P1.14 Satellite estimate of specific humidity over the ocean using microwave radiometry

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1- Introduction

The latent heat flux (LHF) plays a major role in heat exchanges between air and sea, the understanding of which is critical for studying climate variability. Flux fields may be derived from existing in situ data, but observations are generally too sparse to provide spatial fields with a reasonable time sampling. Fields output from operational meteorological models are not enough accurate in areas where data are not assimilated. Thus, using satellite data is crucial, because many years of data are now available over the world oceans.
Calculation of LHF requires knowledge of sea surface temperature (SST), surface wind speed at 10m height, and surface layer air specific humidity (qa). Bourras [2006] highlighted the need for smaller errors for qa to improve retrievals of satellite-derived LHF.
Several authors have investigated the estimation of qa from passive microwave instruments. Liu and niiler (1984) described a simple statistical technique to determine marine surface-layer humidity with accuracy of of 0.8g/kg, but in 92-day period, in North Atlantic and tropical Pacific, and at monthly scale. Schlussel and al. (1995) determined a method to retrieve qa from instantaneous measurements of the SSM/I but with an accuracy of 1.1g/kg. entamy and al. found a rms of 1.4g/kg at weekly scale.
Jackson and al. investigated the use of another type of sensor, AMSU onboard NOAA platforms, which was never used before for the specific task of estimating surface humidity over the ocean. Firstly, they used linear regression method.The accuracy of their qa estimates is 0.83g/kg (rms),using both AMSU-A and SSM/I sensors, at daily scale. Validation of this method with independent observations indicated similar accuracy with rms differences of 0.96g/kg. Unfortunately, too few observations were accounted for at middle latitudes and in moist regions. They used only one channel of AMSU-A, 52.8GHz, which is not very sensitive to surface humidity, the use of which could be questionable for tropical regions.
Next, they used a neural network method for estimating qa. The rms found between estimated and surface qa is 0.57g/kg for training, but only 2.13g/kg for validation data, which could be related to the few number of collocated satellite/ships data used in their study, but also they don't represent sufficiently seasonal variation of the atmosphere in training sets.

In order to attempt to further improve the quality of humidity estimates, we propose to revisit the use of AMSU (Advanced Microwave Sounder Unit A and B) and SSMI (Special Sensor Microwave/Imager) sensors. The use of more AMSU channels as well as more validation data is investigated.

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First, we propose an algorithm that links brightness temperatures (TBs) provided by microwave sounder radiometers AMSU-A and AMSU-B to TAO (Tropical Atlantic Ouest) and PIRATA (Pilot Research Moored Array in the Tropical Atlantic) buoys data, using linear regression method firstly, for year 2004, at daily scale. The same process is applied to SSM/I TBs, so that the performances of two instruments can be compared.
Next, backpropagation Neural Networks (NN) method are applied to retrieve near surface specific humidity from AMSU measurements. NN usually have

advantages over linear regression method in that they can build nonlinear method based on the data used to train them, and thus provide more accurateresults.
Last, sea surface temperature (SST) provided by MODIS (Moderate Resolution Imaging Spectroradiometer) satellite, is added to TBs in order to improve algorithms

2- Datasets:

a- Buoys data

TAO and PIRATA buoys permit measurements in differents locations over the ocean of air temperature, relative humidity for year 2004. TAO buoys are distributed from 8°S to 9°N and from 135°E to 95°W. PIRATA buoys are located from 20°S to 20°N and from 20°E to 50°W

b-Satellite data:

The satellite data used are AMSU and SSMI brightness temperatures, and MODIS SST.
The AMSU sounding unit contains two modules A and B. He's operational onboard NOAA satellite since 1998.
NOAA has a swath width of 2340km and his period is 1h42mn.
AMSU-A uses 15 spectral regions (23.8 to 89 GHz). It is conceived for sounding of atmospheric temperature from the earth's surface to 45km. Spatial resolution is 50km.
AMSU-B has 5 spectral regions (89 to 183.31 GHz), and is designed for humidity sounding. Spatial resolution is 16km.
AMSU observations angle varies from -48° to +48°. The SSMI instrument onboard DMSP (Defense Meteorological Satellite Program) whose period is 102mn and swath width is 1400km, has 7 spectral regions (19 to 85GHz). Spatial resolution depends on frequency. SSM/I observations are used primarily for retrieval of precipitable water, cloud liquid water, surface wind speed and precipitation.

3-Methodology:

The first step consists to do collocation between satellite data and buoys data. Two approaches are used to find algorithm which retrieve specific humidity:

3-1 Linear regression multiple which consists to suppose that specific humidity is a linear combination of brightness temperatures: qa = A0 + A1*TB1 + A2*TB2 + A3*TB3 + . . . + An*TBn
TBi: brightness temperatures at frequency number i.
Tab.1 shows differences of statistics between AMSU and SSMI when we apply Linear regression approach, at instantaneous scale. We see that AMSU is better than SSMI, because rms is less than 1 (0.98g/kg), and correlation is most important (0.82).

radiometers	AMSU (all 20 channels used)	SSMI (all 7 channels used)
Number of buoys	48	48
Number of points	20614	15232
rms (g/kg)	0.98	1.12
correlation	0.82	0.77
bias	-0.0003	0.000003

Tab.1 Statistic comparison of regression maked using instantaneous data, for year 2004, between AMSU and SSMI

a- Choice of AMSU channels:

We have chosen 7 channels using a statistic method: we do many linear regressions with all possible combination of 7 channels among 20 AMSU channels, and we look for the one which has the best statistics, and we select it. We find that the best combination corresponds to following channels: 23.8, 31.4, 53.59, 54.9, 57.29±0.217, 89, and 150GHz.

3-2 Neural network method

We used Neural networks (NN) approach whose principle consists to associate brightness temperatures satellite data (inputs) to buoys data (output), taking into account non linear aspects. The NN used a supervised feed-forward network

employing 7-8-1 architecture, which consists seven inputs (brightness temperatures TB), eight nodes in the hidden layer, and one output (qa).
In order to train NN, we take randomly 2/3 of satellite data and buoys data available in our database, and give him name of "training data". The rest (1/3) is the "testing data). The training data is run through the network with the weights at each node of the NN updated using a back-propagation algorithm. Inversely, testing data is used to control the mean error between observed and estimated qa values.

4- Results

4-1 Neural network approach:

a- Training

The performance of this approach is presented on Fig.1. It shows an improvement of retrieval compared to previous retrievals, because rms is low and equal to 0.75g/kg. Also, fig.1 shows that fit slope is important (0.80), and correlation is 0.90. This means AMSU channels are efficient for qa retrieval. This good result can be explained by presence of window channels 23.8, 31.4, 89 and 150GHz. They provide most direct information of surface.

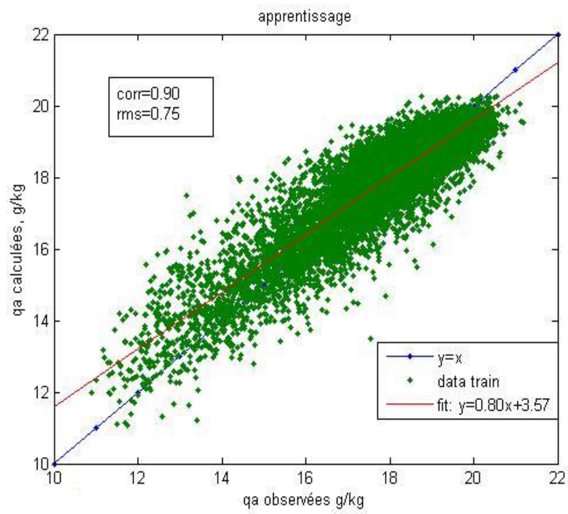

Fig.1 Neural network result for daily qa using training data- AMSU

b- Validation:

Validation confirms performances provided by the training. We find (fig.2) a rms of 0.77g/kg, and a slope of 0.82. Correlation becomes 0.88. This is a good result compared to Jackson and al. (2006) which found for his neural network validation a rms of 2.13g/kg.

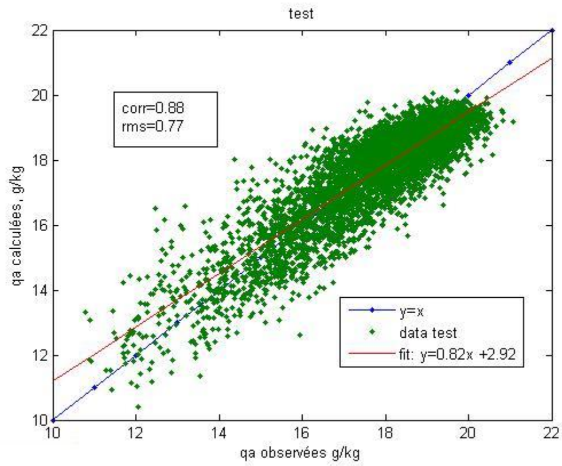

Fig.2 Comparison between retrieved qa by Neural Network and qa observed by buoys. AMSU

4-3 Comparison between neural network approach and linear regression method

a- Learning

Compared with the linear regression approach, the rms of neural network 0.16g/kg smaller and fit slope is 0.08 greater (Tab.2)

Approach	Linear regression	Neural network
Rms (g/kg)	0.91	0.75
correlation	0.85	0.90
Number of points	9426	9426
Fit slope	0.72	0.80

Tab.2 Comparison between NN method and linear regression / learning data

b- Validation

The neural network rms is always smaller than linear regression rms. But here, difference is of 0.12 g/kg. In general, the NN statistics is better than those of linear regression (Tab.3).

Approach	Linear regression	Neural network
Rms (g/kg)	0.89	0.77
correlation	0.84	0.88
Number of points	5399	5399
Fit slope	0.73	0.82

Tab.3: comparison between NN method and linear regression method / validation data

c- **Retrieval improvement when adding MODIS SST**.

Tab.4 shows that addition of MODIS SST in input data of regression, and neural networks, decreases error and, thus improves retrieval. Here, we find rms less (0.72g/kg with neural network method) than all rms given by previous algorithms

Approach	Linear regression	Neural network
Rms (g/kg)	0.85	0.72
correlation	0.87	0.91

Tab.4 Statistic comparison between two approaches when MODIS SST is added in inputs

Conclusions:

We found in this study that neural network is capable to connect nonlinear relation between AMSU measurement and near surface specific humidity. The retrieval result shows a better accuracy (rms of 0.75g/kg for training and 0.77g/kg for validation) due to the use of NN method and the importance of AMSU sensor for qa retrieval over the ocean.

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