Principal Components of Multifrequency Microwave Land Surface Emissivities. Part I: Estimation under Clear and Precipitating Conditions

F. JOSEPH TURK and ZIAD S. HADDAD
Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California

YALEI YOU
Department of Earth, Ocean and Atmospheric Sciences, Florida State University, Tallahassee, Florida

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ABSTRACT

The upcoming Global Precipitation Measurement mission will provide considerably more overland observations over complex terrain, high-elevation river basins, and cold surfaces, necessitating an improved assessment of the microwave land surface emissivity. Current passive microwave overland rainfall algorithms developed for the Tropical Rainfall Measuring Mission (TRMM) rely upon hydrometeor scattering-induced signatures at high-frequency (85 GHz) brightness temperatures (TBs) and are empirical in nature. A multi-year global database of microwave surface emissivities encompassing a wide range of surface conditions was retrieved from Advanced Microwave Scanning Radiometer for Earth Observing System (EOS; AMSR-E) radiometric clear scenes using companion A-Train [CloudSat, Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO), and Atmospheric Infrared Sounder (AIRS)] data. To account for the correlated emissivity structure, the procedure first derives the TRMM Microwave Imager–like nine-channel emissivity principal component (PC) structure. Relations are derived to estimate the emissivity PCs directly from the instantaneous TBs, which allows subsequent TB observations to estimate the PC structure and reconstruct the emissivity vector without need for ancillary data regarding the surface or atmospheric conditions. Radiative transfer simulations matched the AMSR-E TBs within 5–7-K RMS difference in the absence of precipitation. Since the relations are derived specifically for clear-scene conditions, discriminant analysis was performed to find the PC discriminant that best separates clear and precipitation scenes. When this technique is applied independently to two years of TRMM data, the PC-based discriminant demonstrated superior relative operating characteristics relative to the established 85-GHz scattering index, most notably during cold seasons.

1. Introduction

The joint National Aeronautics and Space Administration (NASA) and Japanese Aerospace Exploration Agency (JAXA) Global Precipitation Measurement (GPM) core satellite will provide considerably more overland observations over complex terrain, high-elevation river basins, and cold surfaces, which are problematic for existing Tropical Rainfall Measuring Mission (TRMM) radar and radiometer precipitation algorithms (Fu and Liu 2007). Current passive microwave (PMW) overland precipitation algorithms developed for the nine-channel (10, 19, 21, 37, and 85 GHz) TRMM Microwave Imager (TMI) rely upon hydrometeor scattering-induced signatures at high frequencies (85 GHz) and are empirical in nature (Gopalan et al. 2010). To improve physically based overland PMW precipitation retrieval techniques (Kummerow et al. 2011), it is important to identify the key geophysical factors that control the underlying surface emissivity variability. In contrast to oceanic surfaces, these factors are not so clearly defined for the finescale, diverse, and dynamic composition of land surfaces. Fundamentally, the microwave emissivity is influenced by properties such as the surface roughness, scale length, and profile of the dielectric constant within the top several centimeters, which are quantities that are not directly measureable, except at instrumented ground
sites. PMW-based precipitation retrievals from the asynchronously orbiting TRMM and GPM core satellites have to function across changes in the underlying soil moisture and vegetation (Ringerud et al. 2013) and diurnal heating and cooling of the underlying land/near-surface interface (Norouzi et al. 2012). A recent Special Sensor Microwave Imager (SSM/I)-based emissivity intercomparison (Ferraro et al. 2013) illustrated the dynamic emissivity nature of certain surface types, where SSM/I emissivities of lightly vegetated land surfaces decreased abruptly with the onset of rain and gradually increased during subsequent dry periods. The purpose of this manuscript is to exploit the information contained within the multichannel PMW observations to 1) enable the simultaneous retrieval of the full emissivity spectrum and its conditional variance under a wide range of surface conditions and 2) demonstrate how its degradation under precipitating conditions can serve as a conditional precipitation screen.

A considerable amount of recent activity in the modeling of microwave land surface emissivity stems from the impact of assimilating satellite-based microwave radiances into numerical weather prediction (NWP) models (Bauer et al. 2011). In many models, the underlying emissivity is estimated by inverting the satellite-observed brightness temperatures (TBs), given some measure of the atmospheric state and surface temperature at the time of the satellite overpass (Ruston and Vonder Haar 2004). Owing to uncertainties in modeling the scattering and emission properties of hydrometeors, these approaches are most accurate when the scene is determined to be cloud-free. Using International Satellite Cloud Climatology Project (ISCCP) (Rossow and Schiffer 1999) data to assess cloud-free scenes, Aires et al. (2011) established a tool to estimate land surface emissivities at microwave frequencies (TELSEM), based on an analysis of the frequency, angular, and polarization dependences of emissivities derived from multiple years of SSM/I, TMI, and Advanced Microwave Sounding Unit (AMSU) observations (Prigent et al. 2006). In many cases, the estimation of the emissivity at each PMW radiometer channel is carried out independently of the other channels. Since the emissivity at typical microwave window frequencies between 10 and 85 GHz is correlated, it is more physically realistic to jointly estimate or adjust the emissivity vector given the natural variability in surface conditions. For example, the Microwave Integrated Retrieval System (MIRS; Boukabara et al. 2011) inherently carries an estimate of the emissivity covariance to adjust all emissivities simultaneously. For precipitation retrievals from a set of TMI-like channels, it would be beneficial to understand how the emissivity vector is controlled by specific surface properties, such as vegetation properties or soil conditions. However, these properties are not routinely or directly observed over all land surfaces. The coupled Land Information System (LIS; Kumar et al. 2006) and the Community Radiative Transfer Model (CRTM; Han et al. 2006) uses a land surface model to analyze soil moisture content, soil temperature, land surface temperature, and snow depth that are required for the CRTM land emissivity model (Weng et al. 2001). More recently, the multichannel physical retrieval developed for the WindSat-based soil moisture retrieval algorithm (Li et al. 2010) has been adapted for TMI emissivity estimation (Turk et al. 2012).

In this study, the results of a principal component (PC) analysis of a global emissivity dataset gathered under a wide variety of surface conditions are investigated. A PC analysis of the emissivity vector is appropriate to identify a smaller set of channel combinations that may be related to certain surface properties, without requiring the surface properties to be known. Petty and Li (2013) developed a two-stage PC analysis of the TMI TBs to separate the precipitation signal from the surface, for separate surface classes. In this investigation, the emissivity PC structure is expressed by a set of nonlinear TB combinations and then jointly transformed back into the desired emissivity vector. The unique feature of this approach is that it allows the emissivity PCs to be estimated directly from the TB observations, without need for ancillary information regarding the atmospheric profile, surface temperature, or classification. Since this technique was developed with nonprecipitating observations, we demonstrate how its degradation under precipitating conditions can be adapted as a conditional precipitation screen. Another potential use of this technique is to allow emissivity adjustments to be done in PC space and then jointly transformed into emissivity. This adjustment of the emissivity following precipitation events may provide a more realistic emissivity structure, for example, during or after sustained precipitation (where clear-scene emissivity retrievals are not designed to function) (Ferrazzoli et al. 2010; You et al. 2013).

The technique is demonstrated with Advanced Microwave Scanning Radiometer for Earth Observing System (EOS; AMSR-E) overland observations collected from Aqua satellite overpasses during cold and warm season precipitation events and is restricted to the nine AMSR-E channels that are similar to the TMI. However, the formulation could also be applied to the across-track sounding radiometers such as AMSU and the Advanced Technology Microwave Sounder (ATMS), provided that the channels have sensitivity to the surface and that proper accounting for the view angle and variable resolution is taken into consideration.
2. Data preparation

The following analysis will draw upon two observational datasets. The first, a clear-scene AMSR-E emissivity dataset, was used to develop the PC-based emissivity estimation technique. The second dataset is a matched TRMM TMI and Precipitation Radar (PR) dataset that was used to examine the ability of the PC methodology to screen precipitating from nonprecipitating scenes.

a. Clear-scene AMSR-E emissivities

Identification of cloud-free PMW scenes typically relies upon ancillary data sources that are interpolated in space and time, such as coarse-resolution model analyses, or passive-based thermal infrared or daytime-only (visible) cloud properties. Misidentification owing to variable day–night conditions may contaminate the emissivities retrieved from instantaneous PMW satellite observations, as cloud emission–scattering processes become increasingly significant at 85 GHz and above. In this work, we develop a 3.5-yr (June 2006 to February 2010) set of global cloud-free emissivities derived from AMSR-E TB observations, using coincident A-Train satellite data for assessing the cloud vertical structure and associated atmospheric and surface conditions. The merger of the W-band (94 GHz) CloudSat Profiling Radar (CPR; Tanelli et al. 2008) and the Cloud–Aerosol Lidar with Orthogonal Polarization (CALIOP) onboard the companion Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) satellite aids in more consistent detection of upper-level thin cirrus and low-level stratocumulus. These active sensors are preferred owing to their independence on solar illumination and day–night cloud detection differences that affect the Moderate Resolution Spectroradiometer (MODIS) onboard Aqua. Mace et al. (2009) developed a merged cloud product (2B-GEOPROF-lidar), which provides cloud base and height levels for up to five cloud layers. An AMSR-E pixel was declared cloud-free when all 21 2B-GEOPROF-lidar profiles (10 profiles on either side of the CloudSat beam closest to the AMSR-E center) indicated vertically cloud-free profiles.

The emissivity retrieval method of Mathew et al. (2008) was adapted for use with the successive order of interaction (SOI) radiative transfer model (Heidinger et al. 2006) at nine of the AMSR-E vertical (V)/horizontal (H) polarization channels (10.7V/H, 18.7V/H, 23.6V, 36.5V/H, 89.0V/H GHz) similar to TMI (10.7V/H, 19.35V/H, 21.3V, 37.1V/H, 85.5V/H GHz). AMSR-E and TMI scan conically at approximately the same Earth incidence angle. The atmospheric temperature and specific humidity profile were accounted for with the coincident Atmospheric Infrared Sounder (AIRS) Level 2 Standard Retrieval Product (AIRX2RET; Olsen et al. 2007), including the AIRS land surface temperature that incorporates spectral emissivity details (Hulley et al. 2009). Both AMSR-E and the AIRS instrument are onboard Aqua in the A-Train orbit (the CloudSat overpass is 1 min later, with CALIPSO following 15 s after CloudSat). Since AMSR-E scans conically, this gives an approximate 3-min offset between the AMSR-E and CloudSat–CALIPSO observation times. This merger produces an observational-based set of derived AMSR-E emissivities, where all cloud screening and parameters needed for radiative transfer modeling were taken from coincident A-Train satellite observations. While this dataset was produced globally, only overland scenes are considered in the analysis below. A caveat is that the cloud screening is only possible in one direction (along track), owing to the nonscanning CloudSat–CALIPSO instruments. Therefore, for broken cloud fields there is likely to be some cloud contamination in this dataset. Chen et al. (2008) used the CloudSat radar-only cloud water content product (2B-CWC-RO) to verify the CRTM and did not find a noticeable increase in bias when comparing observed and simulated AMSU observations.

b. Matched TRMM radar profiles

The second dataset is a merged TRMM product that will be used to discriminate rain from no-rain TB radiiances, using the TRMM PR as a precipitation reference. For this, the TMI nine-channel radiances (1B11 version 7) were extracted within the narrower 220-km swath of the PR (2A25 version 7). For each of the TMI beam positions, the $3 \times 3$ average attenuation-corrected Ku-band reflectivity profile was calculated, along with the average surface rain rate, and the surface flag (land, water, or coast) and elevation. No TMI beam averaging or deconvolution was performed. To gather a representative sample set across many surface conditions and precipitation events, all TRMM orbits from the first and fifteenth day of each month of 2008 and 2009 were processed (over 700 orbit files). The asynchronous TRMM orbit covers provide more observations over different surfaces and local times than CloudSat, but PR coverage is restricted to latitudes between approximately $\pm 40^\circ$, with known deficiencies in precipitation detection below $-1$ mm h$^{-1}$. Berg et al. (2010) concluded that CloudSat detected rainfall about 2.5 times as often as PR, but their analysis was restricted to overwater scenes. The TRMM instrumentation is used to mimic the characteristics and sampling of the asynchronous GPM core satellite, where the Dual Frequency Precipitation Radar (DPR) scans a narrow region within the wider swath of the GPM Microwave Imager (GMI).
3. PC-based emissivity analysis

Recent studies have demonstrated substantial correlations between overland microwave emissivities for typical PMW window channels between 10–89 GHz (Bytheway and Kummerow 2010; Aires et al. 2011). An emissivity principal component (PC) analysis is appropriate to locate a reduced number of channel combinations to explain variability within the microwave surface emissivity, and it provides a means to jointly vary all elements of the emissivity vector (denoted by \( \mathbf{e} \)). The vector \( \mathbf{e} \) can be broken down into its nine PCs (denoted by \( \mathbf{u} \)) via a transformation expressed by an orthogonal matrix \( \mathbf{E} \), whose columns are the eigenvectors of the emissivity covariance matrix \( \mathbf{S} \) (Wilks 2006). If \( \mathbf{E} \) is known, \( \mathbf{e} \) can be exactly reconstructed: \( \mathbf{e} = \mathbf{E} \mathbf{u} \). The purpose of this section is to demonstrate a simple technique to estimate \( \mathbf{u} \) directly from the TB observations, which is applicable to clear scenes of AMSR-E (or other conically scanning PMW radiometers with similar channels) and carries additional information to discriminate clear and precipitating scenes.

\( \text{a. Estimation of emissivity principal components} \)

A principal component analysis was performed on the entire AMSR-E clear scene emissivity dataset to determine \( \mathbf{S} \) and \( \mathbf{E} \). As mentioned in the previous section, the results of this analysis will be applied later to a separate set of TRMM observations, where the PR will be used to test for rain and no-rain TMI scenes. Therefore, for this study the PC analysis was restricted to only overland AMSR-E data within ±40° latitude and used the nine AMSR-E channels that correspond to similar TMI channels. Since the geophysical factors that control these emissivities are very likely to be nonlinear processes, an attempt was made to estimate \( \mathbf{u} \) directly from linear and nonlinear TB combinations. Each PC [the nine elements of \( \mathbf{u} \) are denoted by \( (u_1, u_2, \ldots, u_9) \)] was estimated (estimates denoted by primes) by combinations of the nine TMI-like TBs and the four polarization ratios at 10, 18, 36, and 89 GHz; for example, for \( u'_1 \),

\[
\begin{align*}
u'_1 &= a_0 + a_1 T_{10H} + a_2 T_{10V} + \cdots + a_{10} T_{10H}^2 + \cdots + a_{19} \left( \frac{T_{10V} - T_{10H}}{T_{10V} + T_{10H}} \right) + \cdots + a_{22} \left( \frac{T_{89V} - T_{89H}}{T_{89V} + T_{89H}} \right),
\end{align*}
\]

Least squares regression was used to determine the above 23 \((9 + 9 + 4)\), plus the constant term) coefficients for each PC. The estimated emissivity is then reconstructed from

\[
\mathbf{e}' = \mathbf{E} \mathbf{u}'.
\]

Table 1 summarizes the overall statistics of the fit to each PC in Eq. (1) and also to the emissivity in Eq. (2). A total of \( N = 1164356 \) values were used from the dataset described in section 2a. Correlations of 0.9 or higher were obtained for most of the nine terms of \( \mathbf{u} \) and \( \mathbf{e} \), and the root-mean-square error (RMSE) for \( \mathbf{e} \) is 0.02 or smaller (the PC histograms are presented in the next section). This estimation strategy has heritage in early algorithms developed for the SSM/I, such as total water vapor where a smaller number of terms \((T_{19V}, T_{22V}, T_{85V})\) were used to account for variations owing to the oceanic background, and the 85-GHz scattering index \((\text{SI}_{85})\) used to screen precipitating scenes from the surface \((T_{19V}, T_{22V}, T_{85V}, T_{85V}; \text{Grody 1991})\). The difference is that this method estimates the emissivity PC structure and then reconstructs the emissivity vector. If the nonlinear terms in Eq. (1) were not included, there would be no advantage, for the procedure would then be equivalent to estimating the emissivity directly from linear TB combinations.

For graphical purposes, all nine PCs were averaged into 1° latitude–longitude bins for all June–August data between 2006 and 2009, and the resultant maps of the first two PCs \( u'_1 \) and \( u'_2 \) are shown in Figs. 1a and 1b, respectively. Since the first two PCs explain the majority of the emissivity variability, they are compared to the
Fig. 1. (top to bottom) One-degree maps of the first two estimated PCs, $u_1'$ and $u_2'$ (values scaled by 10); three-month (June–August) composite of volumetric soil moisture estimated by WindSat between 2006 and 2009 inclusive; associated vegetation water content (kg m$^{-2}$) estimated by WindSat; and the 19H emissivity reconstructed from the estimated PC vector $u' = (u_1', u_2', \ldots, u_9')$. 
WindSat-based physical retrievals of soil moisture ($M_s$) and vegetation water content (W) from the physical modeling developed by Li et al. (2010), shown in Figs. 1c and 1d, respectively. From a visual comparison of the geographical pattern of these products, $u'_2$ resembles (inversely related to) the map of $W$, and $u'_1$ appears related to the map of $M_s$. However, there are regions where the connection between $u'_1$ and $u'_2$ and the geophysical properties $M_s$ and $W$ are less and more readily apparent than others, and further analysis of the physical retrieval model emissivity is ongoing (Turk et al. 2012). Figure 1e shows the associated PC-based 19H GHz emissivity (other channels not shown), whose pattern appears related to features in $u'_1$ and $u'_2$.

The global histograms of the nine PCs are shown in the blue line (clear-AMSRE) in Fig. 2 (the other lines will be explained below). The smaller secondary hump near $u'_1 \approx -2.2$ represents the deserts in northern Africa and the Saudi peninsula, where there are known to be unique lithographic spectral signatures (Jiménez et al. 2010), and in these very dry soils the thermal emission can originate below the surface at a depth of many wavelengths (Grody and Weng 2008) with a greater likelihood of multiple scattering. The fact that the ascending node AMSR-E observation time occurs in the afternoon (1330 local time) during the maximum in subsurface thermal contrast has also been shown to lead to errors in retrieved emissivities (Prigent et al. 1999; Galantowicz et al. 2011; Norouzi et al. 2012).

While the formulation can be applied to arbitrary AMSR-E observations falling within this same latitudinal domain, it assumes clear scenes so the interpretation of these PCs is different when the scene is not cloud-free. This will be discussed further below where the displacement of the PC structure (relative to its clear-scene structure) is exploited for precipitation detection. Petty and Li (2013) carried out a PC analysis on the TMI TBs (from a similar set of matched TMI/PR data) to reduce the nine TMI channels to three pseudochannels that are blind to most background variations occurring within each of seven surface classes. The PC analysis in this work is carried out directly on the emissivity, and there is no clustering or classification of land surface types considered.

b. Separation between precipitating and nonprecipitating scenes

Since this procedure was determined from a collection of clear-scene TB observations, it is not unreasonable to expect the distribution of $u'$ (and hence $e'$) to move away from their clear-scene range when applied to precipitation-affected conditions. To see if this is the case, the matched TMI/PR dataset described in section 2b was analyzed for all land-only scenes, and a similar set of PC histograms was computed for all nonprecipitating and precipitating scenes, represented by the black and red lines in Fig. 2, respectively. Since the center frequencies of the TMI radiometer are similar but not identical to the corresponding AMSR-E channels (e.g., 85 GHz versus 89 GHz), technically, Eq. (1) is not directly applicable to TMI data. However, from Fig. 2, the clear-scene histograms for AMSR-E and TMI (blue and black lines) line up closely over the same horizontal range. The difference in the vertical shapes of $u'_1$ and $u'_2$ owes itself to time sampling differences between the two sensors. As shown in Fig. 1, the smaller secondary humps in $u'_1$ and $u'_2$ originate from observations of very dry desert regions, which are more frequently sampled by the 1440-km swath AMSR-E relative to the 220-km swath PR (at a latitude of 25°, AMSR-E observes a given location about 3 times as often as the PR).

Most importantly, the precipitating TMI scenes exhibit a noticeable horizontal shift in the range of (in particular) $u'_5$, $u'_4$, and $u'_7$ relative to the nonprecipitating TMI scenes. There is some overlap, since there will always be surfaces that appear radiometrically similar to precipitation and cannot be cleanly distinguished from a limited set of channels (Munchak and Skofronick-Jackson 2013). This is noticeable in $u'_1$, which shifts to a smaller value in the precipitating scenes but still has considerable overlap with nonprecipitating scenes. A more distinct separation is noted for $u'_3$ and $u'_4$, which begin to decrease relative to the clear-scene conditions, and $u'_7$ (while having a small clear-scene value) increases relatively substantially relative to the clear-scene range, rising from near −0.05 to near 0.02. As the scene moves from nonprecipitating to precipitating, it is therefore constructive to examine how various combinations of PCs perform as a discriminator to better separate precipitating and nonprecipitating radiometric scenes relative to any one PC. Based on the results of Fig. 2, a linear discriminant (Wilks 2006) was tested using three different PC combinations: a three-PC set ($u'_3$, $u'_4$, $u'_5$), a four-PC set ($u'_1$, $u'_3$, $u'_4$, $u'_5$), and a five-PC set ($u'_1$, $u'_2$, $u'_3$, $u'_4$, $u'_5$). Defining $\mu_C$ and $\Sigma_C$ as the mean and covariance matrix of the clear-scene PCs, and $\mu_R$ and $\Sigma_R$ for the raining scene PCs, a discriminant $D$ is computed for each TB-estimated $u'$:

$$D = (\mu_C - \mu_R)^T (\Sigma_C^{-1} + \Sigma_R^{-1})^{-1} u'.$$ (3)

This formulation essentially takes the form of a linear discriminant $D = \Sigma_d u'$, where precipitation is declared detected if the value of the discriminant $D$ fell on one side of a threshold value and not detected if $D$ fell on the opposite side. The three results (the subscript denotes
the number of PCs used) are shown in Fig. 3 and the coefficients are given by

\[ D_3 = -2.25u_3' + 15.1u_4' - 17.34u_7' \]
\[ D_4 = 1.45u_1' - 2.16u_3' + 17.10u_4' - 17.98u_7' \]
\[ D_5 = 1.48u_1' + 0.27u_2' - 2.22u_3' + 17.06u_4' - 17.96u_7' \]  

(4)

From a visual inspection in Fig. 3, \( D_4 \) improves upon \( D_3 \), but \( D_3 \) does not seemingly introduce any significant improvement to \( D_4 \). A qualitative way to test the effectiveness of this type of precipitation screen is to compute the detection and miss ratios for a wide range of threshold values and compare it to several known precipitation screen techniques (Kacimi et al. 2013). When the plot of hit rate versus false alarm rate (FAR) is connected with line segments, the result is the relative operating characteristic (ROC), as shown in Fig. 4. The further the line pushes into the upper left-hand corner, the more effective the screen is at both a high hit rate and a low FAR. In the top row of Fig. 4, the ROC is plotted for these same TMI data, using the \( D_3 \) and \( D_4 \) linear discriminant (red and aqua lines, respectively), the 85-GHz scattering index (black line; Grody 1991), and the 22V minus 85V difference used in the current version 7 TMI overland
2A12 precipitation products (blue line; Gopalan et al. 2010). Both of the PC-based screens are at least as effective as these other two, which is not surprising since the multichannel formulations of these latter two (composed of TB and TB$^2$ terms) are essentially embedded within the multiple terms of Eq. (1). However, the PC-based screen is clearly superior in the most challenging cold season months (December–January above 30° latitude), shown in the lower-left panel of Fig. 4, with a slight overall improvement for the four-PC discriminant relative to the three-PC discriminant.

By quantifying the error structure (e.g., hits, misses, and false alarms) across a range of threshold values from a sufficiently large number of PMW scenes coincident with independent precipitation observations (section 2b), a detection threshold can be established given desired operating characteristics (trade-off between a high hit rate and a low false alarm ratio). Since the discriminant can be estimated from the TB structure, it provides an estimate of the detection error, that is, the likelihood that the retrieved emissivity is affected by precipitating conditions.

Up until this point, the analysis and statistical conclusions were drawn from multiple years of satellite overpasses, rather than on the instantaneous swath-level satellite overpasses upon which PMW-based retrievals operate. In the next section, we will examine the PC structure derived from several AMSR-E overpasses, during both warm and cold season events.

4. Application to AMSR-E overpasses

In this section, the methodology of section 3 is applied to AMSR-E data over regions covering two recent GPM ground validation campaigns. The Midlatitude Convective Continental Clouds Experiment (MC3E) took place between 22 April and 6 June 2011, centered on the Department of Energy Atmospheric Radiation Program (DOE-ARM) Southern Great Plains (SGP) Central Facility site in northern Oklahoma (Petersen and Jensen 2012). Primary GPM-related field campaign objectives focused on gathering observations of precipitation to support refinement of GPM retrieval algorithm physics over land; however, there were several days of aircraft flights dedicated to “clear air” overpasses to observe land surface properties. The MC3E period is particularly relevant for overland emissivity studies, since during early to late spring 2011 many major rivers and tributaries of the Red River (which flows northward into Canada along the North Dakota–Minnesota border) and upper and lower Mississippi basin were over or near flood stage, with wide variability in soil moisture conditions and associated emissivity. While the MC3E domain was located near the upper limit of TMI coverage, there were abundant day and night Aqua–AMSR-E overpasses to analyze surface conditions before, during, and following precipitation events. To examine precipitation during cold season, snow-covered conditions, a similar analysis is presented over the eastern United States and southern Canada during February 2011. This region encompasses the domain of the 2012 GPM Cold Season Precipitation Experiment (GCPEX; Hudak et al. 2012). The AMSR-E sensor ceased functioning in early October 2011, prior to GCPEX.

a. Convective precipitation: 11 May 2011

Figures 5a and 5b depict the AMSR-E observed 10H and 89H GHz channels on 11 May 2011 near 2003 UTC,
mapped over the central United States (the other AMSR-E channels are not shown). The presence of surface water or high soil moisture content across North Dakota and Minnesota, small inland water bodies, and irrigated lands along the Platte River in southern Nebraska gives rise to a radiometrically colder 10H-GHz TB relative to the surrounding regions. During this time of year, a dryline often separates the warm moist air to the east from the drier air mass and warmer surface temperatures to the west, and regions of convection are noted by 85H-GHz TBs under 200 K (Fig. 5b).

Figures 6a–d depict the first four estimated PCs \( u_0^1, u_0^2, u_0^3, u_0^4 \) for this scene using Eq. (1) (other PCs not shown). The first two PCs \( u_0^1, u_0^2 \) exhibit variations for both high soil moisture and precipitation and have the largest magnitude (within the range in the histograms of Fig. 2), where \( u_0^1 \) shows a larger (and \( u_0^2 \) shows a smaller) value for both wet surfaces and precipitation. For reference, Fig. 6e depicts the 1-h average precipitation from the National Mosaic and Multi-Sensor Quantitative Precipitation Estimation (QPE; NMQ) radar product (Zhang et al. 2011) encompassing the Aqua overpass time, verifying the presence of precipitation in central Nebraska, Texas/Oklahoma, and Wyoming/Colorado with nonprecipitating areas elsewhere. Both \( u_0^3 \) and \( u_0^4 \) exhibit a reduced value in the regions of precipitation relative to all land backgrounds, but they appear to better discriminate the precipitation signal from soil moisture conditions. Both \( u_0^3 \) and \( u_0^4 \) exhibit increasingly smaller values (\( u_0^3 \) falls below 0.4 in several places, and \( u_0^4 \) falls below 0.15), which are values are on the far left side of the histograms of \( u_0^3 \) and \( u_0^4 \) shown earlier in Fig. 2. At first glance, the four-PC discriminator (Fig. 6f) appears very similar to \( u_0^4 \), taking into account the color scale and range of values. However, the four-PC discriminant has the effect of pushing all nonprecipitating scenes more to one side (more positive, red colors in Fig. 6f) and the precipitating scenes to the other (more negative, blue colors). The lighter precipitation noted in the NMQ data over portions of Wyoming–Colorado is
FIG. 5. *Aqua* overpass over the MC3E domain on 11 May 2011 around 2003 UTC. Observed AMSR-E (a) 10H and (b) 85H GHz. The PC-based retrieval of (c) 10H- and (d) 85H-GHz emissivity applied to all scenes. Simulated (e) 10H- and (f) 85H-GHz AMSR-E imagery using the surface emissivities from (c),(d) and the MERRA reanalysis.
FIG. 6. As in Fig. 5, but for maps of the estimated emissivity principal components (a) $u'_1$, (b) $u'_2$, (c) $u'_3$, and (d) $u'_4$ (the values are scaled by 10 in the scale labeling). (e) Hourly NMQ rain rate encompassing this overpass time. (f) Map of the four-PC discriminator.
noted in the four-PC discriminant, with weaker values near ~20. However, from Fig. 3, this value is near the tail end of the clear-scene discriminant histogram, which is indicative of a high probability of precipitation.

Using these nine estimated values for $u^i$, the emissivity vector was estimated using Eq. (2) for all pixels in the scene, and the results are shown in Figs. 5c and 5d for the retrieved 10H- and 85H-GHz emissivities, respectively. As expected, the emissivity at 10H GHz falls to ~0.7 over the high soil moisture areas in the upper Midwest. Over the precipitating regions where this technique is not designed to operate, the 10H emissivity rises to 0.98 or more and 85H falls to 0.7 or less, which are unrealistic values. To test if the emissivity values are consistent over the clear-scene regions, the AMSR-E TB observations were compared to simulated AMSR-E TBs by intentionally assuming cloud-free conditions everywhere. The radiative transfer modeling discussed in section 2 was adapted using an independent atmospheric profile and surface skin temperature taken from the NASA Goddard Modeling and Assimilation Office (GMAO) Modern Era Retrospective Analysis for Research and Applications (MERRA; Rienecker et al. 2011), interpolated to the AMSR-E overpass times and pixel locations. The resultant simulated 10H and 85H TBs are shown in Figs. 5e and 5f, respectively. The agreement with the observed TBs (Figs. 5a and 5b) is very good in the known nonprecipitating areas. The overall root-mean-square difference (RMSD) between the nine observed and simulated nine-channel TBs,

$$\text{RMSD} = \sqrt{\frac{1}{9} \sum_{i=1}^{9} (TB_{i}^{\text{obs}} - TB_{i}^{\text{sim}})^2},$$

is typically no more than 5 K in the known clear areas, but substantially larger (20 K or more) as clouds and rain entered the scene (coincidently, the agreement is very good over water bodies, where the technique was not designed to operate). The difference between observed and simulated TBs was examined by Bytheway and Kummerow (2010), who concluded that a ~10-K difference between the observed 89-GHz TBs and simulated 89-GHz TBs (assuming the absence of precipitation) could be used to identify precipitating scenes, with smaller differences (more negative values) providing an increasingly better indicator of precipitation. Other techniques utilize similar differences between observations and simulated TBs in order to speed up the per-orbit processing [e.g., the operational implementation of the MIRS retrieval scheme (Boukabara et al. 2011) assumes nonprecipitating conditions in its first iteration]. Rather than rely upon TB differences to identify precipitation, the four-PC discriminator is shown in Fig. 6f. Recalling from Fig. 3 that a decrease in value of the discriminant indicates an increasingly higher probability of precipitation, it follows for this case that the values below ~20 are qualitatively matched to the pattern of the NMQ precipitation in Fig. 6e.

In this processing, AMSR-E channel resolution differences were not taken into account, and as a result, Fig. 6f also shows that a similar discriminant value to light precipitation is also noted near some coastline areas. This is a limitation of the technique as currently designed.

b. Cold season: 25 February 2011

The previous examples have represented precipitation scenes and related surface conditions from early summer conditions in the central United States, notably afternoon overpasses with thermally warm land surface temperatures. The ROC analysis presented in Fig. 4 indicated that the PC discriminant-based screen exhibits superior performance to the 85-GHz scattering index most notably during the “coldest” seasons that TRMM samples (Northern Hemisphere winter above 30°N latitude). Both snow covered surfaces and falling snow hydrometeors scatter microwave radiation, masking extraction of the desired radiative signal contributed by the hydrometeors and hindering the interpretation of PMW observations (Grody 2008; Skofronick-Jackson and Johnson 2011). Additionally, the emissivity of typical wintertime latitude scenes (e.g., partially frozen lakes and snow cover) is highly variable owing to the changing snow morphology (Cordisco et al. 2006).

To examine the detection during cold season precipitation and snow cover, a similar analysis is carried out for the nighttime Aqua overpass on 25 February 2011 near 0741 UTC and is presented in Figs. 7 and 8. This snowstorm was one of several to impact the eastern United States during early 2011. Analysis of snow cover from the Snow Data Assimilation System (SNODAS; National Operational Hydrologic Remote Sensing Center 2004) during this time (Fig. 8a) showed that the snow cover border extended across much of the central and eastern United States. The MERRA reanalysis showed that the 0°C 2-m air temperature transition separated rain and snow precipitation across the southern edge of the snow cover (not shown). In Fig. 7b, the 85H-GHz TB falls near 200 K because of precipitation scattering within the rain extending up from the Gulf of Mexico and also across much of the snow-covered regions. The NMQ hourly precipitation (Fig. 8c) clearly identified the convective precipitation moving across the southern United States and light precipitation extending across the snow-covered regions.
Fig. 7. As in Fig. 5, but during the nighttime AMSR-E overpass on 25 Feb 2011 around 0741 UTC.
Fig. 8. As in Fig. 6, but during the nighttime AMSR-E overpass on 25 Feb 2011 around 0741 UTC. Panel (a) has been replaced with the snow depth (cm) obtained from the SNODAS system.
Comparing observed and simulated 89H-GHz TBs (top and bottom rows of Fig. 7, respectively) over the snow-covered regions, there is poor contrast between precipitating and nonprecipitating regions, indicating the difficulty of discriminating light snowfall precipitation from snow on the ground (Munchak and Skofronick-Jackson 2013). From Fig. 8c, the value of $u'_3$ falls below $-0.1$ over nearly all of the snow-covered regions regardless of any precipitation, but $u'_4$ falls below $0.3$ over a smaller region whose pattern is more similar to the NMQ precipitation. There are artifacts due to coastline effects along the eastern edge of Lake Michigan. This is unlike the MC3E case, where both $u'_3$ and $u'_4$ decreased more substantially over precipitation. The resulting four-PC discriminant (Fig. 8f) identifies the liquid precipitation and some of the snowfall. However, the discriminator also assigns a low value to regions where NMQ indicates little or no precipitation (southern Michigan). While promising, analysis of additional cold season cases is needed before the effectiveness of the PC-based discrimination can be fully established.

5. Conclusions

In this manuscript, the information contained within multichannel passive microwave observations was examined for development of a method that enables the joint retrieval of the emissivity vector directly from the observed TB. A principal component (PC) analysis was applied to a set of a large, clear-scene emissivity data gathered under a wide variety of different surface conditions, using coincident CloudSat, CALIPSO, and AIRS data to perform the cloud screening and also to provide the coincident environmental profiles needed to simulate AMSR-E and TMI observations. The emissivity PC vector was expressed by a nonlinear set of TB combinations, allowing the emissivity vector to be reconstructed from the PMW TB observations. The approach varies the emissivity vector in a joint, coherent fashion across diverse surface, soil moisture, and vegetation conditions.

While no independent emissivity ground validation data exist from which to validate the retrieved emissivities, the technique was demonstrated by forward simulating AMSR-E observations collected from Aqua overpasses during several cold and warm season precipitation events. The overall RMSDs between the observed and independently simulated AMSR-E TBs were between $5$ and $7$ K in the nonprecipitating regions that occurred during May 2011 during the MC3E experiment. Since this technique was developed with nonprecipitating observations over land, it was demonstrated how the displacement of the precipitation-sensitive PC components relative to their clear-scene values can be exploited as a conditional precipitation screen. From two years of TRMM observations, where the TRMM PR was used to separate precipitating and nonprecipitating scenes, a linear discriminant built from linear combinations of three and four PCs was shown to exhibit superior relative operating characteristics compared to both the Grody (1991) 85-GHz scattering index and the TRMM 2A12 version 7 screen (Gopalan et al. 2010). While promising, the single cold season precipitation case shown is insufficient to determine the overall efficacy of the PC-based approach for emissivity estimation and precipitation detection over cold and snow-covered surface conditions.

The analysis in this investigation was restricted to the TMI and the TMI-like AMSR-E channels. In the GPM era, PMW radiometer-based precipitation algorithms will have to operate for various constellation radiometers with no companion radar. However, there is no reason why the formulation could not be applied to the across-track sounding radiometers, provided that the channel has sensitivity to the surface and that proper accounting for the viewing angle is taken into consideration. The coarser resolution Special Sensor Microwave Imager/Sounder (SSM/IS) (which lacks 10 GHz capability, but adds key 150 and 183 GHz capabilities) and will be a key sensor for conically scanning PMW-based observations of cold season precipitation in the initial GPM era. Future efforts are steered toward adapting the PC-based formulation to accommodate high-frequency channels for application to SSM/IS using surface and aircraft observations during GCPEx to examine land surface characteristics before, during, and after precipitation events.

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REFERENCES


