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## Comparisons of Ocean Radiative Transfer Models with SMAP and AMSR2 Observations

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### <sup>11</sup> Key Points:

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12	•	Ocean radiative transfer simulations are compared with satellite observations from
13		1.4 to 89 GHz
14	•	The analysis focuses on the accuracy of the models as a function of key ocean vari-
15		ables
16	•	Major discrepancies are found for strong wind speeds and cold sea surface tem-

peratures

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#### 18 Abstract

The sea surface temperature (SST), ocean wind speed (OWS) and sea surface salin-19 ity (SSS) are fundamental variables for understanding, monitoring and predicting the 20 state of the ocean and atmosphere. The analysis of these ocean parameters from pas-21 sive microwave satellite measurements requires a Radiative Transfer Model (RTM). In 22 this study, we compare three ocean RTMs from 1.4 to 89 GHz. A dataset of satellite ob-23 servations from SMAP and AMSR2 collocated with surface and atmospheric parame-24 ters from ECMWF ERA-Interim and Mercator reanalysis has been developed. The se-25 26 lected ocean RTMs are: LOCEAN a physical model with parameters adjusted to L-band measurements, FASTEM (FAST microwave Emissivity Model) a fast parameterized model, 27 and RSS (Remote Sensing Systems) an empirical model fitting satellite observations. Global 28 systematic errors between simulations and observations tend to increase with frequency, 29 and are generally higher at horizontal than at vertical polarizations. Then, the analy-30 sis focuses on the accuracy of the RTMs as a function of the key ocean variables, SST, 31 SSS, and OWS. Major discrepancies are found at frequencies above 1.4 GHz, for OWS 32 higher than 7 m/s, with the LOCEAN and the FASTEM models, with differences strongly 33 increasing with increasing OWS. Cold SSTs are identified as a source of disagreement 34 between the simulations and the observations, regardless of the model. This is a criti-35 cal issue, especially at 6 GHz which is the key channel for the SST analysis from satel-36 lite. The present study is the first step toward the development of a new physically-based 37 community model. 38

#### <sup>39</sup> Plain Language Summary

The sea surface temperature, ocean wind speed, and sea surface salinity are fun-40 damental variables for understanding, monitoring and predicting the state of the ocean 41 and atmosphere. The analysis of these ocean parameters from passive microwave satel-42 lite measurements requires a radiative transfer model. In this study, we compare three 43 different ocean radiative transfer models from 1.4 to 89 GHz. The analysis focuses on 44 the accuracy of the radiative transfer models as a function of the key ocean variables. 45 Major discrepancies with the observations are found at frequencies above 1.4 GHz, for 46 wind speeds higher than 7 m/s, for two of the three models. Cold sea surface temper-47 atures are also identified as a source of disagreement between the simulations and the 48 observations, regardless of the model. The present study is the first step toward the de-49 velopment of a new physically-based community sea surface emissivity model. 50

#### 51 **1 Introduction**

<sup>52</sup> Observation of the ocean is important for oceanic forecasting, Numerical Weather <sup>53</sup> Prediction (NWP), oceanic circulation, mesoscale analysis, and for the study and mod-<sup>54</sup> eling of climate change. The Sea Surface Temperature (SST), the Sea Surface Salinity <sup>55</sup> (SSS), and the Ocean Wind Speed (OWS) are fundamental variables for the ocean char-<sup>56</sup> acterization. These variables can be analyzed from satellite observations with spatial res-<sup>57</sup> olution, time sampling, and uncertainty that differ upon the sensor type.

SST is a key input to atmospheric and oceanic forecasting in NWP systems (e.g., 58 Bell et al. (2000); Martin et al. (2007)) and helps to better characterize the air-sea in-59 teraction. "All-weather" SST is required for NWP and other meteorological applications. 60 The most important characteristics of SST analyses are not only their uncertainty, but 61 also their ability to represent fine scale horizontal structures and their time evolution (Chelton 62 & Wentz, 2005). Infrared sensors such as the Advanced Very-High-Resolution Radiome-63 ter (AVHRR) can retrieve SST at fine scale resolution (1 km), but only for clear sky con-64 ditions. Cloud contamination is particularly problematic as it covers  $\sim 70\%$  of the globe 65 in average at all the time. Microwaves can provide "all-weather" SST with their low sen-66

sitivity to clouds and aerosols, at frequencies < 12 GHz. The current Advanced Microwave</li>
 Scanning Radiometer 2 (AMSR2) (Imaoka et al., 2010), which observes at frequencies
 between 6.9 and 89 GHz, provides SST with a spatial resolution of 50 km and a preci-

<sup>70</sup> sion of 0.55 K (Gentemann & Hilburn, 2015).

SSS measurements are important for the study of the ocean dynamics, the marine 71 biogeochemistry (Carmack et al., 2016), and the global hydrological cycle (Reul et al., 72 2014). Variations of the SSS force the global thermohaline circulation. Small variations 73 in SSS may modify the vertical stratification in ocean density and thus strongly influ-74 75 ence the ocean-atmosphere exchanges. Moreover, SSS is a passive tracer of freshwater flows from river discharges, melting ice, and ocean-atmosphere exchanges. SSS was first 76 retrieved from space from the Soil Moisture and Ocean Salinity (SMOS) mission (launched 77 in November 2009), using passive microwave observations at 1.4 GHz (Kerr et al., 2010). 78 It has been followed by the Aquarius mission launched in June 2011 (Lagerloef et al., 79 2008), and the Soil Moisture Active Passive (SMAP) mission launched in January 2015 80 (Fore et al., 2016). 81

OWS determines the air-sea interactions, such as surface stress, sensible heating, evaporation, and gas exchange (Atlas et al., 2011). Generally, OWS and wind direction are retrieved from microwave scatterometers with 12-25 km spatial resolution, and Synthetic Aperture Radar with 500 m spatial resolution with an uncertainty of less than 2 m/s (Monaldo et al., 2014). It is also possible to derive OWS from passive microwave observations but with less sensitivity to the wind direction.

The analysis of these ocean parameters from passive microwave satellite measure-88 ments requires a Radiative Transfer Model (RTM) in order to interpret the satellite Bright-89 ness Temperatures (TBs) in terms of SST, SSS, and OWS. Ocean RTMs are developed 90 to be applicable over a large range of frequencies, incidence angles and conditions but 91 sometimes they are fine-tuned for a specific application and/or instrument, i.e., a selected 92 range of frequencies and incidence angles. For the first time, with the Copernicus Imag-93 ing Microwave Radiometer (CIMR) mission (Kilic et al., 2018), 1.4 GHz (L-band) ob-94 servations will be combined with 6.9, 10.6, 18.7 and 36.5 GHz (C, X, Ku, and Ka-bands) 95 observations and will provide coincident SST, SSS, and OWS measurements. Therefore, 96 an evaluation of the existing RTMs working at these frequencies is needed, with com-97 parisons against satellite observations. Section 2 describes the selected ocean RTMs and 98 the collocated surface and atmospheric datasets used to compare the RTM simulations with SMAP and AMSR2 observations. Section 3 presents the differences between ob-100 served and simulated TBs for frequencies from 1.4 to 89 GHz as a function of SST, SSS, 101 and OWS. In section 4, we discuss possible approches to improve the ocean RTMs. Sec-102 tion 5 concludes this study. 103

#### <sup>104</sup> 2 Materials and Methods

#### 105

#### 2.1 Ocean Radiative Transfer Models

The microwave ocean emissivity varies with the Sea Surface Temperature (SST), 106 the Ocean Wind Speed (OWS), and the Sea Surface Salinity (SSS), with sensitivities that 107 depend upon the frequency, the polarization, and the incidence angle of observation (Wilheit 108 & Chang, 1980). There are essentially three classes of emissivity models. Firstly, there 109 are physical models, although some of their components may be empirically tuned: they 110 tend to rigorously represent the complex physical interactions between the ocean sur-111 face and the radiation and are generally rather slow. Secondly, there are fast models that 112 attempt to replicate the results of the previous physical models, using parameterizations. 113 Lastly, there are empirical models, partly derived from matchups between in situ ocean 114 observations and satellite observations. 115

Usually, an ocean RTM has three main components 1) a dielectric model, 2) a rough-116 ness model, 3) an ocean foam model. The dielectric constant needed to simulate the emis-117 sivity of a flat surface depends on the SST, the SSS, and the frequency. Dielectric con-118 stant models are expressed as a Debye law (Debye, 1929) with coefficients that have been 119 adjusted to observations. Some dielectric constant models use a double Debye formula 120 to extend the range of frequencies where the model is valid. A roughness model is then 121 needed to simulate the effect of the wind-induced roughness on the ocean. Here, differ-122 ent types of model can be applied. The geometric optic models consider the large scale 123 waves as an ensemble of facets with different slopes for which the Fresnel reflection ap-124 plies. The double scale models consider the diffusion by the small-scale roughness on each 125 large-scale wave, in addition to the large scale model. Then, when the steepness ratio 126 of the waves is too large, the waves break and foam appears. The presence of foam is 127 characterized by (1) a foam cover that depends on the OWS and is usually written as 128 a power law (Monahan & O'Muircheartaigh, 1980), and (2) a foam emissivity that de-129 pends on frequency and incidence angle. 130

- In this study, three ocean RTMs are compared. They are representative of the three model classes:
- The Laboratoire d'Océanographie et du Climat (LOCEAN) RTM is a full phys-133 ical model adjusted to L-band observations. It was implemented by Emmanuel 134 Dinnat and Xiaobin Yin at LOCEAN (Dinnat et al., 2003; Yin et al., 2016). It 135 is derived from the two-scale model of Yueh (1997). The dielectric constant stems 136 from Klein and Swift (1977), the roughness model uses the wave spectrum from 137 Durden and Vesecky (1985) with an amplitude coefficient multiplied by 1.25 (Yin 138 et al., 2012). The foam cover model follows Yin et al. (2016), and the foam emis-139 sivity model is from M. D. Anguelova and Gaiser (2013). This model was primar-140 ily designed for the analysis of SMOS L-band observations. Its physical basis is 141 nevertheless generic and makes it applicable to a large range of frequencies. 142
- The FAST microwave Emissivity Model (FASTEM) is a fast linear regression fit 143 to the output of a physical two scale model (English & Hewison, 1998; Liu et al., 144 2011). It is distributed with the RTTOV, the community radiative transfer code 145 (Saunders et al., 1999, 2018). It was primarily developed for the assimilation of 146 surface-sensitive microwave satellite observations in NWP centers, at frequencies 147 above 6 GHz. FASTEM version 5 is used here. The fast linear regression fits the 148 output of a physical two scale model in which the dielectric constant model is de-149 scribed in Liu et al. (2011), derived from the permittivity model of Ellison et al. 150 (1998) and adapted with a double Debye relaxation. The roughness model is based 151 on the wave spectrum of Durden and Vesecky (1985) with an amplitude coefficient 152 multiplied by 2. The foam cover model is from Monahan and O'Muircheartaigh 153 (1986). The foam emissivity is described in Liu et al. (2011): it is a combination 154 of the adjustments of Kazumori et al. (2008) and Stogryn (1972). 155
- The Remote Sensing Systems (RSS) model is essentially fitted to satellite obser-156 vations. It is developed with SSM/I and WindSat observations between 6-89 GHz 157 (Meissner & Wentz, 2004, 2012) and with Aquarius observations at 1.4 GHz (Meissner 158 et al., 2014, 2018). For the flat sea surface emissivity, it adopts the dielectric con-159 stant model of Meissner and Wentz (2004), adjusted in Meissner and Wentz (2012). 160 The wind-induced emissivity is fitted to satellite observations and described by 161 a polynomial function: it includes the roughness model as well as the foam con-162 tribution. For the RSS model, there are two wind-induced emissivity parameter-163 izations : one between 6 and 90 GHz based on WindSat and SSMI F13 observa-164 tions (Meissner & Wentz, 2012), and one at 1.4 GHz based on Aquarius observa-165 tions (Meissner et al., 2014, 2018). 166

The sensitivity of the TBs to the key oceanic parameters is calculated for the selected channels. For the three RTMs, Figure 1 shows the derivative of the TB as a func-

RTM	Model type	Dielectric constant	Wave spectrum	Foam cover	Foam emissivity
LOCEAN Dinnat et al., 2003	Full physical model adjusted for L-band	Klein and Swift, 1977	Durden and Vesecky, 1985 with $a_0 \times 1.25$	Yin et al. 2016	Anguelova and Gaiser, 2013
FASTEM Liu et al., 2011	Parameterized and fast	Ellison et al., 1998 +Double Debye	Durden and Vesecky, 1985 with $a_0 \times 2$	Monahan and O'Muircheartaigh 1986	Kazumori et al., 2008 with Stogryn,1972
RSS Meissner and Wentz, 2012	Empirically fitted to observations	Meissner and Wentz, 2004 and 2012	Wind induced emissivity fitted to observations Meissner and Wentz, 2012 Meissner et al., 2014		

Table 1.	Summary	of the	selected	ocean	Radiative	Transfer	Models	(RTMs)	١.
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tion of SST, SSS, and OWS (also called the Jacobians), for the selected window frequen-169 cies, an incidence angle of  $55^{\circ}$ , and the two orthogonal polarizations. The considered oceanic 170 situation is close to the global mean state. The most sensitive frequency to the SST is 171 the 6 GHz (especially in the vertical polarization), followed by the 10 GHz and the 18 GHz. 172 The sensitivity to OWS increases with frequency in the horizontal polarization (limited 173 sensitivity at the vertical polarization). The 1.4 GHz frequency is the most sensitive to 174 the SSS. As a consequence and as expected, the analysis of the SST from satellite ob-175 servations will rely on the 6 GHz observations, coupled with observations at 10 and/or 176 18 GHz: the accuracy of the RTM at these frequencies will be particularly critical for 177 the estimation of this ocean parameter. The sensitivity of these frequencies to the OWS 178 will also have to be accounted for in the analysis. For the analysis of the SSS, the con-179 straints on the 1.4 GHz RTM uncertainties are very stringent, as this is the only frequency 180 sensitive to this parameter. From the comparison of these Jacobians calculated with the 181 three RTMs models, we observe that their largest differences come from the treatment 182 of the OWS. 183

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### 2.2 Dataset preparation

AMSR2 was launched on 18 May 2012 on board JAXA GCOM-W1, and SMAP 185 was launched on 31 January 2015. Three days (5,15, 25) of the months of January, April, 186 July, and October in 2016 are selected for the analysis. For AMSR2, we use the Top of 187 Atmosphere (TOA) TBs Level L1R provided by the JAXA platform (https://gportal 188 . jaxa. jp/gpr/, last access 15/07/2019). Each channel is selected at its own spatial res-189 olution except for the 89 GHz channel which is at the same spatial resolution as the 36.5 GHz 190 channel. For SMAP, we use directly the surface TBs, computed by RSS and provided 191 by NASA Jet Propulsion Laboratory (https://podaac.jpl.nasa.gov/dataset/SMAP 192 \_RSS\_L2\_SSS\_V2, last access 15/07/2019). These L-band TBs are corrected for the galac-193 tic signal, from the Faraday rotation, as well as for atmospheric effects. 194

The SMAP and AMSR2 observations are collocated with surface and atmospheric 195 parameters from the European Centre for Medium-Range Weather Forecasts (ECMWF) 196 Re-Analysis (ERA)-Interim and from the Mercator Ocean reanalysis (Global Analysis 197 Forecast Phy 001 024 distributed by the Copernicus Marine Service, Lellouche et al. (2019)). 198 ECMWF ERA-interim at  $0.25^{\circ}$  is adopted for the atmospheric fields, at different pres-199 sure levels. The OWS, the Total Column Water Vapor (TCWV), and the Total Column 200 Liquid Water (TCLW) are also extracted from ERA-interim, but at  $0.125^{\circ}$ . Both con-201 tain reanalysis information at 00:00 06:00 12:00, and 18:00 UTC. The Mercator data at 202

Figure 1. Jacobians of the ocean surface brightness temperature with respect to SST (top), OWS (middle), and SSS (bottom), as a function of frequency for an incidence angle of  $55^{\circ}$ . The oceanic conditions are SST = 291 K, OWS = 6 m/s, and SSS = 34 psu. The atmosphere is not considered here.



0.083° spatial resolution are selected for SST and SSS. For the SST, the hourly information is extracted and for the SSS the daily averages are used. The collocation with
AMSR2 and SMAP data is performed with nearest neighbor interpolation, spatially and
temporally. Two different datasets are created: one with AMSR2 TOA TBs collocated
with the geophysical parameters, and one with SMAP surface TBs also collocated with
the geophysical parameters.

The quality of the data selected as input parameters to the RTMs is also very im-209 portant, as errors in the input parameters will directly impact the simulated TBs. The 210 accuracy of the Mercator products are documented in Lellouche et al. (2019). The SST 211 has mean error between -1 to +1 K. The SSTs in cold regions tend to be underestimated 212 (up to 1 K) while the SSTs near the equator especially in the Pacific Ocean can be over-213 estimated (up to 0.5 K). The SSS from Mercator data rarely exceeds 0.1 psu. In high 214 variability regions like the Gulf Stream or the Agulhas Current, or the Eastern Tropi-215 cal Pacific, the SSS error can reach more than 0.5 psu locally (Lellouche et al., 2019). 216 Mercator reanalysis uses the atmospheric fields from ECMWF ERA-Interim, therefore 217 inconsistencies between the selected surface and atmospheric fields should be limited. 218 The OWS from ERA-Interim has been studied by Stopa and Cheung (2014). This study 219 shows that ECMWF OWS are overestimated for the lower wind speeds (around 0.25 m/s) 220 and underestimated for the upper wind speeds (around 1.5 m/s). Zhang et al. (2018) com-221 pared wind speed from microwave radiometers (WindSat, SSMI, AMSR-E and AMSR2) 222 with in-situ and ECMWF wind speeds. In comparison with the ECMWF data, positive 223 differences are found at high southern latitudes in January and at high northern latitudes 224 in July. 225

The selection of the geophysical parameters, as well as the selection of the TBs datasets, can affect the comparison results and one has to be aware of it. The RSS RTM has been

developed using OWS derived from WindSat, QuikSCAT, and SSMIS (Special Sensor 228 Microwave Imager Sounder), and NCEP (National Center for Environmental Prediction) 229 GDAS (Global Data Assimilation System) wind directions, while LOCEAN and FASTEM 230 RTMs have been developed using ECMWF wind speed. On the other hand, the L-band 231 data used in this study comes from the SMAP instrument and has been corrected by RSS. 232 whereas LOCEAN model at L-band has been fine-tuned with SMOS L-band data. For 233 this global and systematic analysis of the different models over a large frequency range, 234 choices had obviously to be made. However, these aspects will be remembered and care 235 will be exercised in the interpretation of the comparison results. 236

#### 237 2.3 Methodology

The ocean RTMs (FASTEM, RSS, LOCEAN) are fed with the geophysical param-238 eters to calculate the sea surface emissivity. For SMAP data provided by RSS, we com-239 pare directly the sea surface TBs that are already corrected for the atmospheric effects. 240 For AMSR2 data, the atmospheric contribution is simulated with RTTOV version 12 (Saunders 241 et al., 1999, 2018), with inputs from the atmospheric profiles (pressure, temperature, hu-242 midity, and liquid water), and the sea surface emissivity to compute the TOA TBs. More-243 over, the estimation of a scattering term is needed when computing TOA TBs: it rep-244 resents the part of the downwelling atmosphere radiation scattered by the ocean surface 245 in the satellite direction and it depends on the atmospheric conditions and sea surface 246 roughness. The computation method can be different according to the RTM. For FASTEM, 247 the scattering term is taken into account as a multiplicative coefficient on the reflectiv-248 ity of the sea surface. For RSS, it is computed as an additive term to the final TOA TB. 249 For LOCEAN RTM we apply the same scattering term as in the RSS RTM. 250

To perform the simulation / observations comparison, we filter out the sea ice and the coastal areas at 50 km from the continent. Only cases with TCLW < 0.01 kg.m<sup>-2</sup> are considered to limit the contamination by clouds, especially at frequencies > 18 GHz. This threshold has been carefully tested to minimize the potential cloud contribution, without suppressing too many cases.

Systematic error between the observations and the simulations are first evaluated.
The systematic error (i.e., the bias) is computed as the global mean difference between
the observations and the simulations. Thus, after correction of the systematic errors, the
difference between the simulations and the observations is centered. In a second step,
the precision of the RTMs is estimated as a function of the sea surface parameters.

The observations over the globe are not equally distributed between latitude ranges 261 when using data from a satellite in polar orbit. The observations over the poles are more 262 frequent and the ocean areas are larger at lower latitudes. The high latitude observa-263 tions (>  $60^{\circ}N$  and S) represent around 10% of the total number of observations, while 264 the low latitudes  $(0^{\circ}-30^{\circ}N \text{ and } S)$  and the mid latitudes  $(30^{\circ}-60^{\circ}N \text{ and } S)$  represent both 265 around 45%. This has to be remembered when analyzing the data, and this observation 266 distribution is representative of satellites in polar orbit, often used for oceanic and me-267 teorological applications. 268

SSTs are between 273 and 305 K with a mode value at 303 K, OWSs are between 269 0 and 20 m/s (mode value of 7 m/s), and SSSs between 32 and 38 psu (mode value at 270 35 psu). TCWV distribution is between 2 and 60 kg.m<sup>-2</sup> (mode value at 5 kg.m<sup>-2</sup>) and 271 TCLW is between 0 and 0.01 kg.m<sup>-2</sup>, as higher values have been excluded from the dataset 272 to limit contamination by clouds. The geophysical variables are correlated and interde-273 274 pendent (see Fig. 2). For example, at high latitude regions, TCWV is low, SST is cold, and OWS is in average higher, while at the Equator, TCWV is large, SST is warm, and 275 OWS is lower. These correlations make it difficult to isolate the effect of only one pa-276 rameter on the observed TBs, and it is important to be aware of the distributions and 277 correlations of the parameters to correctly interpret the results. The highest correlation 278

Figure 2. Correlation between the geophysical variables estimated from AMSR2 observations.



is found between SST and TCWV. Some cases are also rarely observed, such as strong
OWS above 15 m/s, or very low SST or SSS. Note that RTMs are usually designed to
work better on frequently observed ocean states.

#### 282 3 Results

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#### 3.1 Systematic error estimation

Systematic errors between the TBs observed from SMAP and AMSR2, and the TBs 284 simulated with the different ocean RTMs are first estimated. The mean value of the dif-285 ference between observed TBs and simulated TBs for each channel is computed consid-286 ering only the cases with OWS < 7 m/s. Higher OWS were excluded to this calculation 287 as large discrepancies were observed between the observations and the models for these 288 higher wind speeds: it does not change the conclusion of the analysis, it just changes the 289 TB references. Figure 3 shows these systematic errors and their respective Standard De-290 viations (StDs) for each channel and each ocean RTM. The systematic errors between 291 the observations and the simulations can come from instrument calibration issues, ocean 292 RTMs, ancillary data used as inputs to run the RTMs, or from time or space mismatch 293 between the geophysical parameters and the observations. 294

Systematic errors between SMAP observations and RTM simulations are < 0.9 K 295 (see Fig. 3). Part of these biases could be related to instrument calibration. Peng et al. 296 (2017) tested the SMAP calibration with respect to SMOS data and found a shift of 0.66 K 297 and 0.21 K respectively for vertical and horizontal polarizations over ocean between the 298 two instruments, which is lower than the biases observed with some simulations. Sys-299 tematic errors estimated between AMSR2 observations and RTM simulations are much 300 larger than with SMAP. AMSR2 instrument calibration has been studied by Alsweiss 301 et al. (2015) and Okuyama and Imaoka (2015). Using the double difference method, they 302 found biases up to 5 K over ocean between AMSR2 and TMI, depending on the chan-303 nels. Therefore, AMSR2 and / or TMI instruments have calibration issues. The com-304 puted systematic errors differ among the ocean RTMs, evidencing nevertheless impor-305 tant differences between the models. 306

In operational applications for the analysis of the ocean variables from satellite data, the systematic errors are subtracted. The key information is the variation of the TBs as a function of the oceanic parameters. In the following analysis, the systematic RTM errors are removed and the difference between the observations and the simulations are studied, as a function of the sea surface parameters (SST, OWS, SSS).

Figure 3. Systematic errors between SMAP/AMSR2 observations and the RTM simulations, computed as the mean value of  $TB_{observed}$  -  $TB_{simulated}$ . The systematic errors are represented in solid lines and their Standard Deviations (StDs) are represented in dashed lines.



# 3.2 Evaluation of the simulated brightness temperatures as a function of sea surface parameters

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#### 3.2.1 Comparisons of the brightness temperatures

Figures 4 and 5 (top panels) show the observed and simulated TBs (corrected from 315 the systematic errors), as a function of SST for different ranges of OWS, at 1.4 and 6.9 GHz 316 for both orthogonal polarizations. The variability of the signal as a function of SST is 317 small at 1.4 GHz and the differences between the observations and the RTM simulations 318 are limited. At 1.4 GHz, LOCEAN and RSS RTMs are close to the SMAP observations. 319 FASTEM differs more from the observations, especially at horizontal polarization and 320 for strong OWS: this is expected as FASTEM has not been developed for applications 321 at L-band. At 6.9 GHz, the TBs increase quasi-linearly with the SST, making this fre-322 quency particularly suitable for the analysis of the SST. At 6.9 GHz and higher frequen-323 cies (not shown here), LOCEAN RTM is closer to the AMSR2 observations at low OWS 324 especially for cold water, as compared to the other RTMs. The sensitivity to SST for cold 325 SST (270-280 K) is not well represented with FASTEM and RSS RTMs. This shows that 326 there is not one perfect RTM, regardless of frequencies and sea surface parameters. 327

Similarly to the previous figures but as a function of the OWS and for different SSTs, 328 Figures 4 and 5 (bottom panels) show the observed and simulated TBs (corrected from 329 the systematic errors), at 1.4 and 6.9 GHz for both orthogonal polarizations. At 1.4 GHz, 330 the variability of the TB as a function of OWS is well represented with LOCEAN and 331 RSS RTMs. At 1.4 GHz, FASTEM fails to represent the correct sensitivity for OWS > 12 m/s. 332 At frequencies from 6.9 to 36.5 GHz (not shown), FASTEM and LOCEAN RTMs un-333 derestimate the TB for OWS > 7 m/s. RSS RTM agrees reasonably well with the ob-334 servations as a function of OWS. The RSS parametrization used to describe the OWS 335 sensitivity is different at 1.4 GHz than at higher frequencies (6.9 to 89 GHz). The LO-336 CEAN RTM fits well the observations at 1.4 GHz but does not at high wind speeds at 337 higher frequencies: this shows some deficiency in the treatment of the OWS dependence 338 at higher frequency, coming from the roughness model and/or from the foam treatment. 339 The same is observed for FASTEM with an acceptable OWS dependence up to 12 m/s 340 at 1.4 GHz and only up to 7 m/s at higher frequencies. 341

**Figure 4.** TB comparisons between observations and RTM simulations at 1.4 GHz at vertical (left) and horizontal (right) polarizations. In the top panels the TBs are plotted as a function of SST for different ranges of OWS (colors). In the bottom panels the TBs are plotted as a function of OWS (bottom) for different ranges of SST (colors). The SSS range is between 34 and 36 psu.



Figure 5. TB comparisons between observations and RTM simulations at 6.9 GHz at vertical (left) and horizontal (right) polarizations. In the top panels the TBs are plotted as a function of SST for different ranges of OWS (colors). In the bottom panels the TBs are plotted as a function of OWS for different ranges of SST (colors). The TCWV range is between 0 and 15 kg.m<sup>-2</sup>.



Figure 6. Difference between the SMAP surface TB observations and the RTM simulations (corrected for the systematic errors) at 1.4 GHz as a function of OWS (left panel), SST (middle panel), and SSS (right panel). For comparisons as a function of SST and SSS, only observations with OWS < 7 m/s are taken into account. The distribution of the number of observations as a function of the sea surface parameters (OWS, SST, SSS) are represented in grey bars with legend in right y-axis.



#### 3.2.2 Analysis of the differences between observed and simulated brightness temperatures

We now focus on the ability of the different RTMs to correctly reproduce the TB variability according to the different sea surface parameters (SST, SSS, OWS). For all considered frequencies, Figures 6 to 11 present the comparison between SMAP or AMSR2 TBs with the TBs simulated with FASTEM, RSS, and LOCEAN RTMs as a function of SST, SSS, and OWS. For the analysis of SST and SSS dependences, only the cases where OWS is less than 7 m/s are considered, to avoid the large and possibly misleading errors introduced when OWS is strong.

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At 1.4 GHz, RSS and LOCEAN simulations are in good agreement with the ob-351 servations (see Fig. 6). The variability of the TBs as a function of SST, SSS, and OWS 352 is correctly simulated, as the differences between the simulated and the observed TBs 353 are rather stable. For FASTEM at 1.4 GHz, the TBs are overestimated for  $OWS > 12 \text{ m.s}^{-1}$ . 354 For cold SST, the errors at 1.4 GHz are larger. At very low OWS (0-2 m/s) there are 355 also larger errors. The ocean surface can actually be rough even at very low OWS, due 356 to the swell which is not taken into account in the RTMs here. At horizontal polariza-357 tion, the OWS dependence is less well represented than at vertical polarization. For the 358 comparison with SMAP observations, the RSS model is advantaged, as the SMAP TB 359 surface observations used in this study are generated by RSS. 360

At frequencies above 1.4 GHz (see Fig. 7 to 11), the OWS dependence is not correctly simulated with FASTEM (as already observed by Bormann et al. (2012)) or with LOCEAN model for high wind speeds: the TBs are underestimated at OWS > 7 m/s. To describe the OWS dependence, LOCEAN model and FASTEM use 3 components: a roughness model, a foam coverage, and a foam emissivity, whereas the RSS model uses a parametrization of the OWS dependence based directly on observations, from Aquarius at 1.4 GHz and from SSMI and WindSat at frequencies between 6.9 and 89 GHz. For

Figure 7. Difference between the AMSR2 top of atmosphere TB observations and the RTM simulations (corrected for the systematic errors) at 6.9 GHz as a function of OWS (left panel), SST (middle panel), and SSS (right panel). For comparisons as a function of SST and SSS, only observations with OWS < 7 m/s are taken into account. The distribution of the number of observations as a function of the sea surface parameters (OWS, SST, SSS) are represented in grey bars with legend in right y-axis.











the RSS RTM, the difference with the observations are lower than 1 K up to 10.65 GHz. At higher frequencies in horizontal polarization, the differences between simulations and observations are larger. At these frequencies and especially for the horizontal polarization, the sensitivity to water vapor and liquid water is larger: uncertainties in the atmospheric RTM and in the ancillary atmospheric fields can also introduce errors in the results, despite the filtering of most cloudy scenes.

The analysis of the SSS dependence shows that the discrepancy between simula-374 tions and observations increases with decreasing SSTs. For cold waters, the models tend 375 to show large differences with the observations (especially FASTEM). The possible con-376 tamination of the observations with sea ice has been carefully examined, and eliminated 377 as much as possible. Note that the difference between LOCEAN and the observations 378 has often the opposite sign that the two other models. For frequencies above 18 GHz in 379 horizontal polarization, all RTM simulations disagree with the observations for the low 380 SSTs. These frequencies and polarization are more sensitive to the atmospheric param-381 eters but the reason of the increased discrepancy is not clear at that stage. 382

For large SST above 303 K, a peak in the absolute differences with the observations is observed for all RTMs above 10 GHz, especially in the horizontal polarization. It is explained by the strong correlation between the large SSTs and the high TCWVs, typically in tropical areas. The tropical atmosphere is saturated with water vapor. First, uncertainty in the water vapor content and modeling can introduce additional errors. Second, the probability of clouds increases in these atmospheres, and they are not necessarily well characterized in the ECMWF reanalysis (Geer et al., 2017).

For the SSS dependence, the differences between observations and RTM simula-390 tions are limited, even at 1.4 GHz despite its high sensitivity to this parameter. This is 391 rather encouraging as this is the key frequency for the analysis of the SSS from satel-392 lites. Note that the increase of the errors at SSS close to 38 psu in horizontal polariza-393 tion at 1.4 GHz is associated to a very limited number of observations and should be con-394 sidered with caution (see the related histograms of occurence). At frequencies above 1.4 GHz, 395 the sensitivity to the SSS is very limited (Figure 1). Small changes in the differences as 396 a function of SSS are likely due to correlation with other parameters (SST or OWS). 397

#### 398 4 Discussion

#### 399 4.1 Dielectric Constant

The sensitivity of the sea surface emissivity to SST and SSS is related to the di-400 electric constant module of the ocean RTMs. In the previous section, we observed that 401 the TB for cold SST is underestimated with the RSS and FASTEM RTMs between 6.9 402 and 89 GHz, and mostly overestimated with LOCEAN RTM above 10 GHz. From 6.9 GHz 403 to 10.6 GHz at vertical polarization, the LOCEAN RTM with the dielectric constant of 404 Klein and Swift (1977) is closer to the observations than FASTEM or RSS RTMs using, 405 respectively, Liu et al. (2011) and Meissner and Wentz (2012) dielectric constants. With 406 increasing frequencies, LOCEAN results degrade as the Klein and Swift (1977) dielec-407 tric constant model is supposed to be valid only for low frequencies with its simple De-408 by formula. The models of Liu et al. (2011), and of Meissner and Wentz (2012) use a 409 double Debye formula and should be more appropriate at higher frequencies. 410

SST strongly correlates with water vapor, and at higher frequencies (18-89 GHz) 411 the contribution of the atmospheric attenuation by water vapor strongly increases. There-412 fore, the SST dependent biases in Figures 9-11 could also be caused by imperfections in 413 the atmospheric vapor absorption model or the vapor input rather than the dielectric 414 constant model. The combination of the TBs :  $2 \times TB_{V-pol} - TB_{H-pol}$  is less sensi-415 tive to errors in the atmospheric absorption than the single V-pol and H-pol channels 416 are Meissner and Wentz (2002). When simulating this combination and comparing it to 417 observations (not shown here), the differences do not change much with SST. This in-418 dicates, that the observed biases in the FASTEM and RSS at the higher frequencies in 419 Figures 9-11 are likely due to issues with the water vapor absorption and not with the 420 dielectric constant model. 421

The dielectric constant module of the ocean RTMs can be changed to better fit the 422 observations. The difficulty is to develop an accurate dielectric constant model over a 423 large range of parameters (frequency, angle, SST, SSS). Lawrence et al. (2017) tested FASTEM 424 with a range of measurements for the dielectric constant, and compared the simulated 425 TBs to satellite observations, with the objective of detecting SST dependent biases that 426 could indicate errors in the dielectric constant model for seawater. Their results also plead 427 for reference quality measurements of the dielectric constants, covering the large vari-428 ability of the different parameters, and including uncertainty estimates. Lang et al. (2016): 429 Zhou et al. (2017) initiated such efforts at 1.4 GHz, but it should be extended to higher 430 frequencies, especially at 6 GHz which is the preferred frequency for SST analysis. 431

432

#### 4.2 Foam and roughness models

Errors in the OWS dependence of LOCEAN and FASTEM RTMs are evidenced 433 in Section 3. They can come from three different components of the models. To increase 434 the simulated TB with increasing OWS, there are different possibilities: (1) increase the 435 foam emissivity (noting that it is already close to one, except for L-band), (2) modify 436 the foam coverage model, or (3) modify the roughness model. The key input of the rough-437 ness model is the wave spectrum. Different combinations of foam coverages, foam emis-438 sivilies, and wave spectra are tested to analyze how these terms impact the simulated 439 TBs. 440

Foam cover models such as Tang (1974), Wu (1979) or Monahan and O'Muircheartaigh (1980) lead to an overestimation of the sea surface emissivity at high OWS. Other foam coverage models such as Monahan and O'Muircheartaigh (1986), Yin et al. (2012) or Yin et al. (2016) tend to underestimate the sea surface emissivity above 1.4 GHz. M. D. Anguelova and Webster (2006) show that the foam coverage in the microwaves is underestimated using data from photos or video as it detects only the bright active whitecap and does not reveal the aged whitecap that is less bright. M. D. Anguelova and Webster (2006)

developed a foam cover dataset derived from satellite microwave observations and found 448 two different foam coverages at 10 and 37 GHz. The foam coverage, or more precisely 449 the fraction of foam which impacts the signal at a given frequency, increases with the 450 frequency. At low microwave frequencies (e.g., 1.4 GHz), the penetration depth is ex-451 pected to be larger, meaning that only thick foam layers are detected. With increasing 452 frequency, the penetration depth decreases and the signal becomes sensitive to thiner foam 453 layers. Therefore, at higher frequencies (e.g., 37 GHz) the signal is sensitive to a larger 454 range of foam thicknesses, and the effective foam coverage increases. Based on the M. D. Anguelova 455 and Webster (2006) datasets, Salisbury et al. (2013) and Albert et al. (2016) proposed 456 foam cover models for selected frequencies (see Figure 12, left). Meunier et al. (2014) 457 and M. Anguelova et al. (2014) suggested the possibility of deriving the foam coverage 458 from wave dissipative energy calculated from a wave model: this possibility will have to 459 be further investigated. 460

The foam emissivity model also has an impact on the total foam signal. The foam 461 emissivity is generally close to 1 for the microwaves between 6 and 90 GHz (e.g., Kazumori 462 et al. (2008) and Liu et al. (2011)), whereas it is lower for the L-band RTM (Yin et al., 463 2016). Stogryn (1972) already introduced a dependence with the frequency but it can-464 not be applied at frequencies > 60 GHz (see Figure 12, right). More recently, M. D. Anguelova 465 and Gaiser (2013) suggested a foam emissivity model taking into account the foam thick-466 ness and depending on the frequency. For a given thickness, the emissivity increases with 467 frequencies (see Figure 12, right). 468

In Figure 13, the RTM results are tested with different combinations of foam cover 469 and foam emissivity models. The RSS model is taken as the reference as it shows the 470 best results in terms of TB variability with OWS. FASTEM RTM is tested with the orig-471 inal foam cover of version 5 (Monahan & O'Muircheartaigh, 1986), with the foam cover 472 of version 4 (Tang, 1974), as well as without any foam cover: it clearly underlines the 473 impact of the foam model on the results. For the LOCEAN RTM, we tried several com-474 binations of foam coverage and emissivity models, with the objective of fitting the ob-475 servations as well as possible from 1.4 to 37 GHz. The Albert et al. (2016) model at 37 GHz 476 predicts large foam cover for intermediate wind speeds (Figure 12, left). To simulate the 477 dependence with the frequency, the foam emissivity model of M. D. Anguelova and Gaiser 478 (2013) is tested with different foam thicknesses (as shown in Yin et al. (2016)) to obtain 479 the maximum emissivity at 37 GHz, and the appropriate emissivities at lower frequen-480 cies. Associated to the foam emissivity of M. D. Anguelova and Gaiser (2013) (with a 481 thickness of 2 mm), a reasonable agreement is obtained between model and observations 482 at 1.4 and 6 GHz. Future work will be necessary to refine the combination of foam cover 483 and emissivity, with sound physical basis (e.g., a foam thickness distribution instead of 484 a foam cover). 485

The wave spectrum influence can be studied only with the LOCEAN physical model, 486 as RSS and FASTEM RTMs are parameterized. Dinnat et al. (2003) and Yin et al. (2016) 487 already tested different wave spectrum models such as Elfouhaily et al. (1997), Kudryavtsev 488 et al. (1999), and Durden and Vesecky (1985). They chose the model of Durden and Vesecky 489 (1985) and optimized it to L-band observations by multiplying the spectrum amplitude 490 coefficient of Durden and Vesecky (1985) by 1.25. For its double-scale ocean RTM, Yueh 491 (1997) used the model of Durden and Vesecky (1985) and multiplied the amplitude co-492 efficient by 2 (referenced as DV2 in the figures): it results in a twice larger slope and height 493 variances of the waves. Figure 13 shows some tests and illustrates the impact of the wave 494 spectrum on the LOCEAN model at 1.4 and 6.9 GHz. By multiplying the wave spec-495 trum amplitude coefficient of Durden and Vesecky (1985) by 2 compared to 1.25, we can 496 observe that at 1.4 GHz the emissivities at medium and strong OWS are overestimated, 497 and at 6.9 GHz in vertical polarization the emssivities at strong OWS are still under-498 estimated, while in horizontal polarization at low OWS the emssivities are overestimated. 499

**Figure 12.** Comparison of the foam coverage models as a function of OWS (left) and comparison of foam emissivity models as a function of frequency (with t the foam thickness) (right).



Figure 13. Brightness temperature at 1.4 GHz and  $40^{\circ}$  incidence angle (top) and at 6.9 GHz and  $55^{\circ}$  incidence angle (bottom) as a function of OWS, for different combinations of wave spectrum, foam cover, and foam emissivity models. DV2 refers to the wave spectrum of Durden and Vesecky (1985) (DV) with the amplitude coefficient multiplied by 2. t is the foam thickness in the model of M. D. Anguelova and Gaiser (2013).



#### 500 5 Conclusion

Three ocean emissivity models have been compared with satellite observations from 501 1.4 GHz to 89 GHz. They are representative of the three classes of models: LOCEAN 502 a physical model with parameters adjusted to L-band, FASTEM a fast parameterized 503 model, and RSS an empirical model fitting satellite observations. This comparison ex-504 ercise was based on a dataset of satellite observations from SMAP and AMSR2, collo-505 cated with surface and atmospheric parameters from ECMWF ERA-Interim and Mer-506 cator reanalysis data. The database samples the global ocean over a year. The TBs were 507 simulated for the three ocean emissivity RTMs, adding the atmospheric contribution cal-508 culated from RTTOV when needed. 509

The simulations were carefully compared to the observed TBs. Firstly, global sys-510 tematic errors between simulations and observations were computed. The biases tend 511 to increase with frequency, and are generally higher at horizontal than at vertical po-512 larizations. This is partly due to the increasing effect of the atmospheric contribution 513 with frequency (essentially undetected clouds), especially at horizontal polarization. Part 514 of it can also stem from AMSR2 calibration issues. Secondly, the analysis focussed on 515 the accuracy of the RTMs as a function of the key ocean variables, SST, SSS, and OWS 516 (once the global biases are subtracted). 517

Major discrepancies with the observations were found at frequencies above 1.4 GHz, 518 for OWS higher than  $\sim 7 \text{ m/s}$ , with the LOCEAN and the FASTEM models, with dif-519 ferences strongly increasing with increasing OWS. Possible model improvements were 520 discussed. The analysis tended to show that a frequency dependence needs to be added 521 to the foam cover model or / and to the foam emissivity model. The study also stressed 522 that these two components have to be considered consistently and jointly, all over the 523 frequency range. Efforts should be devoted to the modeling of the foam contribution, 524 taking into account the OWS, but also the frequency dependence, and possibly the wave 525 dissipative energy, as already suggested by Reul and Chapron (2003), Meunier et al. (2014), 526 and M. Anguelova et al. (2014). 527

Cold SSTs were identified as a source of disagreement between the simulations and 528 the observations, regardless of the model. This is a critical issue, especially at vertical 529 polarization at 6 GHz which is the key channel for the SST analysis from satellites. Larger 530 uncertainties at cold SST are partly due to uncertainties in the modeling of the dielec-531 tric constants of sea water, but they can also come from inaccuraccy in the reanalisys 532 data or due to high wind speed effects in cold regions. New laboratory measurements 533 of the dielectric properties of ocean water have recently been undertaken at 1.4 GHz (Lang 534 et al., 2016; Zhou et al., 2017): their extension to a larger range of SST and SSS at higher 535 frequencies should be encouraged, insisting on the uncertainty estimation and with spe-536 cial attention to the 6 GHz. 537

Here, observations from the conical imagers SMAP and AMSR2 have been analyzed, at fixed incidence angles. Observations from the Global Precipitation Mission (GPM) Microwave Instrument (GMI), from 10 to 190 GHz, should be considered soon as this instrument has been shown to be very well calibrated. Future work will also study the angular dependence of the emission signal with observations from the sounders such as the Advanced Microwave Sounding Unit - A (AMSU-A) that measure with incidence angles from nadir up to 60°.

New mission projects such as the Copernicus Imaging Microwave Radiometer (CIMR) (Kilic et al., 2018) requires the development of consistent and accurate ocean surface emissivity models over a large frequency range (here from 1.4 to 36 GHz). More generally, the lack of a reference quality ocean emission model in the microwaves has already been identified at several occasions by the international community (https://www.jcsda.noaa .gov/meetings\_JointEC-JC\_Wkshp2015\_agenda.php,http://cimss.ssec.wisc.edu/ <sup>551</sup> itwg/itsc/itsc21/). The present study identified major issues in the current models.

<sup>552</sup> It is the first step toward the development of a new physically-based community model

to provide consistent results over the microwave range currently (or soon-to-be) observed

<sup>554</sup> from satellites and for all the observing conditions.

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- -V2 (last access 15/07/2019), ECMWF reanalysis data are available at https://apps
- .ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/ (last access 15/07/2019)
- and Mercator Ocean reanalysis data are available at http://marine.copernicus.eu/
- 561 services-portfolio/access-to-products/?option=com\_csw&view=details&product
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