RESEARCH ARTICLE

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Key Points:

- Global comparison of land surface temperature (T_s) from multiple sensors (AMSR-E, MODIS, SEVIRI, GOES, and MTSAT)
- The use of microwave T_s leads to an increase of more than 250% on the number of available observations
- Discrepancies between infrared and microwave T_s can be of the same order as the ones between infrared T_s products

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Inversion of AMSR-E observations for land surface temperature estimation: 2. Global comparison with infrared satellite temperature

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Abstract A comparison of land surface temperature (T_s) derived from the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) with infrared T_s is presented. The infrared T_s include clear-sky estimates from the Moderate Resolution Imaging Spectroradiometer (MODIS), the Spinning Enhanced Visible and Infrared Imager, the Geostationary Operational Environmental Satellite (GOES) Imager, and the Japanese Meteorological Imager. The higher discrepancies between AMSR-E and MODIS are observed over deserts and snow-covered areas. The former seems to be associated with T_s underestimation by MODIS, whereas the latter is mostly related to uncertainties in microwave emissivity over snow/ice. T_s differences between AMSR-E and MODIS are significantly reduced after masking out snow and deserts, with a bias change from 2.6/4.6 K to 3.0/1.4 K for daytime/nighttime and a standard deviation (STD) decrease from 7.3/7.9 K to 5.1/3.9 K. When comparing with all infrared sensors, the STD of the differences between microwave and infrared T_s is generally higher than between IR retrievals. However, the biases between microwave and infrared T_s are, in some cases, of the same order as the ones observed between infrared products. This is the case for GOES, with daytime biases with respect to AMSR-E and MODIS of 0.45 K and 0.60 K, respectively. While the infrared T_s are clear-sky estimates, AMSR-E also provides T_s under cloudy conditions. For frequently cloudy regions, this results in a large increase of available T_s estimates (>250%), making the microwave T_s a very powerful complement of the infrared estimates.

1. Introduction

Land surface temperature (T_s) is a key variable in the diagnosis of surface conditions, being particularly relevant in the characterization of energy exchanges at the surface-atmosphere boundary [Wang *et al.*, 2014; Trigo *et al.*, 2015]. Satellite remote sensing allows consistent estimation of T_s over large areas and on a regular basis. T_s estimation from remote sensing instruments is widely used and generally relies on measurements in the thermal infrared (IR) window, since this band includes the peak of Earth's spectral radiance and, at the same time, presents relatively weak atmospheric attenuation under clear-sky conditions.

Although there is a large number of IR sensors performing T_s retrievals with different temporal and spatial resolutions, the use of IR data prevents these retrievals to be performed under cloudy sky conditions, a restriction that may severely affect the sampling of observations both in space and time. Passive microwave (MW) measurements are in turn much less affected by clouds and may constitute an alternative when generating “all-weather” estimates of T_s . However, retrieval of T_s from MW observations poses some challenges, and there is no operational product available yet. On the one hand, MW emissivity presents high variability associated to surface properties such as soil moisture, vegetation cover, or presence of snow [Prigent *et al.*, 2006]. These generate spatial and temporal variability that should be accounted for when retrieving T_s . On the other hand, MW observations present a coarser spatial resolution than IR due to the longer wavelengths. In addition, MW spatial resolution degrades with decreasing frequency. Finally, for some surface conditions, MW radiation can emanate from the subsurface [Prigent *et al.*, 1999] unlike IR that only measures skin emissions. Nevertheless, low-frequency MW radiation penetrates clouds and is able to provide physical information of the land surface that is not available through the IR, representing an important added value.

Several methods have been proposed for the retrieval of MW T_s [Aires *et al.*, 2001; Holmes *et al.*, 2009; Prigent *et al.*, 2016]. Here T_s is estimated from observations performed by Advanced Microwave Scanning

Radiometer–Earth Observing System (AMSR-E) onboard Aqua using a neural network approach as proposed in Part 1. The methodology derives a fast mapping between the radiance and the T_s space by training a neural network with a database of coincident AMSR-E radiances, retrieved T_s from the AMSR-E inversions presented in *Lipton et al.* [2015], and a monthly AMSR-E emissivity climatology derived using as ancillary T_s data from Moderate Resolution Imaging Spectroradiometer (MODIS) on the same Aqua satellite [*Moncet et al.*, 2011].

The purpose of this study is to perform a comprehensive comparison between T_s derived from AMSR-E observations and T_s derived from IR sensors, namely, from MODIS onboard Aqua, Spinning Enhanced Visible and Infrared Imager (SEVIRI) on board the Meteosat Second Generation (MSG) satellites, the Geostationary Operational Environmental Satellite (GOES) Imager, and Japanese Meteorological Imager on board the Multifunction Transport SATellite (MTSAT-2). The consistency between MW and IR-derived T_s is analyzed for clear-sky observations under different surface conditions and using the T_s IR products as the baseline. Section 2 describes the satellite data and the space-time collocation methodology. Results of the comparison between MODIS and AMSR-E, together with a detailed analysis for different surface conditions, are presented in section 3. Lastly, in section 4, an intercomparison is performed of all IR and MW products. Section 5 concludes this study.

2. Methods and Data

2.1. Data Sets

MW T_s was estimated by applying the methodology of Part 1 to brightness temperature measurements (T_b s) from the AMSR-E sensor at 18.7, 23.8, 36.5, and 89.0 GHz. T_s was retrieved in the swath grid of the 36.5 GHz channels, corresponding to an approximate footprint size of 14 km $\times$ 8 km. However, information from the larger footprint of the lower frequency channels (27 $\times$ 16 km) also affects the retrieval, and as a result, the effective spatial mean resolution will be between 12 and 21 km depending on the weight of each individual channel for each specific inversion. In many situations the 36.5 GHz channels have more weight on the retrieval and therefore for many inversions the effective resolution will be close to 12 km. AMSR-E T_s is produced twice daily for both clear and cloudy sky at equator crossing times (local time) of 1.30 A.M. (P.M.). Given the relatively narrow swath grid, revisiting times are 1–2 days depending on location.

MODIS T_s used in this study corresponds to the L2 daily product (MYD11) from collection 5 [*Wan and Li*, 2008] and was derived with a split-window algorithm [*Wan and Dozier*, 1996] from top-of-atmosphere (TOA) brightness temperature measures in the thermal infrared. This product is available at a spatial resolution of 1 km at the subsatellite point and with a maximum of two clear-sky observations per day.

The SEVIRI T_s product is produced within the framework of the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Satellite Application Facility on Land Surface Analysis (LSA-SAF) [*Trigo et al.*, 2011]. T_s data are generated using a generalized split-window algorithm [*Madeira*, 2002; *Freitas et al.*, 2010] which was adapted from the original MODIS algorithm. The data are available over the full MSG disk that encompasses Europe, Africa, and part of South America, with a 15 min sampling interval and a spatial resolution of 3 km at the subsatellite point (which degrades with increasing distance from nadir).

GOES and MTSAT T_s data are produced by the Copernicus Global Land Service within the framework of the GEOLAND-2 [*Lacaze et al.*, 2010]. T_s is estimated using a Dual Algorithm [*Freitas et al.*, 2013] applied to TOA brightness temperature measurements from one middle infrared and one thermal window channel overnight and from a single thermal window channel during day. Both products are available in the geostationary projection (as for SEVIRI) with a 4 km resolution at subsatellite point and with a 3-hourly temporal resolution. The GOES disk encompasses all the American continent, while MTSAT covers the eastern most part of Asia and Australia.

All IR T_s data sets were extracted from the product versions archived at the data portal of the European Space Agency (ESA) Data User Element (DUE) GlobTemperature project (<http://www.globtemperature.info/>). The objective of the GlobTemperature project is to provide high-quality T_s data and to facilitate wider use of global-scale satellite T_s in research and operational user communities. The AMSR-E data set was specifically processed for this comparison, but the 3 year period from 2008 to 2010 is available from the same data portal.

Backscattering coefficients (σ_0) are estimated from active microwave observations performed by a wind scatterometer operating at 5.25 GHz on board the European Remote Sensing (ERS) satellite [*Frison and Mougin*, 1996] and are used here to indicate regions with large microwave penetration depth. As the radar

backscattering is a combination of surface and volume scattering, at places where surface roughness is low and wave penetration is large very little power is reflected back to the instrument and the backscattering coefficient takes small values. A threshold of -20 dB is used here to identify places with large penetration depth, selected by comparison of maps of the backscattering coefficient with maps of variables that help identify these locations, such as maps of sand dunes and shifting sands, roughness lengths, and microwave surface emissivity variability [Prigent *et al.*, 2005]. The coefficients are estimated globally for a viewing angle of 45° , at 0.25° spatial resolution, averaged over 8 years (1993–2000).

To identify snow/ice-covered surfaces in this comparison, the Global Multisensor Automated Snow and Ice (GMAI) Mapping System product developed by NOAA National Environmental Satellite, Data, and Information Service (NESDIS) is used [Romanov, 2016]. The snow and ice mask is derived from combined observations in the visible, IR, and MW bands from different sensors, on a daily basis, with a $0.04^\circ \times 0.04^\circ$ resolution.

Information on land surface cover is obtained from ESA Global Land Cover Product (v2.2) [Bicheron *et al.*, 2008]. This land cover map is derived from surface reflectance as measured by the Medium Resolution Imaging Spectrometer Instrument on board the Envisat satellite with a resolution of 300 m. The product is characterized by 22 land cover classes and represents the period from December 2004 to June 2006. The 22 original classes were grouped into eight main classes as follows: (1) permanent or regularly flooded forest and croplands, (2) cropland, (3) equatorial forest, (4) high-latitude forest, (5) shrubland/grassland, (6) sparse vegetation, (7) bare areas, and (8) other (urban, water, and permanent snow).

2.2. Data Processing

The time period under analysis corresponds to the first 6 days of each month from January to September 2011. Collocation of MODIS and each geostationary satellite (GEO) T_s data sets was performed within the GlobTemperature project and was only available for the full year 2011. Unfortunately, due to malfunctioning of the AMSR-E sensor the respective data production ceased on 4 October 2011. Nevertheless, the chosen time period still encompasses different seasons and is representative of intraannual variability. MODIS and AMSR-E sensors are on board the same satellite, and therefore, observation times are coincident. GEO data were matched to MODIS/AMSR-E observation time by using the closest observation, up to 7.5 min.

All data sets were reprojected onto an equal-area grid with a resolution of $0.125^\circ \times 0.125^\circ$ at the equator and fixed latitude intervals. IR T_s data sets were reprojected by plain averaging, while the MW T_s and backscatter data were reprojected using the nearest neighbor. Statistics are only performed for grid cells where 100% of MODIS (or GEO) pixels have T_s values with the best quality, in order to limit cloud contamination in the IR data. Snow cover data were reprojected to the comparison grid by counting the number of GMAI pixels within each grid cell where snow was identified; if at least one GMAI pixel is identified as snow or ice, the grid cell is marked as being snow/ice covered. Land cover data were reprojected using the mode value.

3. Comparison Between MODIS and AMSR-E T_s

Figure 1 shows maps of the overall bias (a, b) and STD (c, d) of the differences between AMSR-E and MODIS, for daytime (a, c) and nighttime (b, d) separately. Overall, AMSR-E presents a root-mean-square difference relative to MODIS of 7.76/9.16 K, a bias of 2.64/4.64 K, and STD of 7.29/7.90 K for daytime/nighttime. There is a positive bias associated to desert areas, where penetration effects are more prone, especially for daytime observations. High latitudes are associated to a positive bias and high standard deviation that may be attributed to the presence of snow/ice cover. A high positive bias near the coast is also noticeable.

A great advantage of MW over IR observations is the ability to estimate T_s in cloudy sky conditions. Figure 2 shows the number of available observations for AMSR-E and MODIS as a function of latitude for the considered time period. It is evident that, even after masking problematic areas like sand deserts and snow-covered areas (as will be described in sections 3.1 and 3.2), MW observations represent a significant increase of the sampling. Regions with high cloud coverage like equatorial areas present an increase of more than 250% in sampling size, and subtropical areas show an increase of more than 150%.

3.1. Arid and Semiarid Areas

MW radiation penetration is one of the factors that can affect the T_s differences between MODIS and AMSR-E, and may lead to significantly different T_s values for AMSR-E. Due to its larger wavelength, microwave radiation may emanate from the soil layers below the surface skin, as opposed to IR radiation that emanates from the

Figure 1. Spatial distribution of (a, b) bias and (c, d) standard deviation of T_s differences between AMSR-E and MODIS for daytime (Figures 1a and 1c) and nighttime (Figures 1b and 1d) observations.

skin. This effect is especially relevant over bare ground and for the lower frequencies [Prigent *et al.*, 1999]. For this reason, arid and semiarid regions are here analyzed to assess the impact of such effects on the retrieved MW T_s .

Regions where penetration is more likely to occur may be identified using the backscattering coefficient (σ_0) obtained from active microwave observations [Prigent *et al.*, 2005]. Figure 3 (top) shows the global averaged σ_0 . Vegetated areas like the equatorial forests present large σ_0 values due to the high volume scattering. Arid regions, on the other hand, are associated to low σ_0 values due to the combined effects of low surface roughness and wave penetration.

Figure 2. Latitudinal distribution of the number of observations available in the considered time period for AMSR-E with (green) and without (blue) snow and desert masking and for MODIS (red/cyan). For this specific figure the criterion to have a valid MODIS observation has been relaxed (a MODIS observation is considered valid here if at least 30% of MODIS pixels within the grid cell are valid, while for the comparison 100% is required).

Figure 3. (top) Global map of 8 year mean backscattering ERS coefficient σ_0 and (bottom) bias between AMSR-E and MODIS T_s as a function of backscattering coefficient σ_0 (dB), for daytime (red) and nighttime (blue), for the region encompassing the Sahara and Arabian Peninsula between the latitude circles of 0° and 40° and between longitude -20° and 70° . Respective sample size of each backscattering coefficient bin is represented by the bars (right y axis; Figure 3 (bottom)).

The bias between AMSR-E and MODIS T_s is shown in Figure 3 (bottom), as a function of the backscattering coefficient. The biases between AMSR-E and MODIS T_s show an increase as the backscattering coefficient decreases, but this effect cannot be directly attributed to penetration. As penetration increases (lower values of σ_0), the MW sensor measures radiation emitted from layers below the surface, usually resulting in lower (higher) temperature values during daytime (nighttime) and therefore negative (positive) bias values [Prigent *et al.*, 1999]. For nighttime, the temperature gradient below the surface is reduced compared to mid-day, penetration having an almost null impact. The histograms show a dependence of the night bias values with backscattering that is very close to the one observed for daytime, which suggests that penetration does not play a major role in the observed bias values.

Moreover, the visual comparison of the bias maps (Figure 1a) and the σ_0 map (Figure 3, top) suggests limited correspondence between high bias values and the backscattering. There is a conspicuous positive bias over the whole Sahara and Arabian Peninsula during daytime. However, it was expected that penetration effects would lead to negative bias values and the observed spatial patterns do not resemble those of the backscattering. This suggests that these high positive bias values could also be related to a T_s underestimation by MODIS over arid regions. Several studies [e.g., Trigo *et al.*, 2008; Ermida *et al.*, 2014] have reported an underestimation of T_s by MODIS that is likely related to an overestimation of IR land surface emissivity over those areas [Göttsche and Hulley, 2012]. Desert areas tend to present higher uncertainties for IR T_s retrievals, particularly for the products used in this comparison. The major drawback is the use of IR emissivity based on biome classification, which results in a single emissivity value for all desert areas, independent of the soil type [Göttsche and Hulley, 2012]. As pointed by Jiménez *et al.* [2010] the IR emissivity may vary with soil type for desert areas. Recently, NASA's Land Processes Distributed Active Archive Center team reported that T_s values over bare

Figure 4. Bias between AMSR-E and MODIS as function of MODIS T_s for pixels marked as snow (orange/green) and clear of snow (red/blue), for daytime (red/orange) and nighttime (blue/green). Respective sample size of each MODIS T_s bin is represented by the bars (right y axis in logarithmic scale).

soil/sand sites were underestimated by more than 3 K, for both versions 4 and 5 of the product [Wan, 2014]. This systematic underestimation may explain part of the bias observed between MODIS and AMSR-E over the deserts.

These results suggest that the neural network approach used to estimate MW T_s is able to compensate some of the penetration effects described. Nevertheless, microwave inversions in these locations have higher uncertainties, and the threshold of -20 dB in σ_0 is used to flag the dry sand regions that are likely affected by penetration in the AMSR-E product (see section 2.1). In the global comparisons with MODIS discussed here, masking regions below this threshold change the overall bias, from 2.64/4.64 K to 2.48/3.75 K for daytime/nighttime.

3.2. Snow-Covered Areas

The largest differences between AMSR-E and MODIS T_s are observed over high latitudes, where the surface is covered by snow or ice. Figure 4 shows the biases between AMSR-E and MODIS as a function of the MODIS T_s , separating snow-covered and snow-free areas. Snow pixels are associated to larger bias, as expected. There is still a small number of pixels with T_s lower than 270 K that are not marked as snow but present large bias, indicating that they are probably covered by snow. The MW response over snow is highly variable in space and time. This response is related to the microwave signature over snow that may vary between a blackbody behavior for wet snow to high reflectivities associated to strong volume scattering by a very inhomogeneous snowpack [Prigent et al., 2003; Cordisco et al., 2006]. Therefore, microwave emissivities are particularly sensitive to snow water equivalent, grain size, and snow wetness, resulting in a large emissivity variability. As the retrieval uses a monthly mean emissivity value, large differences with the real emissivity are likely, which can translate into a large retrieval error. Therefore, it is still possible to estimate T_s from MW observations but with higher uncertainties, especially for conditions of highly variable snow (e.g., melting and refreezing over a short time period). For regions with more stable snow properties and coverage, the uncertainties are expected to be much lower. For instance, the large oscillation in the daytime bias observed around 270 K in Figure 4 may reflect the higher uncertainty for highly variable snow, which is more prone to occur during the warmer seasons and close to 270 K.

Snow-covered surfaces may also present higher IR T_s uncertainties. First, the cloud masking presents higher errors/uncertainties over these surfaces, especially at nighttime when the visible channels cannot be used to derive the cloud mask (which corresponds to the winter time in the poles). Second, IR emissivity is also affected by snow coverage. Snow presents higher emissivity (above 0.99 at $10.8 \mu\text{m}$) than vegetated soil (around 0.97 to 0.98 at $10.8 \mu\text{m}$). This means that if a pixel is erroneously masked as snow (vegetation) by MODIS, T_s will be estimated with an emissivity larger (lower) than the real surface emissivity leading to T_s values that are lower (higher) than the real skin temperature and inducing a positive (negative) bias in the comparison with AMSR-E. This feature could partially explain the strong oscillation observed in the bias for T_s values around 270 K (Figure 4).

Figure 5. Bias (solid line) and standard deviation (dashed line) of the T_s differences between AMSR-E and MODIS as function of the distance to the coast up to 100 km, for daytime (red) and nighttime (blue). Respective sample size of each T_s difference bin is represented by the bars (the right y axis).

At the global scale, masking of snow pixels leads to a change in bias from 2.64/4.64 K to 3.20/1.64 K for daytime/nighttime and a significant decrease in STD from 7.29/7.90 K to 5.10/3.88 K. The increase in bias observed for daytime snow pixels seems to be associated to the daytime bias oscillation described above (Figure 4).

3.3. Coastal Areas

Proximity to water bodies may have a strong impact on MW T_s estimates because of the very low microwave emissivity of water. For that reason, and considering the lower resolution of MW observations, AMSR-E T_s presents larger differences from MODIS close to the coast. Figure 5 shows the bias and standard deviation of these T_s differences as a function of the distance from the coast line. There is a maximum of the bias around 20 km for both daytime and nighttime, and the STD presents a slow decrease with distance up to approximately 30 km. These are reasonable values considering that the spatial resolution of AMSR-E is ~ 21 km at the lower frequencies (18.7 GHz and 23.8 GHz) and ~ 12 km at the higher frequencies (36.5 GHz and 89.0 GHz). These resolutions correspond to the 3 dB field of view of the antenna, but energy measured by the antenna sidelobes can also be affected by ocean emission, contaminating the measured radiances. Water contamination of the field of view is particularly relevant in the case of the emissivity estimation since water presents values much lower than land (~ 0.4 over water compared to ~ 0.9 over land). For this reason, climatological emissivity values attributed to coastal pixels are generally lower than inland pixels. In the case of the T_b s, however, this effect is not systematic as the fraction of sensed water surface depends on the swath position. The observed positive biases indicate that for many swath positions close to the coast the climatological values underestimate the real emissivity, resulting in an overestimation of the T_s .

3.4. Vegetation Cover

T_s differences between AMSR-E and MODIS are further evaluated here as a function of land cover. Figure 6 (top) shows the spatial distribution of the aggregated seven main classes.

Figure 6 (bottom) presents the distribution of the bias of T_s differences between AMSR-E and MODIS for the regrouped land cover classes. Note that the distributions were calculated from snow-masked T_s . Most classes present similar distributions centered at approximately 2 K. Vegetation classes associated to dense forest show contrasting behaviors between equatorial forests (light green line) and high-latitude forests (dark green line), the former presenting a negative bias. This could be attributed to the different seasonal behaviors of the two types of forests. Equatorial forests present a fairly constant coverage throughout the year, and for that reason, emissivity values are closer to the climatological emissivity resulting in lower biases. High-latitude forests, in contrast, may present a significant foliage reduction during winter and may even be covered by snow. Desert areas present a larger positive bias, as it was discussed in section 3.1.

The overall decrease in bias and STD associated to the masking of sand deserts and snow is depicted in Figure 7. As expected, the snow masking presents a higher impact on the overall statistics, resulting in a

Figure 6. (top) Classes of land cover as defined by ESA Globcover and (bottom) distribution of the bias between AMSR-E and MODIS for classes of vegetation cover. Sample size is normalized by the total number of observations in the each class.

significant decrease of the STD over high latitudes. In contrast, desert masking presents a lower impact on the statistics since penetration of the MW seems to not significantly affect the MW T_s estimates.

4. Comparison Between T_s From Geostationary Satellites, MODIS, and AMSR-E

ASMR-E and MODIS differences were extensively analyzed given the common platform and near to perfect time agreement. Here we compare both MODIS and AMSR-E with the other infrared sensors to place the AMSR-E-MODIS biases in perspective. The biases between the GEOs and AMSR-E and between the GEOs and MODIS are presented in Figure 8, for daytime and nighttime. A summary of the T_s comparisons is given in Table 1 by presenting the bias and standard deviation of the differences between each GEO and AMSR-E, between each GEO and MODIS, and between AMSR-E and MODIS over the GEO area.

4.1. GEO-MODIS Comparison

Discrepancies between IR T_s products are generally attributed to differences (1) in the top-of-atmosphere measurements (sensor calibration, spatial resolutions, and spectral channels), (2) in the algorithm and auxiliary data used for atmospheric and surface emissivity correction, (3) in cloudmask, and (4) in angular anisotropy [Barroso *et al.*, 2005; Pinheiro *et al.*, 2006; Trigo *et al.*, 2008; Rasmussen *et al.*, 2010; Guillevic *et al.*, 2013; Ermida *et al.*, 2014].

MODIS presents overall lower T_s values than the GEOs (Table 1). Bias values tend to be positive over most of the GEO scan area but negative close to the scan edge (Figure 8). At the edge of the geostationary disk, high view angles favor the observation of shadows and vegetation objects by the sensor resulting in lower T_s retrievals. This is particularly noticeable in heterogeneous surfaces during daytime [Pinheiro *et al.*, 2006; Rasmussen *et al.*, 2010; Guillevic *et al.*, 2013; Ermida *et al.*, 2014]. Emissivity anisotropy may also impact the T_s retrieval. Studies indicate that IR emissivity decreases with view angle for bare ground, but this dependence

Figure 7. Bias and standard deviation (STD) of the T_s differences between AMSR-E and MODIS for 1° latitude bands before (open circles) and after (filled circles) removing snow and desert areas.

is negligible for heterogeneous surfaces [Labed and Stoll, 1991; Sobrino and Cuenca, 1999; Ren et al., 2011]. At the scale of the satellite field of view, however, it is likely that emissivity increases with view angle for sparsely vegetated surfaces, as the fraction of vegetation objects seen by the satellite increases.

Overall, SEVIRI presents the highest discrepancies when compared to MODIS (Table 1 and Figure 8), despite having the closest algorithm and spectral channels [Freitas et al., 2013]. SEVIRI T_s is warmer than MODIS T_s for most of the scan disk, which may be attributed to the contrasting emissivity values used in each retrieval [Qian et al., 2013; Ermida et al., 2014]. As already mentioned, at the scan edge SEVIRI T_s values tend to be cooler due to the angular effects. GOES shows a similar behavior (Figure 8) but presenting overall lower bias values (Table 1). GOES T_s is retrieved using emissivity values estimated from the same library as for SEVIRI but using different methods. Emissivity is estimated as a weighted average of vegetation and bare ground in both cases, but for SEVIRI daily values of fraction of vegetation cover are used as weight, while for GOES (and MTSAT) a static land cover classification is used instead [Freitas et al., 2013]. MODIS has a similar T_s algorithm to SEVIRI, but the emissivity is estimated with a methodology similar to GOES and MTSAT, which might contribute to the lower differences between GOES/MTSAT and MODIS T_s [Wan and Dozier, 1996]. MTSAT presents contrasting bias values, characterized by a negative overall bias during the day and a positive one at night (Table 1 and Figure 8): this is likely related to the predominance of high view angles for MTSAT. Over Australia, biases are much lower that supports the fact that the high negative bias observed over Asia is likely related to angular effects as seen in the other sensors.

4.2. GEO-AMSR-E Comparison

AMSR-E shows better agreement with SEVIRI T_s than with MODIS T_s , especially during daytime (Table 1). AMSR-E also agrees better with GOES than with MODIS. Regarding MTSAT, AMSR-E is in closer agreement with MTSAT during nighttime, with lower bias than with MODIS, but for daytime the bias with respect to MTSAT is much larger than with MODIS. Overall, the agreement between the different sensors improves when problematic areas such as snow and sandy deserts are masked. Arid, semiarid areas, and high latitudes are characterized by positive bias, while tropical forests are associated to negative biases (Figure 8). This is consistent with the result obtained when comparing AMSR-E and MODIS (Figures 1 and 6). Values of the bias between the GEOs and AMSR-E tend to increase toward the GEO scan edge, as a result of the angular effects on the GEO T_s .

Table 1 shows that, in some cases, the biases between AMSR-E and the GEOs are of the same order as the ones observed between MODIS and the GEOs. For instance, GOES presents a daytime bias with respect to AMSR-E of 0.45 K, whereas the bias with respect to MODIS is 0.60 K. MTSAT also presents a nighttime bias with respect to AMSR-E of 0.26 K, while MODIS bias is 0.59 K. However, the standard deviation of the differences between AMSR-E and the GEOs or MODIS is generally higher when compared to the ones observed between MODIS

Figure 8. Spatial distribution of the bias (K) of T_s differences between the GEOs and MODIS and between the GEOs and AMSR-E for daytime and nighttime observations.

and each GEO. This can be partially related to the differences between measuring a skin temperature (MODIS and GEOs) and measuring a depth-integrated temperature (AMSR-E), i.e., that MODIS and the GEOs observe a more similar physical temperature by using similar wavelengths and also to more uncertain MW retrievals associated to a relatively large dependence of the MW radiation processes on the emissivity (emission in the IR regime is less dependent on the emissivity) and how this is captured in the retrieval. To reduce the dependence on ancillary data, the AMSR-E inversion approach uses a climatological monthly emissivity, instead of the actual emissivity estimates corresponding to the specific date of the inversion (see Part 1). At location and times where the emissivity is highly variable the climatological emissivity may poorly represent the real

Table 1. Bias and Standard Deviation (in Parenthesis) of the Difference Between AMSR-E and Each Geostationary Sensor (GEO), Between AMSR-E and MODIS (Limited to the GEO Area) and Between Each GEO and MODIS, for Daytime (Upper Row) and Nighttime (Lower Row), and With and Without Deserts and Snow Masking

	SEVIRI				GOES				MTSAT			
	Not Masked		Masked		Not Masked		Masked		Not Masked		Masked	
AMSR-E-GEO	2.29	[5.51]	2.15	[5.50]	0.63	[5.25]	0.45	[5.96]	2.41	[4.85]	2.51	[4.55]
	1.66	[4.34]	1.46	[4.30]	1.70	[4.71]	1.38	[3.88]	1.87	[5.56]	0.26	[4.06]
AMSR-E-MODIS	3.66	[5.13]	3.45	[5.13]	1.22	[4.47]	1.05	[4.04]	1.54	[4.46]	1.47	[4.00]
	1.91	[4.18]	1.67	[4.12]	1.74	[4.77]	1.40	[3.90]	2.40	[5.46]	0.85	[3.79]
GEO-MODIS	1.37	[3.03]	1.31	[3.03]	0.59	[2.71]	0.60	[2.72]	−0.87	[3.20]	−1.03	[3.03]
	0.25	[1.90]	0.21	[1.86]	0.04	[1.73]	0.01	[1.67]	0.52	[2.08]	0.59	[1.91]

emissivity, resulting in larger retrieval errors. A similar result was found in Part 1 when AMSR-E and MODIS were compared with ground IR T_s from a selection of stations, with overall larger standard deviations in the differences between the AMSR-E and the in situ T_s compared with MODIS.

5. Summary

An intercomparison study was performed between T_s retrieved from MW and IR sensors. MW-based T_s was derived from microwave data from the AMSR-E sensor on board the Aqua satellite with the methodology described in Part 1. Microwave T_s values were compared against clear-sky IR T_s estimates recorded by MODIS, SEVIRI, GOES, MTSAT. First, T_s differences between AMSR-E and MODIS products were analyzed globally taking into account the surface conditions, paying special attention to the cases where larger discrepancies are expected due to the contrasting physical behavior of IR and MW radiation. To put in perspective the AMSR-E and MODIS T_s differences, AMSR-E and MODIS were then compared with each GEO product.

The largest differences between AMSR-E and MODIS products, characterized by high (positive) bias and standard deviation, are found over regions prone to the occurrence of snow/ice. These regions are particularly problematic for both MW and IR T_s retrievals. MW emissivity is highly variable for snow-covered ground and not always properly accounted for by the climatological emissivity used in the retrieval. Concurrently, IR emissivity, despite presenting a lower contrast between snow and snow-free conditions, is highly dependent on the correct snow masking, with misclassifications impacting the retrieval. Desert areas also present large discrepancies between the AMSR-E and MODIS T_s products, also with a positive bias in the AMSR-E and MODIS difference. T_s differences over these regions seem mostly related to an underestimation of T_s by MODIS. Nevertheless, MW inversions over dry sand areas with larger penetration depth are prone to larger uncertainties and are, for that reason, flagged in the AMSR-E T_s product. Coastal areas present overall higher MW T_s values than IR due to the emission from the water within the observations footprint not accounted for in the MW retrieval. T_s differences between AMSR-E and MODIS are significantly reduced after masking out snow/ice and sandy deserts, with a bias change from 2.64/4.64 K to 2.99/1.45 K for daytime/nighttime and a STD decrease from 7.29/7.90 K to 5.06/3.87 K.

Results from the comparison between AMSR-E and the GEOs and between MODIS and the GEOs point out that some of the high discrepancies observed between AMSR-E and MODIS are reduced when the comparison is performed against other IR sensors. This is the case of the positive bias observed over the Sahara and the Arabian Peninsula. AMSR-E T_s presents a better agreement with SEVIRI over these regions, and the bias between MODIS and SEVIRI is as high as 5 K for daytime. This means that the IR retrieval is very sensitive to the emissivity hypothesis over desert, and additional work has to be done in this area. The high discrepancies associated to snow coverage are consistent when comparing MW and IR estimates from the different sensors. Bias values between AMSR-E and the GEOs are, in some cases, of the same order as the ones observed between MODIS and the GEOs. In particular, GOES presents a daytime bias with respect to AMSR-E of 0.45 K, whereas the bias with respect to MODIS is 0.60 K. MTSAT presents a nighttime bias with respect to AMSR-E of 0.26 K, while with MODIS the bias is 0.59 K.

Results presented here indicate that discrepancies observed between MW and IR may be close to the ones observed between IR products, and that the areas of larger uncertainty in MW T_s can be identified and filtered out if required. The estimation of T_s from MW measurements represents an added value to IR estimates,

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providing consistent global all-weather T_s estimates. This advantage is especially relevant over areas of prevailing cloudy conditions, where the amount of available observations in the MW is more than double that in the IR. As such, the two types of T_s estimates can be considered to provide complementary information, and the combined use of MW and IR is planned within the GlobTemperature project. However, inconsistencies between the products will need to be further studied before a merging strategy can be designed, paying attention not only to differences between MW and IR but also to those between IR-based products.

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