Assessment of the consistency among Global Microwave Land Surface Emissivity Products

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Abstract

The goal of this work is to inter-compare four global land surface emissivity products over various land-cover conditions to assess their consistency. The intercompared retrieved land emissivity products were generated over five-year period (2003-2007) using observations from the Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E), Special Sensor Microwave Imager (SSM/I), The Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) and Windsat. First, all products were reprocessed in the same projection and spatial resolution as they were generated from sensors with various configurations. Then, the mean value and standard deviations of monthly emissivity values were calculated for each product to assess the spatial distribution of the consistencies/inconsistencies among the products across the globe. The emissivity products were also compared to soil

moisture estimates and satellite-based vegetation index to assess their sensitivities to the changes in land surface conditions.

Results show the existence of systematic differences among the products. Also, it was noticed that emissivity values in each product has similar frequency dependency over different land cover types. Monthly means of emissivity values from AMSR-E in the vertical and horizontal polarizations seem to be systematically lower than the rest of the products across various land cover condition which may be attributed to the 1:30 AM/PM overpass time of the sensor and possibly a residual skin temperature effect in the product. The standard deviation of the analysed products was the lowest (less than 0.01) in rain forest regions for all products and the highest in northern latitudes, above 0.04 for AMSR-E and SSM/I and around 0.03 for WindSat. Despite differences in absolute emissivity estimates, all products were similarly sensitive to changes in soil moisture and vegetation. The correlation between the emissivity polarization differences and NDVI values showed similar spatial distribution across the products with values close to the unit except over densely vegetated and desert areas.

1 Introduction

In Numerical Weather Prediction (NWP) models, instantaneous microwave land surface emissivity is an important boundary condition that needs to be determined accurately in order to retrieve reliable atmospheric profiles. It was suggested that 1 percent accuracy level in emissivity retrievals is required in applications such as NWP and microwave satellite-based precipitation algorithms (Karbou et al., 2006) to ensure the development of reliable weather products. Other applications of emissivity values include determination of changes in land surface condition as well as understanding the variabilityof land emissivitywhich implies relying on estimates from different sensors and therefore the importance of investigating the consistency among the available products.

A number of microwave land emissivity products that are associated to different sensors were proposed in the literature. The used sensors to infer land emissivity have common and in certain cases unique frequency channels. Relying on a single sensor's estimates reduces the potential of the available retrievals from the other sensors. It is therefore important to integrate all retrievals to maximize the spectral range of land emissivity products for an effective use in NWP or land surface classification. However, this requires understanding the consistency among the existing products which is the first necessary step towards integrating land surface emissivity values from different sensors. Ultimately, a single blended land emissivity product which should minimize the limitation of each individual standalone product from a single sensor could be proposed.

The sources of discrepancies among the existing land emissivity products are various and they mainly fall into one of the two following categories. The first category includes the sensor's parameters. As microwave land surface emissivity values are impacted by several surface and subsurface parameters like soil moisture, vegetation structure and density, freeze and thaw states, soil texture, and topography, a change in one or a number of these land parameters should impact the determined land emissivity differently depending on the configuration of the sensor, i.e. frequency, polarization, overpass time, incident angle, footprint, etc. In addition, even if two sensors concur in terms of frequency and observation geometry, a difference in their calibration process may introduce a gap between their readings. Polar orbiting satellites, which observe the earth at least twice a day, have different acquisition times that make their corresponding brightness temperature vary.

The second category of factors which may affect the consistency among the land emissivity products is relative to the retrieval method and used ancillary data which may introduce an inherent difference in the emissivity estimates. Physical models and retrieval techniques have commonly been utilized to estimate land surface emissivity with their own benefits and pitfalls. The retrieval of land emissivity involves the use of land surface temperature which could be obtained from another sensor like the Moderate-resolution Imaging Spectroradiometer (MODIS) or from reanalysis like the National Centers for Environmental Prediction (NCEP) outputs. Theoretically, in emissivity retrievals the effect of temperature is removed and one should expect similar surface condition from different sensors regardless of their acquisition time, especially when they are aggregated in a monthly scale. Emissivity is calculated using a radiative transfer models traditionally for cloud-free scenes since clouds greatly affect the signal. However, even over cloud-free pixels, accounting for the atmospheric contribution was necessary especially for frequencies higher than 19 GHz. Many studies attempted to estimate emissivity using forward modeling (Boukabara et al., 2011; Ringerud et al., 2014; Weng et al., 2001). These models often use emissivity retrieval from satellite observations as a reference in their algorithms. Physical radiative transfer models benefit from including all controlling parameters in algorithms.

However, such comprehensive approach requires several inputs such as soil type, moisture, and temperature that are difficult to obtain in large or global scales (e.g. (Ringerud et al., 2014; Weng et al., 2001)). Global land emissivity retrieval first was developed by Prigent et al (1998) when brightness temperatures (TB) from the Special Sensor Microwave Imager (SSM/I) were used. Other available products later were proposed from other sensors such as the Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E) (Moncet et al., 2011; Norouzi et al., 2011), the Advanced microwave sounding unit (AMSU) (Karbou et al., 2005), and the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) (Furuzawa et al., 2012). To retrieve land emissivity values, those studies did not necessarily use the same ancillary data, radiative transfer model, and assumptions to account for the atmospheric contribution. Also, microwave brightness temperatures from a variety of sensors with varying configurations (i.e., observation geometry, frequency, resolution. etc) were used to generate the global land emissivity maps. Therefore discrepancies among the available land global emissivity maps are expected.

Emissivity estimates from different products were first intercompared as part of a joint effort by members of Land Surface Working Group (LSWG) part of Global Precipitation Measurement (GPM) mission with the goal of improving retrievals from the recently launched GPM satellite (Ferraro et al., 2013). The emissivity estimates were compared at three points that coincide with previous and ongoing in situ measurements for Soil Moisture Active and Passive (SMAP) and GPM missions. The results showed noticeable differences among estimates, with similar seasonal trends and variability.

In another study, the emissivity estimates from various sensors and providers at four locations with different land cover types: 2 desert and 2 rain forest locations, were evaluated, and large discrepancies were found across the sensors with different spectral signatures (Tian et al., 2014). Tian et al.'s study accounted for random and systematic errors using statistical approaches and suggested that the differences among retrievals are caused likely by cloud or rain contaminations.

The goal of this study is to expand the point-based inter-comparisons to the global scale and investigate the relative consistency among different land surface emissivity products. The lack of ground truth measurements at a global scale made the validation and the benchmarking of each land emissivity product difficult. In this study, we propose to overcome this lack of ground truth data by investigating the consistency among the available global land emissivity estimates from different sensors. We assume that the consistency among the existent land emissivity products is an indicator of the reliability of the retrievals. The analysis of the consistency among the products was conducted over different land classes. It quantitatively compares available estimates from different sensors. It is, to our knowledge, a first attempt to assess the consistency among land emissivity products over different land cover types in a global scale. It also aims to examine the dynamics of the products in monthly scale and find their relationships with surface properties such as soil moisture and vegetation change both spatially and temporally. This study focuses on emissivity retrievals from microwave sensors with constant incidence angle over a five-year period.

2 Data Sets

Five years (from January 2003 to December 2007) of land emissivity data from different providers were collected. The sensors included in this study are AMSR-E, SSM/I, TMI, and WindSat. SSM/I-based emissivity product is generated by Centre National de la Recherche Scientifique (CNRS) in France (Prigent et al., 2006; Prigent et al., 1998). This data set has the longest available record of emissivity estimates for frequencies of 19 to 85 GHz. The data set uses International Satellite Cloud Climatology Project (ISCCP) skin temperature and the National Centers for Environmental Prediction (NCEP) reanalysis for air temperature and water vapor column.

The AMSR-E instantaneous emissivity is produced by National Oceanic Atmospheric Administration (NOAA) Cooperative Remote Sensing and Technology (CREST) center for more than six years and is available in monthly scale on the National Snow and Ice Data Center (NSIDC) website (Norouzi, 2013). This retrieval uses ancillary data from ISCCP and The TIROS Operational Vertical Sounder (TOVS) for skin temperature, cloud mask, and atmospheric information (Rossow and Schiffer, 1999).

Emissivity product based on TMI observations is provided by Nagoya University in monthly format (Furuzawa et al., 2012). This product uses Japanese 25-year ReAnalysis (JRA-25) as ancillary data (Onogi et al., 2007). It finds required parameters from JRA-25 by an interpolation technique based on TMI acquisition time for each pixel.

WindSat emissivity estimates are derived based on Atmospheric Infrared Sounder (AIRS) and NCEP data (Turk et al., 2014).

All sensors, except TMI, are sun-synchronous and have ascending and descending overpasses. They are all microwave imagers (not sounders) and have few years of overlap in their life span. There are some differences in frequencies, incidence angle, acquisition time, footprint, and calibration of these microwave sensors. Unlike to other polar orbiting sensors that are considered in this study, the geographic coverage of TMI does not includes areas above and below 38^0S and 38^0N latitude, respectively. The details of these differences are listed in Table 1.

A vegetation and land use global data set compiled from a large number of published sources at 1° equal area grid resolution by Matthews (1983)adopted by Prigent et al. (2001) in 0.25° is used in this study to distinguish various surfaces types. The land classes include rain forest, evergreen forest, deciduous forest, evergreen woodland, deciduous woodland, cultivation, grassland, tundra, shrub land, and desert.

3 Method

Resampling of data products; first, it was necessary to reprocess the selected land emissivity products by re-projecting them in a common equal area grid (0.25° at equator) projection and resampling them to the same spatial resolution. This step is required to make the intercomparison possible despite the systematic differences that it may introduce. There were no further adjustments done, in terms of interfrequency or interangles interpolations, to account for the differences in the sensors' configurations and observation geometries. The intercomparison was performed on a global scale except in the case of TMI where the spatial coverage of the sensor was limited to ±38 degree latitude region.

The mean values of monthly emissivity products from each sensor were calculated for the period of 2003 to 2007 to determine the relative differences among the monthly variation of emissivity products.

Moreover, standard deviation of monthly estimates from each product for each pixel is calculated as representative of dynamics of emissivity using 5 years of monthly data.

Microwave emissivity Polarization Difference Index (MPDI): the intercomparison of different land emissivity products included analysis of their sensitivity to the different land surface parameters. To this end, a polarization index, Microwave emissivity Polarization Difference (MPDI) was calculated. The MPDI should exhibit greater sensitivity to surface parameters and mitigate the effect of the atmosphere and land surface temperature and therefore reduce their impact on the reliability of the products' intercomparison. In addition, it has been shown that differences between horizontal and vertical polarization signals contain a wealth of information regarding soil moisture and vegetation density (Felde, 1998). There are many indices that take into account this difference which Microwave brightness temperature Polarization Difference Index is amongst them. Emissivity-based MPDI is defined as:

$$MPDI = \frac{\varepsilon_v - \varepsilon_h}{\varepsilon_v + \varepsilon_h} \tag{1}$$

where $\varepsilon_v, \varepsilon_h$ are emissivities at vertical and horizontal polarization respectively for a specific frequency. This index is calculated for each pixel and then is evaluated with satellite-based soil moisture and Normalized Difference Vegetation Index (NDVI).

4 Results and discussion

Monthly mean values were calculated for all products from January 2003 to December 2007. The obtained results were averaged over the different land cover types, namely, rain forest, evergreen woodland, grassland, and deserts. Figure 1 reveals clear differences among the emissivity products which are sensitive to frequencies and land cover conditions. Over densely vegetated areas such as rain forests the discrepancies among the products are larger in high frequencies to reach, for instance, 0.06 between AMSR-E 89 GHz and TMI 85 GHz horizontal emissivity values. The products show better agreement in lower frequencies which involve less scattering and deeper penetration into the canopy unlike high frequency brightness temperature which penetrates less and reflects the top of the canopy microwave radiating temperature. The use of the canopy skin temperature, in rain forest region, to approximate the canopy effective temperature for low and high frequencies in the emissivity retrieval can lead discrepancies among the products that are frequency dependent (Norouzi et al., 2011; Prigent et al., 1999). The effective optical depth of the canopy depends on the vegetation water content, intercepted water in rain forests, and the vegetation structure and type. Moreover, the differences can be attributed to the divergences among the products when accounting for the atmospheric perturbations which are considerable in the high range of frequencies due to the higher water vapour effect in tropical and rain forest regions.

In desert, unlike rain forest regions, maximum differences are in lower frequencies and agreements relatively improve in higher frequencies particularly in the horizontal polarization values. The deeper penetration of the microwave signal especially in low frequencies in desert which leads to differences in the diurnal amplitude and phase of skin temperature and microwave brightness temperature can introduce considerable error in emissivity retrievals (Norouzi et al., 2012). This issue is more highlighted in desert areas due to moisture scarcity and minimal vegetation interferences. These results are consistent with previous study by Tian et al (2014) in terms of systematic differences at various frequencies. Also, a wider gap can be noticed between the average monthly emissivity values in the horizontal and vertical polarizations over desert. The horizontal polarization increase with increasing frequencies while the vertical polarization declines with the frequency increase (Yubao et al., 2014). This behaviour was consistent among all investigated products.

According to Figure 1, AMSR-E has the highest variation of emissivity spectrally. AMSR-E has lower emissivities for 10, 19, and 37 GHz, and higher at 89 GHz. At 89 GHz, the microwave signal is more affected by the atmosphere and the impact of the differences in ancillary data and radiative transfer modelling can be critical. It was noticed that both horizontal and vertical polarizations reflect the same variability in terms of differences with other sensors (solid and dashed lines). However, the differences between horizontal and vertical polarization emissivity values increase as vegetation density decreases from rain forests to desert land-cover.

Previous studies have shown that differences in channel frequencies and incidence angles between AMSR-E and SSMI/I channels may lead to around 0.01 error in the emissivity retrieval (Norouzi et al., 2011). This change could be more important when emissivities are higher than 0.95. Therefore, large syTMI and SSM/I have similar emissivity values especially at 10, 19, and 37 GHz. The discrepancies are noticeable in 89 GHz. SSM/I and TMI emissivities are more stable with varying frequency. The emissivities from AMSR-E and WindSat are less consistent than other products almost at all frequencies and land cover types. The results for other land-cover types are the same as the presented ones.

The seasonality of the different land emissivity products was analysed. Standard Deviations of monthly land emissivity estimates for five years of data at different frequencies were calculated (Figure 2). Higher variation is observed across all products (higher standard deviation) in monthly estimates over areas where surface properties such as moisture and vegetation change more significantly over the seasons due to the presence/melting of snow during winter/summer, vegetation growth, and seasonal precipitation. Figure 2 depicts the calculated standard deviations of monthly emissivity means at 37 GHz (Horizontal Polarization) for all sensors. SSM/I and AMSR-E emissivity values show high standard deviations more than 4 percent (dark red) in high latitude and boreal regions which does not seem to be present in the WindSat values in the horizontal polarization. The highest standard variation for WindSat in northern latitude was less than 0.03. Das et al (2014) reported a higher disagreement between AMSR-E and WindSat brightness temperatures in Dom-C area in Antarctica in horizontal polarization. The relatively high standard deviation values across all sensors could be explained by the transition between freeze and thaw conditions throughout the seasons. However, one should expect a consistency between AMSR-E and WindSat because of their similar configurations. In line with what was stated in Das et al (2014), the difference in incident angles (49.9° WindSat and 55° AMSR-E) seems to have a considerable impact on the northern latitude retrieval which affect more the horizontal polarization observation than the vertical polarization ones. Moreover, the snow-covered regions are also flagged in the retrieval of WindSat emissivities which has caused lower variability in Northern hemisphere (Turk et al., 2014).

Other land cover signatures are also seen in monthly standard deviations. For instance, WindSat shows clearly low emissivity standard deviation (less that 0.005 percent) over the Amazon and Congo with persistent and steady dense vegetation. Sahara Desert is clearly distinguishable from SSM/I emissivity values when low emissivity values contrast with the transition region (South of the Sahara Desert) with higher emissivity variation because of seasonal variation of moisture and vegetation cover. Surface properties in terms of soil moisture do not change in Sahara desert with almost no vegetation cover. This can explain the low emissivity change and standard deviation. AMSR-E and TMI also show the same pattern, but it is less recognizable in WindSat map. There are small regions that show very high standard deviation in South America which correspond to floodplains that are seasonally inundated which are represented with high standard deviation values in all products except WindSat. Moreover, the standard deviation of the TMI emissivity values in the Amazon seem to be higher (around 0.01-0.015) than the values obtained with the other sensors (around 0.005-0.01). In WindSat, owing to the simplified parameterizations of the vegetation in the retrieval, the variability of emissivity is not very high in transition areas (Turk et al., 2014). Similar results of standard variation analysis also were found in other channels that are not presented here. Overall, despite the relative differences in standard deviation values, the dynamics of emissivity products tend to be related to known changes in surface condition across the globe.

The relationship between the investigated products and two key surface parameters, namely, soil moisture and vegetation cover was assessed. The emissivity MPDI values are plotted against soil moisture content and Normalized Difference Vegetation Index (NDVI) values over the TMI coverage region for all products (Figure 3). Soil moisture estimates are microwave-based from WindSat C-band observations because of its availability over the time period of this study (Turk et al., 2014). NDVI estimates are from the Moderate Resolution Imaging Spectroradiometer (MODIS) which are available every 16-day globally. Monthly averages of NDVI and soil moisture estimates are calculated in this study. Emissivity-based MPDI values for the range of soil moisture and NDVI values at 19 GHz is shown in Figure 3 for all products for July 2003. High emissivity-based MPDI values more than 0.06 are found for low soil moisture and low NDVI values in all products. This is in line with previous studies that suggest that the contrast between horizontal and vertical microwave signals is higher in desert regions with almost no vegetation [e.g. (Norouzi et al., 2011; Prigent et al., 2006)]. Soil moisture has been found to decrease the emissivity across the frequencies (Basist et al., 1998). Lower emissivity-based MPDIs are seen as vegetation density and soil moisture increases in all products. Higher vegetation causes more scattering of microwave signal and therefore the difference between horizontal and vertical polarizations decreases. The pattern is very similar for all products except WindSat that shows lower values (about 0.05) in low soil moisture range. This could be because the soil moisture data is based on WindSat observations. Consequently, one can conclude that emissivity retrievals are consistent in terms of their relationship between emissivity-based MPDI and surface condition.

Last part of this study focuses on the temporal evaluation of emissivity values and NDVI values as indicator of vegetation density and surface condition. The differences between Horizontal and Vertical emissivity values (e_H-e_V) have been shown that have positive correlation with vegetation and soil moisture values (Norouzi et al., 2011; Prigent et al., 2006) using AMSR-E and SSM/I values. Monthly temporal correlation between e_H-e_V and NDVI values were calculated for 5 years globally for each pixel. The calculated correlation values for all products at 19 GHz are shown in Figure 4. At the first glance, all products present high correlation (more than 0.9) with monthly NDVI variations in most regions. This shows that emissivity estimates in these regions are in phase with what is expected from the surface in terms of vegetation. However, desert regions in Sahara desert, Australia, and Middle East and regions with very high vegetation density show much lower correlation (around -0.2 to 0). This is because, in desert regions there is almost no vegetation and the surface vegetation and soil moisture do not change. Besides, in highly vegetated areas such as the Amazon and Congo, the vegetation density remains high throughout the year. Therefore, the NDVI and e_H-e_V variation comparisons are not representative of the surface condition variation in highly vegetated and desert areas and could be because of noises or atmospheric residuals in the emissivity retrievals. WindSat has a different spatial pattern, especially in semi-arid region that marks the transition zone between desert and rain forest regions in Africa.

One key factor in emissivity retrievals is the cloud mask information that is utilized to mask out the cloudy scenes and to ensure that the retrieval of emissivity is only performed over cloud-free pixels. The investigated data products do not necessarily use the same cloud mask. The inconsistency among the detected cloudy pixels in the analysed products could be an additional source of discrepancy which can also explain the differences in the mean monthly maps. The differences between emissivities could be up to 10 percent in higher frequencies with false detection of cloudy scenes.

NWP models rely on Radiative Transfer (RT) models (e.g. Community radiative Transfer Model (CRTM)) that are used to determine the state of the atmosphere and account for the radiative transfer at different spectral ranges, among others the microwave frequencies (window and sounding channels). Estimates of land surface emissivity are particularly important as NWP models attempt to assimilate passive microwave observations over land (Prigent et al., 2006). Specifically, when it comes to window channels, the surface radiance that is controlled by the land emissivity should be determined. The simulations using the RT models should be carried across a wide range of angles and frequencies. Sensors can only provide estimates at specific angles and frequencies values.

The results of this study can serve the development of a global blended land emissivity product that accounts for the identified spatial inconsistencies among the different existing land emissivity products. A blended product may balance the errors amongst the distinct products as such product could be obtained using a weighted regression among all emissivity retrievals where weights should vary spatially to account for the spatial variability of the consistency among the products (Sahoo et al., 2011). The use of such blended product in NWP model for instance may lead to weather forecasts that are closer to the outcome when any individual land emissivity product is used. Moreover, emissivity is a representative of the soil wetness that can affect the microwave signals when they are used in NWP models which its error due to soil moisture effect may propagate significant error in atmospheric information estimates from such models. Soil moisture may have diurnal variation in some locations, and since the sensors have different acquisition time may reflect some variability in their estimates (especially AMSR-E with 1:30 am/pm crossing times) (Jackson et al., 1997). This variability may have imposed some discrepancies among sensor, although they are aggregated to a monthly scale. A cross-calibration that involves data from all the used sensors in this study is necessary to detect the magnitude of the discrepancies in the raw data and the determined brightness temperatures and apply appropriate corrections to mitigate its impact on land emissivity retrievals.

5 Conclusion

The global emissivity retrieval products from various passive microwave sensors over land were inter-compared in a monthly scale for a five-year period of time. The sensors have general configuration difference that can induce some systematic differences among them. Previous studies have shown that differences due to channel frequency and incidence angle are not significant especially in lower frequencies. stematic differences among retrievals could be due to ancillary data and radiative transfer models used. All products use relatively similar general retrieval algorithm to estimate emissivity on top of canopy or the surface. However, the differences in ancillary data and the ways they may be interpolated for using in the retrieval may affect the retrieved emissivity values. Different radiative transfer models to account atmospheric contribution are among the sources of differences.

Emissivity values are the signals from microwave observation after removing the effect of temperature and atmosphere from the brightness temperature. The differences in lower frequencies found to be higher in desert regions because of penetration depth and discrepancies between skin temperature and microwave brightness temperature originating depths. At higher frequencies (more than 37 GHz) due to atmospheric residuals in emissivity values, the inconsistencies increase in regions with high vegetation density and water vapor amount. Systematic uncertainties are similar between horizontal and vertical polarizations. The emissivity values from SSM/I and TMI found to be more consistent over different land cover types. The maximum systematic difference among emissivities was found to be about 4 percent at all frequencies and polarizations. This could be an indicator of uncertainty level from emissivity retrievals despite 10 percent error in physical model-based emissivities (Ringerud et al., 2014).

The seasonal variation of emissivities was evaluated by looking at monthly standard deviation values and they found to be consistent with what is expected qualitatively from the surface in most regions except the Amazon and South America. Moreover, the dynamics of the emissivity estimates compared to surface properties such as soil moisture and vegetation found to be more promising than the absolute value estimates.

Results of this study highlight the need for more thorough review of emissivity values before using them in physical models or precipitation measurement algorithms. Daily or instantaneous emissivity estimates from different sources may also yield more information about systematic and random uncertainties from retrievals. For more in depth error analysis and finding the sources of discrepancies, an analysis can be done by applying the same inputs for different algorithms that were used for all four sensors. Moreover, different inputs can be applied to each retrieval methods to opt out systematic errors for such differences.

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References

Basist, A., Grody, N. C., Peterson, T. C., and Williams, C. N.: Using the Special Sensor Microwave/Imager to Monitor Land Surface Temperatures, Wetness, and Snow Cover, Journal of Applied Meteorology, 37, 888-911, 1998.

Boukabara, S.-A., Garrett, K., Chen, W., Iturbide-Sanchez, F., Grassotti, C., Kongoli, C., Chen, R., Liu, Q., Yan, B., Weng, F., Ferraro, R., Kleespies, T. J., and Meng, H.: MiRS: An All-Weather 1DVAR Satellite Data Assimilation and Retrieval System, Ieee Transactions on Geoscience and Remote Sensing, 49, 3249-3272, 2011.

Das, N. N., Colliander, A., Chan, S. K., Njoku, E. G., and Li, L.: Intercomparisons of Brightness Temperature Observations Over Land From AMSR-E and WindSat, Geoscience and Remote Sensing, IEEE Transactions on, 52, 452-464, 2014.

Felde, G. W.: The effect of soil moisture on the 37GHz microwave polarization difference index (MPDI), International Journal of Remote Sensing, 19, 1055-1078, 1998.

Ferraro, R. R., Peters-Lidard, C. D., Hernandez, C., Turk, F. J., Aires, F., Prigent, C., Xin, L., Boukabara, S., Furuzawa, F. A., Gopalan, K., Harrison, K. W., Karbou, F., Li, L., Chuntao, L., Masunaga, H., Moy, L., Ringerud, S., Skofronick-Jackson, G. M., Yudong, T., and Nai-Yu, W.: An Evaluation of Microwave Land Surface Emissivities Over the Continental United States to Benefit GPM-Era Precipitation Algorithms, Geoscience and Remote Sensing, IEEE Transactions on, 51, 378-398, 2013.

Furuzawa, F. A., Masunaga, H., and Nakamura, K.: Development of a land surface emissivity algorithm for use by microwave rain retrieval algorithms, 2012, 85231W-85231W-85212.

Jackson, T. J., Oneill, P. E., and Swift, C. T.: Passive microwave observation of diurnal surface soil moisture, Ieee Transactions on Geoscience and Remote Sensing, 35, 1210-1222, 1997.

Karbou, F., Gerard, E., and Rabier, F.: Microwave land emissivity and skin temperature for AMSU-A and -B assimilation over land, Quarterly Journal of the Royal Meteorological Society, 132, 2333-2355, 2006.

Karbou, F., Prigent, C., Eymard, L., and Pardo, J. R.: Microwave land emissivity calculations using AMSU measurements, Ieee Transactions on Geoscience and Remote Sensing, 43, 948-959, 2005.

Matthews, E.: Global Vegetation and Land-Use Data-Bases For Climate Studies, Bulletin of the American Meteorological Society, 64, 793-794, 1983.

Moncet, J., Liang, P., Galantowicz, A., Lipton, A., Uymin, G., Prigent, C., and Grassotti, C.: Land Surface Microwave Emissivities Derived from AMSR-E and MODIS Measurements with Advanced Quality Control, Journal of Geophysical Research-Atmospheres, 116, D16104, 2011.

Norouzi, H., M. Temimi, W. B. Rossow, and R. Khanbilvardi: AMSR-E/Aqua Monthly Global Microwave Land Surface Emissivity, NASA DAAC at the National Snow and Ice Data Center, 2013.

Norouzi, H., Rossow, W., Temimi, M., Prigent, C., Azarderakhsh, M., Boukabara, S., and Khanbilvardi, R.: Using microwave brightness temperature diurnal cycle to improve emissivity retrievals over land, Remote Sensing of Environment, 123, 470-482, 2012.

Norouzi, H., Temimi, M., Rossow, W. B., Pearl, C., Azarderakhsh, M., and Khanbilvardi, R.: The sensitivity of land emissivity estimates from AMSR-E at C and X bands to surface properties, Hydrol. Earth Syst. Sci., 15, 3577-3589, 2011.

Onogi, K., Tsutsui, J., Koide, H., Sakamoto, M., Kobayashi, S., Hatsushika, H., Matsumoto, T., Yamazaki, N., Kamahori, H., Takahashi, K., Kadokura, S., Wada, K., Kato, K., Oyama, R., Ose, T., Mannoji, N., and Taira, R.: The JRA-25 Reanalysis, Journal of the Meteorological Society of Japan. Ser. II, 85, 369-432, 2007.

Prigent, C., Aires, F., Rossow, W., and Matthews, E.: Joint characterization of vegetation by satellite observations from visible to microwave wavelengths: A sensitivity analysis, Journal of Geophysical Research-Atmospheres, 106, 20665-20685, 2001.

Prigent, C., Aires, F., and Rossow, W. B.: Land surface microwave emissivities over the globe for a decade, Bulletin of the American Meteorological Society, 87, 1573–1584, 2006.

Prigent, C., Rossow, W. B., and Matthews, E.: Global maps of microwave land surface emissivities: Potential for land surface characterization, Radio Science, 33, 745-751, 1998.

Prigent, C., Rossow, W. B., Matthews, E., and Marticorena, B.: Microwave radiometric signatures of different surface types in deserts, Journal of Geophysical Research-Atmospheres, 104, 12147-12158, 1999.

Ringerud, S., Kummerow, C., Peters-Lidard, C., Yudong, T., and Harrison, K.: A Comparison of Microwave Window Channel Retrieved and Forward-Modeled Emissivities Over the U.S. Southern Great Plains, Geoscience and Remote Sensing, IEEE Transactions on, 52, 2395-2412, 2014.

Rossow, W. B. and Schiffer, R. A.: Advances in understanding clouds from ISCCP, Bulletin of the American Meteorological Society, 80, 2261-2287, 1999.

Sahoo, A., Pan, M., Troy, T., Vinukollu, R., Sheffield, J., and Wood, E.: Reconciling the global terrestrial water budget using satellite remote sensing, Remote Sensing of Environment, 115, 1850–1865, 2011.

Tian, Y., Peters-Lidard, C. D., Harrison, K. W., Prigent, C., Norouzi, H., Aires, F., Boukabara, S. A., Furuzawa, F. A., and Masunaga, H.: Quantifying Uncertainties in Land-Surface Microwave Emissivity Retrievals, Geoscience and Remote Sensing, IEEE Transactions on, 52, 829-840, 2014.

Turk, F. J., Li, L., and Haddad, Z. S.: A Physically Based Soil Moisture and Microwave Emissivity Data Set for Global Precipitation Measurement (GPM) Applications, Geoscience and Remote Sensing, IEEE Transactions on, 52, 7637-7650, 2014.

Weng, F. Z., Yan, B. H., and Grody, N. C.: A microwave land emissivity model, Journal of Geophysical Research-Atmospheres, 106, 20115-20123, 2001.

Yubao, Q., Lijuan, S., and Wenbo, W.: Study of the microwave emissivity characteristics over Gobi Desert, Earth and Environmental Science, 17, 012249, 2014.

Table 1. list of global land surface emissivity products used in this study.

Sensor	Provider	Frequencies	Incidence Angle	Ancillary Data
AMSR-E	NOAA-CREST	6.9, 10.65, 18.7, 23.8, 36.5, and 89.0	55^0	ISCCP-DX, TOVS
SSM/I	CNRS-France	19.35, 22.235(v), 37.0, and 85.5	53^0	ISCCP-DX, NCEP Re-analysis
TMI	Nagoya Uni.	10.65, 19.35, 21.3(v), 37.0, and 85.5	53.4^0	JRA-25
WindSat	JPL/NRL	6.8, 10.7, 18.7, 23.8, and 37.0	49.9^0 to 55.3^0	NCEP- Re-analysis, AIRS

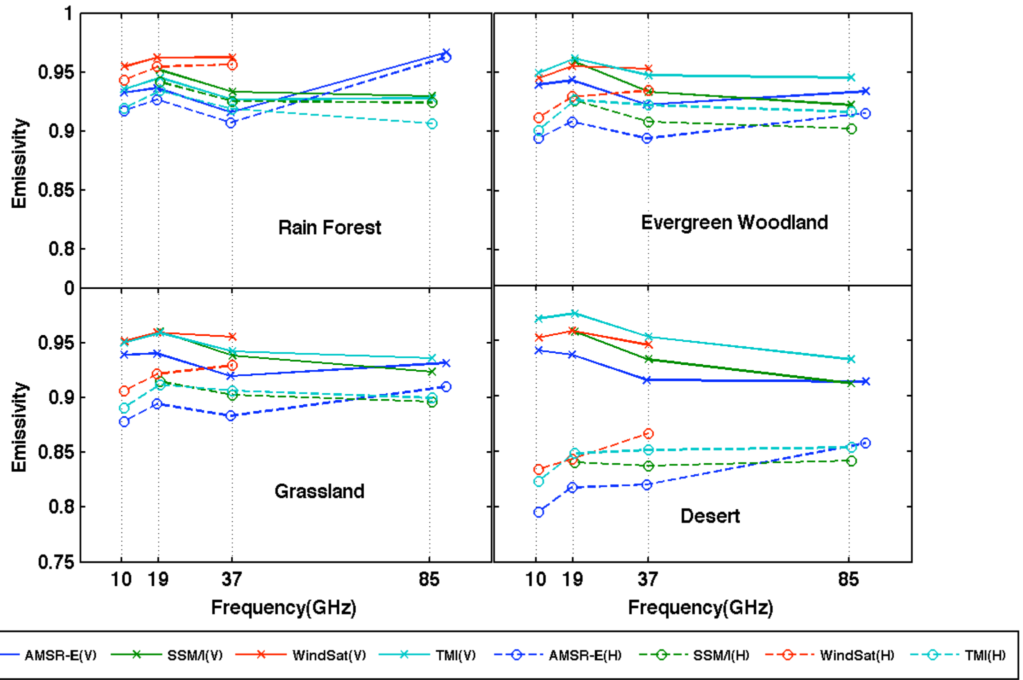

Figure 1. Mean of monthly emissivity values (from 2003 to 2007) for rain forest, evergreen woodland, grassland, and desert regions in global scale from AMSR-E, TMI, SSM/I, and WindSat. The solid lines present vertical polarization and dashed lines are for horizontal polarization.

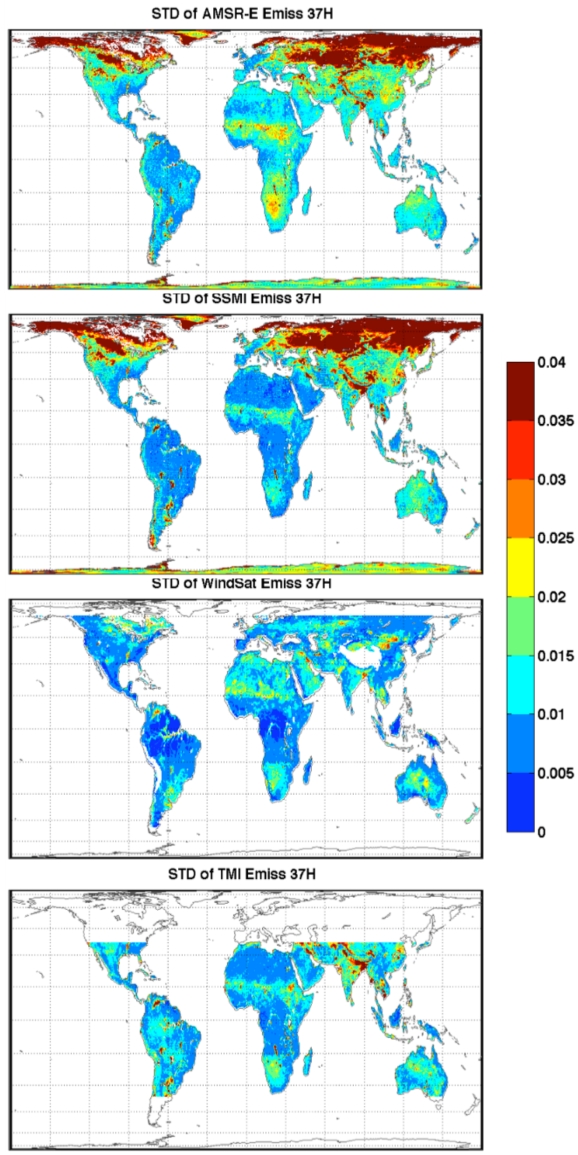

Figure 2. Monthly Standard Deviation of emissivity estimates from AMSR-E, SSM/I, WindSat, and TMI from 2003 to 2007 at 37 GHz (horizontal polarization).

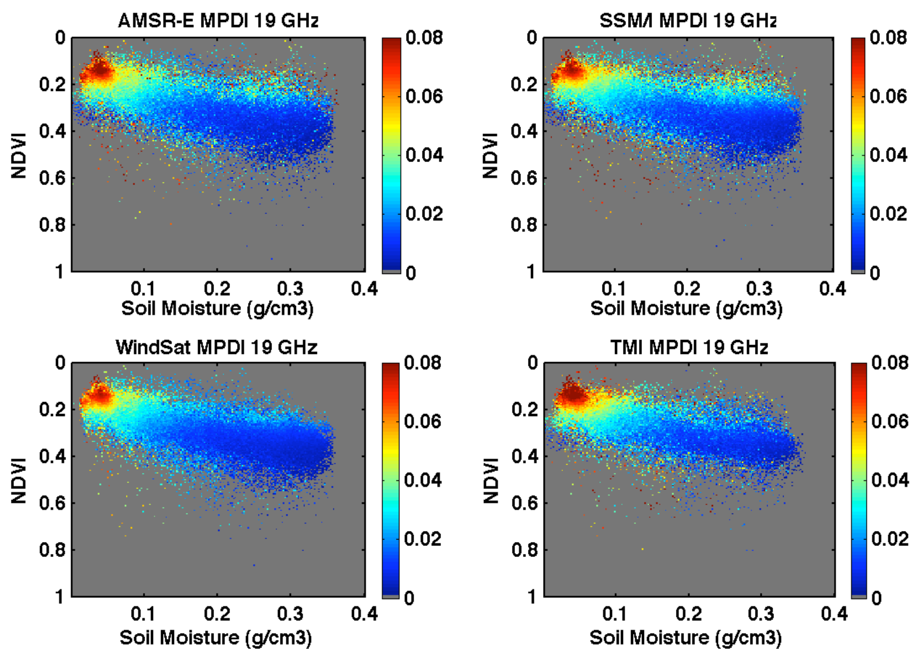

Figure 3. Emissivity MPDI values from various sensors/providers at different NDVI and soil moisture ranges at 19 GHz for July 2003.

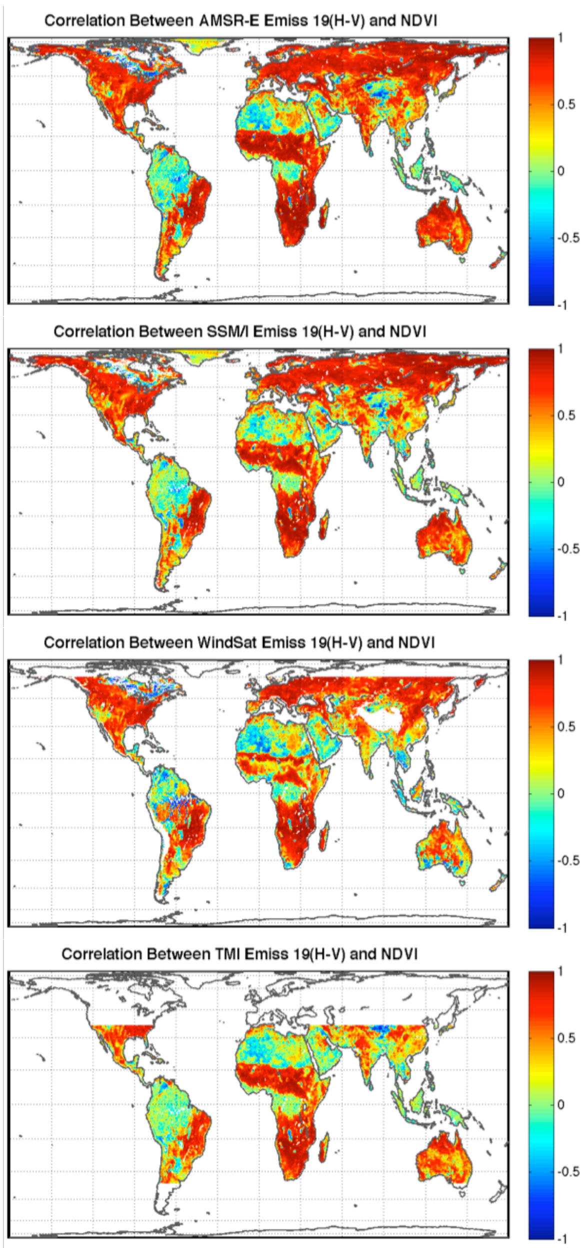

Figure 4. Correlation maps between temporal variations of e_H-e_V from all sensors at 19 GHz with monthly NDVI values from 2003 to 2007.