A Microwave Occultation Observing System Optimized to Characterize Atmospheric Water, Temperature, and Geopotential via Absorption

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ABSTRACT

A new remote sensing concept extrapolated from the GPS occultation concept is presented in which the signal frequencies are chosen to determine atmospheric water, temperature, and the geopotential of atmospheric pressure surfaces. Using frequencies near the 22- and 183-GHz water lines allows not only the speed of light to be derived as a GPS occultation but also derivation of profiles of absorption caused by atmospheric water. Given the additional water information, moisture and temperature as well as the geopotential of pressure surfaces can be separated and solved for. Error covariance results indicate that the accuracies of individual water profiles will be 0.5%–3% extending from roughly 1–75-km altitude. Temperature accuracies of individual profiles will be sub-Kelvin from -1- to 70-km altitude depending on latitude and season. Accuracies of geopotential heights of pressure will be 10–20 m from the surface to 60-km altitude. These errors are random such that climatological averages derived from this data will be significantly more accurate. Owing to the limb-viewing geometry, the along-track resolution is comparable to the 200–300 km of the GPS occultation observations, but the shorter 22- and 183-GHz wavelengths improve the diffraction-limited vertical resolution to 100–300 m. The technique can be also used to determine profiles of other atmospheric constituents such as upper-tropospheric and stratospheric ozone by using frequencies near strong lines of that constituent. The combined dynamic range, accuracy, vertical resolution, and ability to penetrate clouds far surpass that of any present or planned satellite sensors. A constellation of such sensors would provide an all-weather, global remote sensing capability including full sampling of the diurnal cycle for process studies related to water, climate research, and weather prediction in general.

1. Introduction

Water vapor is the dominant greenhouse gas in the earth’s atmosphere (Manabe and Wetherald 1967) and is the one significant atmospheric constituent whose mixing ratio is controlled to first order by its saturation vapor pressure. Its extreme sensitivity to temperature is reflected in the five orders of magnitude change in concentration from the tropical surface to the tropopause. Nonetheless, fractional changes in moisture in the upper and lower troposphere exert similar radiative influences on surface temperatures (Shine and Sinha 1991). The large latent heat associated with phase changes of water moves energy through the earth system driving atmospheric circulation, and the resulting precipitation largely controls the extent and character of the continental biosphere.

Our continual quest toward a deeper understanding of weather and climate and a significantly improved skill
to predict their future behavior depends critically on our knowledge of the present distribution of atmospheric water and how it varies. However, our knowledge of the present distribution is remarkably incomplete and our understanding of the mechanisms controlling the distribution is necessarily even more so. This is due in no small part to the wide range of spatial and temporal scales over which atmospheric water varies. Characterization of water must span spatial scales from microphysical to global scales and timescales of seconds to decades and beyond. The large range of scales combined with the high opacity of atmospheric water particularly in its condensed states make remote sensing of water extremely challenging. In fact no observing system to date can provide all the features required to characterize atmospheric water across the temporal and spatial scales and conditions over which it varies.

Here we present and discuss a particular implementation of the spacecraft radio occultation technique designed to characterize atmospheric water that we will refer to as Bi-static Radar Imaging of Geopotential, Humidity and Temperature (BRIGHT). The spacecraft radio occultation technique has proven quite powerful in characterizing the major planetary atmospheres of our solar system including that of earth. In this technique one or more monochromatic signals are transmitted from a spacecraft across the planet’s limb to a receiver on the far side of the limb (see Fig. 1). Since the transmitters and receivers are independent, the system is referred to as bistatic radar. The orbital motion of the transmitter and receiver cause the signal path to slice down through the atmosphere providing a vertical limb scan of the atmosphere. Like other techniques, BRIGHT will not capture atmospheric water at all of its scales, but it will provide a unique combination of dynamic range, accuracy, high vertical resolution, all-weather sensing, and global coverage.

Historically, radio occultation observations have utilized preexisting spacecraft signals such as the occultation observations of the outer planets using Voyager’s telecommunications signals (Tyler et al. 1989) or the observations of earth’s atmosphere using signals from the global positioning system (GPS) satellites (Ware et al. 1996; Kursinski et al. 1996). In the present work, we describe what could be accomplished if we were to choose the occultation signal frequencies and develop the associated instrumentation. In earth’s atmosphere at frequencies less than 300 GHz, refractivity, defined as $N = (n - 1) \times 10^6$, where $n$ is the index of refraction, is related to temperature ($T$), total pressure ($P_t$), and partial pressure of water ($e$) as

$$N = 77.6(P_t/T) + 3.73 \times 10^5(e/T^2).$$

In the GPS case, very accurate profiles of the atmospheric refractivity are derived that lead directly to density, pressure, and temperature in the upper troposphere through the stratosphere because the contribution of moisture to (1) is negligible at these altitudes. In the lower half of earth’s troposphere, water vapor contributes significantly to the index of refraction such that additional information such as temperature from a weather analysis is required to determine the wet and dry contributions to the index of refraction. Given present knowledge of atmospheric temperature to roughly 1.5 K, one can derive moisture from GPS occultations to an accuracy of roughly 0.1–0.2 g kg$^{-1}$, which is useful in the lower to middle troposphere (Kursinski et al. 1995; Healy and Eyre 2000; Kursinski and Hajj 2001). The approach of combining temperature with the GPS-derived refractivity to determine moisture is sub-optimal in that it essentially assumes the temperatures are known perfectly, which of course is incorrect. A more optimal approach combines the GPS observations with weather analysis estimates of temperature, pressure, and moisture in a least squares framework based on the respective error covariances of the observations and the analysis. Such least squares schemes are under development (e.g., Zou et al. 1999; Healy and Eyre 2000; Kursinski et al. 2000a,b; Poli et al. 2002, hereafter PJK). While quite powerful, we would like an observational system that directly provides profiles of moisture and temperature independent of models with the accuracy and vertical resolution of the GPS refractivity profiles.

The BRIGHT system described here would measure the phase and amplitude of several monochromatic signals near the 22- and 183-GHz water lines as they pass through the atmosphere during an occultation. From the measured phase and amplitude, we can derive profiles of both the speed of propagation and the attenuation due to water absorption and in turn solve for the wet and dry density profiles directly from the occultation observations. Because we control the signal source characteristics, BRIGHT provides very high signal-to-noise ratios (SNRs). The result is a high vertical resolution, all-weather active limb sounder yielding very precise and accurate moisture, temperature, and geopotential profiles from the surface to the mesopause.
2. Overview of the occultation absorption concept

Spacecraft radio occultations (such as those using GPS) have generally focused on deriving bending angle profiles from the changing Doppler shift during an occultation that is derived from measurements of the carrier phase. (For a detailed description of the GPS occultation technique, resolution, and theoretical accuracy, see Kursinski et al. 1997.) In such cases, the index of refraction \( n \) is taken to be real. However, \( n \) is in general complex because a medium will affect both the speed of propagation and the amplitude of signals via absorption as they pass through it. The information in \( n \) is contained in the refractivity \( N \), the nonunity portion of \( n \) defined such that \( N = (n - 1) \times 10^6 \). Here \( N \) is also complex having real \((N')\) and imaginary \((N'')\) parts such that \( N = N' + iN'' \). Knowing profiles of both \( N' \) and \( N'' \) provides the constraints to solve for profiles of moisture concentration, temperature, and pressure. Spacecraft radio occultation observations have inferred ammonia concentrations in the outer planets (Lindal et al. 1981) and \( \text{H}_2\text{SO}_4 \) concentrations in the atmosphere of Venus (Jenkins and Steffes 1991; Jenkins et al. 1994) by utilizing absorption measurements. In the rest of the paper, for simplicity, we will write \( N = N' \) as representing the real part of \( N \) as was done in (1).

\[ \tau = \int k \, dl = 2 \int_{\tau_0}^{\infty} \frac{nr \, dr}{(n^2 r^2 - n_0^2 r_0^2)^{1/2}} \quad (3) \]

\[ k = -\frac{1}{\pi \, da} \left[ \int_{a_0}^{a} \frac{d\tau}{da} \frac{da}{(a^2 - a_0^2)^{3/2}} \right] \quad (4) \]

Equation (3) represents the forward problem of the extinction coefficient integrated along the occultation path. Equation (4) is the inverse relation allowing us to derive the extinction coefficient profile from the measured, path-integrated optical depth. Equation (4) can be derived from (3) via standard Abel integral transform pair relations (Tricomi 1985; Feng et al. 2001). Note that the independent variable in (4) is \( a \), the asymptotic miss distance (see Fig. 1) defined as \( a = nr \sin \theta \), where \( \theta \) is the angle between the ray path and radial direction. Note that a is a constant for each ray path under the assumption of spherical symmetry and is derived from the atmospheric Doppler profile as described in Kursinski et al. (1997). Then \( k \) is derived as a function of \( r \) in (4) using the fact that \( a_0 = r_0 n(r_0) \), where \( r_0 \) is the tangent radius of the ray path such that \( \theta = \pi/2 \) and \( n(r_0) \) is derived from the bending angle profile via the standard Abel equation.

To remove noise and provide dynamic range, profiles of optical depth will be measured at several frequencies. We will then take the ratio of the amplitudes of signals with similar frequencies to eliminate unwanted common noise and atmospheric effects. Therefore, the optical depth used in (3) will actually be the difference between the optical depths measured at two different frequencies,

\[ \tau_{12} = \tau_1 - \tau_2 = \ln \left( \frac{I_1}{I_2} \right) \]

where the subscripts 1 and 2 refer to two frequencies \( f_1 \) and \( f_2 \). The resulting extinction coefficient profile derived from (4) will be \( k_1 - k_2 \).

A point worth emphasizing is the absolute signal amplitude is not relevant. Rather, it is the variations in amplitude that occur during an occultation that are the signatures of interest. The signal amplitudes will be normalized to the amplitude observed immediately before or after each occultation when the signal path is entirely above the atmosphere. The amplitude normalization of every occultation will eliminate long-term drifts yielding a technique extremely well suited for observing long-term climate variations.

b. Conversion of absorption coefficients and refractivity into temperature, pressure, water vapor, and cloud liquid

In the upper troposphere and stratosphere, where there is no liquid water, we have profiles of two observables, \( k_1(r) - k_2(r) \) and \( N(r) \), from which we can derive temperature \((T)\), total pressure \((P_t)\), and partial pressure of water vapor \((e)\) by simultaneously solving three equa-
The absorption coefficient, which simultaneously solve (1), (6a), (6b), and the hydrobservables, additional frequency. We will then take the three observations provide additional constraints. At altitude throughout the troposphere and middle atmosphere, the provide the dynamic range needed to sense water sphere. By measuring static integral such as temperature in the upper mesosphere, we need a boundary condition to initialize the hydrostatic boundary condition.

Since the hydrostatic relation is a differential equation we need a boundary condition to initialize the hydrostatic integral such as temperature in the upper mesosphere. By measuring \( N \) and \( k \) at several frequencies to provide the dynamic range needed to sense water throughout the troposphere and middle atmosphere, the observations provide additional constraints. At altitude intervals where two different pairs of frequencies each provide independent estimates of the extinction coefficients and therefore \( e, P, \) and \( T, \) the overlapping constraints provide the information needed to determine the hydrostatic boundary condition.

In the lower troposphere, we must solve for the liquid water \( C_l \), along the path as well. We therefore must measure the occultation signal intensity at an additional frequency. We will then take the three observables, \( k_1(r) - k_2(r), k_2(r) - k_3(r), \) and \( N(r), \) and simultaneously solve (1), (6a), (6b), and the hydrostatic equation:

\[
k_1(r) - k_2(r) = F(f_1, f_2, P, e, T), \tag{5}
\]

where \( f_1 \) is positioned on the line to measure absorption and \( f_2 \) is positioned offline to calibrate out unwanted effects. The absorption coefficient, which includes individual lines as well as the water vapor continuum, is a strong function of \( e \) and weaker function of \( P, \) and \( T, \) and therefore constrains primarily \( e. \) The line shape and the absorption due to \( O_2 \) is determined by \( P, \) and \( T. \)

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\[
k_1(r) - k_2(r) = F(f_1, f_2, P, e, T), \tag{6a}
\]

\[
k_2(r) - k_3(r) = F(f_2, f_3, P, e, T). \tag{6b}
\]

3. Error analysis

We will now discuss the types of errors for such a system, and the impact of instrumental errors and elimination of the effects of diffraction.

a. Sources of ambiguity and error

We want to derive the extinction coefficient due to absorption from signal amplitude variations measured during an occultation. However, several unwanted factors contributing to these variations group into three classes: unwanted atmospheric effects, instrumental errors, and retrieval errors.

1) UNWANTED ATMOSPHERIC EFFECTS

(i) Defocusing

Defocusing causes large changes in the occulted signal intensity due to variations in the occultation bending angle caused in turn by the second derivative of \( N. \) Since \( N \) has little frequency dependence below 300 GHz, two signal frequencies will be used with one being on the line and the other sufficiently offline such that their amplitude ratio cancels the common defocusing but retains the line absorption.

(ii) Diffraction

According to the Fresnel–Huygens concept, light propagation is the result of the superposition of spherical radiators (Green’s function for electromagnetic radiation) distributed along the light path. Diffraction is associated with interference patterns caused by atmospheric structures smaller than the diameter of the first Fresnel zone \( F_D, \) which alter the phase and amplitude of the spherical waves; \( F_D \) is determined by the signal wavelength \( \lambda \) observing geometry and atmospheric bending. Figure 2 shows an example of diffraction limited vertical resolution versus altitude at the GPS and BRIGHT wavelengths adapted from Kursinski et al. (1997). At the top of the atmosphere for an occultation between two satellites orbiting at the same altitude, \( F_D \) is approximately \((2\lambda D)^{1/2}, \) where \( D \) is the distance from each satellite to earth’s limb. Given its dependence on wavelength, removing the effects of diffraction poses a more challenging problem than defocusing. We have identified two approaches for reducing the effects of diffraction. The first is to take the ratio of the amplitudes of two signals with similar frequencies and then apply some smoothing. The second approach involves deriving the \( N \) profile from the measured phase data, forward estimating the amplitude effects of diffraction using the \( N \) profiles, and then ratioing the estimated diffraction effects out of the observed amplitude profile. We will show later some simulation results suggesting that the first approach can reduce diffraction effects to a few tenths of a percent.

Fig. 2. Diffraction-limited occultation vertical resolution at 1.6, 22, and 183 GHz.
(iii) Multipath

Atmospheric multipath refers to the situation often encountered in the lower troposphere where occultation signal paths cross due to variations in bending angle. As a result, more than one signal path can reach the receiver at a time and the amplitude of each must be isolated and determined. The Doppler shift of each signal path is unique, which allows the signals to be separated. Multipath can be dealt with via a combination of back propagation to undo the ray path crossings (and improve vertical resolution) and multisignal detection techniques, such as the Fourier transform (see Kursinski et al. 2000a and the references therein).

(iv) Extinction

Although O$_2$ and H$_2$O are the primary atmospheric gases causing significant absorption of the BRIGHT signals, absorption due to ozone will contribute slightly to the absorption measured near the 183-GHz water line with a maximum contribution of about 1% near 20-km altitude. With a full implementation of BRIGHTO (where the “O” refers to ozone), we would also measure absorption near the 195-GHz ozone line to estimate ozone along the occultation path (Feng et al. 2001) and reduce the unknown ozone contribution to the 183-GHz water absorption measurements by a factor of 10 or more. Absorption by liquid water droplets will be important and will be the subject of a separate paper. For the present, we will briefly summarize some of our initial conclusions regarding liquid water absorption in the conclusions section. Scattering by particulates can also affect the signals. The scattering effects at 22 GHz will be negligible because the signal wavelengths are large relative to the particulates. However, the scattering effects of ice are nonnegligible at 183 GHz. Since these scattering effects are quite broadband, the amplitude ratioing of signals near 183 GHz separated by at most a few gigahertz will largely cancel the effects of ice scattering.

2) Instrumental Errors

Because instrumental gain variations common to two frequencies being ratioed will be reduced by ratioing, we will design the signals to pass through the same transmit and receive amplifiers and antennas to the extent possible. Local multipath will be small because we will use directional antennas for high gain and small spacecraft. The thermal variations associated with the finite SNR are independent from one signal to the next and will not cancel with ratioing. Thermal errors can be reduced by increasing the signal strength and smoothing as much as allowed by the desired vertical resolution.

3) Retrieval Errors

(i) Abel and hydrostatic integral initialization

Because the abel and hydrostatic integrals extend to infinite heights, while the occultation observations only extend to finite heights, some high-altitude error is inevitable. The resulting errors in initializing these integrals have been discussed in much detail for a GPS-based occultation system (Kursinski et al. 1997; Healy 2001). The high-altitude BRIGHT errors will be similar to the GPS errors except that the maximum altitudes at which these integrals can begin will be significantly higher (because the ionospheric effects scale inversely with the signal frequency squared) and therefore influence lower altitudes much less than the GPS system. BRIGHT provides another substantial advantage over the GPS system in that the BRIGHT amplitude observations provide constraints that allow pressure to be determined very accurately from the surface to about 40-km altitude completely independent of external observational information.

(ii) Horizontal refractivity structure

The traditional bending angle to refractivity abel transform and (4) assume local spherical symmetry such that horizontal refractivity variations will produce errors in the abel-based retrieval results. Although not a focus of the present work, we will provide some assessment of the impact of horizontal refractivity structure in the conclusions section leaving a more detailed analysis to a future discussion.

(iii) Spectroscopic knowledge

There are spectroscopic measurements of line strengths and shapes of the 22- and 183-GHz H$_2$O lines considered here. However, based on past microwave limb sounder experience (D. Wu 2001, personal com-
munication) and the highly accurate retrievals predicted here, we suspect that some additional spectroscopic work will be required to bring the knowledge of the collisionally induced line shapes observed in the earth’s atmosphere to a level consistent with the accuracies predicted here.

(iv) Correlation

Correlation between dependence of the refractivity and extinction coefficients on \( T, P, \) and \( e \) and between the dependence of liquid and vapor extinction coefficients on frequency becomes important in the lowermost tropical troposphere and will be discussed in section 4b.

b. Error behavior

We will now focus on and describe the impact of measurement and diffraction errors in two steps. First, we will describe how the errors affect the optical depths derived from the amplitude measurements that are used in the inverse Abel equation (4) to derive radial profiles of extinction coefficient. Then we will describe an error covariance analysis that maps the observational errors into moisture, temperature, and pressure errors. We will use our understanding of errors developed in the first step to help interpret covariance results from the second step.

We begin with signal amplitudes observed at two frequencies, \( f_1 \) and \( f_2 \). We have chosen to use amplitude rather than intensity because the occultation signals are phase-coherent, monochromatic signals described as \( A(t)e^{-i\phi(t)} \), where \( A \) and \( \phi \) are the signal amplitude and phase. Since amplitude scales as the square root of intensity, the amplitude observed at \( f_1 \) can be written as

\[
A_1 = A_{10}M^{1/2}F_1G_1^{1/2}e^{-\frac{\tau_1}{2}},
\]

where \( A_{10} \) is the signal amplitude in the absence of defocusing and absorption, \( M \) is the intensity defocusing, \( F_1 \) represents the effects of diffraction at \( f_1 \), and \( G_1 \) is the instrumental gain change at \( f_1 \) since calibration of the signal intensity above the atmosphere immediately before (or after) the occultation. Note that \( A_{10} \) varies with elapsed time during the occultation such that \( A_{10}(t) = A_{10}(0)\frac{L(t)}{L(0)} \), where \( L(t) \) is the pathlength between the transmitter and receiver at time \( t \) and 0 is the time the signal amplitude is estimated above the atmosphere. From (7), the optical depth difference, \( \tau_1 - \tau_2 \), is given as

\[
\tau_{12} = (\tau_1 - \tau_2) = 2 \ln \left[ \frac{A_{10}A_2F_1(G_1/G_2)^{1/2}}{A_1A_{20}F_2(G_2)^{1/2}} \right].
\]

The accuracy to which we can estimate \( \tau_{12} \) depends on how accurately we can measure \( A_{10}, A_1, A_{20}, \) and \( A_2 \); estimate \( F_1/F_2 \); and control or calibrate \( G_1/G_2 \). To obtain the fractional error in \( \tau_{12} \) and its relation to errors in the ratios on the rhs of (8) we differentiate (8) and obtain

\[
\frac{d\tau_{12}}{\tau_{12}} = \frac{2}{\tau_{12}} \left[ \frac{dA_{10}}{A_{10}} - \frac{dA_1}{A_1} + \frac{dA_2}{A_2} - \frac{dA_{20}}{A_{20}} + \frac{d(F_1/F_2)}{F_1/F_2} + \frac{1}{2} \frac{d(G_1/G_2)}{G_1/G_2} \right]
\]

Based on (9), assuming all errors are uncorrelated and writing \( \tau_{12} = a_{12}\tau_1 \), the fractional mean-square error in \( \tau_{12} \) is

\[
\frac{\langle \delta^2 \rangle_{\tau_{12}}}{\langle \tau_{12} \rangle^2} = \frac{4}{(1 - a_{12})^2} \left[ \frac{\delta_{10}}{S_{10}^2} + \frac{\delta_0}{S_{0}^2} + \frac{\delta_{12}}{S_{12}^2} + \frac{\delta_{012}}{S_{012}^2} \right] + \frac{\langle \delta_{012}^2 \rangle}{\langle F_1/F_2 \rangle^2} + \frac{\langle \delta_{0}^2 \rangle}{\langle G_1/G_2 \rangle^2} + \frac{\langle \delta_{12}^2 \rangle}{\langle F_1/F_2 \rangle^2} + \frac{\langle \delta_{01}^2 \rangle}{\langle G_1/G_2 \rangle^2},
\]

where \( \langle \delta \rangle \) means expected value of \( \delta \), \( S_{10} \) is equal to \( A_{10}(0)\langle \delta_{10}^2 \rangle^{1/2} \) and represents the voltage SNR in the absence of any atmospheric effects for an integration time of \( \delta_0 \) (typically 1 s), and \( \delta_{12} \) is the integration times over which the \( f_1 \) signal is measured above the atmosphere and during the occultation respectively with \( \delta_{20} \) and \( \delta_2 \) being defined analogously. The rate at which the ray path descends during an occultation depends on the defocusing, \( M \) (Hajj et al. 2002). Therefore, \( \delta_0 \) is set by the vertical resolution divided by the vertical velocity of the signal path tangent height \( V \), which equals \( V_0M \), where \( V_0 \) is the vertical velocity of the ray path in the absence of the atmosphere. If the vertical resolution is chosen to be the diffraction limited diameter of the first Fresnel zone, \( \delta_0 = F_{20}(V_0M)^{1/2} \) where \( F_{20} \) is the diameter of the first Fresnel zone in the absence of the atmosphere. If the vertical resolution is chosen to be some value, \( Z_{zd} \), larger than and unrelated to the Fresnel diameter, then \( \delta_0 = Z_{zd}(V_0M) \). Under these conditions, (10) becomes
Fig. 4. Signal amplitude at 1.6 GHz (approximately the GPS L1 signal frequency) and 22.6 GHz resulting from occultation diffraction simulation using vertical refractivity structure from Fig. 3.

Fig. 5. Ratio of 22.6- and 20.0-GHz signal amplitudes created via occultation diffraction simulation.

\[
\frac{\langle \epsilon^2_{\tau_2} \rangle}{\tau^2_{\tau_2}} = \frac{4}{(1 - a_{\tau_2})^2 \tau^2_{\tau_2}} \left[ \frac{\delta_0 V_0}{S^2_{\tau_1} Z_0} F_2 G_1 e^{\tau_2} + \frac{\delta_0}{S^2_{\tau_2} Z_0 F_2 G_2} + \frac{\delta_0}{S^2_{\tau_2} Z_0} + \frac{\langle \epsilon^2_{\tau_1} \rangle}{(F_1/F_2)^2} + \frac{1}{4} \frac{\langle \epsilon^2_{\tau_1} \rangle}{(G_2/G_1)^2} \right].
\]  

Notice the dependence on \( M \) has disappeared in (11) because we have utilized the slowing of the ray path descent velocity to integrate long enough to reduce the noise by the same amount that the signal amplitude has decreased due to defocusing.

1) RESIDUAL DIFFRACTION ERRORS

We now use a simulation to evaluate the effectiveness of ratioing and smoothing or reducing the effects of diffraction. Figure 3 shows a high vertical resolution temperature and dewpoint profile from a radiosonde. Figure 4 shows a portion of two simulated amplitude profiles through the refractivity structure corresponding to the radiosonde profile. Separation angle is the angle between the line from the center of earth to the transmitter and the line from the center to the receiver. The effects of diffraction were simulated using the approach described by Kursinski (1997). The two amplitude profiles correspond to occultations at 22.6 and 1.6 GHz (approximately the GPS L1 frequency) and do not include absorption. The similar overall behavior is due to defocusing while the finescale variations reflect the effects of diffraction. To accurately isolate the effects of absorption, we must dramatically reduce these large nonabsorption variations in amplitude shown in Fig. 4. Figure 5 shows the residual amplitude variations after ratioing the amplitude variations at 22.6 and 20.0 GHz with some subsequent smoothing applied. Note the change in scale between Figs. 4 and 5. The peak variations of the amplitude ratio are of order 0.4%, a dramatic reduction from the 70% variations in Fig. 4. Because collisional line widths narrow with increasing altitude and are independent of line frequency, the online and offline signal frequencies can be much closer in a fractional sense at 183 GHz than at 22 GHz, such that cancellation of diffusive effects by amplitude ratioing will work significantly better at the high band frequencies.

2) MINIMIZING THE FRACTIONAL ERROR IN \( \tau_{\tau_2} \)

We now determine the minimum fractional mean-square \( \tau_{\tau_2} \) error in (11). We will ignore the gain error term in (11) under the assumption that we can design the instrumentation to cancel out most of the \( G_1/G_2 \) variations
and those that remain we can measure and remove during each occultation. We will assume the fractional diffraction error after ratioing is approximately constant and a few tenths of a percent in magnitude. We will also ignore the first and fourth terms on the rhs of (11) relative to the second and third terms because $e^{a}V_{0}/Z_{R} \gg 1/\delta_{10}$ using representative values of $\tau - 2$, $V_{0} \sim 3 \text{ km s}^{-1}$, $Z_{R} \sim 0.25 \text{ km}$, and $\delta_{10} \sim 5-10 \text{ s}$.

As a point of reference, let us consider the case where diffraction errors are negligible, and we simply minimize the fractional error in $\tau$ at a single frequency. Under these conditions, $a_{12}$ is 0 and we consider only the second term in the right-hand bracket of (11). The resulting minimum rms fractional error in $\tau$ occurs when $\tau_{1} = 2$. The corresponding fractional rms error is

$$\left\langle \frac{\delta_{10}^{2}V_{0}^{2}}{S_{\tau_{10}}} \right\rangle^{1/2} = \frac{2a_{1}^{2}}{S_{\tau_{10}}} \left( \frac{\delta_{10}}{Z_{R}} \right)^{1/2}.$$ 

Note that we have approximated the term in the denominator as 1 because we are smoothing over vertical scales larger than $F_{D}$, the diffraction limited vertical resolution. We also have assumed the instrumental gain variations are small over the length of the occultation so $G_{1}$ can be approximated as 1.

Figure 6 shows how the fractional rms $\tau_{12}$ error varies as a function of SNR assuming $a_{12} = 0.2$, $S_{\tau_{10}} = S_{\tau_{20}}$, and the fractional rms diffraction error is 0.3%. Also shown is the dependence of the optimal value of $\tau_{1}$ on $S_{\tau_{10}}$. For $S_{\tau_{10}}$’s less than about 3000, the $S_{\tau_{10}}$ contribution to the error dominates in (11) and the fractional error decreases linearly with increasing $S_{\tau_{10}}$ until about $S_{\tau_{10}} = 2000$. In this regime, the optimal $\tau_{1}$ is slightly larger than the single frequency value of $\tau = 2$. At $S_{\tau_{10}}$’s higher than 3000, the diffraction error tends to dominate in (11) and the fractional error continues to decrease but more slowly. Note that in this regime, the optimum $\tau_{1}$ increases significantly as $S_{\tau_{10}}$ increases because of the $\tau_{1}^{-2}$ term outside the brackets on the rhs of (11).

Fig. 7. Dependence of the minimum fractional rms $\tau_{12}$ error and the optimum $\tau_{1}$ on $\tau_{2}/\tau_{1}$ for several representative values of $\text{SNR}_{\tau_{10}}/\text{SNR}_{\tau_{20}}$. Solid lines represent minimum fractional rms $\tau_{12}$ error. Dotted lines represent $\tau_{1}$ values. $\text{SNR}_{\tau_{10}} = 3000$ and fractional rms diffraction error is 0.3%.

Fig. 8. Variation in the fractional $\tau_{12}$ error as a function of $\tau_{1}$ for $\text{SNR}_{\tau_{10}} = \text{SNR}_{\tau_{20}} = 3000$, $\tau_{2}/\tau_{1} = a_{12} = 0.2$, and an rms diffraction error = 0.3%.
The dependence of the minimum fractional rms $\tau_{12}$ error on $a_{12} (= \tau_2/\tau_1)$ is shown in Fig. 7 for $S_{\alpha 0} = 3000$, three representative values of $S_{\alpha 0}/S_{\alpha 20}$, and an rms fractional diffraction error is 0.3%. The fractional $\tau_{12}$ error grows as $a_{12}$ increases such that the fractional $\tau_{12}$ error has increased by about a factor of 2 at $a_{12} = 0.5$ relative to the $a_{12} = 0$ error, representing the penalty for spacing two ratioing signals too close in frequency. The optimal
value of $\tau_1$ that minimizes the full rms $\tau_{12}$ error in (11) is also shown in Fig. 7 as a function of $a_{12}$ is somewhat larger than the $\tau_1 = 2$ result for the single frequency result because $S_{\tau_{10}} = 3000$.

Figure 8 shows how the minimum fractional $\tau_{12}$ error varies with $\tau_1$ for $SNR_{v_{10}} = SNR_{v_{20}} = 3000$. The minimum fractional $\tau_{12}$ error lies close to $\tau_1 = 3$, consistent with Figs. 6 and 7. For small $\tau_1$, the fractional $\tau_{12}$ error varies approximately as $1/\tau_1$. For large $\tau_1$, the fractional $\tau_{12}$ error varies approximately as $e^{-c_{12}}$. The range of $\tau_1$ for which the fractional $\tau_{12}$ error is within a factor of 4 times the minimum value extends from 0.4 to 8 indicating the approximate interval over which observations at a given frequency will be useful. Figures 9a and 9b show the occultation $\tau$’s at several frequencies near the 22.2 and 183.31 GHz water lines for the tropical conditions represented by the profiles in Figs. 10a and 10b. The thick vertical line near $\tau = 2$ represents approximately the $\tau$ at which the fractional $\tau_{12}$ error is minimum.

Based on Fig. 8, we see that Figs. 9a and 9b show the range of frequencies using the 22- and 183-GHz lines required to accurately characterize water vapor in earth’s lower and middle atmosphere via occultation.

4. Covariance results

We now discuss the covariance results using the set of frequencies shown in Fig. 9. We have a vector of observations $y$ from an occultation profile from which we want to derive the atmospheric state vector $x$ consisting of the atmospheric variables of interest: water vapor, temperature, and surface pressure. Assuming a linear set of equations relate $y$ and $x$, the statistically optimal weighted least squares solution for $x$ is

$$x = [K^TS_y^{-1}K]^{-1}K^TS_yy,$$

(12)

where $K$ represents the gradient of $y$ with respect to $x$ and $S_y$ is the observation error covariance. The error covariance, $S_x$, of $x$ is

$$S_x = [K^TS_y^{-1}K]^{-1}.$$

(13)

While (1) and (5) are somewhat nonlinear, the fractional observational errors are quite small and (13) provides a representative estimate of the error in $x$ resulting from errors in $y$ (Rodgers 1990).

For the present analysis, we take the vector $y$ to consist of a profile of refractivity as a function of height and a set of amplitude ratio profiles. Each amplitude ratio profile is for a unique pair of signal frequencies. We estimated $S_y$ as follows. For the refractivity observations, the diagonal terms are shown in Fig. 11 based on the refractivity errors estimated by Kursinski et al. (1995, 1997). For the off-diagonal refractivity covariance elements we assumed an exponential decay with a scale length of 3 km used by Healy and Eyre (2000). For the amplitude ratio portion of $S_y$, we generated the diagonal elements based on the signal-to-noise ratios,
Fig. 12. Square root of the diagonal terms of the water error covariance, $S_x$ (a) results from 0 to 90-km altitude for tropical clear sky conditions defined in Fig. 10. (b) Same as (a) except 0–15-km altitude. (c) 0–10-km altitude for four latitudinal cases, equatorial (Fig. 10), midlatitude summer (35° N in Jun), midlatitude winter (35° S in Jun), and high-latitude winter (60° S in Jun). See text for details.

Integration times, and absorption. We assumed the raw observational amplitude errors were uncorrelated with one another and the refractivity errors. To account for the fact that we are smoothing the amplitude results to reduce the noise, we added a triangular off-diagonal dependence for heights that are within one vertical smoothing interval of one another. The off-diagonal terms are defined as
TABLE 1. Summary of instrument performance parameters used in error covariance study. Loss was assumed to be 3 dB at each frequency. The antenna diameter was 30 cm for each frequency.

<table>
<thead>
<tr>
<th>Frequency (GHz)</th>
<th>Radiated power (W)</th>
<th>System noise temperature (K)</th>
<th>SNR_{\text{SNR}}</th>
</tr>
</thead>
<tbody>
<tr>
<td>8.0</td>
<td>12</td>
<td>150</td>
<td>4710</td>
</tr>
<tr>
<td>13.0</td>
<td>7</td>
<td>150</td>
<td>5840</td>
</tr>
<tr>
<td>17.5</td>
<td>6</td>
<td>150</td>
<td>7280</td>
</tr>
<tr>
<td>20.0</td>
<td>6</td>
<td>150</td>
<td>8320</td>
</tr>
<tr>
<td>22.21</td>
<td>6</td>
<td>150</td>
<td>9240</td>
</tr>
<tr>
<td>32.0</td>
<td>6</td>
<td>150</td>
<td>13300</td>
</tr>
<tr>
<td>179.0</td>
<td>0.02</td>
<td>1500</td>
<td>1860</td>
</tr>
<tr>
<td>182.2</td>
<td>0.02</td>
<td>1500</td>
<td>1900</td>
</tr>
<tr>
<td>183.0</td>
<td>0.02</td>
<td>1500</td>
<td>1900</td>
</tr>
<tr>
<td>183.2</td>
<td>0.02</td>
<td>1500</td>
<td>1900</td>
</tr>
<tr>
<td>183.3</td>
<td>0.02</td>
<td>1500</td>
<td>1900</td>
</tr>
<tr>
<td>183.31</td>
<td>0.02</td>
<td>1500</td>
<td>1900</td>
</tr>
</tbody>
</table>

\( S_{a_{ij}} = S_{a_{ij}} = (S_{a_{ii}}S_{a_{jj}})^{1/2}(1 - |z_i - z_j|/H), \)

for \( (i, j) \) and \( |z_i - z_j| \leq H \)

\( S_{a_{ij}} = S_{a_{ij}} = 0, \)

for \( (i, j) \) and \( |z_i - z_j| > H, \)

where \( i \) and \( j \) are indices, the subscript \( a \) refers to the amplitude portion of the \( S_{a} \) covariance, \( z \) is height, and \( H \) is the vertical smoothing interval used at that height.

We then estimated \( K \) numerically by varying each element in \( x \), performing the forward calculation, and then determining the change in each element of \( y \).

**a. Retrieved water accuracy**

We focus our discussion primarily on the tropical, clear sky case defined in Fig. 10 because the Tropics tend to contain extremes of vertical mixing ratio variations. Cloudy conditions will be briefly discussed in the conclusions and characterized in more detail in a subsequent paper. The square roots of the diagonal terms of \( S_{a} \) for water are shown in Figs. 12a–c. The important instrumental characteristics assumed in estimating this particular \( S_{a} \) are summarized in Table 1. Vertical resolution is 250 m between the surface and 8-km altitude, 500 m between 8- and 20-km altitude, and 1 km at higher altitudes. The resolution is larger than that in Fig. 2 to smooth and reduce data errors.

The dotted line indicates the errors associated with frequencies near 20 GHz that we refer to as “lo-band” frequencies. The solid line includes the lo-band frequencies and several frequencies near 183 GHz that we refer to as “hi-band.” The lowest frequencies probe the lowest portion of the atmosphere. Given that the accuracies of present satellite water observations range from approximately 20% near the surface to 50% in the midtroposphere and even higher in the upper troposphere as reflected in the error covariances used by operational data assimilation centers like the European Centre for Medium-Range Weather Forecasts, the Met Office, and the National Aeronautics and Space Administration’s (NASA) Data Assimilation Office and comparisons with GPS occultation data (Healy and Eyre 2000; Kursinski et al. 2000b; PIJK), the lo-band fre-
Figure 13. Orthogonality between the real part of the refractivity (\(N\)) and the extinction coefficient (\(k\)) constraints on temperature and moisture under warm near-surface conditions (1000 mb). Solid line represents the \(k\) constraint. Dotted line represents the \(N\) constraint. Dashed lines represent the \(\pm1\%\) observational uncertainty. (a) Moderately moist conditions (\(e = 7\) mb). (b) Very moist conditions (\(e \sim 24\) mb).

Figures yield useful water vapor profiles up to approximately 12 km under tropical conditions limited by the small amounts of water vapor in the upper troposphere and the weak 22-GHz water line (see Fig. 9b). Figure 12a shows observations near the much stronger 183-GHz absorption line yield very accurate results in the upper troposphere beginning near 8-km altitude and extending through the middle atmosphere. The dashed line shows that accurate values can be obtained at altitudes below 50 km even without the high-altitude pressure boundary condition.

Annotations along the curves on Figs. 12a and 12b indicate the pair of signal frequencies most strongly constraining errors near that altitude. Relative minima in the water vapor errors are clearly associated with the altitudes where \(\tau\) is 2–3 in Figs. 9a and 9b as expected based on the minimal fractional \(\tau\) error behavior summarized in Figs. 6–8. Figure 12c shows how the near-surface water vapor error varies with latitude and season indicating that, under warm and wet conditions, the error grows from 8% to 10% at the surface. From Fig. 12, we see that the combination of occultation signal frequencies near the 22- and 183-GHz lines yields water vapor accurate to 1%–3% roughly between 1- and 75-km altitude. Such a capability would be a quantum improvement over present satellite water vapor sensors that provide accuracies of 20%–50%.

\(\text{b. Errors in the lowermost tropical troposphere}\)

We now turn our attention to understanding why the water vapor errors in the lower troposphere in Fig. 12b increase significantly with decreasing altitude below 7-km altitude. Several factors are responsible for this behavior. First, refractivity errors are larger in the lower troposphere because of larger horizontal gradients associated with water vapor there (see Fig. 11). The second reason results from our keeping the signal frequencies relatively close to ratio out the effects of diffraction. As a result, because of the collisional line broadening in the lower troposphere, the \(\tau\)'s of adjacent frequencies in the lower troposphere differ only by about a factor of 2 (see Fig. 9). Therefore, as indicated in Fig. 7, the fractional \(\tau\) error is amplified by a factor of \(\sim2\) relative to the error if the second frequency experienced no absorption. Frequencies farther off the line center could be used if the diffraction effects could be reduced by a back-propagation technique rather than relying on amplitude ratioing. Under such conditions, the errors below 5-km altitude in Fig. 12b could be reduced by roughly a factor of 2.

The third and most important factor causing the relatively large errors in the lowermost troposphere is reduced orthogonality between the refractivity and extinction coefficient information under very moist, near-surface tropical conditions. Figures 13a and 13b provide a graphical representation of the near-surface orthogonality between the \(N\) and \(k\) observations and how it varies with increasing moisture content. In these figures, pressure is taken to be 1000 mb. In reality, pressure must be solved hydrostatically, but we have taken pressure to be known to simplify our graphical discussion from 3D to 2D. The horizontal and vertical axes in each figure are temperature (\(T\)) and water vapor partial pressure (\(e\)). The thick solid line defines the set of values of \(T\) and \(e\) consistent with an observed value of the extinction coefficient \(k\). The thick dashed line defines the values of \(T\) and \(e\) consistent with an observation of refractivity \(N\). Thin dashed lines drawn parallel to and on each side of the \(k\) and \(N\) lines represent \(\pm1\%\) observational uncertainty in \(k\) and \(N\). The area between the \(N \pm1\%\) lines represents the range of possible \(T\) and \(e\) solution space consistent with the \(N\) observation and its 1% uncertainty. The range of possible \(T\) and \(e\) so-
solutions constrained by the $k$ observation and its uncertainty is defined analogously. The range of possible $T$ and $e$ solutions consistent with both the $N$ and $k$ observations and their respective uncertainties is the area of overlap between the two sets of ±1% lines.

When the $k$ and $N$ lines are approximately orthogonal on a $T$ versus $e$ set of coordinates, the area of overlap is relatively small and $T$ and $e$ are both tightly constrained. In the case shown in Fig. 13a, moisture amounts are moderate for the Tropics and $k$ largely constrains $e$. The constant $N$ line is tilted and constrains both $e$ and $T$. However, since $k$ constrains water so well, the information in $N$ largely constrains temperature. In Fig. 13b, $e$ has increased by a multifold factor, causing the $k$ and $N$ dependence on $T$ and $e$ to become far more parallel. This causes the area of overlap between the
two sets of $\pm 1\%$ lines to increase, causing the $T$ and $e$ estimates to become increasingly noisy and correlated. Notice in Fig. 12b that this extreme behavior where the water vapor errors exceed the 3% level is confined to the lowermost 1.5 km in the Tropics. Notice also in Fig. 13b that both the $k$ and $N$ observations at high moisture levels tend to constrain moisture more than temperature. Therefore, additional temperature information perhaps from a 60-GHz molecular oxygen temperature radiometer could significantly improve the accuracy under these conditions.

We have identified and characterized an additional temperature constraint embedded in the occultation observations themselves. The constraint comes from the band of $O_2$ absorption lines centered near 60 GHz, which, due to pressure broadening, cause appreciable absorption at the BRIGHT wavelengths used in the lowermost troposphere. The measured absorption at the lowest frequency contains relatively little water absorption but significant ($\sim 3$ dB) absorption due to the $O_2$ line yielding a useful constraint on the $O_2$ density and therefore temperature and pressure. The one problem in utilizing this constraint is that it requires that we reduce the diffraction effects on the signal amplitude without ratioing with another signal amplitude because ratioing would largely cancel the $O_2$ absorption. Reducing the diffraction effects will require back-propagation processing that undoes much of the diffraction effects by numerically propagating the received signal from the actual receiver location to a location much closer to the atmosphere (Gorbunov 2001; Sokolovskiy 2001). The dashed line in Fig. 12b shows how the water vapor accuracy improves when the unratioed 8-GHz amplitude information is included in the retrieval. The surface error in the Tropics is reduced from 10% to about 6.5%. The improvement extends to about 3-km altitude. Using the occultation data itself to derive near-surface temperature constraints would be advantageous over a passive observation simply because it would not require the cost of developing additional observations and the additional information is derived from measurements along the same path as the rest of the occultation data.

c. Retrieved temperature accuracy

The estimated accuracy of individual temperature profiles is shown in Fig. 14a. Overall the temperature observations can provide sub-kelvin temperature accuracies from a few km to 80-km altitude with a few hundred meter vertical resolution. Averaging of many profiles will average down the random errors and produce significantly better absolute accuracy. We have estimated the errors in the uppermost regime by scaling the results of Kursinski et al. (1997) to the conditions of these observations. Accuracy in the uppermost region is limited by the SNR and the initialization of the Abel and hydrostatic integrals at 90-km altitude with local multipath also contributing some. Unlike GPS, the ionosphere contributes very little error to the 183- and 22-GHz observations because ionospheric refractivity scales inversely with the signal frequency squared. The resulting insensitivity of the 22- and 183-GHz occultation temperatures to solar cycle ionospheric variations make them better suited than GPS observations for measuring long-term temperature trends in the middle atmosphere.

In the middle altitude regime from approximately 65 km altitude down to the lower troposphere, temperature accuracy is roughly 0.4 K limited by horizontal variations responsible for limiting the refractivity profile accuracy to 0.2% in this regime (see Fig. 11). Like the water vapor error in Fig. 12b, the temperature error also increases near the surface with a significant dependence on latitude (Fig. 14b). The extreme error under tropical moisture conditions is approximately 2 K at 3-km altitude and increases to 8 K right at the surface. Under dry winter conditions the error is significantly less than 1 K right to the surface. Figure 14b shows how the near-surface errors under tropical conditions [equator (June)] may be reduced from 8 to 4.5 K by including the $O_2$ absorption measured at 8 GHz in the retrieval process as discussed in the previous section.

d. Relative humidity accuracy

Since the 22- and 183-GHz radio occultations determine both mixing ratio and temperature very accurately, they also determine relative humidity quite accurately. Figure 15 shows the fractional relative humidity accuracy from the surface to 20 km altitude for four cases ranging from tropical to high-latitude winter conditions. A fractional error of 0.1 means that if the true relative humidity were 30%, the error in the relative humidity estimate would be 3% relative humidity. The accuracy is generally about 5% percent through most of the troposphere limited by the uncertainty in temperature rath-
er than that in specific humidity because of the very strong temperature dependence of the Clausius–Clapeyron relation. As expected based on the mixing ratio and particularly the temperature results, relative humidity errors in the Tropics increase close to the surface reaching 10% at 3-km altitude and 20%–30% within a few hundred meters of the surface. Again the errors are reduced significantly by including the O₂ absorption measured at 8 GHz in the retrieval process.

**e. Pressure and geopotential results**

When deriving vertical structure from passive observations, the height versus pressure relation is extrapolated from radiosonde observations. In contrast, the BRIGHT pressure versus height relation is derived using the density versus height profile together with the hydrostatic equation and is completely independent of radiosondes. The information content of the BRIGHT data is sufficient to accurately determine pressure below 40 km altitude without any additional information (see long dashed line in Fig. 16). At altitudes above 40 km, accurate temperature, pressure, and water vapor estimates require one independent estimate of either temperature or pressure at a higher altitude to initialize the hydrostatic integral. Figure 16 shows the estimated accuracy of profiles of geopotential height of pressure as a function of altitude assuming the hydrostatic integral has been initialized at 90-km altitude with a 3% rms error assumed. The relative contributions of the high-altitude errors depend on the starting altitude choice (Kursinski et al. 1997). For the conditions chosen here, the accuracy above 55-km altitude is limited primarily by the orbital velocity error of the satellites. In contrast, at GPS wavelengths, the upper-altitude error is limited by the ionosphere and local multipath above 35-km altitude (Kursinski et al. 1997). Below 55 km, the limiting error is horizontal structure, which cannot be represented by the Abel integral transforms, (2) and (6).

Below 10-km altitude, the hydrostatic pressure error grows by about a factor of 2 because of horizontal variations in refractivity in the lower troposphere. Because of the rapid growth in water vapor and temperature errors near the tropical surface one might expect analogous errors in the geopotential height field. However, such an error contributes little because pressure is a vertically integrated quantity. Therefore, random errors of a few kelvin in the lowest kilometer or two have little influence on the total hydrostatic pressure at the surface. As a result, a major advantage of the BRIGHT water and temperature sensing system over the GPS occultation system is BRIGHT can determine geopotential heights with 8–20-m accuracy right to the surface anywhere on the globe.

**5. Summary and conclusions**

We have presented an overview and first-order assessment showing that combining occultation observations of absorption and propagation speed near the 22- and 183-GHz water lines yields very accurate profiles of the moisture and temperature as well as geopotential in earth’s atmosphere well into the mesosphere. The technique can be used to determine profiles of other atmospheric constituents such as upper-tropospheric and lower-stratospheric ozone by using frequencies near a
strong line of that constituent. The limitation in characterizing other species appears to be more contamination by still other species, in particular the water vapor continuum in the lower troposphere, rather than the measurements themselves. Concerning the high retrieval accuracy, we found one exception where the very high moisture concentrations within 1–2 km of the tropical surface cause the absorption and propagation velocity information to become almost redundant. Measuring the absorption due to $O_2$ at the lowest BRIGHT signal frequency can be used to reduce the near-surface temperature and moisture errors by about a factor of 2 under tropical conditions. The addition of accurate temperature information from a passive microwave sounder or a weather forecast/analysis would also improve the retrieval accuracies for these conditions.

A caveat to the results presented here is we have not considered two important sources of error: horizontal refractivity structure and liquid water. The importance and complexity of each of these topics is sufficient to require separate papers under preparation on each topic. Here, we can summarize some important points with regard to these two additional sources of error. To evaluate the impact of horizontal structure, we have examined the accuracy of occultation retrievals in the vicinity of fronts that represent a rather severe set of horizontal conditions encountered in earth's atmosphere. It is important to recognize that occultation observations are not point measurements and therefore should not be evaluated as such. For a frontal surface oriented approximately orthogonal to an occultation plane, differences between the occultation-derived moisture and the moisture at the ray path tangent point can be greater than 20%. However, when the occultation-derived moisture is compared with a weighted average along the ray path, the moisture "error" is 5% or less. If the frontal plane is oriented parallel to the occultation ray paths, the moisture errors are no more than 3% and generally a few tenths of a percent or less. Temperature errors are generally less than 1 K for ray path tangent point comparisons and about a factor of 5 less for comparisons with a weighted average along the ray path. Therefore, the 0.5%–3% moisture errors described due to finite measurement SNR and residual diffraction effects here are quite relevant even under the rather severe horizontal conditions of fronts.

The error estimates presented here have been derived for clear sky conditions. As discussed in section 2b, in the lower troposphere, liquid water will cause additional absorption that must be solved for and will be the subject of a future paper. To briefly summarize our estimates to date, water vapor retrievals in the presence of liquid water clouds in the lowermost troposphere will be about a factor of 2 worse than what has been presented here. Contamination by ice above the freezing level should not be a problem because the 22-GHz wavelengths are insensitive to scattering by ice and the scattering by ice near 183 GHz is broadband and will therefore be canceled out by the online/offline amplitude ratioing.

BRIGHT will provide absolute accuracy because viewing the signals immediately before or after each occultation removes any long-term drift. From a climate standpoint BRIGHT's along-track averaging is actually an advantage in terms of recovering representative behavior. It is important to realize radiances measured by passive nadir sounders are unoin predictably related to the temperature and moisture versus pressure structure of the atmosphere. Therefore, some form of additional constraint, typically a background guess from a climatology, model, or analysis, is required to derive a unique set of temperatures and humidities from a set of radiances. Any bias present in the constraint will produce a bias in the derived temperature and moisture results.

In this context it is important to note that the BRIGHT results will be independent of models and therefore not by influenced by underlying model biases. A related point is that high vertical resolution can reveal telltale signatures of underlying processes responsible for the vertical structure. Taking models that incorrectly represent an underlying process and combining them with nadir-viewing vertical radiance weighting functions significantly coarser than that required to reveal the diagnostic signature will yield results consistent with the misrepresented model process. Such results will likely never properly capture the diagnostic signature or the underlying process. Because of its high vertical resolution and independence from models, BRIGHT will offer an ability to evaluate models and their numerous physical parameterizations. Given the significant uncertainty regarding the water vapor feedback in our climate system and the tendency of weather models to lose track of moisture assimilated from observations within 12 h, BRIGHT's ability to evaluate the moisture distribution and processes in models is extremely important as we try to improve significantly upon and reduce the uncertainty in our present predictive skills.

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REFERENCES


