The Role of Soil Texture in Local Land Surface–Atmosphere Coupling and Regional Climate

ELI J. DENNIS^a AND ERNESTO HUGO BERBERY^a

^a CISESS, Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland

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ABSTRACT: Soil hydraulic properties are critical in estimating surface and subsurface processes, including surface fluxes, the distribution of soil moisture, and the extraction of water by root systems. In most numerical weather and climate models, those properties are assigned using maps of soil texture complemented by look-up tables. Comparison of two widely used soil texture databases, the USDA State Soil Geographic database (STATSGO) and Beijing Normal University's soil texture database (GSDE), reveals that differences are widespread and can be spatially coherent over large areas that can eventually lead to regional climate differences. For instance, over the U.S. Great Plains, GSDE stipulates finer soil grains than STATSGO, while the opposite is true over central Mexico. In this study, we employ the WRF/CLM4 modeling suite to investigate the sensitivity of the simulated regional climate to changes in the prescribed soil maps. Wherever GSDE has finer grains than STATSGO (e.g., over the U.S. Great Plains), the soil retains water more strongly, as evidenced by smaller latent heat flux (-20 W m^{-2}), larger sensible heat flux ($+20 \text{ W m}^{-2}$), and correspondingly, a decrease in the 2-m humidity (-1 g kg^{-1}) and an increase in 2-m temperature ($+1.5 \text{ K}$). The opposite behavior is found over areas of coarser grains in GSDE (e.g., over central Mexico). Further, the changes in surface fluxes via soil texture lead to differences in the thermodynamic structure of the PBL. Results suggest that neither soil hydraulic properties nor soil moisture solely dictate the strength of surface fluxes, but in combination they alter the land–atmosphere coupling in nontrivial ways.

KEYWORDS: Atmosphere–land interactions; Land surface; Surface fluxes; Boundary layer

1. Introduction

It has long been understood that the land surface is a critical component of the climate system and that soil moisture is a key factor for determining land surface–atmosphere interactions and coupling (Sellers et al. 1996; Koster et al. 2004; Seneviratne et al. 2010). The strength of the coupling between soil moisture and other variables depends on the time scale, ranging from daily-to-weekly time scales (Santanello et al. 2011; Tawfik and Dirmeyer 2014) to monthly-to-annual time scales (Dirmeyer 2011; Roundy and Wood 2015), and extending into climate scales (Seneviratne et al. 2010; Koster et al. 2006). Soil moisture affects the partitioning of surface fluxes that control the vertical stability of the planetary boundary layer (PBL). Land surface–atmosphere coupling also depends on the spatial extent of a phenomenon, ranging from local scales (Santanello et al. 2018) to basin scales (Betts 2009; Weaver 2004; Ferguson et al. 2012).

In certain synoptic regimes, the effects of soil moisture have been shown to modify the quantity and timing of precipitation events (Song et al. 2016; Baur et al. 2018; Welty and Zeng, 2018). For instance, increased precipitation may result from wet soil conditions, in which, enhanced latent heat flux (LHF)

will moisten the boundary layer, thereby reducing the height of the lifting condensation level (LCL). If the LCL and level of free convection (LFC) lower sufficiently that they intersect the PBL, convective precipitation can be triggered (Gentine et al. 2013; Aires et al. 2014; Findell and Eltahir 2003; Song et al. 2016). Yet, dry soil conditions can also trigger convective precipitation, via thermal eddies interacting with the appropriate mesoscale boundaries such that surface-based parcels intersect the LFC and initiate localized convection (Weckwerth and Parsons 2006; Holt et al. 2006; Gentine et al. 2013). Whether an increase in soil moisture leads to increased or decreased precipitation depends on spatiotemporal scales, season, and region.

Soil moisture, which may feedback into future precipitation events, can provide a “memory” of past precipitation events, thus presenting potentially useful information regarding seasonal-to-interannual variability and prediction (Koster et al. 2000). Further, certain regions are predisposed to stronger influence of the land surface relative to other precipitation forcing mechanisms (Koster et al. 2004; Luo et al. 2007; Dirmeyer and Halder 2017). While the distribution of soil moisture is crucial to simulating the processes at the land surface, the states and changes of soil moisture are strongly dependent on the soil hydrophysical properties. These properties, as well as properties related to vegetation, control the evolution of soil temperature and evapotranspiration (ET), as well as the quantity and timing of runoff.

State-of-the-art LSMs, running in either uncoupled or coupled mode, contain extensive functionality to include the effects of hydrology, biology, chemistry, and radiation that are important to simulating weather and climate (see Kumar et al. 2006; Niu et al. 2011; Kennedy et al. 2019; Lawrence et al. 2019). Analysis of four modern LSMs using the NLDAS test-bed (Xia et al. 2013) reveal that each model has both strong

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Corresponding author: Eli J. Dennis, edennis@umd.edu

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attributes and shortcomings. Specifically, the Variable Infiltration Capacity (VIC) had the best performance reproducing observed streamflow, the Community Land Model version 4 (CLMv4) indicated an increased ability to partition ET into components, and the Noah LSM with multiphysics options (Noah-MP) provided improved soil moisture variability (Cai et al. 2014). Other studies have compared the performance regarding individual components of the hydrological cycle: streamflow (Xia et al. 2012; Bai et al. 2016), ET (Xia et al. 2015; Lawrence et al. 2007; Robock et al. 2003; Nearing et al. 2016), soil moisture (Zhuo et al. 2019; Godfrey and Stensrud 2008; Nearing et al. 2016), and additionally, performance related to local land–atmosphere interactions (Santanello et al. 2013) and climate-scale soil moisture–precipitation interactions (Ferguson et al. 2012; Dirmeyer et al. 2006). Every available LSM is imperfect, but each can provide utility in analyzing land surface behaviors. Many of the LSM shortcomings can be related to the large number of parameters required to represent both soil and vegetation processes, which are often poorly constrained by observations and not scale-aware. To accurately account for land surface processes, LSMs require the prescription of empirically derived soil hydrophysical properties based on soil texture (i.e., the proportions of sand, silt, and clay). Lookup tables link mean soil hydraulic properties to each soil type. In this way, only the percents of sand, silt, and clay are needed for simulating soil-related processes in regional to global simulations.

The identification of soil texture categories originated from a need to group soils with similar properties by subjective mechanical analysis (i.e., grain size and feel) for consistency in agriculture (Davis and Bennett 1927; Hobbs 1941). Similar classes are still used at present for lack of more detailed in situ measurements. Regional and global databases containing gridded values of sand, silt, and clay have been constructed using a combination of campaigns to survey soil profiles and statistical procedures (Hengl et al. 2017; Chaney et al. 2019).

The use of a soil texture map paired with a lookup table is a practical solution for enabling large-scale land surface modeling and a standard practice at operational forecast centers either coupled or uncoupled. The lookup table is an important constraint since it assumes a uniform hydraulic behavior for each soil category anywhere in the world. In recent years, the soil sciences community has been working intensely to advance the development of pedotransfer functions (PTFs) that should improve current simplifications of soil processes [see Van Looy et al. (2017) for a review]. PTFs vary markedly in complexity; some use advanced mathematical techniques like machine learning and neural networks, while others use physically based relationships that allow soil properties to more accurately reflect the environmental conditions. Advanced versions of the PTFs are being developed that will improve the representation of water flow through the intricate soil–vegetation system.

Soil hydrophysical properties vary widely within each soil texture category (especially, as a function of the type of clay present), and there is significant uncertainty in the PTF-derived parameters themselves, suggesting that both the soil hydrophysical parameter values and the soil texture categorizations are imperfect (He et al. 2016). Conventional ground-based measurements of soil properties become unrealistic at

regional to global scales due to the meter-scale variability of soil properties (Montzka et al. 2017). Organic carbon is an additional factor exhibiting a strong influence on the soil–water interface (Rawls et al. 2003; De Lannoy et al. 2014). Further, Duan et al. (2006) question the transferability from one region to another of a priori parameter estimation techniques used for many LSM parameters—questions that extend to include soil hydrophysical parameters, but also to include vegetation parameters, which can be just as important as soil hydrophysical parameters.

Differences in soil texture category assignments yield related differences in the empirically derived hydrophysical parameters assigned to each category. Because the soil hydrophysical parameters exhibit strong controls on the evaporative fraction (Betts and Ball 1995; Dy and Fung 2016; Seneviratne et al. 2010), the classification of soil type can be critically important to the land–atmosphere interactions. However, soil hydrophysical properties are not the only parameters or mechanisms that dictate the behavior of the land surface. Vegetation plays an important role in determining surface characteristics: it modulates the albedo, intercepts falling water, shades the soil, the roots interact with the soil, and it directly impacts transpiration.

While studies like Nearing et al. (2016) have shown that prediction uncertainties due to the forcing data are larger than uncertainties due to model parameters, the uncertainties in soil texture estimation need to be assessed. If properties associated with soil texture drive the availability of soil moisture, and soil moisture affects the magnitude and timing of sensible heat flux (SHF) and LHF, then it is hypothesized that soil texture could also influence the evolution of the PBL and atmospheric stability. Given that important differences exist between soil texture databases, the impacts of using one versus another on simulated ET should be understood and quantified. Accordingly, there is a need to know the spatial distribution of soil classification uncertainty.

In this study, we compare the results of two WRF simulations with different soil classification datasets: the State Soil Geographic (STATSGO) dataset from USDA (Soil Survey Staff 2012) and the Global Soil Dataset for use in Earth System Models (GSDE) from Beijing Normal University (Shangguan et al. 2014; Dai et al. 2019). The goal is to investigate the physical processes that link soil texture to the surface and near-surface states and fluxes influencing planetary boundary layer height (PBLH) evolution and their sensitivity to soil texture classification. The experimental methods and the specific differences in available soil texture databases will be discussed in section 2. Section 3 will focus on the soil-texture-induced thermodynamic differences in the modeled climate in two contrasting regions. Section 4 will present our concluding remarks.

2. Data and methods

a. The model setup

The Advanced Research version of the Weather Research and Forecasting (WRF) Model version 3.9 (Skamarock et al. 2008) is employed to test and evaluate the role of soil texture in regional climate. WRF is a nonhydrostatic, full-physics numerical

weather prediction model commonly used in similar research applications. The model was configured with a 15-km horizontal grid spacing and 51 vertical layers, 13 of which are clustered in the lowest 1 km to ensure a better representation of the PBL structure and dynamics. To realistically represent the surface layer, the lowest model level is close to 10 m AGL (i.e., the level of commonly observed winds) (Zhang and Wang 2003; Zhang et al. 2015).

The LSM coupled to WRF for this experiment is the Community Land Model (CLM) version 4 (Lawrence et al. 2011) available from NCAR. CLM is a widely used LSM originally developed to be used either coupled to the Community Earth System Model (CESM) or in stand-alone (uncoupled) mode. It has since been converted for use with other NWP models, such as WRF. CLM has 10 vertical soil levels increasing in thickness with depth. The WRF version of CLM can accept up to four independent soil columns per grid space. This is different from the version of CLM directly from NCAR, which is designed to incorporate a telescoping structure (i.e., multiple plant functional types inside one soil column, multiple soil columns inside one land use category, and multiple land use categories per grid space). Instead, some of that functionality was removed in WRF to make it compatible with the WRF Preprocessing System (WPS; K. Oleson 2019, personal communication).

The passage of water within the soil column is controlled by a version of Richard's equation. CLM handles vegetation within the context of the water cycle and the radiation budget in very fine detail including the effects of canopy shading, albedo, carbon chemistry, phenology, root density and depth, among others. Zhuo et al. (2019) compare CLM, Noah, and Noah-MP functionality and structure (summarized in their Table 1). CLM is favorable in terms of number of active soil layers, deeper active soil layers, and greater heterogeneity per grid space. For a complete description, see the CLM User Guide (Oleson et al. 2010).

The PBL scheme for each simulation is MYNN2, a second-order closure, local PBL scheme (Nakanishi and Niino 2006) along with the compatible MYNN surface layer scheme. Due to the horizontal grid spacing, a convective parameterization is necessary—the Betts–Miller–Janjić (BMJ) was selected (Janjić et al. 2001). Other parameterizations include the single-moment Thompson microphysics scheme (Thompson et al. 2008), and the Rapid Radiation Transfer Model (RRTM; Iacono et al. 2008). The horizontal domain covers the majority of North America, as well as Central America (see Fig. 1). The boundary condition data are taken from the GFS Final Analysis (GFS-FNL; NCEP 2015) at 6-h intervals.

Model output for each simulation is written at 3-hourly intervals for 92 days, over 3 summers: 1 June–31 August 2016–18. The purpose of doing an “ensemble” of three years is to reduce the dispersion among the individual years that may be related to boundary conditions. The multiyear strategy allows us to more effectively isolate the forcing related to the land surface characteristics amidst the complex internal model variability. Three years is not enough to isolate the internal forcing completely, but it is more robust than a single year.

Observational datasets are used to validate (but not calibrate) the model simulations at a basic level because the goal is

to emphasize the potential implications of changing the soil characteristics on the land surface–atmosphere coupling without an attempt to rank the accuracy of the simulations. The approach used in this study does not constrain the simulations to observed variables, but rather allows the simulations to evolve free of constraint. This is a typical approach when the interest is to explore how free simulations divert depending on the changes to an internal factor (in this case, soil texture).

b. Soil texture

The FAO produced the first global soil dataset, developed through both surveying and by combining coarse soil texture datasets into a single database with a scale of approximately 1:5 000 000 (FAO-UNESCO 1981). STATSGO, which is provided at 1-km resolution, evolved from FAO's soil map, by including datasets from multiple high-resolution sampling campaigns complemented with Landsat information over the conterminous United States (CONUS), Alaska, Hawaii, and Puerto Rico. STATSGO has been defined over the CONUS and U.S. territories; outside CONUS the source of data continues to be FAO.

Recently, other datasets have been developed that are comparable to STATSGO, including GSDE at about 1-km horizontal resolution. GSDE is also based on the FAO Soil Map of the World but uses advanced statistical methods and complex mapping techniques to harmonize multiple sources of soil information into a single high-resolution global dataset of soil type, organic matter, and nutrient contents (Shangguan et al. 2014). GSDE and STATSGO each provide multiple vertical levels, but for uses in WRF they are processed into two levels each. During the preprocessing, the percentages of sand, silt, and clay are calculated by weighted averaging, with soil layer thickness used as the weight, and the soil is then classified into soil categories on the determined model grid in accordance with the USDA 16-class soil classification system. The soils data are fixed to two layers: a top (0–30-cm depth) and bottom layer (from 30 cm to the bottom of soil column), despite the differences in vertical resolution (Dy and Fung 2016).

Figures 1a and 1b depict the top-layer soil texture classifications of WRF default STATSGO and GSDE soil datasets, respectively over the study domain. Note the differences in heterogeneity between the two, particularly throughout Mexico, the central United States, and the Mississippi and Ohio River basins. In the STATSGO soil dataset (Fig. 1a), loam (red) is dominant throughout central Mexico and the mountain west, while silt loam (green) occupies much of the Midwest. In contrast, the GSDE dataset (Fig. 1b) exhibits a larger variety of soil types, with sandy loam (light green), sandy clay loam (light orange), and clay (brown) occupying much of central Mexico. Likewise, over large portions of the U.S. Great Plains (hereafter, GP) clay loam (light purple) and silty clay loam (orange) dominate in the GSDE dataset.

The specific differences are highlighted by category in Fig. 2. Figures 2a and 2b show the proportions of each category in two pie charts, and Fig. 2c shows the number of grid points associated with each category in both datasets. Categories along the y axis of Fig. 2c are from the STATSGO dataset, and categories along the x axis are from the GSDE dataset. The two

FIG. 1. Dominant top-layer soil texture classification in the model domain at 15-km horizontal resolution according to (a) the STATSGO soil texture database (default in WRF) and (b) the GSDE soil texture database. The categories in both maps follow the key in (a). The categorical soil texture triangle has been provided [lower left corner of (b)].

largest differences between these two datasets are 3361 grid cells transitioning from STATSGO loam to GSDE clay loam, and 3309 grid cells transitioning from STATSGO loam to GSDE sandy loam. The former describes a decrease in average

grain size (from loam to clay loam), while the latter is an increase in average grain size (from loam to sandy loam). The diagonal represents grid points that have the same soil category in the two datasets. If the two datasets are identical, there would be values

FIG. 2. Pie charts depicting the proportion of each soil category for each (a) STATSGO and (b) GSDE, and (c) count of grid spaces at 15-km resolution with given soil texture transitions from the STATSGO category (vertical axis) to the GSDE category (horizontal axis) (e.g., 3361 loam grid spaces in STATSGO transitioned to clay in GSDE). In addition to the digits, white boxes denote classification consensus between the two datasets; the higher number of transitions the greater the color intensity (i.e., darker hues show more common occurrences).

only along the diagonal and zeros elsewhere. Zero values mean that there are no dataset transitions between the corresponding soil texture categories represented (e.g., no transitions from STATSGO sand to GSDE silt). The comparison of these two datasets for land-only points over this domain shows that only about 33% of the classification values are the same at 15-km modeled resolution, representing substantial uncertainty. Although some transitions may reflect only minor changes in the hydrophysical properties.

The dataset disagreements are not randomly distributed but tend to be spatially coherent and consistent, leaving a signal at regional scales. Figure 3 illustrates where the seven most common soil type differences occur. The STATSGO-to-GSDE transitions representing increases in average grain size [from loam to sandy loam (gray) and from silt loam to loam (blue)], are primarily located in the western United States, throughout central Mexico, and in the Northeast. The remainder of the most common transitions characterize decreases in grain size and occurred throughout the GP, the western United States, the Mississippi and Ohio River valleys, and the Atlantic Coast states.

c. Soil properties

Soil properties are the critical controllers of soil water infiltration, retention and availability to plants. In NWP, the use of soil parameter lookup tables is common practice. Select parameters from the WRF lookup table are presented in Table 1 and Fig. 4. In both Table 1 and Fig. 4, the soil texture

classes are organized by decreasing saturated hydraulic conductivity, which closely aligns with decreasing grain size. Saturated hydraulic conductivity is a measured quantity (Weil and Brady 2017) that describes the efficiency at which a volume of saturated soil can transmit a volume of water (see values in Table 1 and Fig. 4a).

In unsaturated soils, a primary restricting force for water movement is matric potential (Weil and Brady 2017), which describes the energy deficit that needs to be overcome before water can be removed from the soil system. Matric potential implicitly accounts for the effects of the pore size spectrum, the capillary action within the soil, and the adhesive properties of individual soil grains. Cosby et al. (1984) determined matric potential from 1448 soil samples by fitting a power function, given by

$$\Psi_m = \Psi_s \left(\frac{\theta}{\theta_s} \right)^{-b}, \quad (1)$$

where Ψ_s is the matric potential at saturation, θ_s is volumetric soil moisture at saturation (or porosity), θ represents the actual volumetric soil moisture content, and b is an empirical parameter. The porosity describes the percentage volume of pore space in a volume of soil (Weil and Brady 2017). Physically, as the soil grain sizes decrease, the porosity decreases. The parameter b is highly variable, such that its value in some categories is smaller than the standard deviation of its value in other categories (Cosby et al. 1984).

FIG. 3. Locations of the seven most common soil texture category transitions from STATSGO to GSDE for the model domain. Loam to sandy loam (gray), and silt loam to loam (blue) represent increases in grain size. Loam to clay loam (dark green), silt loam to silty clay loam (light green), silt loam to clay loam (purple), sandy loam to loam (pink), and sandy loam to clay loam (red) represent decreases in average grain size.

As soil moisture decreases, the amount of energy needed to overcome the effects of matric potential increases (i.e., it requires more energy for roots to uptake soil moisture, and it requires more energy to evaporate moisture from the surface). Matric potential is shown here as a negative quantity, and when it exceeds (in magnitude) the wilting point, sometimes defined as matric potential = -1500 J kg^{-1} , it often reduces root consumption to zero and halts transpiration for most plant functional types (Stensrud 2009).

Another important parameter is the field capacity (see values in Table 1 and Fig. 4). The field capacity is the value of soil moisture remaining after free drainage occurs. The

amount of water that can exist for a prolonged period in a soil profile is restricted to a finite range between the wilting point and the field capacity, called the extractable water. The extractable water is a useful metric in estimating the total soil water reservoir (Ritchie 1981). Figure 4 graphically displays the wilting point, field capacity, saturated hydraulic conductivity, and matric potential as a function of soil texture. It can be seen that the wilting point and the field capacity both generally increase as grain size decreases, and so does the extractable water.

Figure 4b displays the matric potential at four soil moisture values, which are calculated as percentages of the extractable

TABLE 1. Select soil hydrophysical parameter values extracted from the WRF Model lookup table, SOILPARM.TBL. Saturated hydraulic conductivity K_s , matric potential at saturation Ψ_s , porosity θ_s , the b parameter, wilting point θ_{wp} , and field capacity θ_{fc} are shown. See text for details.

Soil texture category	$K_s (\times 10^4)$	Ψ_s	θ_s	b	θ_{wp}	θ_{fc}
Sand	0.466	0.069	0.339	2.79	0.010	0.192
Loamy sand	0.141	0.036	0.421	4.26	0.028	0.283
Sandy clay	0.0722	0.098	0.406	10.73	0.100	0.338
Sandy loam	0.0523	0.141	0.434	4.74	0.047	0.312
Sandy clay loam	0.0445	0.135	0.404	6.77	0.069	0.315
Loam	0.0338	0.355	0.439	5.25	0.066	0.329
Silt loam	0.0281	0.759	0.476	5.33	0.084	0.36
Clay loam	0.0245	0.263	0.465	8.17	0.103	0.382
Silt	0.0218	0.955	0.484	3.86	0.061	0.347
Silty clay loam	0.0203	0.617	0.464	8.72	0.120	0.387
Silty clay	0.0134	0.324	0.468	10.39	0.126	0.404
Clay	0.00974	0.468	0.468	11.55	0.138	0.412

FIG. 4. Prescribed parameter values for each soil texture category from the default lookup table in the WRF Model. (top) Field capacity (blue) and wilting point (orange) have units of volumetric soil moisture ($\text{m}^3 \text{m}^{-3}$; top-right axis). Saturated hydraulic conductivity (gray) is a unitless quantity (shown $\times 10^4$; top-left axis). (bottom) Matric potential (J kg^{-1}) calculated according to a percentage of the extractable water range as given by Eq. (2): 40% (solid green), 35% (dashed green), 30% (dashed-dotted green), and 25% (dotted green).

water range. For example, 25% of the extractable water range (EWR, below) is given by

$$25\% \text{ EWR} = \frac{0.25 \times (\theta_{fc} - \theta_{wp}) + \theta_{wp}}{\theta_s}, \quad (2)$$

where θ_{fc} is the field capacity, θ_{wp} is the wilting point, and θ_s is, again, volumetric soil moisture at saturation. Note that for larger grain soils, the matric potential is near zero (i.e., little energy is required before evaporation can occur), but for smaller grain soils like clay, the matric potential gets strongly negative (i.e., significant energy is required before evaporation can occur). Figure 4b shows that two categories (i.e., clay and silty clay) have started to experience the exponential decrease of matric potential at 25% saturation (dotted line), such that plants could likely no longer extract water from a clay profile. As the saturation percentage increases, all categories approach 0 J kg^{-1} , which permits evaporation to occur with only little activation energy required.

d. Soil texture and hydroclimate uncertainty

The impact of the soil properties on ET is susceptible to shifts in hydroclimate. At low moisture content ($<20\%$ saturation, likely the case in “dry regimes”), matric potential decreases for all categories, and the uncertainties in soil hydrophysical properties will have little consequence to WRF simulations. Similarly, at higher

soil moisture contents ($>60\%$, likely the case in “wet regimes”), matric potential approaches 0 J kg^{-1} in all soil texture categories (Fig. 4). It is at moderate values of soil water content that uncertainties in soil hydrophysical properties can play a pivotal role in determining the accuracy of surface water and energy fluxes.

At midrange soil moisture values in smaller-grained soil, instead of LHF occurring, the available incoming energy would be partitioned into SHF. Enhanced SHF would lead to increased temperatures above the surface. Furthermore, increasing the temperature at and above the surface would decrease the relative humidity, increase the localized buoyancy, enlarge the turbulent convective eddies mixing the boundary layer, and increase the PBLH. This series of processes can be linked to the land and further linked in part to soil texture. The connection of physical properties described here follows the local “process chain” in land–atmosphere interactions (e.g., Santanello et al. 2011)—a way to systematically view the linkages between the land and the atmosphere from a physical perspective.

3. Results

a. WRF verification

The WRF simulations are assessed by comparing the 2016–18 JJA seasonal mean 2-m air temperature with gridded surface

FIG. 5. Two-meter air temperature (T2m) and model-minus-observational differences averaged over the period JJA 2016–18. (a) GHCN–CAMS gridded T2m, (b) the WRF–STATSGO T2m, (c) the WRF–GSDE T2m, (d) differences between the WRF–STATSGO and GHCN–CAMS T2m, and (e) differences between the WRF–GSDE and GHCN–CAMS T2m.

observations from the 2016–18 monthly mean Global Historical Climatology Network version 2 and Climate Anomaly Monitoring System (GHCN–CAMS; [Fan and van den Dool 2008](#)). The GHCN–CAMS data are bilinearly interpolated from their native 0.5° resolution to the model grid, and displayed in [Fig. 5a](#). The observations show the warmest temperatures along the Gulf Coast of the United States and Mexico, in the desert Southwest, and along the Gulf of California in Mexico. Temperatures in the central-western United States and throughout central Mexico are cooler as a result of the significant terrain features, notably the Rocky Mountains and the Sierra Madre, respectively. Finer-scale

features, such as the depression in values along the Appalachian Mountains and enhancement of temperature along the interior of California, lend credence to the quality of the dataset.

For comparison, [Figs. 5b and 5c](#) show the average 2-m temperature for the STATSGO and GSDE simulations, respectively, for the 3-yr JJA period. The differences between the model simulations and the observations are calculated for WRF–STATSGO and WRF–GSDE in [Figs. 5d and 5e](#), respectively. The large-scale patterns of 2-m temperature suggest that in both cases the model does a reasonable job in reproducing many features of the observed pattern. Overall, the simulated features correspond well to the observed features.

FIG. 6. Mean (JJA 2016–18) diurnal cycles from model grid spaces collocated with 220 NOAA Integrated Surface Database (ISD) stations in the GP region (approximately 33° – 42° N, 92.5° – 102.5° W) of (a) 2-m temperature (K), (b) 2-m dewpoint temperature (K), and (c) 10-m wind speed magnitude. The WRF-STATSGO simulation is in blue, the WRF-GSDE simulation is in red, and ISD sites are black dotted. The region is shown in Fig. 9a.

Both models show a moderate warm bias (+2 K) throughout the GP, the Gulf Coast states and east of the Appalachian Mountains, with the STATSGO simulation (Fig. 5d) performing slightly better in those regions. A cool bias of ~ 1.5 K is found in the high deserts of Nevada, east of the Sierra Nevada.

Given the role of the diurnal radiative cycle on land-atmosphere interactions, it is important to evaluate the modeled diurnal cycle of near-surface atmospheric variables. Observations for JJA 2016–18 are collected from about 220 stations from the Integrated Surface Database (Smith et al. 2011) throughout the GP region (approximately 32° – 41° N, 91° – 102° E). The timing of the maximum and minimum temperature are consistent with observations of diurnal cycle of 2-m temperature (Fig. 6a). The model simulations exhibit a warm bias of +3 K throughout this region (slightly larger during daytime, smaller at night). The magnitude of the bias agrees with the mean fields shown in Fig. 5. The difference between the model simulations at this time-averaged scale is minor in Fig. 6. Nevertheless, understanding the impact of soil texture should lead to a better understanding of the physical processes involved in the land surface–atmosphere coupling. Figure 6b shows similar patterns in the 2-m dewpoint temperature—consistent timing in the occurrence of the maximum and minimum values, but exhibiting a larger persistent negative bias of approximately 4 K. Both model environments are warmer and drier than observations by similar margins.

The diurnal onset of observed 10-m wind speeds (Fig. 6c) is again consistent between the model simulations and the station observations. The magnitude of the peak diurnal winds is greater than the observed values in both simulations by about 2 m s^{-1} , while the minimum values are closer to the station

observations. Again, both simulations exhibit minor differences from observations, but have similar performances to each other.

In an effort to validate the WRF/CLM simulations against satellite-based hydrological variables, we compared the model simulations to GLEAM (version 3) ET (Martens et al. 2017; Miralles et al. 2011). Both WRF/CLM simulations exceed GLEAM ET (Martens et al. 2017; Miralles et al. 2011) estimates by about 1.5 mm day^{-1} (not shown). Further, the overestimation of total ET in CLM relative to other LSMs has been noted in a global intercomparison of LSM performance (i.e., Ferguson et al. 2012).

GLEAM includes the partitioning of ET into components: bare soil evaporation, transpiration, and evaporation from canopy interception. The ratio of canopy-intercepted evaporation to total evaporation is small and similar in both GLEAM and WRF/CLM. The WRF/CLM bare soil evaporation accounts for about 40%–45% of the total ET, and transpiration accounts for about 30%–35%. GLEAM, on the other hand, assigns about 90% of ET to transpiration. Either the WRF/CLM simulations place too much emphasis on bare soil evaporation (i.e., Lawrence et al. 2007), or GLEAM puts too much weight on transpiration (Or and Lehmann 2019, appendix C). The correct quantity may lie somewhere in the middle of the two. These differences in partitioning seem large, but they are a significant improvement on the CLM3 formulation and are reasonable values compared to previous studies (e.g., Lawrence et al. 2007). The differences between the two WRF/CLM simulations are smaller than the differences between either simulation and the GLEAM product. When the specific parameters, differing equations, and model structures are considered, this is perhaps unsurprising. Additional analysis comparing these WRF/CLM simulations to a calibrated hydrological dataset suggests that total ET compares quite well to an LSM-produced ET climatology, but SM is more model specific. This analysis is presented in the online supplemental material.

b. Modeled sensitivity to soil texture classification

1) GENERALIZED DOMAIN DIFFERENCES

We will examine next the changes in the soil–water system that result from changing the input soil classification dataset (GSDE versus STATSGO). Figure 7a shows the differences (WRF-GSDE minus WRF-STATSGO) in JJA 2016–18 averaged top 30-cm volumetric soil moisture, and Figs. 7b–d show the corresponding differences in porosity, field capacity, and wilting point, respectively. The differences in soil moisture are widespread throughout the model domain, but with prominent positive values along the southern Atlantic coast, and prominent negative differences on the south-facing coast of southern Mexico. Field capacity and wilting point increase with decreasing soil grain size (though, at differing rates), meaning positive differences indicate a reduction in grain size from STATSGO to GSDE within that grid space. Note the majority of positive values throughout the Midwest and the dominant (though, minor) negative differences in central Mexico, consistent with Fig. 3. The differences in soil moisture (Fig. 7a) are

FIG. 7. Differences (WRF–GSDE minus WRF–STATSGO) in (a) top 30-cm JJA 2016–18 averaged volumetric soil moisture, and the assigned values of (b) θ_s , (c) field capacity, and (d) wilting point.

highly correlated to the differences in both wilting point and field capacity. Calculating the Spearman rank correlation coefficient between the fields in Figs. 7a and 7d yields $\rho = 0.927$, suggesting that the mean soil moisture is highly related to the assigned parameters.

Porosity is not so straightforward, showing negative differences throughout the Midwest. This is because the range of porosity values (with the exception of sand) is small (see Table 1), and therefore, the values in the Midwest, though negative, are very minor. Differences in the long-term average of soil moisture are most similar to the differences in the assigned wilting point. Between rainfall events, as the soil dries, the soil moisture has a propensity to return to the wilting point and rarely goes below it. This behavior explains why the differences in soil moisture mirror the differences in assigned wilting point, and it emphasizes the importance of assigning hydrophysical properties via the placement of soil texture.

Figure 8 presents JJA-averaged differences (WRF–GSDE minus WRF–STATSGO) in relevant surface fluxes and variables. The corresponding differences can be predominantly attributed to changes in the soil physical properties. Wherever GSDE has finer grains than STATSGO, e.g., over the Midwest, the soil moisture will be nearer to the wilting point at a higher value leading to slightly positive or neutral differences in SM (Fig. 7a) but mostly negative differences in LHF (Fig. 8a). Larger negative values in LHF are collocated with larger

positive SHF values (Fig. 8b). On the contrary, areas of coarser grains in GSDE, e.g., over central Mexico, exhibit an increase in LHF (positive values in Fig. 8a) and a corresponding decrease in SHF (Fig. 8b).

Surface fluxes directly impact conditions within the PBL. Over the Midwest, where WRF–GSDE has smaller surface LHF, the 2-m moisture also has smaller values (Fig. 8c). Over central Mexico and western United States, the opposite is true: the coarser grain sizes/smaller matric potential (in magnitude) lead to an increase in LHF and a corresponding increase the 2-m moisture content. A similar analysis of the SHF and 2-m temperature is possible. Incoming energy that could not remove moisture from the surface due to the matric potential constraints is instead partitioned into SHF. Therefore, Figs. 8b and 8d shows an increase in SHF in the Midwest and a corresponding near surface warming. The opposite is true in central Mexico, where the decrease of SHF yields reduced temperatures at 2 m. Note that the patterns of differences in 2-m temperature and 2-m mixing ratio do not correspond exactly to those of the fluxes. The net radiation R_{net} and ground heat flux G were investigated as a potential cause of these discrepancies, but the diurnal cycle of R_{net} , G , and the component terms of the radiation budget did not show any substantial differences (not shown). The differences in the spatial distribution of 2-m temperature and 2-m moisture are likely related to the dynamic effects of advection that are implicitly included above the surface (not discussed here).

FIG. 8. Three-year averaged JJA (2016–18) model simulation differences (WRF–GSDE minus WRF–STATSGO) of (a) surface LHF (W m^{-2}), (b) surface SHF (W m^{-2}), (c) 2-m specific humidity (g kg^{-1}), (d) 2-m temperature (K), (e) precipitation (mm day^{-1}), and (f) PBLH (m AGL).

Changes in the SHF induce changes in the turbulent eddy growth and thus affect the PBLH. Because soil texture modulates the placement and intensity of SHF, this sequence of processes corroborates the idea that the PBLH is sensitive to changes in the soil texture. As a result, Fig. 8f shows that PBLH increases over the Midwest and decreases over central Mexico—a pattern consistent with that of SHF (Fig. 8b) responding to changes in soil grain sizes (Fig. 3).

Precipitation in models is an inherently integrative process involving appropriate thermodynamic conditioning, dynamic lifting, as well as a triggering mechanism. The reference profiles for the BMJ convective scheme are calculated by lifting parcels

from the boundary layer, and their time dependence responds directly to the land surface forcing. Patterns of precipitation in Fig. 8e do exhibit an impact from changes in the soil properties. Although these results do not necessarily imply a cause–effect behavior, differences in precipitation are likely due to the ET component of land–atmosphere interactions.

2) GREAT PLAINS REGIONAL DIFFERENCES

WRF–GSDE minus WRF–STATSGO soil texture differences over the GP show the prevalence of three major category changes that represent a decrease in grain size. The region delimited by 91° – 102°W , 32° – 41°N (see Fig. 9a) has 468 grid

FIG. 9. WRF–GSDE minus WRF–STATSGO differences averaged over seven specific soil category transitions most common in the GP subdomain (approximately 32°–41°N, 91°–102°W). Changes in soil parameters: (a) soil categories (similar to Fig. 3), (b) matric potential (J kg^{-1}) calculated following Eq. (1) using average top layer soil moisture and appropriate parameters, (c) wilting point ($\text{m}^3 \text{m}^{-3}$), (d) field capacity ($\text{m}^3 \text{m}^{-3}$), and (e) the b parameter. Differences in the JJA 2016–18 averages of (f) volumetric soil moisture ($\text{m}^3 \text{m}^{-3}$), (g) LHF (W m^{-2}), and (h) SHF (W m^{-2}).

spaces that shift from silt loam to silty clay loam, 338 from loam to clay loam, and 247 from silt loam to clay loam. Together, they account for about 25% of the total grid cells in this region. The locations of these differences are shown in Fig. 8a (along with some additional less frequent category changes). The changes in grain size from one category to another are not uniform. For example, the difference in grain size between silt loam and clay loam is much smaller than the difference in grain size between sandy loam and clay loam. Consequently, differences in the corresponding hydrophysical parameters over the region will also be nonuniform.

Decreasing the soil grain size reduces soil water availability to ET due to changes in matric potential [Fig. 9b; see Eq. (1)]. The fine-grained soils retain soil moisture more vigorously than coarse-grained soils and thus more energy will be required to extract this moisture. Figure 9b shows averaged differences in matric potential for each of the soil texture transitions in Fig. 9a calculated using the seasonally averaged volumetric soil moisture. Changes in matric potential suggest that in one soil category ET could be occurring while in the other category, ET may not be occurring. For example, in the case of silt loam to silty clay loam (dark green), if the simulation

with silt loam (WRF-STATSGO) had matric potential values conducive to ET, and the simulation with silty clay loam (WRF-GSDE) in those same grid spaces had matric potential values not conducive to ET, then $\Delta\Psi$ would be greater than zero. The $\Delta\Psi_m$ was positive in each of the 468 grid spaces that underwent this transition.

According to Fig. 9c, the differences in wilting point are positive for coarse-to-fine transitions, and negative for fine-to-coarse transitions. The same is true for differences in field capacity (Fig. 9d), which follow a similar pattern as the wilting point. It is apparent that the differences in wilting point and field capacity will change depending on which categories are compared. Certain transitions [i.e., from sandy loam to loam, (red)] denote a minor shift in grain size with relatively small differences in the parameters' values. Other shifts in categories (i.e., from sandy loam to clay loam) represent a considerable shift in grain size, resulting in large differences in the parameters. These differences are further noted in the b parameter (Fig. 9e), the exponential term in Eq. (1). The differences in b between certain categories, such as between sandy loam and loam are very small, while between other categories (e.g., from sandy loam to clay loam) the differences are substantial. In areas where the soil grain size decreases, it is expected that the average value of the LHF (Fig. 9g) in that area will also decrease. The decreases in LHF are compensated by increases in SHF (Fig. 9h), which is apparent in the category-averaged differences. As a result of the partition between the two heat fluxes, Figs. 9g and 9h are similar but of opposite sign.

Not all reductions in soil grain size are as intuitive, however. The differences in parameter values (Figs. 9c–e) are much larger for the transition from sandy loam to clay loam than they are for the other most common transitions, yet, the differences in the matric potential for sandy loam to clay loam are only moderate (Fig. 9b) compared to the other categories. This alludes to the definition of matric potential [Eq. (1)], which considers both the hydrophysical parameters and the value of soil moisture (Fig. 9f). In the case of the sandy loam to clay loam transition, the large differences in parameter values and the large differences in soil moisture (Fig. 9f) result in a competing effect that reduces the differences in matric potential rather than enhancing it. Further, the moderate differences in matric potential yield only moderate differences in the LHF (Fig. 9g), and, likewise, only moderate differences in SHF (Fig. 9h). One would expect large differences in LHF corresponding to large differences in soil moisture. However, the transition from sandy loam to clay loam supports the assertion that neither soil moisture, nor soil properties solely control surface fluxes, but rather it is the combination of the two that dictate the surface fluxes. For that matter, it is not only the soil characteristics but a combination of all surface hydrophysical characteristics (including the effects of vegetation) and soil moisture that determine the nature of the land–atmosphere coupling. Furthermore, changes in the PBL characteristics and stability may affect precipitation processes.

The effect of grain sizes on the surface variables is further analyzed by examining the diurnal cycle in the two WRF simulations (Fig. 10). The solid lines are area averages over the GP region, while dashed lines correspond to averages in grid

spaces that underwent a certain transition: silt loam (WRF-STATSGO) to silty clay loam (WRF-GSDE). The evolution of the variables throughout the day has the same shape, but with important differences in magnitude. Nighttime values of LHF and SHF are close to zero. LHF rises up to a maximum at noon of about $150\text{--}200\text{ W m}^{-2}$, while noontime SHF is about $250\text{--}300\text{ W m}^{-2}$. These values are of the same order of magnitude as those reported in the literature from observations in Oklahoma (e.g., Marshall et al. 2003). According to Fig. 10a, LHF (dashed, blue) achieves the largest values for the WRF-STATSGO simulation where silt loam (the coarser grains) dominates. LHF is reduced when STATSGO silt loam classification is replaced with GSDE silty clay loam classification. The smaller soil grains in the WRF-GSDE simulation lead to a higher energy requirement to extract water from the soil system, and thus the reduction in LHF. Differences between the two specific soil types are as large as 50 W m^{-2} at 1300 LT, which is about 10%–20% of the daily peak, while the effect of the changed soil classification over the entire GP is only about 10 W m^{-2} at 1300 LT (Fig. 10). Regardless of the magnitudes, uncertainties in estimating LHF and SHF exist and can be related to soil hydrophysical properties.

Changes in the diurnal cycle of SHF (Fig. 10b) are consistent with the changes in LHF Fig. 10a. The WRF-GSDE simulation with its finer grain sizes (silty clay loam) displays increased values of SHF over the WRF-STATSGO simulation with its coarser silt loam. Again, this is noticed both in the area averages over the specific categories (dashed lines) as well as over the whole GP (solid lines). The diurnal cycle of 2-m temperature (Fig. 10c) follows similar patterns to SHF: greater values over finer soils, and largest differences in the afternoon, though now the separation between soil texture classes and the regional averages is not as great because the dynamic effects of advection are implicitly incorporated. Last, during daytime, with well-mixed conditions, differences between the PBLH over silty loam (STATSGO) and silty clay loam (GSDE) average 75 m (Fig. 10d), indicating that even PBLH can be partially related to the soil hydrophysical properties.

3) CENTRAL MEXICO REGIONAL DIFFERENCES

Contrary to the changes in the GP, in central Mexico the change from STATSGO to GSDE implies the largest coherent increase in average grain size in the full model domain (see Fig. 3). While this region represents a convenient contrast in grain size, it also contains significant terrain features such as the Sierra Madre Occidental, the Sierra Madre Oriental, and the high plateaus of central Mexico that are more complex than the relatively flat terrain that is present in the GP. Also, there are precipitation differences present in central Mexico in the full simulation mean, as well as in the individual years (not shown). Due to its location, this region is susceptible to influence from the North American monsoon and the ITCZ, which influence precipitation and add additional complexity to the environment.

Figure 11a depicts the distribution of soil texture differences (GSDE to STATSGO) in the central Mexico subdomain, showing that the most common shift is from loam to sandy loam, an increase in grain size representing a small change in

FIG. 10. Area-averaged JJA 2016–18 diurnal cycles of (a) LHF (W m^{-2}), (b) SHF (W m^{-2}), (c) 2-m temperature (K), and (d) PBLH (m AGL) over the GP subdomain shown in Fig. 9a. The full-region mean values for the WRF-STATSGO simulation are shown in solid blue, while the full-region means for the WRF-GSDE simulation are in solid red. Dotted lines represent area averages only over the 468 grid spaces that transitioned from WRF-STATSGO silt loam (dotted blue) to WRF-GSDE silty clay loam (dotted red).

the soil hydrophysical properties (Figs. 11c–e). Particularly, the differences in matric potential between loam and sandy loam are about $100\text{--}200 \text{ J kg}^{-1}$ —large enough to modulate LHF values, but not exceedingly large. These differences in matric potential contribute to the differences in LHF (Fig. 11g), which are positive in that category consistent with the increase in soil grain size. Correspondingly, the averaged differences in SHF are negative (Fig. 11h).

Another noteworthy aspect of this analysis is that despite the categories undergoing reductions in grain size having increased average soil moisture (Figs. 9f and 11f), those categories experience reductions in LHF (Figs. 9g and 11g). This phenomena can be related to the assigned wilting point in each category. During dry down, finer grain soils have higher wilting points meaning they have an increased minimum value for soil moisture (excluding extreme circumstances). Therefore, despite consistently elevated soil moisture, these grid spaces will also experience reduced LHF because the soil moisture will achieve its minimum value during dry down at a greater soil moisture value.

Contrary to the GP, where the three most common transitions were of the same sign (i.e., decreases in grain size), in central Mexico, the second most common shift, from loam to clay, represents a reduction in grain size instead of an increase. Therefore, in principle, the competing effect of both increasing and decreasing the soil grain size within the region should

mitigate the regionally averaged differences in the surface fluxes between the simulations. The loam-to-clay transition toward the south of the region (dark green, Fig. 11a) exhibits considerable differences in the hydrophysical properties (θ_{wp} , θ_{fc} , and b ; Fig. 11c–e, respectively). The corresponding differences in soil moisture (Fig. 11f) are also large. Despite the significant differences in hydrophysical parameters and the relatively large differences in soil moisture (Fig. 11f) and matric potential (Fig. 11b), this transition results in only modest differences in the surface fluxes. While the differences in surface fluxes are consistent in sign with the differences in hydrophysical properties and in soil moisture, the magnitude of the surface flux differences (Figs. 11g,h) is smaller than expected, considering the differences in hydrophysical properties. Again, while soil hydrophysical properties are important in determining surface fluxes, so are other surface hydrophysical characteristics, such as those associated with vegetation, topography, and land cover type.

4. Summary and conclusions

The effects of soil moisture on weather and climate have been widely discussed in recent decades, though the underlying role of soil texture and corresponding properties in that relationship has only recently started to be considered. The capacity of soil to retain moisture depends on its hydrophysical

FIG. 11. As in Fig. 9, but for the central Mexico region (approximately 20°–30°N, 98°–105.5°W).

properties, which are dictated in part by the size of the soil grains. This article discusses the implications of soil properties, via the assignment of soil texture, for the computation of surface variables relevant to the PBL structure. Two widely used soil texture datasets were compared (the STATSGO dataset from the U.S. Department of Agriculture and the GSDE dataset from Beijing Normal University). In comparison to the STATSGO dataset, the GSDE dataset exhibits a spatially coherent decrease in soil grain size over the Midwest, while over central Mexico it has a spatially coherent increase in soil grain size. This study contrasts WRF 2016–18 JJA simulations employing the STATSGO soil texture dataset against similar simulations using the GSDE soil texture dataset. This study does not intend to compare the accuracy of the datasets. Rather, it seeks

to understand how modeled surface and near-surface variables are affected by the use of one dataset versus the other.

It has been shown that the changes in soil texture and corresponding properties affect the soil moisture content, since it is highly correlated to the wilting point. In the Midwest, the GSDE simulation with its finer grains results in a reduction in LHF and an increase in SHF. The change in surface fluxes leads to enhanced warm and dry conditions in the multiyear average. Consistent with the impacts of soil grain size, the opposite is true over central Mexico. There, GSDE identifies larger size grains than STATSGO, resulting in an increase in LHF with a corresponding decrease in SHF.

The changes in surface fluxes due to soil hydrophysical properties lead to differences in the thermodynamic structure

of the PBL. The decrease of LHF over fine soils is consistent with the decrease in low-level humidity, while the increase in SHF corresponds to an increase in low-level atmospheric temperature. Furthermore, the PBL height is a function of turbulent eddy growth, which can be closely related to SHF. In the Midwest, the increase in SHF over the smaller-grain soils of the GSDE experiment lead to a deeper PBL. The opposite is true for central Mexico, where the PBL becomes shallower. Notably, the use of finer grains over the Midwest results in a reduction of the mean precipitation while the use of larger grains over central Mexico tends to increase it. The mechanisms by which these changes occur are the subject of current research.

Surface fluxes are crucial elements of land–atmosphere interactions, and they act through different mechanisms. The most common mechanism discussed in the literature involves vegetation properties, which are not discussed here. This paper highlights the role of soil hydrophysical properties in surface fluxes. At present most models do not represent processes that link vegetation with soil properties. The combined effects of soil and vegetation on surface fluxes warrant further investigation.

The analysis of the individual contributions of each soil type reveals that the soil properties themselves do not alone dictate the surface fluxes, but rather, it is a combination of soil properties and soil moisture that do it. The choice of soil texture database, as well as the soil parameter values in the lookup table should be made with care, as they can have considerable consequences on simulated regional climate.

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