P8.14 NEAR-SURFACE RETRIEVAL OF AIR TEMPERATURE AND SPECIFIC HUMIDITY USING MULTI-SENSOR MICROWAVE SATELLITE OBSERVATIONS

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1. INTRODUCTION

A new method for retrieving near-surface humidity (Q_a) and temperature (T_a) combining microwave observations from multiple satellite sensors is presented in this study. Previous methods using only one satellite sensor can be improved upon by combining information from multiple satellites. Improvements in accuracy of these parameters can ultimately improve retrievals of the heat flux exchange between air and sea (Curry et al., 2004).

Retrieval of near-surface air temperature and specific humidity using satellite remote sensing methods has proven difficult. Satellite sounding radiometers generally are designed for retrieval in broad vertical layers, thus making estimation of T_a and Q_a problematic. Initial efforts to infer the near-surface specific humidity were based on empirical relationships between monthly mean retrieved precipitable water and in situ observations of Q_a (Liu and Niiler, 1984; Liu 1986, 1988) and later refined to directly retrieve Q_a from SSM/I observations (Schlüssel et al., 1995). Retrieval methods of near-surface air temperature from satellite observations have evolved in a similar manner. Liu (1988) estimated T_a by using his near-surface specific humidity retrieval (Liu, 1986) and assuming constant relative humidity of 80% near the surface. Subsequent T_a methods such as Jourdan and Gautier (1995) and Konda et al. (1996) used additional parameters such as precipitable water, sea-surface temperature, wind speed and specific humidity to estimate T_a. More recently a dual T_a and Q_a retrieval method using a neural network approach was developed by Jones et al. (1999).

The goal of this study is to improve upon the accuracy of retrieving T_a and Q_a by combining microwave sounder data from the AMSU-A and SSM/T-2 with the imager data from SSM/I. The following sections will describe a simple method to retrieve these parameters using multiple sensors and compare results with previously published methods.

2. METHOD

A description of the method used to match satellite and ship observations and the regression method used to retrieve Q_a and T_a from satellite observations are described in the following two sections.

Table 1: Cruise ship observations containing observations of near-surface temperature and humidity used for satellite retrieval and validation. KWAJEX: TRMM Kwajalein Experiment, FRAMZY: Fram Strait Cyclone Experiment, JASMINE: Joint Air-Sea Interaction Experiment, PACS: Pan-American Climate Study, EPIC: Eastern Pacific Investigations of Climate Processes, GASEX: Gas Exchange Experiment.

Projects	Period	Longitude	Latitude
KWAJEX	7/29/99–9/11/99	167E	8N
FRAMZY	4/8/99–4/14/99	6W	62N-71N
MOORINGS	9/14/99–10/13/99	167E-148W	8N-50N
JASMINE	5/15/99–5/31/99	88E-96E	5S-11N
PACS	11/4/99–12/2/99	95W-110W	12N
NAURU	6/18/99–7/18/99	145E-167E	10S-9N
EPIC	9/10/01–10/24/01	101W-71W	EQ–20N
GASEX	2/14/01–2/28/01	125E-131E	2N-3N

2.1 *Matching Procedure*

Matches were constructed using individual ship observations and scan-line satellite data from all available SSM/I, AMSU-A, and SSM/T-2 sensors. Most of the ship observations were obtained as a part of the Environmental Technology Laboratory (ETL) Turbulent Flux System. The source, time, and location of the ship data from are given in Table 1. Ship observations were matched to each satellite instrument using a matching criterion of 3 hours and 50 km. Matches containing satellite observations within 30 km of land were removed from the match data set to avoid contamination of the microwave data. An SSM/I precipitation screen, using the Ferriday and Avery (1994) method, was applied to

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all matched data containing SSM/I data. Sea ice did not exist near any of the cruises, so no sea ice detection was applied to the matched data. Matched data sets were created for each ship and each instrument, which are hereafter named Type 1. Matched data sets from Type 1 data were further combined into matched data sets, each containing matched data between ship data and two satellite instruments (Type 2) and ship data and three satellite instruments (Type 3). Matched data sets with two or three satellite instruments required that all satellite observations matched one ship observation in both time and space.

Table 2: Regression coefficients for multi- and single-instrument Q_a algorithms. RMS is the root mean square difference for the forward selection regression and C_0 is the regression coefficient indicated in equation (1). Channel frequency in GHz is given for each instrument. Grey boxes indicate the channels unavailable for regression. M represents SSM/I, T represents SSM/T-2, and A represents AMSU-A.

	A/M/T	A/M	M/T	A	M
RMS (g/kg)	0.87	0.87	0.91	1.04	1.13
C_0 (g/kg)	-95.59	-95.59	-72.52	-98.48	3.16
A23.8				.204	
A31.4				-.133	
A50.3				-.060	
A52.8	.284	.284		.265	
A53.6					
A54.4				.173	
A89.0					
M19V	.616	.616	0.498		.186
M19H	-.115	-.115			
M22V	.021	.021	0.056		.297
M37V	-.360	-.360	-0.169		-.443
M37H			-0.115		
T183±3					
T183±1			-0.036		
T183±7			0.133		
T91.6					
T150.0					

2.2 *Regression Method*

A multiple linear regression of satellite brightness temperature observations from the matched data sets was performed to derive formulas for near-surface air temperature and specific humidity from satellite observations. A forward regression method for selecting the appropriate channels for the retrievals was applied to all AMSU-A and SSM/T-2 channels and all of the SSM/I channels except the 85 GHz channels. The forward selection method is an iterative process where χ^2, a measure of the regression error, is used to determine the order of the channels used for the regression. The method begins with a single variable regression and tests each channel to identify the channel with the lowest χ^2. Subsequent channels are added one at a time, while previous channels are saved in the regression, thus increasing the number of variables of the regression. To prevent over-fitting the regression, a stopping rule was applied to terminate the channel selection process. If the gradient in χ^2 became less than 0.1 when selecting the next channel, then the regression was considered complete.

Table 3: Regression coefficients for multi- and single-instrument T_a algorithms. A, M and T are same as in Table 2.

	A/M/T	A/M	A/T	A
RMS (g/kg)	1.47	1.55	1.60	2.16
C_0 (g/kg)	-162.42	-178.80	-198.41	-330.68
A23.8			.314	
A31.4		-.078	-.190	
A50.3			.102	
A52.8	.788	.854	1.000	1.268
A53.6				
A54.4				.0925
A89.0	-.068	.005		
M19V	.292	.510		
M19H				
M22V	.249	.125		
M37V	-.565	-.657		
M37H				
T183±3				
T183±1	-.131		-.092	
T183±7	.122			
T91.6				
T150.0			-.239	

The Type 3 matched data sets were separated into two parts: a training data set to develop the regression equations for predicting Q_a and T_a, and a validation data set used to test the robustness of the regression equations. The training set and validation set were chosen so that both have a diverse set of humidity and temperature observations. The training set consisted of observations from the FRAMZY, PACS, JASMINE, and KWAJEX experiments, while the validation data used data from MOORINGS, EPIC, GASEX, and NAURU.

All regression analyses were derived from Type 3 data in this study. The regression equations for Q_a and T_a have the form

$$T_a, Q_a = C_0 + \sum_{n=1}^{N} C_n T_n^M , \qquad (1)$$

where T^M indicates brightness temperatures in Kelvin from one of the three M instruments, C_n indicates coefficients from the regression, and N indicates the number of channels used for the regression.

2.3 *Regression Results*

Table 2 provides Q_a regression results for several combinations of instruments. Q_a regression results indicate the best fit occurs for the AMSU-A and SSM/I instrument combination with an RMS difference of 0.87 g/kg relative to the surface observations. The 52.8 GHz AMSU-A and all SSM/I channels except the 37H channel were selected for this retrieval. The dominant channel in the regression was SSM/I 22V followed by AMSU-A 52.8 GHz. SSM/T-2 was not selected for the three-instrument regression, but the 183±3 channel is selected for the two-instrument combinations with SSM/I. The single-instrument regressions show that both AMSU-A and SSM/I predict Q_a with a 0.15-0.20 g/kg increase in RMS difference from the best multi-instrument regression. The corresponding T_a regression results are shown in Table 3. The three-instrument regression provides the lowest RMS difference of 1.47°C and includes all three sensors. The AMSU-A 52.8 channel provides most of the T_a information as can be seen by heavy weighting of this channel for all combinations of instruments using AMSU-A. Instrument combinations without AMSU-A had RMS differences exceeding 2°C, so they did not provide a good estimate of T_a and are not shown in Table 4. Scatter diagrams showing the best T_a and Q_a regression results from multi-sensor retrievals are given in Figure 1. Both the specific humidity and air temperature satellite retrievals fit well with the full range of observed ship data

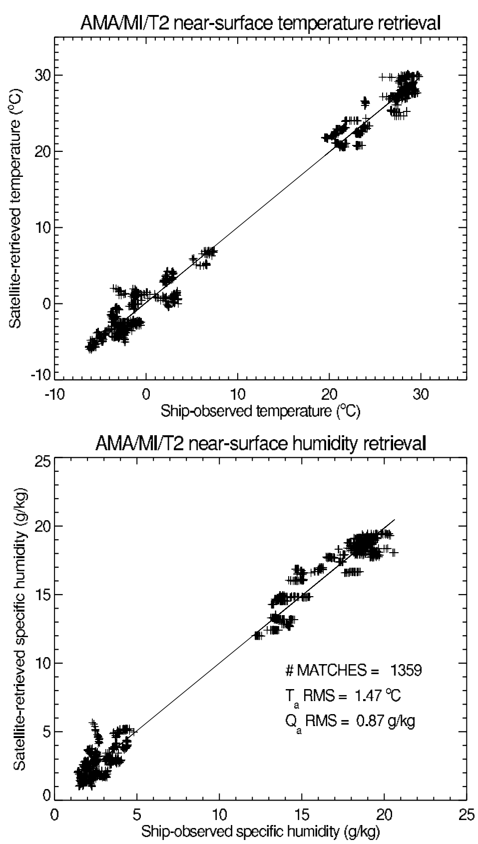

Figure 1: Multi-instrument regression results for Qa and Ta using Type 3 training data set.

3. VALIDATION

Scatter diagrams of ship- and satellite-retrieved specific humidity data are presented in Figure 2 for our current method and three previously published approaches. The independent algorithms used for comparison are those of Liu (1986), Schulz et al. (1993) and Schlüssel et al. (1995). The current SSM/I and AMSU-A retrieval is shown to have a very small bias of 0.04 g/kg and an RMS difference of 0.94 g/kg, which is only 0.07 g/kg higher than for the regression results. A negative bias is evident for the wettest observations, while a positive bias occurs for most other conditions. The other three retrievals exhibit greater RMS differences ranging from 1.25 g/kg to 1.44 g/kg as well as larger biases for Schlüssel et al. (1995) and Liu (1986). The other retrievals generally overestimate the humidity for the wettest observations and underestimate at the driest observations. Schlüssel et al. (1995) had problems with observations over 15 g/kg, where retrievals can exceed observations by as much as 5 g/kg. Schulz et al. (1993) had the largest errors for the driest observations. These results indicate the additional temperature information provided by AMSU-A improved the accuracy of Q_a particularly for the driest and wettest observations.

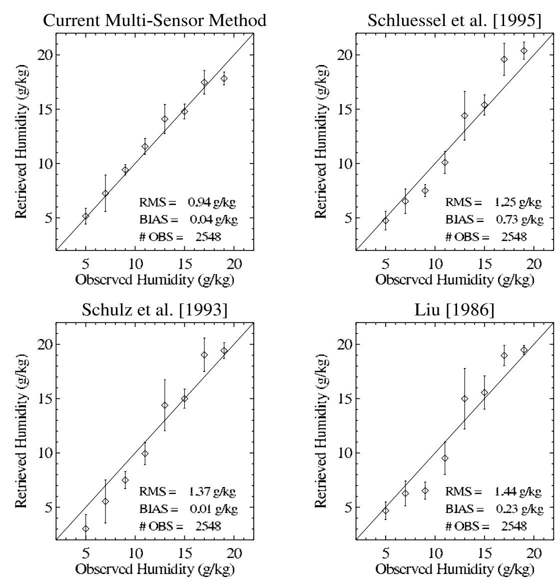

Figure 2: Scatter results comparing the four Q_a retrievals of the current multi-sensor method, Schlüssel et al. (1995), Schulz et al. (1993), and Liu (1986) using Type 2 validation data. Error bars indicate one standard deviation for data residing in 2 g/kg bins.

The evaluation of the near-surface temperature retrievals is shown in Figure 3. The previous approaches included for comparison are those of Liu (1988), Jourdan and Gautier (1995) and Konda et al. (1996). A 3.4°C bias was identified in the Konda et al. (1996) results and is applied to the Konda et al. (1996)

results presented in this study. The current SSM/I and AMSU-A retrieval generally performed more poorly with the validation data than in its derivation. The RMS difference with the direct observations increased by nearly 0.75^{o}C to 2.22^{o}C and a bias has the satellite retrieval generally underestimating T_a. A similar degradation was also observed in tests of the three-sensor algorithm. The bias is most affected by cold satellite retrievals for temperature observations less than 15^{o}C. This result also holds true for three other retrieval algorithms. While two of the approaches exhibit smaller biases, the RMS differences for all the comparison algorithms are 1 – 2^{o}C greater than for the current retrieval. The reduction in bias is mainly due to cancellation of positive and negative bias at the warmest and coldest temperatures. Liu (1988) and Jourdan and Gautier (1995) are very similar and both show significant warm bias for the warmest observations, while current retrieval compares more favorably to ship observations. Konda et al. (1996) had fewer observations since they require a wind speed estimate using the Goodberlet et al. (1989) SSM/I algorithm. Many of these matched observations had to be discarded because the algorithm became unstable for wind speeds less than 1 m/s. Konda et al. (1996) generally did poorly in this comparison with retrieved temperatures generally 3^{o}C colder than the other retrievals.

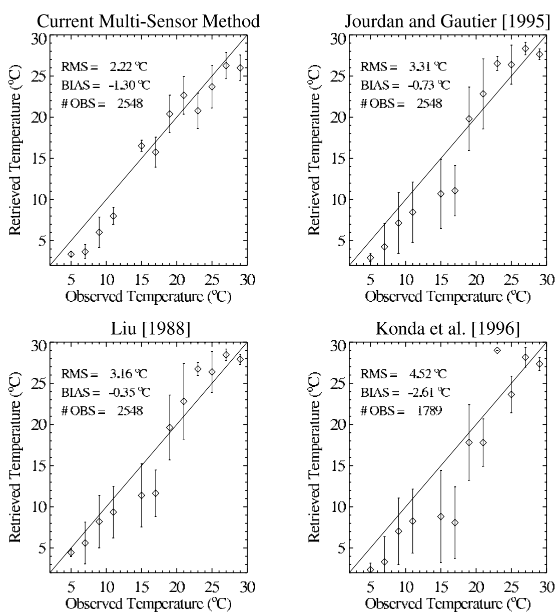

Figure 3: Scatter results comparing the four T_a retrievals of the current multi-sensor method, Jourdan and Gautier (1995), Liu (1988), and Konda et al. (1996) using Type 2 validation data. Error bars indicate one standard deviation for data residing in 2^{o}C bins.

Though the current retrieval algorithm outperforms the other methods in this evaluation, it should be noted that the other methods were previously shown to have accuracies better than the best results observed here. The neural network approach of Jones et al. (1999) reported RMS differences of 0.72 ^{o}C and Konda et al. (1996) found RMS differences of 1.2 ^{o}C for their T_a retrievals. Those previous evaluations were performed using monthly averaged data, so higher frequency weather fluctuations have been averaged out. Overall correlations of T_a and Q_a with more integrated measures are higher for monthly averages than for shorter periods, making comparison of the results difficult. These potential issues will be considered further in the Discussion section.

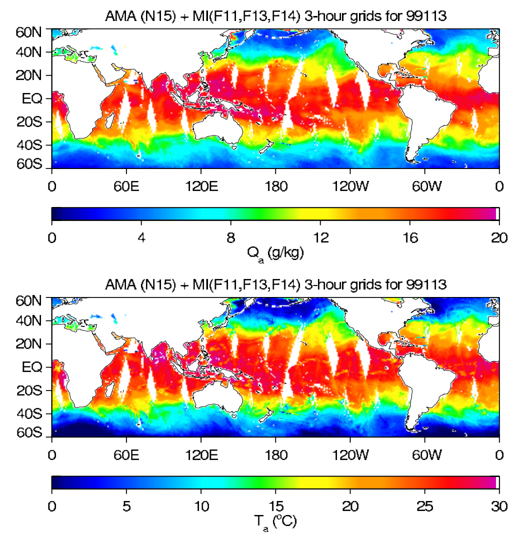

Figure 4: Q_a and T_a retrievals for a 24-hour period on April 23, 1999, using the multi-sensor (AMSU-A and SSM/) retrievals.

An example of one-day coverage for Q_a and T_a retrievals using the AMSU-A and SSM/I multi-sensor regression formula using three-hour matches is given in Figure 4. Coverage is nearly complete with the exception of diamond-shaped regions located in the subtropical zones. The Tropics are dominated with warm and wet conditions, while mid-latitude regions are much colder and drier. Synoptic-scale exchanges of heat and moisture between the Tropics and Mid-latitudes are evident in the zone between 30S-40S. Regions covered in sea ice are evident in the Northern Hemisphere in Hudson Bay and the Sea of Okhotsk, and highlight the requirement for screening sea ice from the retrieval.

4. DISCUSSION

The results demonstrate that using multiple microwave sensors provides the potential for more accurate retrievals of Q_a and T_a. Adding coarse vertical resolution sounder data from the AMSU-A and SSM/T-2 to SSM/I data incorporates valuable additional information. The addition of AMSU-A, in particular, improves the retrievals of both quantities. The best single-sensor retrievals for both Q_a and T_a came from AMSU-A instrument. While this is not surprising for T_a since AMSU-A is a temperature sounder, it was somewhat unexpected that AMSU-A added more to the Q_a retrievals than did the SSM/T-2 moisture sounder.

The radiometric channels contributing the most to the retrievals are generally similar for both Q_a and T_a. The AMSU-A 52.8 GHz channel is important in both retrievals mainly because this channel is most sensitive to changes in lower tropospheric temperature. The SSM/I 22V GHz channel is also a dominant channel because it is most sensitive to changes in precipitable water. The similarity of the leading channels is consistent with the generally small relative humidity variations over the ocean and the relative success of previous T_a routines assuming a near static relationship between T_a and Q_a.

Combining the data from the multiple sensors improves the retrievals because the different channels help identify unique atmospheric and oceanic conditions and provide more information on the vertical structure. In several cases, key contributing channels have a limited direct relationship to the quantity being retrieved but help isolate other variabilities that could influence the retrieval. T_a retrievals rely on the AMSU-A 31.4 GHz and the 89 GHz channels to help isolate the impact of surface temperature effects on the T_a retrieval. The SSM/T-2 183+/-3 channel is invoked in the two-instrument Q_a retrievals (see Table 2) because it is sensitive to mid-level tropospheric water vapor variations and enables removal of variability at that level that is not reflected at the surface. This information may prove to be useful for those vertical profiles where precipitable water is not a good indicator for Q_a. For example, Mapes and Zuidema (1996) identify tropical soundings where very dry air protrudes the middle troposphere. In such cases, a Q_a retrieval will benefit from middle tropospheric water vapor information provided by the SSM/T-2.

Three potential problems with the new retrieval were investigated that could adversely effect the quality of the retrievals. The first problem is that the comparison algorithms derived retrievals based on a different training data sets. Tests made with the Schulz et al. (1993) and Schlüssel et al. (1995) algorithms using our training data set indicate that the current multi-sensor retrieval still gives lower bias and RMS differences. A second problem is that the regression method best fits observations that have a linear response to Q_a and T_a. This assumption is invalid for some of the SSM/I and AMSU-A channels particularly for observation taken over warm or moist conditions. While it was found that the RMS difference and bias could be improved by removing these observations from the training data set, it severely limited retrievals in the Tropical regions. A third problem was that different SSM/I sensors were known to have biases of greater than 1^oC. However, it was found that these biases had minimal effect on the overall accuracy of the retrieval.

The ultimate choice of which algorithm form to apply will depend on many factors such as the desired time period, available sensors, desired accuracy, and desired sampling interval. For the greatest accuracy, it is beneficial to utilize multiple sensors including the AMSU-A. AMSU-A data became available, however, only in November 1998. For periods back to 1991, SSM/T-2 data do enable improved accuracy over previous SSM/I-only Q_a retrievals. Use of multiple sensors in the retrieval also limits the potential sampling frequency. If high sampling frequency is critical, single-sensor retrievals might be desirable despite the reduced accuracy. Use of AMSU-A offers advantages both in terms of improved accuracy and coverage extent

5. CONCLUSIONS

A new method for instantaneous retrievals of near-surface specific humidity (Q_a) and air temperature (T_a) over the oceans was developed by combining satellite microwave observations from AMSU-A, SSM/I and SSM/T-2. The most accurate Q_a retrieval method had an RMS difference of 0.87 g/kg relative to direct surface observations when using a combination of AMSU-A and SSM/I channels, while the most accurate T_a retrieval had an RMS difference of 1.47^oC when using all three instruments. These differences were found to be significantly lower than those computed from previously published algorithms applied to daily values.

6. REFERENCES

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