Estimation of Temperature and Humidity Profile Information from Microwave Radiances over Different Surface Types

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ABSTRACT

Existing use of passive microwave radiances to improve temperature and humidity analyses in the troposphere has been largely restricted to ocean applications. Recent studies have shown that useful information can be extracted from the Special Sensor Microwave Imager (SSM/I), particularly for cloud liquid water and precipitation, over many land and ice surfaces. Furthermore, new work has provided improved estimates of emissivity at frequencies well above those normally used for land surface applications using satellite, airborne, and ground-based methods. In the light of these new developments, information theory was used to investigate the potential for microwave atmospheric temperature and humidity sounding over varied land and ice surfaces using the Advanced Microwave Sounding Unit. It was found that significant information is available even at low altitude over land and sea-ice surfaces. With extensive land areas poorly served by conventional in situ sounding methods, this result gives considerable promise for the enhanced use of satellite sounding data over land. For temperature sounding, the results show that the sensitivity to emissivity depends strongly on the assumptions made about cloud cover. For humidity sounding, and temperature sounding in cloudy areas, an accurate model of emissivity and an accurate a priori estimate of skin temperature are both required to use sounding data effectively.

1. Introduction

Radiances measured at the top of the atmosphere now form a key part of the global meteorological observation network for numerical weather prediction (NWP) (Eyre et al. 1993; Gadd et al. 1995; Derber and Wu 1998). Effort rightly has focused on the use of data over the oceans, where conventional data are sparse. However, there are extensive land areas where existing observations do not meet the requirement for NWP. This study is limited to instruments that are sensitive to atmospheric parameters in the troposphere and will focus on the Advanced Microwave Sounding Unit (AMSU) (see Saunders 1993), first flown on NOAA-15, launched in May 1998. Reference will be made to studies of other instruments, primarily the Special Sensor Microwave Imager (SSM/I) (see Hollinger 1990), Initial exploitation of passive microwave radiance information for atmospheric variables was limited largely to the oceans. Other than the general need for more observations over the ocean, there were several technical reasons for this focus: the ocean generally has a low emissivity (~0.2–0.8), the surface is highly polarized, the forward model that relates emissivity to wind speed and sea surface temperature is sufficiently fast and accurate for operational applications, and a priori data exist to constrain the retrieval (e.g., NWP wind fields). Emissivity of land and ice surfaces is often greater than 0.9 although it can be much lower, especially in the presence of snow or ice.

Use of passive microwave observations for non-ocean surfaces has been confined largely to retrieving surface parameters rather than atmospheric parameters. Microwave imagery data are used extensively for sea-ice detection (see Cavalieri et al. 1991) although temperature profile information has been retrieved from microwave sounding units (MSU) (Gadd et al. 1995) and from the Special Sensor Microwave Temperature Sounder (SSM/T) combined with the SSM/I (Miao et al. 1995). The use of radiances over land has been restricted largely to land surface applications using L, S, C, and X bands (1–12 GHz), with some use of higher frequencies (e.g., Van de Griend and Owe 1994; Mätzler 1994). Progress has been made in the use of passive microwave precipitation estimates over land (see Barrett and Kniveton 1995). Some of these estimates make adjustments for different surface types (e.g., Basist et al. 1998). However, some studies have attempted to extend the retrieval of cloud liquid water to land surfaces (Jones and Vonder Haar 1990, 1997; Greenwald et al. 1997; Combs et al. 1998). These studies are in agreement that liquid water path (LWP) retrievals over land agree qual-
Table 1a. Temperature error correlation (× 100) matrix used to calculate B and corresponding standard deviations for background temperature error at each level. Only 200–1000 hPa are shown. The B matrix that was used also had levels from 0.1–200 hPa. Temperature units are K × 100.

<table>
<thead>
<tr>
<th>Pressure</th>
<th>Correlation of background temperature errors</th>
<th>Std dev</th>
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<tr>
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<td>239</td>
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<td>250</td>
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<td>163</td>
</tr>
<tr>
<td>920</td>
<td></td>
<td>122</td>
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</table>

Information content of satellite measurements

The method presented in Rodgers (1976), and subsequently used by Eyre (1990) for the Television Infra-red Observation Satellite (TIROS) Operational Vertical Sounder (TOVS) and by Smith et al. (1996) for multifrequency imaging microwave radiometers (MIMR), is employed. Here the Hessian of a quadratic cost function relates retrieval error to background error as derived by Rodgers (1976) such that, using the notation of Ide et al. (1997),

$$A^{-1} = B^{-1} + H^T(x^b)(E + F)^{-1}H'(x^b), \quad (1)$$

where $H'(x^b)$ is the observational Jacobian matrix $\nabla_x H(x^b)$ linearized about the background $x^b$, where $H$ is the observation operator relating geophysical variables $y$ to observations $y^o$. The matrix $F$ denotes the error covariance matrix associated with $H, E$ is the error covariance matrix associated with the observations $y^o$ and $B$ is the error covariance matrix associated with the background $x^b$ (the B matrix used is shown in Table 1). The $A$ is the error covariance matrix associated with the solution. This solution for $A$ is exact in the linear case but approximate for nonlinear problems. Comparison of the diagonals of the $A$ and $B$ matrices is particularly useful in the relative sense. One can see how much information is available over land and sea ice compared to that available over the sea, where the data have a proven quantitative value (see, e.g., Phalippou 1996).
Furthermore, this technique clarifies what requirements are needed for the emissivity model accuracy, for example, to achieve useful skill in estimating geophysical quantities over a range of surfaces. The matrices $A$, $B$, $E$, and $F$ describe random errors. Systematic errors are not discussed in this paper.

3. Information used to estimate $B$, $E$, $F$, and $H'$
   
   a. The radiative transfer model

   The Jacobian matrix $H'$ is calculated exactly using the adjoint method adopted by the fast radiative transfer model for TOVS (RTTOV) (Eyre 1991). This method is implemented with 40 discrete vertical levels to allow the integration of the radiative transfer equation. A plane-parallel atmosphere is assumed and no scattering by hydrometeors is allowed. The main value of RTTOV is that the Jacobians are an exact gradient of the direct model. New emissivity routines have been added compared to the Eyre (1991) model along with their adjoints.

   b. Error covariance matrices

   The background error covariance matrix $B$ is taken from the U.K. Meteorological Office operational variational processing of TOVS data (Gadd et al. 1995). Gadd et al. (1995) increased the error for skin temperature and near-surface temperature profile terms over land, but in this study the ocean $B$ matrix is used in all simulations, and skin temperature errors are varied as part of the investigation. In section 4 the error on the skin temperature is varied to investigate the coupling effect of emissivity and skin temperature errors. The $B$ matrix used is given in Table 1.

   Estimates are required for the observation error covariance matrix $E$ and the forward model error covariance matrix $F$. Measured radiometer output noise (NEAT) for the AMSU channels varies from channel to channel, ranging in value from 0.1 to 1.0 K (Saunders 1993) based on a specification of 0.25–1.20 K. Table 2 lists the AMSU channels, their NEAT, and the estimates of $E$ and $F$ used in this study. Table 2 also compares these values with typical validation against radiances calculated from NWP profiles for channels close to the AMSU channels from existing passive microwave radiometers (MSU and SSM/I). A baseline value of 0.28° K is used for the diagonal of $E$ for all channels, and all correlation terms are set to zero. This value is realistic for most channels, assuming the AMSU-B observations are averaged to the AMSU-A grid, and is used for simplicity and to ease interpretation of the results (English and Hewson 1998), based on airborne measurements. Cosmic radiation is included with a brightness temperature of 2.73 K. All 20 channels of AMSU-A and AMSU-B are used.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Std dev</th>
<th>Units</th>
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<tr>
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<td>122</td>
<td>$K \times 100$</td>
</tr>
<tr>
<td>$ln(q)_{s,15m}$</td>
<td>20</td>
<td>$ln(g kg^{-1}) \times 100$</td>
</tr>
<tr>
<td>$T^*$</td>
<td>Variable</td>
<td>$K \times 100$</td>
</tr>
<tr>
<td>$P^*$</td>
<td>250</td>
<td>Pa</td>
</tr>
<tr>
<td>LWP</td>
<td>Variable</td>
<td>$ln(g kg^{-1}) \times 100$</td>
</tr>
<tr>
<td>$ln(e_{s,1-1,s})$</td>
<td>1</td>
<td>$ln(dimENSIONLESS) \times 100$</td>
</tr>
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</table>

Table 1b. Natural log humidity error correlation ($\times 100$) matrix used to calculate $B$ and corresponding standard deviations for background natural log humidity errors at each level. Only 300–1000 hPa are shown. The $B$ matrix that was used also had levels from 0.1 to 300 hPa. Humidity units are $ln(g/kg \times 100)$. Information used to estimate $B$, $E$, $F$, and $H'$.
The forward model error covariance matrix also is assumed to be diagonal, and the diagonal can be varied to estimate the impact of different forward model errors. If the emissivity model error is zero then a baseline value for forward model error of 0.28 K² is chosen, such that the diagonal of E + F is 0.4² K².

The contribution of these errors can be modeled. The radiative transfer model can be written as:

\[ T^\uparrow = [eT^\uparrow + (1 - e)T^\downarrow] \tau + \text{atmospheric emission terms,} \]

where \( T^\uparrow \) is the top of atmosphere radiance, \( T^\downarrow \) is the zenith radiance at the surface, \( e \) is the surface emissivity, \( \tau \) is the surface to space transmission, and \( T_s \) is the surface skin temperature. Differentiating with respect to emissivity,

\[ \delta T^\uparrow = (T_s - T^\downarrow)\tau \delta e. \]

One can write \( \langle (T^\uparrow - T^\downarrow)^2 \rangle = \langle (T_s - T^\downarrow)^2 \rangle \langle (e - e')^2 \rangle \), where subscript \( t \) denotes true value and \( \langle x \rangle \) denotes average of \( x \). For numbers typical of an 89-GHz window channel (\( T_s = 300 \) K, \( T^\downarrow = 50 \) K, \( \tau = 0.8 \)), then for \( \langle (e - e')^2 \rangle = 0.0025 \) (i.e., emissivity errors of typically 5%), the contribution to the forward model random error from random emissivity errors is 10 K. If the random emissivity errors are typically only 0.5% the contribution to the forward model error will be only 1.0 K. So the \( i \)th channel of the diagonal of \( E + F \), \( R_i^2 \), can be related to the emissivity model error \( \delta e \) by

\[ R_i^2 = 0.4 + (T_s - T^\downarrow)^2 \tau^2 \delta e^2. \]

This assumption implies that when emissivity model errors are high the total forward model error for that channel is dominated by emissivity errors, assuming that the surface can be seen (i.e., \( \tau \gg 0.0 \)). This procedure may underestimate forward model errors in cloudy regions, where the breakdown of the plane-parallel assumption will increase forward model noise. Estimated values of \( F \) for emissivity model errors of 1% and 10% are included in Table 2. Note that for SSM/I window channels the standard deviation of observation minus calculation is lower than that expected for a 1% emissivity error at 22.235 and 37 GHz and comparable to that expected at 85.5 GHz. By assuming other sources of error are small, this study will show the largest possible sensitivity to emissivity model error.

c. Atmospheric profile vector

To test regional variability, the studies have been repeated for a number of profiles. Results will be shown for the three representative mean profiles, which are plotted in Fig. 1. Hereinafter the three profiles will be referred to as the tropical, midlatitude, and Arctic profiles. When cloud liquid water is added it is spread between the layer containing the 0°C isotherm and 900 hPa. The emissivity curves used are shown in Fig. 2 for nadir view for the four surfaces studied. When the dry-snow emissivity curve is combined with a warm, dry profile it clearly no longer represents dry snow, but some desert surfaces have a similar spectral emissivity dependence. Therefore the four surface types have been chosen to represent four different emissivity curves, but are linked to the four surfaces (ocean, snow, ice, forest) for ease of reference and interpretation. Because this
study focuses on a cross-track scanning single polarization instrument (AMSU), no account is taken of polarization information, which is important for a fixed-angle dual polarized instrument like SSM/I. In addition to the atmospheric profile screen temperature and humidity, surface skin temperature, surface-level pressure, cloud liquid water content, and five emissivity model parameters are included in the profile vector. Table 1 gives a complete list and indicates the errors assumed in B.

4. Information content analysis

The terms of the equation for the Hessian matrix (section 2) were evaluated using the information described in section 3. In particular, microwave emissivity was estimated for a wide range of surface types based on observations from two airborne microwave radiometers observing at 23.8, 50.1, 89, and 157 GHz. These observations were fitted to a formula based on Grody (1993) and Petty and Katsaros (1994) in order to interpolate to the other AMSU frequencies and to generate emissivity-related terms in the Jacobian matrices. The sensitivity of the atmospheric temperature and humidity profile information to emissivity errors was investigated. The simulations in sections 4a and 4b neglect cloud (i.e., assume perfect prior knowledge that there is no cloud). A simplified model is used to explain the results in section 4c and the impact of cloud liquid water is assessed in section 4d. A wide range of surfaces has been studied, but only results from the four represented in Fig. 2 are shown. Emissivity forward model error and background skin temperature error are both varied in the study, but it is assumed that prior knowledge of emissivity coefficients is similar for the four surfaces. This prior knowledge is assumed to be equivalent to an emissivity error of 1%. We therefore assume that we have an approximate emissivity model using readily available a priori information which itself has a low error. This situation will be the normal one because models will be simplified to use the a priori data available, and this simplification is certainly the nature of the model used in this study. The forward model errors
in the emissivity model used are 1% and 10%. The higher value (10%) is intended to correspond to errors in emissivity if fixed values were used (say 0.6 over sea and 0.95 over land), making no attempt to model emissivity but rather allowing the retrieval or assimilation process itself to retrieve emissivity. MSU data have been processed operationally at the U.K. Meteorological Office in this way using the system of Dibben and Chapman (1991). The lower value (1%) is intended to represent the likely “best possible” forward model error. Therefore, the difference between the simulations with 1% and 10% is intended to represent the difference between making a considerable effort to represent emissivity accurately and not doing so. Similarly, skin temperature errors of 1 K and 5 K are used where 5 K again represents a minimum effort scenario and 1 K assumes full use of other sources of information being made.

a. Temperature profile

Figure 3 shows the columns of the temperature Jacobian matrices for AMSU channels 3 (50.3 GHz) and 4 (52.8 GHz), both evaluated using the midlatitude profile for nadir view, and the corresponding diagonals of the background and retrieval error covariance matrices under two different error assumptions. Channel 3 is a window channel, and channel 4 peaks just above the surface and has a surface contribution to the measured radiance. Four lines are plotted, corresponding to the four emissivity curves in Fig. 2. It can be seen that the changing emissivity does not modify greatly the form of the Jacobians. As a consequence, the information for temperature soundings over the four surfaces is similar. Two different error assumptions are shown: first that the random emissivity model error is 1% and the skin temperature error is 1 K and second that the errors are 10% (emissivity model) and 5 K (skin temperature background). Retrieval error profiles are shown for the four surfaces and the background error, but, because the retrieval error varies so little, the retrieval error profiles are almost inseparable, even with the high error values. To ease interpretation, the same data are plotted in Fig. 4, but the percentage improvement \( P \) of the retrieval over the background is presented, defined as

\[
P = 100\left(1 - \frac{a_{ii}}{b_{ii}}\right)
\]

where \( a_{ii} \) and \( b_{ii} \) are the variances of the a posteriori (\( A \)) and a priori (\( B \)) error covariance matrices, respectively. The percentage improvement for the mid-latitude profile is shown in Figs. 4c,d. The improvement over background is 20%–30% for all four surfaces when the errors are low. When the emissivity error is increased to 10% and the skin temperature error to 5 K the percentage improvement becomes more dependent on surface type, but only surfaces that are nearly black give significantly less improvement over background than the other surface types. For all four surfaces, less information is gained from the radiances because more
FIG. 4. The same information as in Figs. 3c,d but instead of the diagonals of the matrices the quantity $P = 100\left(1 - \frac{a_{ii}}{b_{ii}}\right)$ is plotted, where $a_{ii}$ are the diagonals of the retrieval error covariance matrix and $b_{ii}$ are the diagonals of the background error covariance matrix. Results are shown for three atmospheric profiles. The quantity $P$ is referred to as percentage improvement in the text. This display makes differences more obvious, but they still are very small. Results are shown for the Arctic profile in (a) and (b), the midlatitude profile in (c) and (d), and the tropical profile in (e) and (f). Results are shown for low errors and high errors, as defined for Fig. 3.

information is used to estimate the surface temperature and less information is available because of the high forward model error. Figures 5a–d show the percentage improvement for 750-hPa–to–surface mean layer temperature as a function of emissivity error and skin temperature error for the four surfaces. Naturally, the least information is gained when the errors are highest. Also interesting is that the percentage improvement is only weakly dependent on emissivity error, especially for high emissivity surfaces, whereas it depends strongly on the skin temperature error. Therefore it is wrong to consider that emissivity model and background skin temperature errors have a similar effect on the potential information in the radiances. Also, the information is often most sensitive to emissivity error when skin temperature errors are low suggesting there is little benefit in addressing the emissivity issue without improving the realism of the skin temperature.

Considering again the comparison of different surfaces, it is apparent that significant information is available for surfaces other than ocean, even in the lowest 3 km. If emissivity is high, temperature profile information is still available as long as the skin temperature is specified accurately. Therefore the use of microwave temperature sounding channels over land is not limited by the high emissivities or inaccurately modeled emissivities, but rather by the difficulty of defining skin temperature and specifying surface type. For some snow and land surfaces the definition of skin temperature is problematic, as penetration depth is on the order of millimeters to meters and varies from channel to channel, and it varies with the permittivity of the medium. For these surfaces, temperature sounding information in the lower troposphere from microwave radiometers may be limited, but for other land and ice surfaces (e.g., open agricultural land, snow-free sea ice) good information still is available. The results can be placed in context by comparing the information gain with that achieved if all surfaces that can see the surface are excluded (i.e., AMSU channels 1–5, 15–17, and 20). Over the ocean,
percentage improvement for mean layer temperature falls from 27% to 7% in the 750-hPa-to-surface layer and for forest it falls from 24% to 6%. Clearly there is significant benefit from using the low-altitude channels, even when errors are high and the information at low altitude is not introduced through the B matrix by correlation with higher altitude. This finding is why the results are not very sensitive to the details of B.

The percentage improvement for the Arctic and tropical profiles are included in Figs. 4a,b and Figs. 4e,f. Overall there is little difference from the results for the midlatitude profile (Figs. 4c,d). The tropical profile is more sensitive to skin temperature and emissivity model errors than are the Arctic and midlatitude profiles, and when the Arctic profile is used there is slightly less information available when the surface is a close to emitting like a blackbody, compared to that for the three nonblackbody surfaces. The result that temperature sounding errors near the surface depend most strongly on the a priori knowledge of skin temperature is true for all the profiles used.

The main conclusion is that, in clear air, temperature sounding information even at low levels normally is not sensitive to the magnitude of the emissivity or its error. This conclusion was tested using the MSU radiometer on NOAA-12, using the processing system described by Dibben and Chapman (1991). The difference between retrievals from MSU with and without the window channel (MSU channel 1) were studied for clear-air fields of view. When the window channel was used, emissivity was retrieved. When the window channel was not used, emissivity was held fixed. The retrievals were compared with collocated radiosondes. The impact was neutral, as would be expected from the theoretical study. For example, the standard deviation of retrieval-minus-radiosonde thickness for the layer 1000–500 hPa was 31.9 m in both systems. Similarly tiny differences were found in bias. This finding supports the finding that temperature sounding errors are almost independent of emissivity and emissivity error.

b. Humidity profile

By contrast with temperature Jacobians, the humidity Jacobians are modified strongly by changing emissivity. Examples for AMSU channel 17, a water vapor–contaminated window channel at 150 GHz, and channel 20, the lowest altitude of the three 183.3-GHz humidity sounding channels, are given in Fig. 6. The Jacobians are calculated with respect to the natural logarithm of the specific humidity \( q \). This method has two advantages. First, the Jacobian calculated with respect to \( \log q \) is independent of the units of \( q \). Second, humidity sounding is more nonlinear than temperature sounding, so the Jacobians are less variable with \( \log q \) than with \( q \), because the value of \( q \) varies through five orders of magnitude. The background and retrieval error values taken from the diagonals of A and B also are shown in Fig. 6, again with one plot using low errors (1%, 1 K = emissivity model error, skin temperature error) and

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**Fig. 5.** The information (expressed again as percentage improvement) for 750-hPa-to-surface (1013 hPa) mean layer temperature as a function of model emissivity error for three different skin temperature errors (continuous line = 1 K, dotted line = 3 K, dashed line = 5 K) for the four surface types of Fig. 3, (a) ocean, (b) dry snow, (c) new bare ice, and (d) forest, using the midlatitude profile and assuming clear air.
the other high errors (10%, 5 K). Unlike in the temperature sounding case, it now is easy to distinguish the four curves. Nonetheless it still is helpful to use the percentage improvement profiles shown in Fig. 7 (laid out identically to Fig. 4) to present the differences more clearly. In the low error case, the log water vapor percentage improvement for snow and water surfaces is 35%–55%. Below 700 hPa, less improvement is possible for new sea ice (around 30%), but for the most emissive (“forest”) surface much less information is available and the percentage improvement falls to 10%–15%. Above 700 hPa, little sensitivity to surface type is found. If the assumed errors are increased to 10% for emissivity and 5 K for SST, the percentage improvements fall for all four surfaces. Figure 8 shows the percentage improvement in 750-hPa–to–surface integrated water vapor content as a function of background skin temperature error and emissivity forward model error. This figure shows that the information available depends strongly on emissivity forward model error, in contrast to results for temperature sounding. It still is useful to have an accurate background skin temperature, but the largest gain in retrieval skill will arise from reducing the emissivity forward model error below 1%–2%. Figure 8 also shows that for ocean and especially for dry snow (where the 183.3 GHz emissivity is low), the percentage improvement is more robust against emissivity model and background skin temperature error. So, unlike for the temperature sounding problem, results are now very sensitive to the surface type or, more specifically, the surface emissivity. If the emissivity is very low, it does not need to be specified very accurately. If it is high, as is the case for new ice, the accuracy requirement is very high if the same skill is to be achieved as in the low emissivity case. For the most emissive (forest) case the percentage improvement is limited to 15% even if the skin temperature background error is only 0.5 K and the emissivity model error is only 0.5%. There is a large contrast between this case and the new ice case, where emissivity $\approx 0.92$, indicating that information content rises rapidly as the surface becomes less and less black.

The other significant difference between water vapor sounding and temperature sounding is the sensitivity to variations in the atmospheric profile. Because the Jacobians are very sensitive to the amount of water vapor, they peak much higher in the Tropics than in the Arctic. More channels see the surface in the Arctic, and consequently the Arctic retrievals of water vapor are more sensitive to emissivity than are the tropical retrievals. Figures 7a,b and Figs. 7e,f plot the percentage improvement profile for the Arctic and tropical profiles. Consider first the low error (1%, 1 K) case (Figs. 7a, 7c, and 7e). For low-emissivity surfaces, there is little sensitivity to the atmospheric profile changes, but for the most emissive surface considerably more information is available in the Tropics. Interestingly, the tropical profile shows the largest sensitivity to increased errors in skin temperature and emissivity model. Increasing the errors to 10%, 5 K makes little difference for the Arctic profile but more than halves the information available in the tropical profile, especially for the higher-emis-
sivity surfaces. The tropical profile has the least sensitivity to surface type, because fewer channels see the surface, but has the most sensitivity to errors in the surface terms. This finding can be interpreted as a function of the number of window channels. For the Arctic profile, there are at least four independent clean window channels, a number sufficient to specify emissivity and skin temperature accurately even when good a priori information is not available. For the tropical profile, only one channel (31 GHz) is a clean window and one channel is not sufficient to describe the surface accurately, so a priori skin temperature information and an accurate forward model for the window channels are required. This result emphasizes that the relationship between individual channel sensitivity and actual information often is very complex.

In summary, the information available for water vapor at low levels is sensitive to emissivity, emissivity error, and background skin temperature error. It is most sensitive to the value of emissivity in the Arctic but is most sensitive to emissivity error and skin temperature error in the Tropics. It is much less sensitive to emissivity error for low-emissivity surfaces. For those land and ice surfaces where (a) it is possible to model emissivity with an error of less than 2%, (b) the background skin temperature error is less than 2 K, and (c) emissivity is less than 0.95, it is possible to retrieve nearly as much humidity information as it is over sea surfaces.

c. Reproduction of results using a simple model

The large difference in the sensitivity of the Jacobians to emissivity can be understood more easily by considering a very simple case. Consider the atmosphere as a single layer with temperature $T$, transmission $\tau$, and surface emissivity $e$. Ignoring cosmic radiation and assuming specular reflection at the surface, the radiative transfer equation can be written as

$$ T^\uparrow = eT_s\tau + (1 - \tau)(1 - e)T\tau + (1 - \tau)T. \quad (5) $$

Differentiating with respect to an absorber amount $X$ leads to

$$ \partial T^\uparrow / \partial X = [e(T_s - T) - 2(1 - e)\tau T] \partial \tau / \partial X. \quad (6) $$

and the second derivative with respect to emissivity is

$$ \partial^2 T^\uparrow / \partial e \partial X = [(T_s - T) + 2\tau T] \partial \tau / \partial X. \quad (7) $$
Therefore the variation of the gradient of brightness temperature with respect to \( X \) with emissivity is directly proportional to the gradient of transmission with respect to \( X \). Note that because the constant of proportionality depends on \( \tau \) and hence on \( X \), \( \partial^2 T \uparrow/\partial \epsilon \partial X \) will depend on \( X \). This relation implies that the problem is nonlinear and therefore that the sensitivity of the Jacobian matrix to emissivity is airmass dependent, as was found in section 4b.

If the radiative transfer equation now is differentiated with respect to temperature, it is found that

\[
\frac{\partial T \uparrow}{\partial T} = [\epsilon(T_s - T) - 2(1 - \epsilon)\tau T]\frac{\partial \tau}{\partial T} + (1 - \tau)(1 - \epsilon)\tau + (1 - \tau),
\]

(8)

and the second derivative with respect to emissivity is

\[
\frac{\partial^2 T \uparrow}{\partial \epsilon \partial T} = [(T_s - T) + 2\tau T]\frac{\partial \tau}{\partial T} - (1 - \tau)\tau.
\]

(9)

For AMSU channel 17 (150 GHz), the term \( \partial^2 T \uparrow/\partial \epsilon \partial X \) is large and negative because \( \partial \tau/\partial X \) is large and negative. By contrast, for AMSU channel 4 (52.8 GHz), the term \( \partial^2 T \uparrow/\partial \epsilon \partial T \) is close to zero because the terms \([T_s - T] + 2\tau T]\partial \tau/\partial T \) and \((1 - \tau)\tau \) are both positive (when \( \tau \gg 0 \), i.e., for window channels) and are similar in magnitude. For example, for AMSU channel 4, which peaks near 900 hPa, the term \((1 - \tau)\tau \) is slightly larger than \([T_s - T] + 2\tau T]\partial \tau/\partial T \) and the sum is small and negative, the exact values being given in Table 3. However, as Fig. 3 showed, the sum can become small and positive, hence the change in sign of \( \partial^2 T \uparrow/\partial \epsilon \partial T \) at 900 hPa that occurs when \((1 - \tau)\tau \) becomes small. Therefore, the lack of sensitivity of temperature Jacobians to emissivity when using the microwave oxygen band is a fortuitous consequence of the value of \( \tau \).

It is not a general result and should not, for example, be assumed to be the case for infrared temperature sounding using the carbon dioxide (CO2) band, where the temperature dependence of the absorption is different. Table 3 shows that for High-Resolution Infrared Radiation Sounder (HIRS) channel 6, which peaks at a similar altitude to that of AMSU channel 4, the term \((1 - \tau)\tau \) is almost identical, because the layer optical depth and surface-to-space transmission are similar, but the term involving \( \partial \tau/\partial T \) is large and negative. As a result, \( \partial^2 T \uparrow/\partial \epsilon \partial T \) is almost an order of magnitude higher, and therefore the columns of the Jacobian matrix for HIRS are much more sensitive to emissivity than they are for AMSU.

d. Effect of cloud liquid water

The simulations in sections 4a and 4b assumed that there is prior knowledge that there is no cloud, that is, the cloud amount is known perfectly and is zero. The sensitivity of microwave radiances to liquid water cloud

```latex
\begin{table}
\centering
\begin{tabular}{|c|c|c|}
\hline
Channel number & \( [T_s - T] + 2\tau T\partial \tau/\partial T \) & \( (1 - \tau)\tau \) & \( \partial^2 T \uparrow/\partial \epsilon \partial T \) \\
\hline
AMSU channel 4 & 0.013 & 0.021 & -0.008 \\
HIRS channel 6 & -0.043 & 0.023 & -0.066 \\
\hline
\end{tabular}
\caption{Relative size of two terms in Jacobian sensitivity to emissivity. Variables are defined in section 3.}
\end{table}
```
has three effects: first, the potential presence of cloud must be allowed for by including it in the state vector $x$; second, the absorption by cloud will reduce sensitivity to the atmosphere below the cloud layer; and third, forward model errors are likely to be higher in cloudy areas because of increased heterogeneity, scattering, and errors arising from the dielectric model. The first effect occurs even in clear air if prior knowledge of the cloud-free state does not exist. The second and third effects only occur if there is actual cloud present. Note that we are not concerned in this paper with the impact on systematic errors.

English et al. (1997) showed that cloud liquid water amounts of less than 100 g m$^{-2}$ have a negligible impact on the sounding channels of AMSU (that is channels 4–14 and 18–20), because the sensitivity of the top-of-atmosphere radiance is well below the best estimate of the forward model noise $\mathbf{F}$. Of course, the window channels (channels 1–3, 15–17) are very sensitive to liquid water path. A preprocessing scheme can be used to determine whether the observation is likely to be above this threshold. AMSU observations can be divided into those in which no prior knowledge is assumed for LWP and those in which the LWP is assumed to be zero, with an uncertainty below 100 g m$^{-2}$. In the context of analyzing AMSU data, those observations in which no prior knowledge of LWP exists will be referred to as “cloudy,” although strictly they are potentially cloudy. Those observations in which the prior uncertainty is less than 100 g m$^{-2}$ and the expected value of LWP is zero will be referred to as “clear,” although such observations could have complete cover of thin cloud, sufficient to be opaque at infrared wavelengths. The simulations in sections 4a and 4b are appropriate for clear observations defined in this way, because the effect of residual clouds with LWP less than 100 g m$^{-2}$ on the atmospheric profile retrieval is negligible (English 1995). The errors caused by the residual cloud effectively are “absorbed” by the forward model error covariance matrix.

Although there are sources of information on LWP (NWP model, visible channels) it is difficult to obtain an accurate estimate of the LWP in the microwave field of view from external sources. Once prior uncertainty exceeds 100 g m$^{-2}$ the retrieval error in LWP becomes insensitive to further increases, because the cloud LWP retrieval becomes independent of the prior information.

In this section, the impact of allowing for cloud of liquid water path ranging from 0 to 1000 g m$^{-2}$ with prior uncertainty of 500 g m$^{-2}$ (which equates to no prior knowledge) is studied. As discussed earlier, random errors in the forward model error will be higher for deep cloud than for thin cloud or clear air because of inadequacies in the dielectric model and the plane-parallel assumption. In this study, $\mathbf{F}$ is held fixed as LWP is changed, which means the retrieval error in cloudy areas will be underestimated by an amount that will become progressively larger as the cloud becomes deeper. The results are therefore representative for an idealized forward model in which the scientific and technical difficulties of modeling cloud absorption have been overcome. This approach is used because in this paper we are attempting to evaluate sensitivity to emissivity and emissivity model error, not cloud model error. The results show the sensitivity to emissivity as the cloud liquid water changes for an idealized forward model (i.e., one which has a baseline noise and a sensitivity to emissivity model error, as discussed in section 3b). For large amounts of liquid water, the atmosphere becomes optically thick for the 183.3-GHz humidity channels on AMSU-B, and therefore the humidity retrieval error will become less sensitive to surface emissivity, skin temperature, and lower tropospheric water vapor and temperature. Figures 9a–d show 750-hPa–to–surface mean layer temperature percentage improvement for a cloud liquid water content of 500 g m$^{-2}$, which corresponds to deep but usually nonprecipitating cloud, and give optical depths ranging from 0.04 at 24 GHz and 0.2 at 50 GHz to 1.1 at 183 GHz using the cloud liquid water absorption model validated in English (1995). Figures 9a–d compared with Fig. 5 demonstrate that the presence of cloud increases the sensitivity of temperature information to emissivity model error, as reported previously by Eyre (1990). This finding is true for all four surfaces. In section 4a it was concluded that temperature sounding is not sensitive to emissivity model error when no cloud is present. This conclusion becomes increasingly invalid as cloud liquid water is increased. Note that this is a sensitivity to actual cloud and not a sensitivity to the potential presence of cloud (i.e., prior cloud LWP error).

The prior uncertainty in LWP is only important when emissivity model error is high. Figures 10a–d show percentage improvement with 500 g m$^{-2}$ water cloud for the retrieval of water vapor integrated through the 750-hPa–to–surface layer and should be compared with Fig. 8 for the cloud-free case: the loss of information with increasing emissivity error in Fig. 10 is very rapid. For new snow-free (bare) ice and forest the information content becomes marginal (less than 10% improvement) when emissivity errors exceed 2% and skin temperature background exceeds 2 K, a situation that will be very common over land. For the most emissive surface, information gain is marginal even if errors are reduced to 1% and 1 K for emissivity model and skin temperature background, respectively.

The effect of changing cloud and emissivity is shown in Figs. 11a–d, in which the percentage improvements in 850-hPa temperature and humidity (which are in the cloud layer) are plotted against emissivity and cloud LWP. The corresponding changes in percentage improvement for cloud LWP itself and skin temperature are shown in Figs. 12a–d (the background errors for cloud and skin temperature are set at 500 g m$^{-2}$ and 2 K, respectively). In Figs. 11 and 12, the plots against emissivity have four curves corresponding to LWP of 0, 200, 500, and 1000 g m$^{-2}$; and the plots against LWP have four curves corresponding to the four surface types.
(ocean, dry snow, ice, and forest). Theoretically, percentage improvement for temperature is actually increased in the cloud layer as cloud LWP increases because the strong cloud absorption gives a narrowing of the weighting function in the region of the cloud. This sharpening of the weighting functions due to cloud depends very much on the assumptions that cloud top and cloud base are known perfectly and that the cloud is much less deep than the clear-air weighting function. In this, study cloud top and cloud base are held fixed (i.e.,...
Fig. 11. Change of percentage improvement with increasing liquid water path and emissivity for errors of 2 K/2% in background skin temperature and emissivity model: (a) 850-hPa temperature error with increasing cloud LWP; (b) 850-hPa humidity with increasing cloud LWP; (c) 850-hPa temperature with increasing emissivity; (d) 850-hPa humidity with increasing emissivity. Plots against LWP are for the four surfaces: ocean (continuous line), snow (dotted line), bare ice (dashed line), and forest (dashed–dotted line). Plots against emissivity show four curves that correspond to LWP’s of 0 (continuous line), 200 (dotted line), 500 (dashed line), and 1000 g m$^{-2}$ (dashed–dotted line).

Fig. 12. Change in information for (a) cloud liquid water path with changing emissivity for liquid water paths of 0, 200, 500, and 1000 g m$^{-2}$ (same key for lines as in Fig. 11); (b) cloud liquid water path with changing liquid water path and emissivities corresponding to the four surfaces using same key as in Fig. 11; (c) skin temperature with changing emissivity for liquid water paths of 0, 200, 500, and 1000 g m$^{-2}$; (d) skin temperature with changing liquid water path and emissivities corresponding to the four surfaces used in Fig. 11.
perfect knowledge is assumed). In practice, nonlinearity errors considerably reduce the benefit of the sharper weighting function. Water vapor information is lost rapidly as the cloud LWP increases, most especially at high emissivity. At 850 hPa, this effect tends to saturate for LWP above 400 g m\(^{-2}\). Skin temperature and cloud LWP retrieval errors are shown in Fig. 12 so that direct comparison can be made with past results that were discussed in the introduction. When emissivity is low, the cloud LWP can be retrieved, but this skill falls very rapidly for emissivity above 0.9 when the cloud is thin and above 0.8 if the cloud is deep. These results show that LWP can be retrieved over surfaces with emissivity as high as 0.9 if the cloud is not too thick, emissivity is modeled accurately, and some information on skin temperature is available, a result that supports the results of Greenwald et al. (1997). When emissivity is zero, no information is available for skin temperature. Information increases with increasing emissivity at a rate that is fastest when cloud is thinnest. For high-emissivity surfaces, 30% improvements over a background error of 2.0 K are possible. For surfaces that are very emissive, this improvement falls only slowly with increasing cloud, whereas for gray surfaces it falls away sharply to less than 20% once the cloud LWP reaches 400 g m\(^{-2}\). This result also supports past work that shows that information is available on land and ice skin temperature. In summary, optically thin clouds increase the sensitivity to emissivity and emissivity model error. This effect is particularly true for temperature sounding. As the optical thickness rises, the sensitivity of top-of-atmosphere radiances to emissivity falls until eventually (at around an LWP = 800 g m\(^{-2}\)) the percentage improvement becomes independent of surface type. If nonlinearity errors are correctly handled, then it may be possible to extract more temperature profile information from emission from the cloud drops than can be extracted from the emission from air molecules in clear air, because of the higher absorption. Below and, to a lesser extent, above the cloud, less information is available on the temperature profile. In practice, the additional information on cloud temperature may be difficult to achieve because of nonlinearity errors. The retrieval of cloud LWP is not very sensitive to emissivity except when emissivity exceeds 0.9. By contrast, skin temperature information rises as emissivity rises, and once the emissivity exceeds 0.95 then skin temperature retrievals have very low sensitivity to cloud LWP. Note that the situation for measuring skin temperature is improved if dual polarization is available, especially at low emissivity.

5. Conclusions

Errors in the retrieval of temperature and humidity over various surfaces using microwave radiances have been studied. Temperature profile information is only weakly sensitive to emissivity and emissivity model error if prior knowledge that cloud liquid water path is less than 100 g m\(^{-2}\) exists, but even thin liquid water clouds increase this sensitivity if there is no prior knowledge of the amount of liquid water. However, for humidity information, the sensitivity to both emissivity and emissivity model error is large and cannot be ignored or treated in a very simple manner. These statements hold for random emissivity errors. If the emissivity model is biased, then bias correction will be required to prevent these biases from being passed to the retrieval (see Eyre 1987).

This study showed that when emissivity is high (e.g., land, ice), nearly as much humidity information can be gained as for low emissivity, as long as the emissivity error in the forward model is low, and the background skin temperature is specified accurately. When cloud liquid water is present, the requirement for an accurate emissivity model increases, as reported in Eyre (1990), most especially for high-emissivity surfaces. As microwave data are most important in cloudy regions, where information from infrared radiances is limited by optically thick clouds and the difficulties of cloud detection, the accuracy requirement in cloudy areas should be regarded as the real accuracy requirement for most practical applications.

The method used in this paper has some deficiencies. First, it is only exact in the linear case and the effect of nonlinearity is to increase errors and reduce information. Therefore, the results tend to represent the best possible retrieval and real retrieval errors may be higher. Nonetheless it does provide insight into what could be achieved if the retrieval or assimilation method can be made sufficiently robust. A specific example of a nonlinearity issue is the spatial scaling of emissivity. The curves used in this paper are based on airborne radiometer observations on the scale of hundreds of meters. There is evidence that nonlinearity effects in the scaling lead to different spectral emissivity changes at scales of tens of kilometers (Jones and Vonder Haar 1997). Therefore, the results should be interpreted simply as the difference in information for four different emissivity curves. The link to ocean, sea ice, forest, and snow allows easy labeling of these curves but may not correspond to the true emissivity curves for these surfaces at large spatial scales. Another deficiency is the sensitivity to the choice of \(B\). The matrix \(B\) is a function of application. The conclusions reached in this paper are not found to change if a different \(B\) matrix associated with a different NWP model is used [that from the European Centre for Medium-Range Weather Forecasts, see Phalippou (1996)]. However, this lack of change may not be the case if a \(B\) matrix is used that is associated with a completely different application (e.g., climatology). Therefore the conclusions in this paper should be regarded as specific to the NWP application. It is generally true of any retrieval or analysis problem that the conclusions must be understood in the context of the application.
The results provide much evidence, backed up by practical experience, that temperature sounding information retrieved from observations of top-of-atmosphere spectral radiance between 50 and 60 GHz can be retrieved without the need for an accurate emissivity model in areas where cloud LWP is known to be very low (less than 100 g m\(^{-2}\)). This knowledge can be derived from the observations themselves or from other methods of cloud detection. This method requires adequate preprocessing to identify the clear/thin-cloud fields of view necessary to ensure that the radiances presented to the retrieval or assimilation stage are consistent with the method and radiative transfer model used. However, if temperature information in areas of thicker cloud (100–500 g m\(^{-2}\) but still assumed to be nonprecipitating) or humidity information in clear or cloudy regions is to be retrieved, an accurate emissivity model must be used.

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