Principal Components of Multifrequency Microwave Land Surface Emissivities. Part II: Effects of Previous-Time Precipitation

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ABSTRACT

The microwave land surface emissivity (MLSE) over the continental United States was examined during 2011 as a function of prior rainfall conditions using two independent emissivity estimation techniques, one providing instantaneous estimates based on a clear-scene emissivity principal component (PC) analysis and the other based on physical radiative transfer modeling. Results show that over grass, closed shrub, and cropland, prior rainfall can cause the horizontally polarized 10-GHz brightness temperature (TB) to drop by as much as 20 K, with a corresponding emissivity drop of approximately 0.06, whereby prior rain exhibited little influence on the emissivity over forest because of the dense vegetation. The correlation between emissivity and its leading principal components and the prior rainfall over grass, closed shrub, and cropland is $r^2 = 0.6$, while it is only $r^2 = 0.1$ over forested areas. Forward-simulated TB using the PC-based emissivity derived from instantaneous Tropical Rainfall Measuring Mission (TRMM) satellite overpasses agrees much better with TRMM Microwave Imager (TMI) observations relative to a climatologically based emissivity, especially after a period of heavy rain. Two potential applications of the PC-based emissivity are demonstrated. The first exploits the time history change of the MLSE to estimate the amount of prior rainfall. The second application is a method to estimate the emissivity underneath precipitating radiometric scenes by first adjusting the surface-sensitive principal components that were derived under clear-sky scenes and then by reconstructing the joint emissivity (all channels simultaneously) from the modified PC structure. The results are applicable to future overland passive microwave rainfall retrieval algorithms to simultaneously detect and estimate precipitation amounts under dynamically changing surface conditions.

1. Introduction

Microwave land surface emissivity (MLSE) is a fundamental parameter in physical overland rainfall retrieval algorithm development involving space-based passive microwave (PMW) radiometer observations since it influences the thermal emission and scattering of radiation at the surface. In general, MLSE retrieved from brightness temperature (TB) differs from the soil emissivity in a way that MLSE is an effective emissivity that includes the effects of vegetation. Despite its importance, little previous research has been dedicated to the estimation of MLSE under raining conditions because of a lack of knowledge of how it varies in the presence of clouds and precipitation.

Currently, most MLSE estimations are performed under clear-sky conditions, as discriminated by satellite-based
cloud products or numerical model cloud analysis fields. The estimation approaches can be broadly grouped into three categories: 1) TB-based retrievals that estimate the emissivity by matching radiative-transfer-model (RTM) simulations and satellite-observed TB for each PMW radiometer channel; 2) land surface model (LSM)-based retrievals, where LSM models are coupled to bulk land surface RTM models; and 3) physical emissivity retrieval methods based on PMW TB observations, originally developed for PMW-based soil moisture retrievals (Ferraro et al. 2013). Using a TB-based technique, Jones and Vonder Haar (1990) examined early Special Sensor Microwave Imager (SSM/I) data and estimated the MLSE between 19 and 85 GHz over Colorado. They pointed out that the emissivity at horizontally polarized 19 GHz can decrease to 0.8 because of prior heavy precipitation events or irrigated lands, which significantly wet the surface. Jones and Vonder Haar (1997) further presented a composite emissivity map for a 70-day period over the central United States, which showed that the emissivity over parts of the central Great Plains appeared to be more sensitive to prior heavy rain events, compared with that over other areas in the continental United States. Prigent et al. (1997, 1998) investigated the MLSE at continental and global scales also using SSM/I data under clear sky. They found that the emissivity characteristics vary greatly over different land surface types. For example, compared with less vegetated areas, the microwave emissivity is not strongly polarized over forest, and the horizontally polarized emissivity over forest is generally lower, while the vertically polarized one is higher. Such a phenomenon, that is, vegetation is able to depolarize the emissivity relative to bare soil, has been realized by numerous studies (e.g., Brunfeldt and Ulaby 1986; Tian et al. 2013). Prigent et al. (2005) showed that the PMW emissivities at frequencies of 19 GHz and higher are more sensitive to vegetation than to soil moisture over dense vegetated regions. Their findings were recently condensed into the Tool to Estimate Land Surface Emissivities at Microwave Frequencies (TELSEM; Aires et al. 2011). TELSEM can interpolate the climatological monthly mean emissivity database from a collection of multiyear SSM/I, Advanced Microwave Scanning Radiometer for Earth Observing System (EOS; AMSR-E), and Advanced Microwave Scanning Unit (AMSU) TB at 0.25° × 0.25° resolution. Aires et al. (2011) showed that the use of TELSEM produced an overall positive impact upon numerical weather prediction model forecasts.

Even under clear sky conditions, there exist large errors and uncertainties in the emissivity estimation. Ruston and Vonder Haar (2004) analyzed the SSM/I-based MLSE over the continental United States during three summer seasons and pointed out that the dominant error sources in the MLSE retrieval include inaccurate land surface temperature, subpixel impacts, and undetected clouds. Yang and Weng (2011) showed that the land surface temperature is the primary source of error in emissivity estimation for frequencies lower than 19 GHz. Instead of using surface skin temperatures in the MLSE retrieval algorithm, Norouzi et al. (2012) developed a lookup table of surface effective temperatures, which take the TB diurnal cycle into consideration. Results showed that the differences between day and night emissivities are reduced to less than 0.01 by integrating such a lookup table. By evaluating several MLSE datasets, Tian et al. (2013) demonstrated that there exist large discrepancies among the estimates from different sensors and from different investigators for the same targeted region.

Furthermore, it has been realized that MLSE from different channels are highly correlated. Using data from the Atmospheric Radiation Measurement (ARM) program Southern Great Plains (SGP) site, Lin and Minnis (2000) noticed that the correlation coefficients between emissivity at 19 GHz vertical polarization and emissivities from all other channels on SSM/I are −0.98. Therefore, they suggested that only two or three independent components are needed to determine all other emissivities from SSM/I channels. Based on this premise, Bytheway and Kummerow (2010) proposed an empirical model to estimate emissivities from other AMSR-E channels by using the emissivity from the horizontally polarized 10.7 GHz channel. They also utilized the calculated emissivity at 89 GHz to perform the precipitation detection over three regions in United States and noted improved results.

Once precipitation has been flagged or deemed certain, physically based precipitation estimation from PMW radiometers requires the MLSE under raining conditions. As mentioned, current estimation methods and their subsequent estimates are performed almost exclusively for clear-sky conditions. In Part I of this manuscript, Turk et al. (2013) utilized a principal component (PC) analysis of a multiyear set of clear-sky over land AMSR-E emissivity retrievals collected over all latitudes and seasons and showed that the clear-sky PC structure can be reasonably well estimated by linear and nonlinear TB combinations. Their study focused on instantaneous conditions and did not analyze any prior-time (antecedent) surface conditions. In this Part II manuscript, the PC-based emissivity method of Turk et al. (2013) is further analyzed under clear-scene conditions, where these data are separated by the amount, location, and duration of prior-time precipitation. Therefore, the objective is to quantify how prior rainfall affects MLSE from AMSR-E and similar channels on the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI;
i.e., between 10 and 85 GHz). By doing this, one is able to obtain the emissivity over wet land surfaces, which may be considered as proxy for the emissivity under raining conditions. Recent investigations (Ferraro et al. 2013) noticed that the impact of prior precipitation on the emissivity at one site over the SGP region is most noticeable only after moderate rainfall events (more than 10 mm day$^{-1}$). In this study, the emissivity response to prior rainfall is performed over a portion of the continental United States using hourly rainfall estimations from the National Mosaic and Multi-Sensor Quantitative Precipitation Estimation (QPE; NMQ) data (Zhang et al. 2011). Additionally, we compare these instantaneous MLSE with the climatological TELSEM emissivity (Aires et al. 2011) to illustrate how they differ under various surface wetness conditions and utilize an RTM to evaluate the performance of climatological and instantaneous emissivities under different surface wetness circumstances and under different land cover types. Last, the study explores two unique applications of the instantaneous PC-based emissivity. The first is a means to retrieve some measure of the amount of prior rainfall from the relative time history change of the MLSE. The second is a method to estimate the emissivity underneath precipitating scenes by first adjusting the surface-sensitive principal components that were derived under clear-sky scenes and then reconstructing the joint MLSE (all channels simultaneously) in the presence of precipitation.

2. Data

In this study, the targeted region encompasses the land portion of the domain from 20°–40°N, 70°–130°W, where the surface is lightly vegetated and has seasonal vegetation changes. NMQ, TMI, and AMSR-E data were analyzed from May to August 2011 to capture the period of summer rain and avoid snow events. Primary data sources include the hourly, 1-km gridded NMQ data and the TRMM version 7 1B11 TB datasets, with its nine TMI TBs at frequencies ranging between 10.7 (V/H), 21.3 (V), 37.1 (V/H), and 85.5 (V/H) GHz (V = vertical and H = horizontal polarization) (Kummerow et al. 2000).

Central to this study are two simultaneous emissivity datasets. The first of these is the physically based soil moisture dataset and emissivity retrieval technique developed for the WindSat sensor at the Naval Research Laboratory (Li et al. 2010) that was adapted to version 7 TMI data (Turk et al. 2012). This dataset provides joint retrievals of the soil moisture, vegetation water content, surface temperature, and emissivity at six channels (H/V at 10.7, 19.35, and 37 GHz) under nonprecipitating and non-snow-covered surfaces on a daily 25-km Equal-Area Scalable Earth (EASE) grid, identical to the grid used for AMSR-E land products. Although this physically based MLSE dataset was produced on daily ascending and descending swath composites, each grid point carries the overpass time of the TMI scan that was used, enabling close time alignment with prior-time NMQ precipitation data. Specifically, in this retrieval algorithm, the vegetation is represented as a single-scattering layer above the soil. The effective microwave land surface emissivity can be approximately expressed by the following tau-omega model (Njoku and Li 1999):

$$e_p = e_{sp} \exp(-\tau_c) + (1 - \omega_p)(1 - \exp(-\tau_c))$$

$$\times [1 + r_{sp} \exp(-\tau_c)],$$

(1)

where $e_{sp}$ and $r_{sp} = 1 - e_{sp}$ are the soil emissivity and reflectivity, respectively, at polarization $p$; $\omega_p$ is the vegetation single scattering albedo; and $\tau_c$ is the slant vegetation optical depth. The first term accounts for soil emission attenuated by vegetation. The second term represents emission contribution from vegetation. It is noted that the contribution of $e_{sp}$ to $e_p$ decreases with increasing optical depth $\tau_c$, and that $\tau_c$ itself increases with vegetation water content and frequency.

The second is the Jet Propulsion Laboratory’s (JPL) PC-based MLSE dataset based on an AMSR-E clear-sky PC analysis, described in Part I of this manuscript (Turk et al. 2013), that provides the nine-channel (e.g., TMI-like) MLSE on an instantaneous basis. This PC-based MLSE dataset is based upon first estimating the PC structure from the observed AMSR-E TB and then reconstructing the MLSE vector. The advantage of this technique is that emissivities from all channels are computed simultaneously and without the need for ad hoc (e.g., clustering based) surface classifications. Briefly summarized, the PC-based technique used a PC analysis from an extensive set of clear-sky AMSR-E MLSE, whereby the MLSE vector (denoted by $\tilde{\mathbf{u}}$) was 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 $\mathbf{S}$. Since $\mathbf{u}$ is not known and the factors that control the MLSE are nonlinear processes, each PC element $(u_1, u_2, \ldots, u_9)$ was estimated (estimates denoted by primes) by nonlinear combinations of the nine TMI-like TBs and the polarization ratios at 10, 18, 36, and 89 GHz; for example, for $u_1'$,

$$u_1' = a_0 + a_1 T_{10H} + a_2 T_{10V} + \cdots + a_9 T^2_{10H}$$

$$+ a_{11} T^2_{10V} + \cdots + a_9 (T_{89V} - T_{89H})$$

$$+ \cdots + a_{22} \left(\frac{T_{89V} - T_{89H}}{T_{89V} + T_{89H}}\right).$$

(2)
Least squares regression was used to determine the above 23 \((9 + 9 + 4, \text{ plus the constant term})\) coefficients for each PC. The MLSE can then be jointly estimated from subsequent TMI or AMSR-E data by the PC reconstruction equation,

\[ e' = E \alpha' . \]  

Ancillary datasets employed in this study include climatological TELSEM emissivity (Aires et al. 2011), land surface type (Hansen et al. 2000), and Modern-Era Retrospective Analysis for Research and Applications (MERRA) reanalysis data (Rienecker et al. 2011). TELSEM provides monthly mean emissivities at 0.25° resolution. The relative humidity and temperature profiles from MERRA reanalysis data are provided 8 times daily at an approximate 0.5° resolution from the 3D instantaneous state on pressure levels (inst_3d_asm_Cp) data product and every hour for surface temperature data from the 2D surface and radiation fluxes (tavg1_2d_rad_Nx) data product. Hansen et al. (2000) classified global land surface into 14 categories at 1-km resolution using 1992–1993 Advanced Very High Resolution Radiometer (AVHRR) data. For purely graphical purposes, in the targeted regions we regroup the land cover types into six categories, including forest, wooded grassland, grassland, closed shrub, cropland, and bare ground. The regrouped “forest” includes evergreen needleleaf forest, evergreen broadleaf forest, deciduous broadleaf forest, and mixed forest.

Since the spatiotemporal resolution of different datasets in this study differs significantly, collocation is needed before performing data analysis. Spatially, all TB data are collocated to a 25 km \(\times\) 25 km nominal grid. More details about the TB collocation are provided by Turk et al. (2013). Physically based and PC-based instantaneous emissivities are computed at this nominal resolution. The 1-km native NMQ precipitation pixels are averaged to match this resolution. For all other data (TELSEM, surface temperature, temperature profile, and relative humidity profile), we use data from the closest grid. Temporally, surface temperature, temperature profile, and relative humidity profile are linearly interpolated to match the time of the TB observation.

3. Influence of prior rainfall on MLSE

All emissivity datasets described above were taken from satellite overpasses under nonprecipitating conditions. However, different surface and vegetation types may respond very differently depending upon how much rainfall had fallen prior to the satellite overpass. Therefore, in this section, we will analyze how prior-time accumulated precipitation affects MLSE over different land covers, using the hourly NMQ precipitation data described above.

a. Correlation between emissivities and prior rainfall

The correlation between PC-based emissivity from H10 and prior 1–24-h rainfall amount is calculated at three locations (Fig. 1), whose land cover types are closed shrubland, cropland, and forest, respectively. The purpose of performing this analysis is to investigate whether there exists temporal-resolution dependence for the emissivity response to prior rainfall over different land cover types. That is, how do the duration, timing, and accumulation of the prior-time rainfall affect the current emissivity? Over closed shrubland, the correlation between prior rainfall and emissivity from H10 could be as large as \(-0.6\) (Fig. 1a). It is also noticed that correlation coefficient peaks at the prior 18 h. Different from over shrubland, for cropland it is the prior 24-h accumulated rainfall that has the largest correlation with emissivity from H10. Over forest, prior 8-h rainfall has the largest correlation with emissivity at H10, though such correlation is quite weak. Interestingly, there exists a positive correlation between H10 emissivity and prior 1- and 8-h rainfall over cropland dominated location, with correlation as large as 0.2. Similar to over forest, this phenomenon may be caused by the water intercepted by

![Fig. 1. Correlation coefficients between prior 1–24-h rainfall and emissivity from the H10 channel over (a) closed shrub, (b) cropland, and (c) forest land using PC-based emissivities.](http://journals.ametsoc.org/doi/pdf/10.1175/JHM-D-13-07.1)
crop leaves, to increase the optical depth and therefore cause the “bulk” emissivity increase.

Clearly, the correlation between the number of hours of accumulated rainfall and the emissivity from H10 depends on land cover types. It is also noticed that prior 1-h rainfall always has a very weak correlation with emissivity from H10 in this case study, which is rather counterintuitive. We hypothesized that prior 1-h rainfall should have the largest influence on surface emissivity compared with previous other hours’ accumulated rainfall. The reason why we do not see this in our results is presently unclear. The inaccurate estimation of the surface temperature in the first hour after rainfall may contribute to this low correlation. In addition, the correlations between emissivity from other channels and prior rainfall have similar characteristics over these three locations.

In summary, the influence of the duration of the prior rainfall differs among the land cover types. Throughout the remainder of this study, the prior 24-h accumulated rainfall is used, since the correlation coefficient between emissivity and prior 24-h accumulated rainfall is close to the largest correlation coefficient between emissivity and prior 1–24-h accumulated rainfall, regardless of land cover type.

Next, the correlation between emissivity from H10 and prior 24-h rainfall is calculated over each 1° latitude × 1° longitude grid box (Fig. 2a). It is noted that the largest correlation locates over the SGP and the Mississippi alluvial plain, which are approximately −0.6. Over these regions, the dominant land cover types are grass, closed shrub, and crop. Over New Mexico and Arizona, there also exist some scattered areas with large correlations. In contrast, over the more vegetated eastern United States, the correlation is about 0.1. The opposite sign of this correlation coefficient may due to the fact that the PC-based emissivity, being purely observationally based, inherently accounts for any effects of intercepted rain drops by tree leaves. In Fig. 2b, the correlation between emissivity from H10 and the first PC is shown. For comparison purposes, this correlation coefficient is multiplied by −1. Obviously, the correlation pattern is very similar to those calculated using PC-based emissivities, though the magnitude of this correlation coefficient is slightly smaller. It is worth mentioning that using emissivities from other channels will lead to similar results.

To summarize, the prior 24-h accumulated rainfall has the largest correlation with emissivity over closed shrub and crop-dominated regions, such as the SGP. On the other hand, over forest region, prior rainfall has little impact on the emissivity, thus resulting in a much weaker correlation between prior rainfall and emissivity.

b. Two case studies

As an example, two locations over different land cover types are chosen to demonstrate how the MLSE responds to prior rainfall. The center latitude–longitude for these two locations are (31.83°N, 85.44°W) and (32.06°N, 100.81°W), where dominant land cover types are forest and closed shrubland, respectively. For every TRMM satellite overpass under clear-sky conditions, the TMI PC-based emissivities are compared to the prior 24-h rainfall from NMQ at these two locations. The results are...
shown in Figs. 3 and 4. Over closed shrubland (Fig. 3), the emissivities from the H10 GHz to H37 GHz channels show noticeable decrease when it previously rained. In particular, emissivity from the H10 GHz channel can drop as much as ~0.07 after previously heavy rain (Fig. 3a). The first and third PCs show a large increase corresponding to periods of prior heavy rainfall, whereas the fourth PC varies little at this location.

In contrast to the emissivity response to prior rainfall over shrubland, both emissivities from H10 to H37 and PCs show little variation over forest land, regardless of prior rain amounts (Fig. 4). It is worth mentioning that emissivities from vertically polarized channels respond similarly to the prior rainfall, though the magnitude is smaller. In summary, over shrubland-dominant location, the emissivities decrease greatly corresponding to periods of prior heavy rainfall, while little variation is observed over forest area regardless of prior raining conditions.

c. Emissivity variations caused by prior rainfall

Next, using the PC-based instantaneous emissivities, we calculate the difference between emissivities when no rain occurred in the prior 24 h and when it rained more than 20 mm in the prior 24 h, in each $1^\circ \times 1^\circ$ grid box in the study region, as shown in Fig. 5. The largest difference (~0.05 from H10) is located over the SGP region and the Mississippi alluvial plain, where the dominant land cover types are grass and cropland, respectively (Fig. 5d). Such a characteristic is apparent from all frequencies. In contrast, over more vegetated regions in the eastern United States, prior rainfall causes a much smaller emissivity variation (~0.01). The magnitude of emissivity difference caused by prior rainfall is larger from the H10 channel than that from the H19 and H37 channels because of its stronger sensitivity to wet–dry soil changes. It is noticed that prior rainfall may result in a small emissivity increase (~0.01) over forest-dominant areas. Such an increase probably stems from the optical depth increase due to water-covered leaf structure (e.g., Li and Min 2013), though other possible explanations cannot be excluded and deserve further investigation in the future.

The TB difference caused by the emissivity change has been computed and is shown in Fig. 6. Not surprisingly, the large TB decrease is located over the SGP and the Mississippi alluvial plain, where the emissivities decrease is most obvious. Over the aforementioned two regions, the magnitude of the TB decrease at H10 could be as large as ~25 K. However, the surface temperature

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**Fig. 3.** PC-based emissivity over a closed-shrub-dominant location. (a) Emissivity from the H10 channel response to the prior 24-h rainfall. (b) As in (a), but for the H19 and (c) the H37 channel. Responses to 24-h rainfall: (d) PC1, (e) PC3 and (f) PC4. (g) Prior 24-h rainfall. The “Number of Obs.” stands for the intermittent satellite observations over this specific area.
may also decrease by ~5 K over such regions, along with prior rainfall (Fig. 6d). Therefore, the net TB decrease at H10 caused by emissivity drop over these two regions is approximately 20 K. For the H19 and H37 channels, the net TB decrease is ~5–10 K. Though not shown, both emissivity and TB variations from the H85 channel caused by prior 24-h rainfall (>20 mm) are less than 0.01 and 5 K, respectively. Indeed, when using a larger prior 24-h rainfall as criteria (e.g., 40 mm), the corresponding emissivity and TB variation will increase.

To summarize, the large emissivity and TB decrease caused by prior 24-h heavy rainfall (>20 mm) appears over the SGP and the Mississippi alluvial plain. The different responses to prior rainfall over shrubland and forest have been explained by prior works (e.g., Jackson 1993; Li et al. 2010), which can be summarized in two major reasons. First, the soil moisture is generally higher over forest region than that over shrub-dominated land, which will lead to a relatively weaker response over forest for the same amount of prior rainfall. Additionally, the larger optical depth of forest canopy will more effectively attenuate emission from soil, as shown in Eq. (1).

Finally, we would like to mention that similar analysis has also been conducted using the physically based emissivity. The major conclusions still hold, though the numerical value is somewhat different.

4. Model simulations using three different emissivity datasets

Since the in situ MLSE cannot be measured at such a large spatial scale, it is difficult to directly evaluate or verify different MSLE datasets. As an alternative, RTM simulations are used to simulate the observed TB corresponding to TRMM satellite overpasses using these three emissivity datasets (i.e., TELSEM, PC-based emissivity, and physically based emissivity), and then these emissivity datasets are evaluated by comparing the simulated TB with TMI observations. The microwave RTM used in this study was developed by Liu (1998) and updated later with improved ice particle handling by incorporating results from single-scattering properties of ice particles (Liu 2008). The model applies a discrete ordinate method to solve microwave radiation transfer for the plane parallel atmosphere at specified frequencies using profiles of the atmosphere (e.g., relative humidity and temperature profiles) and hydrometeors (e.g., snow and raindrops). Additionally, this RTM itself
does not account for the soil and vegetation properties. These properties are taken into consideration through varying surface emissivities.

The surface temperature plays an important role in the process of retrieving the surface emissivity under clear-sky condition. We are aware that different surface temperature products are used in the emissivity calculations for the different emissivity databases. Specifically, International Satellite Cloud Climatology Project (ISCCP) skin temperature and Atmospheric Infrared Sounder (AIRS) temperature are used for TELSEM and PC-based emissivities, respectively. For the physically based emissivity, the surface temperature is directly retrieved from microwave brightness temperatures together with emissivity, soil moisture, and vegetation water content. We compared these products by calculating the differences among them (not shown). It is found that approximately 90% of the ISSCP, AIRS, and physically based surface temperatures are within 5 K of those from the MERRA reanalysis that is employed in this study. There indeed exist large temperature differences over desert areas that may be caused by the temperature gradient in the soil emitting layer. This feature has also been noticed by prior investigators (e.g., Prigent et al. 2005; Mathew et al. 2008). We focus on the prior rainfall impact on surface emissivity. The large differences over desert areas are shown in Fig.

![Figure 5](http://example.com/figure5.png)

**Fig. 5.** Difference between PC-based emissivities from the (a) H10, (b) H19, and (c) H37 channels when no rain occurred in the prior 24 h and when it rained ≥20 mm in the prior 24 h. (d) Dominant land cover types over the study region.
areas will not change our major conclusions since it rarely rains over desert regions.

a. Case study from 12 August 2011

A clear-sky scene on 12 August 2011 was selected where heavy rain had occurred in the prior 24 h, over the area of 32.5°–36.5°N, 100°–97°W (Fig. 7i), since it has already been demonstrated in section 3 that over this region the prior rainfall can greatly impact the surface emissivity. Because it is clear sky in this case, there are no hydrometeors or clouds taken into consideration in the model simulation, only the temperature, humidity, and surface temperature information from the MERRA data (section 2) interpolated in time and space to the TMI locations. Only the surface emissivity varies in the simulations; all the other parameters (surface temperature, temperature, and humidity profiles) are exactly the same in these simulations. TB simulations for the V19, V37, and V85 channels are shown at Figs. 7a–h. The root-mean-square error (RMSE) for simulated TBs for the V19 channel is 5.33, 3.68, and 4.82 when using the TELSEM, PC-based, and the physically based emissivities, respectively (Figs. 7a–c). Clearly, the RMSE using the PC-based emissivity is the smallest. Furthermore, the correlation coefficient between the simulated and observed TB for the V19 channel is the largest (0.92, see Fig. 7b) when utilizing the PC-based emissivity. It is worth mentioning that the simulated TB for V19 using the TELSEM emissivity is almost a straight line because, being a climatological value, there are only a few different emissivity values in this case. For all three emissivity datasets, the simulated TBs for V37 agree well with the observed TBs when the surface is relatively dry (corresponding to observed TBs between 280 and 290 K). However, when it rained heavily previously (corresponding to observed TBs less than 280 K), the simulated TBs at V37 using the TELSEM emissivity vary little (Fig. 7d). The simulated TBs for the V37 channels using the

![Fig. 6. As in Fig. 5, but for TBs and (d) as in (a)–(c), but for surface temperatures.](http://journals.ametsoc.org/doi/pdf/10.1175/JHM-D-13-07.1)
PC-based emissivity (Fig. 7e) agree much better with observations than when using the TELSEM emissivity dataset, though there is a slight overestimation when it previously rained heavily. Simulated results for V37 using the physically based emissivity (Fig. 7f) are in between the TELSEM and the PC-based results. For the simulated results from V85 (Figs. 7g,h), the TELSEM emissivity seems better in terms of correlation coefficient and RMSE because there exist several outliers in the simulations using the PC-based emissivities. All the simulations for the corresponding horizontal polarized channels (H19, H37, and H85) are illustrated in Fig. 8. Similarly, the simulations using the PC-based emissivity are the closest to observations in terms of correlation and RMSE.

In summary, for this case, the simulated TB using the PC-based emissivity tends to agree best with observations, and the TELSEM emissivity does not represent wet surface very well. The physically based MLSE performs better than TELSEM, but worse than the PC-based MLSE.

b. Simulations over entire study region

Employing the same procedure as in the above case study, simulations are carried out over the whole study area, and the results are shown in Fig. 9. The simulated TBs at the H19 channel (Fig. 9a) show two tails using the TELSEM emissivity, which leads to a large RMSE (13.57 K) and smaller correlation (0.42). Further examination shows that the upper-left tail is caused by wet surface (i.e., prior heavy rain conditions). The vast majority of the points at the bottom-right tail are located over coastal regions. The simulated results for the H19...
channel (Fig. 9b) using the PC-based emissivity agree much better with observations, with RMSE and correlation being 4.86 K and 0.87, respectively. It is worth mentioning that simulated TBs using the PC-based emissivity are slightly positively biased, especially when the surface is wet. Simulations for the H19 channel using the physically based emissivity also show clear upper-left tails, indicating that this emissivity does not perform well under wet surface conditions. For the simulations for the H37 channel using all three emissivity datasets, similar characteristics as for H19 channels are observed (Figs. 9d–f). Interestingly, the upper-left tails are evident for both simulations using the TELSEM and the PC-based emissivities from the H85 channel (Figs. 9g,h), which is probably caused by cloud contamination within the assumed clear-sky scene. Simulations from vertically polarized channels show very similar characteristics (not shown).

In summary, simulated TBs using the PC-based instantaneous MLSE dataset show the best agreement with observations. The simulations using the TELSEM climatological emissivity dataset do not perform well under wet surfaces and over coastal regions. In addition, the physically based emissivity dataset does not perform well over wet surfaces, either.

5. Applications of instantaneous PC-based emissivity

In section 3, we showed that over the SGP the prior 24-h rainfall is able to significantly impact the MLSE, especially for low frequencies (e.g., 10 GHz). Therefore, in this section, we examine whether it is possible to employ this correlation to retrieve prior 24-h rainfall. If possible, this implies that one could estimate precipitation accumulations directly from individual TMI-like satellite

Fig. 8. As in Fig. 7, but for the horizontally polarized channels.
overpasses and alleviates the sampling issues associated with merging intermittent, sometimes widely spaced satellite overpasses, especially in the tropical latitudes (Huffman et al. 2007).

a. Using clear-sky emissivity to retrieve prior rainfall

A case study over the area from 31°–32°N, 99°–100°W is conducted to show the ability of using H10-derived emissivity to retrieve prior 24-h rainfall. Over this selected area, there are 220 data points of both PC-based emissivity from H10 and prior 24-h rainfall. These observations are randomly separated into two subsets, each including half of the data (110 observations). The first subset is used to train a curve between emissivity from H10 and prior 24-h rainfall, shown in Fig. 10a. The solid line ($y = 0.67x^{-2.5}$) depicts the fitting curve using a power-law relationship. Using this relation, the prior 24-h rainfall in the second subset is predicted, and the results are shown in Fig. 11b, as compared with observed prior 24-h rainfall. The predicted values agree reasonably well with the observations, with the correlation coefficient and RMSE being 0.59 and 11.39 K, respectively. It is also noticed that there exists noticeable underestimation for prior 24-h heavy rainfall (>40 mm), which could be due to the minimal number of observations in this range or to effects stemming from the saturation of the soil conditions. However, this limited study showed that it is possible to use clear-sky emissivity to retrieve prior 24-h rainfall over particular regions where there exists a good correlation between prior rainfall and emissivity.

It is worth mentioning that studies have already been performed to use soil moisture information to improve
the accumulated rainfall accuracy (e.g., Crow et al. 2009). In our case study, emissivity derived from clear-sky brightness temperatures from the H10 channel is used to directly retrieve the prior 24-h accumulated rainfall amount. This approach has the potential to increase the utility of brightness temperature since approximately 85% of brightness temperatures are obtained under clear-sky conditions.

b. Adjusting emissivities under raining conditions

As stated in section 1, all the emissivity datasets are currently developed for clear skies. In this section, we will explore the possibility of using the relation between the surface-sensitive PCs and the amount of prior rainfall to adjust the clear-sky emissivity and use this as a proxy for the emissivity under precipitating scenes. Turk et al. (2013) in Part I showed that three PCs (first, third, and fourth) are the most sensitive components to surface conditions. Therefore, Eq. (2) is employed to estimate PCs under raining scenarios. Because this equation was developed under clear sky conditions, the three PCs are then further adjusted or modified prior to the emissivity reconstruction in Eq. (3). The underlying assumption for this adjustment technique is that, regardless of clear-sky or raining conditions, the relationship between PCs and surface wetness is similar. That is to say, under clear-sky or under raining conditions, the relationship between emissivities and surface wetness is similar since the PCs and emissivities are directly related through Eq. (3). The adjustment procedure developed in this study is based on matching simulated and observed multichannel TB.

An area (31°–32°N, 99°–100°W) over the SGP was selected to demonstrate how this emissivity adjustment is performed under raining conditions. The scatterplots between three PCs (first, third, and fourth) and prior rainfall over the selected area are shown in Fig. 11, where solid lines denote the least squares linear fitting curves. When it is raining over this area, in most cases, this emissivity estimation is positively biased since Eq. (2) was developed under clear sky. Therefore, an adjustment procedure is needed. To do the adjustment, we choose

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**Fig. 10.** Analysis of prior rainfall and emissivity change over the region 31°–32°N, 99°–100°W. (a) Scatterplot between emissivity from H10 and the prior 24-h rainfall using trained subset data. Solid curve denotes the least squares fit line. (b) Scatterplot between predicted and observed prior 24-h rainfall using validation subset data.

**Fig. 11.** Scatterplots between (a) PC1, (b) PC3, and (c) PC4 and prior 24-h rainfall.
a fairly heavy prior rainfall amount (20 mm day$^{-1}$) from the $x$ axis of Fig. 11, and then the three corresponding PCs on the red curves from Figs. 11a–c are obtained (e.g., $-24.2$, $0.1$, and $3.3$). Instead of using directly estimated PC1, PC3, and PC4, these three new PCs are used in their place when applying Eq. (3). By doing this, nine new emissivities are obtained, but for this study only the emissivity from the H10 channel is chosen for the simulation. If the difference between simulated and observed TBs from the H10 channel is less than 10 K, the nine emissivities are taken as estimated emissivities under raining condition. Otherwise, the same procedure is repeated by randomly choosing three other PCs (corresponding to the same prior rainfall amount) until the difference between simulated and observed TBs from the H10 channel is less than 10 K.

Between May and August 2011, there existed 112 observed raining pixels in this area. The hydrometeor profiles for these 112 pixels are taken from the TRMM 2A25 version 7 Precipitation Radar (PR) water content retrievals. For RTM inputs, hydrometeors are assumed to be snow above and rain under the freezing level. All

FIG. 12. Scatterplots between simulated and observed TBs from channels: (a),(b) H10, (c),(d) H19, and (e),(f) H37 channels (left) before and (right) after adjustment.
other variables, such as surface temperature, temperature, and relative humidity profiles, are taken from the MERRA reanalysis dataset. Figure 12a shows the simulated TBs for H10 before applying such an adjustment procedure (i.e., using clear-sky emissivity). Clearly, the vast majority of the simulated TBs has a warm bias, due to using the clear-sky emissivities. After the adjustment, the differences between simulated and observed TBs are less than 10 K for H10 (Fig. 12b). Similarly, Fig. 12d shows for H19 that simulated TBs using the adjusted emissivities agree much better with observations than those when using clear-sky emissivities (Fig. 12c). For the H37 channel (Figs. 12e,f), the adjusted emissivity has little impact on the majority of simulations. However, it is noticed that the simulations are closer to observations when the observed TBs are greater than 280 K, corresponding to rainfall less than ~6 mm h~1. When the rainfall is ~10 mm h~1, the emissivity adjustment may have very little influence to the simulated TB. Because of the high sensitivity to the hydrometeors, not surprisingly, the emissivity adjustment has little influence to the simulations for H85 (not shown). Figure 13 shows the simulations for vertically polarized channels with and without applying this adjustment. Similarly, without...
such adjustment, there exist obvious positive biases for most of the simulations; particularly for TB simulations from the V10 and V19 channels.

The emissivities with and without adjustments (blue and red curves, respectively) for the 10, 19, and 37 GHz channels are shown in Fig. 14 for data over the selected box. The mean value of raining-scene emissivity from H10 (Fig. 14a) is ~0.09 lower than the mean of non-adjusted emissivities, which leads to a ~25 K decrease of the associated TBs. For the emissivities from V10, the mean value drops ~0.05 with respect to the nonadjusted emissivities. On several occasions, the raining emissivities from V10 are less than 0.9 because of heavy rain (>10 mm h$^{-1}$). Under such circumstances, this adjustment technique will lead to an inaccurate emissivity because of strong absorption by the rain droplets. In fact, when it is raining heavily (>10 mm h$^{-1}$), the surface emissivity has little influence to the eventually observed TB. Similar characteristics are observed for emissivities from the 19 GHz and 37 GHz channels.

In summary, using the relationship between PCs and prior rainfall, we dynamically and consistently adjust nine emissivities, and a proxy for the emissivity under raining conditions is obtained. Results showed applying such adjusted emissivities will greatly reduce the positive biases in simulated TB (resulting from using clear-sky emissivities in the rain), and bring the simulated TB closer to observations. It is worth mentioning that
rainfall will decrease to a larger extent, horizontally polarized channel emissivities than emissivities from vertically polarized channel. It is also noticed that this adjustment technique does not perform well under heavy rainfall (>10 mm h⁻¹), probably because the heavy rainfall will obscure the surface emission. Additionally, under a raining scenario, the land surface is much more prone to be saturated. Therefore, more data obtained under previously heavy rain conditions are needed to investigate how the PCs behave when the surface is saturated. In addition, we understood that there exists large uncertainty in the hydrometeor profiles employed in this study (e.g., Munchak and Kummerow 2011). Therefore, the estimated emissivities can only be taken as approximations. In essence, our major objective for this case study is to show that the nine TMI emissivities can be investigated how the PCs behave when the surface is saturated. In addition, we understood that there exists large uncertainty in the hydrometeor profiles employed in this study (e.g., Munchak and Kummerow 2011). Therefore, the estimated emissivities can only be taken as approximations. In essence, our major objective for this case study is to show that the nine TMI emissivities can be reconstructed simultaneously through only varying three PCs, even under raining scenarios.

6. Conclusions

Using NMQ hourly rainfall and the PC-based and the physically based instantaneous microwave land surface emissivity (MLSE) datasets, we investigated the correlation between emissivity and prior rainfall. Large correlations were found over the Southern Great Plains and the Mississippi alluvial plain. The correlation coefficients over the SGP were as high as ~0.6. On the other hand, the correlation over forest regions was much weaker, indicating that emissivities over forest respond weakly to prior rainfall. We also investigated the response of the MLSE to prior rainfall duration, timing, and amount. It was found that prior rainfall produced large emissivity decreases over the SGP and the Mississippi alluvial plain. The dominant land cover types over these two regions are grass, closed shrub, and crop. In particular, prior 24-h heavy rainfall (>20 mm) can lead to a ~0.06 emissivity decrease for the H10 channel; this corresponds to a net ~20 K TB decrease. In addition, for the same prior rainfall, the higher the frequency, the smaller such emissivity decreases will be. In contrast, over forest-dominant areas (e.g., eastern United States), emissivities do not vary much with prior rainfall (~0.1 from the H10 channel).

The comparison among the PC-based MLSE, physically based MLSE, and the TELSEM climatological MLSE datasets was conducted over continental United States. Results show that the simulated brightness temperatures (TBs) using the PC-based emissivities agree the best with TRMM satellite observations with correlation and RMSE being ~0.80 and ~5.0 K, respectively, for all channels. For the climatological TELSEM emissivity, there exist two major biases. One is that it overestimates the wet-surface emissivity, leading to higher simulated TBs relative to the TMI-observed TBs. The other is that it underestimates the coastal region emissivity, resulting in lower simulated multichannel TBs than observed. These biases lead to a lower correlation (~0.45) between simulated and observed TBs. The overestimation for wet surfaces in the physically based emissivity dataset is also noticeable. We note that while the NMQ data were used to screen precipitating scenes, there is likely nonprecipitating cloud contamination that may contribute significantly to the emissivity estimation errors, especially for the 85 GHz channels.

Two potential applications of the instantaneous emissivity were investigated. First, it was demonstrated that clear-sky emissivity from low frequency (e.g., H10) channels is well correlated with prior 24-h rainfall over the SGP. Using such a relationship, we estimated the prior 24-h rainfall that is needed to produce this same emissivity and which agreed fairly well with the observed prior 24-h rainfall (correlation coefficient of 0.59). Additionally, using the relationship between PCs and prior rainfall, the raining-scene emissivities from the 10, 19, and 37 GHz can be estimated. The applications of proper raining-scene emissivities will greatly reduce the positive biases in simulated TBs (resulting from using clear-sky emissivities in the rain) and bring the simulated TBs closer to observations. This emissivity adjustment technique does not work well under moderate to heavy rain (>10 mm h⁻¹) since the rain particles almost completely obscure the surface. Because of the promising results in these case studies, further application of these techniques over a much larger scale is under current development.

Finally, we would like to emphasize that the primary objective of this study was to investigate the emissivity response to the precipitation in the summer over a portion of United States. Investigation of the emissivity response in other seasons is currently underway. Such an analysis will be particularly beneficial for the physical rainfall retrieval algorithm development for global precipitation measurement.

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