Land-snow data assimilation including a moderately coupled initialization method applied to NWP

Stanley G. Benjamin\(^1\), Tatiana G. Smirnova\(^2,1\), Eric P. James\(^2,1\), Liao-Fan Lin\(^3,1\), Ming Hu\(^1\), David D. Turner\(^1\), Siwei He\(^2,1\)

\(^1\) NOAA Global Systems Laboratory, Boulder, Colorado
\(^2\) Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, Colorado
\(^3\) Cooperative Institute for Research in Atmospheres, Colorado State University, Ft. Collins, Colorado

Submitted to *J. Hydrometeorology*
18 October 2021
Resubmitted 2 February 2022

Corresponding Author: Stan Benjamin, stan.benjamin@noaa.gov

**Early Online Release:** This preliminary version has been accepted for publication in *Journal of Hydrometeorology* may be fully cited, and has been assigned DOI 10.1175/JHM-D-21-0198.1. The final typeset copyedited article will replace the EOR at the above DOI when it is published.

© 2022 American Meteorological Society
Abstract

Initialization methods are needed for geophysical components of earth-system prediction models. These methods are needed from medium-range to decadal predictions and also for short-range earth-system forecasts in support of safety (e.g., severe weather), economic (e.g., energy), and other applications. Strongly coupled land-atmosphere data assimilation (SCDA), producing balanced initial conditions across the land-atmosphere components, has not yet been introduced to operational numerical weather prediction (NWP) systems. Most NWP systems have evolved separate data assimilation (DA) procedures for the atmosphere vs. land/snow system components. This separated method has been classified as a weakly coupled DA system (WCDA). In the NOAA operational short-range weather models, a moderately coupled land/snow-atmosphere assimilation method (MCLDA) has been implemented, a step forward from WCDA towards SCDA. The atmosphere and land (including snow) variables are both updated within the DA using the same set of observations (e.g., aircraft, radiosonde, satellite radiances, surface, etc.). Using this assimilation method, land-surface state variables have cycled continuously for 6 years since 2015 for the 3-km NOAA HRRR model and with CONUS cycling since 1997. Month-long experiments were conducted with and without MCLDA for both winter and summer seasons using the 13-km Rapid Refresh model with atmosphere (50 levels), soil (9 levels) and snow (up to 2 layers if present) on the same horizontal grid. Improvements were evident for 2-m temperature for all times of day out to 6-12h for both seasons but stronger in winter. Better temperature forecasts were also shown in the 1000-900 hPa layer corresponding roughly to the boundary layer.

Significance Statement

Accuracy of weather models depends on accurate initial conditions for soil temperature and moisture as well as for the atmosphere itself. This paper describes a moderately coupled data assimilation method that modifies soil conditions based on forecast error corrections indicated by atmospheric observations. This method has been tested for month-long period in summer and winter and shown to consistently
improve short-range forecasts of 2-m temperature and moisture. This coupled data assimilation method is used already in NOAA operational short-range models to improve its prediction skill for clouds, convective storms, and general weather conditions.

1. Introduction

Today’s numerical weather prediction (NWP) models are, in fact, numerical earth-system weather prediction (NEWP) models (e.g., Benjamin et al 2019) including internal prognostic treatment of land/vegetation, snow, ice, lakes, waves, and atmospheric composition. Representation of transfers of energy and moisture through these earth system boundaries is an essential component of these prediction models. Lewis Richardson (1922) foresaw 100 years ago the importance of diabatic and viscid processes for successful atmospheric NWP, dedicating 40% of his book on them and 10% of the book on processes related to surface, soil and sea (Lynch 2006). Land-surface models representing vertical transfers of heat and moisture to better represent surface fluxes were first introduced into climate models by the 1970s and 1980s (Randall et al 2019). For weather-prediction models, initial slab models were later replaced by multi-level soil models (e.g., Ek et al 2003, Smirnova et al 1997).

With significant reservoirs of heat and moisture in the top few meters of depth in the soil, snow and water, accurate specification of these conditions has been recognized as critical for NWP accuracy but difficult to accomplish (e.g., Koster et al 2004). We assert that available observations, including atmospheric observations, should be used as effectively as possible to correct forecast errors in all earth-system components including near-surface soil/snow conditions. Here, we describe an effective one-way coupling from the atmospheric analysis increments to the land/snow state using approximate coupled correlations, a method we call a ‘moderately coupled’ land data assimilation (MCLDA). MCLDA follows other efforts on land data assimilation but it is
coupled within the 3-dimensional atmospheric data assimilation technique with all atmospheric observations including screen-level measurements.

We describe details on the problem and possible approaches in Section 2. Next in Section 3, before describing a solution, we briefly describe an NWP system in which it is applied and tested: the NOAA regional 3-km High-Resolution Rapid Refresh (HRRR, Dowell et al 2022 - D22, James et al 2022 – J22) and its parent 13-km Rapid Refresh (RAP) modeling systems (Benjamin et al 2016 – B16). Section 4 provides a detailed description of the coupled data assimilation method itself, and Section 5 describes the complementary snow-cover assimilation technique. Results from a set of experiments using the RAP model/assimilation system to test this method are presented in Section 6, followed by conclusions in Section 7.

2. Motivation – the problem and the opportunity:

Daytime warm biases in 2-m temperature and dry biases in 2-m dewpoint forecasts have been evident in warm season over continental areas in hourly-updated operational weather models despite reduction in recent years (Benjamin et al 2016, Lee et al 2019, Fovell and Gallagher 2020). This problem has a longer history: a warm daytime bias over continental areas in warm season has been singled out as an outstanding continuing issue for many climate and weather models (e.g., Klein et al 2006, Morcrette et al 2018, Ma et al 2018). Koster et al (2004) linked this problem to a soil moisture bias. Mitchell et al (2004) stated that the main error sources in land state forecasts are errors in precipitation and shortwave radiation, eventually leading to biases in soil states, as suggested earlier by Viterbo and Beljaars (1995). As in the real world, land-surface models (LSMs) are ‘reservoirs’ of the days-weeks-months-long outcome from the modeled atmospheric processes, and as models, these LSMs collect a longer-term signal of potential biases in atmospheric forcing. Their evolving soil moisture and temperature fields are the ‘canaries in the coal mine’, collecting over time the effects of thermal/radiative and water-cycle errors from components of the atmospheric models.
and therefore, a possible early signal of the mean errors in the model representations of the atmospheric processes.

As precipitation analyses based on infrared and microwave satellite data became available (e.g., Xie and Arkin (1996, 1997)) along with satellite-based cloud products, better atmospheric forcing variables enabled stand-alone “land data-assimilation systems” (LDASs) to estimate updated values of soil moisture/temperature, a vast improvement over climatological soil moisture. A pioneering LDAS applied for North America (NLDAS) using prescribed atmospheric forcing including precipitation, temperature, wind, water vapor, and radiation (Mitchell et al 2004) in a separate domain for the land. The current NOAA Global Land Data Assimilation System (GLDAS) was updated in March 2021 as part of GFSv16 to use an updated version of its land-surface model (Noah LSM) with updated soil parameters (Xia et al 2020, 2021). The US GLDAS follows the design of the NOAA NLDAS (Mitchell et al 2004) in its reliance on precipitation analyses. Satellite-based estimates of precipitation have improved with increased availability of microwave data (e.g., TRMM (Tropical Rainfall Measuring Mission, Huffman et al 2007, mission over 1997-2015), and its successor GPM IMERG (Global Precipitation Mission Integrated Multisatellite Retrievals, Huffman et al 2019)).

Meanwhile, an initial coupled DA used screen-level observations of temperature and humidity to improve soil moisture (Mahfouf 1991), a technique still foundational for many centers to initialize land-surface fields (e.g., Giard and Bazile (2000), Bélair and Boone 2020). Currently, operational NWP centers use some kind of LDAS approach to update land-surface fields in their regional and global models. Table 1 provides a summary of some of these land-assimilation techniques including that presented in this paper. The LDAS approach is applied with coupled DA with 2-m temperatures and satellite observations for Canada (ECCC – Environment and Climate Change Canada, Bilodeau et al 2016, Carrera et al 2019), France (Météo-France, Giard and Bazile 2000), UK MetOffice (Gomez et al 2020), and the European Centre for Medium-Range Forecasts (ECMWF, de Rosnay et al 2013, 2014; Muñoz-Sabater et al 2019, Balsamo and Mahfouf 2020).
Using the nomenclature of Penny et al (2017), the LDAS framework utilized in these offline NWP systems is a weakly coupled data assimilation (WCDA) framework with separate land-surface and atmospheric data analyses. An assignment of the level of coupling by the Penny et al. nomenclature is included for some different coupled data assimilation frameworks in Table 1.

<table>
<thead>
<tr>
<th>Model</th>
<th>Atmos and land DA</th>
<th>Atmos observations used for land</th>
<th>DA coupling</th>
<th>Variables updated</th>
<th>Soil obs used for land</th>
<th>Snow updating</th>
<th>Refs</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOAA GFS</td>
<td>Separate (LDAS)</td>
<td>None directly</td>
<td>Driven by precipitation analysis and atmospheric analyses</td>
<td>Soil moisture (SM), soil temp</td>
<td>None</td>
<td>USAF snow, not coupled, not updated from model forecast.</td>
<td>Xia et al 2020, 2021</td>
</tr>
<tr>
<td>NASA LIS</td>
<td>LDAS, no atmospheric component</td>
<td>N/A</td>
<td>Coupled ensemble-based covariances</td>
<td>SM, soil temp</td>
<td>SMAP, SMOS</td>
<td>None</td>
<td>Kumar et al 2008, 2018</td>
</tr>
<tr>
<td>NOAA HRRR / RAP</td>
<td>Joint - MCLDA</td>
<td>All atmospheric obs including 2m temp/humidity, raob, aircraft, radar, sat radiance /cloud, etc.</td>
<td>Assumed simple covariance between full atmos and soil moisture/ temp increments (MCLDA)</td>
<td>SM, soil temp, snow temp</td>
<td>None for soil.</td>
<td>Cycled snow temp modified in MCLDA, Cycled SWE, snow depth. Updated sat-based snow cover (IMS)</td>
<td>This paper</td>
</tr>
<tr>
<td>Lin and Pu 2020</td>
<td>Joint - SCDA</td>
<td>radiosondes, radar-derived winds, 2m temp/humidity</td>
<td>Coupled ensemble-based covariances</td>
<td>SM</td>
<td>In situ probes</td>
<td>N/A</td>
<td>Lin and Pu 2020</td>
</tr>
<tr>
<td>NCAR ensemble</td>
<td>Cycling only, no coupled DA</td>
<td>N/A</td>
<td>Cycling only</td>
<td>none</td>
<td>none</td>
<td>None</td>
<td>Koukoula et al 2021</td>
</tr>
<tr>
<td>ECMWF</td>
<td>WCDA (LDAS)</td>
<td>2m temp, 2m humidity</td>
<td>Point-wise simplified extended Kalman filter (SEKF)</td>
<td>SM, soil temp, snow</td>
<td>ASCAT, SMOS Tb</td>
<td>Updated snow cover (IMS), depth via separate 2D OI</td>
<td>Muñoz-Sabater et al 2019</td>
</tr>
<tr>
<td>ECCC - Canada</td>
<td>WCDA (LDAS)</td>
<td>2m temp, 2m humidity</td>
<td>EnKF</td>
<td>SM, soil temp, snow</td>
<td>SMAP, SMOS</td>
<td>Updated sat-based snow cover (IMS)</td>
<td>Carrera et al 2019</td>
</tr>
</tbody>
</table>
Satellite-based retrievals of soil moisture variables (e.g., SMOS – Satellite Moisture and Ocean Salinity, SMAP – Soil Moisture Active Passive, ASCAT – Advanced Scatterometer, AMSR – Advanced Microwave Scanning Radiomter) have allowed further refinement on initial soil moisture accuracy through their assimilation in the NASA Land Information System (LIS, Kumar et al. 2008, Santanello et al. 2018) and in ECMWF, UKMO (Gomez et al. 2020), and Météo-France models (e.g., Mahfouf 2010, Draper et al. 2011, Dharssi et al. 2011, de Rosnay et al. 2014, Rodriguez-Fernandez et al. 2019). Assimilation of in situ soil moisture observations has been demonstrated by Lin and Pu (2020) in an experimental mode. However, the in situ probe measurements are often strongly limited in horizontal representativeness by local variations (often sub-km-scale) of soil type and recent convective-storm precipitation. Satellite retrievals of soil moisture are also limited by land-surface heterogeneity and uncertainty in vertical depth of soil and vegetation contributions to satellite-based radiances. Carrera et al. (2019) summarize positive results in the Canadian NWP model with joint assimilation of screen-level temperature and moisture and satellite-based soil moisture estimates as improved for soil moisture (vs. soil moisture observations) but also experienced increased biases for atmospheric screen-level humidity.

Table 1. Coupling of land/snow and atmospheric data assimilation for different NWP systems.

<table>
<thead>
<tr>
<th><strong>Météo-France</strong></th>
<th>WCDA (LDAS)</th>
<th>2m temp, 2m humidity</th>
<th>OI scheme</th>
<th>SM, soil temp, snow</th>
<th>none</th>
<th>Sat-based snow cover (IMS)</th>
<th>Giard and Bazile 2000</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>UKMO</strong></td>
<td>WCDA (LDAS)</td>
<td>2m temp, 2m humidity</td>
<td>SEKF</td>
<td>SM, soil temp, snow</td>
<td>ASCAT</td>
<td>Updated snow cover (IMS), snow depth</td>
<td>Gomez et al 2020</td>
</tr>
<tr>
<td><strong>Planned for NOAA UFS</strong></td>
<td>Fully coupled – SCDA (likely)</td>
<td>All atmospheric obs, including 2m T/Td, tropospheric obs, radar, sat rad/cloud, etc.</td>
<td>Coupled ens-based covariances, soil/snow state is included into analyzed variables in SCDA</td>
<td>SM, soil temp, snow water equivalent (SWE), snow depth</td>
<td>SMAP, SMOS, in situ, snow cover</td>
<td>Cycled, soil temp, SWE, snow depth/moisture and snow temp modified in SCDA</td>
<td></td>
</tr>
<tr>
<td>Component</td>
<td>Coupling via</td>
<td>variables</td>
<td>layers</td>
<td>Year intro - experim.</td>
<td>Year intro - NCEP</td>
<td>DA</td>
<td>Other</td>
</tr>
<tr>
<td>-----------</td>
<td>-------------</td>
<td>-----------</td>
<td>--------</td>
<td>-----------------------</td>
<td>-------------------</td>
<td>----</td>
<td>-------</td>
</tr>
<tr>
<td><strong>Soil</strong></td>
<td>LSM</td>
<td>Temp, moisture</td>
<td>9 starting 2012, 6 before</td>
<td>1996</td>
<td>1998</td>
<td>Cycling, atmos-to-soil DA</td>
<td>Moderately coupled land DA</td>
</tr>
<tr>
<td><strong>Snow (on both soil and sea ice)</strong></td>
<td>LSM</td>
<td>Water equivalent, temp, density</td>
<td>Up to 2</td>
<td>1997</td>
<td>1998</td>
<td>Cycling, atmos-to-soil DA, trim/build from satellite</td>
<td>Moderately coupled land DA. Snow-free and snow-covered.</td>
</tr>
<tr>
<td><strong>Sea ice</strong></td>
<td>LSM</td>
<td>Temp</td>
<td>9</td>
<td>2010</td>
<td>2012</td>
<td>Specified from satellite</td>
<td>Subgrid fraction for sea ice from GFS, introduced 2018</td>
</tr>
<tr>
<td><strong>Smoke</strong></td>
<td>Atmos model</td>
<td>Smoke mixing ratio</td>
<td>50 (all) atmospheric layers</td>
<td>2017</td>
<td>2020</td>
<td>Cycling, fire rad power from sat</td>
<td>No direct DA, only cycling</td>
</tr>
<tr>
<td><strong>Small lakes</strong></td>
<td>Coupled lake model</td>
<td>Temp, ice, mixing</td>
<td>10 lake layers, 10 soil layers under the lake, up to 5 layers in snow</td>
<td>2018</td>
<td>2020</td>
<td>Cycling</td>
<td>No direct DA, only cycling</td>
</tr>
<tr>
<td><strong>Large lakes (Great Lakes)</strong></td>
<td>Separate lake model</td>
<td>Temp, mixing</td>
<td>FVCOM levels</td>
<td>2018</td>
<td>2020</td>
<td>Independent</td>
<td>FVCOM driven by HRRR wind, rad, temp, 6h lag</td>
</tr>
</tbody>
</table>

**Table 2.** Earth-system coupling introduced to NOAA hourly-updated regional models (HRRR, RAP, RUC). More information in section 3.

A frequent cycling approach has been implemented in the NOAA hourly updated RAP and HRRR models over North America. It was also used earlier from 1998-2012 with the NOAA Rapid Update Cycle model (RUC, Benjamin et al 2010). In these models, accurate frequent observations related to precipitation and cloud conditions, including
assimilation of radar reflectivity and lightning data (Weygandt et al. 2022, B16, D22) and cloud observations (Benjamin et al. 2021), have allowed more accurate forward cycling (see Table 2) to improve the accuracy of the initial and short-term surface energy budgets. But even with these rapid high-resolution observations with land cycling, some drift in soil conditions can still occur due to systematic errors in precipitation or cloud/radiation forcing, especially in mountainous areas without complete radar data (including over much of the western US). A recent example of ongoing cycling of land-surface fields with 3-km modeling (similar to HRRR) and 3-hourly atmospheric DA (not coupled) was demonstrated by Koukoula et al. (2021), showing closer agreement to NLDAS-2 soil fields than from the GFS.

Increased sophistication has been incorporated over the years within these WCDA/LDAS approaches. The LDAS schemes have evolved to more accurate ensemble-based schemes. As cited by Duerinckx et al. (2017), the advantage of the extended Kalman filter (EKF) technique over a simpler optimal interpolation (OI) approach is that it has a more generic formulation of the gain coefficients and thus can be extended towards new observation types (Mahfouf et al. 2009). However, weakly coupled land and atmospheric data assimilations without simultaneous increments may lead to sudden shocks to latent and sensible heat fluxes by abruptly changing the temperature and moisture vertical gradients across the atmosphere/surface interface. Mulholland et al. (2015) demonstrated and quantified this initialization shock from independent atmospheric and oceanic DA. These shocks (also evident for atmospheric-land DA) from the independent updating using disjoint information from these different components of the earth system are a main disadvantage of the WCDA LDAS schemes (Penny et al. 2017).

A strongly coupled land-atmospheric data assimilation (SCDA) technique is possible, as demonstrated by Lin and Pu (2020), who used a full ensemble data assimilation method to update at least soil moisture (not temperature) as a control variable (also in Table 1). Despite representativeness limitations for in situ soil observations mentioned earlier, their study produced successful results and even used a convection-allowing (4-km grid
spacing) model configuration. However, this SCDA method hasn’t been implemented yet in the operational NWP models. Moreover, further evaluation of SCDA is needed, including assessment on if land-atmosphere SCDA might overly fit atmospheric observations at expense of soil measurements and not produce optimal results for non-atmospheric applications such as agriculture or hydrology.

A method presented in this study is a first step towards implementing a SCDA technique in the NOAA NWP regional models. It was developed out of a pre-existing full 3-D atmospheric analysis (including 2-m temperature and moisture observations), using its increment to infer an analysis increment for soil conditions (and for snow, where appropriate) rather than use a separate LDAS. It does not include assimilation of microwave (MW) satellite-sensed soil retrievals (e.g., SMOS, ASCAT, SMAP) and bypasses difficulties with estimating surface emissivity at MW frequencies for a variety of land surfaces (Aires et al. 2011, Hirahara et al. 2020). Therefore, it is an interim solution but provides a benchmark for land DA techniques including MW data. For reasons to be explained below, we consider this a moderately coupled land DA (MCLDA) method, using a level of DA coupling between weakly and strongly coupled DA methods described by Penny et al. (2017). In weakly coupled DA methods, only 2m observations are assimilated from the atmosphere in the LDAS. However, a previous observation impact study with the RAP model including MCLDA, James and Benjamin (2017, their Fig. 20), showed often equal impact and sometimes even larger impact (in summer daytime) on surface (2mT/Td) forecasts from upper-level observations (especially aircraft) than from DA of 2m temp/moisture observations themselves. This means that these upper-level observations are important contributors for land-surface analyses.

3. Description of model framework (RAP and HRRR) for experiments

The hourly updated NOAA 13-km RAP and 3-km HRRR model/assimilation NWP systems provide a mesoscale environment to apply and test a high-frequency coupled data assimilation component. The short-range predictions from the HRRR (covering
the lower 48 US and Alaska at 3-km resolution) and from the RAP (covering North America and parts of Europe and Asia at 13-km resolution) are central for the NOAA NWP guidance out to 48 h for many applications including severe weather, transportation, energy, and hydrology (D22, J22, B16). For these applications, accurately predicted evolution of the boundary layer is essential, so much attention has been given also to accurate prediction of land-surface conditions, necessary, in turn, for heat, moisture, and momentum fluxes.

<table>
<thead>
<tr>
<th>System</th>
<th>HRRRv1/ RAPv2</th>
<th>HRRRv2/ RAPv3</th>
<th>HRRRv3 / RAPv4</th>
<th>HRRRv4 / RAPv5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>WRF-ARWv3.4.1+</td>
<td>WRF-ARWv3.6+</td>
<td>WRF-ARWv3.8.1+</td>
<td>WRF-ARWv3.9.1+</td>
</tr>
<tr>
<td>Domain</td>
<td>CONUS, North America</td>
<td>CONUS, North America</td>
<td>CONUS, North America, Alaska</td>
<td>CONUS, North America, Alaska</td>
</tr>
<tr>
<td>Init Frequency</td>
<td>1 h</td>
<td>1 h</td>
<td>1h, 3h</td>
<td>1h, 3h</td>
</tr>
<tr>
<td>Map projection</td>
<td>Lambert conformal (CONUS), rotated lat/lon (North America)</td>
<td>Lambert conformal (CONUS), rotated lat/lon (North America)</td>
<td>Lambert conformal (CONUS), rotated lat/lon (North America), polar stereographic (AK)</td>
<td>Lambert conformal (CONUS), rotated lat/lon (North America), polar stereographic (AK)</td>
</tr>
<tr>
<td>Atmospheric vertical layers</td>
<td>51</td>
<td>51</td>
<td>51</td>
<td>51</td>
</tr>
<tr>
<td>Vertical coordinate</td>
<td>Sigma, lowest mid-level=0.999</td>
<td>Sigma, lowest mid-level=0.999</td>
<td>Hybrid sigma - terrain-following, lowest mid-level=0.999</td>
<td>Hybrid sigma - terrain-following, lowest mid-level=0.999</td>
</tr>
<tr>
<td>Soil levels</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Horizontal/ vertical advection</td>
<td>Fifth-order upwind</td>
<td>Fifth-order upwind</td>
<td>Fifth-order upwind</td>
<td>Fifth-order upwind + IEVA (see D22)</td>
</tr>
<tr>
<td>Computational horizontal diffusion</td>
<td>None</td>
<td>6th order (0.25)</td>
<td>6th order (0.25), horizontal only (not on slopes), applied to all variables</td>
<td>6th order reduced to 0.04 for tracers, including water vapor and hydrometeors, and to 0.12 for other model variables</td>
</tr>
<tr>
<td>Run frequency</td>
<td>Hourly</td>
<td>Hourly</td>
<td>Hourly, 3h</td>
<td>Hourly, 3h</td>
</tr>
<tr>
<td>Forecast duration</td>
<td>15h</td>
<td>18h</td>
<td>36h every 6h, otherwise 18h</td>
<td>48h every 6h, otherwise 18h</td>
</tr>
</tbody>
</table>

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-21-0188.1.
Table 3. Model physics and data assimilation configurations for the NOAA hourly-updated HRRR (3km) and RAP (13km) regional models.  HRRR domains are the contiguous US (CONUS) and Alaska (AK) domains (more detail in section 3 and in D22).

1) Model

A cohesive set of subgrid-scale parameterizations (Table 3) has been developed and evolved for HRRR and RAP, including use of MYNN (Mellor-Yamada-Nakanishi-Niino) scheme for its boundary and surface layers (Olson et al 2019 a,b) including subgrid-scale cloud representation and a multi-species bulk cloud-microphysics representation (Thompson and Eidhammer 2014). The lowest computational level in HRRR/RAP is ~8 m above ground level (computational level at \( \sigma=0.999 \), see Table 7 in B16). The configuration of parameterization suite is described in more detail by D22 and B16.
A component of the RAP/HRRR model is the RUC land-surface model, a 9-layer soil-vegetation-snow model treating heat and moisture transfer including frozen soil conditions (Smirnova et al. 2000, 2016). The RUC LSM implements an implicit solution of heat and moisture budgets for a thin layer spanning the ground surface across a thin top layer in soil or snow and the lowest layer in the atmosphere (Smirnova et al. 1997). The RUC LSM is an LSM option for the WRF (Weather Research and Forecast) community model (Skamarock et al. 2019) through which it has been widely used in many WRF applications other than the NOAA HRRR/RAP models. RUC LSM has been evaluated in many soil- and snow-model intercomparisons, including ESM-SnowMIP (Krinner et al. 2018), and found to be an effective snow model compared to other international snow models (Menard et al. 2021) despite its intentional design choosing simplicity where possible. Fixed and surface fields (for example, land use and albedo) are prescribed largely through MODIS datasets (Smirnova et al. 2016), with real-time-varying VIIRS-based greenness vegetation fraction, and use of the Beijing Normal University (BNU) soil dataset (Dy and Fung 2016). More details on the RUC LSM and its land-use fields are provided in He et al (2021), especially in their Table A1.

2) Data assimilation

As short-range forecast models, the HRRR and RAP are especially dependent on effective data assimilation and both rely on a 1-h update frequency. The HRRR/RAP data assimilation (DA) uses a configuration of the NOAA community Gridpoint Statistical Interpolation (GSI, Kleist et al. 2009). The HRRR/RAP DA design includes a hybrid ensemble/variational assimilation (Hu et al 2017) of in situ observations from rawinsonde and aircraft as well as satellite radiances (Table 4). It also includes unique components for 3-d assimilation including 2-m/10-m surface observations (B16), radar reflectivity and lightning stroke density observations (Weygandt et al 2022, D22), and cloud/clear observations from satellites and surface-based ceilometers (Benjamin et al 2021).
### Table 4.

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Variables</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rawinsonde (including special obs)</td>
<td>T, RH, V, z</td>
<td>/12 h</td>
</tr>
<tr>
<td>Boundary-layer (915 MHz) profiler wind</td>
<td>V, T&lt;sub&gt;v&lt;/sub&gt;</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Radar - VAD winds (WSR-88D radars)</td>
<td>V</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Radar</td>
<td>Reflectivity, radial wind</td>
<td>/ 1 h (or higher)</td>
</tr>
<tr>
<td>Lightning</td>
<td>Stroke density rate converted to reflectivity</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Aircraft</td>
<td>V, T, q&lt;sub&gt;v&lt;/sub&gt;</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Surface/METAR – land</td>
<td>V, p&lt;sub&gt;s&lt;/sub&gt;, T, T&lt;sub&gt;d&lt;/sub&gt;</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Surface/METAR – land</td>
<td>Ceiling/visibility</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Surface/mesonet – land</td>
<td>V, p&lt;sub&gt;s&lt;/sub&gt;, T, T&lt;sub&gt;d&lt;/sub&gt;</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Buoy/ship</td>
<td>V, p&lt;sub&gt;s&lt;/sub&gt;</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>GOES atmospheric motion vectors</td>
<td>V, p</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>GOES cloud-top</td>
<td>p, T</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>AMSU-A/HIRS-4/MHS/GOES / IASI/ATMS/CrIS /SEVIRI</td>
<td>Radiance</td>
<td>/ 1 h (or higher)</td>
</tr>
<tr>
<td>MODIS/VIIRS fire radiative power</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GPS precipitable water</td>
<td>PW</td>
<td>/ 1 h</td>
</tr>
<tr>
<td>Tropical cyclone vitals (TCVitals)</td>
<td>p&lt;sub&gt;s&lt;/sub&gt;</td>
<td>/ 6 h</td>
</tr>
<tr>
<td>National Ice Center snow cover</td>
<td>snow cover</td>
<td>/ 24h</td>
</tr>
<tr>
<td>National Ice Center ice cover</td>
<td>ice cover</td>
<td>/ 24h</td>
</tr>
</tbody>
</table>

RH is relative humidity with respect to water, V refers to horizontal wind components, T is temperature, T<sub>v</sub> is virtual temperature, p<sub>s</sub> is surface pressure, T<sub>d</sub> is dewpoint, q<sub>v</sub> is water vapor mixing ratio, and p is pressure.

For the 3-km HRRR model, the same forward atmospheric DA is introduced from the 13-km RAP with a 1-h spin-up cycle at 3 km (see D22). For both RAP and HRRR models, soil/snow conditions have been cycled over a multi-year period from early 1997 (Berbery et al 1999), improved by the MCLDA soil/snow DA method described in this paper starting in 2004. Long-cycled soil temperature/moisture fields have been interpolated intermittently to new grids with next-generations of NOAA hourly updated...
models to minimize LSM spin-up. Thus, the soil state in 1997 from the Rapid Update Cycle (Berbery et al 1999, Benjamin et al 2004) has been continuously evolving into the 2021 RAP and HRRR land-surface fields over the lower 48 US using nearest-neighbor interpolation as needed when transferring to new model grids. Cycling of different earth-system components for RAP/HRRR models is described through Table 2.

Surface observations (2-m temperature, dewpoint) are incorporated directly within the full atmospheric DA for HRRR/RAP, different from the separate LDAS design used by other NWP models as shown in Table 1. This design for HRRR/RAP includes a forward model for surface observations with a correction to 2-m temperatures to account for the elevation difference between observation and model using local prognostic lapse rates (Benjamin et al. 2004). Furthermore, observation-minus-background innovations (Benjamin et al 2010, James and Benjamin 2017) for temperature and moisture from surface observations are used as additional observations via upward replication in the local boundary layer.

This overall hourly DA design in HRRR/RAP with components assimilating clouds, precipitation, and surface observations uniquely constrains the short-range prediction that drives the 0-1-h forcing for the land-surface fields in HRRR/RAP, as demonstrated by J22. The DA here includes a snow-cover update component found to be effective and more effective for the RAP assimilation/model than those for other NCEP models (Dawson et al 2016). Accurate fluxes are important even in the first model time step and certainly in the first prediction hour for the hourly updated HRRR/RAP models; more error is introduced by requiring the model to readjust by itself. Using an appropriate coupling of the data assimilation between land surface and atmosphere reduces initialization shock with both atmosphere and land/snow surface updated simultaneously. The evolution of the HRRR/RAP models since 2014 is provided in Table 3 here for users of HRRR/RAP data including land-surface fields (see Data Availability Statement at end with acknowledgments). More details on the evolution of HRRR/RAP model and data assimilation are available in D22.
4. **Design for moderately coupled DA for soil and snow variables**

Land-surface fields of temperature (for soil and snow) and volumetric moisture content (for soil only) are modified *vertically* in each column based on the full 3-d atmospheric analysis increment extracted for the lowest model level. The evolution of data assimilation for the hourly updated NOAA models (RUC, RAP, HRRR) was to first develop a full 3-d atmospheric assimilation including (e.g., B16) and then add a component to infer a soil increment (moisture and temperature). This is different from ECMWF and UKMO, who developed near-surface and soil LDAS capabilities separate from their atmospheric DA. In other words, the land-surface analyses of this study as used in the NOAA HRRR and RAP models are affected by all available atmospheric measurements (e.g., soundings, aircraft, satellites, and 2-m screen-level data), while the land-surface analyses in ECMWF and UKMO (and also from Météo-France and ECCC) assimilate only 2-m screen-level measurements and other soil-related satellite data. (We note that these LDAS analyses from these centers do use short-range forecasts that were previously affected by all observations.) Snow cover and ice cover are also modified *horizontally* based on satellite-based observations (entries in Table 4). These two components comprise the land-snow data assimilation described in this paper.

We first describe the vertical component of the moderately coupled data assimilation technique presented in this paper. Only in this vertical component is the atmospheric data assimilation directly applied to the land/snow fields. The RAP and HRRR use the GSI data assimilation system (Kleist et al 2009, B16). An extension of the GSI was developed to link the full soil/snow prognostic fields with the atmospheric prognostic fields during the data assimilation procedure (Appendix A - B16).

<table>
<thead>
<tr>
<th>k</th>
<th>$\alpha_{T}(k)$ for 9-level soil configuration</th>
<th>Soil depth (cm) for 9-level configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.60</td>
<td>0</td>
</tr>
</tbody>
</table>
Estimated correlations ($\alpha_T(k)$) between forecast error for soil temperature and near-surface atmospheric temperature (eqn 1) as a function of the k level in the land-surface model.

<table>
<thead>
<tr>
<th>k</th>
<th>$\alpha_T(k)$</th>
<th>$\Delta T_s(k)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.55</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>0.40</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>0.30</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>0.20</td>
<td>30</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>60</td>
</tr>
</tbody>
</table>

Table 5. Estimated correlations ($\alpha_T(k)$) between forecast error for soil temperature and near-surface atmospheric temperature (eqn 1) as a function of the k level in the land-surface model.

After the atmospheric increment is calculated (hybrid var-ens, Hu et al 2017), increments for temperature fields in the multi-level ($T_s(k)$) soil are then calculated using

$$\Delta T_s(k) = \alpha_T(k) \cdot \Delta T_a$$  \hspace{1cm} (1)

where $\Delta T_a$ is the atmosphere temperature analysis increment at the model level closest to the surface and $\alpha_T(k)$ is the assumed correlation ratio for temperature for the $k^{th}$ soil or sea-ice level, ranging from 0.6 at the top level down to 0.2 at the fifth level at 30-cm depth (see Table 5). A value of $\alpha_T(k=1)$ of 0.6 reduces the post-analysis soil-atmospheric temperature contrast by 60%, reducing initial flux shock (more in section 6).  $\Delta T_s(k)$ is the soil temperature increment in K at the $k^{th}$ soil or sea-ice level. The soil or sea-ice temperature analysis increment applied in each analysis is limited to maximum value of 1.0 K and to a minimum value using

$$\text{Min } \Delta T_s(k) = -2.0 \times f \times 0.6$$  \hspace{1cm} (2)

where $f = 1 + \min (1.5, \max (0., \frac{T-283.0}{15.0}))$

and where $T$ is the 1st model level air temperature. Values of $T$ used in $f$ are bounded to 283-305K. Below 283 K, $f$ is set = 1.0 and Min $\Delta T_s(k) = -1.2$ K, and above 305 K, $f$ is...
allowed to be larger and set as 2.5, and \( \text{Min } \Delta T_s(k) = -3 \text{ K} \). The larger negative increment threshold is appropriate for nighttime conditions especially in winter.

If snow cover is present in the background field and covers the grid cell at a given grid point partially, the skin temperature and snow temperature at the interface between the two layers in the RUC snow model (Smirnova et al 2016) are also modified with the same relationship used in (1) and (2). The snow temperature cannot be increased over 273.15 K.

<table>
<thead>
<tr>
<th>( k )</th>
<th>( \alpha_\eta(k) ) for 9-level configuration - Daytime</th>
<th>( \alpha_\eta(k) ) - nighttime</th>
<th>Depth of soil levels (cm) for 9-level configuration</th>
<th>( k / \text{Depth of soil layers(cm)} ) - Lin and Pu – Noah LSM 4-layer config</th>
<th>Lin and Pu 2018 –Fig. 6e. Q-SM correlation - daytime</th>
<th>Lin and Pu 2018 –Fig. 6f. Q-SM correlation - nighttime</th>
<th>Mahfouf 1991 –Table 2. RH-( w_p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.2</td>
<td>0</td>
<td>0</td>
<td>1 / 10</td>
<td>0.23</td>
<td>0.07</td>
<td>0.54 (6 LT) - 0.87 (18 LT)</td>
</tr>
<tr>
<td>2</td>
<td>0.2</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.2</td>
<td>0</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.1</td>
<td>0</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>2 / 30</td>
<td>N/A</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0</td>
<td>60</td>
<td>3 / 60</td>
<td>N/A</td>
<td>0</td>
<td>N/A</td>
</tr>
</tbody>
</table>

**Table 6.** Estimated correlations \( (\alpha_\eta(k)) \) between forecast errors of near-surface humidity and soil moisture (eqn 3). Values shown for daytime and nighttime. Also, in 3 rightmost columns: correlation factors for analysis increments between atmosphere and soil moisture at 4 layers \( (k) \) from Lin and Pu (2018, Fig. 6), also varying for day vs. night, and from Mahfouf (1991, Table 2) for a single layer for different local times (LT).
Next, an analysis increment for soil volumetric water content ($\Delta \eta_s(k)$) is calculated during daytime only also from the atmospheric analysis increment as

$$\Delta \eta_s(k) = \alpha_\eta(k) \cdot \Delta RH_a$$  \hfill (3)  

where $\Delta RH_a$ is the analysis increment of atmosphere relative humidity (calculated from temperature and water vapor mixing ratio background fields and newly analyzed fields) at the lowest model level, $\eta_s(k)$ is the soil volumetric water content limited by porosity for the given soil type (Smirnova et al 1997, 2016) in dimensionless units ($m^3/m^3$) and defined at each $k^{th}$ soil level, $\alpha_\eta(k)$ is the assumed correlation ratio for moisture for the $k^{th}$ soil level. $\Delta RH_a$ is limited to -0.15 to 0.15. Similar ensemble-based correlations were found by Mahfouf (1991) and Lin and Pu (2018) with a different coarser land-surface models than used for HRRR and RAP (Table 6). Application to soil moisture using MCLDA only in daytime (since correlation expected only during an active boundary layer) is consistent with coefficients found by Lin and Pu (2018) for daytime vs. nighttime (larger in daytime, near zero at night, Table 6 here).

For a 9-level soil model configuration, a correlation between the atmospheric moisture increments and the soil moisture increments is assumed down to the top 4 levels (down to 10 cm) with parameters shown in Table 6. The correlation factors, $\alpha_\eta(k)$, have non-zero values only during daytime (cos (solar zenith angle) > 0.3) and when there is no snow cover. A soil moisture increment is applied only when atmospheric temperature and RH increments are of opposite sign and when the atmospheric temperature analysis increment at a given grid point at the lowest atmospheric level $|\Delta T_a| > 0.15 \text{ K}$. This treatment is consistent with the negative correlation between soil moisture and near-surface temperature forecast error found by Mahfouf (1991) and mainly in daytime by Lin and Pu (2018, their Fig. 6) but a stricter condition (requiring opposite-sign atmospheric temperature/RH increments) in the technique shown in this paper. The soil moisture analysis increment applied in each analysis is limited to maximum value of 0.03 and to a minimum value of -0.03 $m^3/m^3$.

The soil moisture increment design in MCLDA is based on the assumption that Bowen ratio (between sensible and latent heat fluxes, e.g., Monteith 1973) errors related to soil
moisture errors produce opposite atmospheric errors of near-surface temperature and moisture. A warm/dry bias in the atmospheric near-surface forecast is often caused by or at least associated with too-low soil moisture, and a cold/moist near-surface atmospheric bias is often associated with too-high soil moisture. This overall cross-variable daytime-only dependency used in our method is very consistent with the cross-variable correlations for forecast errors for 2-m temperature and 2-m humidity in daytime. Similarly with the ensemble-based forecast error covariances found by Lin and Pu (2020, Fig. 6a) and Lin and Pu (2018, their Fig. 6e,f), a soil moisture error was found to be inversely correlated with near-surface atmospheric temperature errors. A similar opposite relationship in 2m temperature and 2-m moisture errors related to soil moisture errors was found by Mahfouf (1991). In his Table 2, similar correlations between soil moisture and near-surface temperature \( (\rho_{ws, T}) \) were found to range from about -0.5 to -0.9. Mahfouf (1991) also found that the atmosphere is not informative during cloudy or precipitating periods when downward solar radiation is small and coupling with the underlying surface is weak. This condition is roughly similar to the requirement for opposite signs of increments for near-surface temperature and near-surface RH in our method.

We consider the described technique as a moderately coupled land data assimilation (MCLDA), a step forward from a WCDA technique toward SCDA. The atmosphere and land or snow variables are both updated within the same DA using the same full set of atmospheric observations (Table 4). Hourly assimilation of 2-m temperature and dewpoint observations within the atmospheric DA are a critical enabler for MCLDA, but this has been routine for the GSI-based DA for RAP and HRRR (B16, James and Benjamin 2017).
An example of soil temperature and moisture analysis increments for daytime (1500 UTC) during 12 July 2019 using the described MCLDA technique is shown in Fig. 1. Soil temperature increments are much more widespread than moisture increments and are related directly to the 2-m temperature increment (diagnosed from lowest model level increment) shown on the left in this figure. Application of MCLDA for soil (ice or snow) temperature increments has no dependency on time of day while for soil moisture MCLDA is not applied at night. The soil moisture increments shown in this example are related to the 2-m atmospheric RH increment (not exactly the lowest-level (8m AGL) RH used in MCLDA but very close to it) but are constrained and are not applied without opposite signs of 2-m temperature and 2-m RH atmospheric increments. For example, the region along the Iowa-Illinois border has positive RH increments (low left panel in
Fig. 1); however, due to MCLDA constraints, the soil moisture does not have any moistening in this region. For both soil temperature and soil moisture, the increment’s magnitude decreases for deeper soil levels, consistent with the $\alpha_T(k)$ correlations for temperature shown in Table 5 and the $\alpha_m(k)$ correlations for moisture shown in Table 6.

5. Horizontal snow cover modification

The MCLDA is applied for snow-covered grid points in the land-surface conditions and for temperature only. As part of the overall land-surface updating process (assimilation in a broad sense), changes in horizontal snow cover are also applied once per day at 0000 UTC using daily products (valid ~2300 UTC) of Northern Hemispheric snow and ice cover (Table 4) provided by NOAA (US National Ice Center 2008, Helfrich 2007). The Interactive Multisensor Snow and Ice Mapping System (IMS\(^1\)) data are used as part of this overall land-snow assimilation. The IMS-Snow data are available at 4-km resolution over the entire Northern Hemisphere and based on data from polar-orbiting and geostationary satellites.

The IMS-Snow data are interpolated to the 13-km RAP grid or the 3-km HRRR grid, both of which have prior information on snow cover, snow temperature, and snow water equivalent (SWE) from the 1-h cycling of those models including assimilation of radar and satellite-cloud data (see section 3.b). Snow building is applied at grid points when IMS-Snow indicates snow cover present and the model background showed none, and also when the lowest-level atmospheric temperature is <278 K. In this case, the snow-building algorithm searches for nearby grid points (up to +/- 2 points in each direction) with snow, determines the mean SWE for these nearby points, and adds this mean SWE to the grid point without prior snow. This procedure compensates for possible spin-up problems in the 1-h model snow precipitation or for misplaced snow precipitation. When there are no adjacent snow-covered points, a small amount of SWE (1 mm) is added to the grid points that should have snow cover, enough to survive daytime heating of a few hours. For points with added snow cover, skin temperature

\(^{1}\) https://usicecenter.gov/Products/ImsInfo
and soil temperature at the top 3 levels are reduced, if needed, so that these temperatures do not exceed 272 K. If the IMS-Snow data indicates that model grid points should not have snow and requiring clearing, this is only performed under the condition that the model has shown no precipitation during the previous hour. (In this case, the IMS-Snow data indicating that clearing is needed may have become obsolete at that grid point over the last hour.) The trimmed snow is relocated to adjacent grid points with missed snow cover if they exist to preserve conservation of water.

IMS-Snow data are also applied similarly for clearing and building by other NWP centers (Table 2) including ECMWF (de Rosnay et al 2014), UKMO (Pullen et al 2011), and both Canadian and French NWP systems (Bélair and Boone 2020). These NWP centers use this dataset only for revising horizontal snow cover, part of a two-step procedure with a separate initialization for snow depth and SWE (e.g., de Rosnay et al. 2014).

![Fig. 2. Snow water equivalent from a) RAPv5 control (upper left) and b) noMCLDA (upper right) experiments (Table 7) valid 16 February 2019 after a 16-day cycling period. Also shown (c), below) is the snow-water equivalent estimate for the same time from the NOAA National Snow Analysis.](image-url)
A comparison of SWE fields is shown in Fig. 2 from two experiments using the NOAA RAPv5 model with (Fig. 2a) and without (Fig. 2b) application of the overall land-snow DA including MCLDA and use of the IMS-Snow snow-cover modification. There are small differences over areas of the western United States (e.g., Oregon and Nevada), with greater snow cover in the DA simulation over many areas. A comparison is also provided in Fig. 2c with the SWE from the NOAA National Snow Analysis (NSA, see National Operational Hydrologic Remote Sensing Center, 2004), showing more agreement with the MCLDA/snow-update SWE field in these areas of small differences. The general accuracy of the snow cover and SWE fields even in the no-MCLDA experiment is attributable to the other data assimilation methods (e.g., clouds, radar, etc.) used in the RAP and HRRR hourly cycles as described in section 3b and the accuracy of physical parameterizations including the land-surface and boundary-layer schemes as described in section 3a.

6. Experiments to assess effect of MCLDA/snow modification

In this section, results from experiments with and without the land/snow assimilation during two seasons are presented.

<table>
<thead>
<tr>
<th>Exp no.</th>
<th>Experiment name</th>
<th>Experiment purpose</th>
<th>Application of MCLDA to soil and snow</th>
<th>Daily revision of snow cover with IMS Snow</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MCLDA</td>
<td>Control – with MCLDA and land-snow DA</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>2</td>
<td>NoMCLDA</td>
<td>No MCLDA or land-snow DA</td>
<td>N</td>
<td>N</td>
</tr>
</tbody>
</table>

Table 7. RAPv5 cycled experiments for testing the moderately coupled land data assimilation (MCLDA) technique to modify soil/snow conditions. Hourly data assimilation was performed with forecast duration out to at least 3 h and up to 24 h every 6 h. These experiments were carried out for winter (Feb 2019) and summer (July-August 2018) periods as explained in text.
A set of Rapid Refresh assimilation/forecast experiments in both summer and winter was conducted to test the effectiveness of the MCLDA/snow data assimilation. These experiments were conducted over 1-month periods for 18 July – 16 August 2018 for the summer period and for 1 February – 1 March 2019 for the winter period (Table 7). The 13-km RAPv5 (implemented at NOAA NCEP in December 2020) was used for all of these experiments with all other data assimilation and modeling configurations the same (as described in section 3) for experiments with and without the MCLDA/snow DA. Initial conditions for these 1-month experiments used RAPv5 conditions including evolved land fields with MCLDA/snow DA.

Fig. 3. RAP 6-h forecast skill for 2m temperature in summer experiments with and without MCLDA (Table 7). Above (a, b) showed RMS error differences for no-MCLDA minus MCLDA experiments. RMS errors vs. METAR observations are calculated using the NOAA MATS (Turner et al 2020). Differences in RMS error between noMCLDA and MCLDA experiments are plotted by valid time of day (horizontal axis) and forecast duration (vertical axis). Black dots are shown for 95% significant differences. In the lower row (c, d), bias vs. 2m temperature observations is shown for both MCLDA and noMCLDA experiments for the same period. The left column (Figs. 3a,c) is for eastern US (east of 100°W) and the right column (Figs. 3b,c) is for western US. Forecasts were run out to 6 h on an hourly basis and out to 24-h duration every third hour. For the study domain, the nighttime is approximately during 0-12 UTC while the daytime is during 12-24 UTC.

These experiments were evaluated primarily with atmospheric observations of temperature and dewpoint at 2 m (“2mT” and “2mTd”, respectively) and rawinsondes. RMS errors were calculated for each pair of experiments (MCLDA and noMCLDA). The
figures in this paper present differences in RMS errors between the pair of experiments and biases against these variables for both experiments. Figure 3 shows the difference in the RMSE relative to METAR observations as a function of both forecast length (1-24h) and time-of-day (“valid time”), as well as the bias in 6-h forecast over valid time, results for the summertime comparison. Because of the strong differences in terrain across the continental U.S., the statistical results are separated into “eastern US” (east of -105°E) and “western US” areas. Figure 3a and 3b demonstrate that the forecasts that use MCLDA have smaller RMSE values than the forecasts where the surface properties were not updated via the MCLDA approach; samples that are statistically significant are indicated with black dots. The strongest impacts for reduced summer 2mT RMSE are at 09, 12, 15 UTC (late night to morning). This is true especially during the nighttime in the eastern US (significant out to 6h and even out to 15h for forecasts valid at 1200 UTC) and especially in morning hours in the western US (significant out to 24h). Furthermore, the bias in the summer 2mT (Figs 3c and 3d) are also smaller when MCLDA is used. The warm bias for 2mT (at 6 h) is decreased at night and especially for the western US (Fig. 3c,d). A daytime cold bias in the eastern US is also decreased by MCLDA (Fig. 3c). During nighttime, the 2mT improvement from application of MCLDA is confined to the shallower boundary layer near the surface and with some residual into the mornings hours, especially in the western US (Fig. 3b,d). These figures include the initial ‘spin-down’ period for the first few days as the noMCLDA cycle evolved from initial fields with MCLDA, so are slightly muted.
Fig. 4. Same as Fig. 3 but now for 2-m dewpoint forecast skill, again for the summer experiment period and again for 6-h forecasts.

The effect of MCLDA on 2mTd RMSE in summer (Fig. 4) is positive (especially in western US, Fig. 4b) in the summer and only very slightly positive in the east (Fig. 4a). For the western US, the 2mTd RMSE improvement is during the daytime and into the early evening hours (Fig. 4b). An overall dry bias for 2mTd for 6-h RAP forecasts in the west was slightly decreased by application of MCLDA (Fig. 4d). Dewpoints (2mTd) are drier in the eastern US with MCLDA applied (Fig. 4c), which is an improvement during the overnight hours. There are 2 factors involved with the diurnal variation of the MCLDA impact – the diurnal variation of the boundary layer itself and the MCLDA design constraint to not allow soil moisture increments at night.
An evaluation of summer temperature forecasts, using RMSE differences between the two forecast configurations as a function of both height and lead time, was also made.
against rawinsonde data (Fig. 5) to inspect the depth of MCLDA impact. Since rawinsonde data is available only twice daily, plots in Fig. 5 are shown with the x-axis reflecting lead time (initial time also shown) for forecasts valid at 00 UTC only (Fig. 5.a), 12 UTC only (Fig. 5b), and 00 and 12 UTC combined (Fig. 5c). A slight improvement is shown for approximately the 1000-800 hPa layer especially for forecasts valid at 00 UTC (Fig. 8a, daytime) that are initialized at 09-18 UTC (i.e., those with a lead time of 6-15 hours). This suggests that improvement in soil conditions in summer in the lower troposphere from MCLDA had the most important effect during the morning period with growth of the planetary boundary layer (PBL). This is consistent with the maximum improvement of 2mT and 2mTd predictions in the western US (Fig. 3b, 4b).

A similar analysis to evaluate the impact of the MCLDA and snow modifications (henceforth we will use “MCLDA” for both) was performed for the winter period. For the winter experiment period for 2mT, the impact from MCLDA was also uniformly positive at all times of day and for 1-24h, with the magnitudes of the reduction in RMSE even larger than for the summer period. In winter, improvement (reduction in RMS error vs. METARs) from MCLDA for 2mT prediction (Fig. 6a) was as large as 0.12K (larger than in summer), significant at 1-3h at all times of day, and significant out to 9-12h at 1200-
1500 UTC in the eastern US (Fig. 6a) and out to 3-5 hours in the western US (Fig. 6b). The reduction in 2mT RMSE from MCLDA was matched by a notable decrease in 2mT bias from MCLDA at all times of day, especially in the eastern U.S. (Fig 6a and Fig. 6c). The eastern US reduced 2m cold bias in winter from MCLDA is fairly strong (by 0.2-0.4 °C, Fig. 6c), significant or almost so at all times of day.

For 2mTd in winter (Fig. 7), 2mTd forecast improvement from MCLDA was very evident and focused sharply during afternoon-to-evening hours (1800-0000 UTC) for both eastern (Fig. 7a) and western US (Fig. 7b), significant out to 3-h forecasts for these times. This behavior, especially for winter, is considered to be related to the diurnal variation of the boundary layer depth. The moist bias in eastern US was also improved by 0.2-0.3°C in the daytime hours (Fig. 7c). Little change in winter in 2mTd bias (Fig. 7c,d) from MCLDA was evident.

Fig. 7. Same as Fig. 4 for 6-h forecast skill for 2-m dewpoint but for winter experiments.
A positive effect from MCLDA for temperature in the lower troposphere (1000-850 hPa) was stronger in winter (Fig. 8) than in summer (Fig. 5), similar to the larger effect on 2mT in winter (Fig. 6) than summer (Fig. 4). Breaking out by valid time (00 UTC – Fig. 8a, 12 UTC – Fig. 8b) shows that the most pronounced positive effect from MCLDA is at 00 UTC (Fig. 8a) from forecasts initialized 6-18 h prior (18-06 UTC). For 12 UTC valid
time, the impact from MCLDA is smaller and is mostly from forecasts with 1-6 h lead
time (i.e., initialized overnight at 11-06 UTC).

Overall, a positive effect of the MCLDA soil/snow assimilation on temperature
predictions was most evident, at least statistically, under more stable conditions, which
are more common in winter, during the night, and in the early morning hours during
summer. The effect of MCLDA is cumulative within the forward RAP data assimilation
cycle, of course. The effect of presumably more accurate sensible flux from MCLDA is
more focused in a shallower boundary layer at night and in winter but is apparently
more diffused in the daytime deeper boundary layer, especially during afternoon in
summer. For moisture, the largest impact is for forecasts valid during the afternoon
hours with the strongest land-atmosphere coupling.

a) 2m Temp. and Dewpoint 6h Forecast RMSE

b) 2m Temp. and Dewpoint 6h Forecast Bias
Fig. 9   Forecast error for 2m temperature (red) and 2m dewpoint (blue) over eastern US for RAP model experiments with MCLDA (solid) and without MCLDA (dashed) for a week (12-18 Feb 2019) within the winter test period. Panel a) shows RMS errors, and panel b) the bias errors. Vertical lines show the date of snapshots (16 February 2019) shown in Figs. 2 (06 UTC), and Figs. 10 and 11 (18 UTC).

Figure 9 shows the hourly variation of 6-h forecast skill for 2mT and 2mTd with and without the land/snow DA for a 1-week period during the winter. Generally, 2mT RMS errors in Eastern US are reduced at all times of day by MCLDA (Fig. 9a, red), while improvements to 2mTd errors (also in Fig. 9a, blue) are most evident in daytime when the errors are the highest in their diurnal cycle. This pattern of 2mTd RMS errors justifies the design of MCLDA when soil moisture is adjusted only during the daytime hours when its impact on the surface layer moisture is the largest. For this winter period, the cold (2mT) and moist (2mTd) biases (both in Fig. 9b) are both reduced by the land/snow DA including MCLDA. The 2m cold bias for 2mT was reduced by MCLDA over all times of day for this period.

![Image of forecast error for 2m temperature and dewpoint](image)

Fig. 10. Difference fields for MCLDA experiments (noMCLDA minus control with MCLDA) at 16 Feb 2019 1800 UTC. Differences are shown for a) atmospheric 2-m dewpoint, b) 2-m temperature, c) soil volumetric moisture content (m^3/m^3) at first level below surface (1 cm depth), and d) soil temperature (also at 1 cm).
The vertical lines in Fig. 9 correspond to the same date for a specific analysis increment comparison shown in Fig. 10 and for the snow-cover state in Fig. 2. For this time, the improvement from MCLDA in both RMS error and bias in 2mT in Fig. 9 are quite substantial while neutral for 2mTd. Although the snow cover patterns are very similar in Eastern US for this day (Fig.2), the soil moisture and temperature at 1-cm depth (Fig. 10c,d) show large differences over Eastern US after two weeks of cycling with and without MCLDA starting with the same initial conditions. There are many regions where the soil temperature is markedly (2-4 K) colder when MCLDA is not used (e.g., Florida, Missouri, West Virginia, and Michigan), and in these areas the soil is also 0.10-0.12 m$^3$/m$^3$ moister without MCLDA; this is consistent with 2mT and 2mTd RMS errors and biases shown in Fig. 9. A comparison of analysis increments for 2mT for the same time is shown in Fig. 11, with MCLDA (Fig. 11a) and without MCLDA (Fig. 11b). Both analysis increments are positive over the eastern US as the assimilation warms up the too-cold 1-h forecast, but the analysis increment is larger without MCLDA (Fig. 11b).

![Fig 11. The 2m temperature analysis increments from a) control with MCLDA and b) noMCLDA experiments for 1800 UTC 16 Feb 2019.](image-url)
Fig. 12. Latent and sensible heat fluxes valid at first time step (1 min) from RAP experiments with and without MCLDA (only CONUS area shown). Valid at 1801 UTC 15 August 2019. Latent (a) and sensible (b) heat flux for control with MCLDA, and same in (c), (d) but for noMCLDA experiment.

We also made careful comparisons of latent and sensible heat fluxes for a midday time (1800 UTC) for MCLDA and noMCLDA experiments from 15 August 2018 during the summer test period. Our goal was to investigate for any ‘shocks’ in fluxes from imbalance in initial soil and atmospheric temperature and moisture without MCLDA, similar to the ocean-atmosphere initialization shock studied by Mulholland et al. (2015). The latent and sensible heat fluxes (LHF, SHF) for 1801 UTC (after a single 1-min time step) are presented in Fig. 12, with larger latent heat fluxes over the eastern US where soil moisture is generally higher, and larger sensible heat fluxes generally over the western US. Both flux estimates were affected by recent precipitation over western Mexico and AZ (southwest monsoon) and the US east coast resulting in increased LHF and decreased SHF. Differences (MCLDA minus noMCLDA) are shown for LHF in Fig. 13a and for SHF in Fig. 13b. In many of the LHF maximum areas (>400 W/m$^2$) with apparent recent precipitation (e.g., OK, FL, east coast), application of MCLDA increases...
LHF. For one of these points in central PA, a time series of LHF for the first 20 time steps of this model run (Fig. 13c) shows a sudden drop (‘shock’) for the noMCLDA experiment with an LHF decrease of ~100 W/m² in the first time step. By contrast, with a more balanced initial state in the MCLDA run, the first time step only shows a decrease of ~10 W/m², a much reduced shock. During the forecast the two runs slowly grow closer at this point, reducing the difference in LHF from ~100 W/m² at time step 2 to ~50 W/m² after 20 min of integration, but still the noMCLDA experiment remains drier.

Fig. 13. More flux comparisons for RAP experiments from 15 August 2019 at 1801 UTC. Differences (noMCLDA minus control-MCLDA) for latent heat flux (a) and sensible heat flux (b). Latent heat flux time-series for each time step comparison out to 20 min for MCLDA and noMCLDA experiments is shown in (c) for a point in central PA (black dot in (a)). Similarly, sensible heat flux time series (from 1800-1820 UTC) are shown in (d) for the same 2 experiments for a point in northern California (black dot in (b)).

Sensible heat flux over this summer mid-day case after one time step was generally lower with MCLDA (Fig. 12b vs. 12d, Fig. 13b), with somewhat less area with MCLDA showing at least 300 W/m² in the western US. A point over northern California was selected for a time-series comparison (Fig. 13d), showing a very large SHF shock of 400 W/m² at the first time step for the experiment without MCLDA, but little perturbation...
with MCLDA. Without MCLDA, a strong negative atmospheric temperature increment but without any change to the soil temperature had resulted in the spike in SHF. Overall, the primary shocks without MCLDA shown in Fig. 13c,d last only a single time step, far less than the 12h initialization shock for ocean shown by Mulholland et al. (2015). However, some difference in LHF and SHF at these grid points continued through the first 20 time steps (and beyond). The ongoing hourly assimilation in RAP, with cumulative minimizing of these hourly shocks via application of MCLDA, results in the improvements in 2mT and 2mTd and lower-troposphere temperature evident in Figs. 3-9.

7. Conclusions

Accurate land surface evolution is critical for determining land-atmosphere fluxes of heat, moisture, and momentum, which are in turn important for weather prediction on short, medium, and longer-range timescales. Initialization of land-surface fields (soil and snow temperature, volumetric soil moisture) faces limitations in soil observations: the sparseness and very limited horizontal representativeness of in situ observations and the assumptions and resulting (potential) systematic errors inherent in satellite retrievals of the land state despite progress in new instruments. However, analysis increments in the lower atmosphere can provide information on probable errors in land-surface fields within a frequently updating NWP system. The MCLDA technique described here does not use in situ or remotely sensed soil observations or full DA covariances, but instead relates near-surface atmospheric analysis increments to soil/snow analysis increments within an overall hourly cycled data assimilation and forecast system. Its soil increments are affected by all available atmospheric measurements (including soundings, aircraft, satellites, and 2-m screen-level data), while soil increments in ECMWF and UKMO are affected primarily by 2-m measurements and soil-related satellite data. As cited earlier, James and Benjamin (2017) showed a clear improvement in 2m temp/moisture forecasts especially in daytime from aircraft and other upper-air observations.
Varying levels of sophistication are possible for coupling land surface and atmospheric data assimilation, ranging from WCDA (in which land surface and atmospheric analyses are carried out separately) to SCDA (in which land surface and atmospheric variables are updated in a unified DA system, with two-way coupling and cross-variable covariances). The MCLDA method is an intermediate approach, taking advantage of the inherent tight coupling between soil/snow evolution and near-surface atmospheric behavior in an NWP system with a continually cycled land surface state. The MCLDA is one component of the larger set of earth-system coupling used in NOAA’s rapidly updating RAP and HRRR models (B16; D22; see Table 3 here).

The MCLDA described here is applied in the vertical to soil and snow temperatures and volumetric soil moisture, and also features a horizontal update to the extent of snow (and ice) cover, with both building and trimming based on satellite-derived daily snow and ice analyses. The MCLDA is applied subject to a number of constraints intended to avoid unrealistic land surface evolution. The land-surface fields in the RAP and HRRR models are allowed to evolve via continuous cycling driven by hourly assimilation applied from the observations shown in Table 4, with the MCLDA approach also applied. The land-surface fields for these models have been evolving for many years via the model forecasts themselves in combination with hourly data assimilation and MCLDA. First, an earlier version of the MCLDA method was introduced in the late 1990s on a coarser horizontal scale over CONUS in the Rapid Update Cycle (Benjamin et al. 2004), then in 2011 this evolved land-surface state was grafted into the RAP, and since 2012, 3-km land-surface variables initialized from the 13-km RAP has been evolving independently in the HRRR. The MCLDA approach has been critical for avoiding any significant drift in soil temperature and moisture evolution over more than two decades on 13-km and 3-km resolutions.

In this paper, we demonstrate short-range forecast improvements coming from the application of MCLDA within the hourly 13-km RAP system (B16) compared to an experiment without any land DA. Lower atmosphere observations (both 2-m and
rawinsonde-based temperature and humidity) are significantly improved for 6-12h forecasts and sometimes out to 24h when MCLDA is applied, most notably during winter when errors in predicting location and amount of snowfall can substantially affect modeled surface properties. The daily snow and ice update based on IMS snow data leads to a more accurate spatial distribution of snow cover, important for predicting the evolution of the planetary boundary layer. Dawson et al. (2016) showed an improved snow evolution from RAP (using MCLDA) vs. other NCEP models. The moderately coupled DA described in this paper within the full atmosphere-soil-snow state enables an initialization of the full atmosphere-soil-snow state and thus avoids initial shock to surface-energy-balance via ensuring accurate fluxes across atmospheric/land (and snow) interface especially in initial forecast hours.

Overall, in this paper, we show the impact of coupled land/snow data assimilation on short-range forecasts from the hourly updated NOAA Rapid Refresh assimilation/modeling system (B16). A coupled data assimilation is important for applications of the short-range rapidly updating NWP, including severe weather/convection, aviation, clouds, energy, precipitation, and extreme cold conditions in winter. Erroneous surface fluxes from strong non-equilibrium land-atmosphere contrasts in the first few timesteps of the model can lead to short-range forecast error for these applications.

Upcoming studies will show comparisons for RAP/HRRR using MCLDA with in situ soil observations (similar to those by Santanello et al (2018) and Carrera et al (2019)) and also with PBL surface-energy flux observations. A strongly coupled DA will be developed to initialize the soil, snow, and atmosphere simultaneously. We plan to test the 36-member 3-km HRRR data assimilation system (HRRRDAS; D22) ensemble to evaluate prognostic land-atmosphere vertical covariances, as shown by Lin and Pu (2020), to improve over the MCLDA technique described here. The application of a carefully designed soil parameter perturbation approach will likely be essential for improving ensemble data assimilation and prediction (as demonstrated by Jankov et al. 2017 and refined by Draper 2021). Assimilation of microwave indicators of soil moisture (SMAP, SMOS, ASCAT) will be added following effective techniques.
described by de Rosnay et al (2013), Muñoz-Sabater (2019), Bélair and Boone (2020) and others. This work will be conducted under the coupled data assimilation effort for the NOAA Unified Forecast System (UFS).

Acknowledgments
Our manuscript was significantly improved through reviews by and discussions with Jean-Francois Mahfouf (Météo-France), Stéphane Bélair (ECCC), Clara Draper (NOAA PSL) and Xia Sun (NOAA GSL). We are grateful also for helpful suggestions from 2 anonymous reviewers.

Data Availability Statement

References


Wu, Q., and Y. Wang, 2019: Comparison of oceanic multisatellite precipitation data from Tropical Rainfall Measurement Mission and Global Precipitation


