

The relative importance of random error and observation frequency in detecting trends in upper tropospheric water vapor

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[1] Recent published work assessed the amount of time to detect trends in atmospheric water vapor over the coming century. We address the same question and conclude that under the most optimistic scenarios and assuming perfect data (i.e., observations with no measurement uncertainty) the time to detect trends will be at least 12 years at approximately 200 hPa in the upper troposphere. Our times to detect trends are therefore shorter than those recently reported and this difference is affected by data sources used, method of processing the data, geographic location and pressure level in the atmosphere where the analyses were performed. We then consider the question of how instrumental uncertainty plays into the assessment of time to detect trends. We conclude that due to the high natural variability in atmospheric water vapor, the amount of time to detect trends in the upper troposphere is relatively insensitive to instrumental random uncertainty and that it is much more important to increase the frequency of measurement than to decrease the random error in the measurement. This is put in the context of international networks such as the Global Climate Observing System (GCOS) Reference Upper-Air Network (GRUAN) and the Network for the Detection of Atmospheric Composition Change (NDACC) that are tasked with developing time series of climate quality water vapor data.

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1. Introduction

[2] Water vapor is one of the most important components of the atmosphere when considering atmospheric chemistry, radiation, dynamics and clouds. For example, increases in stratospheric water vapor can lead to cooling of the stratosphere, warming of the troposphere [Forster and Shine, 2002] and delay the recovery of ozone [Shindell, 2001; Weatherhead and Andersen, 2006]. Solomon *et al.* [2010] have recently shown that decreases in lower stratospheric water vapor have slowed the rate of global surface temperature increase over the last decade. Trends in upper tropospheric water vapor concentrations and temperature will influence cirrus cloud frequency and composition. For these reasons and others, significant effort has been put into both measurements and modeling of UT/LS water vapor to assess long-term

trends in water vapor concentrations and thus address the consequences of changes in UT/LS water vapor amounts.

[3] A recent work by Boers and van Meijgaard [2009] (hereafter referred to as BM2009) considered an ensemble of 150-year simulations of upper tropospheric water vapor at 300 hPa over the Netherlands using a regional climate model to study the measurement needs for revealing trends in atmospheric water vapor. Their simulations indicated nearly a doubling in upper tropospheric water vapor concentration over the coming century. Applying a well-known statistical model [Weatherhead *et al.*, 1998] to their time series indicated that a statistically significant trend in water vapor concentration could be discerned within 30 years using a perfect data set with no random errors imposed. We have studied the same problem using a global climate model, different data sources, different geographic location, and different pressure levels. We then extend our discussion to the main purpose of this paper, which is to consider the relative importance of observation random error and observation frequency on the time to detect trends.

2. Trend Detection Tools

[4] The statistical model employed here, which assumes autoregressive of the order 1 (AR-1) behavior in the data, is that described by Weatherhead *et al.* [1998, 2002] and is the same as used in BM2009. We summarize here the technique

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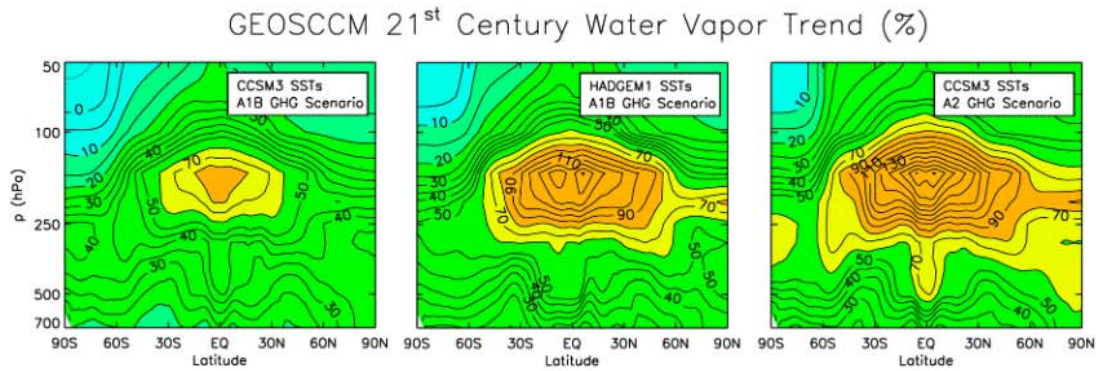


Figure 1. Three 100-year simulations of water vapor concentrations using the GSFC Earth Observing System Chemistry Climate Model. The contours show the percentage change in water vapor concentrations over the 100-year simulation period. See text for further description.

as we used it. A time series of water vapor concentrations can be described by the following equation where the unit of time is one month

$$Y = \mu + \omega \frac{t}{12} + S + N, \quad (1)$$

where Y is the water vapor concentration, μ is a constant, ω is the mean trend per year ($\% \text{ year}^{-1}$), S is the seasonal term, t is the time in months, and N is the monthly mean noise of the time series. The time to detect a trend at the 95% confidence level with probability 0.9 can be approximated by

$$n^* = \left[\frac{3.3\sigma_N}{|\omega_0|} \sqrt{\frac{1+\phi_N}{1-\phi_N}} \right]^{2/3}, \quad (2)$$

where n^* is the number of years to detect a trend, ω_0 is the trend magnitude ($\% \text{ year}^{-1}$), σ_N is the standard deviation of the total noise in the time series ($\%$ of mean value), and ϕ_N is the autocorrelation of the noise.

[5] Equation (2) implies that after the calculated number of years, there is a high probability (90%) that a trend of the correct sign will have been detected if we assume that detecting a trend means identifying a trend at the 95% confidence level. As discussed in BM2009, higher levels of certainty about the exact magnitude of the trend require longer measurement periods. However, the use of equation (2) will permit us to make the main conclusions of the paper that are discussed later.

[6] To evaluate equation (2), values for the anticipated trend, the standard deviation and autocorrelation of the noise of the data time series are needed. Previous research has shown that these values vary by location and altitude, which helps to explain why the time to detect trends in environmental variables can be strongly a function of site location [Weatherhead *et al.*, 2002]. For the purposes of the study here, we obtained a value for the anticipated trend using the Goddard Earth Observing System Chemistry Climate Model (GEOSCCM) [Pawson *et al.*, 2008] along with the Intergovernmental Panel on Climate Change (IPCC) greenhouse gas scenarios [Intergovernmental Panel on Climate Change (IPCC), 2000] and 3 different sea surface temperature simulations. The results are shown in Figure 1. Two simulations were run using the IPCC Special Report on Emission

Scenarios (SRES) A1B greenhouse gas scenario [IPCC, 2000]. The runs differ in the sea surface temperature (SST) and Sea Ice boundary conditions used. The first one used was the Hadley Centre climate model (HadGEM1) [Johns *et al.*, 2006] which has a larger than average climate sensitivity. The second was the Community Climate System Model version 3 (CCSM3) [Collins *et al.*, 2006] which has a lower than average climate sensitivity. The runs were conducted for the IPCC Fourth Assessment Report [IPCC, 2007] and the output was used in GEOSCCM. An additional simulation was conducted using the IPCC SRES A2 greenhouse gas scenario [IPCC, 2000]. This represents a higher-end emissions scenario and this run was conducted using only CCSM3 SST and Sea Ice boundary conditions.

[7] There are several points to be made from Figure 1. The simulated water vapor concentration increases are largest in the tropical upper troposphere with maximum values ranging from approximately 75%–150% at a pressure level of approximately 150–200 hPa. Moving to higher latitudes, smaller anticipated increases in water vapor concentration are found with the maximum increases shifting to higher pressure levels/lower altitudes. Taking the middle panel results (A1B with HADGEM1 SSTs) as representative of an average simulation, the maximum mean annual increase in upper tropospheric water vapor concentration over the 100-year simulation is approximately 1% with larger increases occurring in the latter part of the century. These results are in general agreement with those of BM2009 and earlier studies [Soden *et al.*, 2005]. A point can be made here, however, of a significant difference between the methods of BM2009 and those used here. BM2009 considered an ensemble of regional climate model runs and, not knowing which run was more representative of the future, performed calculations of times to detect trend such that trends would be detected in *any* of the climate scenarios. Here, we consider the results of *one* climate run that is something of the average of the three climate runs shown in Figure 1. The more conservative approach of BM2009 contributes to the longer times to detect trend calculated in their paper.

[8] The standard deviation and autocorrelation of the noise of atmospheric water vapor are also needed to evaluate equation (2). To estimate these values, we studied two time series of water vapor measurements from the Department of

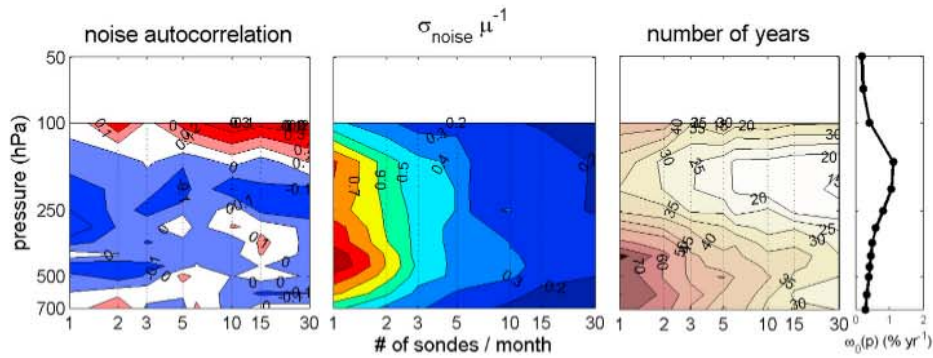


Figure 2. The first panel shows monthly mean noise autocorrelation versus the number of measurements per month derived from the DOE/ARM radiosonde times series using only data after 2001. The second panel gives the standard deviation of the noise divided by the mean of the time series. The third panel provides the number of years to reveal a trend and the fourth panel gives the water vapor trend from the middle GEOSCCM run shown in Figure 1. The results in the first three panels have been restricted to 100 hPa due to increased concerns over radiosonde accuracy at higher altitudes.

Energy’s (DOE) Southern Great Plains (SGP) Climate Research Facility (CRF) in northern Oklahoma. The first was a 15-year record of Vaisala radiosonde data from 1994–2010 and the second was a 5-year record of Raman lidar data [MacDonald, 2005]. We will first perform the analysis without considering measurement error, which will be considered in the next section. Figure 2 presents the monthly mean autocorrelation and noise as well as the number of years to detect a trend based on the radiosonde data analysis under the assumption that all variability in the time series is due to the atmosphere (i.e., no measurement error). The analysis of the lidar data gave reasonably similar results although the lidar data set had significant gaps that complicated the analysis lending less confidence in the analysis. Also plotted as a function of pressure level on the fourth panel of Figure 2 is the 100-year mean increase in water vapor concentration at the latitude of the SGP site in northern Oklahoma based on the Figure 1 (middle). Figure 2 indicates that monthly autocorrelation of the noise in the range of 200–300 hPa is relatively independent of sampling frequency at an approximate value of -0.1 – 0.1 for most frequencies. Monthly mean fractional variability (standard deviation divided by the mean) of the noise in this same height range varies depending on sampling frequency from approximately 0.2 to 0.8 with lower values corresponding to higher sampling frequencies, consistent with the relationship found in the earlier study [MacDonald, 2005] of atmospheric temperature. The third and fourth panels of Figure 2, considered together, indicate that the number of years to detect a trend is smallest at the peak in the 100-year mean anticipated trend of approximately 1% per year at a pressure level of approximately 150–200 hPa. At this level, the time to detect a trend varies from less than 15 to more than 30 years for sampling frequencies ranging from one to thirty times per month. At 250 hPa the range of times to detect trends increases to 18–45 years due to the smaller anticipated trend and the higher noise at 250 hPa versus 150–200 hPa.

[9] The radiosonde and lidar data were processed into time series of daily water vapor profiles so that, similar to BM2009, we were able to study the effects of varying

sampling frequencies on the calculated noise and autocorrelation. This technique is similar to one used previously in the context of temperature trend detection from radiosonde data [MacDonald, 2005]. We will first perform the analysis without considering measurement error, which will be considered in the next section. Figure 2 presents the monthly mean autocorrelation and noise as well as the number of years to detect a trend based on the radiosonde data analysis under the assumption that all variability in the time series is due to the atmosphere (i.e., no measurement error). The analysis of the lidar data gave reasonably similar results although the lidar data set had significant gaps that complicated the analysis lending less confidence in the analysis. Also plotted as a function of pressure level on the fourth panel of Figure 2 is the 100-year mean increase in water vapor concentration at the latitude of the SGP site in northern Oklahoma based on the Figure 1 (middle). Figure 2 indicates that monthly autocorrelation of the noise in the range of 200–300 hPa is relatively independent of sampling frequency at an approximate value of -0.1 – 0.1 for most frequencies. Monthly mean fractional variability (standard deviation divided by the mean) of the noise in this same height range varies depending on sampling frequency from approximately 0.2 to 0.8 with lower values corresponding to higher sampling frequencies, consistent with the relationship found in the earlier study [MacDonald, 2005] of atmospheric temperature. The third and fourth panels of Figure 2, considered together, indicate that the number of years to detect a trend is smallest at the peak in the 100-year mean anticipated trend of approximately 1% per year at a pressure level of approximately 150–200 hPa. At this level, the time to detect a trend varies from less than 15 to more than 30 years for sampling frequencies ranging from one to thirty times per month. At 250 hPa the range of times to detect trends increases to 18–45 years due to the smaller anticipated trend and the higher noise at 250 hPa versus 150–200 hPa.

3. Partitioning the Noise

[10] The preceding analysis assumed that all time series noise was due to natural atmospheric variability and that the

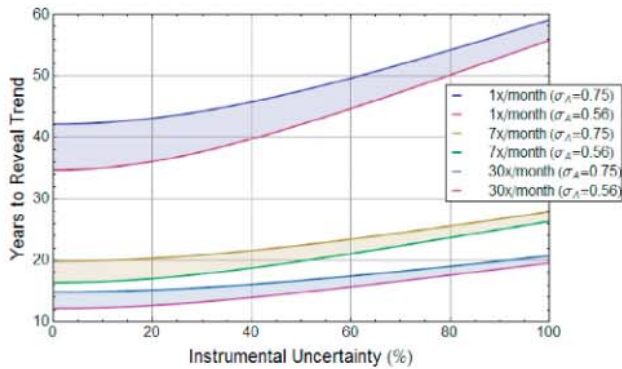


Figure 3. The number of years to detect a trend in upper tropospheric water vapor concentration versus the total uncertainty in the measurement system used to create the time series for various sampling frequency. The range of natural water vapor variability, σ_A , is 0.56 to 0.75.

instrument contributed no noise. But certainly the instrument does contribute noise to the time series. So our goal now is to consider the influence of variable instrumental noise on the time to detect trends. In BM2009, 10% random errors were simulated to represent the best currently available sounding systems. We would like to vary this error value and study the effects on the time to detect trends. To do so, we assume that the noise derived from the measurements can be expressed as follows [Tiao *et al.*, 1990]:

$$\sigma_N = \sqrt{\frac{\sigma_A^2}{1 - \phi_N^2} + \sigma_{I_{tot}}^2}, \quad (3)$$

where σ_A is the atmospheric noise and $\sigma_{I_{tot}}$ is the total instrumental noise. The instrumental noise is taken to include both random and systematic components. The use of equation (3), therefore, assumes that any systematic effects average out over time to become a random variable with mean of zero. This assumption places constraints on instrument calibration and any corrections that are applied to the data [e.g., Miloshevich *et al.*, 2009] in a climate quality time series. Any errors introduced by such calibrations and corrections must average to zero over time for this assumption to be valid. The task of separating the atmospheric and instrumental contributions to the noise could, in principle, be done almost perfectly with the DOE/ARM (Department of Energy/Atmospheric Radiation Measurements) water vapor lidar time series if one assumes that the dominant noise in the lidar data in the upper troposphere is random and not systematic. The reason for this is that the magnitude of the random errors in Raman lidar data are easily calculated using Poisson statistics [Whiteman, 2003]. However, the lidar time series has significant gaps in the data record and periods of reduced signal-to-noise that significantly complicate the analysis task. In particular, de-seasonalizing the lidar data is complicated by the presence of these data gaps. The radiosonde time series is much more robust in this sense and possesses few data gaps. However, there is no random error specification that comes with the radiosonde data. We can, however, appeal to recent work in studying radiosonde data to get estimates of reasonable values for radiosonde instrumental variability. Miloshevich

et al. [2009] report a sonde-to-sonde variability of approximately 3% for the Vaisala RS92. This same work shows a standard deviation of comparisons between uncorrected RS92 and the frostpoint hygrometer reference instrument of approximately 10–15% at 200 hPa. In light of this result and in order to make the main point of this paper, we will consider the noise in the radiosonde time series to range up to 50%. We consider this to likely be an overestimate of the actual random error introduced into the time series by the radiosonde instrument errors. However, doing so will provide high confidence that the range of values for the natural variability in atmospheric water vapor at 200 hPa that is extracted from the radiosonde time series includes the actual value of atmospheric variability of water vapor at this level.

[11] The analysis of the ARM radiosonde daily noise shows a value of σ_N/\bar{Y} of approximately 0.75 at 200 hPa. Assuming the range of random errors in the radiosonde time series of 0–50%, and using equation (3) to separate the atmospheric and instrumental contributions, yields a range of values for the atmospheric contribution to σ_N/\bar{Y} of approximately 0.56–0.75 at 200 hPa. We will use this range of atmospheric noise values in the following computations.

4. The Effects of Variable Instrument Noise

[12] The questions of the optimum sampling frequency and what instrumental noise is acceptable for climate data records are important ones for networks, such as the Global Climate Observing System (GCOS) Reference Upper Air Network (GRUAN) [World Meteorological Organization, 2007] and the Network for the Detection of Atmospheric Composition Change (NDACC) [Leblanc *et al.*, 2008; Whiteman *et al.*, 2010], that attempt to monitor changes in atmospheric water vapor. We address those questions here by use of equation (2), where the values of monthly mean noise and autocorrelation are calculated from the DOE/ARM radiosonde time series discussed above and the assumed trend at the DOE/SGP site is determined from Figure 1 (middle) and shown on the fourth panel of Figure 2.

[13] Figure 3 shows the time to detect trends in upper tropospheric (200 hPa) water vapor for sampling frequencies of 1, 7 and 30 times per month and instrumental uncertainties ranging from 0–100%. There are two curves for each sampling frequency corresponding to the estimated range of atmospheric noise of 0.56–0.75 based on the radiosonde time series as discussed above. The predictions based on intermediate values of atmospheric noise are indicated by the shaded regions in the figure. For a perfect measurement system, i.e., one with no instrumental uncertainty, that provides measurements of upper tropospheric water vapor (200 hPa) on a daily basis, the time to detect trends ranges from approximately 12–15 years depending on the amount of atmospheric noise. The lower the atmospheric noise, the smaller the number of years to detect the trend. A daily time series of water vapor measurements created using an instrument possessing total noise of 50% increases the estimated range of times to detect trends by about 2–3 years to approximately 15–17 years. The larger increase corresponds to the assumption of lower atmospheric noise. By contrast, a time series created by a perfect measurement system operating 7 times per month will need to extend from 16 to 22 years to detect the same trend. Once monthly measurements will

require a minimum of 35–42 years to reveal the trend. One can see that, due to the natural auto-correlation of atmospheric parameters measured on short time scales, the time to detect trends decreases less rapidly as measurement frequency increases.

5. Discussion and Conclusions

[14] The analysis here yields somewhat lower times to detect trends than BM2009. The number of years to detect a trend at 200 hPa, assuming daily measurements by a perfect measurement system, were calculated here to be 12–15 years at the SGP site as opposed to 30 years at 300 hPa for the northern Netherlands location considered in BM2009. Several differences in the analysis presented here and that of BM2009 were noted that likely contribute to these differences. Our noise assumptions are based on past behavior of the atmosphere recorded by radiosondes at the SGP site of DOE/ARM and therefore, do not account for the anticipated increase in noise in the water vapor time series in the future [Boers and van Meijgaard, 2009]. The anticipated increase in water vapor is also lower at a higher latitude such as in the northern Netherlands than at SGP and contributes to the longer times to detect a trend in the upper troposphere calculated by BM2009. There is evidence as well that the day-to-day autocorrelation may be higher at higher latitudes [Weatherhead *et al.*, 2010] and the magnitude of the natural variability of upper tropospheric water vapor is likely different between the two studies. And finally, and perhaps most importantly, BM2009 used the more conservative approach of specifying the time to detect trends for all the climate runs that they studied whereas we chose the climate run that showed “average” trend behavior among the three that we studied.

[15] The use of radiosonde data to calculate water vapor noise and autocorrelation in the upper troposphere, as done here, may seem suspicious given the known measurement uncertainties of radiosondes in this part of the atmosphere [Miloshevich *et al.*, 2006, 2009]. There may well be some errors in the calculated values of water vapor noise and autocorrelation because of these radiosonde measurement limitations. However, the calculation of both noise and autocorrelation are not affected by static systematic errors such as a constant calibration error. Calibrations that change over time would introduce additional noise into the time series, but the documented standard deviation of the differences between RS92 and the reference cryogenic frostpoint hygrometer (CFH) sensor were approximately 10–15% while the range of noise assumed for the instrument was 0–50%. We believe that the considerably larger range of assumed instrumental uncertainty is likely to include the effects of radiosonde calibration changes and production-related biases assuming that these effects average out over time to become random variables. Likewise, calculations based on the Raman lidar water vapor time series are plagued by missing data and possible changes in calibration. However, the fact that the analysis of the two data sets provided similar results for the value of atmospheric noise lends confidence in the range of real atmospheric water vapor noise used in the study here. That range is indicated by the shaded regions in Figure 3. Furthermore, the major conclusions of this work relating to the relative merits of

increasing sampling frequency versus decreasing instrumental uncertainty are quite robust since even a 50% instrumental error budget increased the time to detect trend by only a few years. We conclude that the influence of the known errors in the radiosonde and lidar time series are not significant to the major conclusion based on Figure 3 that, in order to reveal trends in upper tropospheric water vapor in a shorter amount of time, increasing the frequency of measurement is more important than decreasing the random error in the measurement. Large errors in the magnitude of calculated atmospheric noise would change the time to detect trends significantly, but not in this relationship and, again, the general agreement in the magnitude of the real atmospheric noise calculated from radiosonde and lidar lends confidence in the range of real atmospheric noise values used.

[16] Our analysis indicates that at the SGP site, there are not large changes in atmospheric noise and autocorrelation at different levels in the upper troposphere. According to the climate simulations, however, the anticipated trend in water vapor shows a reasonably well-defined peak at approximately 200 hPa. Therefore, to improve the efficiency of trend detection at the SGP site it is important for the measurement system to provide quality data where the peak in water vapor trend occurs, *i.e.*, in the region of 200 hPa. The climate simulation also shows that anticipated trends in the lower stratospheric water vapor concentrations are considerably smaller than in the upper troposphere. Furthermore, extended time series of water vapor concentrations in the lower stratosphere [Hurst *et al.*, 2011] indicate that the variability in lower stratospheric water vapor in the mid-west of the U.S. is also much smaller than in the upper troposphere. Considering equation (2), both of these results indicate that detecting trends in lower stratospheric water vapor will be more sensitive to additional measurement noise than in the upper troposphere. It is for this reason that the work done here implies that trend detection of water vapor over the coming century may be more easily performed in the upper troposphere than in the lower stratosphere. A combination of Microwave Limb Sounder data and the Boulder time series could be studied in the future to attempt to address this question further.

[17] Scheduling protocols are presently being discussed within international networks such as GRUAN and NDACC. The desire to respond to these needs was a motivation for BM2009 and for the work presented here. We have extended the work of BM2009 to address the question of the influence of total instrumental uncertainty on the quality of a climate data record for UT water vapor trend detection. The analysis presented here indicates that, due to the high natural variability in tropospheric water vapor, it is much more important to sample the atmosphere more frequently than to use a measurement system with the smallest error budget less frequently. Measurement systems with total error of even 50% do not extend the time to detect UT trends by a large amount provided that the total uncertainty of the measurement approximates a random variable over time. This implies that whatever recalibrations or adjustments are made to the measurement system and the data series created by it vary more or less randomly around some mean value. The tolerance for relatively large random error budgets in creating a climate quality time series of upper tropospheric

water vapor implies that remote sensing systems such as Raman lidar [Whiteman et al., 2006, 2010; Leblanc et al., 2008], where the random error in the measurement of water vapor typically increases with altitude, could contribute usefully to monitoring trends in upper tropospheric water vapor although it will be necessary to have stringent quality control procedures in place to guard against errors [Whiteman et al., 2006; Leblanc et al., 2008; Boers and van Meijgaard, 2009] in upper tropospheric Raman lidar water vapor measurements. It should be noted in this context, though, that a large random error could mask the presence of a small systematic error making its detection more difficult.

[18] Our results also indicate that a time series created with a sampling frequency of seven times per month, or approximately every four days, will reveal a trend in a period of time approximately 1/3 longer than a time series created from daily measurements. Given the expense and complexity of daily soundings with good quality upper tropospheric measurements and the diminishing returns for more rapid measurements, every 4 days or approximately twice per week may be a reasonable goal for sampling frequency for developing a climate quality time series of water vapor. This result is similar to an analysis of atmospheric temperature trend detection that indicated that the uncertainty in the calculated trend increased significantly for sampling frequencies of less than once every 3 days [MacDonald, 2005].

[19] It should be made clear that we did not consider in this analysis various real-world problems that can plague atmospheric data. Step jumps in the time series, drifts in calibration and gaps in the data record, for example, are not considered. A real time series of atmospheric water vapor is likely to have one or more of these present, which would serve to increase the amount of time to detect trends. These effects could be studied in the future using a Monte Carlo approach where a large number of possible biases are considered and the mean and standard deviation of times to detect trend are assessed. Given the large amount of natural variability in upper tropospheric water vapor and the general robustness of the results, we do not expect that the presence of systematic biases of moderate magnitude in the data will influence one of our main results – that it is more important to increase the measurement frequency than the accuracy of the measurements in order to reveal trends more efficiently.

[20] However, both GRUAN and NDACC are at the beginning of their efforts to create useful time series measurements of atmospheric water vapor. The likely presence of contaminating influences, such as gaps, drifts and changes in calibration, needs to be considered at the outset of the implementation of these networks. Previous research in homogenizing time series of radiosonde temperature data [Free et al., 2002] has demonstrated that different methods used to homogenize historical data sets can produce divergent results. Therefore, it is important for the GRUAN and NDACC communities to consider implementing data quality procedures now that will help to assess data quality on an operational basis with the goal of minimizing the influence of systematic errors on the time series that are being acquired.

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