Detecting Discontinuities in Time Series of Upper-Air Data: Development and Demonstration of an Adaptive Filter Technique

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ABSTRACT

Recognizing the need for a long-term database to address the problem of global climate change, the National Climatic Data Center has embarked on a project called the Comprehensive Aerological Reference Data Set to create an upper-air database consisting of radiosondes, pibals, surface reports, and station histories for the Northern and Southern Hemispheres. Unfortunately, these data contain systematic errors caused by changes in instruments, data acquisition procedures, etc. It is essential that systematic errors be identified and/or removed before these data can be used confidently in the context of greenhouse-gas-induced climate modification.

The purpose of this paper is to illustrate the use of an adaptive moving average filter in detecting systematic biases and to compare its performance with the Schwarz criterion, a parametric method. The advantage of the adaptive filter over traditional parametric methods is that it is less affected by seasonal patterns and trends. The filter has been applied to upper-air relative humidity and temperature data. The accuracy of locating the time at which a bias is introduced ranges from about 600 days for changes of 0.1 standard deviations to about 20 days for changes of 0.5 standard deviations.

1. Introduction

In recent years the issue of global climate change due to increased anthropogenic emissions of greenhouse gases in the atmosphere has gained considerable attention and importance. Recognizing the need for a long-term database to address global climate changes, the National Climatic Data Center (NCDC) has embarked on a project called the Comprehensive Aerological Reference Data Set (CARDS) to create an upper-air database consisting of radiosondes, pibals, surface reports, and station histories for the Northern and Southern Hemispheres (Eskridge et al. 1995). Unfortunately, these data contain systematic errors caused by changes in instruments and data acquisition procedures (Elliott and Gaffen 1991; Schwartz and Doswell 1991; Garand et al. 1992; Gaffen 1993). It is essential that systematic errors be identified and/or removed before these data can be used confidently in the context of greenhouse-gas-induced climate modification.

The detection of abrupt changes due to instrumentation or data reduction procedures is complicated by the nature of daily temperature and humidity data. The time series of upper-air data can be characterized as high-frequency change combined with low-frequency seasonal and trend components. The seasonal components vary from year to year and, in the presence of the high-frequency component, are difficult to separate from abrupt discontinuities using parametric methods. In addressing this problem we presume that changes in data due to instrument change are characterized by their abrupt and persistent nature. This behavior is contrasted with long-term climate or short-term weather systems.

In this paper, we use purely statistical methods for the detection of biases in the upper-air temperature and humidity data. A purely statistical approach can be a valuable supplement to knowledge of radiosonde instrumentation, data reduction methods, and changes in data acquisition procedures, providing independent confirmation of and information about suspected inhomogeneities in the data. When good station histories are lacking, purely statistical methods can alert data users to potential biases.

The purpose of this paper is to describe and demonstrate an adaptive moving average filter. The low-pass filter, termed the adaptive Kolmogorov–Zurbenko filter (KZA filter), is a modification of the low-pass Kolmogorov–Zurbenko filter (KZ filter) described in

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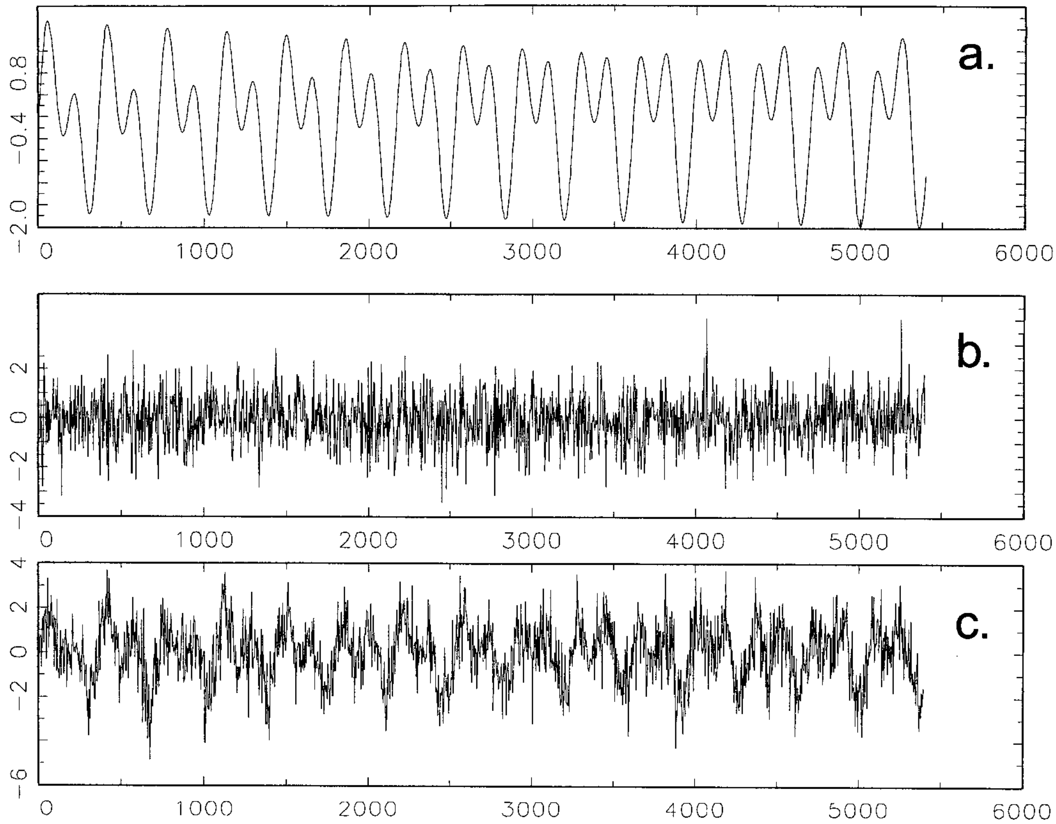

FIG. 1. Synthetic seasonal data (a) seasonal pattern, (b) normal independent noise (0, 1), and (c) sum of noise and seasonal pattern.

Zurbenko (1986) and Rao and Zurbenko (1994). The KZ filter has been used to separate different phenomena in time series data, namely, short-term fluctuations and seasonal and long-term variations. The KZ filter tends to smooth abrupt discontinuities, which makes it difficult to estimate their time of introduction. The KZA filter is an adaptive form of the KZ filter that reveals abrupt discontinuities in time series without modifying changes occurring slowly in time.

TABLE 1. Accuracy of break location estimation applied to normal, independent, random numbers. Values are root-mean-square error (RMSE) in the break location.

			RMSE	
Break pattern	Sample size	Break size	KZA ($q = 100, k = 3$)	SC
Single break in center	3000	0.1	556	458
		0.2	501	146
		0.5	46	25
Two breaks opposite direction	3000	0.1	584	369
		0.2	336	141
		0.5	41	24
Two breaks same direction	3000	0.1	552	238
		0.2	371	155
		0.5	44	20

The KZ and KZA filters have the spectral characteristics of rectangular filters, but do not require the latter's complicated parameter estimation. As such, the KZ and KZA filters cleanly separate frequencies in the data and leave them undistorted, permitting physical scientists to apply their expertise and intuition to filtered data. In other words, data filtered by the KZ or KZA filters reflect physical phenomena, unlike data treated by techniques that may remove unwanted components of the data but at the same time distort phenomena of interest.

The adaptive filter is compared with the Schwarz criterion, a parametric method (Schwarz 1978; Yao 1988), that fits a series of independent Gaussian observations to a model with a mean level that changes abruptly by unknown amounts at unknown times. The true model structure (i.e., the number of change points) is that which minimizes the Bayes information criteria (BIC), which combines the residual variance of models estimated with maximum likelihood with a penalty

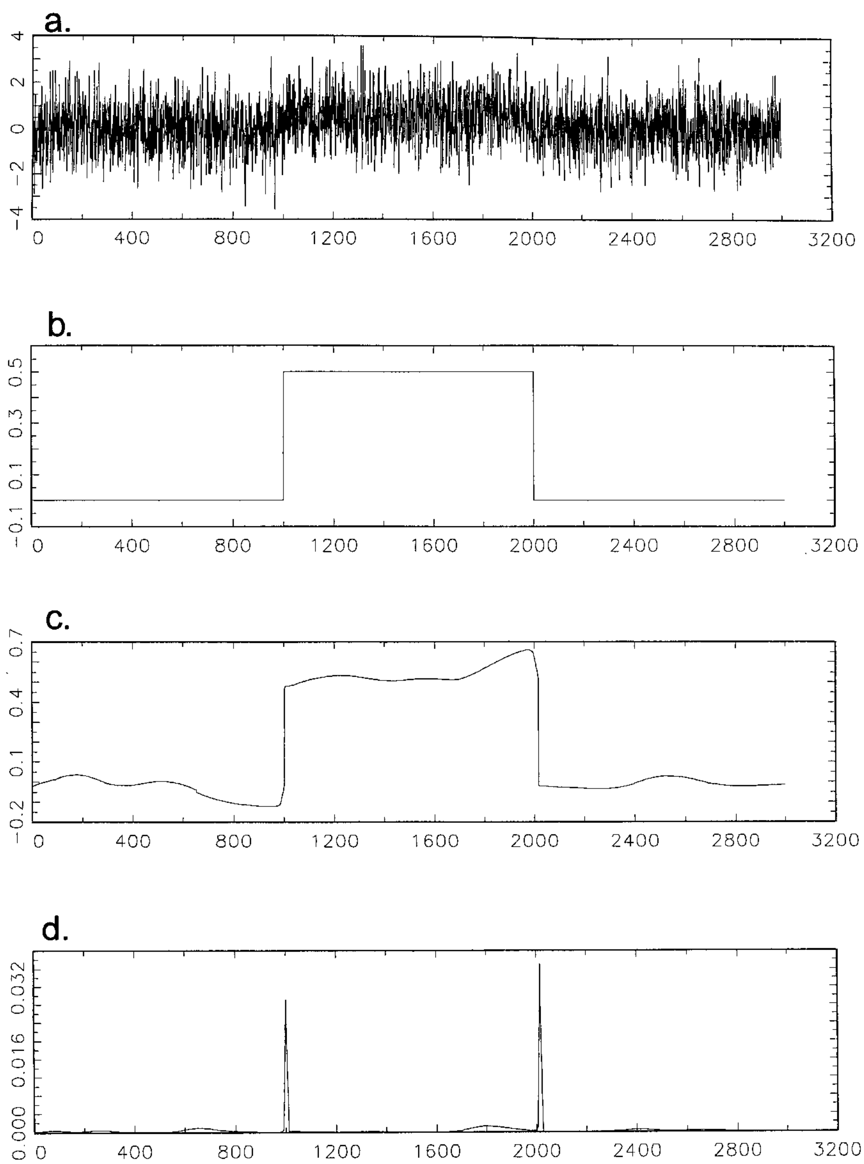

FIG. 2. KZA (q = 100, k = 3) filter result for 3000 standard normal random numbers with breaks of size 0.5 at 1000 and 2000: (a) Raw data, (b) baseline showing breaks, (c) filtered data, and (d) variance of filtered data.

for the number of parameters in the model. The Schwarz criterion provides an automatic method for choosing the number of break points that seems more appropriate for multiple-change point problems than hypothesis testing.

Synthetic data with known characteristics and actual data from stations with well-known histories (Oakland, California; Hilo, Hawaii; and Hong Kong) are used to illustrate the methods. Simulations with synthetic data provide operating characteristics of statistical methods under controlled conditions. Actual data were used to design appropriate simulation conditions and, in the case of stations with well-documented histories, to also provide some insight into the capabilities of the methods.

2. Methods

a. Adaptive moving average filter (KZA)

A long-term moving average filter separates seasonal variation and high-frequency change from long-term trend components, but dampens sharp breaks. There-

TABLE 2. Accuracy of break location estimation applied to a simulated pattern with trend = 0.0001/day. Values given are RMSE of the break location estimate.

Break pattern	Sample size	Break size	RMSE KZA ($q = 100, k = 3$)	RMSE SC
Single break in center	3000	0.1	711	739
		0.2	485	450
		0.5	40	22
Two breaks in opposite direction	3000	0.1	395	240
		0.2	423	278
		0.5	171	134
Two breaks same direction	3000	0.1	468	*
		0.2	198	493
		0.5	175	499

* No breaks detected.

fore, an adaptive filter was developed that dynamically adjusts the length of the moving average according to the rate of change of the process. As the rate of change increases, the length of the filter decreases.

The adaptive filter depends on an iterative moving average, which separates high-frequency variation from the original data. The simple moving average is computed according to

$$y_i = \frac{1}{2q+1} \sum_{j=-q}^{q} x_{i+j}, \tag{1}$$

where x_i are the original data, y_i the filtered data, and $2q + 1$ the filter window (Rao and Zurbenko 1994). The moving average process is iterative in that further time series "y_i" are created by replacing x_i with y_i in Eq. (1). Termed the KZ filter, this iterative simple moving average is an efficient low-pass linear filter discussed in detail in Zurbenko (1986).

The adaptive filter is defined as follows:

- The original time series $X(t)$ is subjected to the $KZ_{q,k}$ filter, where q is the half-length of the simple moving average and k is the number of iterations of the same filter:

$$Z(t) = KZ_{q,k}[X(t)]. \tag{2}$$

- The absolute values $D(t)$ of the differenced $Z(t)$ are defined by

$$D(t) = |Z(t+q) - Z(t-q)|. \tag{3}$$

- The rate of change of $D(t)$ is defined by

$$D(t)' = D(t+1) - D(t). \tag{4}$$

When a data point is located on an area of increasing $D(t)$, the half-length of the moving average before the data point (tail, q_T) is equal to q [same q as Eq. (1)], while the half-length ahead of the data point (head, q_H) is shortened as a function of $D(t)$. In the decreasing area of $D(t)$, only the half-length behind the data point (tail) will be reduced. In the vicinity of a break point, the filter length is reduced, "sharpening" the moving average.

The adaptive filter is defined by

$$Y_t = \frac{1}{q_H(t) + q_T(t)} \sum_{i=-q_T(t)}^{q_H(t)} X_{t+i}, \tag{5}$$

where

$$q_H(t) = \begin{cases} q, & \text{if } D'(t) < 0 \\ f(D(t))q, & \text{if } D'(t) \geqslant 0, \end{cases}$$

$$q_T(t) = \begin{cases} q, & \text{if } D'(t) > 0 \\ f(D(t))q, & \text{if } D'(t) \leqslant 0, \end{cases}$$

and q is the half-length in the initial $KZ_{q,k}$ filter. The term $f(D(t))$ is defined by

$$f(D(t)) = 1 - \frac{D(t)}{\max[D(t)]}. \tag{6}$$

The raw data are then iteratively filtered as described by Eq. (1), but using the new filter lengths q_t and q_h.

Plots of the filtered data (Y_t) provide visual evidence of discontinuities in time series. More quantitative estimates of discontinuity significance can be based on an analysis of the sample variances of Y_t, defined by

$$\hat{\sigma}_t^2 = \frac{\sum_{i=q_t}^{q_h} \{Y_i - \bar{Y}_t\}^2}{q_t + q_h}. \tag{7}$$

When there are no breaks, the local maxima of $\hat{\sigma}_t^2$ (peaks in the variance) are approximately independent

TABLE 3. Accuracy of break location estimation applied to a simulated seasonal pattern. Values given are RMSE of the break location estimate.

Break pattern	Sample size	Break size	RMSE KZA ($q = 36, k = 3$)	RMSE SC
Single break in center	5400	0.1	177	2255
		0.2	99	305
		0.5	46	19
Two breaks in opposite direction	5400	0.1	222	1472
		0.2	165	888
		0.5	95	30
Two breaks same direction	5400	0.1	353	1149
		0.2	151	744
		0.5	86	58

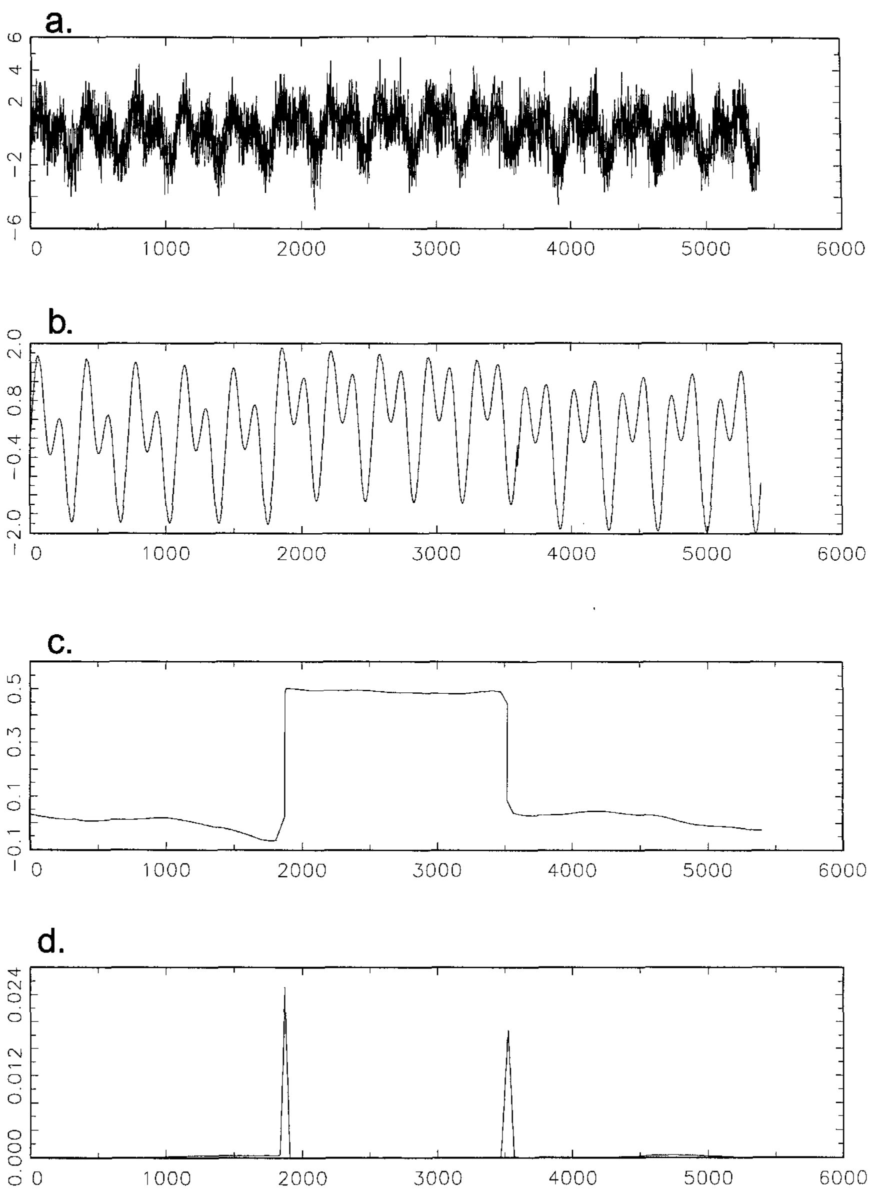

FIG. 3. KZA (q = 360, k = 3) filter applied to 5400 synthetic seasonal data with breaks of size 0.5 at 1800 and 3600: (a) Raw data, (b) noise-free pattern, (c) KZA filtered data, and (d) variance of filtered data.

and exponentially distributed. The expected value of a variance peak is a function of q and k (half-length and number of iterations) and the variance of the high-frequency component of the unfiltered time series. The expected number of peaks is about $n/(2qk^{0.5})$.

The distribution of local maxima of $\hat{\sigma}_t^2$ in the absence of breaks, including the relationship between q, k, and the average peak size, was determined via simulation. When the value of $\hat{\sigma}_t^2$ exceeded the 95% upper tail of the exponential distribution with the same expected value, it was attributed to a break.

b. The Schwarz criterion

The Schwarz criterion (Schwarz 1978; Yao 1988) is given by

$$SC(R') = \frac{n}{2} \ln \sigma_{R'}^2 + R' \ln n, \qquad (8)$$

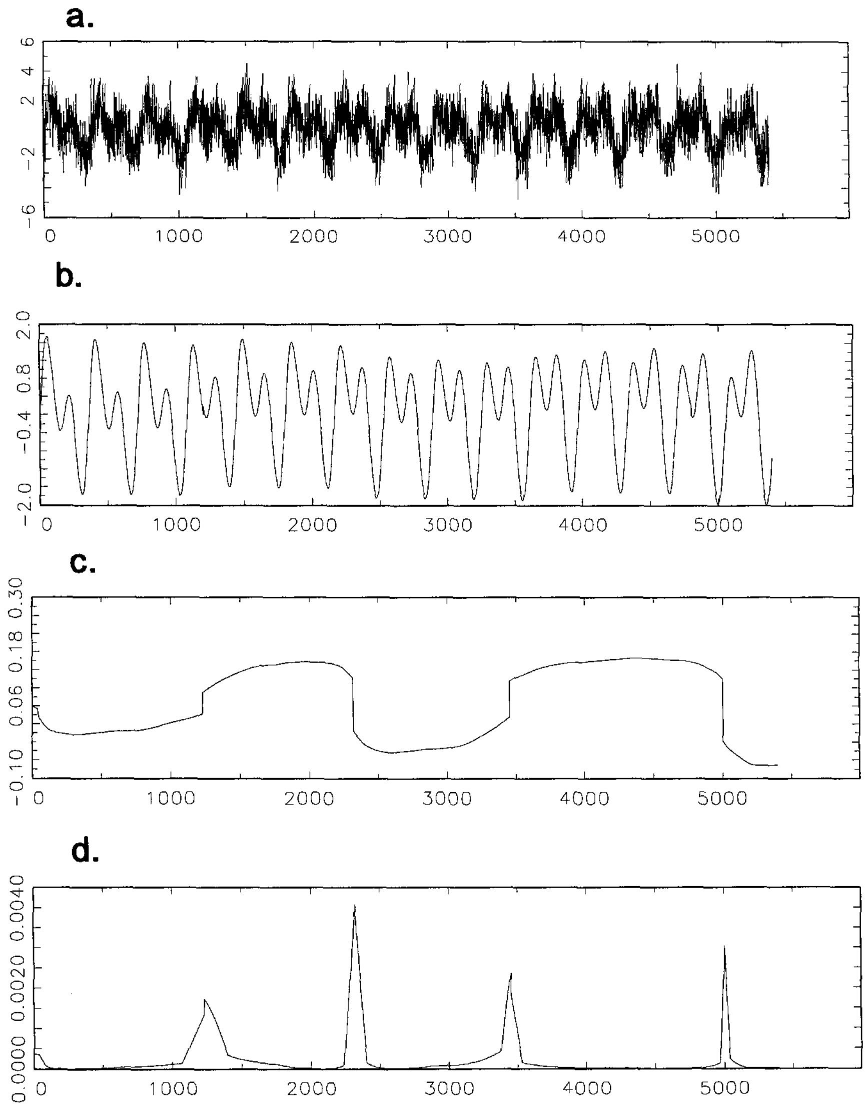

FIG. 4. KZ ($q = 360$, $k = 3$) and KZA ($q = 360$, $k = 3$) filters applied to 5400 seasonal data and standard normal random numbers with breaks of size 0.2 at 1200, 2400, 3600, and 4800: (a) Raw data, (b) noise-free pattern, (c) KZA-filtered data, and (d) variance of KZA filtered data.

where R' is the number of break points minimizing $SC(R')$, n is the sample size, and σ_R^2 is the variance of the residuals created by subtracting the $R' + 1$ means that result from R' break points. The $SC(R)$ is computed for all possible values of R and break locations, the minimum being $SC(R')$. The advantage of a method such as the Schwarz criterion over hypothesis testing is that it automatically estimates the dimension of a model (number of breaks), as well as their sizes and locations. The Schwarz criterion is based on Bayes information criterion (Akaike 1974).

c. *Seasonal adjustment*

When parametric methods were applied to actual or synthetic data having seasonal patterns, the original series of daily observations were first averaged in bimonthly periods and seasonally adjusted using the program PEST (Brockwell and Davis 1987). The seasonal adjustment of PEST is a difference between a simple seasonal average and a one-year moving average. The simple seasonal average contains both seasonal fluctuation and long-term trend, while the one-year moving average contains only long term variation. Their dif-

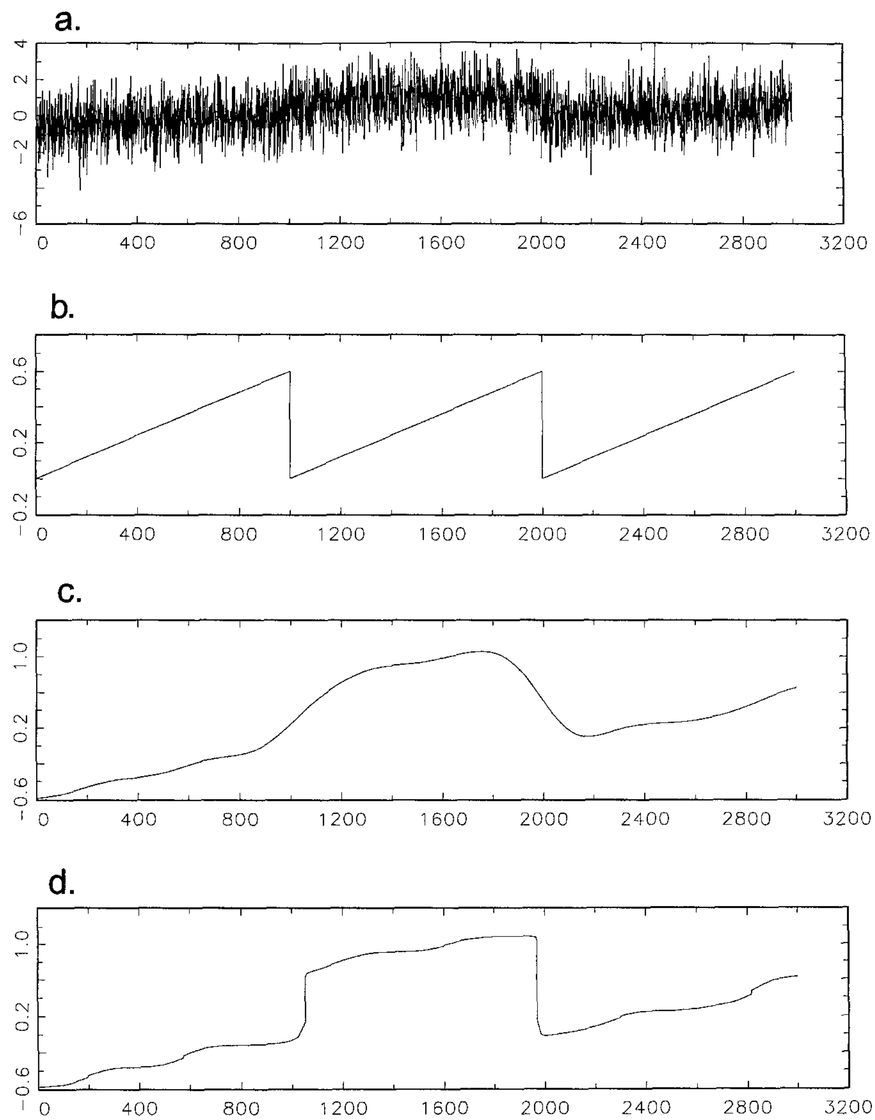

FIG. 5. KZ (q = 100, k = 3) and KZA (q = 100, k = 3) filters applied to 3000 standard normal random numbers with breaks of size 0.6 at 1000 and 1.2 at 2000, and a trend magnitude of 0.0006 day: (a) Raw data, (b) baseline showing trend and breaks, (c) KZ filtered data, and (d) KZA filtered data.

ference, therefore, is seasonality without longer-term variation.

The adaptive filter and the Schwarz criterion were evaluated under conditions described below.

d. Simulation studies

Simulated series have been generated by adding Gaussian white noise to a determinisitic "mean series," where the latter has breaks, trends, and seasonal patterns. Break sizes ranged from 0.1 to 0.5 standard deviations of the random numbers, denoted "σ." Seasonal patterns consisted of the sum of three sine functions plus white noise. The period of the synthetic seasonal data was 360 days. The cycle did not repeat exactly from year to year in order to simulate the variable seasonal effects observed in actual data. The white noise represented 50% of the total variability of the data, and break sizes ranged from 0.1 to 0.5 standard deviations of the white noise (Fig. 1).

When the KZA filter was applied to synthetic data, the parameters were q = 1 yr, k = 3 for data with seasonal patterns and q = 100 days, k = 3 for all other cases.

TABLE 4. Estimated break locations and sizes for Hilo relative humidity at 850 mb and 0000 UTC. Station history (h): (a) change in station elevation, Feb 1954; (b) observation times changed from 0300 and 1500 to 0000 and 1200, Jul 1957; (c) carbon hygristor was introduced on 27 Feb 1965; (d) a new sensor was put into operation on 2 May 1972; (e) new carbon hygristor, Oct 1980; (f) change from VIZ ACCU-LOK to VIZ B, Oct 1988; and (g) no station history to support these changes.

Day				Day − night				
Location		Size		Location		Size		
KZA (mo/d/yr)	Schwarz (mo/yr)	RH	σ	KZA (q = 365, k = 3)	Schwarz	RH	σ	h
	12/54	2.0[b]						a
04/22/57	3/57	−0.3[a]	0.02	06/10/57	7/58	−0.4[a]	0.02	b
	1/62	−3.8[b]			5/63	−3.7[b]		g
03/19/65	2/65	−3.8[a]	0.27	01/14/65	5/65	−9.7[a]	0.58	c
04/01/72	5/72	14.0[a]	1.01	03/18/72	5/72	13.0[a]	0.78	d
				02/05/83		−0.2[a]	0.01	g
	1/85	3.0[b]						g
02/12/87		0.1[a]	0.01	04/19/88	5/88	0.2[a]	0.01	f

[a] Size of break = $Y_{t+1} - Y_t$; Y_t = value of KZA filtered data at time t.
[b] Size of break = $\bar{X}_{i+1} - \bar{X}_i$, where $\bar{X}_{i+1}$ = mean of seasonally adjusted values occurring between breaks i and $i + 1$, and $\bar{X}_i$ = mean of seasonally adjusted values occurring between breaks $i - 1$ and i.

Methods were compared on the basis of root-mean-square error (RMSE) of the estimated break location, defined by

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{N} (\hat{t} - t)^2}{N}\right]^{1/2}, \qquad (9)$$

where N is the number of simulations, $\hat{t}$ is the estimated break time, and t is the actual break time. Sequences of random numbers were meant to simulate daily data. Therefore, RMSE values can be considered to have units of days.

For each combination of break pattern, break size, and noise level at least 50 repetitions were carried out. This number is adequate for determining approximate operating characteristics of the methods used and for comparing them, the principal purposes of this paper.

e. *Database of upper-air measurements*

The actual data used for illustrations were relative humidity data collected at 850 mb for Hilo, Hawaii, and Oakland, California, and temperature data collected at 850 mb at Hong Kong. For Hilo and Oakland, data collected at 0000 and 1200 (all times UTC), and the difference between 0000 and 1200 were used. For Hong Kong, only 0000 data were used due to the large number of missing data in the 1200 record. The difference series can indicate whether a suspected break is due to observation inhomogeneities or natural variability. The time frames for the data used are 1950–90, 1948–90, and 1956–91 for Hilo, Oakland, and Hong Kong, respectively. All of these stations have relatively well-documented histories. The simulated seasonal patterns more closely resembled relative humidity data than temperature data with its relatively small component of short-term variability.

f. *Adjustment of bias*

A procedure to remove bias detected by the KZA was illustrated with the Hilo relative humidity. Bias adjustment included the following steps: 1) The KZA filter is used to estimate the location of step changes in time series data. 2) Using the filtered data, the magnitude of the break (step change) is calculated from the difference between average values calculated before the break and after the break. The averages comprise q values on either side of the break (one filter half-length, before and after). 3) The magnitude and the location of the break are then used to adjust the original time series data, with the most recent data presumed to be correct. The overall trend in the time series was determined before and after adjustment of the two largest breaks using linear regression.

3. Results and discussion

a. *Independent, normally distributed random numbers*

A break size of 0.1 σ severely tests both methods. RMSE values for all three break patterns were not much better than if the locations had been selected at random (Table 1). A window of ± a single RMSE would span about 3 years for either method. A break of 0.1 σ, not well located by either method, may be of significance from a climatological point of view.

For break sizes of 0.2 and 0.5 σ, the Schwarz criterion more precisely detects breaks than the KZA filter

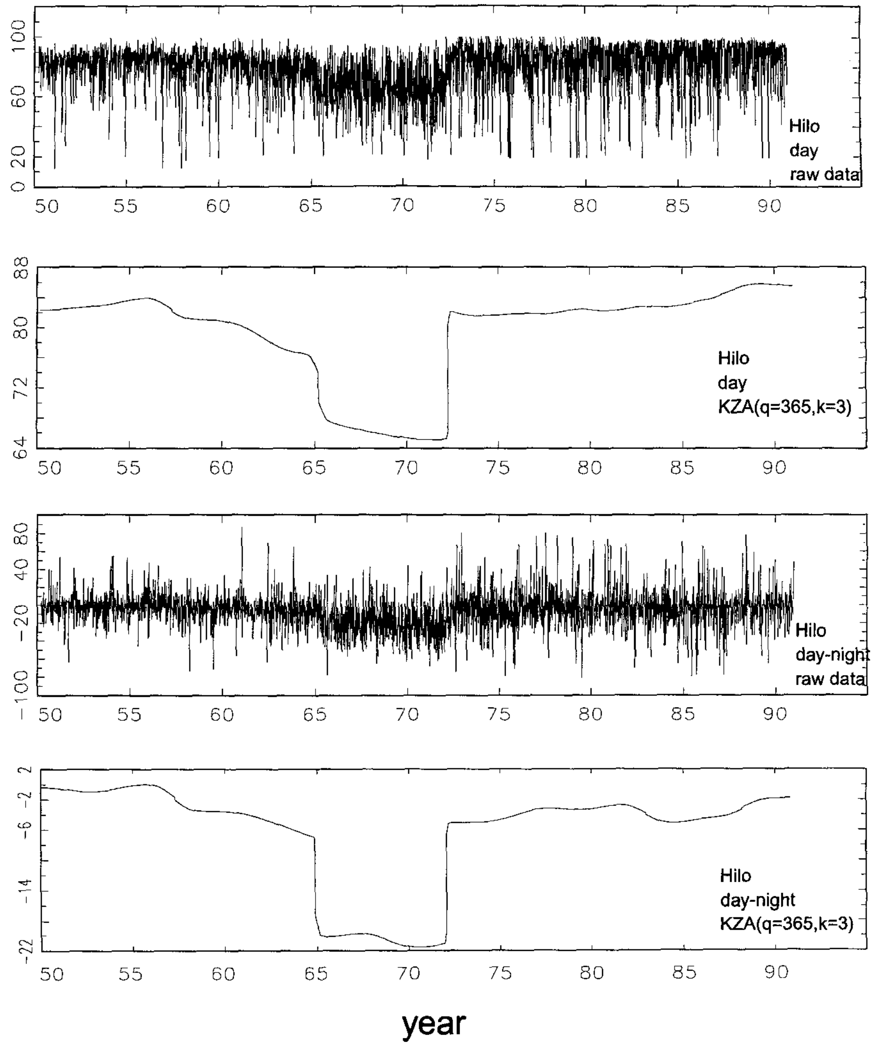

FIG. 6. KZA (q = 365, k = 3) filter for Hilo (a) raw daytime data, (b) Daytime filtered data, (c) raw day − night differences, and (d) and filtered day − night differences.

(Table 1). The KZA filter has a range of RMSE values from about 40 to 600 days for breaks of 0.5 to 0.1 σ, respectively. The Schwarz criterion has a range of RMSE values of about 20 to 500 days for breaks ranging from 0.5 to 0.1 σ. In the case of two breaks, RMSE values are not much affected by their direction. Figure 2 is a typical result with KZA filter and normal random numbers.

Locating a break of size 0.5 σ with an RMSE of 20 to 40 days is not a remarkable achievement because breaks of that size can easily be discerned from a time series plot.

The KZA filter's minimum detectable break size is a function of the filter parameters (q and k). The variance due to short-term variability of the filtered data decreases by a factor $2qk^{0.5}$ relative to the unfiltered data. Variance components due to long-term trend or discontinuities are unaffected by the filter. Therefore, one could conceivably detect discontinuities of any size simply by increasing the factor $2qk^{0.5}$. However, variance reduction is accompanied by an increase in the filter window. Breaks within the window (size $2qk^{0.5}$) cannot be easily distinguished.

b. *Random numbers with a linear trend*

The performance of both methods deteriorates in the presence of a trend. In addition, the Schwarz criterion tends to have a smaller location RMSE than the KZA filter for normal random numbers plus a linear trend (Table 2) for single breaks in the center and two breaks in opposite directions. When two breaks occur in the

TABLE 5. As in Table 4 but for Oakland relative humidity at 850 mb and 0000 UTC. Station history (h): (a) observation times changed from 0300 and 1500 to 0000 and 1200, Jul 1957; (b) carbon hygristor was introduced on 3 Apr 1963; (c) change from Hypsometer to Transponder type, May 1969; (d) relative humidity duct, 12 Mar 1972; (e) new carbon hygristor, Dec 1980; (f) change from Transponder type to VIZ ACCU-LOK, Feb 1981; (g) change from VIZ ACCU-LOK to VIZ B, Oct 1988; and (h) no station history to support these changes.

Day				Day − night				
Location		Size		Location		Size		
KZA (q = 365, k = 3)	Schwarz	RH	σ	KZA (q = 365, k = 3)	Schwarz	RH	σ	h
01/20/56	12/56	2.0[a]	0.09					h
02/10/59	9/58	−9.2[a]	0.41					a
				07/28/63	1/64	−1.4[a]	0.07	b
10/02/72	9/72	3.9[a]	0.17	03/16/71	5/72	4.7[a]	0.22	d
					1/73	−1.9[b]	0.10	h
10/13/77		0.9[a]	0.04					h
09/24/81	9/81	2.2[a]	0.10	09/28/80		−0.6[a]	0.03	e, f
08/04/84	12/83	−1.5[a]	0.07					h
04/14/90		0.8[a]	0.04					g

[a] Size of break = $Y_{t+1} - Y_t$; Y_t = value of KZA-filtered data at time t.

[b] Size of break = $\bar{X}_{i+1} - \bar{X}_i$, where $\bar{X}_{i+1}$ = mean of seasonally adjusted values occurring between breaks i and $i + 1$, and $\bar{X}_i$ = mean of seasonally adjusted values occurring between breaks $i - 1$ and i.

same direction, however, the Schwarz criterion does not perform as well as the KZA filter.

c. Seasonal patterns

In the presence of a simulated seasonal pattern and break sizes of 0.1 and 0.2 σ, the location RMSE of the KZA filter is much smaller than for the Schwarz criterion (Table 3). The Schwarz criterion tends to detect breaks near the end points of a time series, leading to RMSE values that are larger than if break locations had been selected at random. For break sizes of 0.5 σ, the location RMSE of Schwarz criterion is smaller than for the KZA filter. Figure 3 is a typical result for the KZA filter applied to a simulated seasonal pattern.

d. Other simulated patterns

Other simulated patterns were also tested. Figure 4 illustrates a KZA filter result with seasonal data having breaks every 1200 days. The filtered data clearly indicate the breaks, while the Schwarz criterion was unable to detect any breaks in data with this break pattern because the multiple breaks disrupt attempts at seasonal adjustment. Similarly, Fig. 5 shows data with a linear trend and breaks that negate the trend. The filter clearly shows the breaks and the trend as well. This example identifies the problem that one may have with parametric trend adjustment when the trend is interrupted by the breaks.

e. Hilo and Oakland relative humidity data

1) HILO RELATIVE HUMIDITY, (0000, 850 MB)

Breaks found by the KZA filter and the Schwarz criterion are summarized in Table 4 along with a summary of changes in instrumentation and observation times. Possible explanations for three of four breaks identified by the KZA filter in the daytime data and four of five breaks found in the day–night differenced data can be found in the station histories. Those with possible explanations were the largest detected and are evident in the figures of the raw data (Fig. 6). Those breaks not supported by station histories are quite small, on the order of 0.01 to 0.02 σ (standard deviation of process noise). The Schwarz criterion identified several breaks not detected by the KZA filter.

2) OAKLAND RELATIVE HUMIDITY (0000, 850 MB)

Breaks found by the KZA filter and the Schwarz criterion in the Oakland data are summarized in Table 5. Seven and three breaks, respectively, were detected in the day and day–night differenced data by the KZA filter. The Schwarz criterion detected five breaks in the day and three in the day − night differenced data. One might conclude that many of the breaks in the daytime data were due to natural variability and, hence, not apparent in the day − night differenced data. The two largest breaks for each set of data (10 February 1959 and 2 October 1972 for day data, 28 July 1963 and 16 March 1971 for the day − night differences) have possible explanations in the station histories, as do three of the smaller breaks. The Schwarz criterion detected one relatively small break not detected by the KZA filter. This break has no explanation in the station history. In addition, the Schwarz criterion missed several of the smaller breaks detected by the KZA filter. As with

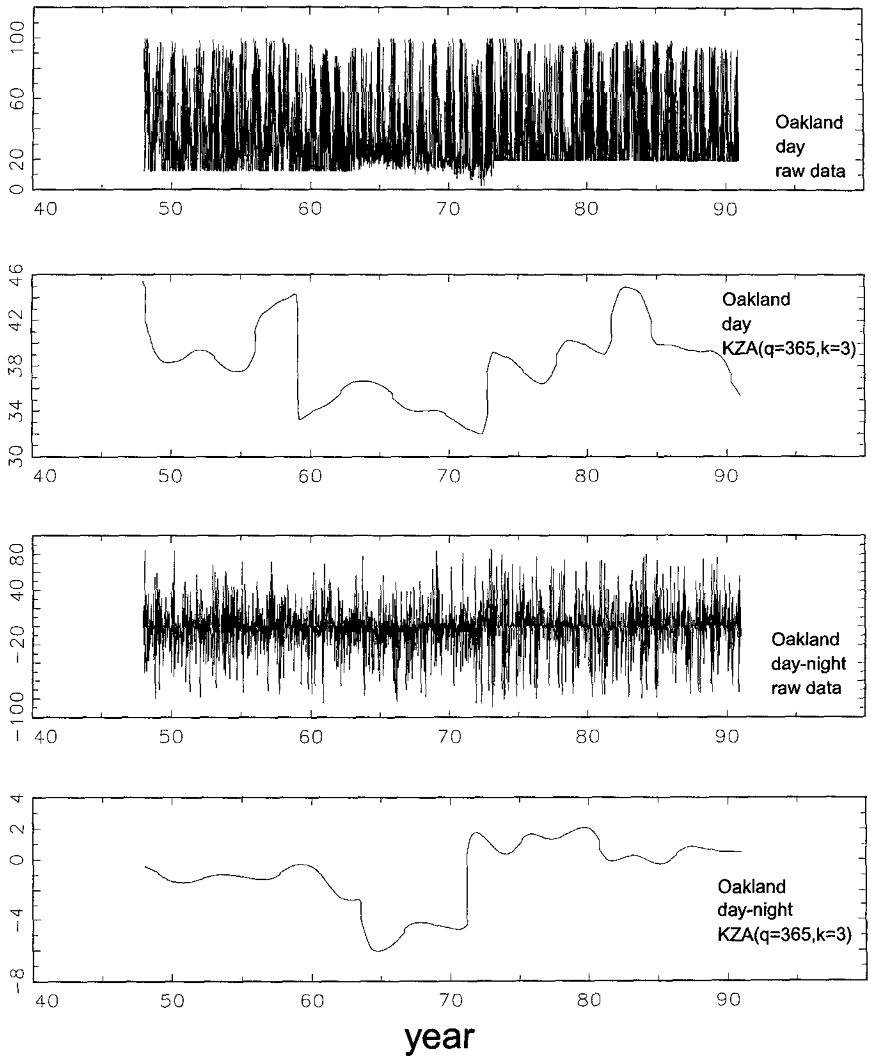

FIG. 7. KZA (q = 365, k = 3) filter for Oakland (a) raw daytime data, (b) daytime filtered data, (c) raw day–night differences, and (d) filtered day–night differences.

the Hilo data, the largest breaks are evident in figures of the raw data (Fig. 7).

3) HONG KONG TEMPERATURE (0000, 850 MB)

The KZA filter detected eight breaks in the Hong Kong data, ranging in size from 0.002 to 0.055°C (0.01 to 0.40 σ, Fig. 8 and Table 6). The station history has possible explanations for three of those breaks. The Schwarz criterion located only three breaks, one of which did not coincide with those detected by the filter.

f. Example of bias adjustment

To illustrate the impact of instrument bias on data analysis, the major trend in the Hilo relative humidity was computed before and after the two largest discontinuities in the Hilo relative humidity data were adjusted. These breaks correspond to a new carbon hygristor (27 February 1965) and a new duct (2 May 1972). Figure 9 shows the smoothed (KZ filter) data and trend line before and after bias adjustment. Notice that the major trend changes from positive to negative when these two instrument modifications are accounted for.

4. Summary

The KZA filter is an exploratory nonparametric method for locating discontinuities in time series of upper air data in the presence of seasonal patterns and trends. The Schwarz criterion is a parametric method,

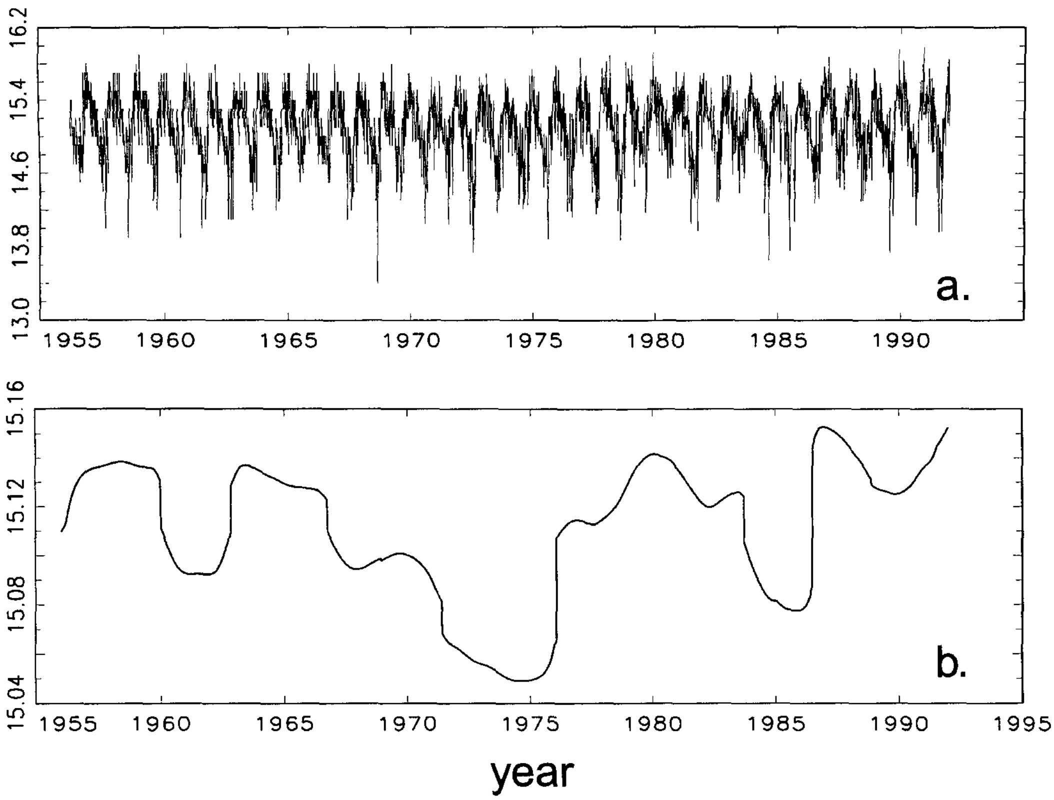

FIG. 8. KZA (q = 365, k = 3) filter for Hong Kong (a) raw data and (b) filtered data.

which tends to more precisely estimate break locations than the KZA filter when tested with normal independent data. The performance of both methods is adversely affected by trends. The KZA filter more precisely estimates break locations in the presence of simulated seasonal patterns.

TABLE 6. As in Table 4 but for Hong Kong temperature data at 850 mb and 0000 UTC. Station history (h): (a) changed from British Met. Office Kev MK to Vaisala RS13, Jan 1969; (b) changed from Vaisala RS13 to Vaisala RS 18, Dec, 1974; (c) changed from Vaisala RS18 to Vaisala RS21, Dec 1980; (d) automated data conversion, 1981; (e) changed from Vaisala RS21 to Vaisala RS80, Dec 1983; and (f) no station history to support these changes.

Location		Size		
KZA (q = 365, k = 3)	Schwarz	°C	σ	h
12/30/59		−0.019[a]	0.14	f
10/29/62		0.019[a]	0.14	f
9/27/66		−0.013[a]	0.09	a
6/01/71	6/72	−0.012[a]	0.09	f
	8/72	0.29[b]		f
1/29/76	6/76	0.041[a]	0.30	b
9/16/83		−0.018[a]	0.13	e
6/26/86		0.055[a]	0.40	f
11/18/88		−0.002[a]	0.01	f

[a] Size of break = $Y_{t+1} - Y_t$, value of KZA-filtered data at time t.
[b] Size of break = $\bar{X}_{i+1} - \bar{X}_i$, where $\bar{X}_{i+1}$ = mean of seasonally adjusted values occurring between breaks i and $i + 1$, and $\bar{X}_i$ = mean of seasonally adjusted values occurring between breaks $i - 1$ and i.

Both KZA filter and Schwarz criterion located relatively large discontinuities in time series of upper-air data that coincided with instrument modifications recorded in station histories. Several breaks not supported by station histories were also detected by both methods.

More accurate location of relatively large breaks may be possible by using the KZA filter to approximately locate them, followed by application of a parametric method such as the Schwarz criterion. The latter methods would not be much affected by seasonality when applied to windows of raw data smaller than about 60 days.

Because the form of the Schwarz criterion used in this paper depends on independent and trend-free data, which are rare in atmospheric science, it should probably be considered an exploratory method to be supported by other methods and/or station histories. An advantage of the Schwarz criterion over many other parametric methods that may partially overcome problems with trends and serial correlation is that it can be modified to incorporate such data structures (i.e., autoregressive moving average models with an abruptly changing mean). Of

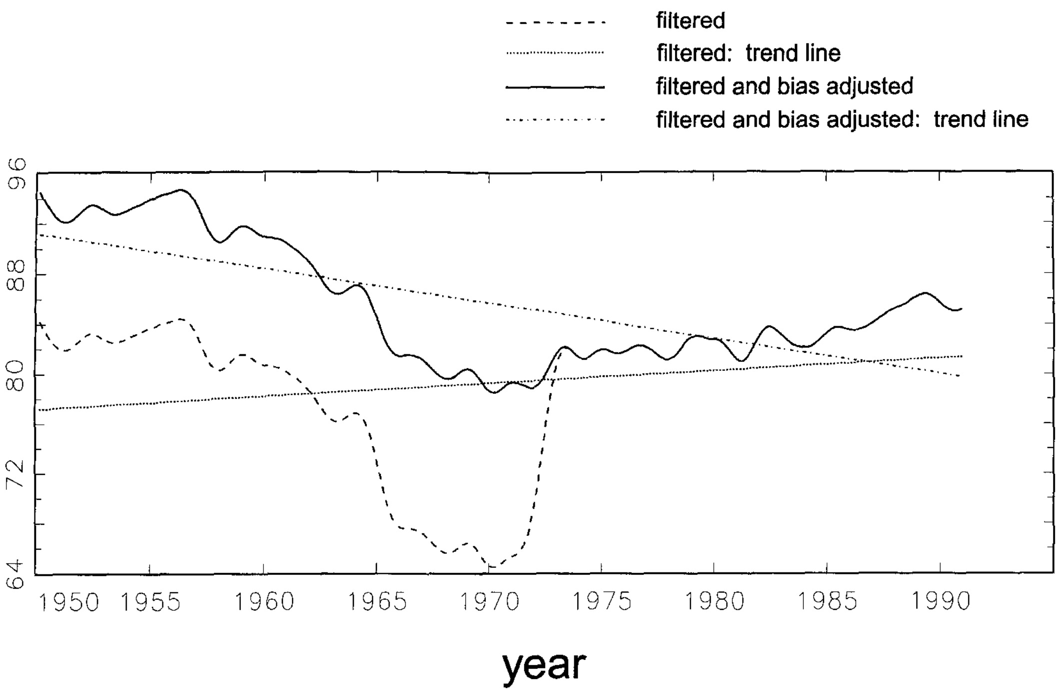

FIG. 9. Smoothed Hilo relative humidity at 850 mb before and after adjustment for the two largest biases (KZ with $q = 365$, $k = 3$).

course, increasing the number of parameters comes with a penalty of increased complexity and decreased sensitivity.

Breaks too small to be detected may be of significance from a climatological point of view, but were not well located in synthetic data by either of the methods used in this paper. Indeed, relatively large breaks, such as those present in the Hilo relative humidity data, are easily discerned without statistical methods. Detecting and precisely locating small breaks may be facilitated with a regional filter that utilizes information from neighboring stations and several elevations at the same time. A regional KZA filter that separates the common low-frequency component of neighboring locations is currently under development.

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