Assimilation of F-16 Special Sensor Microwave Imager/Sounder Data in the NCEP Global Forecast System

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(Manuscript received 26 May 2011, in final form 23 September 2011)

ABSTRACT

The Special Sensor Microwave Imager/Sounder (SSMIS) on board the Defense Meteorological Satellite Program (DMSP) F-16 satellite is the first conically scanning sounding instrument that provides information on atmospheric temperature and water vapor profiles. The SSMIS data were preprocessed by the Naval Research Laboratory (NRL) using its Unified Preprocessor Package (UPP) and then distributed to the numerical weather prediction centers by the Fleet Numerical Meteorology and Oceanography Center (FNMOC). This dataset was assimilated into the Global Forecast System (GFS) using gridpoint statistical interpolation (GSI). The initial assimilation of the SSMIS data into the GFS did not improve the medium-range (5–7 days) forecast skill. The SSMIS bias (O-B) still changes with location and time after the GSI bias-correction scheme is implemented. This bias characteristic is related to residual calibration errors in the correction of the SSMIS antenna emission and warm target contamination. The large O-B standard deviation is probably due to the large instrument noise in the SSMIS UPP data. The large O-B and its standard deviation for several surface sensitive channels are also caused by uncertainty in surface emissivity. In this study, a new scheme is developed to remove regionally dependent bias using a weekly composite O-B. The SSMIS noise is reduced through a Gaussian function filter. A new emissivity database for snow and sea ice is developed for the SSMIS surface sensitive channels. After applying these algorithms, the quality of the SSMIS low-atmospheric sounding (LAS) data is improved; the surface-sensitive channels can be effectively assimilated, and the impacts of SSMIS LAS data on the medium-range forecast in the GFS are positive and similar to those from Advanced Microwave Sounding Unit-A (AMSU-A) data.

1. Introduction

The Special Sensor Microwave Imager/Sounder (SSMIS), which measures the thermally emitted radiation from the earth at 24 channels from 19 to 183 GHz (see Table 1), is the first conically scanning microwave sensor to provide temperature and water vapor sounding information. Today, there are three SSMIS instruments flown aboard the Defense Meteorological Satellite Program (DMSP) F-16, F-17, and F-18 platforms. In the next decade, there will be two more SSMIS instruments flown on the F-19 and F-20 satellites, which will be launched in 2013 and 2015, respectively. The low-atmospheric temperature sounding (LAS) channels in SSMIS are similar to those of the cross-track scanning Advanced Microwave Sounding Unit-A (AMSU-A) instrument on board the National Oceanic and Atmospheric Administration (NOAA) and Meteorological Operations (MetOp) satellites. It is thus expected that the SSMIS LAS data would have positive impacts on forecast skills similar to those of the AMSU-A data. At NWP centers [e.g., the Met Office, European Centre for Medium-Range Weather Forecasts (ECMWF), and Naval Research Laboratory (NRL)], a series of assimilation experiments were made on F-16 SSMIS LAS data with a neutral-to-small positive impact on the medium-range forecast being found in the Southern Hemisphere and the neutral impacts in the Northern Hemisphere (Bell et al. 2008). At the National Centers for Environmental Prediction (NCEP), the Global Forecast System (GFS), an assimilation experiment was conducted on F-16 SSMIS LAS data in early 2007 and a
neutral impact was also found on the global medium-range forecast (Kazumori 2007). Recently, F-18 SSMIS data were assimilated into the U.S. Navy 4D Variational Analysis System with a significant positive impact on NRL global forecast (Swadley et al. 2010). This positive impact is primarily due to several factors: 1) improved calibration of the LAS data from the F-18, 2) use of the data at several upper-atmospheric sounding (UAS) channels (i.e., channels 19–24 in Table 1), and 3) the 4D variational system. This effort more accurately represents the best accumulated impacts of SSMIS data from both LAS and UAS channels thus far. The NCEP GSI is a 3D variational analysis system (Parrish and Derber 1992; Derber and Wu 1998) and its upper level is not high enough to assimilate the SSMIS data at all the UAS channels.

Today, the independent impact of SSMIS LAS data in GFS and other NWP models has not been clearly demonstrated due to some other issues such as a lack of a bias-correction scheme and a preprocessor for SSMIS data. In addition to a regionally dependent bias, the noise of the F-16 SSMIS UPP data is also significant and can be as high as 0.5 K. Prior to 14 August 2008, a noise reduction algorithm (Bell et al. 2008) was developed and applied to F-16 data but it was soon removed from the UPP process. The noise reduction process was not further applied to F-17 and F-18 SSMIS radiance data and there remains a similar level of noise in all three SSMIS instruments. A proper bias correction and noise reduction must be applied to SSMIS radiance data from F-16 to F-18 satellites prior to the data assimilation process.

| Table 1. Channel characteristics of the F-16 SSMIS sensor (Poe et al. 2001). |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Channel | Center frequency (GHz) | 3-db width (MHz) | Frequency stability (MHz) | Polarization | NEDT (K) | Sampling interval (km) |
| 1 | 50.3 | 380 | 10 | V | 0.34 | 37.5 |
| 2 | 52.8 | 389 | 10 | V | 0.32 | 37.5 |
| 3 | 53.596 | 380 | 10 | V | 0.33 | 37.5 |
| 4 | 54.4 | 383 | 10 | V | 0.33 | 37.5 |
| 5 | 55.5 | 391 | 10 | V | 0.34 | 37.5 |
| 6 | 57.29 | 330 | 10 | RCP | 0.41 | 37.5 |
| 7 | 59.4 | 239 | 10 | RCP | 0.40 | 37.5 |
| 8 | 150 | 164 | 200 | H | 0.89 | 12.5 |
| 9 | 183.31±6.6 | 1526 | 200 | H | 0.97 | 12.5 |
| 10 | 183.31±3 | 1019 | 200 | H | 0.67 | 12.5 |
| 11 | 183.31±1 | 513 | 200 | H | 0.81 | 12.5 |
| 12 | 19.35 | 355 | 75 | H | 0.33 | 25 |
| 13 | 19.35 | 357 | 75 | V | 0.31 | 25 |
| 14 | 22.235 | 401 | 75 | V | 0.43 | 25 |
| 15 | 37 | 1616 | 75 | H | 0.25 | 25 |
| 16 | 37 | 1545 | 75 | H | 0.20 | 25 |
| 17 | 91.655 | 1418 | 100 | V | 0.33 | 12.5 |
| 18 | 91.655 | 1411 | 100 | H | 0.32 | 12.5 |
| 19 | 63.283 248±0.285 271 | 1.35 | 0.08 | RCP | 2.7 | 75 |
| 20 | 60.792 668±0.357 892 | 1.35 | 0.08 | RCP | 2.7 | 75 |
| 21 | 60.792 668±0.357 892±0.002 | 1.35 | 0.08 | RCP | 1.9 | 75 |
| 22 | 60.792 668±0.357 892±0.0055 | 0.12 | 0.12 | RCP | 1.3 | 75 |
| 23 | 60.792 668±0.357 892±0.016 | 0.34 | 0.34 | RCP | 0.8 | 75 |
| 24 | 60.792 668±0.357 892±0.050 | 0.84 | 0.84 | RCP | 0.9 | 37.5 |

* NEDT for instrument temperature 0°C and calibration target 260 K with integration times of 8.4 ms for channels 12–16, 12.6 ms for channels 1–7 and 24, 25.2 ms for channels 19–23, and 4.2 ms for channels 8–11 and 17–18.

* RCP denotes right-hand circular polarization.
In satellite data assimilation, microwave emissivity models are important for the assimilation of surface-sensitive channels. With the microwave emissivity models used in forward calculations, more microwave satellite data are being assimilated into global medium-range forecast systems (Wiesmann and Mätzler 1999; Weng et al. 2001; Andreadis et al. 2008; Wójcik et al. 2008). For instance, the Microwave Land Emissivity Model (MELM) developed by Weng et al. (2001) has been used with the NCEP GFS through the Joint Center for Satellite Data Assimilation (JCSDA) Community Radiative Transfer Model (CRTM; Weng et al. 2005a; Han et al. 2006, 2009). The introduction of the MLEM into the NCEP assimilation system has significantly increased the utility of satellite microwave data over most land conditions (Yan and Weng 2011). However, the MLEM model displays a large uncertainty (about 0.05) over snowy surfaces. Due to the lack of a reliable sea ice emissivity physical model, a constant of 0.9 was typically used over sea ice for SSMIS applications in GFS. The actual sea ice emissivity could depart significantly from this default value (Hewison and English 1999). An uncertainty of 0.05 may cause an SSMIS bias (O-B) ranging within several degrees Kelvin for surface-sensitive channels depending on frequency (Yan and Weng 2011). Such a difference can lead to the rejection of many useful measurements in the data assimilation processes. Improved snow and sea ice emissivity models are required in the radiance calculations.

To further improve the assimilation impacts of the SSMIS data, new algorithms are developed for the correction of regionally dependent bias, radiance noise reduction, and snow and sea ice emissivity calculations for assimilation of F-16 UPP LAS data. The quality control scheme in GFS is also revised for SSMIS data assimilation. A series of numerical experiments using the GFS is carried out to test the performance of these new algorithms for assimilating F-16 UPP LAS data at the LAS channels. Specifically, the use of SSMIS LAS data at several surface-sensitive channels and the impact of the LAS data on global medium-range forecasts are assessed.

2. Satellite data assimilation procedure

a. Variational approach

Given a set of observations from satellites, radiosondes, and ground-based measurements, a 3D or 4D variational system can produce a “best” analysis of the atmospheric state at desired resolutions in a statistically “optimal” way by assimilating them into an NWP model. Under the assumptions that the observation errors are nonbiased and follow Gaussian distributions, the best analysis \( \mathbf{X} \) (state of the atmosphere) can be obtained by minimizing a cost function of \( J(\mathbf{X}) \) (Parrish and Derber 1992; Ide et al. 1997; Derber and Wu 1998):

\[
J(\mathbf{X}) = (\mathbf{X} - \mathbf{X}_0)^T \mathbf{B}^{-1} (\mathbf{X} - \mathbf{X}_0) + [H(\mathbf{X}) - \mathbf{Y}_0]^T (\mathbf{E} + \mathbf{F})^{-1} [H(\mathbf{X}) - \mathbf{Y}_0] + J_c,
\]

where \( \mathbf{X}_0 \) is the background, \( \mathbf{B} \) is the background error covariance matrix, \( H \) the forward model (e.g., radiative transfer model for satellite radiance), \( \mathbf{Y}_0 \) the observations, \( \mathbf{E} \) the instrument error covariance matrix, \( \mathbf{F} \) the representativeness error covariance matrix, and \( J_c \) the constraint term. An important computation involves simulating satellite-measured brightness temperatures [i.e., \( H(\mathbf{X}) \)] at various channels with surface emissivity information through the radiative transfer model (RTM). The differences between the simulated and observed brightness temperatures [i.e., \( H(\mathbf{X}) - \mathbf{Y}_0 \)] contribute to the solution of the analysis \( \mathbf{X} \) through Eq. (1). Note that the differences are also affected by the uncertainties in the satellite-observed and RTM-simulated brightness temperatures. For brightness temperatures at window and surface-sensitive channels that are characterized by surface properties, the errors in simulated brightness temperatures are significantly affected by errors in surface emissivity. Thus, any uncertainty in satellite radiance data and surface emissivity can further degrade the quality of the analysis variables, \( \mathbf{X} \).

b. SSMIS bias characteristics in GFS

A powerful approach for monitoring the quality of satellite brightness temperatures is to compare observed radiances with simulations [see the item \( [H(\mathbf{X}) - \mathbf{Y}_0] \) in Eq. (1) above]. Ideally, this difference is determined by the RTM simulation error (e.g., model uncertainty and atmospheric information uncertainty) and satellite observation error (e.g., random noise and calibration anomaly in the data). At microwave frequencies, brightness temperatures at 54–59 GHz under clear atmospheres can be well simulated since the main gaseous absorption is caused by atmospheric oxygen whose concentration is very stable. For example, an error of 1 K in the physical temperature can result in an error of 0.1 K in the simulated brightness temperature (Poe et al. 2001). In this study, the Community Radiative Transfer Model (CRTM; Weng et al. 2005a) is used to simulate the brightness temperatures at SSMIS channels. The parameters input into CRTM include the temperature and water vapor profiles, which are obtained from the NCEP Global Data Assimilation System (GDAS) analysis. The root-mean-square error of the GDAS temperature profiles against radiosonde measurements below
10 mb is smaller than 2 K, which results in an uncertainty of about 0.2 K in simulations from 54 to 59 GHz. Note that the errors in simulated brightness temperatures are less affected by the errors in the GDAS water vapor profile. Also, the effects of cloud and rain are not taken into account in these simulations since cloud-contaminated data are not used because of a lack of information in the GDAS data. Thus, any bias beyond an uncertainty of 0.2 K at these four channels can be attributed to the other error sources such as instrument calibration.

Figures 1a and 1b display distributions of brightness temperature differences ($\Delta T_B$) on 5 August 2008 for F-16 UPP at 54.4 and 55.5 GHz, respectively. For a comparison, the biases at these two frequencies in the data from the AMSU-A onboard the Meteorological Operational Satellite Programme (MetOp) satellite are also shown in Figs. 1c and 1d, respectively. We can see that the biases from the SSMIS UPP data are dependent on region (e.g., latitude and satellite orbit node). The biases are persistently observed on different days. Note that the results in the figures are generated after applying the original GFS bias-correction (BC) algorithm (Derber and Wu 1998). This implies that the above regional biases in F-16 SSMIS data cannot be removed by the GFS BC algorithm. An additional BC algorithm must be developed.

c. F-16 UPP data noise characteristics

The SSMIS instrument oversamples the upwelling radiance in its along-track direction (Bell et al. 2008). All SSMIS channels are sampled every scan and a sampling period of 4.22 ms is used for each field of view (FOV). This integration in time has reduced the data noise significantly but it is not long enough for data applications in NWP models. To reduce the noise, an averaging algorithm consisting of a 2D Gaussian weighting approach was developed by Bell et al. (2008) and applied to the F-16 UPP data. The $\Delta T_B$ uncertainty (the standard deviation of $\Delta T_B$) of the SSMIS LAS data in Figs. 1a and 1b is only about 0.2 K. This uncertainty is determined by the standard deviations due to random noise in the radiance data, short-range forecast errors, RTM uncertainty, and the remaining calibration anomaly in the radiance. At the 54.4-, 55.5-, 57.3-, and 59.4-GHz channels, the error in
the short-range forecasts can result in an uncertainty of up to 0.2 K in radiance simulations (see section 2b above). This makes it difficult to quantify the magnitude of the random noise in the accumulated $\Delta T_B$ uncertainty of 0.2 K. It is believed that the random noise of the UPP LAS data on 5 August 2008 may be lower than 0.2 K. The noise reduction processing in the UPP was stopped after 14 August 2008. Figures 2a and 2b show the distributions of $\Delta T_B$ for F-16 UPP data on 28 August 2008 for 54.4 and 55.5 GHz, respectively. There is no noise reduction applied to this dataset. Compared with the results in Figs. 1a and 1b, the $\Delta T_B$ uncertainty of the data after 14 August 2008 increases due to a lack of noise reduction processing. For example, the standard deviations of brightness temperatures at these channels are approximately 0.4 K. Also, the values of the standard deviations at 57.3 and 59.4 GHz are more than 0.5 K (figures not shown). Table 2 lists the standard deviations of the UPP data for $\Delta T_B$ at the seven LAS channels, which are computed using the data from 16 August through 31 December 2009. The results marked NR in Table 2 indicate there was a noise reduction, which will be discussed in section 3b. The statistical results in Table 2 are similar to those we derived from the data on 28 August 2008. The errors at the 54.4- and 55.5-GHz channels are the smallest compared to those at other LAS channels. The larger errors, at 50.3 and 52.8 GHz compared to those from 53.6 to 57.3 GHz, are due primarily to the uncertainty in the surface emissivity. The errors at 57.3 and 59.4 GHz are similar to or larger than those at 52.8 and 53.6 GHz, which is primarily caused by their larger calibration (residual) anomalies (Yan and Weng 2009). Normally, it is expected that radiances with a noise magnitude on an order of 0.3 K or better can improve the analysis fields and produce better forecasts (Bell et al. 2008, 2010), which may be observed in the MetOp-A and NOAA-18 AMSU-A tropospheric temperature sounding channels (see Figs. 1c and 1d). Therefore, the uncertainty in the UPP LAS data needs to be reduced to an acceptable level through a proper noise reduction processing.

d. Microwave land and sea ice emissivity models

The Microwave Land Emissivity Model (MLEM) was developed using a two-stream approximation that characterizes the emission and scattering processes of various land surfaces such as snow cover, desert, and vegetation (Weng et al. 2001). Currently, this model has demonstrated some significant impacts on the assimilation of various satellite microwave data in GFS, especially over nonscattering surfaces. For a constant emissivity value, about 20% of satellite microwave data at window and surface-sensitive channels over land are used. With the

<table>
<thead>
<tr>
<th>Frequency (GHz)</th>
<th>Std dev of $\Delta T_B$ (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>50.8</td>
<td>1.40</td>
</tr>
<tr>
<td>52.8</td>
<td>0.63</td>
</tr>
<tr>
<td>53.6</td>
<td>0.58</td>
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<tr>
<td>54.4</td>
<td>0.38</td>
</tr>
<tr>
<td>55.5</td>
<td>0.40</td>
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<tr>
<td>57.3</td>
<td>0.55</td>
</tr>
<tr>
<td>59.4</td>
<td>0.60</td>
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</tbody>
</table>

Table 2. Standard deviations of the brightness temperature differences ($\Delta T_B$) from channels 1 to 7 between backgrounds from the CRTM and satellite observations without and with NR processing. The results for channels above 52.8 GHz are computed using the data over global areas; the results at 52.8 GHz are computed using the data under free rainy-clouds (see section 4a) and over global areas above 700 mb; the results at 50.3 GHz are computed using the data under rain-free conditions and over oceans.

Fig. 2. F-16 UPP brightness temperature difference maps on 28 Aug 2008 at (a) 54.4 and (b) 55.5 GHz, where no noise reduction algorithm is applied. As in Fig. 1, std. represents the standard deviation of the brightness temperature differences.
land emissivity model, 30% more satellite data can be assimilated. However, the current MLEM has a large bias over snow conditions. Our analysis shows that the MLEM emissivity simulations at the LAS channels over snow have a mean error of 0.04 (figure not shown), which could cause an uncertainty of a few degrees Kelvin in the simulated brightness temperatures. Over sea ice conditions, the emissivity model has not been developed for the assimilation of microwave data. In the past, a constant (0.9) was used for sea ice emissivity for all microwave data in GFS. In this study, snow and sea ice emissivity models are further developed. To measure the impacts of the surface emissivity model on our data assimilation system, we use a ratio of the data passing a series of quality controls to the total volume of data ingested into the assimilation system, which is called the utilization rate.

3. Improvements in SSMIS data quality and new developments

a. Bias-correction algorithm

For the current UPP data, the biases are persistently high at some regions and do not change on a weekly base. Thus, we generated the weekly composite O-B biases in terms of the nodes and latitudes (θ) of the satellite observations, ∆TB\textsuperscript{Cal}(θ, node). At a given time and location, the brightness temperature will be corrected through

\[
T_B^\text{Cal} = T_B^{\text{Obs}} - \Delta T_B^\text{Cal}(\theta, \text{node}),
\]

where \(T_B^{\text{Obs}}\) represents the original UPP brightness temperatures. The O-B bias \(\Delta T_B^\text{Cal}(\theta, \text{node})\) represents the latitudinal-mean O-B biases during a week. Since some of the LAS channels (e.g., 50.3 and 52.8 GHz) are affected by clouds and/or surface emissivity, a quality control procedure must be developed. For the LAS channel at 52.8 GHz, which is affected by raining clouds, a threshold approach is used to detect cloud contamination, depending on surface type (see section 4a). This channel is also sensitive to surface emissivity, especially for high-elevation terrain. Thus, \(\Delta T_B^\text{Cal}(\theta, \text{node})\) is derived from all the data over the land where the surface pressure is greater than 700 mb.

Figures 3a and 3b display the variations in the daily averaged biases at channels 4 (54.4 GHz) and 5 (55.5 GHz) from 5 to 11 August 2008. The major features of the O-B biases vary slowly with day, including the locations and magnitudes of the maximum and minimum biases, and the magnitude of the longitudinal average of the O-B biases with latitude. The slow change in \(\Delta T_B\) with time is related to the pattern of the original calibration anomaly in F-16 (Swadley et al. 2008; Yan and Weng 2009). As a result, the features of weekly averaged \(\Delta T_B^\text{Cal}(\theta, \text{node})\) do not significantly deviate from those of daily averaged biases within that week. Figures 3c and 3d display time series of the weekly averaged \(\Delta T_B^\text{Cal}\) used to correct the residual biases for each day. Using the correction in Eq. (2) to the original UPP data, the time series of the longitudinal-mean \(\Delta T_B\) at 54.4 and 55.5 GHz is replotted in Figs. 3c and 3d and the bias is more uniform than the original data. After this analysis is applied to other LAS channels except for 50.3 GHz, the same conclusion is obtained (figure not shown). Note that the 50.3-GHz channel is not analyzed here due to a large uncertainty in the simulated brightness temperature caused by surface emissivity uncertainty.

b. Noise reduction algorithm

Our algorithm for noise reduction is based on a 2D Gaussian weighting proposed by Bell et al. (2008) and Yan and Weng (2009) and is used to produce the new sensor data record (SDR) brightness temperatures from the original F-16 SSMIS brightness temperatures; that is,

\[
T_B'(l, p) = \sum_{i=1}^{N} w_i(p)T_B(l + \delta_i, p),
\]

where \(w_i(p) = C \exp(-r_i^2/2\sigma)\). In Eq. (3), \(T_B'(l, p)\) is the noise-reduced or resampled brightness temperature at the position indexed by scan line \(l\) and scan position \(p\), \(w_i(p)\) is a weight assigned to the neighborhood \(i\) to the scan position \(p\), \(T_B(l + \delta_i, p)\) is the brightness temperature at the position indexed by scan line \((l + \delta_i, p)\) and scan position \(p\), \(N\) is the number of the nearest neighbors included in the domain size for the average, and \(\sigma\) represents an average scale of the footprint area. More details are provided in Bell et al. (2008). In this study, \(\sigma = 25\) km; the domain size is selected as \(4 \times 4\); that is, the maximum number in the latitudinal and longitudinal directions is four pixels. Thus, the largest \(N\) value is 16. This is because the pixels outside this domain do not contribute to the radiance according to Eq. (3). Also, increasing domain size (also \(N\)) would help reduce the noise of the data but would increase the computational costs. Most significantly, the spatial averaging over a large domain could smooth out useful information, especially over inhomogeneous surface and atmospheric conditions.
Figures 4a and 4b display the distributions of the F-16 UPP biases ($\Delta T_B$) on 28 August 2008 for 54.4 and 55.5 GHz, respectively, with the new noise reduction algorithm incorporated. Compared with Fig. 2, the biases are reduced to 0.23 K for these two channels. Table 2 provides the standard deviation of the brightness temperature differences at the LAS channels from 50.3 to 59.4 GHz after incorporating the noise reduction algorithm (see the column with NR).

c. Snow and sea ice emissivity regression algorithm

The snow and sea ice emissivity regression algorithms were developed early in 2004 (Yan et al. 2004). A lookup table (LUT) of snow and sea ice emissivity at a few
discrete microwave windows and several discriminator indices (DIs) was derived a priori (see appendix C in Yan et al. 2008a). The LUT is derived from AMSU snow and sea ice emissivity retrievals under clear-sky conditions, ground-based snow emissivity measurements from Mätzler (1994), and aircraft-based sea ice emissivity measurements from Hewison and English (1999). The LUT includes surface emissivity spectra for 16 snow types and 13 sea ice types at the local zenith angle (LZA) of 50°, covering from 5 to 150 GHz for snow and 6.7 to 157 GHz for sea ice. In Fig. 5a, the five new spectra are labeled as being radiometric snow (RS) type, which implies a distinct emissivity spectrum but cannot be directly linked to a physical snow type, while in Fig. 5b, the six new spectra are labeled as radiometric sea ice (RS).

The DIs in Yan et al. (2008b) are used to identify a unique emissivity spectrum that should mimic the spectral feature of the realistic snow or sea ice emissivity from the LUT. The emissivity at the same LZA for a frequency not included in the LUT is directly interpolated from LUT based on the selected spectrum with a proper offset. The offset is defined as the emissivity difference between the DI value and the emissivity calculated using the recognized spectrum from the LUT. The emissivity at other viewing angles is interpolated from the angular-dependent relationship derived from the physical emissivity model such as MLEM. Currently, this methodology has been successfully applied to data assimilation of microwave sensors such as AMSU-A/B, the Microwave Humidity Sounder (MHS), SSMI, and the Advanced Microwave Scanning Radiometer (AMSR-E) in GFS. In this study, the same methodology is used for the SSMIS sensor to identify three SSMIS-derived DIs (see the appendix).

The performance of the above snow and sea ice emissivity algorithm is tested using the satellite-retrieved emissivity through RTM under clear-sky conditions as described in Yan and Weng (2011). The emissivity retrieval data in 2008 are selected every other week and the standard deviations of the emissivity between the satellite retrievals and the regression algorithm are smaller than 0.02 for the AMSU-A/B window channels from 23.8 to 150 GHz. This value for the regression algorithm is much smaller than the standard deviation of the emissivity model, which is 0.05.

4. Assimilation of SSMIS F-16 LAS data in GFS

a. Improved quality control

A QC scheme with a series of criteria is applied to ingested satellite data for detecting cloudy radiances, uncertainty in forward calculations, gross error, and the weighting factor of the data, as described for AMSU-A observations in Yan and Weng (2011). Detecting cloud-affected data is most important. In the current GFS, the cloud liquid water path (CLW) algorithm in Weng and Grody (1994) is used to estimate a CLW value for the SSMI observations over the oceans. The threshold used to detect the cloud-affected data is 0.2 kg m\(^{-2}\), which is similar to that used for other microwave observations in GFS. Note that this threshold can only remove those data that are highly affected by nearly precipitating clouds. A smaller threshold should be used if all data affected by clouds need to be rejected. To apply the SSMI algorithm to the SSMIS observations, the SSMIS brightness temperatures at the seven window channels from 12 to 18 (see Table 1) need to be remapped to the SSM/I channels. In this study, the mapping coefficients in Yan and Weng (2008) are used.

b. Utilization rate of UPP LAS data

As described in section 2, the accuracy of the surface emissivity affects the utilization rate of the data at the
It is important to examine if the new emissivity algorithms increase the amount of SSMIS LAS data used in the NWP systems. This is performed by comparing SSMIS LAS data utilization rates between current and new emissivity calculation algorithms over snow and sea ice surfaces. In the current CRTM, the land emissivities at microwave frequencies can be derived from the MLEM while a constant of 0.9 is assumed for SSMIS observations over sea ice surfaces. This approach is used as a benchmark.

The snow and sea ice emissivity regression algorithms in section 3c are used as a new approach in the assimilation of the SSMIS UPP data.

Figures 6a and 6b display the utilization rate of the UPP LAS data at three LAS channels from 50.3 to 53.6 GHz over snow and sea ice surfaces using current and new emissivity approaches, respectively. The results in Fig. 6 are computed based on the data covering a 2-month period from 1 August to 31 September 2008. As shown in Fig. 6, the utilization rate of the data at 50.3 GHz is below
20% when using the current emissivity approach, while it can exceed 40% when using the new emissivity algorithm. At 52.8 and 53.6 GHz, the improved data utilization rate is observed primarily over snow surfaces. This is because the brightness temperatures at 52.8 and 53.6 GHz are sensitive to surface emissivity, primarily at high-elevation surfaces that are covered by snow. It is thus concluded that the utilization rate of the UPP LAS at 50.3–52.8 GHz is increased by using the new emissivity approach.

c. Impact of UPP LAS data on GFS forecast skill

A key indicator for demonstrating the impact of the data on forecast skill is the anomaly correlation (AC) coefficient, which represents the correlation between the anomaly fields of the forecast and analysis from GFS (Lahoz 1999; Zapotocny et al. 2007). In the following, the AC coefficients over the Northern Hemisphere (NH) and Southern Hemisphere (SH) are calculated for a series of control and experimental runs in GFS. The heritage BC algorithm in Derber and Wu (1998) is used in the following control and experimental runs. The “coefficient(s)” in “AC coefficient(s)” is omitted hereinafter for clarity.

1) IMPACT OF SSMIS LAS DATA AND THEIR COMPARISON WITH AMSU-A

Since the frequencies of the SSMIS LAS channels are similar to many of the AMSU-A channels, it was expected that the SSMIS LAS data would produce similar effects as AMSU-A when they are used in NWP systems. Also, the SSMIS is a conically scanning instrument and has a constant viewing angle, so the bias should be independent of scan position. Using simulated data, Rosenkranz et al. (1997) showed the retrieval accuracy from a conically scanning instrument is better than that from cross-track scanning data. However, assimilation of real satellite data involves a number of other issues, such as bias characterizations and corrections, quality control criteria, etc., which are very different from the uses of simulated data. Therefore, it is necessary to compare the impacts on forecast skill from conically (e.g., SSMIS LAS) and cross-track (e.g., AMSU-A) scanning data in our NWP model. Here, the control run is the data assimilation without any satellite data. Two SSMIS experiments are conducted in which SSMIS UPP LAS data from 52.8 (channel 2) to 59.4 (channel 7) GHz are assimilated with and without the new BC. Two AMSU-A experiments are carried out, assimilating AMSU-A data from channel 4 (52.8 GHz) to channel 9 (57.3 GHz). In the two SSMIS experiments, the data cover one data period with the UPP noise reduction (e.g., from 1 to 14 August) and the other data period without the UPP noise reduction (e.g., from 14 August to 30 September). It is worth remembering that the new noise reduction and emissivity algorithms obtained in this study are not used in these SSMIS experiments since the experiments were performed before these new algorithms were finalized. The 50.3-GHz channel in both the AMSU-A and SSMIS datasets is not used in the experiment since the SSMIS UPP data at this channel have a large uncertainty.

Figures 7a and 7b show the AC for 500-mb geopotential height in the NH and SH, respectively, for a 2-month period from 1 August to 30 September 2008. Both SSMIS
LAS and AMSU-A have positive impacts on global medium-range forecasts in both hemispheres. The impact of the satellite data, including the SSMIS LAS data, in the NH is smaller than that in the SH. More importantly, the impact of the SSMIS LAS data with the new BC is comparable to that of the AMSU-A data from NOAA-18 and MetOp-A, respectively, to the control dataset. SSMIS Exp1 and SSMIS Exp2 are two experimental runs that add the UPP LAS data without and with, respectively, the new BC. Note that the standard deviations of the anomaly correlations (see dash lines vs right vertical axis) are also plotted.

2) IMPACT OF SSMIS LAS DATA ON GFS OPERATIONAL FORECASTS

It is also important to assess the impact of the SSMIS LAS database on the GFS operational dataset, which includes the conventional data, HIRS sounder radiance, AMSU-A/B and MHS radiances, Geostationary Operational Environmental Satellite (GOES) sounder radiances, SSM/I ocean surface wind speeds, Moderate Resolution Imaging Spectroradiometer (MODIS) winds, etc. For this purpose, a new control run and two experimental runs are designed. The control run uses all GFS operational data during the period from 1 August to 15 September 2008 (note that no SSMIS data are used). Two SSMIS experimental runs are conducted by adding the SSMIS UPP LAS data with and without the new BC, where the new snow and sea ice emissivity algorithms are used for emissivity calculations over snow and sea ice conditions. Note that the SSMIS LAS data only includes channels from 52.8 (channel 2) to 59.4 (channel 7) GHz. The channel at 50.3 GHz is not used in the experiment since the SSMIS UPP data at this channel have a large uncertainty.

Numerical results show that in the NH, the impact of SSMIS LAS data on forecast skill at both 500 and 1000 mb is neutral (figures not shown). In the SH, the SSMIS LAS data with the new BC algorithm produce a slightly positive impact on forecast skill at both 500 and 1000 mb (Figs. 8a and 8b). The limited impact of the SSMIS LAS data here is due primarily to the use of many other satellite data sources in the control run. This is also demonstrated by the fact that the AC standard deviations in the SSMIS experiments are similar to those in the control experiment. Note that the impact of the snow and sea ice emissivity regression algorithms is not independently assessed in this study. A major reason is that the regression algorithms for SSMIS follow the same methodology as we did for other microwave sensors such as AMSU-A/B and MHS. The impact of the snow and sea ice emissivity regression algorithms in AMSU and MHS assimilations displays a positive impact on forecast skill (e.g., Yan et al. 2008a).

The above impacts are assessed using the UPP data for which the noise reduction algorithm of Bell et al. (2008) was turned off for the data before 14 August 2008 and turned on for the data after 14 August 2008. To assess the
impact of the noise reduction algorithm developed in this study, the data are selected with a different period from 1 September to 30 October 2009 when the noise reduction algorithm of Bell et al. (2008) was totally turned off. The assimilation experiments are designed as follows. The control run uses the conventional data plus all the sensor data except for data from microwave sounding instruments. Two experimental runs adding the SSMIS UPP LAS data from channels 2–7 to the Cntrl Exp dataset, where one is for the original UPP LAS data (SSMIS Exp1.) and the other one is for the UPP LAS data with the new BC (SSMIS Exp2). The new snow and sea ice emissivity algorithms in section 3 are applied to both experimental runs for the assimilation of SSMIS LAS data. Note that the standard deviations of the anomaly correlations (see the dashed lines vs the right vertical axis) are also plotted.

5. Summary and conclusions

Several algorithms for the assimilation of the SSMIS LAS data into the GFS are developed and tested. A bias-correction algorithm is used for removing the geographically dependent biases in the UPP LAS data. The noise reduction algorithm is used to improve the quality of the SSMIS data observations. The regression algorithms for snow and sea ice emissivity are derived using
the emissivity indices and an LUT consisting of 16 snow and 13 sea ice type emissivity spectra. It is shown that the new bias correction improves the quality of the UPP LAS data. The noise reduction algorithm decreases the random component of the UPP LAS data by approximately 50%. The snow and sea ice emissivity algorithms reduce the uncertainty in the surface emissivity calculations. As a result, much of the SSMIS data at surface-sensitive channels can be assimilated.

The new algorithms further improve the impacts of the F-16 UPP LAS data on forecast skills according to a series of experimental runs based on different types of control run datasets. When the LAS data are added to the control run with satellite-denied data, the positive impact of the SSMIS data becomes comparable with that of the LAS data at surface-sensitive channels. As a result, much of the SSMIS data at surface-sensitive channels can be assimilated.

This study has developed the new bias correction, noise reduction, and snow and sea ice emissivity regression algorithms using F-16 data; the same methodology is applicable for other SSMIS observations. In particular, the radiance noise reduction and snow and sea ice emissivity algorithms can be easily used for the assimilation of F-17 (UPP) and F-18 SSMIS data. This study represents a first step toward assimilating all SSMIS data in GFS. The methodology can also be applied to other instruments that exhibit similar problems related to calibration anomaly, geographically dependent biases, and large noise.

Acknowledgments. This research is jointly supported by Chinese Ministry of Science and Technology Project 2010CB951600 and the Joint Center for Satellite Data Assimilation Program. The authors thank Drs. Russ Treadon and John Derber for their help in running the NCEP GFS and GSI experiments. Thanks also go to Gregory S. Krasowski for his help in preparing for the UPP data. The views expressed in this publication are those of the authors and do not necessarily represent those of NOAA.

APPENDIX

Derivation of Discriminator Indices for SSMIS LAS Data

For the SSMIS LAS data, three DIs at 19.35, 37, and 91.655 GHz are defined in the polarization-weighted emissivity:

\[ D_I^k = \cos^2(\theta_{zen})e_v + \sin^2(\theta_{zen})e_h, \]  

where the subscript \( k \) is an index from 1 to 3 corresponding to frequencies at 19.35, 37, and 91.655 GHz, respectively; \( \theta_{zen} \) is the satellite zenith angle of SSMIS (53.1°); and \( e_v \) and \( e_h \) are the simulated emissivities at the vertical and horizontal polarizations at the above three frequencies, respectively, which are computed using one of the following fitting equations depending on frequency. For the channels from 12 [19.35 GHz on a horizontal polarization (H-Pol) to 16 (37 GHz at vertical polarization or V-Pol)], the emissivity is simulated using brightness temperatures at the following five channels:

\[
e_{ich} = a_0 + a_1 T_{19V} + a_2 T_{19H} + a_3 T_{22V} + a_4 T_{37V} + a_5 T_{37H} + a_6 T_S,
\]  

**Table A1.** Fitting coefficients used in Eqs. (A2) and (A3) for microwave snow emissivity calculations.

<table>
<thead>
<tr>
<th>Coef</th>
<th>19V</th>
<th>19H</th>
<th>22V</th>
<th>37V</th>
<th>37H</th>
<th>91V</th>
<th>91H</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_0 )</td>
<td>8.982 × 10^{-1}</td>
<td>8.047 × 10^{-1}</td>
<td>9.289 × 10^{-1}</td>
<td>8.905 × 10^{-1}</td>
<td>8.413 × 10^{-1}</td>
<td>9.599 × 10^{-1}</td>
<td>9.543 × 10^{-1}</td>
</tr>
<tr>
<td>( a_1 )</td>
<td>3.626 × 10^{-3}</td>
<td>-1.027 × 10^{-3}</td>
<td>1.027 × 10^{-4}</td>
<td>-9.036 × 10^{-4}</td>
<td>-1.486 × 10^{-3}</td>
<td>-5.281 × 10^{-4}</td>
<td>-4.628 × 10^{-4}</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>6.418 × 10^{-5}</td>
<td>4.532 × 10^{-3}</td>
<td>1.681 × 10^{-4}</td>
<td>4.711 × 10^{-4}</td>
<td>7.072 × 10^{-4}</td>
<td>5.403 × 10^{-3}</td>
<td>-6.872 × 10^{-3}</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>7.203 × 10^{-4}</td>
<td>8.102 × 10^{-5}</td>
<td>4.128 × 10^{-3}</td>
<td>4.889 × 10^{-4}</td>
<td>8.234 × 10^{-4}</td>
<td>2.069 × 10^{-3}</td>
<td>-5.297 × 10^{-3}</td>
</tr>
<tr>
<td>( a_4 )</td>
<td>1.097 × 10^{-4}</td>
<td>3.999 × 10^{-4}</td>
<td>3.315 × 10^{-4}</td>
<td>5.158 × 10^{-3}</td>
<td>7.863 × 10^{-4}</td>
<td>5.284 × 10^{-3}</td>
<td>7.954 × 10^{-3}</td>
</tr>
<tr>
<td>( a_5 )</td>
<td>-1.892 × 10^{-4}</td>
<td>-4.281 × 10^{-4}</td>
<td>-2.441 × 10^{-4}</td>
<td>-5.768 × 10^{-4}</td>
<td>-3.777 × 10^{-3}</td>
<td>-4.540 × 10^{-4}</td>
<td>-6.304 × 10^{-4}</td>
</tr>
<tr>
<td>( a_6 )</td>
<td>-3.925 × 10^{-3}</td>
<td>-3.512 × 10^{-3}</td>
<td>-4.197 × 10^{-3}</td>
<td>-4.185 × 10^{-3}</td>
<td>-3.959 × 10^{-3}</td>
<td>5.131 × 10^{-3}</td>
<td>3.386 × 10^{-3}</td>
</tr>
<tr>
<td>( a_7 )</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>( a_8 )</td>
<td>6.851 × 10^{-5}</td>
<td>4.962 × 10^{-3}</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>( a_9 )</td>
<td>-2.795 × 10^{-4}</td>
<td>-3.591 × 10^{-4}</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>( a_{10} )</td>
<td>-4.610 × 10^{-3}</td>
<td>-4.582 × 10^{-3}</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
</tr>
</tbody>
</table>
where the subscript ich is the channel index from 12 to 16 and $T_{19H}$, $T_{19V}$, $T_{22V}$, $T_{37H}$, and $T_{37V}$ are brightness temperatures at the corresponding channels. For the channels from 17 (91.655 GHz at V-Pol) to 18 (91.655 GHz at H-Pol), the emissivity is simulated using brightness temperatures at the following seven channels from 12 to 18 and also channel 8 (150 GHz at H-Pol):

$$e_{jch} = a_0 + a_1 T_{19V} + a_2 T_{19H} + a_3 T_{22V} + a_4 T_{37V} + a_5 T_{37H} + a_6 T_{91V} + a_7 T_{91H} + a_8 T_{150H} + a_9 T_S,$$

where the subscript jch is the channel index from 17 to 18 and $T_{91V}$, $T_{91H}$, and $T_{150H}$ are the brightness temperatures at the 17th, 18th, and 8th channels, respectively (see Table 1). The coefficients from $a_0$ to $a_9$ for snow and sea ice emissivities in Eqs. (A2) and (A3) are given in Tables A1 and A2, and are derived using the training dataset of emissivity and SSMIS brightness temperatures at the following seven channels from 12 to 18:

\begin{table}[h]
\centering
\caption{Fitting coefficients used in Eqs. (A2) and (A3) for microwave sea ice emissivity calculation.}
\begin{tabular}{|c|c|c|c|c|c|c|c|}
\hline
 Coef & 19V & 19H & 22V & 37V & 37H & 91V & 91H \\
\hline
$a_0$ & $8.879 \times 10^{-1}$ & $7.698 \times 10^{-1}$ & $8.934 \times 10^{-1}$ & $8.245 \times 10^{-1}$ & $7.197 \times 10^{-1}$ & $8.653 \times 10^{-1}$ & $8.274 \times 10^{-1}$ \\
$a_1$ & $4.134 \times 10^{-3}$ & $2.563 \times 10^{-4}$ & $9.237 \times 10^{-4}$ & $1.289 \times 10^{-4}$ & $4.377 \times 10^{-4}$ & $8.795 \times 10^{-4}$ & $6.634 \times 10^{-4}$ \\
$a_2$ & $1.157 \times 10^{-4}$ & $4.656 \times 10^{-5}$ & $1.990 \times 10^{-4}$ & $1.053 \times 10^{-4}$ & $2.069 \times 10^{-4}$ & $5.288 \times 10^{-4}$ & $6.571 \times 10^{-4}$ \\
$a_3$ & $-9.471 \times 10^{-5}$ & $-5.527 \times 10^{-5}$ & $3.820 \times 10^{-3}$ & $-7.351 \times 10^{-5}$ & $-1.598 \times 10^{-6}$ & $-8.795 \times 10^{-4}$ & $-7.11 \times 10^{-5}$ \\
$a_4$ & $2.223 \times 10^{-4}$ & $4.077 \times 10^{-4}$ & $4.861 \times 10^{-4}$ & $4.954 \times 10^{-3}$ & $4.320 \times 10^{-4}$ & $3.514 \times 10^{-4}$ & $4.038 \times 10^{-4}$ \\
$a_5$ & $-2.124 \times 10^{-4}$ & $-3.882 \times 10^{-4}$ & $-2.960 \times 10^{-4}$ & $-1.690 \times 10^{-4}$ & $4.348 \times 10^{-3}$ & $9.306 \times 10^{-5}$ & $1.087 \times 10^{-4}$ \\
$a_6$ & $-3.772 \times 10^{-3}$ & $-3.275 \times 10^{-3}$ & $-4.052 \times 10^{-3}$ & $-3.988 \times 10^{-3}$ & $-3.541 \times 10^{-3}$ & $5.175 \times 10^{-3}$ & $3.410 \times 10^{-3}$ \\
$a_7$ & None & None & None & None & None & None & None \\
$a_8$ & $-3.308 \times 10^{-4}$ & $-4.947 \times 10^{-4}$ & $-4.377 \times 10^{-4}$ & $-4.156 \times 10^{-3}$ & $-4.377 \times 10^{-4}$ & $-4.156 \times 10^{-3}$ & $-4.156 \times 10^{-3}$ \\
$a_9$ & None & None & None & None & None & None & None \\
\hline
\end{tabular}
\end{table}


Swadley, S., G. Poe, A. Uliana, and D. Kunkee, 2005: SSMIS Cal/Val calibration anomaly analysis. NOAA–JCSDA Seminar,


