Assimilation of Passive L-band Microwave Brightness Temperatures in the Canadian Land Data Assimilation System: Impacts on Short-Range Warm Season Numerical Weather Prediction

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(Manuscript received 21 June 2018, in final form 29 March 2019)

ABSTRACT

This study examines the impacts of assimilating Soil Moisture Active Passive (SMAP) L-band brightness temperatures (TBs) on warm season short-range numerical weather prediction (NWP) forecasts. Focusing upon the summer 2015 period over North America, offline assimilation cycles are run with the Canadian Land Data Assimilation System (CaLDAS) to compare the impacts of assimilating SMAP TB versus screen-level observations to analyze soil moisture. The analyzed soil moistures are quantitatively compared against a set of in situ sparse soil moisture networks and a set of SMAP core validation sites. These surface analyses are used to initialize a series of 48-h forecasts where near-surface temperature and precipitation are evaluated against in situ observations. Assimilation of SMAP TBs leads to soil moisture that is markedly improved in terms of correlation and standard deviation of the errors (STDE) compared to the use of screen-level observations. NWP forecasts initialized with SMAP-derived soil moistures exhibit a general dry bias in 2-m dewpoint temperatures (TD_{2m}), while displaying a relative warm bias in 2-m temperatures (TT_{2m}), when compared to those forecasts initialized with soil moistures analyzed with screen-level temperature errors. Largest impacts with SMAP are seen for TD_{2m} , where the use of screen-level observations leads to a daytime wet bias that is reduced with SMAP. The overall drier soil moisture leads to improved precipitation bias scores with SMAP. A notable deterioration in TD_{2m} STDE scores was found in the SMAP experiments during the daytime over the Northern Great Plains. A reduction in the daytime TD_{2m} wet bias was found when the observation errors for the screen-level observations were increased.

1. Introduction

For several applications in environmental science and prediction, accurate knowledge of soil moisture has been shown to be important. These applications include numerical weather prediction (NWP) (e.g., Trier et al. 2008; Scipal et al. 2008; Mahfouf 2010; de Rosnay et al. 2013; Schneider et al. 2014; Santanello et al. 2016; Lin et al. 2017b), seasonal prediction (Dirmeyer 2000; Koster and Suarez 2003; Koster et al. 2004), hydrological and flood

prediction (e.g., Lievens et al. 2015a; Crow et al. 2017), and agricultural and drought monitoring (Bolten et al. 2010; Champagne et al. 2011, 2015). Soil moisture levels influence the partitioning of incoming precipitation into infiltration and runoff and govern the energy balance in terms of sensible and latent heat fluxes influencing local boundary level and storm development (Eltahir 1998; Findell and Eltahir 2003; Trier et al. 2008; Seneviratne et al. 2010; Evans et al. 2011).

Under certain meteorological conditions, a correlation is observed between screen-level temperatures and soil moisture (Mahfouf 1991; Seuffert et al. 2004; Drusch and Viterbo 2007; Mahfouf et al. 2009; de Rosnay et al. 2013). At several meteorological centers the initialization of soil moisture is based upon correcting short-range forecast errors in screen-level temperature and

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DOI: 10.1175/JHM-D-18-0133.1

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humidity (e.g., Bélair et al. 2003a; Drusch and Viterbo 2007; Mahfouf et al. 2009; Dharssi et al. 2011; de Rosnay et al. 2014; Milbrandt et al. 2016). These screen-level observations are routinely measured by various operational monitoring networks and are available with a high temporal frequency (hourly). These observations are not direct measures of soil moisture, but their assimilation is designed to improve the estimates of surface turbulent fluxes and the resulting NWP forecasts of near-surface variables (Drusch and Viterbo 2007). Verification studies have shown that the increments added to soil moisture through screen-level temperature and humidity assimilation can lead to an overall degradation of soil moisture scores (e.g., Douville et al. 2000; Hess 2001; Seuffert et al. 2004; Drusch 2007; Drusch and Viterbo 2007; Hess et al. 2008; Draper et al. 2011; Duerinckx et al. 2017), suggesting that the improved NWP forecasts are not necessarily the result of more skillful soil moisture simulations.

Advances in remote sensing technologies, specifically dedicated to the sensing of soil moisture in the preferred L-band frequency, are alleviating the observational gaps in soil moisture (Entekhabi et al. 2010b; Kerr et al. 2010, 2016). The European Space Agency's (ESA) Soil Moisture and Ocean Salinity (SMOS) satellite launched in November 2009 has been providing near global coverage of superficial soil moisture every 3 days (Kerr et al. 2016). More recently, in January 2015, the NASA Soil Moisture Active Passive (SMAP) mission was launched (Entekhabi et al. 2010b). At shorter microwave wavelengths (C and X bands), where soil penetration depths are smaller, passive and active sensors such as the *MetOp-A* Advanced Scatterometer (ASCAT) (Scipal et al. 2008; Mahfouf 2010; Draper et al. 2012; de Rosnay et al. 2013; Schneider et al. 2014), the Scanning Multichannel Microwave Radiometer (SMMR) (Reichle et al. 2004, 2007), and the Advanced Scanning Radiometer (AMSR-E) (de Jeu et al. 2008; Draper et al. 2009; Champagne et al. 2011; Draper et al. 2011) have been providing information on soil moisture.

Several studies have examined the issue of assimilating satellite derived soil moisture information to improve the representation of soil moisture in land surface models (e.g., Draper et al. 2009; Dharssi et al. 2011; Muñoz-Sabater 2015; De Lannoy and Reichle 2016a,b; Lievens et al. 2016; Blankenship et al. 2016; Reichle et al. 2017). Utilizing ensemble Kalman filter (EnKF), variational techniques, and nudging schemes, these studies have shown modest to substantial improvements in simulated soil moisture temporal correlations and reductions in the standard deviation of the errors (STDE) [also called unbiased RMSE (ubRMSE); Entekhabi et al. 2010a] when validated against in situ soil moisture

observations. Focusing upon L-band studies, De Lannoy and Reichle (2016b) noted significant improvements in both anomaly correlations and ubRMSE scores for surface soil moisture, over model-only estimates, when either SMOS brightness temperatures or soil moisture retrievals were assimilated into the NASA GEOS-5 model over agricultural regions of North America. Blankenship et al. (2016) found similarly improved surface soil moisture correlations over the southeastern United States with the assimilation of SMOS soil moisture retrievals. More recently, Reichle et al. (2017) presented the positive impacts of globally assimilating SMAP brightness temperatures with the SMAP Level-4 soil moisture product.

The joint assimilation of screen-level observations and microwave brightness temperatures and/or soil moisture retrievals has been the subject of several papers (e.g., Seuffert et al. 2004; Draper et al. 2011; Dharssi et al. 2011; de Rosnay et al. 2013). Seuffert et al. (2004) examined the joint assimilation of screen-level temperature and relative humidity with L-band brightness temperatures (TB) and noted that the joint assimilation led to superior superficial soil moisture verifications, but the root-zone soil moisture increment, caused by the screen-level observations, resulted from model deficiencies not related to soil moisture. The relative information content of screen-level observations versus L-band TBs was examined in a synthetic environment by Balsamo et al. (2007) who noted for a single observation that the information content of the L-band TBs (screen-level observations) was highest (lowest) for the root-zone soil moisture update in the Interactions between Soil, Biosphere, and Atmosphere (ISBA) land surface model. Draper et al. (2011) noted several issues with the AMSR-E data, emphasizing the relative low-information content of the retrieved soil moisture when compared to the screen-level observations, the presence of a diurnal cycle in the screen-level increments not directly related to soil moisture, and at times, opposing increments between AMSR-E and screen-level observations.

Research studies have extended the soil moisture assimilation efforts to quantify the impact of assimilating satellite derived soil moisture on NWP forecasts (Scipal et al. 2008; Mahfouf 2010; Dharssi et al. 2011; de Rosnay et al. 2013; Schneider et al. 2014; Muñoz-Sabater 2015; Santanello et al. 2016; Lin et al. 2017b). Experiments at the U.K. Met Office using the Unified Model with the MOSES 2 land surface scheme documented improvements in screen-level temperature forecasts over the tropics, North America, and Australia with the assimilation of ASCAT soil moisture (Dharssi et al. 2011). In contrast, de Rosnay et al. (2013) noted mostly neutral impacts with the assimilation of ASCAT soil moisture retrievals for short-range forecasts of soil moisture and

screen-level temperatures at the European Centre for Medium-Range Weather Forecasts (ECMWF) using a simplified extended Kalman filter, while [Mahfouf \(2010\)](#) found a slight degradation of lower-tropospheric temperature scores over France. More recent L-band studies have used SMOS TBs or soil moisture retrievals to assess the impact on short-range NWP forecasts. [Muñoz-Sabater \(2015\)](#) found mixed signals for screen-level temperature forecasts when assimilating SMOS TBs at ECMWF, while [Lin et al. \(2017b\)](#) noted a positive impact on near-surface temperature and humidity scores at longer lead times with the assimilation of SMOS soil moisture retrievals over a localized region in the central United States.

Improvements in precipitation scores have also been challenging. [Schneider et al. \(2014\)](#) noted small improvements in convective precipitation forecasts over flatland in Austria for a one-month period in summer 2009 when ASCAT soil moisture data was assimilated, while [Mahfouf \(2010\)](#) found mostly neutral impacts over France assimilating ASCAT soil moisture retrievals. More recent L-band studies (e.g., [Lin et al. 2017a,b](#)) noted similar small or marginal improvements in precipitation forecasts from the assimilation of SMOS soil moisture retrievals.

The objectives of this study are to quantitatively assess the impacts of using screen-level observations versus SMAP TBs upon the analysis of soil moisture and the subsequent short-range NWP forecasts with the newly developed Soil, Vegetation, and Snow (SVS) land surface model at Environment and Climate Change Canada (ECCC). The manuscript is organized as follows. A description of the different components of the Canadian Land Data Assimilation System (CaLDAS) is provided in [section 2](#). In [section 3](#) the setup of the three data assimilation experiments is outlined. The soil moisture and NWP verification results are presented and discussed in [sections 4](#) and [5](#). A discussion and summary are presented in the final section.

2. CaLDAS

A detailed description of CaLDAS and its coupling with the Community Microwave Emission Modeling Platform (CMEM) microwave radiative transfer model, allowing for the assimilation of microwave TB is given in [Carrera et al. \(2015\)](#). In the following subsections, the individual components of CaLDAS are briefly described and outlined.

a. Land surface models

CaLDAS is built around an external land surface modeling capability which has the advantage of reducing

the computational costs when integrating at higher resolutions, when compared to running the full 3D version of the atmospheric model. Two options for the land surface model component have been implemented in CaLDAS. The Canadian implementation of ISBA ([Noilhan and Planton 1989](#); [Noilhan and Mahfouf 1996](#); [Bélair et al. 2003a,b](#)) has been the most extensively tested in external mode ([Carrera et al. 2010](#); [Bernier et al. 2011](#); [Separovic et al. 2014](#)). The second land surface parameterization scheme is the newly developed SVS scheme which is described in detail in two recent publications ([Alavi et al. 2016](#); [Husain et al. 2016](#)) and has been shown to be skillful in the simulation of soil moisture and its spatial variability as evaluated over two extensive summer field campaigns ([Garnaud et al. 2016, 2017](#)).

In this study, the data assimilation experiments and NWP forecasts will be performed with the SVS land surface model as it has been shown to outperform ISBA in terms of the simulation of soil moisture ([Alavi et al. 2016](#)). The SVS model uses a tiling approach, considering separate energy budgets for bare ground and low vegetation, high vegetation, and snow within a given grid cell for the calculation of surface fluxes. Within the soil column, the vertical discretization consists of N soil layers where the vertical movement of water follows the one-dimensional Richards equation for unsaturated flow ([Alavi et al. 2016](#)). The version of SVS used in this study considers seven soil layers of depths 5, 10, 20, 40, 100, 200, and 300 cm. Soil hydrologic properties (e.g., field capacity, wilting point) are vertically discretized using a multilayer geophysical soil properties dataset (see [section 3a](#)). Within SVS, 26 different land surface classes are defined, including inland water, oceans, and glaciers. For the subset of 23 vegetation classes within SVS, a set of fixed parameters is defined for minimum canopy resistance, spatial coverage, and vertical distribution of roots within the soil layer.

b. Atmospheric forcing

Within CaLDAS, the land surface modeling component is driven by outputs from ECCC's environmental prediction systems. In this study, short-range forecasts (0–6 h) from ECCC's Regional Deterministic Prediction System (RDPS; [Caron et al. 2015](#)) model with a grid spacing of 10 km are used to force SVS. Air temperature, specific humidity, wind along with the surface values of pressure, and incident longwave and shortwave radiation are used. As CaLDAS is based upon an EnKF methodology, an ensemble of atmospheric forcing variables are generated from the single RDPS deterministic forecast by the addition of perturbations to air temperature, radiation and precipitation. For air temperature,

the perturbations are additive Gaussian with a mean of 0 and standard deviation of 1 K.

As detailed in [Carrera et al. \(2015\)](#) considerable effort was devoted to the generation of precipitation ensembles by making use of the Canadian Precipitation Analysis (CaPA) methodology ([Mahfouf et al. 2007](#); [Lespinas et al. 2015](#)). CaPA combines precipitation observations with a first-guess precipitation field using an optimum interpolation (OI) methodology. Both principal inputs to CaPA, the 6-h precipitation gauge accumulations and the first-guess precipitation fields from the RDPS, are perturbed. Gaussian noise is added to the precipitation gauge accumulations consistent with the time-varying observation errors estimated from the experimental semivariogram, while precipitation phasing or timing errors are simulated by spatially shifting the entire 6-h accumulated precipitation background from the RDPS. A mean displacement error of 0 km with a standard deviation of 50 km is used. The radiative forcing fields are spatially shifted exactly as for the precipitation to maintain consistency between cloud cover and precipitation.

c. Observations

Two observation types are considered in this study, L-band TBs from SMAP and screen-level temperature and dewpoint temperature from the land surface synoptic reports (SYNOP) and the aviation routine weather report (METAR) networks. The SMAP TB data are the L1B radiometer half-orbit, time-ordered brightness temperatures, version 3, acquired from the National Snow and Ice Data Center (NSIDC), which have an effective field of view resolution of 39 km × 47 km ([Entekhabi et al. 2014](#)). Only the TB data at horizontal polarization are used in this study, and no distinction is made between the fore- and aft-looking data. Several quality control flags are provided with these L1B data in the product specification document (<https://nsidc.org/data/SPL1BTB/versions/3>) and those TB data suffering from the effects of uncorrected radio-frequency interference (RFI) were eliminated in addition to those data of unacceptable quality owing to sun, Faraday, moon and galaxy contamination. Further details on the RFI detection and mitigation methods can be found in [Entekhabi et al. \(2014\)](#) and [Mohammed et al. \(2016\)](#). The L1B SMAP TBs were disaggregated into hourly files and regridded onto a 50-km grid covering the North American study domain.

The local station observations of screen-level temperature (TT_{2m}) and dewpoint temperature (TD_{2m}) are not directly assimilated in CaLDAS. Rather, a 2D gridded field is generated for both TT_{2m} and TD_{2m} using the OI methodology outlined in [Brasnett \(1999\)](#), combining

first-guess SVS TT_{2m} and TD_{2m} background fields with the station observations ([Drusch and Viterbo 2007](#); [Mahfouf et al. 2009](#)). An observation error standard deviation of 1.5 (2) K is assumed for TT_{2m} (TD_{2m}), while the errors for the perturbed background fields is set to 4.2 K for both TT_{2m} and TD_{2m}. An elevation screening is performed to reject observations where the elevation difference between the station and the model topography exceeds 400 m. A lapse-rate 6.5 K (1000 m)⁻¹ terrain-adjustment is performed for the remaining stations.

d. Microwave radiative transfer model

To transfer the predicted soil moisture and vegetation state into an L-band top of the atmosphere brightness temperature, CMEM developed at EMCWF ([Drusch et al. 2009](#); [de Rosnay et al. 2009](#); [Muñoz-Sabater et al. 2011](#)) is used. As described in [section 2e](#) below, this transformation is required as the observations assimilated are brightness temperatures. CMEM is based on the familiar tau-omega model and contains four separate modules for the calculation of the microwave emission from snow, soil, vegetation, and the atmosphere. The parameterization of [Wang and Schmugge \(1980\)](#) is used for the calculation of the soil dielectric constant, while smooth soil reflectivities are based upon the one-layer model of [Schmugge and Choudhury \(1981\)](#). Soil roughness effects are modeled after [Wigneron et al. \(2001\)](#), and vegetation is accounted for following [Kirdyashev et al. \(1979\)](#). It was also assumed that the atmosphere was transparent at L band ([Jackson 1993](#)). The choice of CMEM submodels are the same as those used in [Carrera et al. \(2015\)](#).

e. EnKF analysis

The EnKF is a sequential algorithm in time consisting of a forecast step followed by an analysis or update step when observations are present. The forecast step used within the EnKF is written as follows

$$\mathbf{x}_k^f(t + \delta t) = F[\mathbf{x}_k^a(t), \alpha, u_{k,t}, w_k(t)], \quad (1)$$

where $\mathbf{x}_k^f(t + \delta t)$ refers to the land surface model state vector at time $t + \delta t$ for ensemble member k , while F is the nonlinear land surface model (i.e., SVS), and $\mathbf{x}_k^a(t)$ refers to the updated model state vector at time t . The length of the forecast step δt is 3 h. The time-invariant model parameters (e.g., soil texture, land–water mask, topography) are represented by the α term, while the various atmospheric forcing variables for ensemble member k are given by $u_{k,t}$, and the final term $w_k(t)$ is the model error term added at time t to ensemble member k ([Carrera et al. 2015](#)).

The nonlinear measurement operator $\mathcal{M}$ converts the model state vector into measurements in observation space as $\mathcal{M}[\mathbf{x}_k^f(t)]$. For the case of SMAP TB observations, $\mathcal{M}$ is the microwave radiative transfer model CMEM, while for screen level observations of temperature and dewpoint temperature, $\mathcal{M}$ is vertical interpolation to screen-level height using Monin–Obukhov similarity theory (Geleyn 1988).

At the time of the EnKF update, each ensemble member k is updated following

$$\mathbf{x}_k^a(t + \delta t) = \mathbf{x}_k^f(t + \delta t) + \mathbf{K}_{t+\delta t} \{ \mathbf{z}(t + \delta t) - \mathcal{M}[\mathbf{x}_k^f(t + \delta t)] + \mathbf{v}_k \}, \quad (2)$$

where $\mathbf{z}(t + \delta t)$ is the observation vector at time $t + \delta t$, $\mathbf{K}_{t+\delta t}$ is the Kalman gain matrix at time $t + \delta t$, and $\mathbf{v}_k$ is a realization of the observation error, described in section 3a below, which is added to the observations as they are considered random variables (Burgers et al. 1998). The Kalman gain matrix is calculated directly from the ensemble members as follows

$$\mathbf{K}_{t+\delta t} = \mathbf{C}_{xz} (\mathbf{C}_{zz} + \mathbf{C}_{vv})^{-1}, \quad (3)$$

where $\mathbf{C}_{zz}$ is the error covariance of the first-guess transformed into observation space, $\mathbf{C}_{xz}$ is the cross covariance between the model state variables and the first-guess transformed into observation space, and $\mathbf{C}_{vv}$ is the measurement error covariance.

As noted in section 2c, the SMAP L1B TB observations are regridded onto a 50-km grid, a coarser resolution than the integration grid in this study (10 km). Following the work of De Lannoy et al. (2010, 2012), the downscaling of the SMAP TB observations is performed in the EnKF filtering algorithm, where one coarse-scale SMAP TB observation is used to update the underlying fine grid cells contained within the observing area, so-called method 3D-C1 in De Lannoy et al. (2010). Correspondingly, the coarse-scale first-guess TBs are calculated as appropriate spatial averages of the finer scale prediction and this is included in the measurement operator $\mathcal{M}$. The $\mathbf{C}_{xz}$ term in (3) is calculated as the covariance between the finescale model states and the coarse-scale first-guess TBs and acts to downscale the coarse scale TBs to the finer scales. Note that the assimilation of the screen-level TT_{2m} and TD_{2m} is performed directly on the 10-km integration grid.

3. Experimental design

The experimental design consists of two components, (i) the offline CaLDAS assimilation cycles

and (ii) series of short-range NWP forecasts. These two components are described below in more detail along with a description of the validation datasets and evaluation metrics.

a. Offline CaLDAS assimilation cycles

A schematic diagram outlining the offline CaLDAS assimilation cycles is given in Fig. 1. For each experiment, 0–6-h outputs from ECCO’s RDPS forecast model (shown in green), run operationally 4 times daily are used to drive the offline SVS within CaLDAS at a 10-km grid spacing over North America. These experiments are termed “offline” as the RDPS atmospheric forcing variables are already generated for the entire period prior to the start of the experiment. The analyzed soil moisture states are not used to update the atmospheric forcing.

As described in section 2b, the RDPS atmospheric forcing variables are suitably perturbed to ensure a sufficient spread among the ensemble members. Every three hours an update is performed assimilating screen-level temperature and dewpoint temperatures and/or SMAP TBs, shown in yellow. Analyses of the CaLDAS control variables are produced every 3 h. The introduction of model errors to the model control variables follows that of Carrera et al. (2015). Table 1 lists the configurations of the separate CaLDAS offline assimilation cycles considered in this study.

For all the experiments 24 members are used, as further increases in ensemble size were shown to provide marginal added benefits (Carrera et al. 2015) and the assimilation cycles extend from 1 June 2015 to 31 August 2015. Experiment SVS-SCREEN uses short-range departures in TT_{2m} and TD_{2m} to analyze soil moisture in the first five soil layers in SVS (depth of 1 m), along with the bare ground and vegetation surface temperatures in the first two force–restore layers. The two experiments SVS-SCREEN-SMAP-BC and SVS-SCREEN-SMAP-NBC combine the assimilation of TT_{2m} and TD_{2m} with SMAP TB. At each update time the SMAP TB observations are used to analyze the soil moisture in the first four soil layers in SVS, while the screen-level data are used to analyze only the force–restore surface temperatures for the two layers. An important distinction among the two SMAP experiments is the bias correction of the SMAP TB.

In experiment SVS-SCREEN-SMAP-BC the SMAP TB observations are rescaled, a priori, to match the climatology of the SVS land surface model, following a cumulative distribution function (CDF) approach (Reichle and Koster 2004; Scipal et al. 2008; Kumar et al. 2012). A seasonal linear CDF matching approach was

FIG. 1. Schematic depicting the functioning of the offline CaLDAS assimilation cycles.

used where modeled TB values for the June–August 2015 and 2016 periods are derived from an open-loop forced with very accurate 0–6-h RDPS forcing and using CaPA as the best estimate for precipitation forcing, commencing 1 March 2014 and referred to as OPEN-LOOP-CaPA. These simulated TBs at 10-km grid spacing are then arithmetically averaged up to the coarser 50-km grid spacing to compare directly with the SMAP observations. Each SMAP TB is corrected independently for each 50-km pixel. For experiment SVS-SCREEN-SMAP-NBC, no a priori rescaling of the SMAP TBs is performed.

Figure 2 shows a comparison of the TB differences between OPEN-LOOP-CaPA and SMAP before and after bias correction for the June–August 2015 period. The simulated TBs are warmer (i.e., drier) than SMAP over the Canadian Prairies and the far Northern Great Plains (Fig. 2a). Notable simulated dry TB biases are seen over the predominant wetlands regions of southern Florida and along Hudson’s Bay. The pronounced dry biases in the Canadian Arctic are most likely related to an underestimation of the inland lake fractions and also to unmodeled Arctic wetlands, a feature noted at ECMWF with modeled SMOS TBs (Muñoz-Sabater 2015;

TABLE 1. Configurations for the different CaLDAS offline assimilation experiments. In the table, TT_{2m} refers to screen-level temperature, TD_{2m} to screen-level dewpoint temperature, and TB to the SMAP horizontal polarized brightness temperatures. For the analyzed variables, w_i refers to the soil moisture for layer i , while TBG_i and TVG_i refer to the bare ground and vegetation surface temperatures for the force–restore layer i . The assimilation frequency is 3 h.

Experiment name	Observations assimilated	Analyzed variables	Bias correction
SVS-SCREEN	TT_{2m} , TD_{2m}	w_{1-5} ; TBG_{1-2} , TVG_{1-2}	None
SVS-SCREEN-SMAP-BC	TT_{2m} , TD_{2m} , TB (SMAP)	w_{1-4} ; TBG_{1-2} , TVG_{1-2}	Linear CDF matching for SMAP TBs
SVS-SCREEN-SMAP-NBC	TT_{2m} , TD_{2m} , TB (SMAP)	w_{1-4} ; TBG_{1-2} , TVG_{1-2}	None

FIG. 2. Difference in TB between the OPEN-LOOP-CaPA and SMAP (OPEN-LOOP-CaPA – SMAP) averaged for the June–August 2015 period (a) prior to CDF bias correction and (b) after application of CDF bias correction. The location of the South Fork core validation site is shown in black.

cf. Fig. 2). Large differences on the order of 10–50 K were also noted for SMOS TBs prior to calibration of the radiative transfer modeling parameters (e.g., De Lannoy et al. 2013; Lievens et al. 2015b). After application of the linear CDF matching there is a much better agreement between the SMAP and modeled TBs, although there are areas where absolute differences can exceed 5 K (Fig. 2b).

SVS is not yet run operationally at ECCO so a spinup period is needed to generate the initial conditions for the assimilation experiments. A 15-month open-loop spinup is run from 1 March 2014 to 1 June 2015, starting with the operational RDPS ISBA analysis, to generate the SVS initial conditions. This open-loop is then continued to the fall of 2016 and used in the bias correction described

above. Specification of land surface characteristics is derived from several different databases. The orography fields along with the land–water mask are derived from a 1-km global U.S. Geological Survey (USGS). Vegetation characteristics including vegetation type and fractional coverage also originate from this USGS database. The source of data for soil properties is the gridded Global Soil Dataset for Earth System Models (GSDE) (Shangguan et al. 2014). This is the same dataset used by Alavi et al. (2016) in their SVS simulation sensitivity experiments and has the advantage of providing soil texture information for eight layers in the vertical allowing for the definition of vertical structure to the soil hydrologic properties (e.g., field capacity, wilting point).

A series of masks are applied for the assimilation experiments using SMAP TB data. No TB assimilation is performed in the presence of snow and/or frozen soil, derived from the SVS first-guess fields. A land–water mask is applied, where SMAP TB assimilation is restricted to 50-km regions where the land fraction exceeds 90%. A constant observation error standard deviation of 4 K is assumed for the SMAP TB data, while the observation error standard deviations for TT_{2m} and TD_{2m} are calculated as the standard deviation of the 24 individual OI analyses.

b. NWP 48-h forecasts

Individual 48-h NWP forecasts are launched using the respective CaLDAS assimilation experiment analyzed soil moisture and surface temperature fields as initial conditions. In offline mode these surface analyses are combined with upper-air initial conditions provided by a regional-based 4DVar scheme as outlined in Caron et al. (2015) and Buehner et al. (2015). For each experiment, the same upper-air initial conditions are used for a given starting date, only the CaLDAS analyzed surface fields change. The Global Environmental Multiscale (GEM) model run in its limited-area configuration with an approximate 10-km horizontal grid spacing and 80 levels in the vertical was used in this study (Caron et al. 2015). The June 2015 period is used for assimilation spinup of the individual experiments and the NWP 48-h forecasts are launched at 0000 UTC, every 2 days, for the period from 1 July to 31 August 2015, for a total of 31 individual forecasts.

c. Validation datasets and metrics

Verification of the soil moisture analyses are performed through quantitative comparisons with a series of in situ sparse networks covering a variety of landscapes across North America, along with a select set of SMAP core validation sites (CVS). Three sparse networks are considered: the Alberta Ground Drought Monitoring Network

(AGDMN), the U.S. Natural Resources Conservation Service Soil Climate Analysis Network (SCAN; Schaefer et al. 2007), and the U.S. Climate Reference Network (USCRN; Bell et al. 2013). The AGDMN sites are spread out over the agricultural regions of Alberta, Canada. Each AGDMN station is equipped with dielectric probes (Delta-T-Theta), installed horizontally, at 5-, 20-, 50-, and 100-cm depths providing hourly measurements (Champagne et al. 2016). These AGDMN data have been used in several previous studies (e.g., Champagne et al. 2011, 2016; Alavi et al. 2016). Focused primarily over agricultural regions of the United States, the SCAN network consists of dielectric probes installed at depths of 2 (~5 cm), 4 (~10 cm), 8 (~20 cm), 20 (~50 cm), and 40 (~100 cm) in. Each USCRN station over the conterminous United States includes the installation of triplicate-configuration soil moisture and soil temperature probes at depths of 5, 10, 20, 50, and 100 cm (Bell et al. 2013).

The verification period extends from 1 July to 31 August 2015 at a temporal scale of 6 h. Simulated soil moisture values were linearly interpolated to the location of the in situ site. The first layer soil moisture depth of 5 cm in SVS is compared against the corresponding 5-cm values from each sparse network. For root-zone soil moisture, a weighted average of the observations in the first meter from each network is compared to a weighted average in the first meter in SVS. A series of automatic quality controls are applied to remove spurious data following the work of Dorigo et al. (2013). These automated controls include geophysical dynamical range checks and spike and break detection along with constant value checks. Subsequent visual inspection of the soil moisture time series with available in situ precipitation was also performed. Only those stations for which there were significant correlations, that is, p values below 0.05, for both the superficial and root-zone soil moisture were considered. After the quality control checks there were a total of 11 AGDMN, 35 SCAN, and 23 USCRN stations whose distribution is shown in Fig. 3a.

Additionally, a total of 8 SMAP CVS are used (see Table 2) to evaluate the skill of the superficial soil moisture analyses. These core validation sites possess a higher-density of well-calibrated in situ sensors to calculate more reliable spatially averaged soil moisture (Crow et al. 2012; Chan et al. 2016; Colliander et al. 2017) and alleviate some of the inherent challenges and uncertainties with direct comparisons of grid-scale and point values. An arithmetic average of the in situ sites for each CVS is compared with an average of the 10-km grid boxes covering the CVS, with each grid box weighted by

the number of in situ stations contained inside. Agreement between the in situ and simulated soil moisture is assessed via the correlation coefficient, the STDE, and the bias.

This study utilizes a verification software package, EMET, developed internally at the Canadian Meteorological Centre, to verify NWP surface scores. Observations from surface SYNOP and METAR networks are used to verify temperature, dewpoint temperature and precipitation as a function of forecast range. The spatial distribution of these surface stations is shown in Fig. 3b.

4. Soil moisture verification

Verifications of soil moisture over the limited 2-month period of the NWP forecasts, to aid in the interpretation of the near-surface NWP forecast scores, are presented in this section. More extensive, multiyear soil moisture verifications can be found in other L-band assimilation studies (e.g., De Lannoy and Reichle 2016a,b; Reichle et al. 2017).

a. Sparse networks

For the two experiments assimilating SMAP TBs, correlations are higher for all sparse networks (Figs. 4a,b), when compared to SVS-SCREEN. The detrimental impacts of using TT_{2m} and TD_{2m} forecast errors to analyze soil moisture are more pronounced for the root zone. Correlation differences between the SMAP experiments and OPEN-LOOP-CaPA are much smaller, although small improvements for superficial soil moisture can be seen over SCAN and USCRN. For the root zone the benefits of SMAP TB assimilation do not provide improvements over the OPEN-LOOP-CaPA. This limited benefit of SMAP TB assimilation in the presence of accurate precipitation forcing is consistent with previous studies (e.g., De Lannoy and Reichle 2016a,b; Reichle et al. 2017; Kolassa et al. 2017).

To assess the impact of CaPA, experiment OPEN-LOOP-GEM is performed, identical to OPEN-LOOP-CaPA except that the precipitation forcing was taken from 0- to 6-h accumulations from the RDPS GEM. Comparing OPEN-LOOP-GEM with OPEN-LOOP-CaPA, correlations are improved for all sparse networks for superficial soil moisture, and over the AGDMN, SCAN and USCRN networks for root-zone soil moisture (Figs. 4a,b). STDE scores are markedly improved when SMAP TBs are used to analyze soil moisture as compared to TT_{2m} and TD_{2m} (Figs. 4c,d) and the root-zone improvements are more pronounced. Superficial soil moistures are wetter in SVS-SCREEN,

FIG. 3. (a) Locations of the in situ soil moisture sites within three sparse networks, AGDMN, SCAN, and USCRN, used to verify the soil moisture analyses. The set of stations labeled SCAN-G refers to the subset of soil moisture sites located over dominantly agriculture and low-grass regions as determined from the USGS vegetation database. (b) Locations of the set of SYNOP and METAR stations used for the verification of the NWP forecasts.

with a pronounced wet bias over AGDMN and SCAN-G (Fig. 4e). Bias correcting the SMAP TBs leads to a dry bias for the superficial layer for the AGDMN network (Fig. 4e), consistent with the drier TBs in OPEN-LOOP-CaPA (Fig. 2a). All experiments possess a dry bias for the root zone (Fig. 4f).

b. SMAP core-validation sites

Correlations for OPEN-LOOP-CaPA exceed 0.80 at 5 of the 8 CVS sites, indicating a high skill level derived from accurate precipitation (Fig. 5). Similarly, STDEs are less than $0.04 \text{ m}^3 \text{ m}^{-3}$, the accuracy threshold set by

the SMAP mission for CVS sites (Colliander et al. 2017), at 5 of the 8 sites. Superficial soil moisture correlations in the SMAP experiments improve at 4 of the 8 CVS sites, when compared to the OPEN-LOOP-CaPA and improve upon SVS-SCREEN at 6 of the 8 CVS sites. STDEs are improved in the SMAP experiments at 4 of the 8 CVS sites, compared to OPEN-LOOP-CaPA, and at 6 of the 8 CVS sites compared to SVS-SCREEN. The impact of CaPA (OPEN-LOOP-CaPA versus OPEN-LOOP-GEM) results in significant correlation improvements at 3 of the 8 CVS sites, while STDEs improve at 4 of the 8 sites.

TABLE 2. List of SMAP core validation sites used for verification.

Site name	Location
Kenaston	Saskatchewan, Canada
Carman	Manitoba, Canada
Walnut Gulch	Arizona, United States
Reynolds Creek	Idaho, United States
South Fork	Iowa, United States
Fort Cobb	Oklahoma, United States
Little Washita	Oklahoma, United States
Little River	Georgia, United States

5. NWP short-range verification

The second component of this study involved a quantitative evaluation of short-range NWP forecasts initialized with the land surface initial conditions from each of the three offline CaLDAS assimilation experiments in Table 1. A total of thirty-one 48-h simulations were performed, initialized at 0000 UTC every 2 days for the period from 1 July to 31 August 2015. Verification scores focus upon TT_{2m} and TD_{2m} along

with precipitation. Owing to the differences in observation density, the set of SYNOP stations are used over Canada, while the set of METAR stations are used over the United States. Note that SYNOP verification for Canada is performed every 3 h owing to significant changes in station density at the hourly time scale, while the METAR verification, where the temporal changes in station density are smaller, is performed hourly. The spatial distribution of these stations is shown in Fig. 3b. One caveat is the concentration of SYNOP stations located in Alberta, Canada, which acts to bias the Canadian verification scores (Fig. 3b). An elevation screening is performed to reject observations where the elevation difference between the station and the model topography exceeds 100 m.

a. Screen-level temperature verification scores

Figures 6–9 present verifications of TT_{2m} and TD_{2m} as a function of forecast range for various geographical domains over North America for experiments SVS-SCREEN,

FIG. 4. Verification of CaLDAS assimilation experiments for superficial and root-zone soil moisture against in situ sparse soil moisture networks. AGDMN refers to the Alberta Ground Drought Monitoring Network, SCAN the Soil Climate Analysis Network, SCAN-G the subset of SCAN stations located over agricultural and short grass regions, and USCRN is the U.S. Surface Climate Observing Reference Network. Correlation, standard errors, and biases are shown for (a),(c),(e) superficial soil moisture and (b),(d),(f) root-zone soil moisture. Scores are calculated for the July–August 2015 period.

FIG. 5. Verification of CaLDAS assimilation experiments for superficial soil moisture against a set of SMAP core validation sites in Canada and the United States. Scores are for the July–August 2015 period. (a) Correlation, (b) STDE, and (c) bias with units provided. Also shown are the 95% confidence limits in yellow.

SVS-SCREEN-SMAP-NBC, and SVS-SCREEN-SMAP-BC. Integrated over both Canada (Fig. 6a) and the United States (Fig. 6b) $\text{TT}_{2\text{m}}$ bias differences indicate that both SMAP experiments are warmer than SVS-SCREEN, and the impact of bias correction is more pronounced over Canada with SVS-SCREEN-SMAP-BC warmer than SVS-SCREEN-SMAP-NBC. Regionally, over Canada it is clear that the warmer $\text{TT}_{2\text{m}}$ are concentrated over the Canadian Prairies region (Fig. 6e), where both SMAP experiments are drier than SVS-SCREEN in both the surface and root-zone layers (Figs. 4e,f), with SVS-SCREEN-SMAP-BC the driest. For the U.S. East (West) region, the effect of bias correcting the SMAP TB data acts to reduce (increase) the warm temperature biases (Fig. 6g).

$\text{TD}_{2\text{m}}$ biases are shown in Fig. 7, where the assimilation of SMAP TB data has larger impacts. Integrated over Canada (Fig. 7a) a clear gradient in $\text{TD}_{2\text{m}}$ bias is evident between experiments, with SVS-SCREEN (SVS-SCREEN-SMAP-BC) wettest (driest). The moist bias in

SVS-SCREEN is pronounced over Canada ($\sim 1^\circ\text{C}$) during the daytime hours, dominated by the wet bias over western Canada ($\sim 1.5^\circ\text{C}$) (Figs. 7e,f). The assimilation of SMAP TB data has an important drying impact upon $\text{TD}_{2\text{m}}$ during the daytime, even leading to a $\text{TD}_{2\text{m}}$ dry bias in SVS-SCREEN-SMAP-BC. A similar pronounced wet bias is seen in SVS-SCREEN during the daytime over the United States (Figs. 7b,g,h), which is reduced in both SMAP experiments. The drier signal in the SMAP experiments does result in an enhanced dry bias in $\text{TD}_{2\text{m}}$ during the nighttime over the United States, when compared to SVS-SCREEN (Figs. 7g,h).

STDE scores for $\text{TT}_{2\text{m}}$ and $\text{TD}_{2\text{m}}$ are shown in Figs. 8 and 9. Integrated over Canada (Fig. 8a) there is a signal of enhanced STDEs for $\text{TT}_{2\text{m}}$ during the daytime in the two SMAP experiments, more pronounced in SVS-SCREEN-SMAP-BC. The differences in STDEs for $\text{TT}_{2\text{m}}$ between SVS-SCREEN and SVS-SCREEN-SMAP-NBC are not significant at the end of day 2 (i.e., beyond 42 h)

FIG. 6. Verification of 48-h forecasts from the set of 31 cases for experiment SVS-SCREEN (blue), SVS-SCREEN-SMAP-BC (green), and SVS-SCREEN-SMAP-NBC (red) as a function of lead time. TT_{2m} biases ($^{\circ}\text{C}$) averaged over (a) Canada, (b) United States, (c) Canadian Maritimes, (d) Ontario-Quebec, (e) Canadian Prairies, (f) British Columbia, (g) U.S. East, and (h) U.S. West. The bottom of each panel shows the differences in absolute bias between experiments SVS-SCREEN-SMAP-NBC and SVS-SCREEN along with the 90% confidence interval (shaded) based upon a block bootstrapping method, where a positive (negative) value indicates that SVS-SCREEN-SMAP-NBC (SVS-SCREEN) is better.

(Fig. 7a). Examining the various subdomains in Canada (Figs. 8c–f), these enhanced STDEs originate from the Canadian Prairies region as over other Canadian regions the impacts of SMAP on TT_{2m} STDEs is mostly neutral.

Over the U.S. East region there is a signal of enhanced STDE for TT_{2m} in both SMAP experiments during the daytime, while STDEs for TT_{2m} for the U.S. West region are neutral when SMAP TBs are assimilated.

FIG. 7. As in Fig. 6, but for TD_{2m} .

For TD_{2m} STDEs scores are deteriorated in both SMAP experiments, when compared to SVS-SCREEN during the daytime hours (Fig. 9). Integrated over Canada, the TD_{2m} STDEs are higher in the experiment where the SMAP TBs are bias corrected (i.e., SVS-SCREEN-SMAP-BC) (Fig. 9a), again originating largely from the poorer scores over the Canadian Prairies region (Fig. 9e). Over eastern Canada (Figs. 9c,d)

the effect of SMAP TBs on TD_{2m} STDEs is neutral. Focusing upon the United States (Figs. 9b,g,h), we again see the problems with enhanced STDEs for TD_{2m} during the daytime hours when SMAP TB are used to analyze soil moisture. At 24-h lead times the STDEs for TD_{2m} are increased by greater than 10% in both SMAP experiments when compared to SVS-SCREEN over the United States (Fig. 9b).

FIG. 8. Verification of 48-h forecasts from the set of 31 cases for experiment SVS-SCREEN (blue), SVS-SCREEN-SMAP-BC (green), and SVS-SCREEN-SMAP-NBC (red) as a function of lead time. Standard deviation of TT_{2m} forecast errors ($^{\circ}\text{C}$) averaged over (a) Canada, (b) United States, (c) Canadian Maritimes, (d) Ontario-Quebec, (e) Canadian Prairies, (f) British Columbia, (g) U.S. East, and (h) U.S. West. The bottom of each panel shows the differences between experiments SVS-SCREEN-SMAP-NBC and SVS-SCREEN along with the 90% confidence interval (shaded), where a positive (negative) value indicates that SVS-SCREEN-SMAP-NBC (SVS-SCREEN) is better.

Figures 10 and 11 present the temporal evolution of the soil moisture correlations, STDEs and biases as a function of forecast range (0, 24, and 48 h), averaged over the sparse networks. The superior soil moisture

correlation scores for both the superficial and root-zone layers are maintained in both SMAP experiments when compared to SVS-SCREEN. It is interesting to note that the decay with forecast range of superficial soil moisture

FIG. 9. As in Fig. 8, but for TD_{2m} .

correlation scores for SVS-SCREEN are not as pronounced when compared to the SMAP experiments, with some increases noted over the AGDMN (Fig. 10a) and USCRN (Fig. 10d) networks. A similar temporal consistency is seen for the STDE scores (Figs. 10e–h and 11e–h) in SVS-SCREEN. These small improvements in correlation and STDEs may reflect more upon the degraded 0-h soil moistures in SVS-SCREEN, which are improved in free

forecasts with the GEM model. SVS-SCREEN maintains a wet bias in surface soil moisture throughout the two day forecast (Figs. 10i–l), which is consistent with the wet TD_{2m} bias seen during the daytime in Fig. 7.

b. Precipitation verification scores

The largest impacts of assimilating SMAP TBs are seen for the precipitation frequency bias index (FBI)

FIG. 10. Verification of superficial soil moisture forecasts against in situ sparse soil moisture networks, for July–August 2015. Shown for each experiment, SVS-SCREEN, SVS-SCREEN-BC, and SVS-SCREEN-SMAP-NBC, is the (a)–(d) correlation, (e)–(h) STDE, and (j)–(l) bias at 0, 24, and 48 h.

scores (Fig. 12). FBI represents the ratio of the frequency of forecast occurrence of a given precipitation event to the actual occurrence, with values larger (smaller) than 1 indicating a tendency to over forecast (under forecast) precipitation events. Figure 12 shows the FBI scores for 24-h accumulated precipitation over North America from 1200 UTC ($T + 12$ h; day 1) to 1200 UTC ($T + 36$ h; day 2) as a function of accumulation threshold in mm. An additional experiment is shown in Fig. 12, labeled ISBA-SCREEN, represents a similar configuration to what is run operationally at ECCO for the HRDPS (Milbrandt et al. 2016), but at a 10-km grid spacing. Similar to SVS-SCREEN, only TT_{2m} and TD_{2m} are assimilated, no SMAP TB data are assimilated, and the ISBA land surface model is used in ISBA-SCREEN.

For all experiments and thresholds, the FBI exceeds 1 indicating a tendency to over forecast the occurrence of precipitation events. There is a clear signal of a significant reduction in FBI in both experiments which assimilate SMAP TBs. This reduction is for moderate to

high accumulation thresholds (≥ 5 mm). Experiment SVS-SCREEN-SMAP-NBC has the best overall FBI scores and when compared to SVS-SCREEN the FBI is reduced by roughly 4%, 8%, and 15% for accumulation thresholds of 5, 10, and 25 mm, respectively. FBI reductions are even larger when compared to ISBA-SCREEN.

c. Discussion of enhanced daytime TD_{2m} STDE

A deterioration in daytime TD_{2m} STDE scores was noted for both SMAP experiments, especially over the U.S. domain (Figs. 9b,g,h). Figure 13a shows a spatial map of the differences in local TD_{2m} STDE between SVS-SCREEN-SMAP-NBC and SVS-SCREEN at $T + 24$ h, integrated over all 31 short-range forecasts over the July–August 2015 period. Over much of the United States differences are small, but the region extending from Illinois westward into the Northern Great Plains through Iowa and eastern Nebraska is associated with a significant deterioration in TD_{2m} STDEs where local differences can exceed 2°C . In Fig. 13b the differences

FIG. 11. As in Fig. 10, but for root-zone soil moisture.

in TD_{2m} correlations between observations and forecasts is shown again at $T + 24$ h, where it is clear that this same geographical region of deteriorated TD_{2m} STDE scores is also associated with a degradation of TD_{2m} correlation scores of up to 0.3. Integrated over the United States, Fig. 13c shows the temporal evolution of these TD_{2m} correlation scores as a function of forecast range, similar in format to those shown in Figs. 6–9. Statistically significant reductions in TD_{2m} correlations are seen for both SMAP experiments, when compared to SVS-SCREEN, during the daytime hours (i.e., from $T + 21$ to $T + 27$ h and from $T + 42$ to $T + 48$ h), whereas at nighttime the differences are much smaller. This region is located in the agricultural heartland of the United States dominated by croplands (Fig. 11d) with very high fractional vegetation cover and lies within the zone where the coupling between soil moisture and precipitation is strong, a so-called “hot spot” of land–atmosphere coupling (Koster et al. 2006).

The SMAP CVS site at South Fork, Iowa, is located within this region and results from Fig. 5 indicate that SVS-SCREEN is relatively wetter in the superficial layer when compared to the much drier SMAP experiments

(Fig. 5c). The South Fork site has been a challenging site for the SMAP soil moisture retrievals algorithms (Chan et al. 2016; Colliander et al. 2017) associated with pronounced dry bias and lower overall correlations. Different reasons have been hypothesized to explain the poor performance, including the annual rotation of corn (C4) and soybeans (C3) crops which can vary considerably in terms of vegetation water content and root depth (Reichle et al. 2017).

The time series of superficial and root-zone soil moisture, averaged over the South Fork CVS site, is shown for experiments SVS-SCREEN, SVS-SCREEN-SMAP-NBC, and SVS-SCREEN-SMAP-BC along with the in situ surface soil moisture observations in Fig. 14. Also shown is the area-averaged soil moisture wilting point to provide a proxy for the available water fraction (Anderson et al. 2007). The observed surface soil moisture time series is dominated by weekly rain events followed by dry-down periods, and the dry-downs are clearly more pronounced in the two SMAP experiments (Fig. 14a). SVS-SCREEN is noticeably wetter than the two SMAP experiments, and appears to maintain a consistent level of wetness during the first and last weeks of August. Integrated soil

FIG. 12. (top) Frequency bias of 24-h accumulated precipitation over North America as a function of precipitation threshold (mm). Accumulations are from $T + 12$ to $T + 36$ h over North America. Experiment SVS-SCREEN-SMAP-NBC is shown in red, SVS-SCREEN in blue, SVS-SCREEN-SMAP-BC in green, and ISBA-SCREEN in black. For ISBA-SCREEN see text for details. (bottom) Differences in frequency bias between experiments SVS-SCREEN-SMAP-NBC and SVS-SCREEN with the 90% confidence interval (shaded), where a positive (negative) value indicates that SVS-SCREEN-SMAP-NBC (SVS-SCREEN) is better.

moisture from the surface to 100 cm are very similar among the three experiments at the beginning of July (Fig. 14b), but a persistent gradual drying signal is evident for the SMAP experiments, compared to SVS-SCREEN which maintains a near constant level of wetness. Figures 14c–e show time series of the vertically integrated soil moisture increments where for SVS-SCREEN (Fig. 14c) there is a distinct diurnal cycle to the increments with a persistent moistening or positive increment signal acting to maintain the higher soil moistures. The persistent drying or negative increments in both SMAP experiments (Figs. 14d,e) act to bring root-zone soil moisture to very dry levels in August. The dry biases in the SMAP TBs of -1.96 K (-0.58 K) before and after bias correction (Fig. 2) are small over the South Fork CVS, nonetheless biased mean innovations of 8.2 K (3.2 K) for SVS-SCREEN-SMAP-NBC (SVS-SCREEN-SMAP-BC) indicate that the SMAP TBs are persistently drier than the first-guess TBs.

d. Sensitivity to observation errors

This section examines the sensitivity of the NWP forecasts to the specification of the SMAP TB and

screen-level TT_{2m} and TD_{2m} observation error standard deviations. Muñoz-Sabater et al. (2018) noted that increasing the SMOS TB errors acted to improve the temporal dynamics of the simulated soil moisture and led to a slight improvement in near surface temperature and humidity forecast scores, while De Lannoy and Reichle (2016b) found that the soil moisture skill metrics changed little when the SMOS TB errors were varied. Two additional experiments were performed, as for SVS-SCREEN-SMAP-BC, but with the SMAP TB observation error standard deviations set to 2 K (SVS-SCREEN-SMAP-BC_2) and 8 K (SVS-SCREEN-SMAP-BC_8), respectively. The sensitivity of TT_{2m} and TD_{2m} STDE scores was small and only the results for the biases for the U.S. East and U.S. West domains are shown in Fig. 15. Over the U.S. East domain there is a tendency for TT_{2m} to be cooler (Fig. 15a) and wetter (Fig. 15b) as the SMAP TB error is increased, while for the U.S. West domain TT_{2m} are cooler and TD_{2m} are wetter as SMAP TB errors are decreased. The relative enhancement of the wet TD_{2m} bias is small ($\sim 0.2^\circ\text{C}$) but significant, especially during the daytime over the U.S. West.

Two final experiments quantify the impact of increasing the observation error standard deviations for TT_{2m} and TD_{2m} by 50% (SVS-SCREEN_1.5) and 100% (SVS-SCREEN_2), respectively. The largest impacts when increasing the errors for TT_{2m} and TD_{2m} are for the temperature bias scores shown in Figs. 16 and 17. In general, for TT_{2m} (Fig. 16), temperatures are warmer as the observation errors are increased concentrated during the daytime period, although differences are small generally less than 0.25°C . The wet TD_{2m} biases noted during the daytime period for SVS-SCREEN (Fig. 7) are reduced as the observation errors are increased (Fig. 17), and this change is seen consistently for all subregions except the Canadian Maritimes (Fig. 17c). The changes in TD_{2m} biases are small, but significant reaching up to 0.5°C over the U.S. West (Fig. 17h), indicating that the specification of the TD_{2m} errors in SVS-SCREEN were too low and the filtering system was probably suboptimal.

6. Discussion and summary

At ECCO satellite information on snow and soil moisture is not yet assimilated operationally for the land surface. This study has explored the potential of using SMAP TBs to analyze soil moisture in the SVS land surface model and has quantified the impacts upon short-range warm season NWP forecasts when compared to the use of the traditional screen-level temperature and humidity data to analyze soil moisture. The assimilation of SMAP TBs has clearly improved the simulations of

FIG. 13. (a) TD_{2m} STDE differences (°C) at observation locations at $T + 24$ h, experiment SVS-SCREEN – SVS-SCREEN-SMAP-NBC. (b) TD_{2m} correlation differences at $T + 24$ h, experiment SVS-SCREEN-SMAP-NBC – SVS-SCREEN. (c) As in Fig. 6, but for TD_{2m} correlation scores for the U.S. domain. (d) Fractional coverage of agriculture and crop vegetation type as derived from a 1-km USGS database.

surface and root-zone soil moistures in terms of correlations and STDEs when compared to the use of screen-level observations and these improvements are consistent with previous L-band data assimilation studies. Additionally, results have shown that over North America where precipitation observations are plentiful, SVS forced with CaPA (i.e., OPEN-LOOP-CaPA) leads to high soil moisture skill scores which make additional skill improvements with SMAP TB assimilation challenging.

A novel aspect of this study was the quantification of skill improvements of short-range NWP forecasts from the assimilation of SMAP TBs. Focusing upon near-surface temperature forecasts, the largest impacts of assimilating the SMAP TB data were found for dewpoint temperatures where the wet daytime bias in SVS-SCREEN over principally agricultural regions was reduced. This reduction in the wet bias led to improved frequency bias scores for precipitation, of up to 15% for

the higher accumulation thresholds. A notable deterioration in the TD_{2m} STDE scores was found for the SMAP experiments which was concentrated over the Northern Great Plains of the United States and was associated with excessively dry dewpoint temperatures. At 24-h lead times the STDEs for TD_{2m} are increased by greater than 10% in both SMAP experiments when compared to SVS-SCREEN over the United States. Further examination found excessive drying in the soil column for the SMAP experiments in this region, with experiment SVS-SCREEN benefitting from more frequent wetting increments. A reduction in the daytime TD_{2m} wet bias was found for SVS-SCREEN when the observation error standard deviation of the screen-level observations was increased.

The specification of model and observation error covariances in EnKF systems is challenging (e.g., Kumar et al. 2017). An important limitation to this study was the suboptimal nature of the filter, where examination of

FIG. 14. Time series of (a) superficial and (b) root-zone (0–100 cm) soil moisture ($\text{m}^3 \text{m}^{-3}$) averaged over the South Fork CVS site from experiment SVS-SCREEN (blue), SVS-SCREEN-SMAP-NBC (red), and SVS-SCREEN-SMAP-BC (green). Observations at 5 cm are shown in black in (a). In (a) and (b) the horizontal line represents the area-averaged soil wilting point. Also shown are the mean soil moisture increments (mm) for (c) SVS-SCREEN (0–100 cm), (d) SVS-SCREEN-SMAP-NBC (0–40 cm), and (e) SVS-SCREEN-SMAP-BC (0–40 cm).

the standard deviation of the normalized innovations demonstrated (not shown) that the actual TB errors were greater than the assumed errors over the central United States and Canadian Prairies for the SMAP experiments, while for the $\text{TD}_{2\text{m}}$ innovations, an underestimation of the actual errors was found over the U.S. Southwest. CaLDAS relies on perturbations to atmospheric forcing variables originating from a single deterministic forecast

to create the desired background covariances. Future work is focused upon coupling CaLDAS directly to the individual members of the atmospheric ensemble data assimilation systems at ECCO which would eliminate the need to introduce perturbations to the atmospheric forcing.

A commonly used approach to rescale the SMAP TB observations, a priori, based upon a linear CDF matching

FIG. 15. As in Fig. 6, but for TT_{2m} and TD_{2m} biases over (a),(c) U.S. East and (b),(d) U.S. West. The bottom panel of each plot shows the differences in the absolute bias between experiments SVS-SCREEN-SMAP-BC_2 and SVS-SCREEN-SMAP-BC_8, along with the 90% confidence interval (shaded), where a positive (negative) value indicates that SVS-SCREEN-SMAP-BC_2 (SVS-SCREEN-SMAP-BC_8) is better.

to an open loop climatology (OPEN-LOOP-CaPA) was performed in this study. The biases in soil moisture for SVS-SCREEN-SMAP-NBC and SVS-SCREEN-SMAP-BC shown in Figs. 4 and 5 are consistent with the TB biases seen in Fig. 2. The impacts on short-range NWP were mixed, with no clear positive signal associated with bias correcting, a priori, the SMAP TBs. The OPEN-LOOP-CaPA was shown to possess biases (cf. Figs. 4 and 5) and projecting the SMAP TBs onto this biased simulated state may have acted to remove some of the information in the SMAP TB signals. There are several more sophisticated methods which can be used to deal with biases in data assimilation systems (e.g., Kumar et al. 2015) and the linear CDF method chosen in this study was based upon the ease of implementation and was probably suboptimal given the inherent biases in the OPEN-LOOP-CaPA. Other methods should be

tested before any robust conclusions regarding the impact of bias correction can be made.

At ECCC the objective is to include passive L-band brightness temperature assimilation for soil moisture, as the analysis of soil moisture is clearly improved, when compared to the use of screen-level data. The outstanding issue with regards to the impacts upon NWP of using SMAP TBs relates to the enhanced TD_{2m} STDE during the daytime. The relationship between soil moisture and atmospheric fluxes in a land surface model is complicated (e.g., Mahfouf et al. 1996; Santanello et al. 2011). All of the SVS simulations performed in this study made use of the so-called Jarvis approach (Jarvis 1976) for the calculation of stomatal resistance. The Jarvis approach employs a bulk stomatal resistance to account for the various mechanisms controlling transpiration and a key parameter is the specification of a

FIG. 16. As in Fig. 6, but for the set of experiments examining the sensitivity to the specification of the observation error standard deviations for TT_{2m} and TD_{2m} . The bottom panel of each plot shows the differences in the absolute bias between experiments SVS-SCREEN_2 and SVS-SCREEN along with the 90% confidence interval (shaded), where a positive (negative) value indicates that SVS-SCREEN_2 (SVS-SCREEN) is better.

minimum stomatal resistance for a given vegetation type which can exhibit considerable temporal variability and uncertainty over croplands (Alfieri et al. 2008). Motivated by the excessive drying over the Northern Great Plains, future work is focused upon

the use of photosynthesis module for the calculation of stomatal resistance (Husain et al. 2016), the specification of the root-zone profile and its associated shape parameter (Maheu et al. 2018), and an improved specification of vegetation fractional coverage over agricultural regions.

FIG. 17. As in Fig. 7, but for the set of experiments examining the sensitivity to the specification of the observation error standard deviations for TT_{2m} and TD_{2m} . The bottom panel of each plot shows the differences in the absolute bias between experiments SVS-SCREEN_2 and SVS-SCREEN along with the 90% confidence interval (shaded), where a positive (negative) value indicates that SVS-SCREEN_2 (SVS-SCREEN) is better.

Acknowledgments. The authors thank Tracy Rowlandson and Aaron Berg from the University of Guelph for providing the SMAP CVS site data for Carman and Kenaston. Mike Cosh of the USDA is thanked for providing the U.S. SMAP CVS site data used in this study. Albert Russell and Xihong

Wang were partially funded under the Government Related Initiatives Program (GRIP) of the Canadian Space Agency. The authors would like to acknowledge the comments and suggestions of Dr. Houtekamer along with those of three anonymous reviewers.

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