Improving Near-Surface Weather Forecasts with Strongly Coupled Land–Atmosphere Data Assimilation

Zhaoxia Pu

Abstract Near-surface weather forecasts are critical for protecting life and human activities. However, they remain a challenging problem in modern numerical weather prediction (NWP) due to difficulties in surface data assimilation and uncertainties in representing complicated land–atmosphere interactions in numerical models. This chapter summarizes recent developments from the author's research team to understand and develop effective data assimilation methods that enhance near-surface weather forecasts. Results from several recent journal publications are summarized and presented to introduce strongly coupled land–atmosphere data assimilation in the context of land–atmosphere interaction. The first part of the mentioned work evaluated the association between near-surface variables and soil moisture with observations, coupled land–atmosphere model, and data assimilation systems. Results indicated a strong coupling between soil moisture and the low-level atmosphere, especially the atmospheric boundary layer. Then, the weakly and strongly coupled land–atmosphere data assimilation methods were compared regarding their influence on the prediction of near-surface atmospheric conditions. Results showed that strongly coupled land–atmosphere data assimilation, with simultaneous corrections to the land and atmospheric conditions, outperformed weakly coupled data assimilation. Finally, strongly coupled land–atmosphere data assimilation in an ensemble Kalman filter data assimilation system was implemented with an NWP model. Its positive impacts on predicting both atmosphere and land states were demonstrated. The potential of strongly coupled land–atmosphere data assimilation for future developments and applications is discussed in the concluding remarks.

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1 Introduction

Near-surface weather forecasts are critical for protecting life and property, economic and operational activities, and routine day-to-day planning. Aviation, military, wind energy, and energy consumption operations rely on accurate near-surface forecasts, and even small forecast errors can have major consequences. Temperature, wind, and precipitation are some of the more important variables to forecast, but visibility-reducing phenomena, such as dust, fog, and smog, also need to be accurately forecast. Therefore, improving forecasts for any of these near-surface variables has far-reaching significance.

However, previous studies of numerical models have demonstrated the unavoidable errors of near-surface atmospheric forecasts (e.g., Liu et al. 2008a, b; Mass et al. 2002; Zhang et al. 2013; Pu 2017). It has also been found that forecast errors in near-surface atmospheric variables (such as 2-m temperature and 10-m winds) are quite large, even in many cases when forecasts in the middle and upper levels of the atmosphere are reasonable. The problem is more serious over complex terrain (Zhang et al. 2013; Pu 2017). These uncertainties in near-surface atmospheric conditions can contribute to inaccurate near-surface weather forecasts (e.g., fog, inversion, etc.) and mesoscale/synoptic-scale weather forecasts in general. More importantly, errors in near-surface atmospheric conditions also present a forecasting challenge at operational NWP centers with both mesoscale and global models. Specifically, near-surface temperature errors in NWP models have been observed in many different modeling systems throughout the world (Werth and Garrett 2011; Viterbo and Betts 1999; García-Díez et al. 2013).

Moreover, near-surface forecast errors also make it difficult to represent land–atmosphere interaction in numerical models, since the near-surface atmosphere is a transition area between the land and the atmosphere. These errors in near-surface atmospheric conditions interact with and influence both soil states and atmospheric boundary layer conditions through numerical model integration processes and contribute to the detriment of short- and medium-range weather forecasting, as well as prediction at sub-seasonal to seasonal and climate scales for climate models. Consequently, this prevents the use of numerical simulations to study the processes, especially the atmospheric boundary layer processes, related to severe weather systems. Meanwhile, it has been found that inaccurate forecasts of near-surface variables are associated with uncertainties in soil state, such as soil moisture. Commonly, uncertainties in representing land use, soil moisture, and terrain conditions on the underlying surface, which affect the land-atmosphere interaction directly, are identified as the major sources of error in near-surface weather forecasting (Massey et al. 2014; Zhang et al. 2013; Ren et al. 2018). Hence, the impacts of underlying surface characteristics and bias corrections on NWP have been investigated in recent years (e.g., Fan and van den Dool 2011; Massey et al. 2016; Chen et al. 2017; Lin et al. 2017). Results indicated that the bias correction of soil moisture could help near-surface temperature prediction in those case studies. Moreover, notable progress has been made recently in studying land–atmosphere interactions at regional and local scales as well as short-range weather forecasting (e.g., Santanello et al. 2005, 2007, 2016, 2018). All these previous works motivate us to seek a way to improve near-surface weather forecasting through improved representation of soil moisture and land–atmosphere interactions in land models.

In current research and operational practices, remotely sensed soil moisture data are typically incorporated into advanced NWP models under a framework of weakly coupled data assimilation, with a land surface analysis scheme independent of the atmospheric analysis component; thus, the land and atmospheric analyses are performed separately (Kumar et al. 2015; Santanello et al. 2018; Xia et al. 2019). So far, there has been limited progress in NWP models with coupled land–atmosphere data assimilation (e.g., de Rosnay et al. 2014).

In order to improve near surface weather forecasting, the author and her research team have made significant progress with observations, numerical simulations, and data assimilation in understanding the correlations between soil moisture and near-surface atmospheric variables as well as the characteristics of their error covariances in coupled data assimilation. This chapter summarizes outcomes from a series of those studies, mostly results from four published journal papers (Lin and Pu 2018, 2019, 2020; Liu and Pu 2019), to introduce the concept of strongly coupled land–atmosphere data assimilation and demonstrate its promise in improving near-surface weather forecasting. Challenges and future developments are also discussed.

2 The Relationship Between Soil Moisture and Near-Surface Atmospheric Conditions

Although earlier studies in the community have demonstrated that soil moisture has an influence on near-surface temperature, no study has yet made it clear whether soil moisture and near-surface temperature are correlated or to what degree they are associated in short-range weather prediction. In Liu and Pu (2019), the relationship between soil moisture and temperature at 2-m height (2-m temperature) was first examined with long-term meteorological and soil observations during 2008–2016 from 16 stations over the United States in four different land cover types, including Shrub and Grassland, Grassland, Shrubland, and Forest. Meteorological observations included surface Mesonet data, and soundings were obtained from the MesoWest Network (http://mesowest.utah.edu) and University of Wyoming Network (http://weather.uwyo.edu/upperair/sounding.html), respectively. Soil moisture data included five layers (5, 10, 20, 50, and 100 cm) from in situ observations from the Climate Reference Network and Soil Climate Analysis Network (https://www.drought.gov/drought/soil-moisture-map).

With the correlation statistics and an information flow analysis method (Liang 2014, 2015; also see details in Liu and Pu 2019), we found that soil moisture at all levels and the near-surface atmospheric temperature had weak to moderate causality with seasonal variability. The distribution of soil moisture depended on land use and land cover, and the dependence decreased with soil depth. Although the correlations between soil moisture and near-surface temperature was moderate, with a correlation coefficient of less than 0.6, there was strong interaction between the top soil layer and the atmosphere, implying that the impact of soil moisture on near-surface temperature was significant.

Two meteorological sounding stations collocated with soil moisture measurements were also used to investigate the relationship between atmospheric profiles and near-surface temperature (i.e., 2-m temperature). It was found that the causality between wind profile and near-surface temperature was retained in most weather conditions. Correlations between near-surface temperature and boundary layer temperature profiles were quite strong, especially during the warm season. Meanwhile, the correlations decreased with height through the atmosphere. Furthermore, correlations between near-surface temperature and upper atmospheric conditions had seasonal variability and also varied with land use and land cover.

The findings from long-term observations were further proved by a series of sensitivity experiments in Liu and Pu (2019) with a single column model (SCM, Hacker et al. 2007) based on the mesoscale community Weather Research and Forecasting (WRF) model (Skamarock et al. 2008) coupled with the Noah land surface model (Chen and Dudhia 2001; Ek et al. 2003). The impact of changes in soil moisture on short-range forecasts (up to 48 h) of near-surface temperature and atmospheric profiles was examined.

A control experiment was conducted with the average soil state, and two other sensitivity experiments were performed with an increase or decrease in soil moisture of 25% (e.g., within the seasonal variation range of soil moisture), respectively. Results showed that the impact of soil moisture on temperature was often focused on the lower levels of the atmospheric boundary layer. An increase (decrease) in soil moisture resulted in cooler (warmer) near-surface 2-m temperature through the redistribution of surface heat flux. Meanwhile, there was seasonal variation, since changes in temperature with soil moisture fluctuations were more obvious during summer and autumn. In general, an increase in soil moisture caused a temperature inversion to appear earlier and disappear later, resulting in longer inversion duration. A decrease in soil moisture had the opposite effect. Moreover, changes in near-surface temperature caused by soil moisture in all seasons were mainly from near-surface (top) soil levels. The evolution of soil thermodynamic characteristics associated with changes in soil moisture could affect surface energy distribution and influence near-surface temperature directly (see details in Liu and Pu 2019).

3 Strongly Coupled Versus Weakly Coupled Land–Atmosphere Data Assimilation

The observational analysis and single column model study mentioned above indicated that soil moisture and near-surface atmospheric conditions were strongly coupled and influenced each other. The results from Liu and Pu (2019) implied that realistic soil moisture states in land surface models could benefit the accurate prediction of near-surface and atmospheric boundary layer conditions. The findings from this study encouraged us to explore using coupled land–atmosphere data assimilation to improve numerical weather prediction.

Coupled data assimilation can be done in two different ways (Lin and Pu 2019): weakly or strongly coupled. With weakly coupled data assimilation, assimilating observations into a model does not affect the control states of the other coupled model(s) during the analysis. Land data assimilation (e.g., Kumar et al. 2014, 2015) and atmospheric data assimilation are done separately, and the analysis results are then input into coupled land–atmosphere data and interact during model integration. Therefore, the impact of weakly coupled data assimilation on the entire domain is seen only via model integration. In contrast, strongly coupled data assimilation (Penny and Hamill 2017; Penny et al. 2017; Lin and Pu 2019, 2020) requires the estimation of error covariance of the control states in all the coupled models and the simultaneous computation of the analysis across the entire domain. So far, most coupled land–atmosphere data assimilation has been done with weak coupling (Mahfouf 2010; Mahfouf and Bliznak 2011; Schneider et al. 2014; Duerinckx et al. 2017; Santanello et al. 2016; Seto et al. 2016; Lin et al. 2017). Almost none of these studies addressed the land–atmosphere data assimilation problems with strongly coupled data assimilation before Lin and Pu (2018, 2019, 2020). However, results in Liu and Pu (2019) indicated a strong response of atmospheric conditions to changes in soil moisture, suggesting that strongly coupled data assimilation is necessary for land–atmosphere data assimilation.

3.1 Characteristics of Background Error Covariance of Soil Moisture and Atmospheric States in Strongly Coupled Land–Atmosphere Data Assimilation

To explore the methodology of strongly coupled data assimilation, a deep understanding of the error covariance between soil moisture and atmospheric states within a strongly coupled land–atmosphere model is the first step. An early study by Zupanski (2017) has formulated that two-component coupled system data assimilation could be implemented through the coupled forecast error covariances cross the variables in different coupling components (e.g., land–atmosphere or aerosol–atmosphere). He conducted a single observation experiment to understand and illustrate the structure of forecast error covariance in both coupled land–atmosphere and atmosphere-chemistry models. Results indicated that the cross-component correlations have a potential to increase the utility of observations in data assimilation by spreading the information throughout the components. Following Zupanski (2017), Suzuki et al. (2017) investigated forecast error covariance and correlation structures between land and atmospheric variables by applying the Maximum Likelihood Ensemble Filter

(MLEF) data assimilation method with a coupled atmosphere–land surface model through a series of single observation experiments. They demonstrated that coupled error covariance methods improve the efficiency of information transfer between the atmosphere and the land surface by allowing the well-observed atmosphere to influence land surface variables.

Different from these previous studies, in our study, instead of using single observation experiments, we used a completed variational framework as an example to examine the error covariance between soil moisture and atmospheric states within a strongly coupled land–atmosphere model (see details in Lin and Pu 2018). A classic one- and three-dimensional variational data assimilation (1D- and 3D-Var) system computes optimal states by minimizing the following cost function (J) in an incremental form (Ide et al. 1997; Courtier et al. 1998):

$$J(\delta\mathbf{x}) = \frac{1}{2}\delta\mathbf{x}^{\mathrm{T}}\mathbf{B}^{-1}\delta\mathbf{x} + \frac{1}{2}(\mathbf{H}\delta\mathbf{x} - \mathbf{d})^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{H}\delta\mathbf{x} - \mathbf{d}) \quad (1)$$

where $\delta\mathbf{x}$ is a vector of the analysis increment, with $\delta\mathbf{x}^{\mathrm{a}} = \mathbf{x}^{\mathrm{a}} - \mathbf{x}^{\mathrm{b}}$ at the minimum of the cost function, in which $\mathbf{x}^{\mathrm{b}}$ and $\mathbf{x}^{\mathrm{a}}$ denote the vectors of the background and analysis, respectively; $\mathbf{H}$ denotes the linear form of an operator that projects the analysis variables onto the observation space; $\mathbf{d}$ is the innovation vector,$\mathbf{d} = \mathbf{y}^{\mathrm{o}} - \mathbf{H}\mathbf{x}^{\mathrm{b}}$, in which $\mathbf{y}^{\mathrm{o}}$ is a vector of observations; **B** represents the background error covariance matrix; and **R** is the observation error covariance matrix. For implementing a variational method in NWP, the estimation of **B** is necessary and important. The **B**-matrix contains information about the weights of the control states and multivariate error correlation, which allows the balanced spread of the information from the observations to the control states.

In weakly coupled data assimilation, the **B**-matrix contains only the background error covariance information for either soil states or atmospheric variables because separate data assimilation procedures are used for the land and atmosphere. However, in strongly coupled data assimilation, the **B**-matrix contains error covariance information for both soil states and atmospheric variables. Let us first use top-layer soil moisture ($\mathrm{SM_1}$) and bottom-layer atmospheric states ($\mathrm{T_1}$, $\mathrm{Q_1}$, $\mathrm{U_1}$, and $\mathrm{V_1}$) as an example. With these five variables, the symmetric and positive definite **B**-matrix of a given pixel can be described as follows:

$$\boldsymbol{B} = \begin{bmatrix} \sigma^2_{\eta_{SM_1}} & - & - & - & - \\ cov(\eta_{T_1}, \eta_{SM_1}) & \sigma^2_{\eta_{T_1}} & - & - & - \\ cov(\eta_{Q_1}, \eta_{SM_1}) & cov(\eta_{Q_1}, \eta_{T_1}) & \sigma^2_{\eta_{Q_1}} & - & - \\ cov(\eta_{U_1}, \eta_{SM_1}) & cov(\eta_{U_1}, \eta_{T_1}) & cov(\eta_{U_1}, \eta_{Q_1}) & \sigma^2_{\eta_{U_1}} & - \\ cov(\eta_{V_1}, \eta_{SM_1}) & cov(\eta_{V_1}, \eta_{T_1}) & cov(\eta_{V_1}, \eta_{Q_1}) & cov(\eta_{V_1}, \eta_{V_1}) & \sigma^2_{\eta_{V_1}} \end{bmatrix}, \quad (2)$$

where the diagonal elements are the auto-covariance of the forecast error of the explained variables and the off-diagonal elements are the covariance.

Using a variational data assimilation framework and the mesoscale community WRF model (Skamarock et al. 2008), Lin and Pu (2018) estimated the WRF-Noah (i.e., the WRF model coupled with the Noah land surface model) background error covariance between the surface soil moisture and atmospheric states. WRF version 3.9.1 (Skamarock et al. 2008; Powers et al. 2017), with the Advanced Research version of the WRF (ARW) solver, was used with WRF's CONUS physics suite. It included the new Thompson microphysics scheme, the Rapid Radiative Transfer Model (RRTM) longwave and shortwave schemes, the Monin–Obukhov-based Eta similarity surface-layer scheme, the Noah land surface model, the Mellor–Yamada–Janji´ć planetary boundary layer scheme, and the Tiedtke cumulus parameterization scheme (see details in Skamarock et al. 2008). A single domain of the Lambert conformal projection was configured with grid spacing of 9 km and 602 × 392 grids horizontally. The Noah land surface model had four soil layers as the default, with thicknesses of 10, 30, 60, and 100 cm from top to bottom. Lookup tables were used for the prescribed parameters of land use (vegetation) and soil types. The study domain covered the entire contiguous United States. The NMC method (Parrish and Derber 1992) was used to compute the **B**-matrix:

$$\mathbf{B} = \overline{\boldsymbol{\eta}\boldsymbol{\eta}^{\mathrm{T}}}, \tag{3}$$

where $\boldsymbol{\eta}$ is the difference in paired forecasts that have different initialization times but are valid at the same time, and the overbar denotes an average of forecast error samples. In a regional application (e.g., WRFDA), $\boldsymbol{\eta}$ is often obtained from paired 12 and 24 h forecasts, as follows:

$$\boldsymbol{\eta} = \mathbf{x}^{\mathrm{f}}_{\mathrm{t+24|t}} - \mathbf{x}^{\mathrm{f}}_{\mathrm{t+24|t+12}} \tag{4}$$

where each of the components on the right-hand side denotes the samples of 24 and 12 h forecasts with bias adjustment with respect to each control state.

To compute the **B**-matrix, we initialized WRF-Noah simulations at 0000 and 1200 UTC nearly every day from 2015 to 2017 to obtain 12 and 24 h forecasts. Every month, we computed the **B**-matrix by using 54 pairs of 12 and 24 h forecasts to show the "all-time" results. For the daytime (nighttime) results, we obtained 27 pairs from forecasts valid at 00 UTC (12 UTC). The 00 UTC corresponds to 6 pm Central Standard Time locally over the United States, and we considered that the forecasts valid at 00 UTC would contain the model errors during the daytime from 6 am to 6 pm local time.

Detailed results are documented in Lin and Pu (2018). Notably, these results indicated that the forecast errors in top-10 cm soil moisture and near-surface air potential temperature and specific humidity were correlated and relatively large during the daytime in the summer. The magnitude of the error correlation between surface soil moisture, temperature, and humidity was comparable, which suggests that (1) part of the error in surface soil moisture comes from atmospheric forcing, and (2) atmospheric initial conditions could potentially be corrected via soil moisture data assimilation. Specifically, the results showed a negative error correlation between soil moisture and potential temperature but a positive correlation between soil moisture and air humidity. In general, the correlation was seen nearly everywhere over the study domain, and the daytime correlation was larger than the nighttime correlation. These results not only suggested strong coupling between soil moisture and the atmosphere, but also identified the correlation structures between soil moisture and atmospheric variables, notably in the near-surface and boundary layer atmosphere (see Figs. 1 and 2, also Lin and Pu 2018).

3.2 Soil Moisture Data Assimilation: Weakly Versus Strongly Coupled Data Assimilation

In subsequent studies, Lin and Pu (2019) implemented the strongly coupled land–atmosphere data assimilation in Lin and Pu (2018) to study the relative effect of assimilating soil moisture data on weather forecasts under a framework of weakly and strongly coupled land–atmosphere data assimilation. Specifically, experiments aimed to quantify the additional impact on lower-troposphere atmospheric forecasts via direct analysis (i.e., a strongly coupled case) relative to the impact on forecasts via the dynamics of land–atmosphere interactions (i.e., a weakly coupled case) when soil moisture data were assimilated. The study used the Noah land surface model coupled with the WRF model and conducted experiments in the summer over the continental United States. The NASA Soil Moisture Active Passive (SMAP) satellite-derived soil moisture data products, SMAP 9 km level-2 enhanced soil moisture retrievals (O'Neill et al. 2016), were assimilated.

In the variational data assimilation framework, strongly coupled data assimilation adopted the background error covariance estimated from Lin and Pu (2018). The results of the numerical experiments during July 2016 showed that strongly coupled data assimilation could provide additional benefits to forecasts of air temperature and humidity compared to weakly coupled data assimilation. Over the U.S. Great Plains, on average, assimilation of SMAP data under weakly coupled data assimilation reduced a warm bias in temperature and a dry bias in humidity by 7.3% and 19.3%, respectively, while strongly coupled data assimilation contributed an *additional* bias reduction of 2.2% (temperature) and 3.3% (humidity). More importantly, improvements in precipitation forecasts and near-surface atmospheric conditions were also found with strongly coupled data assimilation compared with weakly coupled data assimilation (see details in Lin and Pu 2019).

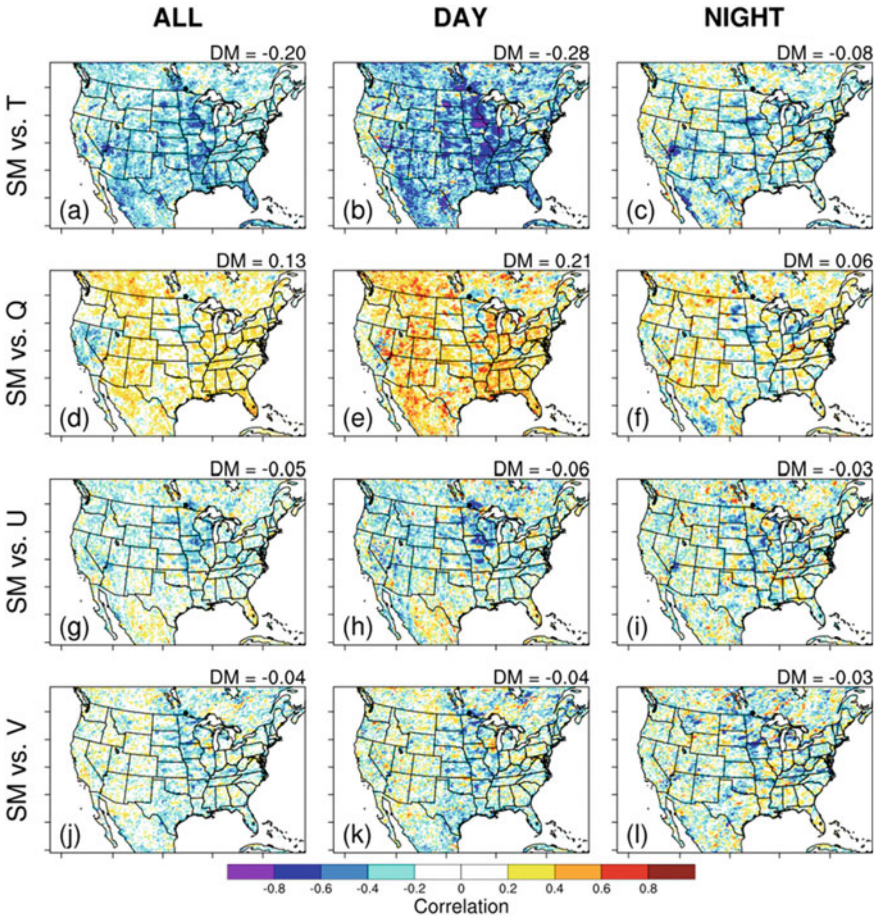

Fig. 1 Error correlations between top-layer soil moisture (SM) and bottom-layer **a**–**c** potential temperature T, **d**–**f** specific humidity Q, **g**–**i** zonal wind U, and **j**–**l** meridional wind V during July 2016. The forecast samples valid at 0000 and 1200 UTC are categorized as "DAY" and "NIGHT" results, and the "ALL" results are computed based on all the samples. Domain-mean (DM) values are computed based on the results of warm land pixels without considering the 10-grid-wide boundary. The 95% confidence intervals of the DM values vary from DM ± 0.001 to DM ± 0.0015 (From Lin and Pu 2018)

4 Enhanced Near-Surface Weather Forecasts Using Strongly Coupled Land–Atmosphere Data Assimilation

Following the outcomes from Lin and Pu (2018) and Lin and Pu (2019), a strongly coupled land–atmosphere data assimilation system was implemented by Lin and Pu (2020) using the U.S. National Centers for Environmental Prediction (NCEP)'s Gridpoint Statistical Interpolation (GSI)-based ensemble Kalman filter (EnKF) data

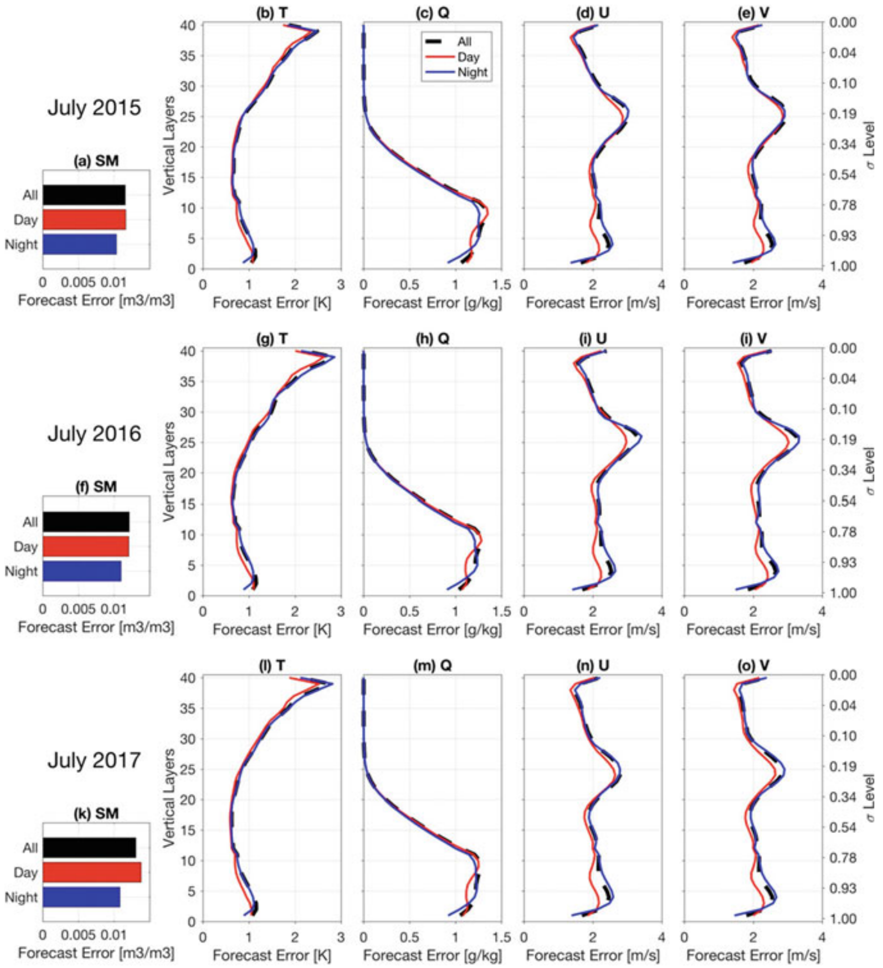

Fig. 2 Horizontal domain mean (DM) values for the error correlation between the top-10 cm soil moisture and atmospheric states including T, Q, U, and V during July from 2015 to 2017 (From Lin and Pu 2018)

assimilation system (GSI-EnKF, a community data assimilation system maintained by the NCAR Developmental Testbed Center). The model used was the WRF model coupled with the Noah land surface model. Two unique implementations enabled the incorporation of soil moisture observations via strongly coupled land–atmosphere data assimilation in our system. The first step was to include soil moisture as a control state, along with the common control analysis states in GSI-EnKF, including potential temperature, specific humidity, zonal and meridional winds, and surface dry air pressure. To enable soil moisture as a control state that was compatible with GSI-EnKF localization, we set all four layers of soil moisture inside the Noah land surface model as a control state in the GSI analysis. In the second step, we added soil moisture as a new type of conventional observation. Overall, this strongly coupled land–atmosphere data assimilation could assimilate both soil moisture and atmospheric observations simultaneously, with consistent cross-model error covariance from ensemble forecasts of land and atmospheric components of the numerical weather prediction model (e.g., WRF).

For the experiment, an ensemble size of 40 was used, as a sample size of around 40 is quite common in regional ensemble-based studies (e.g., Pu et al. 2013; Zhang and Pu 2014; Schwartz et al. 2015; McNicholas and Mass 2018). To keep a reasonable ensemble spread and avoid filter divergence, a tunable inflation coefficient can be set to adjust the posterior ensemble spread to match the prior ensemble spread (relaxation-to-prior spread; Whitaker and Hamill 2012). The inflation coefficient ranges from 0 (no inflation) to 1 (i.e., both prior and posterior ensemble spread are of the same magnitude). Tests with the assimilation of in-situ soil moisture data and all other conventional atmospheric observations indicated that this GSI-EnKF based strongly coupled data assimilation system could simultaneously adjust atmospheric and soil moisture states through assimilating atmospheric observations and soil moisture data.

Key findings included the following: (1) including soil moisture as a control variable in GSI-EnKF resulted in significant reduction of analysis errors in near-surface atmospheric variables, such as temperature and humidity; (2) with the strongly coupled system, soil moisture analysis errors were reduced significantly when soil moisture data were assimilated with all other available atmospheric observations; (3) combined assimilation of soil moisture and atmospheric observations in a strongly coupled data assimilation system resulted in improved analysis and forecasts in an NWP framework. Specifically, strongly coupled land–atmosphere data assimilation led to improved near-surface weather forecasting (See details in Lin and Pu 2020).

5 Discussion and Concluding Remarks

5.1 Summary and Discussion

Near-surface weather forecasts present a challenging problem in modern NWP. A series of studies from the author's research team, as summarized above, led to a significant understanding of the problem and made it clear that coupled land–atmosphere data assimilation, especially strongly coupled land–atmosphere data assimilation, is a promising way to improve near-surface weather forecasting.

In summary, the observational analyses showed significant correlations between soil moisture in the top soil layer and surface 2-m temperature. Sensitivity experiments with a single column model indicated that near-surface weather conditions responded to soil moisture changes, suggesting a strong coupling between soil moisture and the near-surface atmosphere. Results encouraged us to assimilate soil moisture data into a land model for improved near-surface weather forecasting. Strongly coupled land–atmosphere data assimilation was then evaluated in a variational data assimilation framework. It was found that the error covariances between soil moisture and near-surface temperature and humidity were significant during the daytime and warm season in the boundary layer. Based on the error covariance structures and correlations, we can expect that soil moisture changes could cause adjustments in near-surface and atmospheric boundary layer conditions. The increments in atmospheric conditions would lead to changes in soil moisture. The subsequent data assimilation with the WRF-Noah model indicated that strongly coupled land–atmosphere data assimilation in this variational framework successfully assimilated SMAP soil moisture data. More importantly, with simultaneous corrections in both atmosphere and land variables, this strongly coupled data assimilation method outperformed weakly coupled data assimilation. Finally, strongly coupled data assimilation was implemented in an ensemble Kalman filter data assimilation system. Results proved that this strongly coupled data assimilation could indeed improve prediction of both soil and atmospheric states.

Although variational data assimilation is different from the ensemble Kalman filter, both methods have proven the success of strongly coupled data assimilation. In reality, according to Lin and Pu (2020), the structure of ensemble spreads from the strongly coupled system in the GSI-EnKF system (Fig. 3) was very similar to the structure in Lin and Pu (2018) (e.g., Fig. 2), implying that strongly coupled land–atmosphere data assimilation is capable of representing the strong coupling between soil moisture and the near-surface and boundary layer atmospheric states in the EnKF data assimilation system; thus it has great potential to be implemented into NWP models for many forecast applications.

5.2 Concluding Remarks

Land–atmosphere interaction is an essential process in weather and climate systems. Coupled land–atmosphere models and land surface parameterizations are necessary to represent land–atmosphere interactions in weather and climate models. Due to lack of observations, our limited understanding of and capability to accurately represent land–atmosphere interaction in coupled models or parameterizations, and the errors in initial and boundary conditions, uncertainties in weather and climate prediction present significant challenges in weather forecasting and climate prediction. Notably, the near-surface atmosphere and atmospheric boundary layer interact with the land surface directly. Because of the complexity of the water and energy budget in the interface of the land and atmosphere, uncertainties in numerical model parameterizations and initial conditions are significant. As a consequence, near-surface weather forecasting remains a significant challenge in numerical weather prediction (Pu 2017). In light of the strong interaction between the near-surface atmosphere

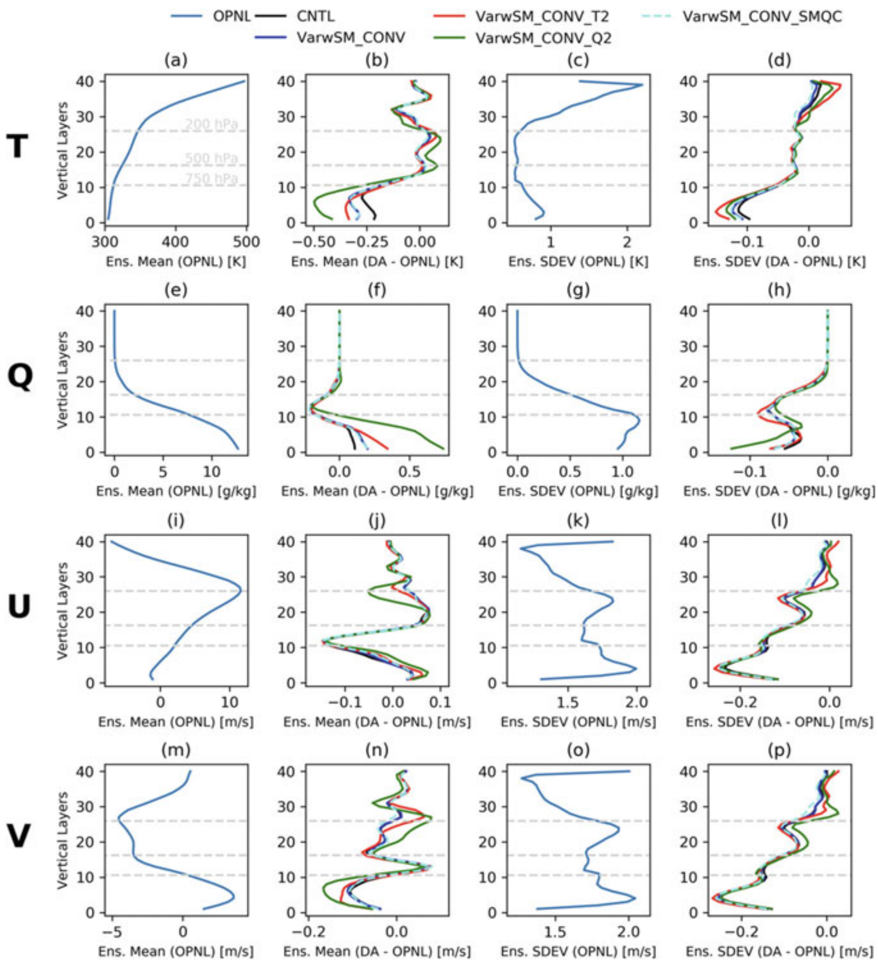

Fig. 3 Ensemble mean and spread (SDEV or standard deviation) of atmospheric first guesses for potential temperature (T), specific humidity (Q), zonal wind (U), and meridional wind (V) during the study period (July 2018) (From Lin and Pu 2020)

and land surface, four research articles (Liu and Pu 2019; Lin and Pu 2018, 2019, 2020) are summarized in this chapter dedicated to understanding the fundamentals of improving near-surface weather forecasting using coupled data assimilation.

The observational analyses showed significant correlations between soil moisture in the top soil layer and surface 2-m temperature. However, the correlation coefficient between soil moisture and 2-m temperature was less than 0.6, implying that soil moisture is not the sole factor that influences near-surface weather conditions. Given the heterogeneous nature of land use and land cover as well as soil types, there are many other factors that could influence land–atmosphere interactions that need to be studied in future work to examine their influence on near-surface weather prediction. Nevertheless, the notable correlation between soil moisture and near-surface atmospheric conditions provides a direct way to implement coupled land–atmosphere data assimilation. More complicated data assimilation systems are still needed in order to fully resolve or mitigate the uncertainties associated with land–atmosphere interactions in weather and climate models.

In addition, near-surface temperature and soil moisture could also influence the atmospheric boundary layer, even upper atmospheric conditions. Most of this influence is in the local atmospheric boundary layer in short-range weather prediction. However, through the integration of atmospheric models with time, the soil moisture influence could propagate to the entire atmospheric column and over a large region. Therefore, the influence of soil moisture in medium-range weather forecasting and sub-seasonal to seasonal climate prediction should be expected. From these perspectives, strongly coupled land–atmosphere data assimilation should be an active research area, not only for weather forecasting but also for climate prediction. Nevertheless, since the temporal scales between land and atmosphere variabilities are not the same, strategies to adjust the temporal scales of land and atmospheric variables during the coupled data assimilation could be another important problem to explore in future studies.

Furthermore, many severe weather and climate events are associated with land–atmosphere interactions, such as hurricane evolution after landfall, floods, droughts, etc. Considering the need to improve forecasts and public warnings for these high-impact weather and climate events, we can foresee the utility of strongly coupled data assimilation in many research applications.

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