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1. INTRODUCTION

Numerical weather prediction models require an accurate representation of initial land surface conditions in order to partition properly the sensible and latent heat fluxes that drive the evolution of the planetary boundary layer. Models accomplish this exchange of energy between the land surface and the atmosphere through land surface parameterizations (e.g., Bhumralkar 1975; Blackadar 1976; Deardorff 1978; McCumber and Pielke 1981; Pan and Mahrt 1987; Noilhan and Planton 1989), in which the ground heat flux plays a critical role in the surface energy balance. The ground heat flux in turn depends heavily upon soil temperature and soil moisture conditions, as well as vegetation coverage, atmospheric conditions, and the physical properties of the soil. Soil moisture provides a key link between the atmosphere and the water and energy balances at the surface of the earth (Wei 1995; Robock et al. 2000; Leese et al. 2001). It influences the available water for plant transpiration, and plays a role in the mass balance for many forecast models. Soil thermal conductivity estimates, which facilitate the proper heat transfer within the soil, also strongly depend upon soil moisture specifications. To calculate soil heat transfer, the most sophisticated land surface parameterizations require not only near-surface soil temperatures, but also temperature profiles (e.g., Viterbo and Beljaars 1995; Chen and Dudhia 2001). Together, soil temperature and moisture work in concert to directly influence ground, sensible, and latent heat fluxes and affect forecasts of temperature, mixing ratio, precipitation, and cloud cover.

Several studies have demonstrated sensitivities of forecasts of near-surface variables to soil water content. An inspection of the relationship between soil moisture variations and surface turbulent energy fluxes for a variety of vegetation types reveals that energy fluxes display more sensitivity for dry soils than for wet soils and that sparsely vegetated areas require more accurate soil moisture observations or simulations (Dirmeyer et al. 2000). Changes in soil moisture modify the balance between latent and sensible heat fluxes and can influence surface

temperatures or affect turbulent transfer in the boundary layer (McCumber and Pielke 1981). For example, Pan and Mahrt (1987) couple a one-dimensional model of the planetary boundary layer (Troen and Mahrt 1986) with a two-layer soil hydrology model (Mahrt and Pan 1984) and find that surface evaporation can drive boundary-layer development.

Soil moisture also influences the development of deep convection due to the influence of soil moisture on latent heat fluxes and boundary layer moisture (Clark and Arritt 1995). Yan and Anthes (1988) investigate the effect of soil moisture variations on precipitation patterns by simulating adjacent strips of moist and dry land. They find that for sufficiently wide horizontal strips under convectively unstable conditions, the inhomogeneities in surface moisture lead to gradients of ground temperature that eventually help produce sea-breeze circulations and an increase in convective rainfall. This result complements the observations of Pielke and Zeng (1989), who show increases in available buoyant energy when irrigated land lies adjacent to natural grassland, compared with natural grassland alone. Soil moisture further affects boundary-layer cloud development by increasing cloud cover for both moist and dry soils, depending on the strength of the stability above the boundary layer (Ek and Holtslag 2004).

Numerical and observational studies of soil moisture reveal that soil moisture anomalies influence regional atmospheric conditions over time scales of two to three months (Liu et al. 1993; Vinnikov et al. 1996), with variations in temporal scales of soil moisture attributable to the seasonal cycle of potential evaporation (Entin et al. 2000). After simulating soil moisture anomalies, there is evidence that soil moisture affects model forecasts of precipitation, atmospheric moisture, and temperature for several weeks (Walker and Rowntree 1977; Rowntree and Bolton 1983). Modeling studies of soil temperature and moisture conditions show that differing soil moisture initializations influence monthly or seasonal temperatures and precipitation patterns (Rind 1982; Betts et al. 1996) and that these initial conditions again possess a persistence time scale of months to seasons (Yeh et al. 1984; Walsh et al. 1985; Vinnikov and Yesserkepova 1991; Gao et al. 1996; Liu and Avissar 1999a,b). Monthly forecasts also show sensitivity to initial soil moisture conditions, displaying increased skill for pre-

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cipitation and air temperature forecasts with more realistic land surface initializations (Koster et al. 2004). Other studies report that soil moisture anomalies also affect extreme precipitation forecasts on monthly time scales (Beljaars et al. 1996; Viterbo and Betts 1999). In seasonal predictions, Fennessy and Shukla (1999) investigate the role of initial soil moisture using ensembles of global climate model simulations and find that increases in initial soil wetness lead to increased seasonal evaporation, decreased seasonal mean surface air temperatures, and generally increased seasonal mean precipitation in many regions. Other authors assert that the seasonal evolution of the atmosphere in a regional atmospheric model is dependent upon initial soil moisture and landscape specification (Pielke et al. 1999). Thus, when compared with soil temperature, soil moisture clearly has more interannual variability and more strongly influences forecasts (Liu and Avissar 1999a,b; Rodell et al. 2005).

While soil moisture appears to be the most important factor for land-surface initializations (Gannon 1978; McCumber and Pielke 1981; Smith et al. 1994), one should not underestimate the role of soil temperature in the evolution of the lower atmosphere, especially for short-range forecasts. Longwave radiation loss is a function of soil temperature and directly affects the radiation budget at the surface. Ground heat flux also is a function of soil temperature (Brotzge and Crawford 2003), and affects the sensible heat flux, boundary layer growth and decay, turbulence, and air temperature. Clearly, forecast models require both accurate soil temperature and soil moisture initializations. Though efforts are under way to provide more extensive networks of soil moisture data from a variety of remote sensing and direct observational sources (Entekhabi et al. 1999; Leese et al. 2001; Seuffert et al. 2004), routine *in situ* observations of soil temperature and moisture suitable for data assimilation are currently unavailable over large areas of the continental United States and the world.

Due to the absence of a large observational soil-monitoring network, many forecast models implement complex land surface models to realistically determine soil hydrology. The National Centers for Environmental Prediction (NCEP) operational Eta model (Black 1994) produces land surface analyses by continuously cycling temperature and moisture fields within the Noah land surface model (LSM, Chen et al. 1996; Koren et al. 1999). In the past, these fields evolved only in response to radiation budget constraints and modeled precipitation, but NCEP recently upgraded the self-cycling process so that soil fields respond instead to adjusted precipitation observations from both radar and gauge data over the United States.

Many modeling efforts have used NCEP Eta model analyses and forecasts over the continental United States as initial and boundary conditions for a variety of applications (e.g., Colle et al. 2001; Bright and Mullen 2002; Stensrud and Weiss 2002; Westrick et al. 2002; Zhen-der 2002; Brennan et al. 2003; Chen et al. 2004; Hart

et al. 2004; Hoadley et al. 2004; Galewsky and Sobel 2005; Zamora et al. 2005; Zhong et al. 2005). The Eta model therefore provides very important initial land-surface conditions that strongly influence forecasts for both operational and research purposes. Unfortunately, many land surface models, including the Noah LSM, do not capture observed soil moisture variations when forced with atmospheric observations or cycled model output (Robock et al. 2000). Marshall et al. (2003) found a strong positive bias in soil moisture from the Eta model in comparison to Oklahoma Mesonet observations, but also noted that a change in the Eta model initialization procedure to a continuous self-cycling initialization for soil moisture significantly mitigated this bias. Marshall et al. (2003) also reported a warm bias in soil temperatures at a depth of 5 cm in the late afternoon and a cool bias in the early morning. On the other hand, Robock et al. (2003) found good agreement when comparing soil temperature and moisture output from a more recently implemented version of the Noah LSM with observations from the Oklahoma Mesonet averaged over all of Oklahoma during 1998–99.

This study compares Eta model analyses of soil temperature and moisture at 0000 UTC and 1200 UTC with observations from the Oklahoma Mesonet between 1 March 2004 and 1 October 2005. In contrast to the findings of Robock et al. (2003), strong biases in soil temperature exist, as well as a severe underestimation of soil moisture at all depths. An important distinction between this and previous studies is that the results derive from point comparisons, rather than large-scale averages. The reasoning behind this decision appears in section 4.

2. MODEL DESCRIPTION

The National Centers for Environmental Prediction (NCEP) Eta model (Black 1994) is initialized from analyses provided by the Eta Data Assimilation System (EDAS, Rogers et al. 1996; Nelson 1999). The EDAS first produces a 3-h forecast from its own analysis over the continental United States. The system then uses this forecast as a background field for assimilating subsequent observations over this 3-h period and produces a new analysis valid at the end of the 3-h window. This process continues indefinitely, with forecasts out to 84 hours produced from the most recent EDAS analysis every six hours. The Eta model produces each EDAS forecast so that initial atmospheric and soil conditions are consistent with the forecast model and match its resolution, physics, and dynamics (Rogers et al. 1996). The absence of a complete set of observations of soil temperature and soil moisture necessitates continuously self-cycled soil fields within the EDAS without observational corrections or soil moisture nudging toward climatology. These soil fields evolve only in response to external forcing from model physics and surface forcing in the form of precipitation and the surface radiation balance within the EDAS.

Prior to a modification on 16 March 2004, the EDAS assimilated hourly precipitation data consisting of radar and gauge observations from NCEP Stage II and Stage IV analyses (Fulton et al. 1998; Lin et al. 2005). These analyses exhibit a systematic dry bias which, when used as the driver for soil moisture, leads to drier soil. After an adjustment on this date, comparisons of the cumulative 24-h precipitation from EDAS against daily gauge analyses, inflated by 10% to correct for catchment errors, yield a long history of net deficits or surpluses in precipitation. Adjustments to the EDAS hourly precipitation input based on this history attempt to eliminate the deficit or surplus over 24 hours. Adjustments remain limited to $\pm 20\%$ of the hourly precipitation analysis values and only apply to grid points in the analysis with non-zero precipitation. The EDAS assimilates the adjusted hourly precipitation input and then models the precipitation field. This modeled precipitation drives the land surface physics, though the modeled precipitation does not necessarily match the bias-adjusted observations (Lin et al. 2005).

A more extensive modification to the land surface scheme occurred on 3 May 2005 in the operational Eta model, now termed the North American Mesoscale (NAM). Previously, the EDAS would create precipitation during the assimilation process in regions where the Eta model did not forecast precipitation. The renamed NAM Data Assimilation System (NDAS) no longer adjusts precipitation totals in locations where the precipitation from the NAM model is less than the bias-adjusted observations. However, the latent heat and moisture fields are reduced where the modeled precipitation is greater than the bias-adjusted observations. More importantly, the NDAS drives the land surface physics directly with the bias-adjusted observations rather than with the NDAS modeled precipitation, resulting in moister soil. The previous version tended toward a dry bias during the assimilation because the modeled precipitation did not exactly replicate observed precipitation coverage and intensities. This allows for a more robust and more accurate precipitation assimilation that increases soil moisture. Additionally, there is no longer an upper limit for cloud water mixing ratios when computing optical depths, which improves radiation absorption, and modifications to the cloud cover parameterization allow for more fractional cloudiness (DiMego and Rogers 2005).

Simultaneous upgrades to the Noah LSM addressed low-level temperature and humidity biases. Vegetation and soil databases have more classes with higher spatial resolution. A 1-km resolution, United States Geological Survey (USGS) 24-class vegetation type database replaced the 13-class, 1-degree resolution simple biosphere (SiB) vegetation types (Sellers et al. 1986). For soil characteristics, the 1-km resolution, 16-class State Soil Geographic Database (STATSGO, Miller and White 1998) data eclipsed the 1-km resolution, nine-class Zoller soil types (Zoller 1986). A 1-degree database of soil temperatures at the lower boundary at 300 cm depth replaced

an old 2.5-degree soil temperature database. In addition, model developers lowered the leaf area index and compensated for the effect of the new precipitation assimilation procedures on the existing soil moisture bias by tuning the canopy conductance and other vegetation parameters within the Noah LSM. A lowered roughness length for heat reduces the skin temperature, thereby lowering the 2-m temperature forecasts and reducing the warm bias, though this does not change latent or sensible heat fluxes significantly. Overall, these modifications reduce drying trends and increase the low-level moisture (DiMego and Rogers 2005).

3. DATA

The Oklahoma Mesonet is an integrated network of 116 automated surface observing stations, with at least one site in each of Oklahoma's seventy-seven counties. Each site measures atmospheric variables every five minutes and soil temperature at a depth of 10 cm every 15 minutes under both bare soil and native vegetation. Most of the sites also measure soil temperature at a depth of 5 cm under both bare soil and native vegetation and at a depth of 30 cm under native vegetation. Many Oklahoma Mesonet sites also report soil moisture at depths of 5, 25, 60, and 75 cm. All data fall subject to rigorous quality assurance procedures to ensure the production of reliable, research-quality data (Shafer et al. 2000). A complete description of the Oklahoma Mesonet, including sensor specifications, appears in Brock et al. (1995), while Basara and Crawford (2000) discuss the soil moisture instrumentation.

4. COMPARISON WITH OBSERVATIONS

Gridded 40-km Eta model analyses of soil temperature and moisture at 0000 UTC and 1200 UTC were bilinearly interpolated to Oklahoma Mesonet observation sites allowing for direct model verification. While Eta model soil analyses are available at the present operational grid spacing of 12 km, researchers seldom use these analyses for initializing forecast models. Comparisons span the period from 1 March 2004 through 1 October 2005. This period is sufficient to characterize the performance of the EDAS soil temperature and moisture schemes both before and after the change from continuously self-cycling modeled precipitation and radiation to assimilation of precipitation observations on 3 May 2005.

Point measurements of soil temperature and moisture are not as spatially representative as atmospheric measurements, primarily due to spatial heterogeneities in vegetation coverage and soil types (Marshall et al. 2003; Brotzge and Crawford 2003). For this reason, spatial and temporal averaging of observations reduces small-scale noise and enables model validation and intercomparisons (e.g., Marshall et al. 2003; Robock et al. 2003). How-

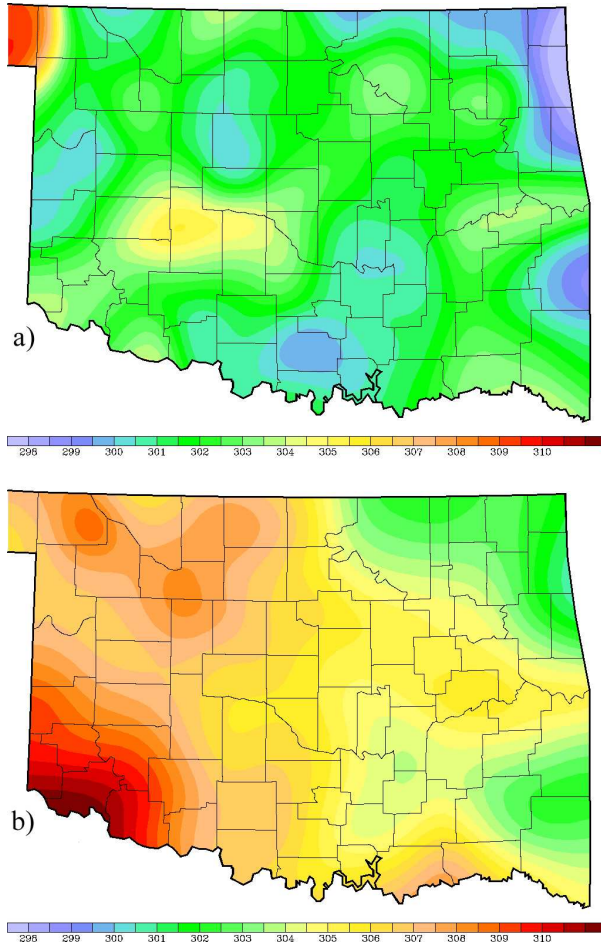


FIG. 1. Soil temperature (K) at 0000 UTC 15 July 2005 from a) Oklahoma Mesonet observations at a depth of 5-cm under sod and b) the 0–10 cm soil layer of the 0000 UTC Eta analysis.

ever, interpolating observations to a model grid yields comparisons that are partly a function of the interpolation scheme rather than the underlying observations. An analysis scheme cannot account for small spatial variations in the observations and thus analyzed and observed values may differ considerably (Schlatter 1975). Moreover, individual observation points, and not areal averages, provide the raw data for objective analysis schemes that produce gridded initial conditions for models. It is therefore important to correctly estimate point values of soil temperature and soil moisture in the Eta model so that these values can provide meaningful initial conditions for other numerical models with different grid sizes. The choice to analyze point comparisons in this study rather than interpolate the observations to the model grid permits a bulk characterization of the model performance over all of Oklahoma without introducing errors through large-scale spatial averaging.

Though comparisons between the Eta model and observations only include point measurements, Figures 1 and 2 provide informative visualizations of the geo-

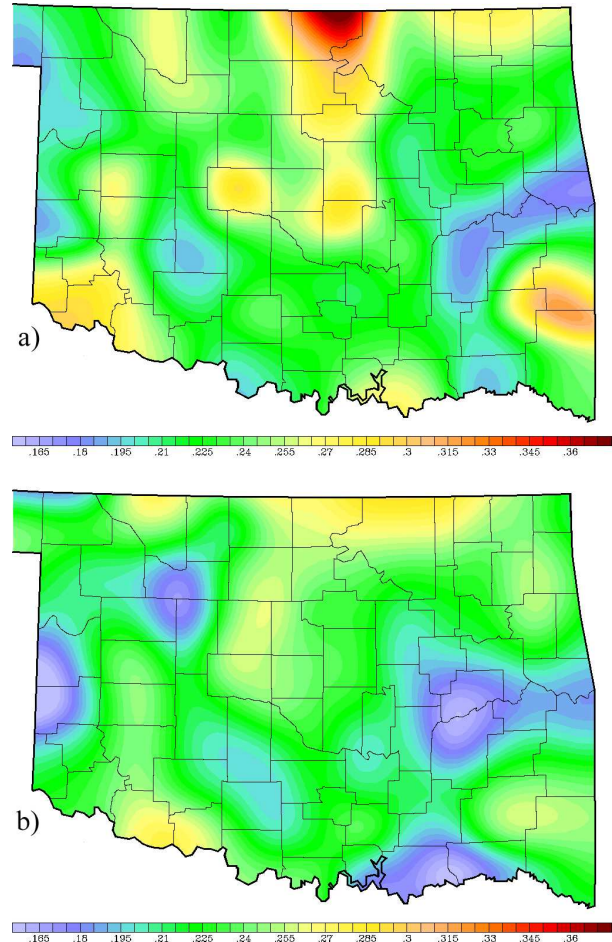


FIG. 2. Soil moisture ($\text{m}^3 \text{m}^{-3}$) at 0000 UTC 15 July 2005 from a) Oklahoma Mesonet observations at a depth of 5-cm and b) the 0–10 cm soil layer of the 0000 UTC Eta analysis.

graphic variability of Oklahoma Mesonet 5-cm soil temperature and moisture observations compared with Eta model 0–10 cm soil temperature and moisture analyses for a representative summer day. The Oklahoma Mesonet observations are interpolated to a 3-km horizontal grid using a two-pass Barnes analysis (Barnes 1973). The Eta analyses, shown here interpolated to the same 3-km horizontal grid, display a cool and dry bias typical of many 1200 UTC analyses. In addition, the differences in the patterns of each field can influence the subsequent forecast.

The Noah LSM model within the EDAS contains five soil layers representing depths of 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm, and a constant reservoir temperature at 300 cm. Soil temperatures in the 0–10 cm model layer are compared with Oklahoma Mesonet observations at a depth of 5 cm and soil temperatures in the 10–40 cm model layer are compared with observations at a depth of 30 cm. For soil moisture, the values from the Eta analysis in the 0–10 cm, 10–40 cm, and 40–100 cm layers are compared with observations at depths

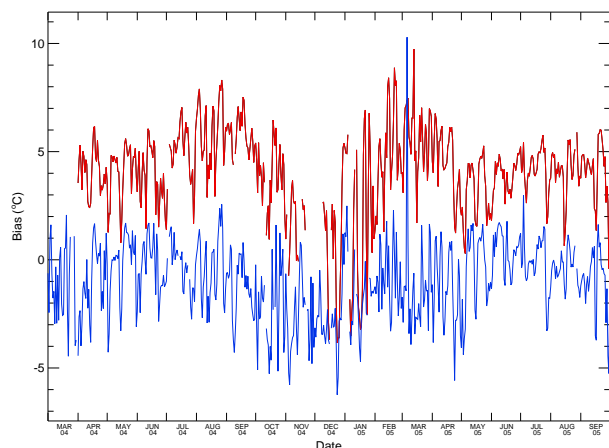


FIG. 3. Point calculations of daily soil temperature bias ($^{\circ}\text{C}$) averaged over all of Oklahoma in the 0–10 cm layer from 0000 UTC (red) and 1200 UTC (blue) Eta analyses compared with 5-cm soil temperature observations from the Oklahoma Mesonet.

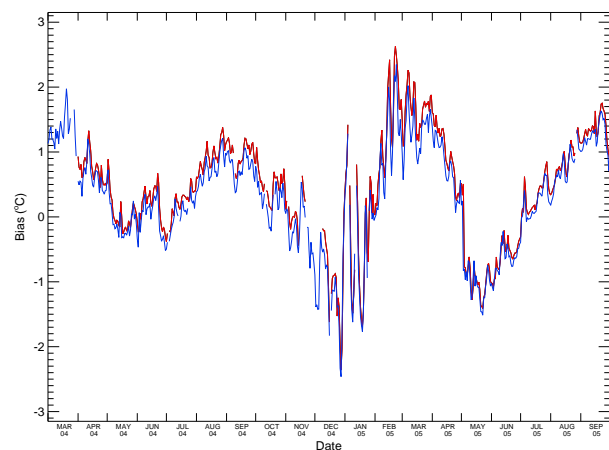


FIG. 4. Point calculations of daily soil temperature bias ($^{\circ}\text{C}$) averaged over all of Oklahoma in the 10–40 cm layer from 0000 UTC (red) and 1200 UTC (blue) Eta analyses compared with 30-cm soil temperature observations from the Oklahoma Mesonet.

of 5 cm, 25 cm, and 60 cm, respectively. These direct comparisons allow computation of root-mean-square error (rmse) and bias (Wilks 1995) across the entire Oklahoma Mesonet.

4.1 Soil temperature

There is a strong positive soil temperature bias in the 0–10 cm layer from 0000 UTC Eta model analyses compared with observations of 5-cm soil temperatures from all Oklahoma Mesonet sites (Fig. 3). Twelve hours later at 1200 UTC, there is a predominately negative bias. Overall, the bias for this most shallow soil layer is 4.1°C (-1.0°C) and the rmse is 5.0°C (2.4°C) for 0000 UTC (1200 UTC) Eta analyses. Errors appear reduced in magnitude in the deeper 10–40 cm soil layer, and the 0000 UTC and 1200 UTC soil temperature analyses differ only

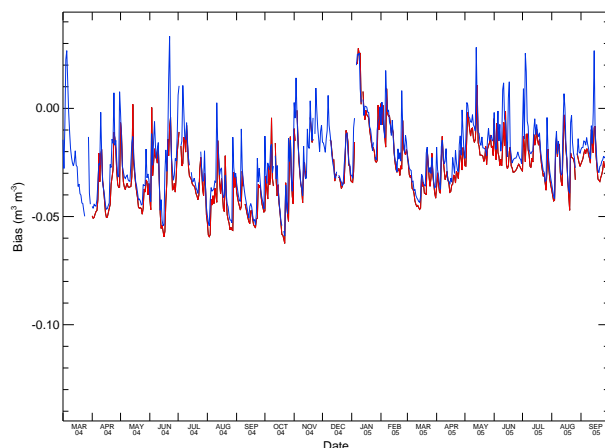


FIG. 5. Point calculations of daily soil moisture bias ($\text{m}^3 \text{m}^{-3}$) averaged over all of Oklahoma in the 0–10 cm layer from 0000 UTC (red) and 1200 UTC (blue) Eta analyses compared with 5-cm soil moisture observations from the Oklahoma Mesonet.

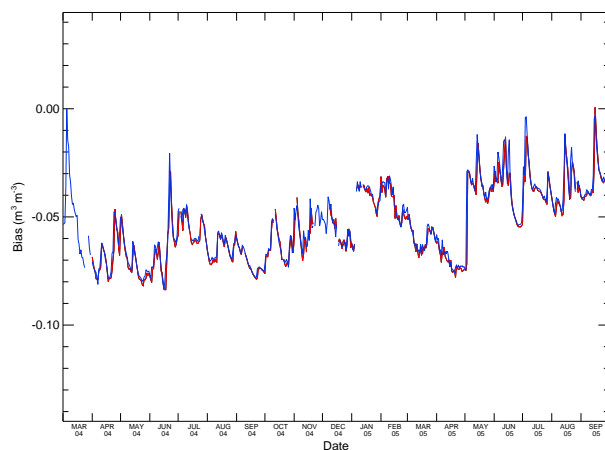


FIG. 6. Point calculations of daily soil moisture bias ($\text{m}^3 \text{m}^{-3}$) averaged over all of Oklahoma in the 10–40 cm layer from 0000 UTC (red) and 1200 UTC (blue) Eta analyses compared with 25-cm soil moisture observations from the Oklahoma Mesonet.

slightly (Fig. 4). There is a temporally coherent pattern of errors throughout the year such that errors of the same sign persist for multi-week periods. This trend appears to follow the more variable pattern of daily biases in the upper soil layer. Modifications to the land surface model on 3 May 2005 do not appear to affect significantly the magnitude of subsequent soil temperature errors.

4.2 Soil moisture

There is a pervasive and persistent dry bias in both the 0000 UTC and 1200 UTC Eta soil moisture analyses. For each day, the Oklahoma-wide average soil moisture in the 0–10 cm model layer of the Eta analyses is generally drier than the observations at 5 cm (Fig. 5). In the 10–40 cm layer, the soil moisture bias slightly exceeds zero for only a single 0000 UTC Eta analysis and in the 40–100

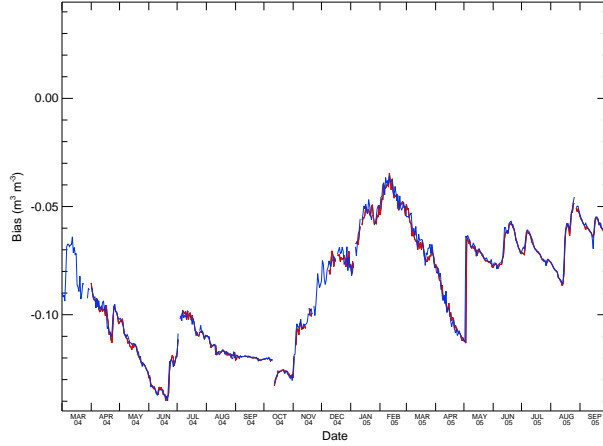


FIG. 7. Point calculations of daily soil moisture bias ($\text{m}^3 \text{m}^{-3}$) averaged over all of Oklahoma in the 40–100 cm layer from 0000 UTC (red) and 1200 UTC (blue) Eta analyses compared with 60-cm soil moisture observations from the Oklahoma Mesonet.

cm layer, the soil moisture bias never becomes positive over the period of study (Figs. 6 and 7). Overall, the bias for each soil layer is $-0.03 \text{ m}^3 \text{m}^{-3}$, $-0.05 \text{ m}^3 \text{m}^{-3}$, and $-0.09 \text{ m}^3 \text{m}^{-3}$ for the 0–10 cm, 10–40 cm, and 40–100 cm Eta model layers, respectively. In the 40–100 cm Eta model layer, the daily average soil moisture error across all of Oklahoma reaches as large as 35% of the typical range of soil moisture when compared with observations at a depth of 60 cm.

There is notable improvement in the analyzed soil moisture fields after the change from self-cycling precipitation to observed precipitation assimilation on 3 May 2005. While this change reduced the magnitude of the errors, and evidences itself as a large discontinuity in the bias time series of Figures 6 and 7, a strong dry bias persists in the soil moisture field.

5. DISCUSSION

Systematic biases clearly exist in both soil temperature and soil moisture. Positive soil temperature errors in 0000 UTC Eta analyses likely stem from the documented excess of solar radiation during the daytime (Zamora et al. 2005), while the generally negative soil temperature biases in 1200 UTC Eta analyses result from underestimated downward longwave radiative fluxes during nighttime hours (Stensrud et al. 2005). Modifications to the land surface physics on 3 May 2005 did not mitigate these errors; soil temperatures in the top soil layer remain too high in the 0000 UTC analyses and dry soil moisture biases continue in each of the top three soil layers. Tests indicate that these systematic biases in both soil temperature and moisture do not appear to be strongly dependent upon soil or vegetation types defined in Eta model grid cells.

Figure 8 shows the EDAS soil moisture at three soil depths compared with observed precipitation totals and

observed soil moisture at the Eufaula Oklahoma Mesonet site. The soil moisture errors in the top two model layers result from both an inappropriate response to rainfall events and accelerated desiccation of the soil compared with observations, particularly in the 10–40 cm layer. The response to precipitation in the 40–100 cm layer appears limited except after several consecutive days of heavy precipitation. The new precipitation assimilation procedure implemented on 3 May 2005 somewhat improved soil moisture estimates at some Mesonet sites, though systematic dry biases remain in the Eta analyses.

An exploration of the influence of soil heat capacity can help to address the effect of such a dry bias on soil temperatures. Soil heat capacity is a function of soil moisture and directly affects the diagnosis of soil temperature. Underestimates of soil moisture such as those in Eta model analyses could therefore result in poorly estimated soil temperatures. A simple, one-layer slab soil model driven by Oklahoma Mesonet observations allows approximate calculations of the influence of errors in soil moisture alone on soil temperature. The composite soil volumetric heat capacity employed in the slab model is

$$C_g = \theta C_{\text{water}} + (1 - \theta_s) C_{\text{soil}} + (\theta_s - \theta) C_{\text{air}}, \quad (1)$$

where θ is the soil volumetric water content, $C_{\text{water}} = 4.2 \times 10^6 \text{ J m}^{-3} \text{K}^{-1}$, $C_{\text{soil}} = 1.26 \times 10^6 \text{ J m}^{-3} \text{K}^{-1}$, and $C_{\text{air}} = 1004 \text{ J m}^{-3} \text{K}^{-1}$ are the volumetric heat capacities of water, soil, and air, respectively, and θ_s is the soil porosity (Chen and Dudhia 2001). The soil porosity depends upon the soil texture (Cosby et al. 1984) determined from soil cores at each observation site. The slab model predicts the soil temperature T at a depth of 5 cm using

$$C_g d_s \frac{\partial T}{\partial t} = Q_{G_s}, \quad (2)$$

where Q_{G_s} is the storage ground heat flux and $d_s = 10$ cm is the depth of the slab. Since the observation frequency for soil temperature is 15 minutes and that for soil moisture is 30 minutes, the slab model linearly interpolates the soil moisture observations to obtain a complete time series of data at 15-minute intervals. Unfortunately, the Oklahoma Mesonet sensors do not directly measure the storage ground heat flux, and instead obtain the best possible estimate based on soil temperature, soil moisture, and average soil properties at selected Mesonet sites. When using Equation (2) with estimated Q_{G_s} , the observed volumetric water content value, and an initial soil temperature equal to the observed value at 5 cm, the slab model produces soil temperatures that slowly diverge from observations. For this reason, an improved estimate of Q_{G_s} is calculated by determining the value of Q_{G_s} needed to produce the observed 5-cm soil temperature, given the observed volumetric water content.

The sensitivity of the slab model to errors in the volumetric water content is explored using the improved estimates of Q_{G_s} for each 15-minute period. Ground temperatures from model simulations produced for equal

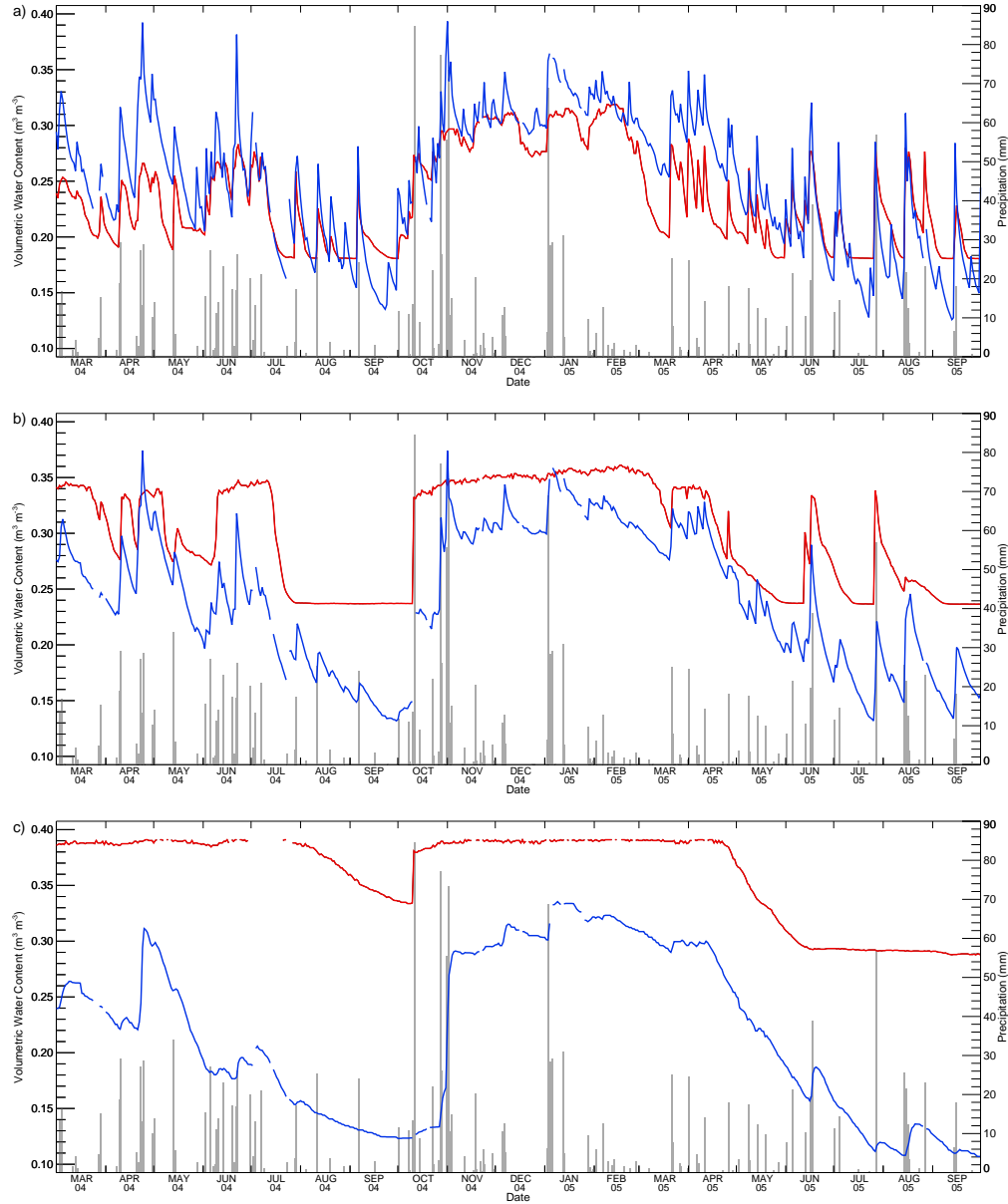


FIG. 8. Observed soil moisture at 1200 UTC at Eufaula (red) at depths of a) 5 cm, b) 25 cm, and c) 60 cm compared with 1200 UTC Eta analyses (blue) in the 0–10, 10–40, and 40–100 cm soil layers, respectively, and observed daily (0000 UTC–0000 UTC) precipitation totals (bars).

positive and negative volumetric water content biases are compared with observations. While this simple model does not account for the influence of differing soil moisture on the storage ground heat flux or the surface energy balance, it represents an idealized approach to determine the effect of soil moisture errors on soil temperature forecasts.

Given observations and soil characteristics at the Watonga Oklahoma Mesonet site for 72 hours beginning at both 0000 UTC and 1200 UTC 20 July 2004, this simple one-layer slab soil model estimates the 5-cm soil temperatures that would develop if the observed 5-cm soil moisture error were equal to $\pm 0.1 \text{ m}^3 \text{ m}^{-3}$ (Fig. 9), or twice

the soil moisture error seen in the Eta analyses. Different initialization times show the effect of a soil moisture bias on each part of the diurnal cycle. Results reveal that negative soil moisture biases alone may account for more than 1.6°C increases (decreases) in maximum (minimum) daily soil temperatures. Positive soil moisture biases account for a more modest reduction of about 0.9°C in the amplitude of the diurnal soil temperature cycle. While underestimates of soil moisture may contribute to the sign of the soil temperature errors shown in Fig. 3, soil moisture alone apparently cannot account for the magnitude of the Eta analysis errors in soil temperature.

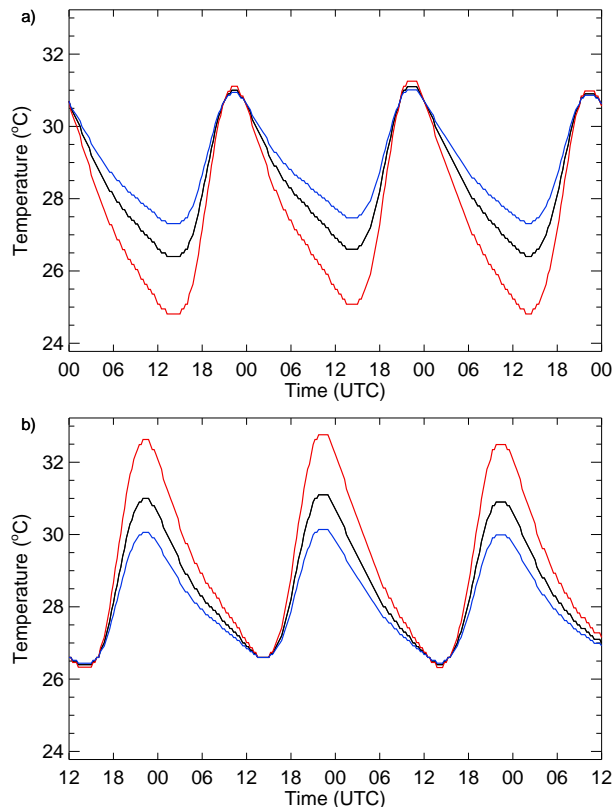


FIG. 9. Slab soil model temperatures initialized by a) 0000 UTC and b) 1200 UTC 5-cm soil temperature observations at Watonga on 20 July 2004. Soil moisture errors of $+0.1 \text{ m}^3 \text{ m}^{-3}$ (blue) and $-0.1 \text{ m}^3 \text{ m}^{-3}$ (red) yield temperatures that differ from observed soil temperatures (black).

6. CONCLUSIONS

This investigation compares soil temperature and soil moisture estimates from 40-km Eta analyses at several different model levels with observations from the Oklahoma Mesonet. Eta analyses exhibit a systematic dry bias at all levels. Consistent with the results of Marshall et al. (2003), soil temperatures in the most shallow soil layer tend to be too warm at 0000 UTC and too cool at 1200 UTC. As previous studies have shown, soil temperature and soil moisture estimates strongly impact forecasts by numerical weather prediction models that implement sophisticated land surface parameterizations. Problems with soil fields in Eta analyses, which provide initial conditions for a variety of research and operational modeling applications, may negatively impact the resulting model forecasts. These existing biases suggest the strong need for an extensive network of soil observations, in addition to atmospheric surface observations, and the necessity for assimilating those observations into land surface initializations.

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