 5.5-day segments with half-day overlap to allow 12-h spinup at the start of each segment. The soil moisture and soil temperature in both soil layers were read from the previous run segment so that soil temperature and moisture are continuous for each entire one-month simulation period.

Figure 7 shows the January 2006 2-m temperature mean bias relative to the NAM analysis (model – analysis) for WRF runs with and without the new deep soil



FIG. 8. Average 2-m humidity mixing ratio bias (g kg⁻¹) relative to analysis for January 2006 (left) with and (right) without deep soil temperature nudging.



FIG. 9. Average 2-m temperature MAE (K) relative to analysis for January 2006 (left) with and (right) without deep soil temperature nudging.

temperature nudging. Clearly, the deep soil temperature nudging technique greatly reduces the mean bias, largely correcting the widespread cold bias in most of the domain. Figure 8 shows that there is even a small improvement in the 2-m humidity bias, even though there is no soil temperature nudging based on the humidity error. However, because a small value of mean bias can result from large compensating errors it is important to also evaluate mean absolute errors (MAEs) as shown in Fig. 9. The nudging scheme reduces MAE in nearly all land areas, with the largest errors improving from almost 3 to 1.5–2 K (e.g., Maryland).

When model-predicted 2-m temperatures are compared with National Oceanic and Atmospheric Administration/National Weather Service/Federal Aviation Administration (NOAA/NWS/FAA) station observations for January, averaged by hour of the day (Fig. 10), the model tends to have a general cold bias for all hours. The nudging technique reduces the cold bias and the MAE for all hours resulting in very little bias (<0.5 K) in the early morning (1000–1300 UTC) and a cold bias of about 1.3 K during the day. It is interesting that the 2-m temperature simulation is improved by the deep soil temperature during the day even though the nudging is applied only at night. Figure 11 shows small improvements in 2-m humidity bias at all hours with a very slightly reduced MAE during the day for the nudged run. This is a secondary or collateral benefit of the



FIG. 10. Diurnal average 2-m temperature bias and MAE (K) relative to NOAA/NWS/FAA station observations for January 2006 with deep soil temperature nudging (solid line), without deep soil temperature nudging (long dashed line), and in NAM analysis (short dashed line).



FIG. 11. Diurnal average 2-m humidity mixing ratio bias and MAE (g kg⁻¹) relative to analysis for January 2006 with (solid line) and without (dashed line) deep soil temperature nudging.

nudging scheme caused by warmed surface temperatures that increase the surface saturation vapor pressure that drives evaporation and evapotranspiration.

In comparing Fig. 10 with Fig. 7, Fig. 10 seems to show a larger overall cold bias than Fig. 7. This is because Fig. 7 shows the bias relative to the NAM analysis while Fig. 10 shows the bias relative to station observations. To relate these two, the bias and MAE for the analysis 2-m temperature is also shown in Fig. 10. Note that at night (0000–1200 UTC) the analysis has a cold bias that is quite similar to the bias of the nudged simulation. The MAE of the analysis is only slightly less than the MAE for the nudged run. Thus, the nudging scheme has effectively eliminated the 2-m temperature bias and most of the error at night relative to the analysis. During the day, however, the nudged run is still biased cool relative to both the analysis and the observations. Although the nudged run is considerably better than the nonnudged run there are clearly model errors, probably in the surface energy forcing, that remain. The prime candidate for the cause of these errors is excessive boundary layer cloudiness. Note that comparisons with WRF simulations using other combinations of PBL and LSM options have shown similar daytime cold biases in January (Gilliam and Pleim 2008, manuscript submitted to *J. Appl. Meteor. Climatol.*).

The effects of the deep soil temperature nudging are less dramatic in August than in January, as shown in Fig. 12, because the model generally performs better during the growing season when the soil moisture nudging



FIG. 12. Average 2-m temperature bias relative to analysis for August 2006 (left) with and (right) without deep soil temperature nudging.



FIG. 13. Average 2-m temperature MAE (K) relative to analysis for August 2006 (left) with and (right) without deep soil temperature nudging.

scheme effectively adjusts the latent and sensible heat partitioning. Nevertheless, the deep soil temperature nudging further improves the 2-m temperature bias and MAE (Fig. 13) in all land areas. The bias is reduced both in areas where the model was too warm, such as most of the northern states, and areas where the model was too cold, such as the southern states and near the western edge of the domain. In many areas the monthly averaged 2-m temperature bias is practically eliminated (white areas are within ± 0.1 K). The 2-m humidity bias and MAE (not shown) in August are essentially unaffected by the soil temperature nudging because humidity is much more affected by soil moisture than soil temperature. Diurnally, the average 2-m temperature bias is warm most of the night and very slightly cool during the day, as shown in Fig. 14. Both warm and cool biases are slightly reduced by the nudging scheme while the MAE, which is quite low for either run, is essentially unaffected by the nudging scheme.

Figure 15 shows an example of modeled temperatures with and without deep soil temperature nudging for an individual grid cell. This particular grid cell was located in south Texas along the Rio Grande where vegetation is sparse and the climate is arid. Hourly 2-m air temperature from both model runs is plotted along with the 2-m temperature from the 3-hourly NCEP analyses. The deep soil temperature (T_2) from each run, which is also shown in Fig. 15, was initialized to the same value on 1 August. The deep soil temperature time scale (τ_2) is set to 10 days, which allows small



FIG. 14. Diurnal average 2-m temperature bias and MAE (K) relative to analysis for August 2006 with (solid line) and without (dashed line) deep soil temperature nudging.



FIG. 15. August 2006 time series of 2-m air temperature and deep soil temperature (T_2) from WRF runs with and without deep soil temperature nudging compared with 2-m temperature analysis for an individual grid cell in south Texas.

amplitude diurnal periodicity and slow multiday trends in response to the surface forcing. Without the deep soil temperature nudging T_2 cools gradually by about 3 K over the first 10 days with very little variation for the rest of the month. For the latter half of the month T_2 is close to the diurnal average of the 2-m air temperature, indicating that it is close to equilibrium with the surface forcing. However, the 2-m air temperature produced by this run shows a significant cool bias at night for most of the latter half of the month, suggesting that the FR model when allowed to seek its own equilibrium may not produce the most realistic results.

After the first night, when the model predicted the 2-m temperature in comparison with the analysis almost perfectly, the deep soil temperatures from the two runs diverged markedly. During 2–5 August the no-nudged run T_2 cooled in response to reduced surface forcing

because of cloudiness while the nudged run T_2 warmed because the nocturnal 2-m temperature was underpredicted. Most of the time the T_2 nudging tendency is slow and usually in the same direction for many days (e.g., 17–25 August), which shows that it is responding to multiday trends. An exception occurs on the night of 5 August when T_2 drops about 2 K in one night because of a persistent 3-K-high bias in the 2-m air temperature for the entire night. The difference between the two runs is greatest during the last 10 days of the month when the nudged T_2 is 4–5 K warmer than the nonudged T_2 . The nudging, in this case, has effectively corrected the nighttime cool bias by raising the deep soil temperature substantially above the equilibrium temperature. Note, however, on some nights (e.g., 25-27 August) the minimum 2-m temperature from the nudged run is too warm. This seems to result from the more curved time series at night produced by the FR



FIG. 16. Average August 2006 diurnal 2-m temperature bias compared with 2-m temperature analysis from WRF runs with and without deep soil temperature nudging for an individual grid cell in south Texas.

model such that the early part of the night tends to be too cold while the minimum temperature is too warm as discussed in section 2. This tendency is also evident in average 2-m temperature biases shown in Fig. 16. For most of the night (0000–0900 UTC) the nudging scheme reduces the cold bias. However, during the coldest part of the early morning (1000–1200 UTC), the nudging scheme tends to result in a warm bias. Figure 16 also shows that on average for this location the nudging scheme reduces the daytime cold bias with almost no bias for the hours of maximum air temperature (1900– 2000 UTC).

4. Conclusions

The Pleim-Xiu land surface model has been incrementally improved by the addition of another indirect data assimilation technique. Previously, an assimilation technique was developed to nudge near-surface and root zone soil moisture according to biases in the 2-m air temperature and relative humidity relative to the NAM analyses. That technique, described by Pleim and Xiu (2003), uses the physical algorithms that describe evapotranspiration in the PX LSM to modulate the soil moisture nudging strength resulting in the strongest nudging during sunny conditions in heavily vegetated areas with no nudging at night. The new soil temperature nudging technique is complementary to the soil moisture nudging technique in that it operates at night and most strongly when latent heat fluxes are small (in arid climates and during the nongrowing season). The soil

moisture nudging reduces errors in surface air temperature and humidity by adjusting the bulk stomatal conductance of the vegetation, which affects the partitioning of surface energy between latent and sensible heat fluxes. This is an effective lever for dynamic adjustment only when the latent heat flux is an important part of the surface energy fluxes. This approach can be seen as an adjustment of the surface energy forcing [first term in Eq. (1)]. The new technique, on the other hand, acts on the restoring tendency of the FR model [second term in Eq. (1)] at times when surface forcing is minimal (at night). Uncertainty in the initialization of the deep soil temperature is a significant source of error for the FR model. Furthermore, left to its own devices the FR model will adjust the deep soil temperature toward the equilibrium temperature at a rate dependent on the deep soil temperature time scale (τ_2) in Eq. (11). The equilibrium temperature is appropriate only if there is no net diurnal heat flux between the deep soil slab and the surface soil slab $[\int_{1 \text{day}} (T_g - T_2) dt = 0]$. Given the variability of the surface forcing the equilibrium condition is more the exception than the rule. Thus, the nudging scheme acts to gradually adjust the deep soil temperature (nudging time scale is about 28 h) according to nocturnal biases in the 2-m air temperature. In addition, setting the deep soil temperature time scale $[\tau_2 \text{ in Eq. (11)}]$ to 10 days allows the model to adjust to seasonal trends in surface forcing while retarding the day-to-day adjustment toward equilibrium.

The evaluation of the new deep soil temperature nudging scheme as implemented in ARW-WRF, version

3.0, shows distinct improvement in 2-m air temperature error and bias when compared with an identical model simulation without the new scheme. The improvement is most dramatic for the winter period (January 2006), particularly during the night when the error and bias are practically as good as the NAM analysis. Daytime performance is also considerably improved, but significant cold bias remains. Further investigation of the cause of these winter daytime errors that were also evident in WRF simulations using other LSM and PBL options (Gilliam and Pleim 2008, manuscript submitted to *J. Appl. Meteor. Climatol.*) is warranted.

Acknowledgments. The U.S. Environmental Protection Agency through its Office of Research and Development funded and managed the research described here. It has been subjected to Agency review and approved for publication.

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