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First Three Years of the Microwave Radiometer aboard Envisat: In-Flight Calibration, Processing, and Validation of the Geophysical Products

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ABSTRACT

The Envisat microwave radiometer is designed to correct the satellite altimeter data for the excess path delay resulting from tropospheric humidity. Neural networks have been used to formulate the inversion algorithm to retrieve this quantity from the measured brightness temperatures. The learning database has been built with European Centre for Medium-Range Weather Forecasts (ECMWF) analyses and simulated brightness temperatures by a radiative transfer model. The in-flight calibration has been performed in a consistent way by adjusting measurements on simulated brightness temperatures. Finally, coincident radiosonde measurements are used to validate the Envisat wet-tropospheric correction, and this comparison shows the good performances of the method.

1. Introduction

The European satellite Envisat was launched from Kourou (French Guyana) on 1 March 2002. It is equipped with many instruments dedicated to the observation of the earth environment. Among them, the Radar Altimeter (RA)-2 is used over sea to determine the ocean topography, thus supporting the research of sea level and ocean circulation. To correct the altimeter range for water vapor path delay over ocean, a nadir-looking microwave radiometer has been added to the mission, as for previous altimetry missions [the *European Space Agency (ESA) Remote Sensing Satellite (ERS)-1*, *ERS-2*, Ocean Topography Experiment

(TOPEX), *Jason-1*]. This radiometer provides at the location of the altimeter footprint brightness temperature (TB) measurements at 23.8 and 36.5 GHz. Because any error in the wet-tropospheric correction directly impacts the sea level determination, the constraints on the quality of the in-flight calibration and data processing of the radiometer are particularly stringent. The uncertainty on the wet-tropospheric correction is today around 1-cm rms (Ruf et al. 1994; Bernard et al. 1993), but remains a significant contribution in the global uncertainty on the sea level estimation (around 4-cm rms; Fu and Cazenave 2001). In this paper, we present the method we used to prepare and improve the processing of the Envisat microwave radiometer (MWR) to perform the in-flight calibration, so to provide at the end of the commissioning phase an accurate wet-tropospheric correction.

The altimeter wet-tropospheric correction depends on atmospheric vertical profiles of humidity, tempera-

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ture, and pressure, and can be retrieved from microwave radiometer measurements. The most classical way to do this consists of the use of multilinear regression between the wet-tropospheric correction and functions of the corresponding brightness temperatures (Ruf et al. 1994; Eymard et al. 1996). Recent improvements in the retrieval algorithm are mainly related to the development of nonlinear statistical methods, such as neural network techniques. We present in section 2 the work performed before launch to prepare and define the neural algorithms dedicated to the retrieval of the microwave radiometer parameters (wet-tropospheric correction, water vapor content, cloud liquid water content, and atmospheric attenuation of the altimeter backscattering coefficient in both the Ku and S bands).

After launch, the major difficulty lies in performing the in-flight calibration of the microwave radiometer. There is no natural blackbody target that could help to control the measured brightness temperatures. The method we used to calibrate the Envisat MWR is therefore a combination of a comparison with its predecessor *ERS-2* MWR flying on the same orbit with a time lag of about half an hour, and simulations over sea using atmospheric profiles, sea surface temperature, wind, and a radiative transfer model. A detailed description of the methodology we used to perform the early in-flight calibration of the radiometer and the estimated uncertainty on the measured brightness temperatures are presented in section 3.

The validation of the wet-tropospheric correction is performed by comparison with collocated radiosonde measurements. But, the weak number of collocations obtained during the first 3 yr of the mission and the heterogeneous geographical distribution of the radiosonde measurements make this validation insufficient. It is therefore completed with a systematic comparison with analyses from a meteorological model. Furthermore, the use of the Envisat retrieval algorithms to retrieve the *ERS-2* wet-tropospheric corrections from the *ERS-2* brightness temperatures allows a more complete validation of the algorithm using radiosonde measurements (7-yr time series). These validation results are presented in section 4.

Finally, conclusions and perspectives are presented in section 5.

2. Retrieval algorithms

Methods have been established since the launch of the *Seasat* scanning multichannel microwave radiometer (SMMR) (Wilheit and Chang 1980) to relate the integrated content in water vapor to the brightness temperatures using empirical relationships. They combine

channels taken inside and outside the water vapor absorption line centered at 22.235 GHz. Two other channels are required to account for the effect of the sea surface and cloud scattering. For these reasons, both the TOPEX microwave radiometer (TMR) and *Jason-1* microwave radiometer (JMR) use three channels—one below the water vapor line (18 and 18.7 GHz, respectively) where the sensitivity to clouds is low, one in the absorption line (21 and 23.8 GHz, respectively), and one at a higher frequency (37 and 34 GHz, respectively) where the sensitivity to cloud liquid water is higher. In the case of the *ERS-1*, *ERS-2*, and Envisat microwave radiometers, which do not include the low-frequency channel, the surface roughness is taken into account either through the altimeter wind speed (Eymard et al. 1996) or the backscattering coefficient in Ku band (Obligis and Eymard 2000).

The retrieval of the geophysical parameters from the radiometric measurements is difficult. This is mainly because of the nonlinearity of the relation linking the brightness temperatures to the geophysical parameters (atmosphere and surface), but also because of the integrated nature of the radiometric measurement. For the formulation of the Envisat MWR retrieval algorithms, we chose a “mixed” method, already used for the *ERS-1* MWR and *ERS-2* MWR processing (Eymard et al. 1996), which is a compromise between statistical and physical methods. It is based on the use of a representative database of surface and atmosphere variables and a radiative transfer model. The database is built with a very large number of meteorological situations to ensure good representativity. Brightness temperatures corresponding to each point of this database are simulated using a radiative transfer model. The improvement with respect to the *ERS-2* methodology is the use of neural networks to perform the regression.

Neural networks have been widely tested these last 10 yr to retrieve atmospheric and oceanographic parameters [see Krasnopolsky et al. (1995) and Mejia et al. (1998) for surface wind, Bourras et al. (2001) for latent heat fluxes, and Aires et al. (2001) and Mallet et al. (2002) for atmospheric parameters]. They exhibit several properties that make them attractive for solving inverse problems. On the one hand, they are able to represent the nonlinear relationships without a priori information and, on the other hand, even if the learning step is time consuming, the retrieval method application is fast and robust.

a. Building of the database

The quality of the retrieval with neural networks algorithms is directly related to the quality of the data-

base used to train the network, and more precisely to its representativity.

The database is built with four global fields from the European Centre for Medium-Range Weather Forecasts (ECMWF) operational model distributed over 1 yr, with one per season between August 2000 and March 2001. We used forecast fields at 12 h, which gives the best compromise between a good impact of data assimilation for each latitude and a good balance in the precipitation–evaporation budget (Gérard and Saunders 1999). These fields contain analyses of surface parameters (temperature, pressure, wind speed) and atmospheric profiles (temperature, pressure, water vapor, and cloud liquid water content). The 60 pressure levels in the model allow for a complete description of the troposphere/stratosphere, and the horizontal resolution is half a degree.

The final database, containing a total of 85 122 geophysical situations, is separated in two parts—a “learning database,” which represents 75% of the initial database, extracted randomly, and a “validation database,” containing the 25% remaining data. This partition allows the parameters of the inversion algorithm (parametric or neural) on the learning database to be tuned and its quality and its capacity of generalization over an unknown dataset to be checked. A random draw function of the latitude is performed to avoid an overrepresentation of high-latitude situations in the learning database.

Because of the particular distribution of the wet-tropospheric correction and cloud liquid water values, the constitution of the learning database requires special care in the case of linear regression. This is not the case with the neural formalism, which will provide an accurate algorithm over the whole interval of values.

b. Simulations on the geophysical database

For each set of geophysical parameters in the database (learning and validation), brightness temperatures (at 23.8 and 36.5 GHz) and backscattering coefficients (in Ku and S bands) are simulated using a radiative transfer model. The double-scale emissivity model has been developed at the Université Catholique de Louvain by Guissard and Sobieski (1987), and improved by Lemaire (1998) and Boukabara et al. (2002). It is associated with the Elfouhaily spectrum (Elfouhaily et al. 1997) to describe the sea surface roughness and is appropriate for a non-fully developed sea state. The foam is represented as a porous dielectric layer of water and air. The sea surface emissivity is corrected using the thickness, the coverage rate, and the foam layer emissivity. The thickness of the foam layer is arbitrarily fixed to 1 cm, following Droppleman (1970). The cov-

erage rate is approximated by a function of the wind speed at 10 m and the sea surface viscosity (Monahan and Lu 1990). The relative dielectric constant of the foam is given by Troitsky (1962) and is a function of the portion of air in the mixed layer (arbitrarily fixed to 0.95). The seawater permittivity follows the model of Ellison et al. (2003). To take into account the radiative transfer in the atmosphere, it has been combined to the Liebe millimeter-wave propagation model (MPM) (Liebe et al. 1993) for gaseous absorption by oxygen and water vapor. The absorption by cloud liquid water is computed using the Rayleigh theory.

This simulation model has been validated in a large number of instrumental configurations: for simulations of backscattering coefficients in Ku, C, and S bands, for simulations of polarized brightness temperatures from nadir to 53° of incidence angle, and for frequencies between 10.7 and 85 GHz (Lemaire 1998; Eymard et al. 2000; Ellison et al. 2003; Obligis et al. 2004).

c. The network and its architecture

A neural network is defined by the number of layers, the number of neurons for each layer, and the transfer function associated to each neuron. The network parameters (the weights and biases associated to each neuron) are adjusted when presenting the inputs and outputs from the learning database to the network. This is what is called “supervised learning.”

In the context of the Envisat MWR algorithm development, the inputs consist of three parameters—the brightness temperatures at 23.8 and 36.5 GHz and the backscattering coefficient in Ku band measured by the altimeter to take into account the surface roughness. The output is one of the geophysical parameters to be retrieved from these satellite measurements: the wet-tropospheric correction (dh), the integrated water vapor content (wv), the cloud liquid water content (wc), and the atmospheric attenuation coefficients of the backscattering coefficients in Ku (att_Ku) and S (att_S) bands.

The resulting neural network has a simple architecture (the same for each parameter) with one hidden layer of eight neurons and the output layer with a linear neuron. The transfer function for each neuron of the first layer is the tan-sigmoid function. The retropropagation algorithm is the Levenberg–Marquardt algorithm because it is the most efficient for the convergence speed.

d. Comparison with parametric algorithm on the validation database

For comparison, we also developed in parallel classical log-linear algorithms for the Envisat MWR con-

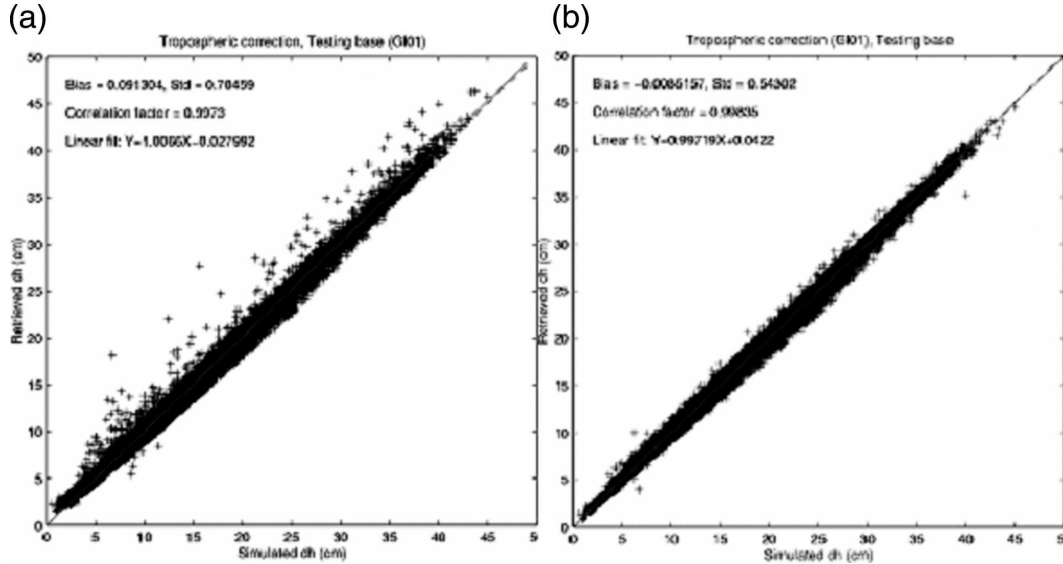


FIG. 1. Scatterplot between dh in the validation database and retrieved dh with (a) the parametric algorithm and (b) the neural algorithm.

figuration following Gérard and Eymard (1998) and Eymard and Boukabara (1997). These algorithms are very similar to the ones used for the *ERS-2* mission, but the surface roughness contribution, which is taken into account with the altimeter wind speed for the *ERS-2* mission (Eymard et al. 1996), is now directly introduced in the retrieval algorithm with the backscattering coefficient in Ku band. This is actually an improvement because the direct use of the backscattering coefficient in Ku band prevents any error coming from the surface wind speed retrieval from being added, itself based on the inversion of the backscattering coefficient. The general form of the parametric algorithm is as follows:

$$P = c0 + c1 \times \ln(280 - TB_{23.8}) + c2 \times \ln(280 - TB_{36.5}) + c3 \times (1/\sigma_{Ku})^2,$$

where P is the parameter to be retrieved (dh is in centimeters, wv is in grams per square centimeter, wc is in milligrams per square centimeter, or att_{Ku} and att_S are in decibels). The brightness temperatures $TB_{23.8}$ and $TB_{36.5}$ are measured at 23.8 and 36.5 GHz (K), and σ_{Ku} is the backscattering coefficient in Ku band (dB).

To compare the quality of the parametric and neural network models, both algorithms are then applied on the “validation database.” Both algorithms are thus compared on the same data, independent of the dataset on which they have been formulated.

Figure 1a (Fig. 1b) shows the scatterplot between the dh values in the validation database and the retrieved dh with the parametric algorithm (with the neural algorithm). Both algorithms present similar correlation factors, but the neural network significantly reduces the standard deviation (0.54 cm instead of 0.70 cm) and corrects the defect observed with the parametric algorithm in the case of a very dry atmosphere (overestimation of wet path delays lower than 8 cm). Gérard (1996) already observed this particular behavior with the parametric algorithm and suggested that it could be because of negative sea surface temperatures or the very dry atmosphere associated with high wind speed. The good performances of the neural algorithm in these particular situations show that it may come from the global log-linear form of the algorithm, which is not enough flexible to model these situations. Here the neural network has the capacity to well adjust locally the retrievals, even in areas where there is a low density of data.

Figures 2a and 2b show the scatterplots between wc in the validation database and wc retrieved with parametric and neural algorithms. The retrieval is better with the neural network, especially for values higher than 100 kg m^{-2} . All of the statistical parameters (bias, standard deviation, and correlation factor) are also improved. This is a significant improvement with respect to the *ERS-2* algorithm, which systematically underestimates the cloud liquid water contents higher than 0.5 kg m^{-2} (Gérard 1996).

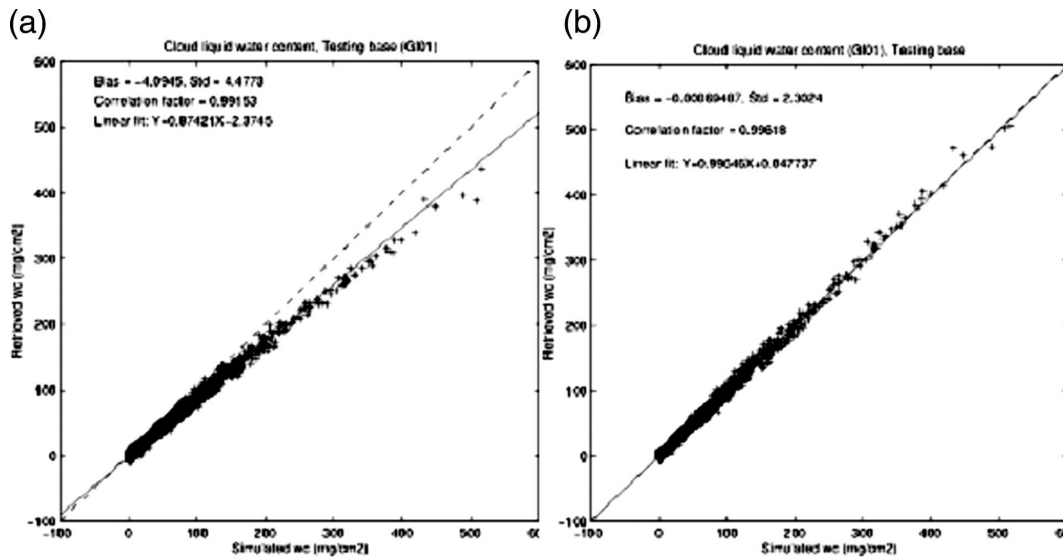


FIG. 2. Scatterplot between wc in the validation database and retrieved wc with (a) the parametric algorithm and (b) the neural algorithm.

Similar comparisons have been performed for the integrated water vapor content and the attenuation of the backscattering coefficients in Ku and S bands. Figures are not reported here, but for each parameter the neural algorithm improves the retrieval when compared with the parametric one. Table 1 summarizes the statistics computed from the difference between each parameter in the validation database and the one retrieved either with a parametric or with a neural algorithm.¹

The use of neural algorithms for the retrieval of Envisat MWR products is a significant improvement with respect to previous missions. The neural algorithms have the following advantages.

- They are easier to develop: the choice of an a priori form of the relation linking the geophysical parameter to the satellite measurements is no longer necessary.
- They are more accurate: in all cases (for each parameter and everywhere in the range of variation of the parameter), the adjustment is better (validation results with radiosonde measurements in section 4).
- They are faster and more robust: the implementation of a neural algorithm is very simple (tables of weights and biases easy to update), with no numerical problem.

The quality of the retrieval algorithms developed with a neural network approach mainly relies on the

representativity of the learning database. This means that any error in the ECMWF meteorological model or in the radiative transfer model (used together to simulate the brightness temperatures) will directly impact the quality of the retrieved product when applied on real measurements. The reliability of our approach mainly comes from the consistency between the retrieval algorithms and the in-flight calibration of the brightness temperatures.

3. In-flight calibration

The on-ground calibration of the receiver consists of the characterization of the receptor in a vacuum chamber in which the reflector cannot be included. The antenna pattern must be separately measured. This instrument characterization is then not fully representative of its behavior in space. Moreover, it is very difficult to properly estimate the emission/reflection by the satellite itself and the earth contribution in the sidelobes. For these reasons, an update of the prelaunch calibration coefficients is required after launch.

TABLE 1. Main statistics (bias, standard deviation, correlation coefficient) of the comparison between products in the validation database and retrievals. Para: with parametric algorithm, NN: with neural algorithm.

	Bias		Std dev		Corr coef	
	Para	NN	Para	NN	Para	NN
dh (cm)	0.09	-0.01	0.70	0.54	1.00	1.00
wc (mg cm ⁻²)	-4.09	0.0	4.47	2.30	0.99	1.00
att_Ku (dB × 100)	-1.58	0.0	1.34	0.90	0.99	1.0
att_S (dB × 100)	-0.05	0.0	0.20	0.10	0.92	0.95

¹ FORTRAN codes for parametric and neural algorithms, with associated tables of coefficients, can be obtained upon request (e-mail the corresponding author at estelle.obligis@cls.fr).

a. Instrument description and radiometric model

Alcatel Alenia Space was responsible for the development and on-ground calibration of the Envisat MWR. The measurement principle is the detection of the natural thermal emission of the earth, converted into brightness temperature, using the Rayleigh–Jeans approximation of Planck’s law. In the microwave range this signal is weak, so a very low noise stable receiver is necessary. In this aim, the radiometer includes a frequent measurement of the receiver gain. In the case of radiometers on board altimetry missions, two alternate circuits are used to measure the cold and hot gain points, as shown in Fig. 3; depending on the calibration switch position, the receiver is connected to the main antenna or to one of the calibration branches (selected by a second switch). The hot point is obtained by measuring the thermal emission of an internal load, and an additional antenna (sky horn) is used to get the cold reference point. To keep the measurement free of low-frequency noise, a Dicke switch is used and the actual measurement is the difference between the microwave circuit and the Dicke load (1-kHz switching frequency for the Envisat MWR). The conversion of these raw data in antenna temperature by the radiometric model closely follows the one used for the *ERS-1* and *ERS-2* microwave radiometers (Bernard et al. 1993).

Then, the brightness temperature is deduced from the antenna temperature by taking into account the different antenna pattern contributions. The total an-

tenna temperature is a combination between the measured temperature in the main lobe (which represents the useful measurement) and the secondary lobe contributions affected by the different efficiency factors. The secondary lobes see the earth (the most important contribution), but also the sun, the cosmic background, and the satellite itself. To extract the brightness temperature measured by the main lobe, the contribution of these elements should be removed by taking into account their respective temperatures and efficiencies (summarized in Table 2). Because frequencies for the Envisat and *ERS-2* radiometers are the same, the brightness temperatures of the earth in the secondary lobes in both channels could be approximated with the mean brightness temperatures of the earth seen by the *ERS-2* MWR for 1 yr. The satellite is considered as a perfect reflector, implying that its temperature is the one of the earth. The sky temperature is slightly different from 2.7 K because of the Rayleigh–Jeans approximation of the Planck’s law, which is no more valid for this range of temperature. The particular position of the radiometer on board the Envisat platform induces strong spill-over problems, which results directly in an unusually large value for the efficiency of the sidelobe aiming the satellite at 23.8 GHz (more than 4%). This coefficient is about 10 times higher than for its predecessors on *ERS-1* and *ERS-2*. These elements (Earth, sky, sun, and overall satellite) provide a mean sidelobe contribution of 8.21 K at 23.8 GHz and 0.41 K at 36.5 GHz. The strong contribution at 23.8 GHz pointed out the weakness of the *ERS-2* correction (the contribution is assumed homogeneous and equal to the one in the

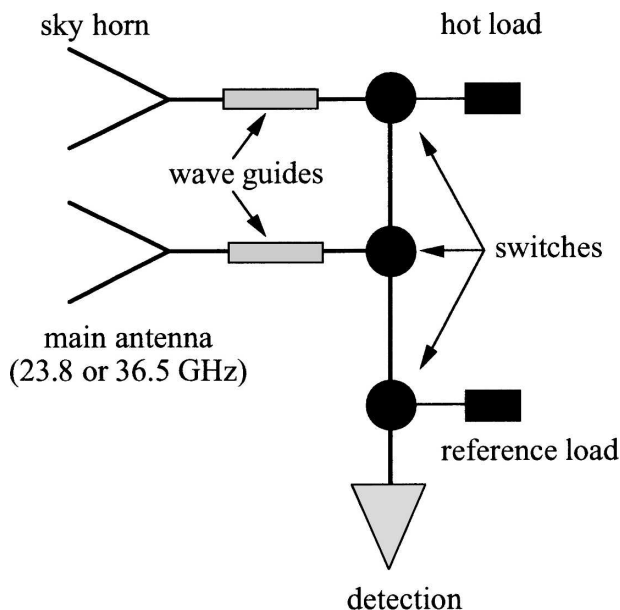


FIG. 3. Schematic view of the radiometric receiver for one channel of the Envisat MWR.

TABLE 2. Efficiency of the beam and corresponding mean brightness temperature for each term implied in the sidelobe (SL) contribution.

	23.8 GHz	36.5 GHz
Efficiency of the SL aiming the earth: η_{earth} (%)	0.0017	0.000 08
Efficiency of the SL aiming the sky: η_{sky} (%)	0.3973	0.0198
Efficiency of the SL aiming the sun: η_{sun} (%)	0	0
Efficiency of the SL aiming the satellite: η_{satell} (%)	4.341	0.216
Temperature of the earth seen by the SL: $T_{\text{sl_earth}}$ (K)	189	191
Temperature of the sky seen by the SL: $T_{\text{sl_sky}}$ (K)	2.74	2.79
Temperature of the sun seen by the SL: $T_{\text{sl_sun}}$ (K)	6000	6000
Temperature of the satellite seen by the SL: $T_{\text{sl_satell}}$ (K)	189	191

main lobe) and the necessity of performing a more accurate correction in the Envisat MWR processing (Obligis et al. 2003).

b. Instrumental monitoring

To provide an instrumental status, to report any change at the instrumental level that would likely impact the quality of the brightness temperatures, and to check the stability of the instrument, the key instrumental parameters of the radiometer were monitored since launch. Figure 4 shows the gains of the 23.8- and 36.5-GHz channels. The gain in the 23.8-GHz channel remains stable around 9.6 counts per kelvin. For the second channel the evolution shows two successive decreasing trends—the first is small (starting around day 25) and there is a stronger one since around 150 days after the launch. The total decrease since the launch is about 14%. The sky horn counts on Fig. 5a to exhibit similar features as the gain for both channels. The counts present a very slight increase with time for the first channel. For the second channel, the values drop from 3600 to 3150 (−12%). The hot load counts on Fig. 5b are stable for the first channel, around 553. They decrease for the second channel from 660 at launch time to about 635 (−4%).

No explanation for these drifts at 36.5 GHz has been provided to date. These features should impact the 36.5-GHz brightness temperature, as reported in Tran et al. (2005), and studies are ongoing to evaluate the impact of these drifts on measured brightness temperatures and the wet-tropospheric correction. As soon as the impact of these drifts are estimated, a strategy of correction will be proposed. Either a correction of the gain drift depending on time will allow the brightness temperature drift to be corrected and restored to the launch level, or a new calibration associated with a new algorithm will be proposed.

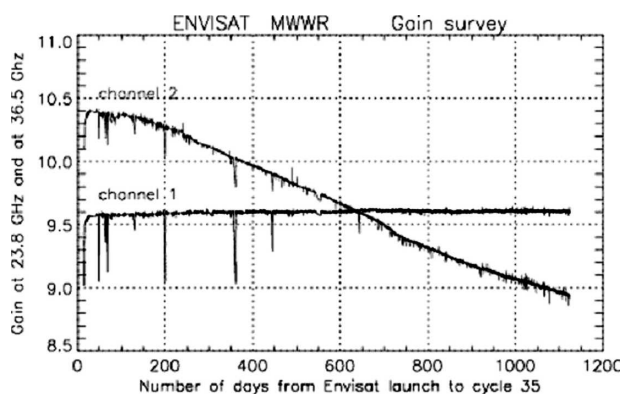


FIG. 4. Time evolution of the gain since the Envisat launch (1 Mar 2002; data available since 15 Mar 2002) for channel 1: 23.8 GHz, and channel 2: 36.5 GHz.

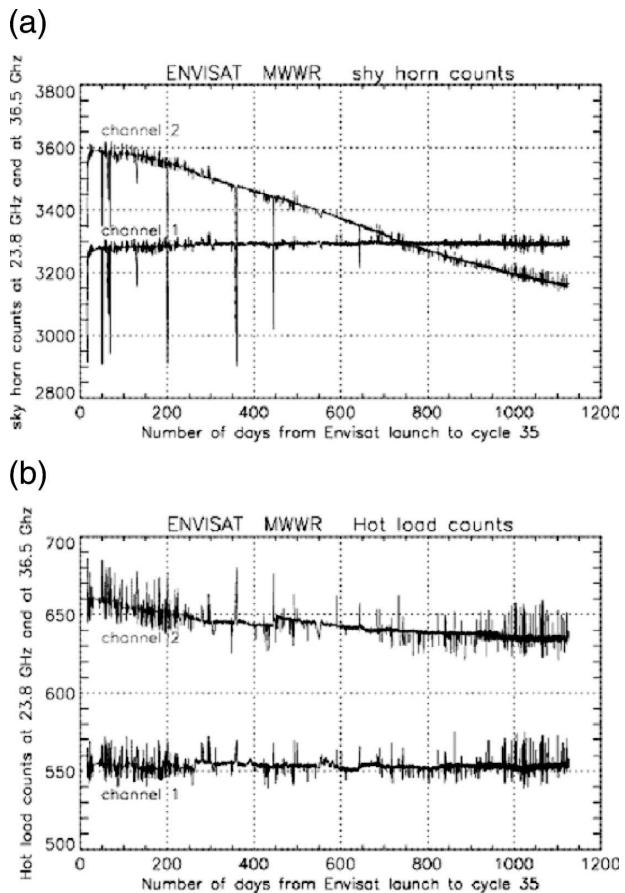


FIG. 5. Time evolution of the calibration counts since Envisat launch for the (a) sky horn count and (b) hot load count.

c. Methodology of the in-flight calibration adjustment

The in-flight calibration is difficult because there is no suitable reference target over the earth.

A possible method for the in-flight calibration is to calibrate systematically a new radiometer on the previous one considered as a reference (Envisat MWR TBs on ERS-2 MWR TBs, itself calibrated on ERS-1 MWR TBs, etc.). This is the method chosen for the JMR calibration in order to get a time series of JMR products as close as possible to that of the TMR (Brown et al. 2004), and therefore to provide the scientists with a consistent long time series, which is actually necessary for the sea level rise survey. Nevertheless, the continuity between the missions (which is even crucial for altimetry missions) does not justify neglecting technological and algorithmic improvements.

The methodology we used for the Envisat MWR is similar to the one used for the in-flight calibration of the ERS-1 and ERS-2 radiometers, and benefits from our new concern on long-term survey and calibration

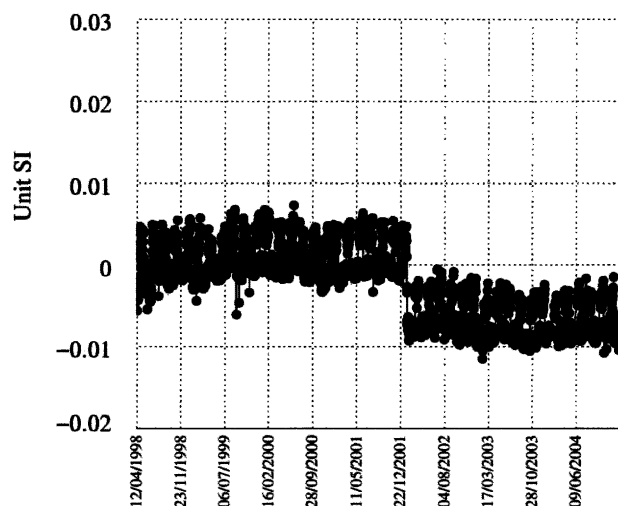


FIG. 6. Variations of the daily mean difference (m) between ECMWF and radiometer wet-tropospheric correction between 1998 and 2004 for the TOPEX mission.

issues (Eymard et al. 2005). It consists of the use of brightness temperatures simulations as a reference for calibration. Furthermore, the use of the same tools (meteorological model, radiative transfer model) to calibrate the radiometer and to develop the retrieval algorithms ensures a consistency in the processing, which guarantees at the end the quality of the products.

As explained in section 2, the retrieval algorithms have been formulated using ECMWF fields of 2001, so the calibration of the radiometer should be done using simulations on the same analyses or analyses generated with the same version of the ECMWF model.

The in-flight calibration of the Envisat MWR was undertaken at the end of the commissioning phase in October 2002. Unfortunately, important changes in the operational ECMWF model occurred in January 2002. These improvements concerned the assimilation of new data and the upgrade of preprocessing and four-dimensional variational data assimilation (4DVAR) analysis algorithms (Lalaurette 2002). These changes impacted many parameters in the model, including atmospheric humidity profile. Figure 6 shows the daily difference between the TMR wet-tropospheric correction and the one analyzed by the ECMWF model for a 6-yr period (1998–2004). The different changes made in the ECMWF model in January 2002 induce a decrease in the humidity content, corresponding to a mean decrease of about 7–8 mm in the ECMWF wet path delay. It was therefore incorrect to calibrate the Envisat MWR brightness temperatures by using ECMWF fields in October 2002, and to use retrieval algorithms formulated with the previous version of the ECMWF model (2001). This problem was overcome by using *ERS-2*

MWR brightness temperatures as a link between the 2001 version of the ECMWF model (used to formulate the retrieval algorithm) and the calibrated Envisat MWR brightness temperatures in 2002.

The four global fields of section 2a and the correspondent simulated brightness temperatures are used as references. *ERS-2* MWR-measured brightness temperatures falling in a mesh within ± 30 min of the analysis time (1200 UTC) are selected, and these observations are averaged to the model resolution. Furthermore, cloudy pixels and ECMWF meshes associated with cloud liquid water higher than 20 mg cm^{-2} were filtered out in both datasets. The *ERS-2* brightness temperatures at 23.8 GHz have corrected the gain drop of 1996 and drift using Eymard and Obligis (2003).

Figures 7a and 7b show the scatterplots between simulations and *ERS-2* measurements obtained for the 23.8- and 36.5-GHz channels, respectively. Considering the simulations as a reference (to be fully consistent with the retrieval algorithms), it appeared that the *ERS-2* brightness temperatures were too low by 4.91 K at 23.8 GHz and by 2.16 K at 36.5 GHz. To perform a calibration of the Envisat MWR consistent with the algorithms, the calibration was performed in such a way that the Envisat MWR brightness temperatures are 4.91 K higher than those of the *ERS-2* at 23.8 GHz and 2.16 K higher at 36.5 GHz.

The relevance of this approach was evaluated in 2000 by performing similar comparisons on several radiometers [Special Sensor Microwave Imager (SSM/I), Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), TMR, *ERS-2* MWR] with the same ECMWF analyses (Eymard et al. 2000), and the main conclusions were that the bias between the simulations and measurements lies within the expected range of ± 5 K in brightness temperatures, and that this approach was reliable.

d. The in-flight calibration tuning

For the Envisat microwave radiometer, the in-flight calibration was performed with the tuning of three internal parameters that were identified as being the most sensitive during the *ERS-1* MWR (Eymard et al. 1996; Eymard and Boukabara 1997) and then the *ERS-2* MWR in-flight calibration (Eymard and Boukabara 1997). First, the sky horn feed transmission coefficient is tuned to provide a gain of the system as close as possible to the value estimated on ground. Then, the transmission coefficient of the reflector is modified to adjust the measured brightness temperatures on the reference ones. Finally, residual biases are corrected for by tuning the main antenna transmission coefficient.

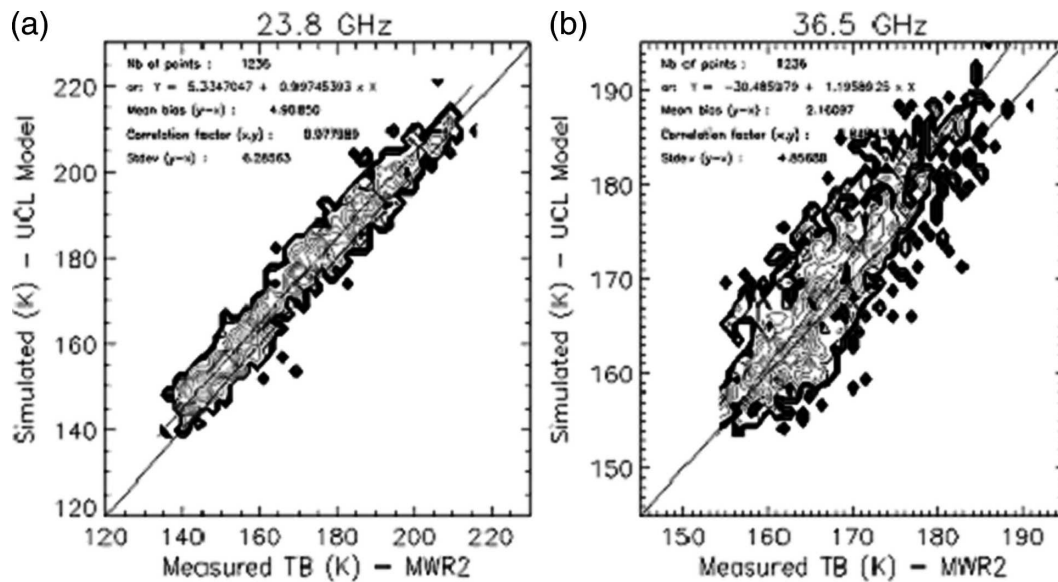


FIG. 7. Scatterplot between *ERS-2* measurements and simulations for the (a) 23.8- and (b) 36.5-GHz channels.

e. Results

ERS-2 and Envisat satellites are flying on the same ground track with a 30-min time lag, which allows for an easy correlation study. Figures 8a and 8b show the scatterplots between the *ERS-2* MWR- (cycle 78) and Envisat MWR- (cycle 10) calibrated brightness temperatures for channels 23.8 and 36.5 GHz, respectively.

ERS-2 TBs have been corrected for the biases indicated in section 3c (+4.91 and +2.16 K). The final biases between calibrated Envisat TBs and reference TBs are -0.6 K at 23.8 GHz and $+0.2$ K at 36.5 GHz. These biases are negligible, ensuring a calibration of the Envisat brightness temperatures at the end of the commissioning phase that is fully consistent with the algorithms used to retrieve the wet-tropospheric correction.

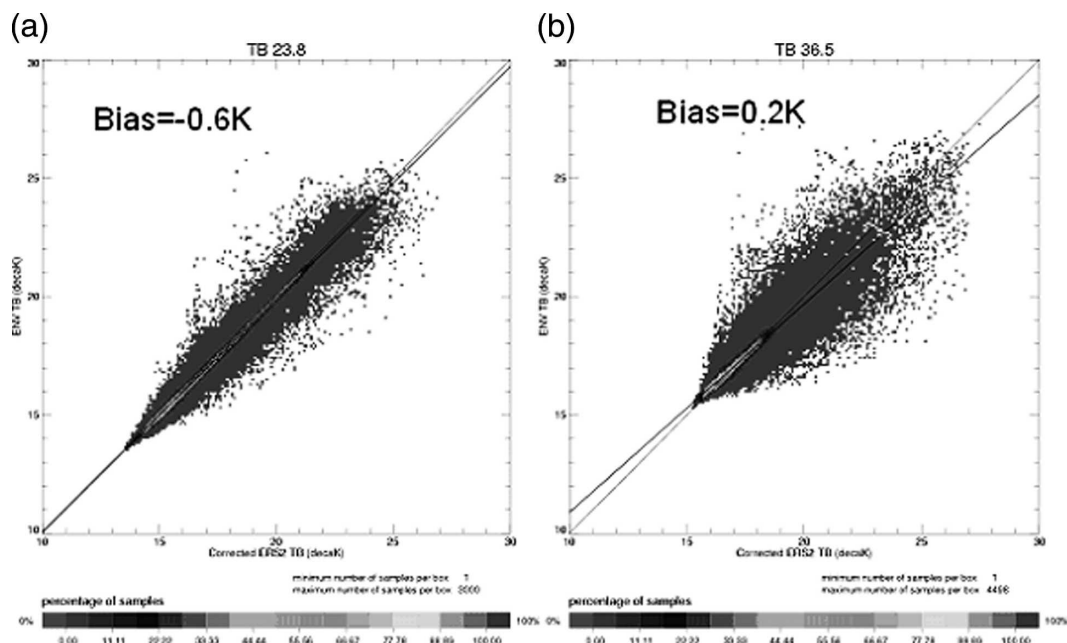


FIG. 8. Scatterplot between *ERS-2* TBs adjusted to simulations on the 2001 version of the ECMWF model and Envisat TBs at (a) 23.8 and (b) 36.5 GHz.

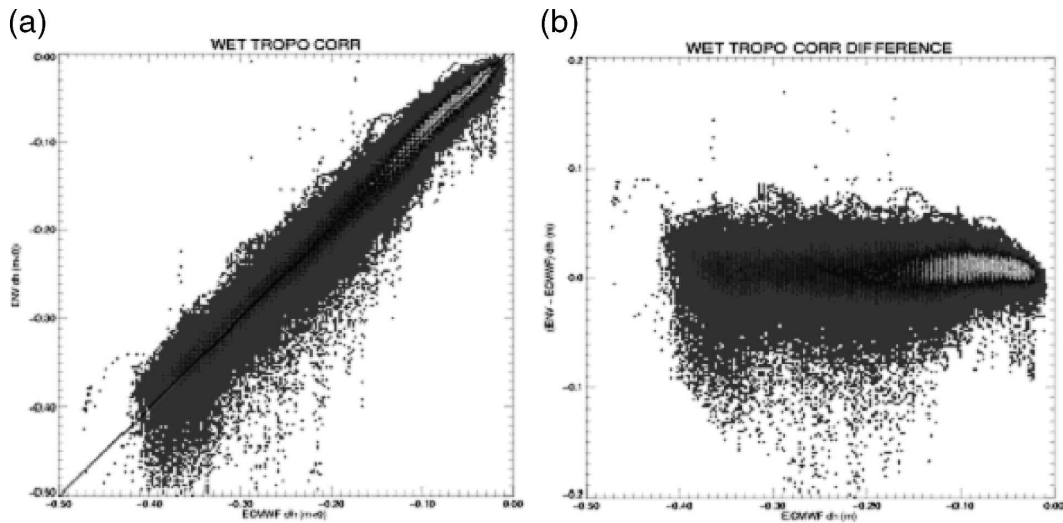


FIG. 9. Scatterplot (a) between the ECMWF wet-tropospheric correction and that of Envisat and (b) of the difference between the two for the GDR cycle 15.

4. Validation of the products

a. With ECMWF correction

The validation of the radiometer products with in situ measurements relies on small datasets (even if they increase in size as the time goes on). The systematic comparison between the wet-tropospheric correction retrieved from the radiometer brightness temperatures and the ones predicted by the ECMWF model allows a rapid check of the products retrieved globally. Figure 9a presents the scatterplot between the ECMWF and Envisat MWR wet-tropospheric correction obtained for the geophysical data record (GDR) cycle 15. Figure 9b shows the difference between the ECMWF and Envisat wet-tropospheric correction as a function of the ECMWF one. These plots show very good consistency between the ECMWF and Envisat MWR wet-tropospheric correction with a mean value of the difference of 4.9 mm and a 1.7-cm standard deviation. The two corrections agree well, with an almost perfect slope agreement (1.02) from an orthogonal regression. The same plots for the *ERS-2* wet-tropospheric correction (GDR cycle 83) are shown in Figs. 10a and 10b, and they show that the agreement between the radiometer and ECMWF wet-tropospheric corrections was slightly lower because of the use of a linear algorithm.

b. With radiosonde measurements

The most conventional and only available method for a “real” validation of the wet path delay is the comparison with in situ measurements over ocean. Radiosonde measurements files from ECMWF contain atmospheric temperature and pressure profiles, along with

the distribution of the water vapor content. Radiometer data over the ocean are selected when the closest distance of the satellite track to the radiosonde location is less than 100 km and is within 1 h. These criteria were chosen to provide 1) a satisfactory consistency between in situ measurements and satellite-retrieved products, and 2) enough collocated measurements. For the Envisat MWR, this approach produces an accumulation of about 5000 comparison points since the Envisat launch (a 3-yr period). The geographical distribution of the radiosonde network shows a majority of the comparison points located in the North Atlantic Ocean. Cases with rain are automatically removed during the collocation process because we are using “validated” radiometer brightness temperatures, which means from only over ocean and in no-rain condition data. Cloudy situations are not filtered out, so wet situations are also represented in the comparison.

Figure 11a shows the comparisons between Envisat MWR and radiosonde wet path delay, and Fig. 11b provides a zoom on (0; 20) cm where most of the data lie. The mean bias is -0.2 mm, with a 22-mm standard deviation on the whole set. This latter decreases slightly to 18 mm for a comparison between 0 and 20 cm. The derived slope of the least squares regression line is not very different from unity (1.08), showing a good agreement between the two corrections. This rms difference is mainly because of the space–time collocation errors and to the atmospheric variability.

c. Envisat processing applied to *ERS-2* data

As explained in section 3, previous missions can benefit from new processing improvements, and therefore

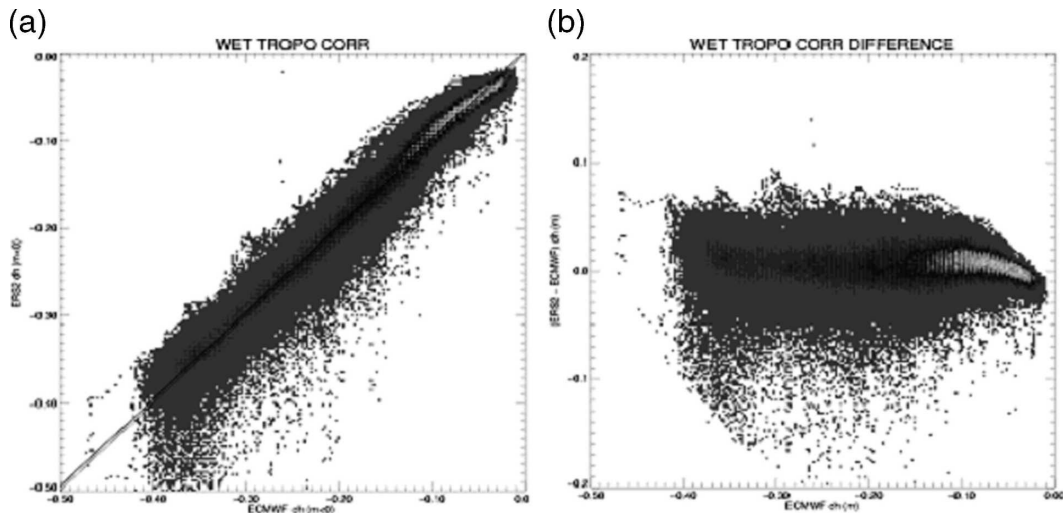


FIG. 10. Scatterplot (a) between the ECMWF wet-tropospheric correction and that of *ERS-2* and (b) of the difference between the two for the GDR cycle 83.

participate in an accurate and consistent long time series. Envisat MWR algorithms are applied to *ERS-2* MWR measurements to provide products that are better and more consistent with those of Envisat. The first

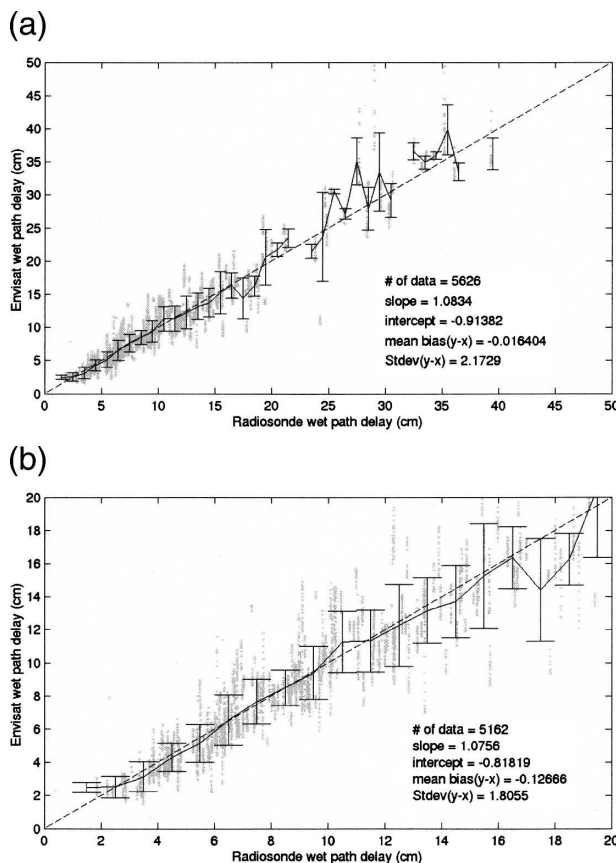


FIG. 11. Scatterplot between radiosonde and Envisat MWR wet path between (a) 0 and 50 cm and (b) 0 and 20 cm.

step consists of adjusting the *ERS-2* brightness temperatures to those of Envisat. In a second step, the *ERS-2* wet-tropospheric corrections were recomputed using Envisat neural algorithms. The comparison with radiosonde measurements is performed, and the quality of the new products can be estimated with respect to the *ERS-2* operational products. Figure 12 shows the comparison with radiosonde measurements for the range of 0–20 cm obtained with the standard *ERS-2* wet-tropospheric dh (Fig. 12a) and with the recomputed dh (Fig. 12b) after 1) correction of the 23.8-GHz drift (Obligis et al. 2003), 2) adjustment of the *ERS-2* brightness temperatures, and 3) retrieval of the dh with the Envisat neural algorithms. The improvement is significant, with a weaker bias and a weaker rms standard deviation. The improvement in the case of the dry atmosphere is obvious and shows the benefit of a neural algorithm thereto.

5. Conclusions

We present in this paper the in-flight calibration of the Envisat MWR and the development of the retrieval algorithms. Our main concern was to use a consistent approach between these two steps that guarantees the quality of the final products (wet-tropospheric correction).

The observed limitations of the retrieval algorithms led us to replace the multilinear parametric regression by a neural network approach. The learning phase of the neural networks is performed using ECMWF geophysical fields and associated TB simulations. The performances of the algorithms over the validation database shows a significant improvement with respect to classical parametric algorithms. Furthermore, because

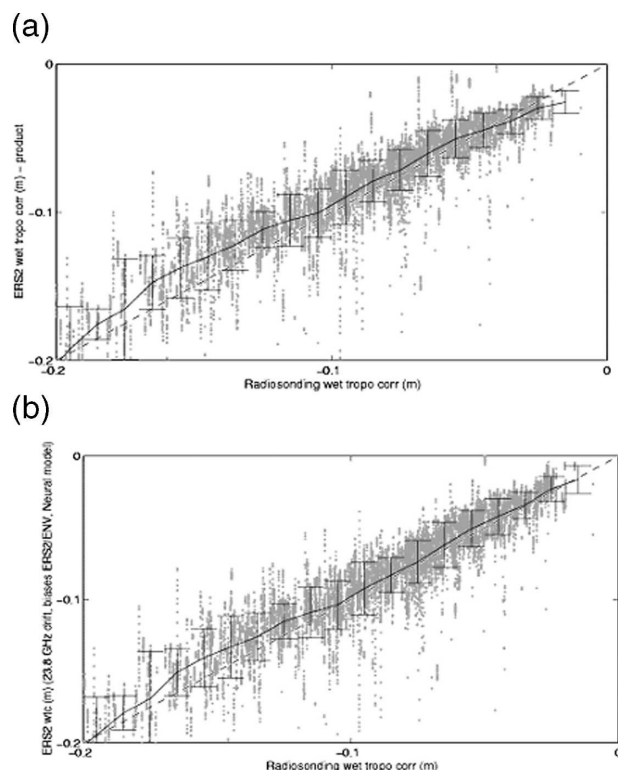


FIG. 12. Scatterplot between radiosonde and ERS-2 wet-tropospheric correction (7-yr period) between -20 and 0 cm: (a) operational products and (b) recomputed products after correction of the 23.8-GHz drift, adjustment of the brightness temperatures, and application of the Envisat neural algorithms.

neural network algorithms are easy to implement, fast, and robust, they are particularly adaptable to operational processing.

The in-flight calibration of the TBs is difficult because there is no natural target that can be used as a reference. Our approach consists of the adjustment of the measured brightness temperatures on simulated ones. This was performed at the end of the commissioning phase using the same version of the ECMWF model and the same radiative transfer model as that of the retrieval algorithm formulation. This consistency between the calibration of the brightness temperatures and the processing used to retrieve the geophysical parameters is necessary to provide high-quality products at the end.

The validation of the methodology (retrieval algorithms and consistent in-flight calibration) has been performed by comparing the radiometer wet-tropospheric correction with that of the radiosonde. Results are satisfactory with a very weak bias and a standard deviation of about 2 cm for the whole range of variation.

The Envisat MWR products result from retrieval al-

gorithms and in-flight calibration based on the 2001 version of the ECMWF model as well as the current version of our radiative transfer model at this time. These last years, changes have been performed [new assimilation in the ECMWF model in 2002, atmospheric instabilities, and wave breaking included in our radiative transfer model (Keriaki 2003)], and the Envisat MWR products should benefit from these last improvements. In this context, we are preparing a new set of retrieval algorithms and a new consistent in-flight calibration. Since the beginning of the mission, the key instrumental parameters at 36.5 GHz have been drifting with time. It appears that the mean drift of the brightness temperatures is around $+0.5 \text{ K yr}^{-1}$, implying a drift of the wet path delay around -1 mm yr^{-1} . Investigations are in progress to identify the source of these drifts and to propose a suitable correction that will be part of the new in-flight calibration of the radiometer.

Moreover, we showed that after a preliminary adjustment of the TBs, it is possible to use the Envisat set of retrieval algorithms to reprocess and improve the ERS-2 MWR products. The adjustment of the brightness temperatures implies a common period for two successive missions and is more accurate if instrumental configurations are similar and if both satellites fly along the same track. This is the case between the ERS-2 and Envisat missions, flying along the same ground track with half an hour time lag, and also between the ERS-1 and ERS-2 missions. In this configuration, it is therefore very easy to adjust the ERS-1 and ERS-2 brightness temperatures to those of Envisat to build a consistent TB time series and to apply on it the last generation of the retrieval algorithms. This would be a significant contribution to build a long, consistent, and high-quality altimetry time series, which is especially needed for the survey of the sea level rise.

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