THE DEVELOPMENT OF AN ALGORITHM FOR GENERATING HOMOGENEOUS TIME SERIES OF SATELLITE DERIVED LAYER MEAN TEMPERATURES

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1. INTRODUCTION

The utilization of satellite derived temperature products for monitoring climate change is highly desirable, since satellites provide not only global coverage but also a single instrument for that coverage. There are two important conditions that would allow satellite temperature products to be even more desirable for long term climate monitoring. First, the temperature products should be derived in such a way that they are independent of any a priori (first guess) information in order to be certain that any observed trends in the data are due to actual climate variability and not to artifacts in the first guess. Second, periodically there is a new generation of sensors with a different ensemble of spectral channels. The temperature products must be derived in such a manner that the characteristics of the product do not change appreciably from sensor to sensor. These two conditions have never been considered operationally, since satellite derived temperature products have always been tailored to numerical weather prediction requirements. Now that information for monitoring climate change is becoming a very important concern, algorithms for the sole purpose of satisfying climate requirements are necessary.

The purpose of this paper is to present such an algorithm. To satisfy the first of the two conditions proposed above, the algorithm removes first guess dependency by directly retrieving deep layer mean temperatures (DLMT) in contrast to the more traditional approach of retrieving pointwise temperature profiles and then averaging. To satisfy the second condition, the algorithm has been successful in producing nearly identical DLMTs from two different sensors - the Microwave Sounding Unit (MSU) and the future Advanced MSU (AMSU). In other words, we are able to determine the correct combination of measurements from one sensor to reproduce with exceptional accuracy the DLMT derived from a completely different sensor. This is a very important result, because it provides a method for constructing a single continuous time series of satellite derived DLMTs from a succession of present and future sensors.

Another very important consideration is the measurements from which the temperature products for monitoring climate change are to be derived from. Microwave instruments measuring thermal emission by molecular
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oxygen in the 50-60 GHz oxygen band are highly desirable for a number of reasons. First, measurements from this band are largely insensitive to clouds, unlike infrared measurements, and any contamination due to precipitation can easily be detected and screened. Second, absorption due to non-uniform gases, such as water vapor, is negligible. In other words, no adjustments or corrections to microwave measurements are required to produce temperature products; consequently one need not be concerned with residual errors that would be introduced had the measurements been adjusted.

A climate record of mean tropospheric temperature, beginning in 1979, was established by Spencer and Christy (1991a) using Channel 2 (53.73 GHz) brightness temperature measurements from the MSU. They were able to monitor tropospheric temperature on a 2.5 x 2.5 latitude/longitude grid with a monthly precision of 0.2 degree Kelvin at high latitudes to as low as 0.1 degree in the tropics. The temperatures are deep-layer mean temperatures (DLMT) weighted vertically by the weighting functions associated with Channel 2 measurements.

Since the first launch in 1979, the MSU instruments have provided continuous daily global coverage of the earth by scanning across the orbital track from nadir to 47.35 degrees at approximately 9.47 degree increments. For this study we assume symmetry about nadir, so we will make reference only to view angles 1 (nadir) through 6 (extreme off-nadir). The MSU has 4 channels at frequencies of 50.31, 53.73, 54.96 and 57.95 GHz. MSU channel 1 is not considered because of its strong surface emissivity effects. The remaining three atmospheric MSU channel weighting functions at each of the 6 view angles are given in Fig. 1. The highest peaked group of weighting functions is for MSU channel 4, followed by MSU channel 3 and 2. The higher weighting functions in each channel grouping are associated with larger view angles.

Inspection of the MSU channel 2 weighting function at nadir viewing reveals that this channel also senses the lower stratosphere. In order to remove this contribution and thereby increase the detectability of tropospheric temperature change, Spencer and Christy (1991b) combined channel 2 measurements from different viewing angles to create a more narrow averaging kernel, the dashed curve in Fig. 1, than the raw nadir-viewing weighting functions. The coefficients for combining MSU channel 2 off-nadir brightness temperatures were subjectively determined by visual inspection of the derived averaging kernel. The coefficient values are 2.0 for view angles 3 and 4, and -1.5 for angles 5 and 6. Note that the coefficients sum to unity. This is a necessary constraint so that the linear combination of brightness temperature represents a weighted average temperature.

The problem of using the Spencer and Christy approach for determining suitable coefficients for creating the desired averaging kernel is that it is clearly subjective and does not necessary lead to an optimal linear combination of brightness temperatures. For example, if one wanted to utilize all atmospheric channels of the MSU instrument and all viewing angles to create other averaging kernels, there would be a total of 18 channel measurements to consider. A subjective approach would not be able to determine the optimum linear
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combination.

As an evolution to the work of Spencer and Christy, an algorithm was developed to objectively determine the optimum linear combination of measurements that best fits a user specified averaging kernel.

2. ALGORITHM DEVELOPMENT

The optimal DLMT is one that is associated with a boxcar function; in other words, a purely arithmetic mean with respect to the logarithm of pressure over some finite depth in the atmosphere. However, the limited resolving power of the radiometer can never produce such a solution, and the true function, commonly referred to as the averaging kernel, is always some linear combination of the weighting functions associated with the channels used.

The deep layer mean temperature \( T \) is a linear combination of \( m \) channel brightness temperatures \( T^* \) for different frequencies and/or view angles. This solution in vector notation is given by the scalar product

\[
T = C^T T^*
\]  
(1)

where, \( C \) is the \( m \)-element column vector of coefficients, the superscript \( T \) denotes vector transpose, and \( T^* \) is the \( m \)-element column vector of brightness temperatures. Using the matrix approximation of the radiative transfer equation, one can define the vector \( T^* \) by

\[
T^* = A t
\]  
(2)

where, \( t \) is a temperature profile of \( n \) levels, and \( A \) is the \( m \times n \) matrix of weighting functions. Substituting Eq. (2) into Eq. (1) yields:

\[
T = C^T A t
\]  
(3)

where the product \( C^T A \) is the \( n \)-element averaging kernel \( K \). In other words, the scalar product of the averaging kernel and the temperature profile defines the DLMT. If one plotted the averaging kernel as a function of height or pressure, the true weighted averaging of the layer which defines \( T \) can be observed. The basis of the algorithm is to compute \( C^T \) so that when multiplied by the matrix \( A \) yields the user specified averaging kernel. In other words, given
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\[ \mathbf{K} = \mathbf{C}^T \mathbf{A} \] (4)

define \( \mathbf{K} \) as the user specified averaging kernel and compute \( \mathbf{C} \) using the approximate pseudoinverse of \( \mathbf{A} \), i.e.,

\[ \mathbf{C}^T = \mathbf{K} \mathbf{A}^T (\mathbf{A} \mathbf{A}^T + \mathbf{D})^{-1} \] (5)

where \( \mathbf{D} \) is a \( m \times m \) diagonal matrix used to ensure that \( \mathbf{A} \mathbf{A}^T \) is well conditioned with respect to matrix inversion. Then use Eq.(1) to compute \( \mathbf{T} \).

A very important feature of this algorithm is that it is independent of any initial approximation of the atmospheric temperature. Not only is no initial first guess required, which is not true for traditional pointwise temperature retrievals, but also the microwave weighting functions we are using have very little temperature and moisture dependence. Hence, the same coefficients can be applied to all conditions. In other words, all of the information contained in the DLMT products using this algorithm is from the sensor’s measurements, and any detected change in the product over time will be due only to changes in the measurements. Again, this is not true for traditional pointwise retrievals, which require ancillary information to produce an initial estimate of the atmosphere.

3. MSU APPLICATION

The algorithm was applied to the MSU weighting functions shown in Fig. 1. Recall that there are a total of 18 "channels" (3 channels x 6 view angles) that can be considered. In the first two experiments, a boxcar is used in defining the user specified averaging kernel. Recall that the optimum shape of an averaging kernel for a DLMT is that of a boxcar. The dotted curve in Fig. 2 is the derived true averaging kernel (from Eq. 4) using view angles 3 through 6 of MSU channel 2. The numerical values in the columns labeled msu2, msu3 and msu4 are the derived coefficients. Each channel is associated with 6 coefficients, one for each view angle, beginning with view angle 1. For this figure it is seen that the only nonzero coefficients are at view angles 3 through 6 for channel 2. As expected, the averaging kernel in Fig. 2 does not have the shape of a boxcar. This derived averaging kernel is very similar to the one obtained by Spencer and Christy, which is the dotted curve in Fig. 2. Note, that the height of the boxcar was purposely selected to demonstrate that the algorithm can approximate Spencer’s averaging kernel. Of course, for global change purposes the averaging kernel does not have to be a boxcar; all that is necessary is that the averaging kernel be known.

Other combinations will produce different averaging kernels. For example, the averaging kernel given by the
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solid curve in Fig. 3 was obtained by using all view angles of MSU channels 2, 3 and 4, and hence all coefficients are nonzero. This kernel is actually more desirable than the other averaging kernels shown in Fig. 2 since there is far less signal from the surface.

There is no reason why the vector $K$, defined as a boxcar function in Eq.(6) cannot be some other distribution. The shape of the weighting functions in Fig. 1, as well as the derived averaging kernels, suggests that a Gaussian distribution can be better approximated by a linear combination of the weighting functions than can a boxcar. A series of averaging kernels derived from Gaussian distributions with standard deviations of 6 pressure levels, beginning at pressure level 67 (100 mb) and separated by 6 levels, are given in Fig. 4. All channels and view angles were used in the construction of these averaging kernels. One hundred pressure slicings were used in this study and have equal spacing in log pressure, where levels 1 and 100 correspond, respectively, to 1 and 1000 mb. The use of Gaussian distributions for the input vector $K$ in Eq.(6) has the advantage that one can better dictate the location and shape of the derived averaging kernel, especially if there are a sufficient number of channels available. Because of the limited number of channels on the MSU sounder, averaging kernels confined solely to the stratosphere cannot be provided. However, the next generation of microwave instruments -- the Advanced Microwave Sounding Unit (AMSU) will have a sufficient number of channels to provide information on climate trends well into the stratosphere.

4. AMSU APPLICATION

In the mid 1990's the MSU will be replaced by the AMSU. The weighting functions of the 50-60 GHz band of the AMSU, along with those from the MSU (dotted curves) are given in Fig. 5. Upon first inspection, the AMSU appears not to have the equivalent channels to continue the record of the MSU channel measurements. Of utmost concern is the ability to continue the record of tropospheric temperature trends established with MSU channel 2. The AMSU channel that is most similar to MSU channel 2 is AMSU channel 5 (53.33 GHz), however this channel is slightly more sensitive to the lower atmosphere and has a larger surface contribution, thereby producing a different signal. A change in the deep layer mean temperature's weighting function could conceivably produce a spurious signal in the time series based solely on MSU channel 2 brightness temperatures. In fact, a special meeting was held between NOAA and NASA to discuss possibly changing this AMSU channel to MSU channel 2 specifications. However, it was decided that the cost would be prohibitive.

The apparent question to be answered is can this algorithm reproduce the MSU channel 2 weighting function from the AMSU channel weighting functions? According to Fig. 6, the answer to this question is a resounding yes! In this figure there are actually four curves. The curves to the left are the actual MSU channel 2 (solid curve) and the AMSU reconstructed MSU channel 2 (dotted curve) for an surface emissivity of 1.0. The other
Figure 1. MSU weighting functions for channels 2, 3 and 4 at all view angles; and Spencer and Christy's derived averaging kernel (dotted curve).

Figure 2. Comparison of the boxcar derived averaging kernel, based on MSU channel 2 at beam positions 3 through 6, and Spencer and Christy's derived averaging kernel (dotted curve).

Figure 3. Boxcar derived averaging kernels using all channels and beam positions.

Figure 4. Gaussian derived MSU averaging kernels using all channels and beam positions.
Figure 5. Comparison of AMSU and MSU (dotted curve) weighting functions.

Figure 6. Actual and AMSU derived MSU channel 2 weighting functions for surface emissivities of 1.0 (a) and 0.5 (b).

Figure 7. Gaussian derived AMSU averaging kernels in three important regions of the atmosphere.
set of curves is for an emissivity of 0.5; the shape is different because the emissivity enters in the computation of the weighting functions. Only the nadir viewing AMSU weighting functions, shown in Figure 5, were used in deriving the coefficients. The selected emissivities are extremes within which surface emissivity in the 50 GHz band varies. By visual inspection, the actual and reconstructed MSU channel 2 weighting functions are virtually identical. It is very important to note that the coefficients, based on an emissivity of 1.0, were used as well for reconstructing the weighting functions for an emissivity of 0.5. In other words, the reconstruction of MSU channel 2 is insensitive to surface emissivity, which is very important since predetermination of surface emissivity would add uncertainty to the final product. Integrating the error between the real and reconstructed MSU channel 2 weighting function with a standard midlatitude summer profile yields an error of 0.15 degrees K. For the same atmosphere, the brightness temperatures of AMSU channel 5 used directly as a substitute for MSU channel 2 was 5.6 degrees warmer than that of MSU channel 2.

The AMSU by itself will be a very important sensor for monitoring temperature trends throughout the atmosphere. Its numerous channels will enable one to monitor temperature in three important regions of the atmosphere -- upper and lower stratosphere and the troposphere. Figure 7 shows examples of AMSU averaging kernels in these three regions. All were derived from initial Gaussian distribution using only nadir measurements. Narrowing of the widths of these averaging kernels is possible by utilizing off-nadir measurements.

5. TOVS PATHFINDER APPLICATION

The algorithm will be used in conjunction with the joint NASA/NOAA TOVS Pathfinder program. The objective of the Pathfinder program is to reprocess the entire TOVS archive with a fixed algorithm in order to produce products that can be used by scientist to study climate variations. At the first TOVS Pathfinder meeting, a decision could not be reached on a single algorithm, instead three algorithms or paths (A, B and C) were selected. Both Path-A and Path-B will produce traditional level temperature and moisture products using a priori information to provide the initial guess profiles. Path-A uses an initial guess from a numerical model, whereas Path-B uses a classification guess from a fixed library of atmospheric profiles. Path-C is independent of a priori information and solves directly for DLMTs. The algorithm described above will be used for Path-C.

The algorithm will be used for the generation of several different products. They include 6 DLMTs based on the averaging kernels in Fig. 4, which uses MSU channels 2, 3 and 4 at all scan angles. Hence, there will be only one product type per scan line. There will be another DLMT based on adjacent spots in order to have a higher spatial resolution product since there will be 10 derived quantities per scan line as opposed to 1. Note, that each pair of adjacent spots will have its own unique set of six coefficients in an attempt to preserve same averaging kernel across the scan line. This DLMT averaging kernel is very similar to the one shown in Fig. 3.
The reprocessing effort has just begun, and will start off with a 20 month period beginning in April, 1987. Fig. 8 shows the change of averaged DLMTs as a function of 20 degree latitude bands for April 1987. There are six curves, one for each of the six corresponding averaging kernels shown in Fig. 4. Each 20 degree latitude bin had a sample size in excess of 11,000. Of course, the variability of these DLMTs as a function of time will be derived as soon as more data is processed.

Fig. 8 Six scanline averaged DLMTs as a function of 20 degree latitude bands for April 1987.

6. SUMMARY
An algorithm for deriving DLMTs from microwave sensors has been developed. The algorithm, in conjunction with the microwave channels considered in this study, is completely independent of a priori information and will be used in support of the TOVS Pathfinder (Path-C) program. Independence from ancillary data is critical for high-precision monitoring of climate trends, so that any observed trends in the DLMT are attributed only to trends in the sensor’s measurements. The algorithm also has been shown to be capable of combining
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measurements from next-generation microwave sensors to reconstruct measurements from current sensors. This enables one to generate continuous time series of satellite-derived temperature trends accurately regardless of changes in satellite instrumentation.

7. REFERENCES


TECHNICAL PROCEEDINGS OF
THE SEVENTH INTERNATIONAL TOVS STUDY CONFERENCE

Igls, Austria

10-16 February 1993

Edited by

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July 1993