Quality Control of Ground-Based Radiometric Observations of Integrated Moisture Using Surface Meteorological Observations

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ABSTRACT

A method of quality control is presented for ground-based, dual-channel microwave measurements of integrated moisture. Such a method is necessary to eliminate spurious data arising from calibration uncertainties, electronic fluctuations, and strong rain and melting snow on the radiometer antenna. The method is based on the prediction of integrated moisture content from surface measurements of temperature and dewpoint temperature. The statistical prediction was based on regression using a carefully screened multiyear training set of surface meteorological observations, and radiosonde and dual-channel radiometric measurements of moisture. Five years of twice-daily data (six years for the summer months) from Denver, Colorado, as well as data obtained from special experiments at Elbert and Platteville, Colorado, formed the training set. Both linear and nonlinear predictions were compared. The method was applied to independent data obtained during 1991–92 experiments at the three locations. The method predicted data quality with a 91% accuracy rate.

1. Introduction

Ground-based microwave radiometric measurements of precipitable water vapor V and integrated cloud liquid L have been used in a variety of meteorological investigations (Askne and Westwater 1986) including weather modification (Reynolds 1988), electrical pathlength correction (Elgered and Lundquist 1984), and turbulent properties of liquid-bearing clouds (Cahalan and Snider 1989). Several current applications may also be noted. In the Federal Aviation Agency's Winter Icing and Storms Project (Rasmussen et al. 1992), several radiometers have been used to determine the presence of supercooled liquid water for monitoring aircraft icing conditions. In the Department of Energy's Atmospheric Radiation Measurements Program (ARM Science Team 1992), several radiometers will be used to monitor V and L for their use in characterization and parameterization of atmospheric radiation. In the National Aeronautics and Space Administration's Advanced Communications Technology Satellite Program (Chakraborty et al. 1993), at seven diverse climatological regions, dual-channel radiometers will be collocated with satellite receivers to monitor atmospheric attenuation from clouds and rain. Several dual- and three-channel radiometers were operated in multiagency climate programs such as the First ISCCP (International Satellite Cloud Climatology Project) Regional Experiment (FIRE) (Cox et al. 1987) and the Atlantic Stratocumulus Transition Experiment (FIRE Project 1990). Finally, the National Oceanic and Atmospheric Administration (NOAA) has continuously operated several (as many as four) dual-channel radiometers since 1979. In addition to the current activities mentioned above, new applications are anticipated in the areas of satellite product validation (Alishouse et al. 1990; Westwater and Fedor 1991) and in the radiometric correction of atmospheric effects in surface sensing from aircraft and satellites (Snider et al. 1993).

The techniques for extracting parameters from dual-channel radiometers are straightforward (Westwater 1993). From zenith observations of brightness temperature at two frequencies, a vapor-sensitive frequency such as 20.6 GHz and a liquid-sensitive one such as 31.65 GHz, 2-min averages of both V and L are obtained. Although we confine our attention to zenith observations at 20.6 and 31.65 GHz, other frequencies and nonzenith observations are commonly used. The accuracy in determining V is of the same order as that of radiosondes, about 0.1–0.2 cm rms (Martner et al. 1993); the accuracy in L is much more difficult to determine since conventional radiosondes do not measure profiles of cloud liquid density. Theoretical estimates of the accuracy of radiometric measurements

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of L are given by Ciotti et al. (1987), and for nonprecipitating clouds, the accuracy is about 0.005 cm rms or 10%–20%.

We apply our methods here to data obtained with microwave radiometers operated by NOAA's Wave Propagation Laboratory (WPL). These instruments were designed to be operated in an unattended mode, although infrequent calibrations are necessary. For example, the four dual-channel radiometers of the Colorado research network (Westwater and Snider 1989) ran for three years with only monthly calibration checks. However, there were periods when measurements from these instruments were incorrect. These errors appeared during a variety of severe meteorological situations, usually precipitation events, and infrequently from causes associated with radiometer electronics. However, by visual observations of time series of brightness temperature and of derived moisture (both V and L), such errors were evident. Such incorrect measurements, which can be easily determined, at least by a trained observer, are shown in Fig. 1. But such visual control is practical only for limited amounts of data and is almost impossible for real-time applications. In this work, we investigate the application of surface meteorological measurements of dewpoint temperature and temperature for automatic control of radiometrically determined relative precipitable water vapor Q (see section 2).

2. Statistical analysis of integrated water vapor

We use the following notations to describe different characteristics of water vapor in the atmosphere:

ρ_W—density of water vapor (kg m^{-3}),
ρ_{aq}—density of liquid water at standard conditions, ($\rho_{aq} = 10^3$ kg m^{-3}),
M_T—total mass of air per unit area (including water vapor) (kg m^{-2}),
M_T—$P g^{-1}$, where P (kg m^{-1} s^{-2}) is the surface pressure,
g—acceleration of gravity (9.8 m s^{-2}),
z—height (m),
W—integrated water vapor (kg m^{-2}), where

$$W = \int_0^\infty \rho_W dz, \tag{1}$$

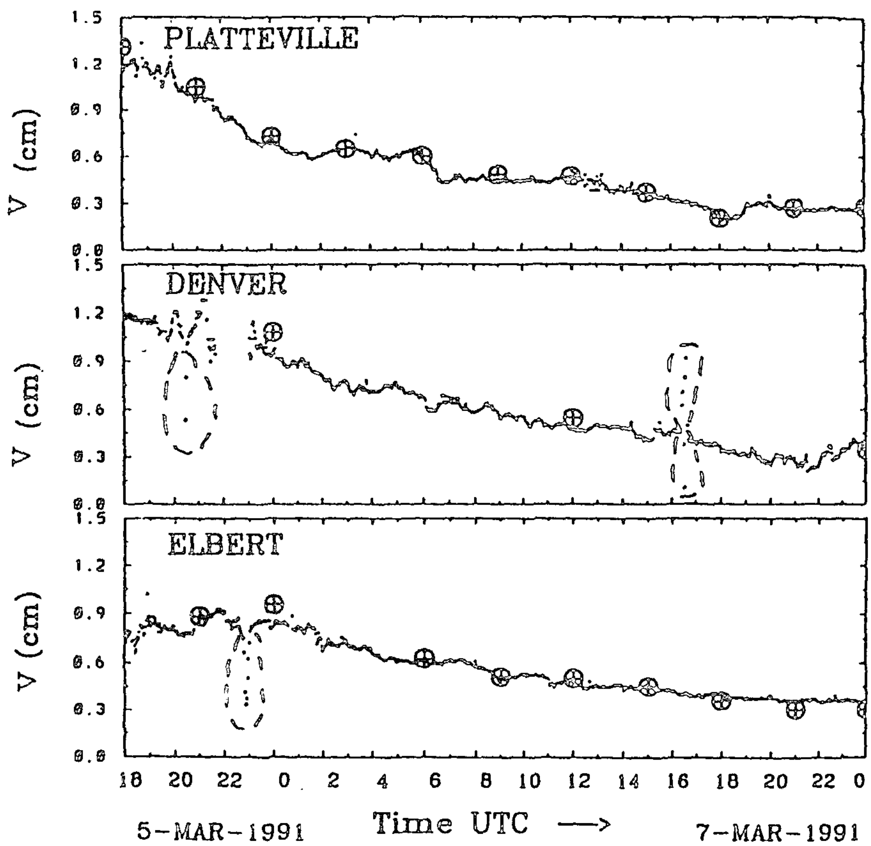

FIG. 1. Time series of precipitable water vapor V during a snowfall on 5–7 March 1991: Circled crosses denote V calculated from radiosondes, while dots denote V calculated from 2-min-averaged radiometer data. Suspected outliers are enclosed within dashed lines.

V—precipitable water vapor (cm; 1 cm = 0.01 m), where

$$V = \frac{W}{\rho_{aq}}, \quad (2)$$

and

Q—dimensionless relative precipitable water vapor, where

$$Q = \frac{W}{M_T} = \frac{gW}{P}. \quad (3)$$

Our method of quality control is based on statistical relations between integrated moisture and surface point measurements of dewpoint temperature t_d (°C) and air (shelter) temperature t (°C). The quantity Q is more convenient to use than V, because it makes it possible to compare integrated moisture content in the points located at different altitudes. The existence of a strong correlation between Q and t_d was noted by Gorelik et al. (1972). We analyze measurements of water vapor content, expressed either through V or Q, obtained in two independent ways: (a) by dual-channel microwave radiometer measurements of WPL radiometers, and (b) by integrating radiosonde soundings of the National Weather Service (NWS). At the NWS facilities at Stapleton International Airport, Denver, Colorado, the radiometer is 15 m from the radiosonde launch site. Independent surface meteorological measurements by WPL and NWS are taken about 40 m apart.

In our approach to obtaining a statistical method of quality control, it is necessary to develop a representative training set of data that is free of outliers. In our case this is possible because we have redundant measurements of each of the quantities, t, t_d, and Q. However, each of the redundant pairs is measured by different instruments. To investigate the statistical relationship between the various quantities measured by different instruments, it is first necessary to eliminate systematic errors. In addition, it is important to evaluate the mean-square values of the random errors of measurement. We first established a correspondence between surface measurements (t_d and t) by NWS and WPL and between radiometer (WPL) and radiosonde (NWS) determinations of Q. We assumed that surface and radiosonde measurements conducted by NWS did not have a systematic error. We also assumed that WPL measurements (t_d^w, t^w, Q^w) could have a systematic error such that the estimated "true" values ($\hat{t}_d$, $\hat{t}$, $\hat{Q}$) were related by the following:

$$\hat{t}_d = a_d + b_d t_d^w, \quad \hat{t} = a_t + b_t t^w,$$
$$\hat{Q} = a_Q + b_Q Q^w. \quad (4)$$

The coefficients a and b were first determined by minimizing the mean-square departure between the estimated (WPL) and true (NWS) values. Next, the adjusted values were again compared with the NWS observations. The measured values were discarded if $|\hat{t}_d - t_d| > \Delta t_d$, $|\hat{t} - t| > \Delta t$, and $|\hat{Q} - Q| > \Delta Q$, where the threshold values were recursively determined in the intervals Δt_d = 1.5°–2.0°C, Δt = 1.0°–1.5°C, ΔQ = 0.08–0.2 g kg^{-1}, or ΔV = 0.06–0.17 cm, which leads to 90% of correct estimations of quality of microwave data. After the first data rejections, all processes were repeated a few times, since the coefficients a and b change after each elimination. This process terminated when no data were eliminated during the last iteration. At this stage, the correlation coefficient within each bivariate series was greater that 0.95. After such control, about 25% of the initial data were lost. Of this 25%, about one-half were due to errors in Q and the other one-half due to errors in t_d. After eliminating noncoincident pairs from the initial sets of data, a dataset that was free of significant outliers was obtained. We show in Table 1 the values of the monthly mean correlation coefficients between t_d, t, and Q measured by WPL (surface and radiometers) and NWS (surface and radiosondes) during the period 1985–90 in Denver.

We also calculated $R(\tau)$, the temporal autocorrelation function of Q, from the radiometric measurements that passed our quality control algorithm. From this function, it is possible to calculate the variance of the random error of measurement. It is known (Gandin 1963) that random uncorrelated measurement errors, in contrast to systematic or time-correlated errors, do not influence $R(\tau)$ for $\tau \neq 0$ (where τ is temporal displacement). But for $\tau = 0$, the value of the autocorrelation function is the sum of the variance of Q and the variance var(ϵ) of the measurement error ϵ. Therefore, the error variance can be obtained by extrapolating $R(\tau)$ to $\tilde{R}(0)$ as $\tau \to 0+$. The difference between $R(0)$ and $\tilde{R}(0)$ yields var(ϵ):

$$\mathrm{var}(\epsilon) = R(0) - \tilde{R}(0). \quad (5)$$

TABLE 1. Correlation coefficients R (after cleaning procedure) between two correlated sets of variables: t^w and t; t_d^w and t_d; Q^w and Q. The parameter N is the sample size.

Month	$R(t^w, t)$	$R(t_d^w, t_d)$	$R(Q^w, Q)$	N
January	0.997	0.974	0.960	137
February	0.998	0.981	0.962	147
March	0.999	0.964	0.962	160
April	0.998	0.972	0.975	122
May	0.998	0.974	0.975	146
June	0.998	0.970	0.966	154
July	0.998	0.968	0.963	189
August	0.998	0.969	0.972	165
September	0.999	0.966	0.976	130
October	0.998	0.978	0.980	104
November	0.998	0.984	0.982	104
December	0.995	0.982	0.979	71

$\delta_t = (1 - R_t^2)^{1/2} = 0.06$, $\delta_{t_d} = (1 - R_{t_d}^2)^{1/2} = 0.225$, $\delta_Q = (1 - R_Q^2)^{1/2} = 0.233$

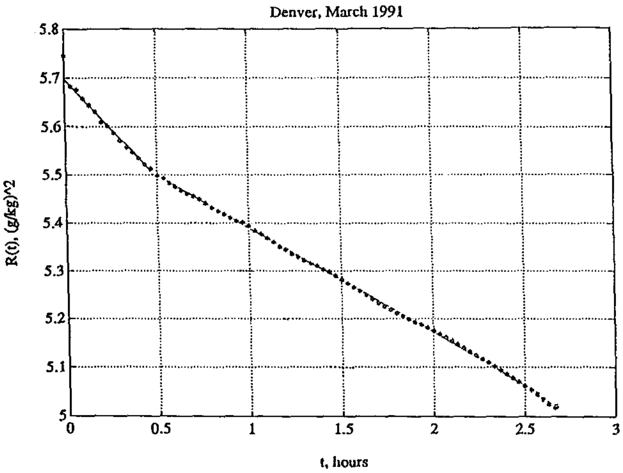

FIG. 2. Temporal correlation function $R(\tau)$ for relative precipitable vapor Q. The difference between the measured (small star) and extrapolated value of R at $\tau = 0$ is a measure of the variance of measurement error.

However, for water vapor radiometers, the error ϵ is composed of three parts:

$$\epsilon = \epsilon_V + \epsilon_L + \epsilon_i, \qquad (6)$$

where ϵ_V is the error due to the departures of the mass absorption coefficient of water vapor from its assumed value, ϵ_L is the error due to the departures of the mass absorption coefficient of cloud liquid from its assumed value, and ϵ_i is the error due to instrumental noise. In addition, each of these three components is also influenced by the value of the average medium temperature, which is used in deriving absorption from emission. Medium temperature and mass absorption coefficients are implicit functions of the vertical profiles of temperature, water vapor, and cloud liquid. In general, each of these components varies with time and, hence, has an autocorrelation function and a spectrum. The spectrum of fluctuations of WPL radiometers was studied by Ciotti et al. (1987) and was shown to be at least two orders of magnitude less than those of water vapor and cloud liquid. In the units of Q, the instrumental fluctuations gave rise to rms errors of 0.01 g kg^{-1}. The errors due to absorption coefficient fluctuations are not exactly known but would presumably be larger than those due to instrumental noise. In addition, as pointed out by an anonymous reviewer, these retrieval errors are correlated on time scales that are dependent on weather dynamics. It is clear, however, from the data of Fig. 2 that the empirical autocorrelation function completely corresponds to the model of the sum of white noise with some time-correlated component. Indeed, the first point $R(0)$ does not agree with the continuation of $R(\tau)$ from the side of positive τ. This means that there are components in the measurement variance that are uncorrelated in time. More precisely, these components have a spectrum whose power is negligible for periods greater than the 2-min averaging time of the instrument. Bias errors that occur on monthly time scales are mainly eliminated by our time-dependent regression analysis. Constructing $R(\tau)$ for $\tau = 2, 4, \cdots,$ min, and using the extrapolation method, we determined the value of var(ϵ) to be 0.05 (g kg^{-1})^2, or 9.5% (see Fig. 2). This value is considerably greater than the 0.0001 (g kg^{-1})^2 value for instrumental fluctuations and is comparable to the 0.20 g kg^{-1} rms difference between radiometric and radiosonde measurements of Q (Westwater 1992). Perhaps, retrieval errors, especially during cloudy conditions, contribute to this relatively high value of the variance. However, these numbers are not strictly comparable, since 20-min averages of radiometer data were used to compare with radiosondes. In addition, the radiometer–radiosonde differences include radiosonde errors, intrinsic radiometer retrieval error, and temporal and spatial differences between the two sensors. Using the regression and the correlation analysis thus allowed us to evaluate both the systematic (relative to radiosondes) and the random error (from a variety of sources) in the measurement of Q.

3. Statistical quality control method

The second part of the work is concerned with the development of an automatic method for revealing random measurement errors in Q. Our method is based on statistical relations between Q and surface observations. Statistics for these variables (Q, t_d, t) were calculated from data that passed the data screening criteria of section 2. Data taken at Denver during 1985–90 were used in the analysis. In Table 2 we show examples of correlation coefficients between the variables for January and July. As is evident from this table, the correlation between Q and t_d is greater than between Q and t. In Fig. 3, we present the distribution of Q as a function of t_d and t for January (1985–90). From this figure, it is evident that for increasing depression of t_d, Q does not decrease if the corresponding air temperature increases. Thus, Q depends not only on t_d but also on air temperature t. An analogous picture was observed for the remaining months. These preliminary investigations were followed by linear regression, using the form

$$\tilde{Q} - \bar{Q} = \alpha(t - \bar{t}) + \beta(t_d - \bar{t}_d), \qquad (7)$$

where $\bar{Q}$, $\bar{t}$, $\bar{t}_d$ is the multiyear average for each month;

TABLE 2. Correlation coefficients R between dewpoint temperature t_d, relative precipitable vapor Q, surface temperature t, and bivariate linear estimate $\tilde{Q}$ for 1985–90 in January and July. The parameter N is the sample size.

Month	N	R_{t_dQ}	R_{tQ}	R_{tt_d}	$R_{Q\tilde{Q}}$
January	137	0.70	0.44	0.68	0.702
July	189	0.62	0.13	−0.32	0.713

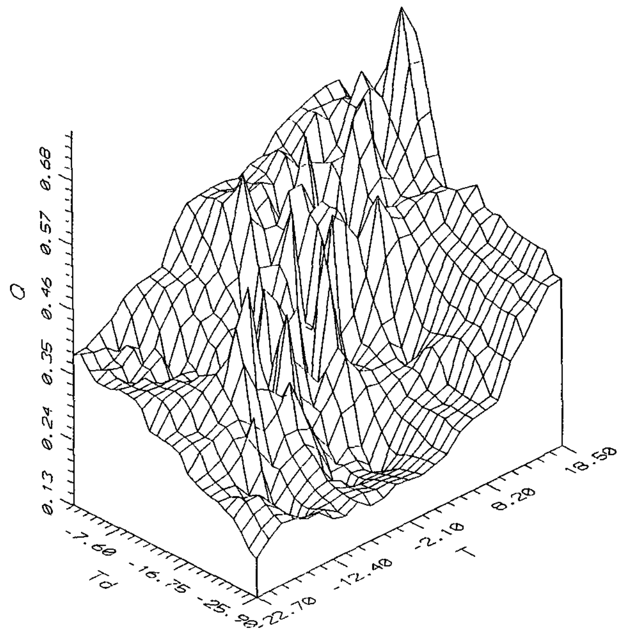

FIG. 3. Distribution of relative precipitable vapor Q as a function of dewpoint temperature t_d and air temperature t, at Denver, Colorado, January, 1985–90.

$\tilde{Q}$ is the predicted value of integrated moisture; and α and β are the regression coefficients calculated by least squares. The multiyear average values of α and β are presented in Fig. 4.

The minimum mean-square deviations of estimated and true values of Q are given by

$$\overline{(Q - \tilde{Q}_1)^2} = \sigma_Q^2(1 - R_{t_dQ}^2), \quad (8)$$

for one predictor t_d, and

$$\overline{(Q - \tilde{Q}_2)^2} = \sigma_Q^2\left[1 - 2\frac{R_{t_dQ}R_{tQ}}{1 + R_{tt_d}} - \frac{(R_{t_dQ} - R_{tQ})^2}{1 - R_{tt_d}^2}\right], \quad (9)$$

for two predictors. The difference,

$$\Delta = \overline{(Q - \tilde{Q}_1)^2} - \overline{(Q - \tilde{Q}_2)^2} = \frac{(R_{tQ} - R_{tt_d}R_{t_dQ})^2}{1 - R_{tt_d}^2} \geqslant 0, \quad (10)$$

is nonnegative. This means that the second predictor always decreases an error of estimation. This improvement can be small ($\Delta = 0$, if $R_{tt_d} = \pm 1$) but it can be significant in the case of small R_{tt_d}. In our case (see Table 2), the improvement is less for the winter ($\Delta^{1/2} = 0.28$ g kg^{-1}) than for the summer ($\Delta^{1/2} = 0.59$ g kg^{-1}).

In Table 2, we also present the correlation coefficients $R_{Q\tilde{Q}}$ for January and July (1985–90) between observed and predicted values of Q. It is seen from this table that $R_{Q\tilde{Q}}$ for all years is greater than the corresponding values for t_d and Q. Obviously, the supplementary information provided by surface air temperature plays a significant role in the estimation of Q.

In addition to the linear estimation of Q, we investigated a nonlinear equation of the form

$$\tilde{Q}_1 - \bar{Q} = \alpha(t - t_0) + \beta(t_d - t_{d0}), + a(t - \bar{t})^2 + b(t_d - \bar{t}_d)^2, + c(t - \bar{t})(t_d - \bar{t}_d). \quad (11)$$

The 5-yr mean correlation coefficients $R_{Q\tilde{Q}}$ are given in Table 3. From this table it is seen that the nonlinear evaluation gives a larger correlation coefficient than the linear (on the average by more than 5%).

We also investigated another nonlinear equation of the form

$$\tilde{Q}_2 - \bar{Q} = \alpha(t - \bar{t}) + \beta(t_d - \bar{t}_d) + A\exp\left[-\frac{(t - t_0)^2}{2a^2} - \frac{(t - t_0)(t_d - t_{d0})}{b^2} - \frac{(t - t_{d0})^2}{2c^2}\right], \quad (12)$$

where A, a, b, c, α, and β are free coefficients. For determining the parameters in (12), we used the method of maximization of the modulus of the correlation coefficient $D = |R_{Q\tilde{Q}_2}|$. However, using this method, it is difficult to find a global maximum, the search for which can lead to a significant computational effort. In Table 3 we present values of the correlation coefficient obtained using (12) for March and April. As is seen, the correlation coefficient is better than for Q_1; however, the increase was associated with a significant increase in computing time.

In the remainder of this work, for the quality control of a large volume of radiometric data, we used only the linear method (7). We compared $\tilde{Q}$, the predicted

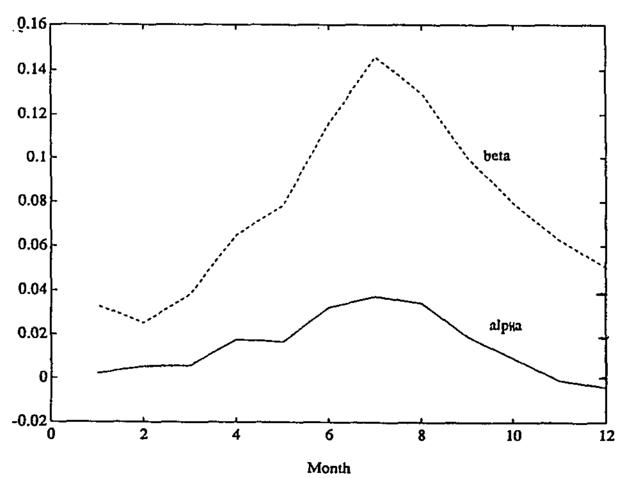

FIG. 4. Monthly plot of the regression coefficients, calculated from six years of quality-controlled data at Denver, Colorado, 1985–90, of the regression of Q on $t_d(\beta)$ and of Q on $t(\alpha)$.

TABLE 3. Comparison of the correlation coefficients $R(Q, \tilde{Q})$ from bivariate linear estimation by plane surface, $R(Q, \tilde{Q}_1)$ by second-order surface, and $R(Q, \tilde{Q}_2)$ by exponential surface.

Month	$R_{Q\tilde{Q}}$	$R_{Q\tilde{Q}_1}$	$R_{Q\tilde{Q}_2}$
January	0.707	0.737	
February	0.685	0.732	
March	0.680	0.687	0.721
April	0.821	0.825	0.829
May	0.752	0.761	
June	0.793	0.799	
July	0.713	0.726	
August	0.755	0.772	
September	0.787	0.812	
October	0.754	0.767	
November	0.789	0.816	
December	0.723	0.768	

value of Q, with the measured quantity Q. If the modulus of the difference $|Q - \tilde{Q}|$ was larger than some threshold value ΔQ, then Q was considered to be in error and was eliminated. The threshold value ΔQ was selected as proportional to the standard error of the estimate of Q: $\Delta Q = 1.3\{\langle(Q - \bar{Q})^2\rangle\}^{1/2} = 0.2\ \mathrm{g\ kg^{-1}}$. The value 1.3 corresponds to an 81% confidence interval.

4. Results of quality control of integrated moisture

We applied the linear method of quality control (7), described in section 3, to the integrated moisture Q observed by dual-channel radiometers in Denver, Platteville, and Elbert, Colorado, in the winter of 1991/92. During this period, frequent radiosondes were launched because of experiments occurring at Elbert and Platteville. The measured values of Q were compared both with $\tilde{Q}$, the quantity predicted from (7) and with Q_S, the value calculated from radiosondes. Comparison of the three quantities Q, Q_S, and $\tilde{Q}$ showed that when all instruments were functioning properly and when there were no anomalous weather conditions, then all three quantities agreed within the confidence limits. In Table 4 we present results of the comparison of these three quantities. A successful (within the confidence intervals) estimation of the quality of the measurements on the basis of comparison with radiosondes or comparison with the predicted values is designated by a plus sign in the table; an unsuccessful estimation is designated by a minus sign. The evaluation of the quality of the measurements on the basis of prediction is considered correct if it agrees, within the confidence limits, with the measurement of the radiosonde. In this manner, correct estimations correspond to the combinations (+, +) and (−, −), and incorrect estimations correspond to the combinations (+, −) and (−, +). The fifth column gives the numbers of correct estimations. From this table we see that the number of correct estimations, that is, the number of simultaneous correspondences of Q with $\tilde{Q}$ and with Q_S (+, +) and the number of correctly discarded values of Q (−, −), constitute 91% of the total. This percentage characterizes the overall success of this method of quality control.

Figure 5 shows examples of quality control applied during various weather conditions. In this figure we show time series of Q in clear conditions for all three Colorado stations, each of which is located at a different

TABLE 4. Estimations of quality control efficiency of relative precipitable vapor Q at three locations.

City	Estimation of Q on the basis of Q_s^*	Estimation of Q on the basis of $\tilde{Q}^*$	Number of combinations	Number of correct estimations**
Elbert	+	+	53	54 (100%)
	−	−	1	
	+	−	0	
	−	+	0	
Denver	+	+	68	75 (87%)
	−	−	7	
	+	−	10	
	−	+	1	
Platteville	+	+	67	72 (89%)
	−	−	5	
	+	−	7	
	−	+	2	
Total	+	+	188	201 (91%)
	−	−	13	
	+	−	17	
	−	+	3	

* Here, Q_s is relative precipitable vapor calculated from radiosondes; $\tilde{Q}$ is relative precipitable vapor predicted from Eq. (5). A plus sign indicates a successful estimation; a minus sign, an unsuccessful estimation.

** A correct estimation is a combination of (+, +) or (−, −) in columns 2 and 3.

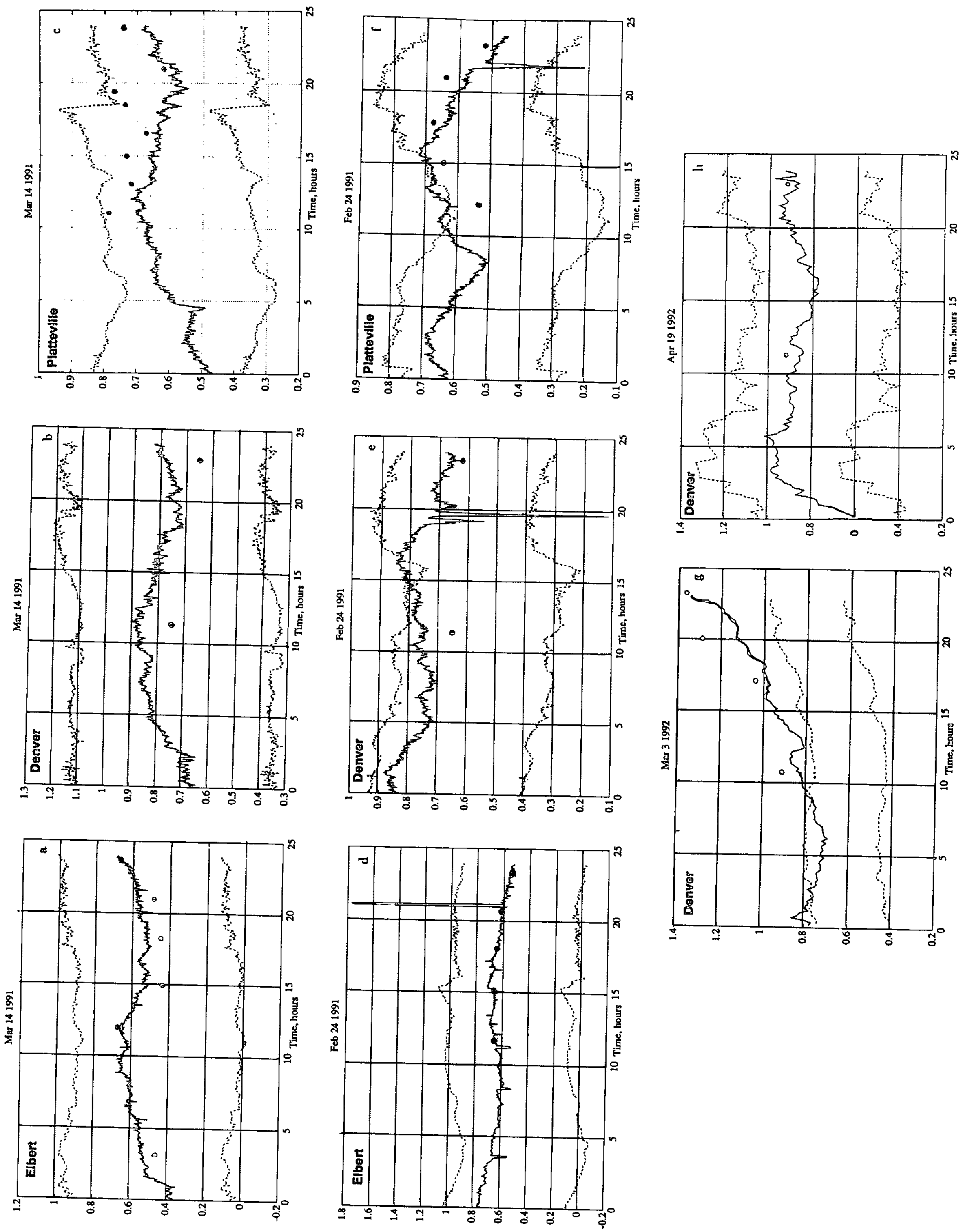

FIG. 5. Time series of radiometrically measured relative precipitable vapor Q (heavy lines), radiosonde measurements of Q (points), and 80% confidence intervals of Q predicted from surface measurements (dotted lines).

height above sea level. These heights are 1611, 1577, and 2103 m for Denver, Platteville, and Elbert, respectively. All three values of relative precipitable vapor, shown on each figure, agree within the confidence limits. The integrated moisture Q calculated from radiosondes is designated by large dots; Q from the radiometer is shown by continuous dashed lines. The dotted lines show the boundaries $\tilde{Q} \pm \Delta Q$, in which, with a probability of 80%, the admissible values of Q must lie. The same notation applies for all curves in Fig. 5. In Figs. 5d–f we show examples during the passage of a cold front on 24 February 1991. The advancing front was accompanied by a significant amount of snowfall. As a result of such weather, antenna effects were observed during 1000–2000 UTC. But the predicted values $\tilde{Q}$ corresponded well with the values Q_S calculated from radiosondes. In Fig. 5g we show an example for 3 March 1992, when the method of prediction of Q worked poorly. A very slowly approaching warm front was observed on that day. The surface air was rather dry (30%–35%), but at the level of 700–750 mb, the relative humidity was quite high (80%–90%). At the same time, a dense altostratus (As) or altocumulus (Ac) cloud was observed. As a result in the lower layers of the atmosphere, low humidity remained for a long time, and the integrated moisture Q was higher than $\tilde{Q}$ because the higher layer with its increased moisture was carried by the approaching warm front. As is evident from Fig. 5g, the method of control suggested in this paper underestimates Q in such a situation. In Fig. 5h, we show a time series of Q, when, during the course of a day, heavy clouds were observed (0.9–1.0 As, Ac), and the surface humidity was also high. In this case, all three values (Q, Q_S, $\tilde{Q}$) agreed very well.

5. Conclusions

In this work, we presented a method of quality control of relative precipitable vapor Q measured by dual-channel microwave radiometers. Our proposed method of control is based on statistical relations between Q, dewpoint temperature t_d, and shelter temperature t. From data taken for five years at Denver, Colorado, we calculated correlation coefficients between Q, t_d, and t. The database was subjected to preliminary quality control by comparing measurements from a radiometer and radiosondes, as well as surface measurements taken by WPL and NWS. As a result of this control, 25% of the data were excluded from further analysis. However, the simultaneous use of three pairs of measurements ensured that no gross outliers were present in this training set. The values of correlation coefficients that we obtained ($R_{t_dQ} = 0.70$, $R_{tQ} = 0.30$) showed that supplementary information on temperature was useful for estimating Q. To estimate Q, we used a linear predictor based on t_d and t. Regression coefficients were calculated for each month using the multiyear (five or six years, depending on the month) training set. Verification using independent data from radiosondes showed that the estimation of quality was correct 91% of the time. In addition, the method is simple and convenient, since the estimation of Q depends only on conventional meteorological surface observations of t_d and t. The radiometric measurement of Q is achieved with a correlation of greater than 0.96; the corresponding accuracy in the linear estimation of Q from surface measurements varied from 0.68 to 0.821. The regression coefficients varied by roughly a factor of 3 during a year; presumably the geographical variation in the coefficients would also be substantial.

Surface observations can be obtained for the Northern Hemisphere from the standard network of surface stations (their number in the Northern Hemisphere is greater than 2500, while the number of radiosonde stations is about 700). However, unless a radiometer is located at one of these stations, it is recommended that dual-channel radiometers have their own collocated, and possibly redundant, surface instrumentation.

In one meteorological situation that we encountered, our quality control method rejected valid data. In this case, an upper-level moisture front was not reflected by surface observations and is clearly a limitation of our method. To improve our entire quality control process, we are investigating multiple criteria, each of which involve completely independent measurement parameters. Currently, our anticipated methods include criteria using physical relations between the 20- and 31-GHz brightness temperatures, as well as those derived from limits on the temporal rate of change of precipitable water vapor.

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REFERENCES

Alishouse, J. C., J. B. Snider, E. R. Westwater, C. Swift, C. Ruff, S. Snyder, J. Vongsathorn, and R. R. Ferraro, 1990: Determination of cloud liquid water content using the SSM/I. *IEEE Trans. Geosci. Remote Sens.*, **28**, 817–822.

ARM Science Team, 1991: *Proc. Second Atmospheric Radiation Measurement (ARM) Science Team Meeting*, Denver, CO, U.S. Department of Energy, 160 pp. [Available from the National Technical Information Service, U.S. Department of Commerce, 5285 Port Royal Rd., Springfield, VA 22161.]

Askne, J. I. H., and E. R. Westwater, 1986: A review of ground-based remote sensing of temperature and moisture by passive microwave radiometers. *IEEE Trans. Geosci. Remote Sens.*, **24**, 340–352.

Cahalan, R. F., and J. B. Snider, 1989: Marine stratocumulus structure. *Remote Sens. Environ.*, **28**, 95–107.

Chakraborty, D., F. Davarian, and W. L. Stutzman, 1993: The K_a-band propagation measurements campaign at JPL. *IEEE Trans. Antennas Propag.*, **35**, 7–13.

Ciotti, P., E. R. Westwater, M. T. Decker, A. J. Bedard, and B. B. Stankov, 1987: Ground-based microwave radiometric observations of the temporal variation of atmospheric geopotential height and thickness. *IEEE Trans. Geosci. Remote Sens.*, **25**, 600–615.

Cox, S. K., D. McDougal, D. Randall, and R. Shiffer, 1987: FIRE—The First ISCCP Regional Experiment. *Bull. Amer. Meteor. Soc.*, **67**, 114–118.

Elgered, G., and G. V. Lundquist, 1984: A three-year study of radio wave propagation delays caused by tropospheric water vapor. *IEEE Trans. Antennas Propag.*, **30**, 390–395.

FIRE Project, 1990: FIRE phase II: ASTEX implementation plan. Astex Drafting Panel and Fire Project Office, 156 pp. [Available from the FIRE Project Office, MS 483, NASA Langley Research Center, Hampton, VA 23665-5225.]

Gandin, L. S., 1963: *Objective Analysis of Meteorological Fields.* Gidromet., 286 pp. (in Russian).

Gorelik, A. G., V. V. Kalishnikov, and Yu. A. Frolov, 1972: Comparison of satellite and radiosonde determinations of moisture content of the atmosphere. *Tr. TsAO,* **103**, 5, (in Russian).

Martner, B. E., D. B. Wuertz, B. B. Stankov, R. G. Strauch, E. R. Westwater, K. S. Gage, W. L. Ecklund, C. L. Martin, and W. F. Dabberdt, 1993: An evaluation of wind profiler, RASS, and microwave radiometer performance. *Bull. Amer. Meteor. Soc.*, **74**, 599–613.

Rasmussen, R., M. Politovich, J. Marwitz, W. Sand, J. McGinley, J. Smart, R. Pielke, S. Rutledge, D. Wesley, G. Strossmeister, B. Bernstein, K. Elmore, N. Powell, E. Westwater, B. Stankov, and D. Burrows, 1992: Winter Icing and Storms Project (WISP). *Bull. Am. Meteor. Soc.*, **73**, 951–974.

Reynolds, D. W., 1988: A report on winter snowpack augmentation. *Bull Amer. Meteor. Soc.*, **69**, 1290–1300.

Snider, J. B., E. R. Westwater, and L. S. Fedor, 1993: Radiometric correction for atmospheric effects in surface sensing from aircraft and satellites. *Proc. ESA/NASA Int. Workshop on Passive Microwave Remote Sensing Research Related to Land-Atmosphere Interactions,* St. Lary, France, ESA/NASA.

Westwater, E. R., 1993: Ground-based microwave remote sensing of meteorological variables. *Atmospheric Remote Sensing by Microwave Radiometry,* M. Janssen, Ed., J. Wiley & Sons, 145–213.

——, and J. B. Snider, 1989: Application of ground-based radiometric observations of millimeter wave radiation. *Alta Freq.*, **58**, 467–474.

——, and L. S. Fedor, 1991: The validation of microwave spaceborne observations by surface-based remote sensors. *Palaeogeography, Palaeoclimatology, Palaeoecology,* **90**, 247–252.