Comparison of X-Band and L-Band Soil Moisture Retrievals for Land Data Assimilation

Xiaoyong Xu, Bryan A. Tolson, Jonathan Li, *Senior Member, IEEE*, and Bruce Davison

***Abstract*—This paper explores for the first time assimilation of the X-band soil moisture retrievals by the advanced microwave scanning radiometer-Earth observing system and the advanced microwave scanning radiometer 2 in Environment Canada's standalone Modélisation Environmentale Surface et Hydrologie model over the Great Lakes basin, in comparison with the assimilation of L-band soil moisture retrievals from the soil moisture and ocean salinity mission. *A priori* rescaling on satellite retrievals is performed by matching their cumulative distribution function (CDF) to the model surface soil moisture's CDF, in order to reduce the satellite-model bias in the assimilation system. The satellite retrievals, the open-loop model soil moisture (no assimilation), and the assimilation soil moisture estimates are validated against point-scale *in situ* measurements, in terms of the daily-spaced anomaly time series correlation coefficient R (soil moisture skill). Results show that assimilating X-band retrievals can improve the model soil moisture skill for both surface and root zone soil layers. The assimilation of L-band retrievals results in greater soil moisture skill improvement $\Delta R^{\text{A-M}}$ (the assimilation skill minus the skill for the open loop model) than the assimilation of X-band products does, although the sensitivity of the assimilation to the satellite retrieval capability may become progressively weaker as the open-loop skill increases. The joint assimilation of X-band and L-band retrievals does not necessarily yield the greatest skill improvement. Overall, $\Delta R^{\text{A-M}}$ exhibits a strong dependence upon the difference between the satellite retrieval skill and the open-loop surface soil moisture skill.**

***Index Terms*—Advanced microwave scanning radiometer-Earth observing system (AMSR-E), advanced microwave scanning radiometer 2 (AMSR2), data assimilation, soil moisture, soil moisture and ocean salinity (SMOS).**

I. Introduction

ASSIMILATION of satellite microwave soil moisture in land surface and hydrologic models as well as numerical weather prediction models has received considerable attention within the past decades [1]–[4]. In particular, ten years (2002–2011) of operations of the advanced microwave scanning radiometer-Earth observing system (AMSR-E) provided key data sources for advances in land data assimilation. The level-2B AMSR-E soil moisture product (X-band), based upon the NASA standard algorithm, was assimilated into the NASA catchment land surface model (CLSM) using the ensemble Kalman filter (EnKF) method [5]. The assimilation led to an overall improvement relative to either the open loop (no assimilation) model estimates or satellite retrievals alone, in terms of soil moisture anomaly time series correlation with *in situ* measurements. In [6], the extended Kalman filter method was used to assimilate the surface soil moisture derived from AMSR-E C-band brightness temperature measurements based upon the land parameter retrieval model (LPRM) algorithm into the interactions among surface, biosphere, and atmosphere land model. The introduction of AMSR-E soil moisture yielded substantial analysis increments (changes in the model estimate between before and after the implementation of the analysis equation) for both surface and root-zone soil moisture, although the assimilation estimates were not validated against real *in situ* observations. The assimilation of AMSR-E soil moisture could be as efficient as the precipitation corrections for enhancing the model soil moisture skill [7]. The study [7] assessed the contributions of two AMSR-E soil moisture products (June 2002 to July 2009), the NASA standard algorithm product archived at the National Snow and Ice Data Center (NSIDC) and the LPRM-derived AMSR-E soil moisture. The assimilation of LPRM product generally led to larger soil moisture skill improvement than the NSIDC product [7]. More recently, studies suggested that the CLSM soil moisture skill could be improved through the assimilation of either AMSR-E or the advanced scatterometer (ASCAT) soil moisture products. A joint assimilation of the two sensor products produced the best soil moisture skill [8]. Note that due to the bias (systematic error) between satellite retrievals and model soil moisture estimates, *a priori* rescaling on satellite retrievals [the cumulative distribution function (CDF) matching] was applied during the aforementioned efforts.

The AMSR-E soil moisture retrievals (derived from the X-band brightness temperatures using single-channel algorithm), without *a priori* scaling, were assimilated into the Noah land surface model [9]. Their work was motivated by the assumption that the mean value of satellite retrievals has potential contribution to improving the model mean values of soil moisture. Although the assimilation resulted in the improved soil moisture estimates (reduced bias and root-mean-square-error values

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against *in situ* measurements, especially for the mass conservation scheme), their analysis typically made systematic corrections to the model soil moisture estimation (a symptom of bias in the assimilation system).

However, X (or C) band sensors are susceptible to vegetation cover and are typically sensitive to only the land surface with low vegetation biomass. The assimilation of L-band ($\sim$ 1.4 GHz) sensor soil moisture products can offer the new opportunities for improving the model soil moisture estimation for a relatively wide range of vegetation conditions because L-band sensors have stronger penetration of vegetation and soils than those operating at X (or C) band frequencies. In recent years, significant progress has also been made for assimilation of L-band soil moisture products, which is attributed largely to the launch of European Space Agency's (ESA) soil moisture and ocean salinity (SMOS) satellite [10], [11]. By applying a vegetation-based disaggregation scheme, SMOS soil moisture was assimilated into a soil–vegetation–atmosphere-transfer model (coupled with MIKE SHE) at a fine scale [12]. In [13], SMOS soil moisture was assimilated into a land surface model over the central Tibetan Plateau at a coarse scale ($\sim$ 100 km). Some researchers investigated the impact of SMOS soil moisture assimilation upon the predictive capability of the variable infiltration capacity model [14]. In [15] and [16], four years (2010–2013) of SMOS soil moisture retrievals were assimilated into a land surface-hydrological model, Environment Canada's Modélisation Environmentale-Surface et Hydrologie (MESH), over the Great Lakes basin with the one-dimensional version of EnKF (1D-EnKF). The newly launched (January 2015) soil moisture active passive (SMAP) mission will surely trigger more research efforts in the field of L-band soil moisture assimilation over the next decade.

Since October 2011, the AMSR-E soil moisture data have been no longer available due to a technical problem with the instrument's antenna. However, as the successor of AMSR-E, the advanced microwave scanning radiometer 2 (AMSR2) onboard the first generation of the global change observation mission-water satellite, launched by the Japan Aerospace Exploration Agency (JAXA) in May 2012, has further extended the X (and C)-band passive soil moisture measurements. Meanwhile, L-band soil moisture retrievals have become increasingly available with the launch of the SMOS and SMAP missions. Although satellite soil moisture products derived from X-band (or C-band) and L-band measurements typically performed differently [17]–[19], their comparison in land/hydrologic data assimilation application has been rarely conducted.

Previous studies have demonstrated that assimilation of either synthetic satellite soil moisture [20] or SMOS soil moisture retrievals [15], [16] could improve the MESH model's soil moisture skill for both the surface and root zone layers. In the present study, we investigate how differently X-band and L-and soil moisture retrievals, via data assimilation, modulate the MESH model's soil moisture estimates. To this end, we assimilate the AMSR-E soil moisture retrievals (2003–2011), derived from NSIDC and LPRM algorithms, as well as the AMSR2 soil moisture (year 2013), derived from JAXA's lookup table algorithm, into Environment Canada's MESH model over the Great Lakes basin. The assimilation of X-band retrievals (AMSR-E/AMSR2) is compared with the assimilation of L-band retrievals (SMOS). The Great Lakes basin (rather than those areas with lower vegetation biomass, such as the Southern Great Plains) is chosen as the study area since it offers a relatively dense vegetation condition that can favor the assimilation performance comparison between the X-band and L-band soil moisture products.

Furthermore, it has been proven that a combined assimilation of X-band and C-band soil moisture retrievals could produce the best assimilation results (i.e., better than assimilation of either product) (e.g., [8]). However, it is still unclear whether a joint assimilation of X-band and L-band soil moisture products can also lead to the best soil moisture skill improvement in practice. In this study, we also perform the combined assimilation of X-band and L-band soil moisture products. These efforts could provide insight into the dependence of the assimilation upon the satellite retrieval capability. There are two primary contributions that make this study original: 1) this study presents for the first time a comparison between the assimilation of X-band soil moisture retrievals and the assimilation of L-band retrievals; and 2) this study demonstrates that the joint assimilation of passive X-band and passive L-band soil moisture products performed differently from the combined assimilation of passive X-band and active C-band products.

II. Data and Methods

A. AMSR-E Soil Moisture Retrievals

The AMSR-E measurements span from 18 June 2002 through 4 October 2011, with a resolution of 1–2 days for either ascending (01:30 P.M. LST) or descending (01:30 A.M. LST) orbits. A number of algorithms have been used to extract soil moisture from AMSR-E brightness temperatures. In this work, we assimilate two AMSR-E soil moisture products: 1) the AMSR-E/Aqua level-2B land surface product archived at the NSIDC (data version V09) [21] and 2) the LPRM algorithm-based AMSR-E level 2 soil moisture product [22] archived at the NASA Goddard Earth Sciences Data and Information Services Center. The two products have been widely used in various validation and assimilation studies [7], [23]–[25]. In the remainder of this paper, the two AMSR-E products are referred to as NSIDC and LPRM products, respectively.

The NSIDC product is delivered at a 25 km equal-area scalable Earth grid cell spacing. The soil moisture retrievals were derived from the X-band (10.7 GHz) brightness temperature measurements using the polarization ratios (PRs) approach (modified from [26] and [27]). The use of normalized PRs (brightness temperature difference between the vertical and horizontal polarizations at a given frequency normalized by their sum) can effectively remove the surface temperature dependence. PRs at 10.7 and 18.7 GHz are used to derive the vegetation/roughness parameter based upon empirical relationships. Soil moisture is then estimated based upon departures of PR at 10.7 GHz from local monthly minima, which is used as a baseline. Except for surface soil moisture and vegetation/roughness parameter, the NSIDC product also contains useful ancillary data, such as surface types and quality control flags. Utilizing the ancillary information, we exclude soil moisture retrievals that are contaminated by dense vegetation, open water, frozen surface, snow cover, radio-frequency interference, rainfall, etc.

The LPRM algorithm uses a forward radiative transfer model to retrieve surface soil moisture and vegetation optical depth through a nonlinear iterative procedure [22], [28]. The LPRM product includes soil moisture retrievals and vegetation optical depths derived from both the AMSR-E's X-band (10.7 GHz) and C-band (6.9 GHz) brightness temperature measurements and the land surface temperature that is separately derived from the vertical polarization brightness temperatures at 36.5 GHz. Here, we use only the X-band LPRM retrievals, to be consistent with the NSIDC product. The LPRM retrievals are not considered whenever the land surface is frozen.

B. AMSR2 Soil Moisture Retrievals

AMSR2 (May 2012–present), as the successor of AMSR-E, is generally the same as the AMSR-E instrument. AMSR2 acquires microwave emission from the Earth's surface and atmosphere with a temporal resolution of 1–2 days for either ascending (1:30 P.M. LST) or descending (1:30 A.M. LST) overpass. In this work, we assimilate the AMSR2 level 2 soil moisture content (SMC) product released by JAXA. The product version is Ver. 1.1 (1.110.100) [during the preparation of this paper, the Ver. 2.0 (2.220.2.00) of AMSR2 products was released]. The inversion of soil moisture is based upon a lookup table method [29]. The lookup table, which was derived from theoretical calculations using a forward radiative transfer model, describes the relation of soil water content and vegetation water content (as well as the fractional vegetation cover) with two indices, the normalized polarization difference at 10.7 GHz (i.e., brightness temperature difference between the vertical and horizontal polarizations normalized by their average) and the normalized frequency difference between 36.5 and 10.7 GHz horizontal polarizations (i.e., difference between brightness temperatures obtained at the two frequencies normalized by their average). By looking up the table, soil moisture and vegetation water content can be estimated based upon the observed polarization difference and frequency difference (as well as the observed fractional vegetation cover). Currently, only volumetric soil moisture data are stored in the AMSR2 level 2 SMC product. Only one year (2013) of AMSR2 retrievals is used in this study.

C. SMOS Soil Moisture Product

The ESA SMOS level 2 soil moisture user data product (MIR_SMUDP2) is used in this study. The MIR_SMUDP2 soil moisture retrievals are equally spaced at about 15 km (oversampled by a factor of nine) with a temporal resolution of 1–3 days for both ascending (6:00 A.M. LST) and descending (6:00 P.M. LST) orbits. The retrieved soil moisture was primarily based upon an iterative algorithm [30]. Three years (2010/2011 and 2013) of SMOS retrievals from both ascending and descending overpasses are used in this study. The processor version of the level 2 product was changed over the years with V501 (REPR data set) for 2010/2011 and V551 (OPER data set) for 2013. Utilizing the attached reference information in the product, we exclude the retrievals those are contaminated by open water, frozen surface, snow, rain, etc. The reader is referred to [16] for details.

D. Assimilation Scheme

Here, we use the 1D-EnKF with 12 ensemble members to assimilate satellite soil moisture into the MESH model. Although the two- or three-dimensional filtering can account for the spatial error correlations in meteorological forcings and/or soil moisture products, the improvement (relative to 1D-EnKF) is generally marginal for satellite soil moisture assimilation [31]. The model configurations and the1D-EnKF assimilation scheme were described in [20]. The meteorological forcing data are derived from Environment Canada's Canadian precipitation analysis and the global environmental multiscale model forecasts. Prior to the assimilation, the satellite retrievals are resampled onto the forecast model grids ($\sim$ 15 km $\times$ 15 km resolution) using a nearest neighbor approach. Whenever and wherever the model (combined with the rainfall forcing data) indicates the presence of precipitation, frozen soils, or snow cover, the corresponding satellite retrievals are removed. In a data assimilation system, to what extent the model forecast will be modified given observations is governed by the model forecast and observation error covariances. The EnKF method estimates the model forecast errors based upon an ensemble of model integrations. The ensemble spreading defines the forecast error variance. Here, the ensemble of model integrations are generated by applying random errors to the forcing data and to the model-forecasted soil moisture to account for uncertainties in forcing inputs and in model physics and/or parameters. The error parameters were specified in [20, Table II].

The observation errors are represented using another ensemble with the mean equal to zero and the variance equal to the observation error variance. Satellite soil moisture retrievals are typically subject to both instrumental errors and representativeness errors. The latter are caused primarily by the observation operator used in the retrieval algorithm and the misfit between the observation space and the model space. In reality, the errors in satellite retrievals, especially the representativeness errors, are difficult or impossible to completely estimate since they vary with time and space. An approximate estimate can be obtained by taking the climatological variance of satellite product as the observation error variance (e.g., [5], [7], [8]). In this study, error standard deviations (stdevs) (unscaled) of 0.02, 0.08, 0.05, and $0.08\ \mathrm{m}^3/\mathrm{m}^3$ are assumed for AMSR-E/NSIDC, AMSR-E/LPRM, AMSR2, and SMOS products, respectively. These quantities are derived from their respective climatological stdevs (across the study period and the study domain).

Since the satellite retrievals and model surface soil moisture exhibit different climatologies, *a priori* rescaling (bias reduction) is applied to the retrievals and the observation error stdevs. The retrievals are rescaled by matching their CDF to the model surface soil moisture's CDF [32]. The observation error stdev is also rescaled by multiplying it with the ratio between the time series stdev of the scaled retrievals (almost identical to

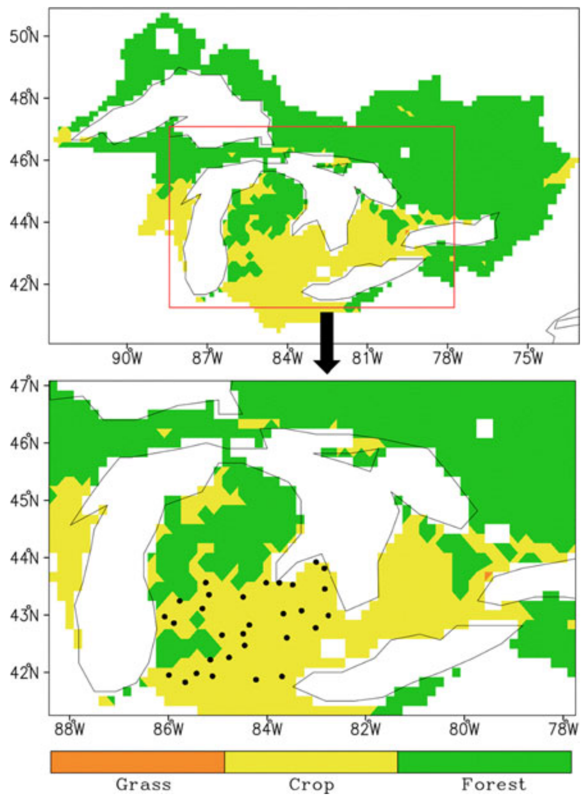

Fig. 1. Vegetation cover over the Great Lakes basin and location of *in situ* stations for soil moisture measurements (black dots). *In situ* soil moisture data are taken from the Michigan automated weather network.

the model surface soil moisture stdev) and that of the unscaled retrievals. The rescaling of the retrievals and their error stdev is conducted locally (independently for each site). Notice that since the absolute magnitude of satellite soil moisture is changed the assimilation products are meaningful only in terms of the time variability of soil moisture, which is consistent with the advantage of point-scale *in situ* soil moisture measurements (see Section II-E).

E. *In Situ Soil Moisture Observations and Skill Metric*

The study domain for this work is the Great Lakes basin (see Fig. 1). In this work, *in situ* soil moisture measurements from the Michigan Automated Weather Network (MAWN; http://www.agweather.geo.msu.edu/mawn/) are used to validate the satellite retrievals, the model, and assimilation estimates. The specification of *in situ* stations and measurements was provided in [16]. MAWN is comprised of 79 stations. Each station uses two Campbell Scientific water content reflectometers (CS615 or CS616) to measure soil moisture. The two probes are horizontally inserted to provide hourly soil moisture measurements at depths of 10 and 25 cm (at 46 stations) or are vertically installed to measure moisture in the top 60 cm of soils (0–30 and 30–60 cm) (at 33 sites). For the Great Lakes basin, the forest cover and open water pose a challenge to satellite remote sensing of soil moisture. The validation sites located in forested areas and near the lakes, relative to inland cropped sites, typically had lower satellite (SMOS) soil moisture retrieval skill and worse assimilation performance [16]. In the present study, the AMSR-E and AMSR2 soil moisture retrievals are more susceptible to forest cover (due to a shorter wavelength) and the presence of lakes (due to a coarser footprint). Therefore, most of the stations that are located in forested areas or near the lakes (within ~ 40 km of the coast) were excluded from the validation. This poses an obstacle to a performance comparison of inland sites and those near the lakes (i.e., the impact of water contamination). Eventually, only 30 *in situ* stations (black dots in Fig. 1) are withheld for this study. A basic quality control is applied to *in situ* soil moisture data at these withheld stations. *In situ* measurements are rejected

1) when the corresponding soil temperature is below 0 °C;
2) if they exceed any realistic ranges (e.g., "spikes" that cannot be explained by physical variability); or
3) if the data series contain sudden changes that are impossibly associated with physical processes.

Although point measurements are not readily converted to the spatial averages, the temporal variability of soil moisture observed by point measurement may be spatially representative [33]–[35]. The neighboring MAWN sites are typically in good agreement for the temporal pattern of soil moisture [16], indicating that point measurements used in this work could represent the areal average (satellite product scale or model grid cell) in terms of the temporal variability of soil moisture.

At each validation site, the satellite retrievals, the open-loop soil moisture, and the assimilation estimates are assessed against *in situ* measurements in terms of the anomaly time series correlation *R* (soil moisture skill). The soil moisture anomalies are defined as departures of the daily soil moisture from the monthly means (averaged over all available years). The satellite retrieval skill and the surface soil moisture skill (open-loop and assimilation) are computed using the satellite retrievals or the model top soil layer (0–10 cm) against *in situ* measurements taken at 10 cm depth or in the top 30 cm of soils (for those sites where the probes are vertically installed). The root-zone soil moisture skill (open-loop and assimilation) is derived using a depth-weighted average of soil moisture estimates in the model's top two layers (0–10 and 10–35 cm) against the arithmetic mean of *in situ* measurements at 10 and 25 cm depths or the 0–30 cm profile measurements. The satellite soil moisture skill *R* is computed only over the days with available satellite data, whereas the model and assimilation skill *R* values are obtained based upon the complete time series (except for the model snow covered or frozen soil periods).

III. Assimilation of AMSR-E Products

First, we present the assimilation of the two AMSR-E soil moisture products, NSIDC and LPRM. The assimilation period is from 1 January 2003 through 04 October 2011. This is also the sample period for the CDF matching and the rescaling of the retrievals and their error stdevs. The rescaled observation error stdevs range from 0.02 to 0.11 m^3/m^3 (across the study stations) for both of the two products. At each validation location, the soil moisture skill (anomaly *R*) is computed based upon the soil moisture anomalies over the assimilation period. The soil

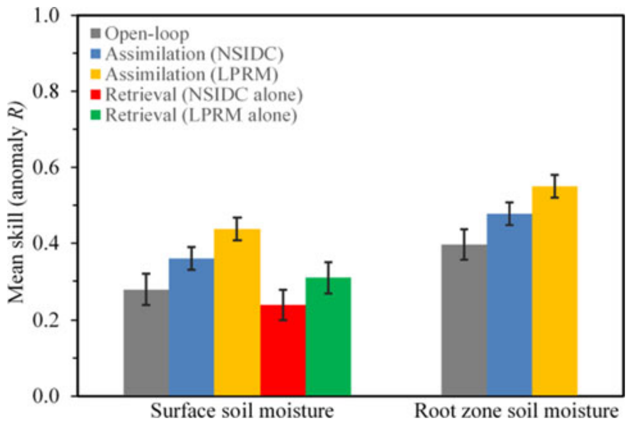

Fig. 2. Mean soil moisture skill (the average across all validation sites) for the AMSR-E retrievals (NSIDC alone and LPRM alone), the open-loop model, and the assimilation estimates (NSIDC and LPRM, respectively). Error bars indicate the 90% confidence intervals for the average values.

moisture anomalies are defined as departures of the daily soil moisture from the climatological monthly means.

A. Comparison Between NSIDC and LPRM Products

The two AMSR-E soil moisture products (NSIDC and LPRM) have been evaluated using *in situ* point or network measurements over different regions such as the United States [23], [36], Canada [24], Europe [25], [37], and Australia [38]. Each product performed differently in different studies. It is generally accepted that the LPRM product has better correlations with *in situ* data than the NSIDC retrievals. In the present work, each product also performed differently at different individual sites (not shown). The soil moisture skill (anomaly R) results averaged over the 30 validation sites are summarized in Fig. 2. The mean skill values with 90% confidence intervals are computed for the AMSR-E retrievals, the open-loop (single integration without assimilation), and the assimilation estimates. The confidence interval for the mean anomaly R is estimated using $[\bar{R} - t\frac{S}{\sqrt{N}}, \bar{R} + t\frac{S}{\sqrt{N}}]$, where $\bar{R}$ is the sample mean of all single R values (single site) for a given soil moisture product, N is the sample size, which is the summation over available validation sites, and S is the sample stdev. The value of t, which depends upon the degrees of freedom (i.e., $N - 1$) and the level of confidence, can be determined from the t table. Here, the calculation of confidence intervals for the mean R is different from [7] and [8], but our method is the conventional way to estimate the confidence interval for a population mean [39], [40]. The calculated confidence intervals likely underestimate the true confidence intervals because the spatial and/or temporal correlations in R values are neglected here.

Fig. 2 shows that the mean retrieval skill is higher for LPRM (anomaly $R = 0.31$) than for NSIDC (anomaly $R = 0.24$), which is fairly consistent with the results over other regions [23], [25], [38]. The mean anomaly R for the model open-loop is 0.28 for surface soil moisture, and is 0.40 for root zone soil moisture (see Fig. 2). After the assimilation of NSIDC product, the mean model skill is increased by about 0.08 for both surface and root zone soil moisture. After assimilating the LPRM product, the mean skill improvement ΔR^{A-M}, defined as the skill for the assimilation minus the skill for the open-loop, is about 0.15 for either surface or root zone soil moisture. As expected, the improvement in the model soil moisture skill through assimilation increases with increasing retrieval skill.

Fig. 2 shows that the mean skill for the assimilation estimates always exceeds that of the open-loop model, even when the retrieval skill (e.g., NSIDC) is lower than that of the open-loop model. Synthetic assimilation experiments suggested that if the open-loop model skill was low to modest even the retrievals of low skill could contribute to the assimilation skill [41]. The study [41] also indicated that the surface soil moisture skill from the assimilation estimates was typically above the satellite observation skill, except for the presence of a poor open-loop model skill and a high satellite skill. Similarly, Fig. 2 reveals that the mean ΔR^{A-S}, defined as the skill for the surface soil moisture assimilation product minus the retrieval (observation) skill, is about 0.12 for the assimilation of either NSIDC or LPRM product. This evidently demonstrates that the assimilation produced superior soil moisture estimates, relative to both the open-loop model and the observation product alone.

In [7], the contributions of both the NSIDC and LPRM products (June 2002 to July 2009), through the EnKF assimilation, to the CLSM model soil moisture skill were assessed using *in situ* measurements from the continental United States Soil Climate Analysis Network (SCAN). We can compare their skill levels with our results. Note that differences between the two studies are expected since the model, forcing data, and *in situ* measurements used in [7] are different from those used in our study. However, the two studies showed similar modulation of the two AMSR-E products on the model soil moisture skill. Both studies showed that the retrieval skill was higher than for LPRM than for NSIDC. Accordingly, the LPRM retrievals resulted in greater skill for the assimilation product. For the CLSM model forced with precipitation from the NASA modern era retrospective analysis for research and applications, which has the mean open-loop skill (0.43 for surface soil moisture and 0.47 for root zone), the mean skill improvement ΔR^{A-M} (for both surface and root zone) is about 0.05 for the NSIDC assimilation and about 0.11 for the LPRM assimilation [7]. In addition, after assimilating 3.5 years (January 2007 to May 2010) of LPRM retrievals in CLS, the mean skill (anomaly R) improvement was about 0.09 (the open loop skill is about 0.45) over the United States SCAN/SNOTEL network and the Murrumbidgee soil moisture monitoring network in southeast Australia [8]. The skill improvement values are smaller than those obtained in the present study (0.08 for NSIDC and 0.15 for LPRM), which may be due to the higher open-loop anomaly R in their studies [7], [8]. However, overall, these studies yield the same general conclusions, especially regarding the assimilation dependence on the satellite retrieval skill.

B. Assimilation Dependence Upon the Retrieval-Model Skill Difference

In general, the skill improvement ΔR^{A-M} (the assimilation skill minus the open-loop skill) increases with the satellite

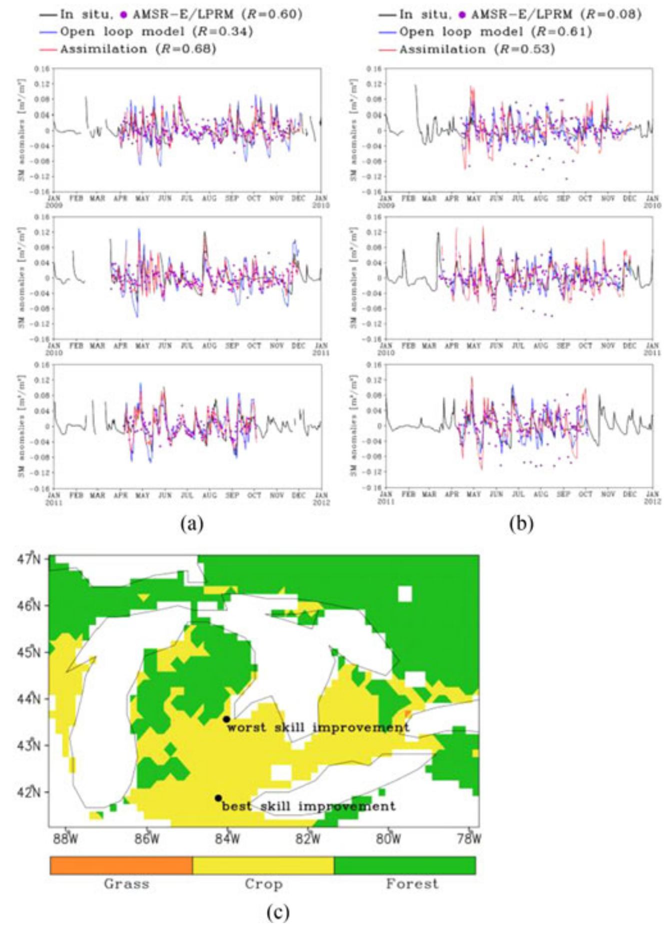

Fig. 3. Time series of surface soil moisture (SM) anomalies (over 2009–2011) corresponding to (a) the best soil moisture skill improvement ($\Delta R^{A-M} = 0.34$) and (b) the worst skill improvement ($\Delta R^{A-M} = -0.08$) for the assimilation of AMSR-E LPRM retrievals (1 January 2003 through 4 October 2011); their locations are denoted in (c). In (a) and (b) panels, the four data sets of soil moisture anomalies (*In situ* measurements, LPRM retrievals, the open-loop model, and assimilation estimates) are provided.

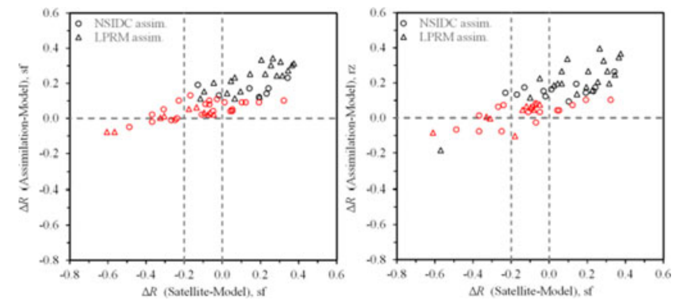

Fig. 4. Skill improvement ΔR^{A-M} (skill for the assimilation minus the open-loop skill, ordinate) for (left) surface and (right) root-zone soil moisture against ΔR^{S-M} (skill for the satellite retrievals minus skill for the open-loop surface soil moisture, abscissa), derived from the assimilation of AMSR-E/NSIDC (circles) and the assimilation of AMSR-E/LPRM (triangles). Symbols in red mean that ΔR^{A-M} are not statistically significant at the 5% level. The horizontal dashed line denotes $\Delta R^{A-M} = 0$. The two vertical dashed lines denote $\Delta R^{S-M} = -0.2$ and 0.

retrieval (observation) skill, but decreases with increased open-loop skill [40]. Therefore, due to the spatial variability of the satellite retrieval skill and/or the open-loop model skill, the assimilation performed differently at different sites. Fig. 3 presents the time series of surface soil moisture anomalies (over 2009–2011) corresponding to the highest [see Fig. 3(a)] and the lowest [see Fig. 3(b)] surface soil moisture skill improvement for the assimilation of AMSR-E LPRM retrievals. At the site with the best ΔR^{A-M} [see Fig. 3(a)], the LPRM retrieval skill is relatively high (anomaly $R = 0.60$) and the open-loop model skill is relatively low (anomaly $R = 0.34$), and thus a strong skill improvement ($\Delta R^{A-M} = 0.34$) is expected. On the contrary, if the satellite retrieval skill is relatively low and the open-loop model skill is relatively high, we usually expect weak or even negative ΔR^{A-M}, as observed for the site in Fig. 3(b). The lowest skill improvement is located in coastal areas [see Fig. 3(c)], reflecting the impact of water on satellite soil moisture observation.

To further investigate the impact of the open-loop skill and the retrieval skill on the assimilation, Fig. 4 provides the skill improvement ΔR^{A-M} against ΔR^{S-M}, defined as the retrieval skill minus the skill for the open-loop surface soil moisture, across the individual validation sites. It is obvious that the skill improvement ΔR^{A-M} approximately increases linearly with ΔR^{S-M} when assimilating either AMSR-E/NSIDC or AMSR-E/LPRM retrievals. As long as ΔR^{S-M} exceeds –0.2 (i.e., assimilating retrievals with a skill no more than 0.2 below the open-loop skill), the assimilation is typically able to increase the model skill (i.e., a positive ΔR^{A-M} is expected). If the retrieval skill is greater than or equal to the open-loop surface soil moisture skill (i.e., $\Delta R^{S-M} \geq 0$), the skill improvement ΔR^{A-M} is often statistically significant. When the skill for the retrievals is more than 0.2 below the open-loop skill (i.e., $\Delta R^{S-M} < -0.2$), the chances for positive ΔR^{A-M} become slim. The results are fairly consistent with [8]. The study showed that the assimilation of AMSR-E and ASCAT retrievals in CLSM typically generated an improved skill (in terms of anomaly *R*) for both surface and root zone soil moisture as long as the satellite observation skill is no more than about 0.2 lower than the open-loop skill. Similarly, the assimilation of SMOS soil moisture may be not helpful and even negatively affect the open-loop skill if the skill (in terms of raw *R*) for SMOS retrievals is more than about 0.3 below the open-loop skill [16].

As shown in Fig. 4, overall the surface soil moisture ΔR^{A-M}, relative to root-zone ΔR^{A-M}, exhibits a better linear relationship with ΔR^{S-M}. For a given ΔR^{S-M}, the skill improvement ΔR^{A-M} is usually more variable (along the ordinate) for root-zone soil moisture than for surface soil moisture. This may be due to the fact that during the assimilation the updating of root-zone soil moisture is subject to the accurate information exchanges between the surface soil and deeper layers, which, in turn, are controlled by factors such as model dynamics and input error parameters. Additionally, some observational noise may be eliminated during their propagation to deeper soil layers. However, notice that a linear relation between ΔR^{A-M} and ΔR^{S-M} is not expected to be perfect since the sensitivity of ΔR^{A-M} to ΔR^{S-M} is additionally affected by the magnitude of open-loop skill *R*. The synthetic experiment [41] showed that along the axis of retrieval skill the contour lines of the skill improvement ΔR^{A-M} are denser at low to modest open-loop skill (anomaly R) than at higher open-loop skill [see Fig. 2(c) and (d) therein], i.e., the skill improvement ΔR^{A-M} is more sensitive to the increase in the retrieval skill when the open-loop skill is low to modest than when the open-loop skill is high. Therefore, the same ΔR^{S-M} typically leads to larger ΔR^{A-M} for a lower open-loop skill.

IV. Comparison Between AMSR-E and SMOS

The assimilation of SMOS soil moisture retrievals (2010–2013) in the MESH model over the Great Lakes region was reported in [16]. The study revealed the impact upon the assimilation of the open-loop skill and the satellite retrieval (observation) skill. The crop-dominated grids typically experienced substantial skill improvement ΔR^{A-M} when the assimilated SMOS retrievals also came from crop surfaces, due to the presence of a high satellite observation skill and a low open-loop skill. Here, we perform the comparison between the assimilation results from SMOS and AMSR-E, which may offer further insight into the dependence of the assimilation upon the satellite retrieval skill. As a reminder, the AMSR-E products covered June 2002 to October 2011 while the SMOS retrievals are available from January 2010 to present. Additionally, the SMOS assimilation is also applicable to some forested locations [16].

Our comparison is based upon only the period (1 January 2010 to 4 October 2011) and locations (black dots in Fig. 1) for which both SMOS and AMSR-E retrievals are available. The satellite/model CDF matching and the rescaling of the retrievals and their observation error stdev, independently for each site and for each satellite product, are all based upon this period. For the same period, however, the length (number) of AMSR-E retrievals (instantaneous values) is typically greater than the length of SMOS data series since the mean revisit time is shorter for AMSR-E than for SMOS. The rescaled satellite retrievals may vary with the length of retrieval samples used in the CDF matching scheme [14], [42]. To minimize the effect of this factor on the intercomparison of the assimilation performance between AMSR-E and SMOS, the CDFs of three satellite products (AMSR-E/NSIDC, AMSR-E/LPRM, and SMOS) are (locally) estimated based upon the same sampling length by extracting the AMSR-E data only at the SMOS overpasses (a nearest sampling in time). However, note that the (temporally) complete AMSR-E retrieval series are used in the assimilation because applications would not intentionally throw away useful observational information and degrade the potential of satellite products. The rescaled observation error stdevs for SMOS and the two AMSR-E products are typically similar (locally), varying between 0.02 and 0.11 $\mathrm{m}^3/\mathrm{m}^3$ across the validate sites.

Fig. 5 shows the mean soil moisture skill (averaged across the validation sites) corresponding to the assimilation of AMSR-E and SMOS retrievals over 1 January 2010 to 4 October 2011. The results further reveal the impact of the satellite retrieval skill upon the assimilation estimates for both surface and root zone soil moisture. For the retrieval skill, SMOS soil moisture (anomaly $R = 0.43$) is significantly higher than the NSIDC product (anomaly $R = 0.21$) and the LPRM product (anomaly $R = 0.27$). The mean open-loop skill is 0.26 for surface soil moisture. After assimilating the three products separately, the mean skill values for surface soil moisture are increased to 0.49 (SMOS), 0.34 (NSIDC), and 0.43 (LPRM). For the root zone soil moisture, the NSIDC, LPRM, and SMOS products lead to gains of 0.12, 0.19, and 0.24 in the mean model skill, respectively.

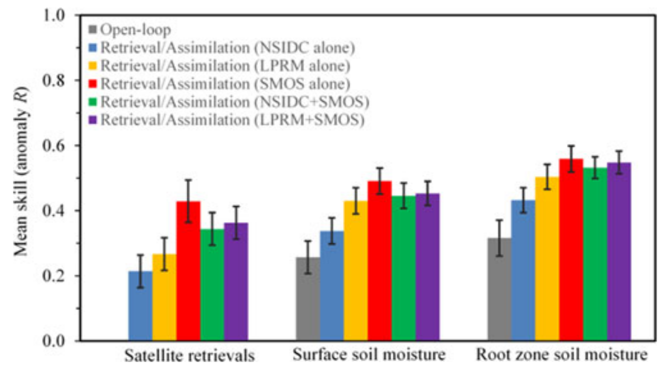

Fig. 5. Soil moisture skill (anomaly R over 1 January 2010 to 4 October 2011) averaged across all validation sites for the satellite retrievals, the open-loop model, and the assimilation estimates. The satellite retrievals and the corresponding assimilation estimates are derived from the AMSR-E/NSIDC product alone, AMSR-E/LPRM product alone, SMOS product alone, combination of NSIDC and SMOS, and combination of LPRM and SMOS. Error bars indicate the 90% confidence intervals for the average values.

Furthermore, since the two sensor systems have different overpasses, we also perform the combined assimilation of instantaneous soil moisture retrievals from the two instruments. The NSIDC and LPRM retrievals are assimilated jointly with the SMOS data into the model (i.e., AMSR-E/NSIDC + SMOS and AMSR-E/LPRM + SMOS in Fig. 5). For the joint assimilation, the AMSR-E and SMOS retrievals are used to update the model simulations at their respective observation times (1:30 A.M./P.M. for AMSR-E and 6:00 A.M./P.M. for SMOS). Their respective observation error stdevs (rescaled) are utilized in the joint assimilation experiments. The skill for the combined AMSR-E and SMOS retrieval series (anomaly $R = 0.34$ for NSIDC + SMOS; anomaly $R = 0.36$ for LPRM+SMOS) is significantly higher than the AMSR-E product alone (anomaly $R = 0.21$ for NSIDC and anomaly $R = 0.27$ for LPRM), but is lower than the SMOS product alone (anomaly $R = 0.43$) (see Fig. 5). Consequently, the assimilation skill (for either surface or root zone soil moisture) from the joint assimilation of AMSR-E and SMOS is higher than that from the assimilation of AMSR-E alone (especially for the NSIDC + SMOS assimilation), but is not superior to that from the SMOS alone assimilation. The joint assimilation of AMSR-E and ASCAT soil moisture could produce slightly better skill improvement (not statistically significant) than assimilating either of them [8]. This happened probably because AMSR-E and ASCAT soil moisture retrievals were derived from X/C-band measurements and exhibited similar observation skills. However, our results indicate that the combined assimilation of passive X-band (AMSR-E) and passive L-band (SMOS) products, relative to the L-band retrieval alone assimilation, does not necessarily yield the greater skill improvement. Note that we did not account for the possible presence of error cross correlation between SMOS and AMSR-E products during the rescaling of satellite products.

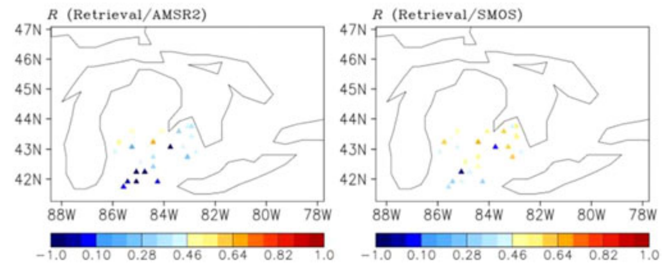

Fig. 6. Site-based soil moisture skill (anomaly *R*) for (left) the AMSR2 retrievals and (right) the SMOS retrievals.

This may limit the performance of their joint assimilation [43]. Nevertheless, the impact of cross-correlated observation errors is expected to be marginal in this work since SMOS and AMSR-E products are assimilated at different overpass times.

V. AMSR2 Versus SMOS

As a complementary work to the AMSR-E versus SMOS comparison, this section compares the contributions of AMSR2 and SMOS retrievals, through data assimilation, to the MESH model soil moisture estimates. The assimilation period is from 1 January 2013 to 31 December 2013. We match the satellite retrievals (either AMSR2 or SMOS) and model CDFs based upon one year (year 2013) of soil moisture data. The AMSR2 retrieval CDF is estimated using only the AMSR2 data extracted at the SMOS overpasses (a nearest sampling in time). However, the (temporally) complete AMSR2 retrieval series are still used in the assimilation. The rescaled observation error stdevs for AMSR2 and SMOS products are typically close (locally), ranging from 0.02 to 0.11 m^3/m^3 across the validation sites. Based upon the data availability, the soil moisture skill (anomaly *R*) values are computed for 23 out of 30 validation sites shown in Fig. 1. The soil moisture anomalies are obtained by deducting monthly means from the daily time series.

A. Soil Moisture Skill for Individual Sites

Fig. 6 shows the AMSR2 and SMOS retrieval skill from the 23 individual validation sites. The retrieval skill for SMOS soil moisture typically exceeds or at least matches that of the AMSR2 product. This is consistent with the dependence of satellite soil moisture retrieval capabilities upon the microwave frequency. The L-band measurements (SMOS) are more sensitive to changes in soil water content than the X-band measurements (AMSR2). Although the two instruments are not in agreement in terms of the magnitude of the retrieval skill, the (spatial) correlation between the two sets of retrieval skill is very high. Note that the retrieval skill is calculated using only the days with available retrievals. Since the AMSR2 and SMOS systems have different observing frequencies, the two sets of satellite retrieval skill are obtained based upon different data sequence lengths. We also computed the AMSR2 retrieval skill using the SMOS sequence length (by temporally resampling AMSR2 data to the SMOS observation times) and found negligible changes in the AMSR2 retrieval skill.

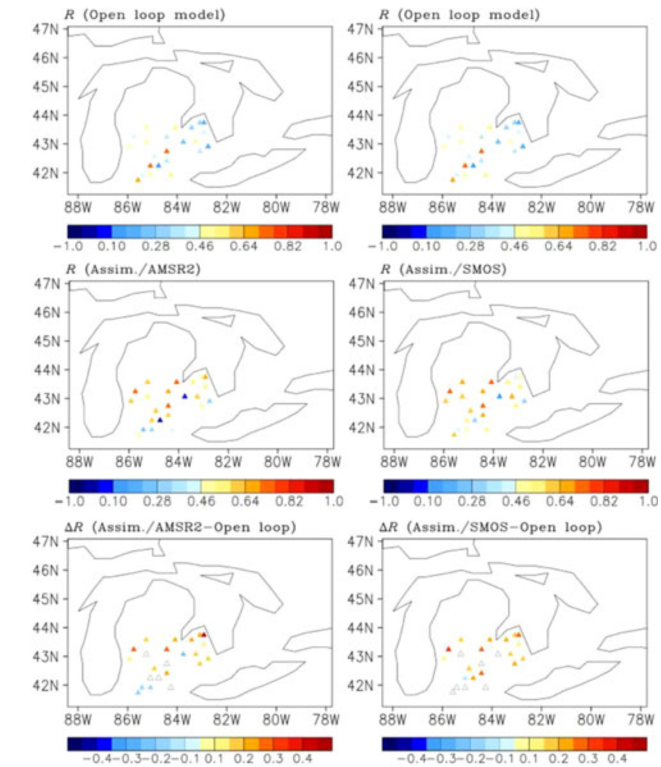

Fig. 7. Site-based surface soil moisture skill (anomaly *R*) for (top) the open loop model, (middle) the assimilation, and (bottom) the skill improvement ΔR^{A-M}: (left) AMSR2 and (right) SMOS. ΔR^{A-M} is denoted by an open symbol if the open-loop skill and the assimilation skill are not significantly (5% level) different from each other.

Fig. 7 shows the AMSR2 versus SMOS comparison, in terms of the surface soil moisture skill for the assimilation estimates and the skill improvement ΔR^{A-M}. The counterpart of Fig. 7 for root-zone soil moisture is provided in Fig. 8. Overall, the assimilation of either AMSR2 or SMOS improved the model soil moisture skill for both the surface and root zone layers. Due to the spatial variability of the satellite retrieval skill and/or the open-loop model skill, the assimilation performance also varies across the validation sites. In contrast with their evident difference in retrieval skill (see Fig. 6), the assimilation soil moisture product skill (and thus the skill improvement ΔR^{A-M}) obtained with the two sets of retrievals is in good agreement for 17 out of 23 validation sites (see Figs. 7 and 8).

However, the assimilation product skill does not always exceed the open loop model skill. Negative ΔR^{A-M} sometimes occurred, especially for the AMSR2 assimilation. In the present work, the model input error parameters are not online (adaptively) tuned. Synthetic experiments have revealed that the assimilation soil moisture estimates are generally not sensitive to the specified input error parameters [20]. However, when a severe underestimation of observation error occurs, the assimilation estimates may be even worse than the open-loop model. This could be the reason for the occurrence of negative ΔR^{A-M} in Figs. 7 and 8. For the retrievals of very low or even negative skill, which generally reflect poor satellite observations, their real errors could be severely underestimated by the input error parameters, thus causing negative ΔR^{A-M}.

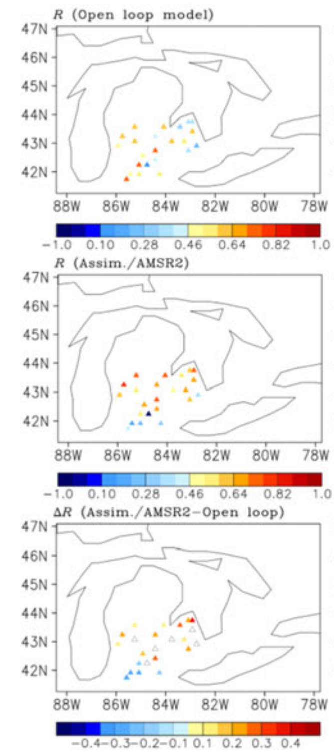

Fig. 8. Similar to Fig. 7, but for root zone soil moisture.

Negative ΔR^{A-M} is severer in root zone (see Fig. 8) than for the surface layer (see Fig. 7). This is because the poorly specified observation error variances have a stronger impact on the assimilation estimates of root zone soil moisture than on surface soil moisture estimates [44]. We also investigated the variance of the normalized innovations, which is defined as the innovations (satellite observation minus model background residuals) divided by the square root of the sum of the model forecast error covariance in observation space and the measurement error covariance [5]. The variance of the normalized innovations is typically much larger than 1 in the presence of negative ΔR^{A-M}. This means that the corresponding assimilation may not operate optimally and the assimilation estimates may be significantly affected by the nonlinearities in the system. To avoid this problem, online quality control routines and online adjusting of input errors parameters [44] need to be added to the assimilation system, which is outside the scope of this paper.

B. Mean Soil Moisture Skill

The averaged soil moisture skill values are presented in Fig. 9. As expected, the mean retrieval skill for SMOS soil moisture (anomaly $R = 0.45$) is significantly higher than that of AMSR2 product (anomaly $R = 0.27$). The mean open-loop skill is 0.42 for surface soil moisture and 0.50 for root zone soil moisture. After assimilating the AMSR2 and SMOS products, separately, the mean skill values are increased to 0.51 (AMSR2) and 0.54 (SMOS) for surface soil moisture, and to 0.55 (AMSR2) and 0.59 (SMOS) for root zone soil moisture. On average, the assimilation skill (and thus the skill improvement ΔR^{A-M}) is only marginally sensitive to the increase in the retrieval skill. This could be attributed to a relatively high open-loop skill because the same increase in the retrieval skill typically leads to a weaker improvement in the assimilation skill for a high open-loop skill than for a lower open-loop skill [41].

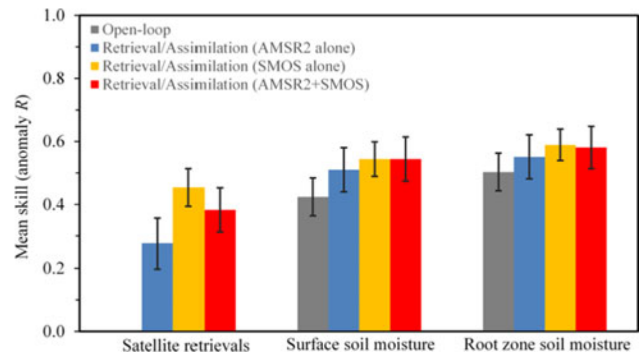

Fig. 9. Mean soil moisture skill (anomaly R). The satellite retrievals and the corresponding assimilation estimates are derived from the AMSR2 product alone, the SMOS product alone, and the combination of AMSR2 and SMOS. Error bars indicate the 90% confidence intervals for the average values.

We also perform the combined assimilation of instantaneous soil moisture retrievals from AMSR2 and SMOS. For the joint assimilation, the two set of retrievals are added into the model simulations at their respective observation times (1:30 A.M./P.M. for AMSR2 and 6:00 A.M./P.M. for SMOS). Their respective observation error stdevs (rescaled) are still utilized. The mean retrieval skill for the combined AMSR2 and SMOS is 0.38, which is between the AMSR2 product skill and the SMOS product skill (see Fig. 9). The joint assimilation of AMSR2 and SMOS increases the mean model skill from 0.42 to 0.54 for surface soil moisture and from 0.50 to 0.58 for root zone soil moisture. On average, the combined assimilation of two sensor products, relative to the SMOS alone assimilation, does not further improve the model soil moisture skill.

VI. Conclusion

The assimilation of satellite soil moisture has been an active research area. In this study, the 1D-EnKF is used to assimilate the two AMSR-E retrieval products, NSIDC and LPRM, as well as the AMSR2 retrievals into the MESH model, in comparison with the assimilation of SMOS soil moisture. The following conclusions can be drawn from this work:

1) Overall, the assimilation of X-band retrievals (AMSR-E/AMSR2) leads to superior soil moisture skill, relative to either the open-loop model skill or the retrieval skill. The AMSR-E/LPRM assimilation typically yields larger skill improvement ΔR^{A-M} for both surface and root-zone soil moisture than the AMSR-E/NSIDC assimilation does.
2) The assimilation of L-band retrievals (SMOS) typically resulted in greater ΔR^{A-M} than the assimilation of X-band products (AMSR-E/AMSR2), although the sensitivity of the assimilation to the satellite retrieval capability may become progressively weaker as the open-loop skill increases. Note that the vegetation conditions could also impact the assimilation performance comparison between the X-band and L-band soil moisture products. In this

work, the Great Lakes basin (the study domain) has a relatively dense vegetation condition (as compared to those areas with lower vegetation biomass, such as the Southern Great Plains) and may favor the advantage of L-band soil moisture product.

3) Unlike the dual assimilation of passive X-band and active C-band soil moisture products, the joint assimilation of passive L-band and passive X-band soil moisture retrievals does not necessarily yield the best skill improvement.
4) The skill improvement ΔR^{A-M}, as is well-known, typically increases with the retrieval skill and decreases with increased open-loop skill, showing a strong dependence upon ΔR^{S-M}.

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