# Techniques for modelling land, snow and sea ice emission and scattering


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**ABSTRACT**

This paper summarizes recent development aiming at enhancing the assimilation of microwave observations over land, sea ice and snow surfaces. Achieving this goal requires an appropriate description of the surface in terms of emissivity and temperature. Most of assimilation experiments discussed in this paper focused on the assimilation of observations from AMSU-A and AMSU-B/MHS instruments.


## 1 On the importance of a good modelling of the surface emissivity

If microwave observations are found beneficial to improve Numerical Weather Prediction (NWP) analyses and forecasts (Karbou et al., 2010b; Kazumuri et al., 2008; English et al., 2014), those receiving contributions from the surface must be carefully handled in order to properly model the effect of the surface (Karbou et al., 2010a-2014; Krzeminski et al., 2008; Di Tomaso et al., 2013). This is due to relatively large uncertainties about the surface emissivity and the skin temperature (English et al. 2008). The uncertainties about the surface are more critical over land than over ocean. Sea emissivities are low, generally close to 0.5, whereas land emissivities are rather close to 1.0. Consequently, the surface contribution to the measured signal is less important over sea than over land. Several studies have been conducted at Météo-France and at ECMWF to improve the surface emissivity modelling for continental and sea ice surfaces. Solutions were tested including the use of (1) climatologies of emissivity on a monthly basis (Karbou et al., 2006) or over a sliding time window using a Kalman filter (Krzeminski et al., 2008; Bormann, 2014), (2) combined use of an emissivity climatology and skin temperature retrieval to improve the assimilation of surface sensitive channels, (3) the use of a dynamically varying emissivity retrieved at well selected window channels and used for sounding channels (Karbou et al. 2010). The emissivity modelling was also examined for some complex surface types such as snow areas (Guedj et al., 2010; Bouchard et al., 2010) and sea ice (Karbou et al., 2014; Di Tomaso et al., 2013). The emissivity developments were carried out for the AMSU-A[1], AMSU-B/MHS[2], SSMI/S[3] sounding instruments but also for imaging instruments such as SSM/I[4], TMI and AMSR-E.

The following figure (from Karbou et al., 2010a) illustrates the effect of the surface on the number of assimilated observations from temperature sounding channels. It shows the density of assimilated observations from AMSU-A channel 7 (which is sensitive to temperature at about 10 km height) over

[1] The Advanced Microwave Sounding Unit-A
[2] The Advanced Microwave Sounding Unit-B / Microwave Humidity Sounder
[3] Special Sounder Microwave Imager/Sounder
[4] Special Sounder Microwave Imager

a grid cells of 2deg x 2 deg when these data are assimilated with an empirical estimation of the surface emissivity (subplot (a) CTL experiment) and with a suitable parametrization of the emissivity (subplot (b) TEST experiment). One should notice that the CTL density map can be used as a land–sea mask since land surfaces can clearly be distinguished on this map. Improvements in the land emissivity modelling in the TEST experiment help improving the assimilation of data over land by increasing the number of assimilated observations with improved radiative transfer performances. It is useful to emphasize that the process of satellite data assimilation can only be beneficial if the model, through the observation operator, is able to accurately simulate the observed brightness temperatures and screen for clouds. The cloud screening is made through a Quality Control (QC) tests mainly based upon evaluation of the difference between the observations and simulations (Obs-Sim) of surface sensitive observations (the difference should be as low as possible). AMSU-A Channel 4 (52 GHz) and AMSU-B channel 2 (150 GHz) are respectively used in QC tests for AMSU-A, and AMSU-B/MHS. The effect of the surface is quite large for these channels which cause a rejection of sounding channels for QC failures.

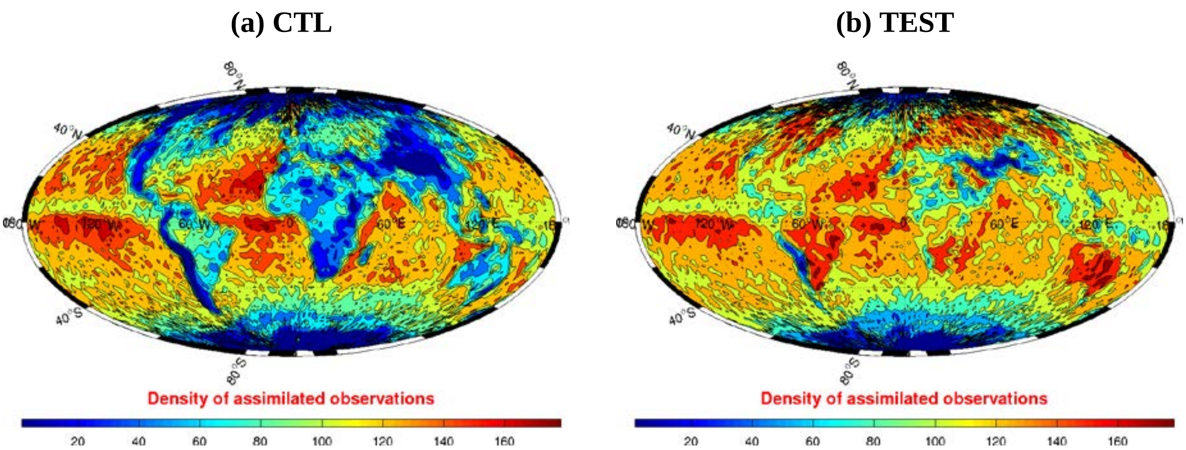


*Figure 1: Map of the density of the assimilated observations from AMSU-A channel 7. The density values have been computed by counting the number of assimilated observations falling in a grid cell of 2°×2° during 45 days (1 Aug–14 Sep 2006). Results are for (a) CTL and (b) TEST experiments (From Karbou et al., 2010a).*

# 2 Surface emissivity estimation for NWP

## 2.1 Emissivity computation

Several studies have shown that land surface emissivities can be estimated from satellite observations (Felde and Pickle (1995), Karbou et al. (2005), Prigent et al. (1997) among others). The surface emissivity computation method is fully described in Karbou et al. (2006): under several assumptions, the integrated radiative transfer equation can be expressed in terms of brightness temperature for a given polarization state:

$$\varepsilon_{(\theta,\vartheta)} = \frac{Tb_{(\theta,\vartheta)} - T_{(\vartheta,\uparrow)} - T_{(\vartheta,\downarrow)} \times \Gamma}{(T_s - T_{(\vartheta,\downarrow)}) \times \Gamma}$$

$Tb_{(\theta,\vartheta)}$ is the brightness temperature measured at frequency $\vartheta$ and with observation zenithal angle $\theta$. Ts, $T_{(\vartheta,\uparrow)}$, $T_{(\vartheta,\downarrow)}$ are the surface skin temperature, the atmospheric upwelling radiation and the atmospheric downwellin radiation respectively. $\Gamma$ is the atmospheric transmission. The RTTOV model, fed by NWP short range forecast of air temperature/moisture and surface temperature, is used to calculate the upwelling, the downwelling radiations and the atmospheric transmission. Emissivity can then be estimated using the radiative transfer equation. The assumptions that are adopted when calculating the emissivity are: (1) the surface temperature and the skin temperature are the same, (2) that there is no volume scattering and (3) that the surface, supposed to be flat, has a specular reflection. The last assumption has been adopted since no a priori information about the surface are available. The use of this assumption for nadir viewing instruments, like AMSU-A & AMSU-B, is questionable for specific cases (Matzler, 2005; Guedj et al., 2010). Karbou and Prigent (2005) have shown that the impact of the specular assumption on the retrieved near-nadir AMSU emissivities when the surface is lambertian, is well below 1% of emissivity bias over natural snow-free areas. Nevertheless, the use of a specularity parameter, when available at a global scale, should correct the effect of the surface assumption. This should be beneficial over, at least, snow and sea ice surfaces involved with volume scattering.

## 2.2 Factors of variability of the emissivity

The surface emissivity varies according to several factors including the surface type, soil moisture and roughness, ground conditions (rain, snow). The emissivity also varies with the observation frequency, the viewing angle, the polarization. An example of surface emissivity outputs is shown in Figure 1 which displays emissivity estimates near 89 GHz using observations from AMSU-A (sub panel (a)), AMSU-B/MHS (sub panel (b)) and ATMS (sub panel (c)). Land global maps as well as sea ice surface emissivities are displayed on this figure. As expected, the emissivity varies in a complex way in space, it varies with frequencies. One can note the very good correspondence between emissivity estimates from AMSU-A, AMSU-B/MHS and ATMS. Snow areas are associated with rather low emissivities at 89 GHz (see for instance the snow signature over North America, Eurasia, and Polar Regions). For the sea ice, the emissivity variation is more complex with emissivity varying with season, ice types, and roughness.

Several factors may change the microwave surface emissivity. These factors include: the surface type, soil moisture, soil roughness, ground conditions (rain, snow), electromagnetic frequency of observation, observation angle, polarisation… Several studies have shown that for a given type of surface (with the exception of the desert and snow) emissivity decreases when the frequency increases. In the case of snow and desert surfaces, the emissivity increases inexplicably between 31 GHz and 50 GHz to decrease again to 89 GHz. Guedj et al. (2010) showed that this frequency variation of the emissivity is due to an overestimation of the surface emissivity near 50 GHz induced by the use of the specular surface hypothesis for the calculation of the emissivity. Besides electromagnetic frequency, emissivity changes according to the angle of observation: this change is lower for high-density vegetation zones and stronger for desert and snow covered areas. In these regions, the change in emissivity could be greater than 5%. Indeed, contrary to the desert and snow areas, forests are associated with a quasi-Lambertian reflection (the viewing angle has a negligible effect on emissivity). For a given frequency, it was also noted that emissivity varies with season.

## 2.3 Impact studies over land surfaces

Several global assimilation and forecast experiments have been run at Météo-France and at ECMWF in order to investigate the usefulness of the assimilation of surface-sensitive observations over land.

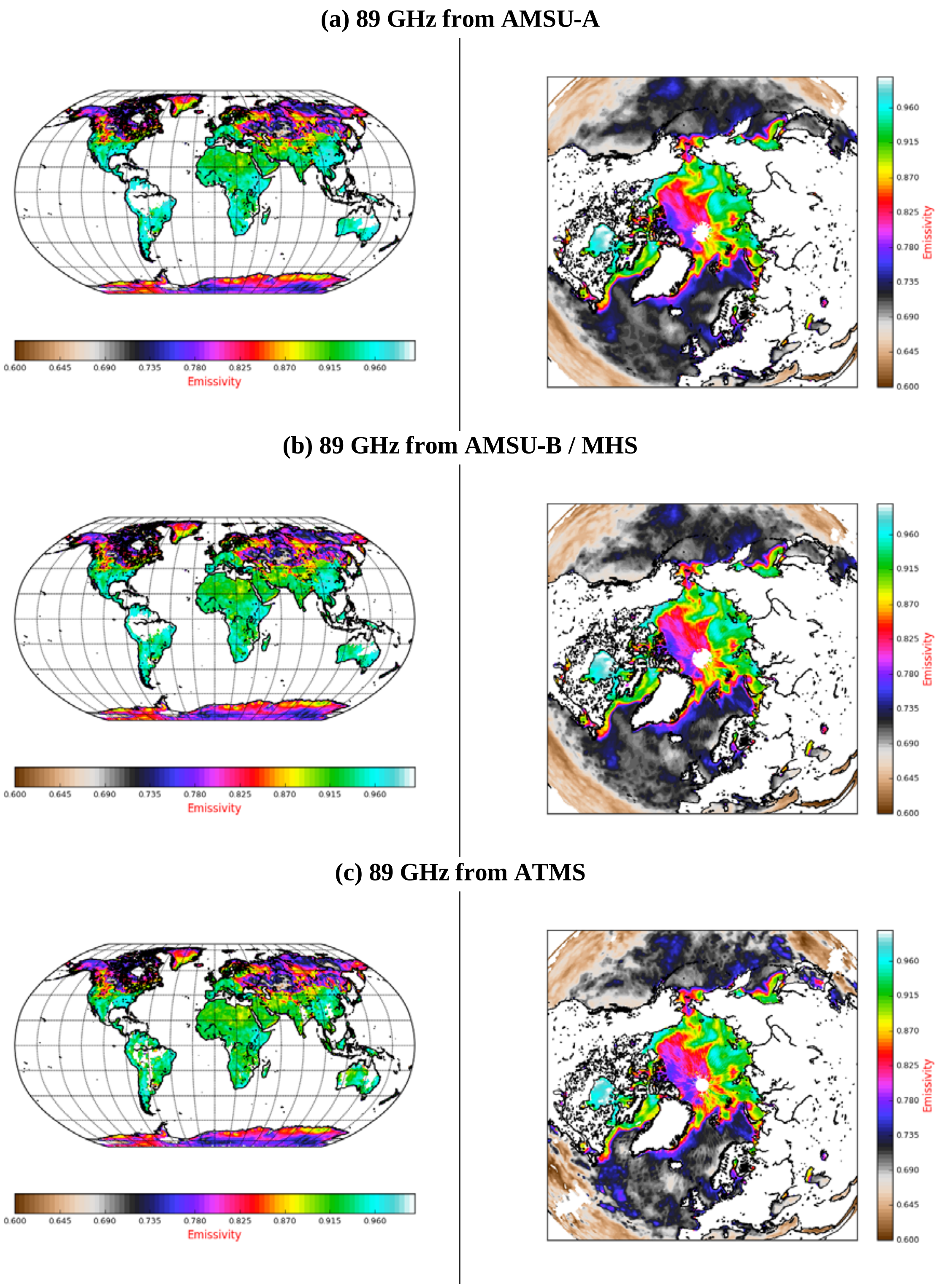


**Figure 2**: *Mean emissivity maps at 89 GHz estimated over land (right panels) and above the sea ice (left panels) using AMSU-A (panels (a) and (b)), AMSU-B/MHS (panels (c) and (d)) and ATMS data (panels (e) and (f)) during one week early February 2014.*

The impacts of this assimilation have been studied with respect to a control experiment, which was representative of the operational model. For AMSU-A, emissivity was dynamically derived at 50 GHz and given to temperature sounding channels whereas it was derived at 89 GHz and given to humidity channels in the case of AMSU-B/MHS instruments. The use of this land surface emissivity scheme was found beneficial for increasing the number of assimilated observations not only from surface-sensitive channels but also from sounding channels. The forecast scores with respect to radiosondes have been found to be positive for geopotential and temperature for forecast ranges up to 72 h. The key finding of these studies was that the largest impacts on the analyses and forecasts when assimilating near-surface microwave observations occur over tropical regions. The experiments assimilating surface sensitive observations produce a moistening of the atmosphere over India, South America, and in West Africa together with a drying of the atmosphere over Saudi Arabia and northeast Africa. The drying or moistening of the atmosphere was far from being negligible and has been successfully evaluated using independent TCWV measurements from the GPS AMMA network. It should be mentioned that very similar humidity features over the tropics have been observed when assimilating TCWV from Medium Resolution Imaging Spectrometer (MERIS) observations over land (Bauer 2009). More details about microwave data assimilation over land surfaces can be found in Karbou et al. (2007-2008-2010ab) and Krzeminski et al. (2008).

# 3 Studies towards the assimilation of observations over the sea ice

Several other studies have been conducted to enhance the use of satellite observations at high latitudes (Di tomaso et al., 2013; Karbou et al., 2014). These studies used the method described in Karbou et al. (2010) to dynamically retrieve the sea ice emissivities to improve the assimilation of AMSU-A and AMSU-B sounding channels over polar regions. Such a method was also found beneficial over Antarctica and surrounding sea (Bouchard et al., 2010; Di Tomaso and Bormann, 2012). These studies have shown that the calculated sea ice emissivities are of a good quality and reflect expected complex variations over sea ice and that the variability of the emissivity depends on many factors, including the age of the ice and this effect should be accounted for at high frequencies (89 and 150 GHz). Figure 3 (a,b) shows mean emissivity maps in the Northern Hemisphere for January 2$^{nd}$ 2009 calculated at 89 and 150 GHz. As expected, the emissivity of sea ice shows a strong variability in space and frequency. Low emissivity values are observed in the boundary areas between sea ice and open water (not shown). These areas are also associated with higher values of emissivity standard deviation during the month of January. Regardless of the frequency, emissivity values are larger for seasonal ice than for permanent sea ice. More generally, the variability of the emissivity appears to be closely related to the type of sea ice. Figure 3 (c, d) shows daily sea ice classification from OSISAF and using Quickscat products. The emissivity of the seasonal ice is generally higher than that of the permanent ice. The gap in emissivities between the two ice types is smaller at frequencies near 23 and 31 GHz compared to frequencies over 50 GHz (except 150 GHz). The emissivity difference is about 5% at lower frequencies while it reaches 10% at 50 and 89 GHz. This is consistent with the results of other recent studies (see, e.g., Mathew et al., 2009) examining the variability of the emissivity according to the frequency of the observations.

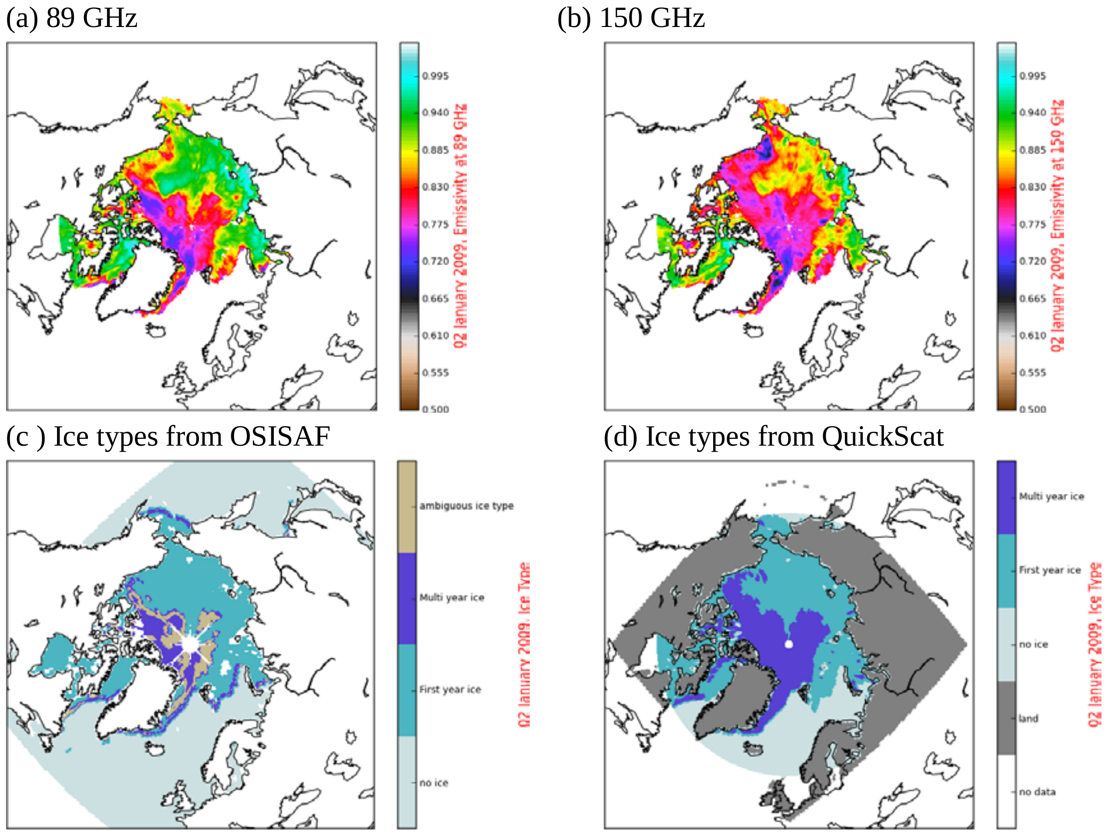


*Figure 3: (a), (b) daily sea ice emissivities retrieved at AMSU-B window channels (89 and 150 GHz respectively) on January 2^nd^ 2009 and (c),(d) sea ice classification from the Eumetsat OSIOSAF and from Quickscat products for January 2^nd^ 2009.*

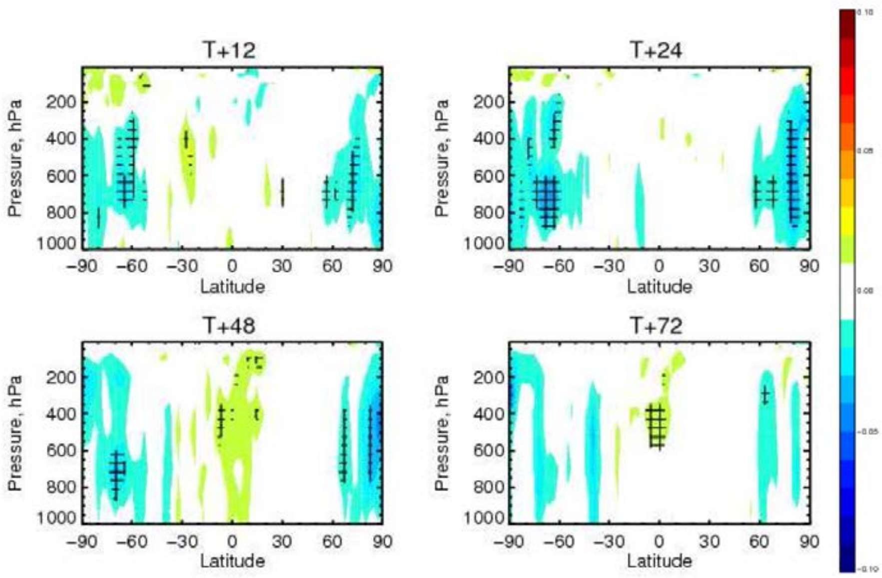


*Figure 4: Normalised differences in the root mean square forecast error between the sea ice experiment (with the assimilation of AMSU observations at high latitudes) and the control experiment in the winter season (January to March 2012) for the 0Z forecast of the geopotential at different pressure levels. Verification is against the experiment own-analysis. (from Di Tomaso et al., 2013)*

In Karbou et al. (2014) more in depth analysis of the emissivity enabled a parameterization of surface emissivity with a correction made to the 89-GHz frequency to be more consistent with the AMSU-B humidity channels. Note that Di Tomaso et al. (2013) have tested the use of 150 GHz channel to derive the sea ice emissivity to be given to humidity sounding channels. For AMSU-A channels, the 50-GHz emissivity of ice was found to be suitable for temperature sounding channels. It has been shown that the assimilation of AMSU measurements over sea ice improves the fit to the assimilated data as compared to background or analysis. The fit to the AMSU observations was improved with nearly 30% more assimilated AMSU-B data (more than 10% for AMSU-A). The assimilation of these data produces a significant change in the atmospheric analyses over polar areas (in particular those of temperature and humidity). The effect on temperature results in a warming of the lower troposphere, which is more pronounced around 850 hPa and weaker close to the surface. This leads to an increase in the Arctic inversion strength over the Arctic ice cap of almost 2 K. Forecasts were generally improved especially over Europe and North America for forecast ranges greater than 48 h. Regarding forecast impact in IFS, Di tomaso et al. (2013) have shown that the assimilation of AMSU observations over the sea ice brings positive impact for the forecast of the temperature, geopotential and winds in the Southern Hemisphere, and an impact mainly neutral elsewhere (experiments during the summer season). Experiments run during the winter show a positive impact for the relevant atmospheric variables in both hemispheres. The normalised differences in the root mean square (RMS) forecast error between the sea ice experiment and the control experiment for the forecast of the geopotential in the winter season are shown in Figure 4. Blue shadings indicate that the sea ice experiment has a smaller RMS error than the control experiment.

# 3 The snow issue

Snow plays a key role in global energy and mass budgets but monitoring its extent and quantifying its water equivalent paradoxically remains a major scientific challenge. The complex natural spatial and temporal variability of snow, the imperfect knowledge of snow physics, the scarcity of in-situ observations, are among the possible reasons for this. It is therefore not surprising that data assimilation over snow is still difficult to achieve because of uncertainties in the estimation of emissivity, lack of knowledge of penetration depths of microwaves in snow and the modeling of the surface temperature. For instance, Antarctica is part of the most covered areas by polar orbiting satellites but paradoxically very few observations are actually used in data assimilation systems over this continent. Like other continental surfaces, emissivity of snow is one of the factors that limit the assimilation of observations. Indeed, uncertainties about the surface are amplified over Antarctica due the high altitude of the continent, leading some temperature sounding channels or humidity behaving like "surface sensitive channels”. In addition, polar snow is a very complex environment, often modeled by the wind. It is a layered medium associated with complex interaction the electromagnetic waves (varying penetration depth). Picard et al. (2007) have shown that the microwaves can penetrate snow up to 2 m at 19 GHz and up to 50 cm at 37 GHz. This phenomenon makes the surface property retrieval very complex.

## 3.1 Assumptions about the surface

When calculating the emissivity from satellite observations, one has to approximate the reflection properties of the surface: specular, Lambertian or intermediate. A surface is called specular if it reflects the received radiation at an angle equal to the incident angle whereas a surface is assumed

Lambertian if it reflects the incident radiation isotropically. In most cases, the surface is considered specular (Jones and Vander Haar, 1997; Prigent et al., 1997; Weng et al., 2001; Karbou et al., 2005; Mathieu et al., 2008...). The use of this assumption brings several simplifications and no significant bias for snow free surfaces (Karbou and Prigent, 2005). Mätzler (2005) found that the use of this assumption is questionable for “cold” surfaces and for near-nadir observations. Mätzler (1987) and Ingold et al. (1998) have derived an effective incidence angle that would correspond to the downwelling radiation for lambertian surfaces. At microwave frequencies, the zenith opacity is generally close to 0.1 which leads to an effective angle close to 55°. If microwave observations are acquired at 53°, which is the case of SSM/I and SSMI/S channels, the effect of the surface assumption will be negligible. For near-nadir observations, the effect of the specular assumption may be rather large. Since natural surface is a complex mixture between specular and lambertian surfaces, Mätzler (2005) suggested the use of a specularity parameter (which varies from 0 and 1) to describe the reflection at the surface:

$$T_{\downarrow}\ (\theta) = sT_{SPEC}^{\downarrow} + (1-s)T_{LAMB}^{\downarrow}$$

$T_{SPEC}^{\downarrow}$ and $T_{LAMB}^{\downarrow}$ are the atmospheric downwelling radiations if the surface is assumed to be specular and lambertian respectively. Guedj et al. (2010) calculated Antarctica surface emissivity using observations from AMSU-A window channels and using 5 assumptions about the surface:

| | |
|---|---|
| ***s*=1** | Specular surface |
| **s=0** | Lambertian surface |
| **s=0.25** | Quasi-lambertian surface |
| **s=0.5** | Semi lambertian surface |
| **s=0.75** | Quasi specular surface |

The validity of the five surface approximations was studied by analyzing the emissivity variation in time, space and frequency. It was noted that AMSU-A channel 3 (50 GHz) is the most sensitive channel to the surface approximation. If the surface is Lambertian, the use of a specular approximation may introduce up to 3% of emissivity bias for nadir observations. RTTOV simulations were also performed at sounding channels to identify the most suitable approximation for Antarctica. Emissivities for these channels were taken from their values at window channels. Figure 5 shows correlation maps between observations and simulations of channel 4 AMSU-A (52.8 GHz) during the month of January 2007. For each of these maps, the emissivity of channel 3 (50 GHz) was used as input to RTTOV: (a) the emissivity from the model of Weng et al. 2001 (operational scheme in 2007 at Météo-France), (b) - (c) - (d) with emissivity calculated assuming Lambertian, specular and semi-Lambertian surfaces respectively. It may be noted that there is a significant increase in correlation when the emissivity is retrieved from satellite data (without regard to surface assumption). The results for January appear best when using a semi-Lambertian approximation. When examining the results for the whole year 2007, Guedj et al. (2010) have shown that it is beneficial to use the Lambertian approximation in the winter because it provides better statistical bias / SD / correlation. Conversely, the use of specular or semi-Lambertian approximation gives rather good results during the summer season.

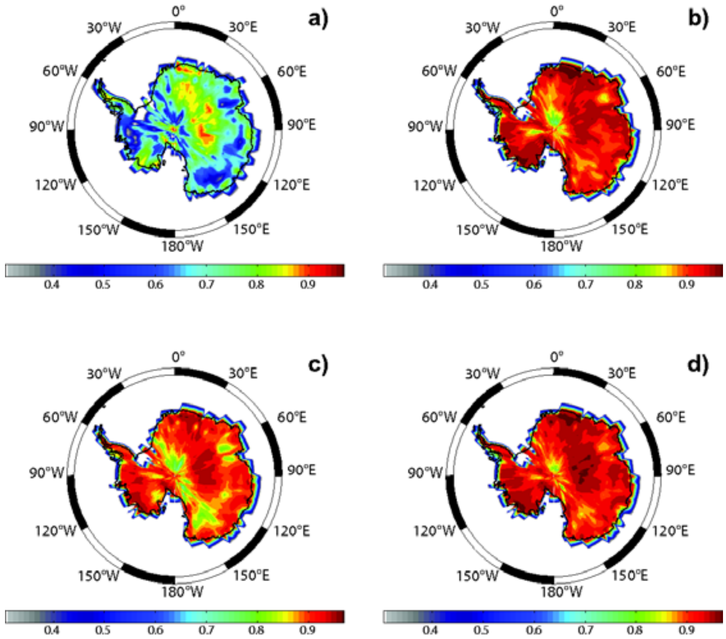


*Figure 5: Correlation maps between observations and simulations of channel 4 AMSU-A (52.8 GHz) during the month of January 2007. For each of these maps, the emissivity of channel 3 (50 GHz) was used as input to RTTOV: (a) the emissivity model comes from Weng et al. (2001) (operational scheme at Météo-France in 2007), (b) - (c) - (d) with emissivity calculated assuming Lambertian, specular and semi-Lambertian surfaces respectively.*

## 3.2 Towards a better understanding of emissivity variation with some snow properties

Crocus is a physically-based snowpack model that simulates energy and mass balance of the snowpack taking into account snow metamorphism using a detailed description of the vertical stratification of snowpack (Brun et al., 1992; Vionnet et al., 2012). Crocus is implemented within the externalised surface module SURFEX of Météo-France, as one of the snow models of the land surface model ISBA (Noilhan and Mahfouf, 1996), which allows the thermodynamical coupling between snow and soil models. Crocus can be forced by observations and reanalyses (e.g. ECMWF ERA Interim) or coupled to atmospheric models. Brun et al. (2013) have shown that the Crocus snow scheme coupled with the multi-layer version of the ISBA soil scheme forced by ERA-interim reanalyses provides snow simulations of very good quality against ground snow depth and SWE observations. Preliminary studies have shown that it is possible to extract relevant information on the state of the snowpack using microwave observations at high frequencies compared to several snow products. Daily SWE estimates are available at the global scale among which one could cite spatial interpolations of in-situ measurements, empirical formulas applied to remote sensing measurements and assimilation techniques that combine a priori information from physically-based models and heterogeneous observations of SWE (synoptic and remote sensing data). So far, most of the studies undertaken to estimate SWE values from remote sensing passive microwave measurements are based upon the use of a brightness temperature (Tbs) difference between two frequencies: 37 GHz at which the electromagnetic signal is scattered by snow crystals and 19 GHz considered insensitive to snow. In the most well known study, Chang et al. (1987) have proposed a linear fit formula using Tbs at 18 and 37 GHz assuming a constant density of snow (300 kg $m^{-3}$). This method has been widely used thereafter to derive SWE from microwave measurements but with a number of critical views on its performances compared to in-situ measurements.

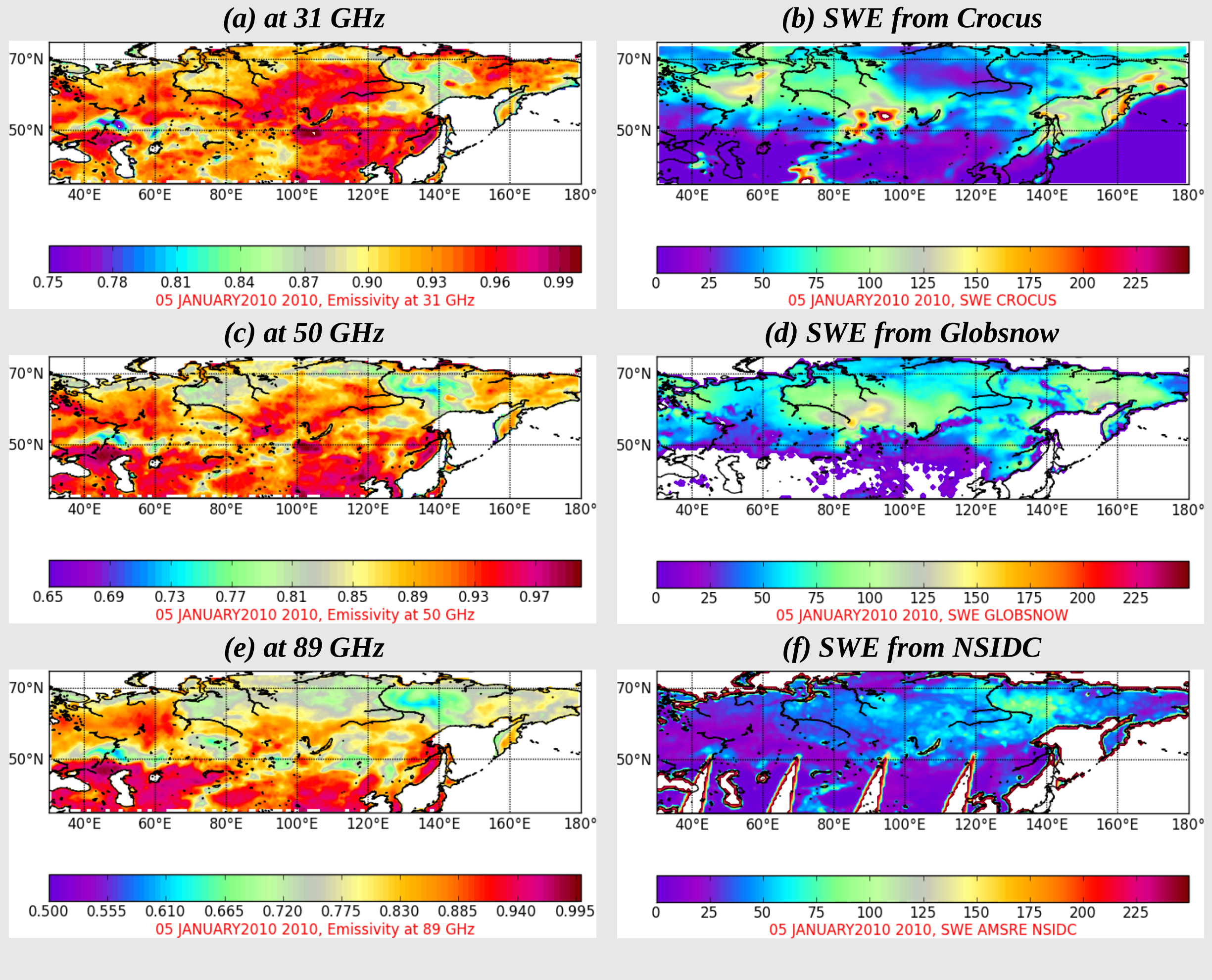


*Figure 6: (left) Estimates of surface emissivity derived from AMSU-A Tbs at 31, 50 and 89 GHz on January 5th 2010 and (right) Estimates of SWE coming from Crocus simulations fed by ERA-Interim meteorological forcing, ESA-DUE Globsnow and NSIDC products for the same day (5 January 2010).*

The performances of the Chang et al. algorithm, in terms of mean values and spatial variability, can vary considerably and appear to be dependent on snow physical characteristics (see for instance Davenport et al. (2012), Armstrong and Brodzik (2000), among many others). Data merging techniques, such as variational assimilation, are increasingly privileged since they can overcome the low density of in-situ measurements. Pulliainen (2006) proposed an assimilation tool that combines information from passive microwave data (18 and 37 GHz) and snow depth measurements from the synoptic ground station network. Within this scheme, snow depth in-situ measurements are used to feed the semi-empirical Helsinki University of Technology (HUT) snow emission model (Pulliainen et al., 1999) having a one-layer snowpack description (depth, density and grain size) to provide simulated Tbs. These Tbs are then compared to satellite observations (from SSM/I, AMSR-E ) near synoptic stations to fit the model estimations by updating effective snow grain size values. These various methods of estimating SWE led to some operational products such as the EUMETSAT HSAF SWE products (http://hsaf.meteoam.it/snow.php), the ESA Globsnow SWE products (Luojus et al. 2010) and NSIDC estimates (Tedesco et al., 2004). Other methods have been defined to produce estimates of SWE for Numerical Weather Prediction models. Drusch et al. (2004) describes an

Optimal Interpolation (OI) method used at the European Centre for Medium range Forecast (ECMWF) to analyse the snow depth by assimilating observations from synoptic stations combined with the NOAA/NESDIS Snow cover extent. Other meteorological centres (the National Weather Service, the Canadian Meteorological Centre) produce snow depth analyses by combining available snow in-situ observations and snow models of varying complexity.

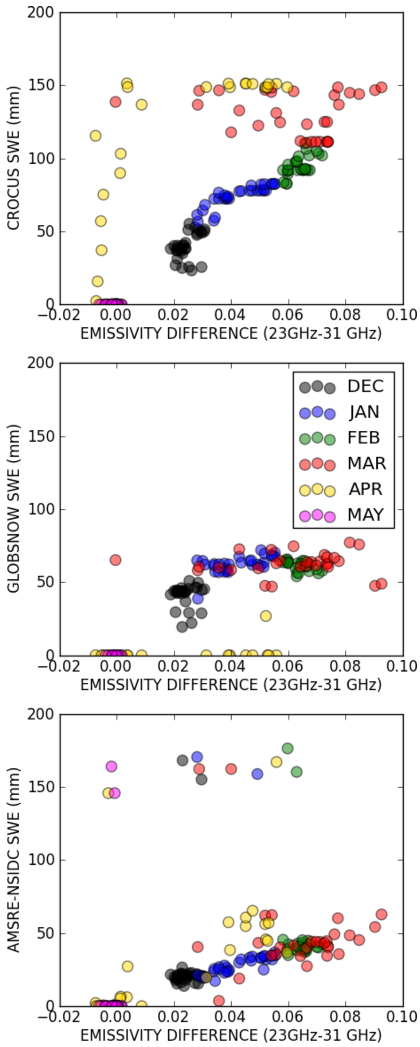


Figure 6 displays a comparison example of snow information from surface emissivities derived at different frequencies and Snow Water Equivalent (SWE) products coming from ERA-Interim / Crocus, ESA-DUE Globsnow and NSIDC. SWE is the water content of the snow if the snowpack melts instantly, and corresponds to the total water mass per unit surface area. SWE can also be viewed as the product of snow depth by the snowpack bulk density and is a key variable of the surface water budget at various spatial and temporal scales, with large fields of applications including land surface hydrology and numerical weather prediction. The emissivities were used rather than Tbs in order to remove the effect of the atmosphere from the observations. One can see that the variability of the microwave emissivity signal is in rather good agreement with the spatial SWE patterns present in Crocus and NSIDC. Figure 7 shows the daily correspondence between emissivity difference (23 GHz minus 31 GHz) as function of SWE from Crocus, Globsnow and NSIDC near a synoptic station. One could notice the rather good agreement between Crocus and microwave observations to describe the variability in time of the SWE.

*Figure 7: Daily variation of emissivity difference (23 GHz minus 31 GHz) near a synoptic station (50.42ºN–80.3ºE) as function of SWE from Crocus, Globsnow and NSIDC). Results are shown for 5 months (12/ 2009 to 05/2010).*

The challenge that should be faced in the next few years is to combine optimally physically based snow evolution models with relevant information on the snowpack properties provided by microwave measurements (Tbs or emissivities). These developments could then be used in NWP framework to better handle observations over snow surfaces.

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