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SEA SURFACE AIR TEMPERATURE AND HUMIDITY RETRIEVALS BASED ON AMSU MEASUREMENT

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1. INTRODUCTION

This study derives sea surface air temperature and specific humidity based on the National Oceanic and Atmospheric Administration (NOAA) polar orbiting satellite measurement. A neural network technique is used to develop the retrieval scheme which connects the relationship between the retrieved variables and the Advanced Microwave Sounding Unit (AMSU) channel brightness temperatures. The air temperature retrieval uses AMSU-A data, while the specific humidity retrieval uses both AMSU-A and AMSU-B observations.

The AMSU-A and AMSU-B are two of the primary instruments on board the NOAA polar orbiting satellite series. The sounders provide routine measurement of the atmosphere on a global scale. The AMSU-A is a fifteen channel, cross-track, line-scanned instrument. It scans in a stepped scan fashion and covers 30 discrete scene resolution cells. The scan pattern and geometric resolution correspond to a 50 km diameter cell at nadir and a 2343 km swath. AMSU-B is also a cross-track, line scanned instrument designed to measure scene radiances in five channels. Ninety contiguous scene resolution cells are sampled in a continuous fashion. The scan patterns and geometric resolution translate to a 16.3 km diameter cell at nadir.

The AMSU instruments are microwave sounders, and can generally "see" through clouds. However, their observations can be contaminated by rain drops or large water path. To remove the rain contaminated pixels, we obtained a rain rate retrieval algorithm developed by Weng et al. (2003) and Zhao and Weng (2001). This algorithm uses AMSU-A channels 1, 2, 3, and 15 (channels at 23, 31, 50, and 89 GHz), AMSU-B channels 2 and 5 (channels at 150 and 183±7 GHz) as input to derive rain rate, total precipitable water, cloud liquid and ice water paths, and cloud ice effective diameter. In addition to the rain rate retrieval algorithm, each pixel is tested by the brightness temperature of AMSU-A channel 1. Any pixel with brightness temperature of AMSU-A channel 1 larger than 230 K is removed for possible rain contamination. In the latitudes higher than 45 degrees in both north and south hemispheres, any pixel with brightness temperature of AMSU-A channel 1 larger than 180 K is removed for possible surface ice contamination.

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2. NEURAL NETWORK RETRIEVAL

The neural network dataset represents the matched patterns of the sea surface air temperature and humidity variables and the AMSU channel brightness temperatures. The training datasets are constructed using a full year of co-located AMSU and buoy/ship data covering the ocean surface from 70S to 70N, in which all four seasons and various weather conditions throughout the year are included to have a global ocean and all weather condition representation.

Backpropagation neural networks similar to the approach used by Shi (2001) are applied in developing the retrieval scheme. A three-layer network, with one input layer, one hidden layer, and one output layer, is constructed. A hyperbolic tangent function is used to propagate to the hidden layer and a logistic transfer function is used to propagate to the output layers. The definition of the hyperbolic tangent transfer function is

$$f(x) = \tanh(x), \qquad (1)$$

and the definition of the logistic transfer function is

$$f(x) = \frac{1}{1+\exp(-x)}\,. \qquad (2)$$

For air temperature retrieval, the input set includes AMSU-A channels 1-4 and 15. For specific humidity retrieval the input set consists of AMSU-A channels 1-4 and AMSU-B channels 1, 2, and 5.

There are a total of 19385 patterns (match-ups) for the air temperature co-located dataset, and 21370 patterns for specific humidity dataset. Among these patterns, 30% are randomly extracted to construct a testing set during training, and another 20% are randomly extracted and set aside as a comparison set for later statistical studies. As a result, there are 9189 patterns remaining for air temperature and 10685 patterns for specific humidity as learning datasets. A backpropagation network is trained by "supervised learning". The network is presented with a series of pattern pairs, each consisting of an input pattern and an output pattern, in random order until predetermined convergence criteria are met. At this time the network presents the input elements in the testing set and retrieves the output elements. Then the retrieved output elements are compared with the output elements in the testing set, and the averaged root mean square (RMS) error of all the output elements is computed. The network parameters are saved if the averaged RMS is less than that computed previously. This process is repeated until no improvement is found for a specified number of test trials.

3. RESULTS

The saved neural network parameters are applied to the data in the comparison dataset and the results are shown in Fig. 1. For air temperature, the RMS is 2.10ºC and for the specific humidity, the RMS is 1.22 g/kg.

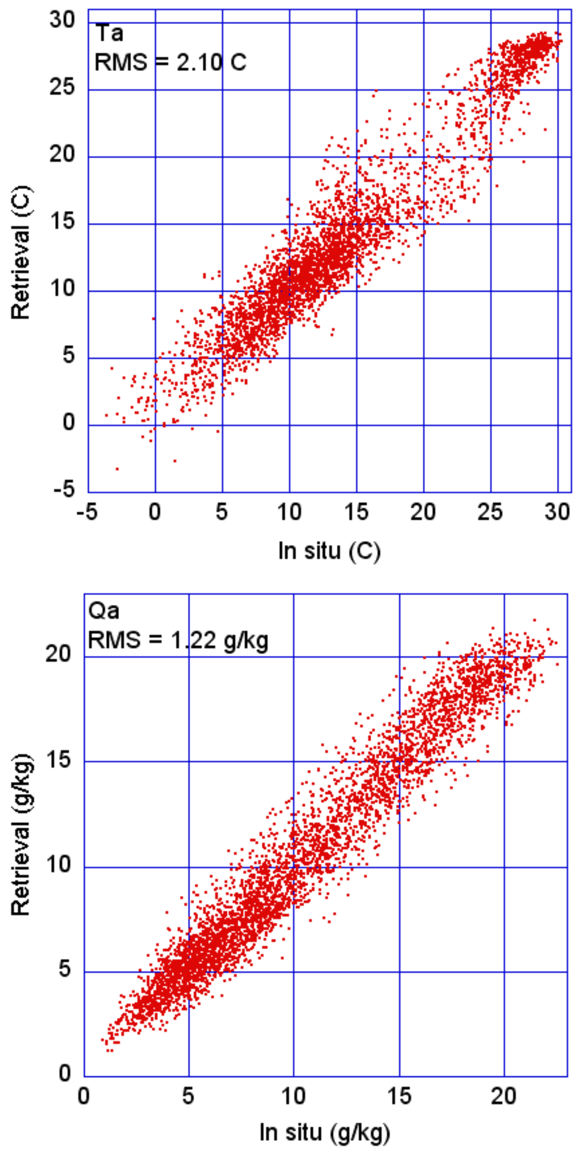

Fig. 1: Comparison of air temperature (Ta) and specific humidity (Qa) retrievals with global in situ buoy and ship measurements.

The results in Fig. 1 are done based on independent global observations. To have a comparison of the retrievals with past studies, the same validation dataset used by Jackson et al. (2005) is obtained. The dataset consists of satellite co-location of high quality research ship measurements from four field experiments. Air temperatures are derived using the AMSU-A data in the validation dataset. A scatter plot of the derived air temperatures and observations from the research ships is shown in Fig. 2. The RMS of air temperature is derived assuming the outputs in the validation database as truth data. The computation shows that the RMS for air temperature is 1.60ºC. This is better than the RMS of 1.96ºC in Jackson et al. (2005). Furthermore, unlike past studies which were based on limited area data, the current results are based on truly global measurements so the retrieval algorithm can be applied globally.

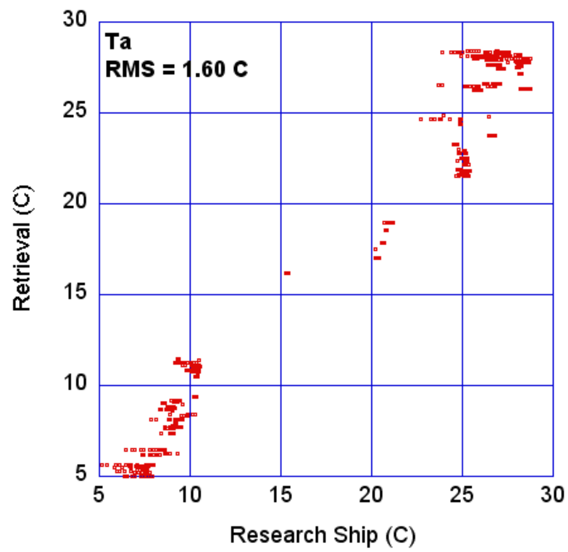

Fig. 2: Comparison of air temperature (Ta) retrieval with research ship measurements.

The co-located research ship dataset does not contain AMSU-B data. However it has data from SSM/T2 with channels in the 150 GHz and 183±7 GHz. These channels represent the same frequencies as the AMSU-B channels used in the retrieval. For an estimate, the SSM/T-2 data in the validation set is used in place of the corresponding AMSU-B channels in calculation of the specific humidity RMS. The derived RMS from this approximation is 1.16 g/kg. Since there are slight spectral differences between SSM/T-2 and AMSU-B, it is expected that the RMS can be further reduced with quality-controlled AMSU-B and surface co-locations.

There is significant difference in RMS errors between Figs. 1 and 2. Examination indicates that the larger RMS error from global buoy/ship comparisons in Fig. 1 is partly due to noise errors in the in-situ data. This indicates the need to reduce errors in co-located global data to derive a better validation set.

Fig. 3 shows an example of derived air temperature and specific humidity from NOAA-16 for six hours on June 9, 2006. The images present a typical day of warm and humid conditions in the tropics and drier and colder conditions in mid- and high latitudes. Several frontal systems in both northern and southern hemispheres are evident.

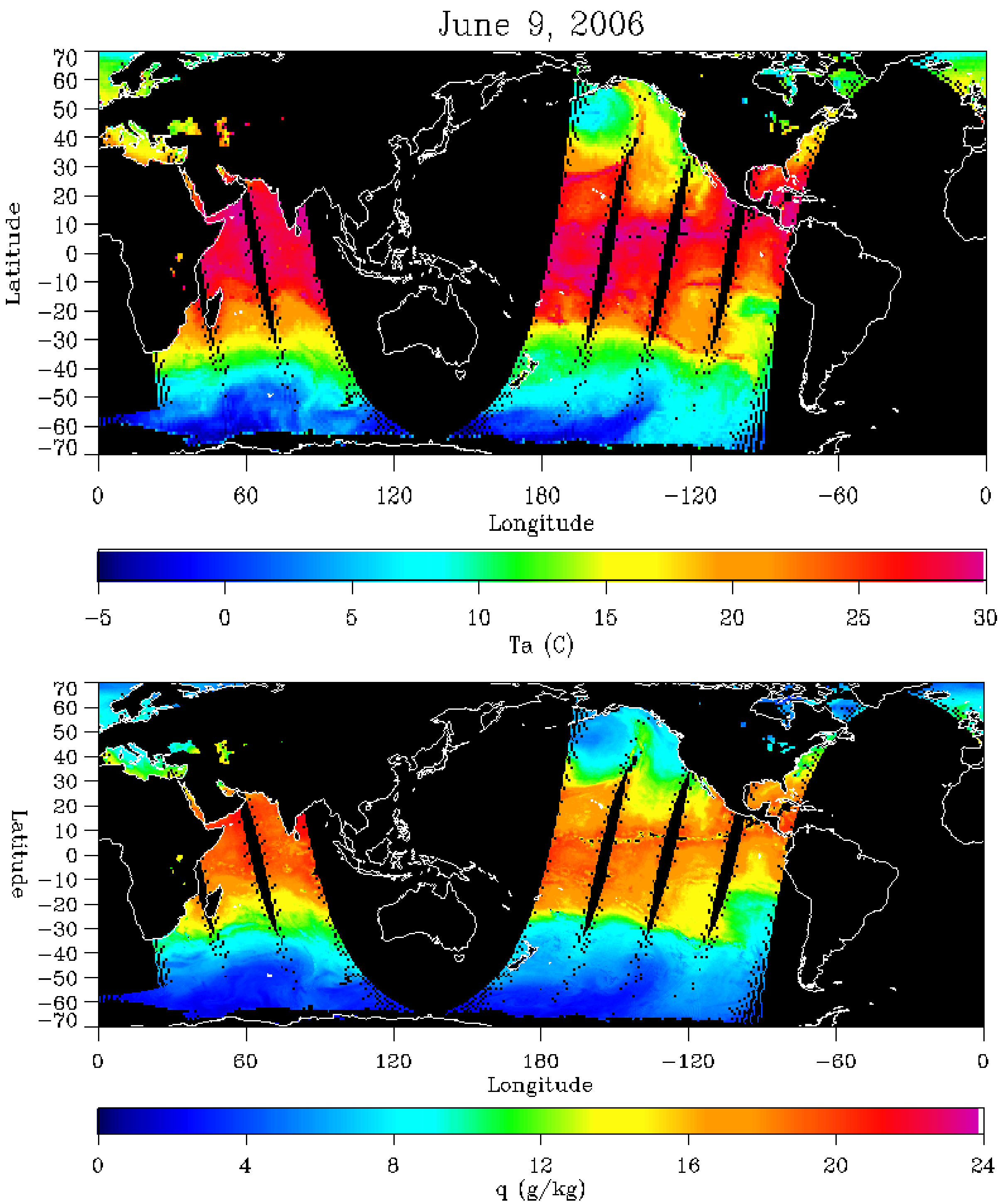

Fig. 3: Retrieved air temperature and specific humidity for 9-15 UTC, June 9, 2006.

4. SUMMARY

An algorithm is developed to derive the sea surface air temperature and specific humidity based on AMSU-A and AMSU-B measurements from the NOAA polar orbiting environmental satellites. The retrieval algorithms are developed with a neural network approach. The training datasets are constructed using a full year of co-located AMSU and buoy/ship data. In addition to the global and all-weather representation of the algorithm, the RMS error for air temperature is reduced compared to past studies. Long-term sea surface air temperature and specific humidity since 2001 have been derived from NOAA-16 and the data are available in NetCDF format. Data processing for other satellites in the NOAA polar orbiting series are ongoing. The data can be used as boundary conditions for numerical modeling, in the computation of air-sea turbulent heat fluxes, as well as in other applications.

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6. REFERENCE

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