Using neural networks to retrieve sea surface salinity (SSS) from SMOS observations raises several difficulties. The variance of incidence angle from one surface point to another results in a set of networks to adopt their inputs to the SMOS observed angle. Moreover, the high noise on the TBs simulated from the geophysical parameters and the geophysical limitations on the retrieval of SSS. A prejudice choice of the learning database leads to these adverse effects of biases.

In this study, we compare the networks obtained with a database containing all the realizations and the networks obtained with a database containing one random realization for each angle, leading to a higher noise level. Furthermore, all the tests have been made using the first Stokes parameter of the TB corresponding to the inputs of the neural networks, which are computed from the antennas to the surface level.

Introduction

The inversion algorithms for the retrieval of the sea surface salinity (SSS) from the brightness temperature (TBs) is a crucial point for SMOS ground segment. To carry it out we have chosen an empirical method using neural networks (NN). This method presents the advantage of being independent of any theoretical forward model, for the in-flight processing. Previous studies [1][2] have shown that we are able to process almost any point on the ocean surface using NN, with satisfactory results. In this study, we focus on the improvement of the learning database, and we use the first Stokes parameter of the TB instead of both polarizations H and V. Besides, we remind the methodology used to overcome the adverse of the variance of incidence angles.

The findings concerning the choice of the learning database will help to build a new learning database for the in-flight processing. This database will use in situ SSS data (provided by the AGEROM network) collected with SMOS observed TBs, in order to update the weights of the neural networks.

Building an improved learning database

The learning database used for training the neural networks consists of a set of 32 492 triplets (SSS, SST, W) for which we simulated the TBs at the suitable incidence angles (depending on the class), using the SSA emissivity model, provided by IFREMER. The geophysical triplets resulted from a random extraction from 12 WERCATOR PSY3V1 daily global fields over one year, associated with noisy simulated TBs.

After fixing the architecture of the networks, they must be trained using a learning database. Since we deal with a high level of noise, we use the minimization process in the neural networks to optimize the NN parameters. This parameter-estimation method is used to the data base drawn from Fig. 3, which shows the geographical distribution of the data on a half-orbit.

The inputs of the neural networks that were designed for the retrieval of SSS consist of a set of TBs (First Stokes) that should correspond to a few representative values of incidence angles. The TBs on these angles are interpolated using the TBs corresponding to the SSS observed incidence angle for each grid point.

The retrieval methodology

Fig. 2. Diagram of the SSS retrieval for a SMOS pixel.

The pixels are processed in two stages, as shown in Fig. 2. First, the observed TBs are transferred onto a series of fixed TBs corresponding to the inputs of the inversion network. This is made using a locally weighted least squares (LWLS), which also allows to deal with missing data, and to reduce the noise level. Then, the pixels are processed through the suitable neural network.

The first stage of the whole procedure is the retrieval of the incidence angles for the fixed input domain. This is achieved using a local regression for the incidence angles, and then to evaluate the retrieval error on the global ocean, at each independent database. The deviations model, provided by IFREMER.

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