New techniques for climate data homogenization

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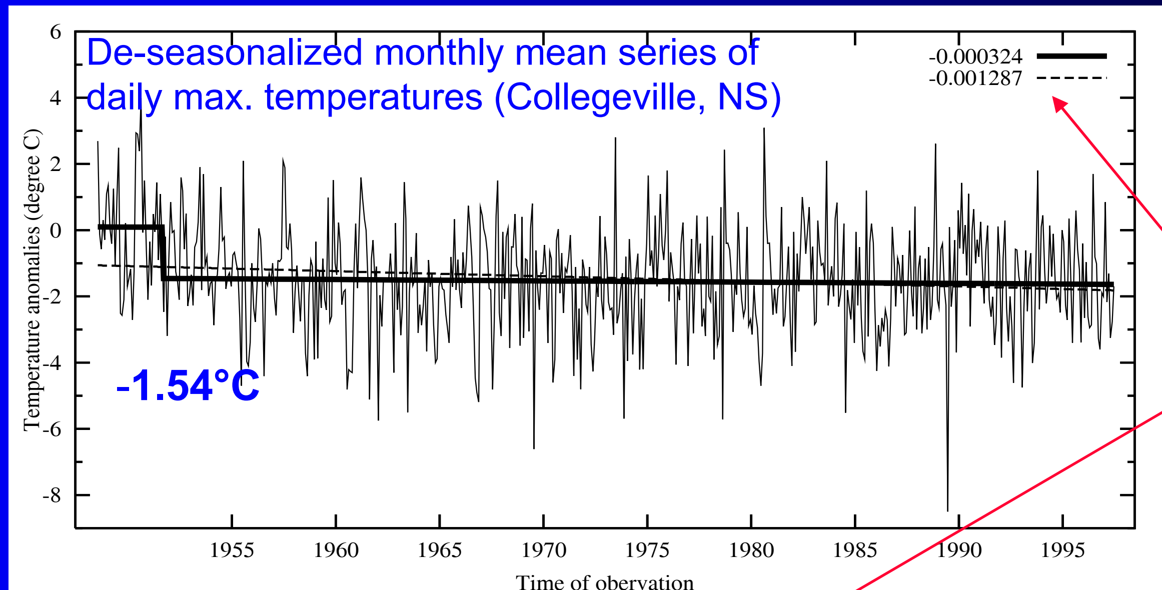
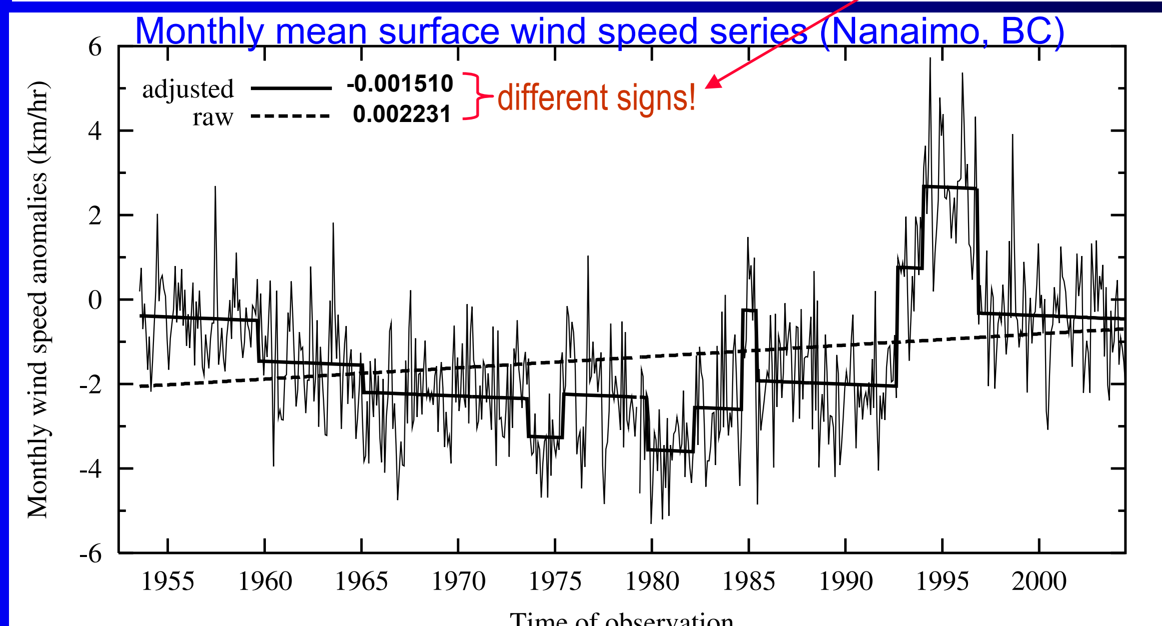
Some examples of discontinuity in climate data series

1. Temperature:



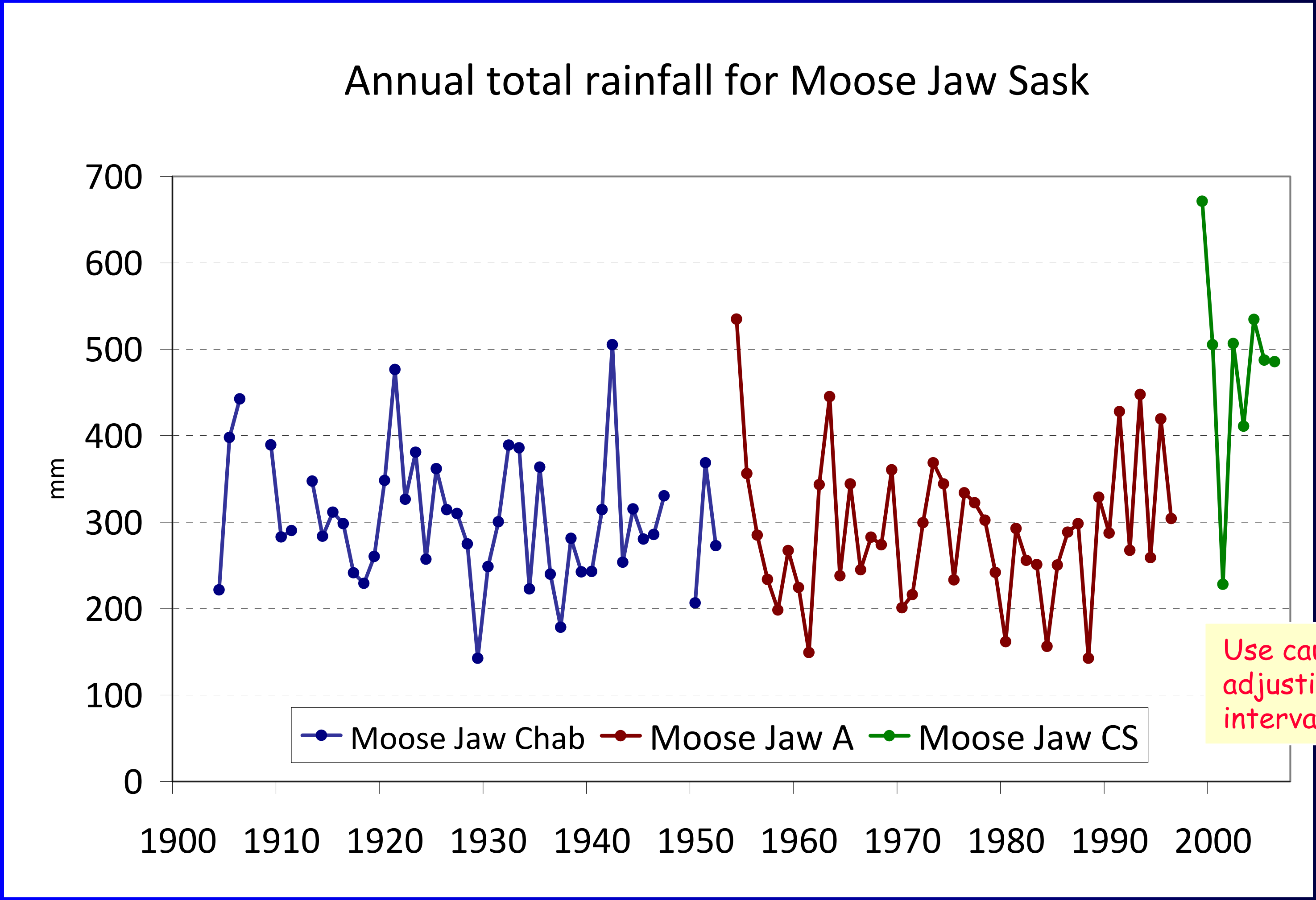
Effects of mean-shift on trend estimation

2. Wind speed:



Mean, var., & extreme indices biased!

3. Precipitation - discontinuity due to joining of observations from nearby stations

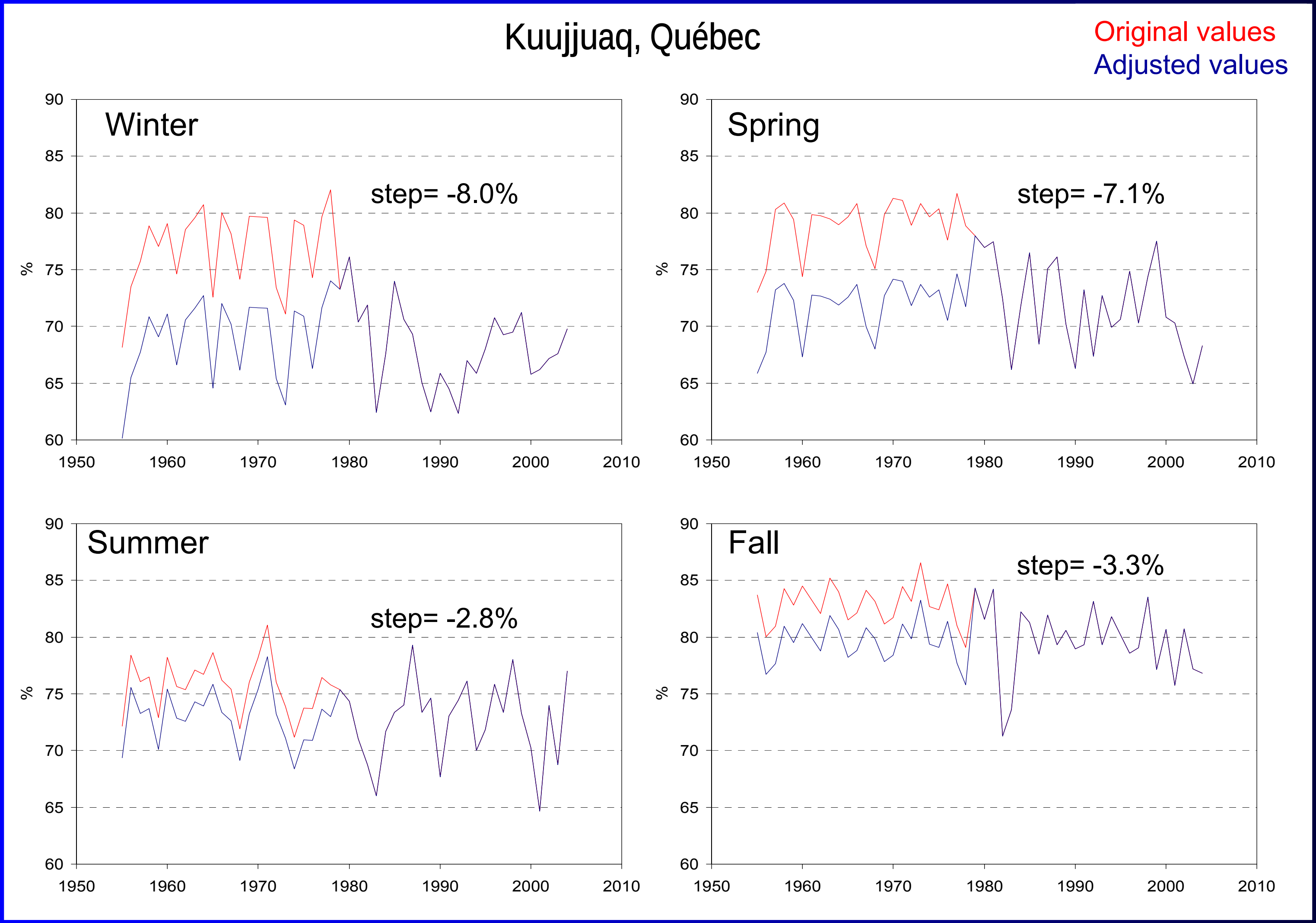


Use caution before adjusting to short interval

Courtesy of Lucie Vincent and Eva Mekis

See Vincent and Mekis (2008), Discontinuities due to joining precipitation station observations in Canada, J. App. Meteor. Climatol., in press.

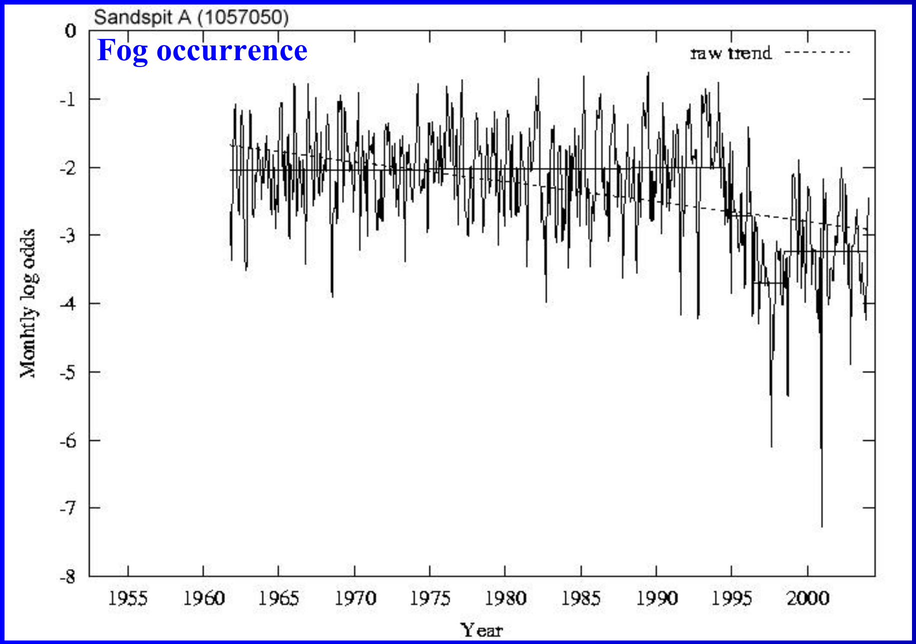
4. Relative humidity – discontinuity due to introduction of dewcel in June 1978

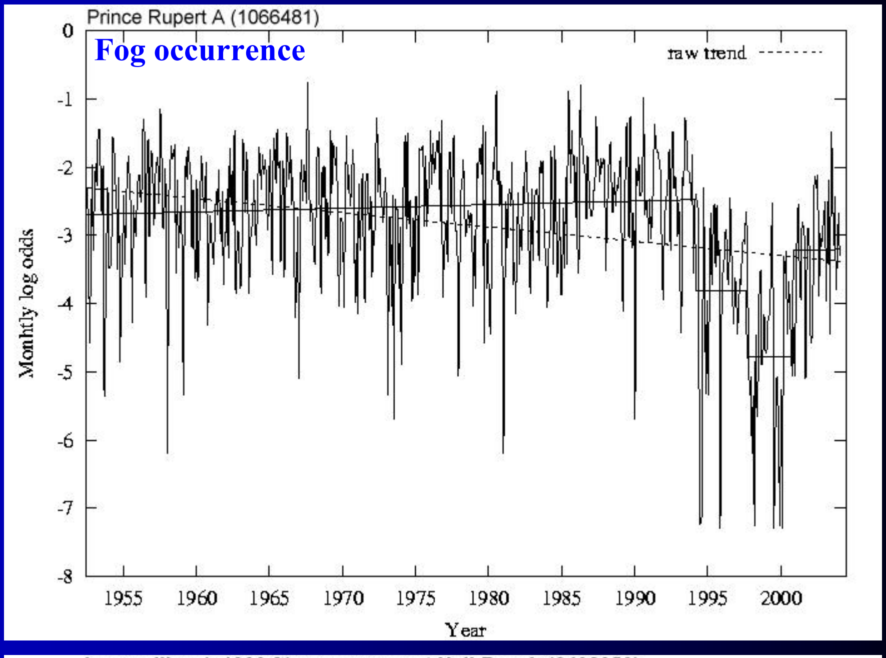


Courtesy of Lucie Vincent

See Vincent et al. (2007), Surface temperature and humidity trends in Canada for 1953-2005. *J. Clim.*, **20**, 5100-5113.

5. Fog & low ceiling occurrence frequency - Effects of mean-shift on trend estimation



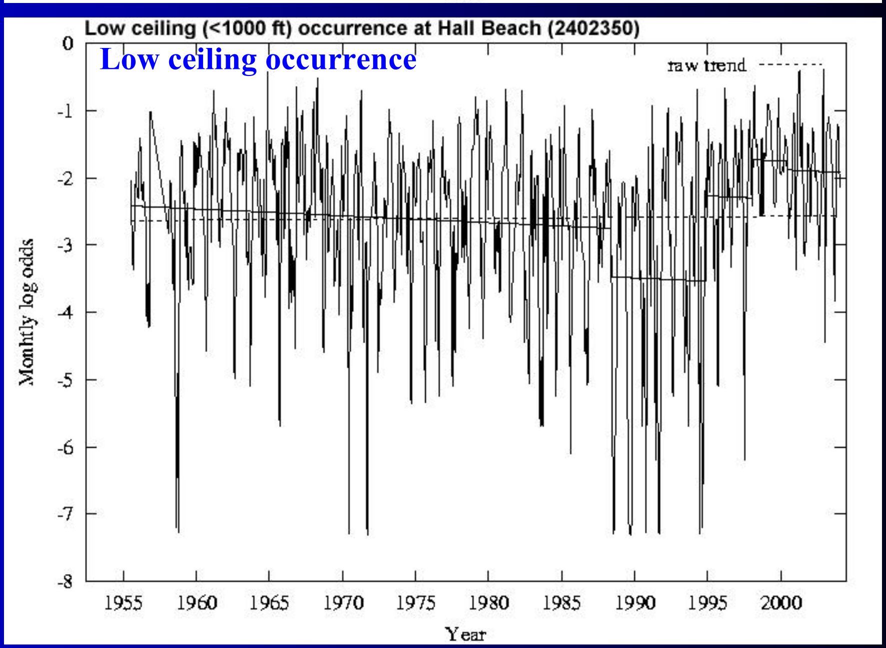


$$\text{Log odds } \eta_t = \log\left(\frac{S_t + 0.5}{M_t - S_t + 0.5}\right)$$

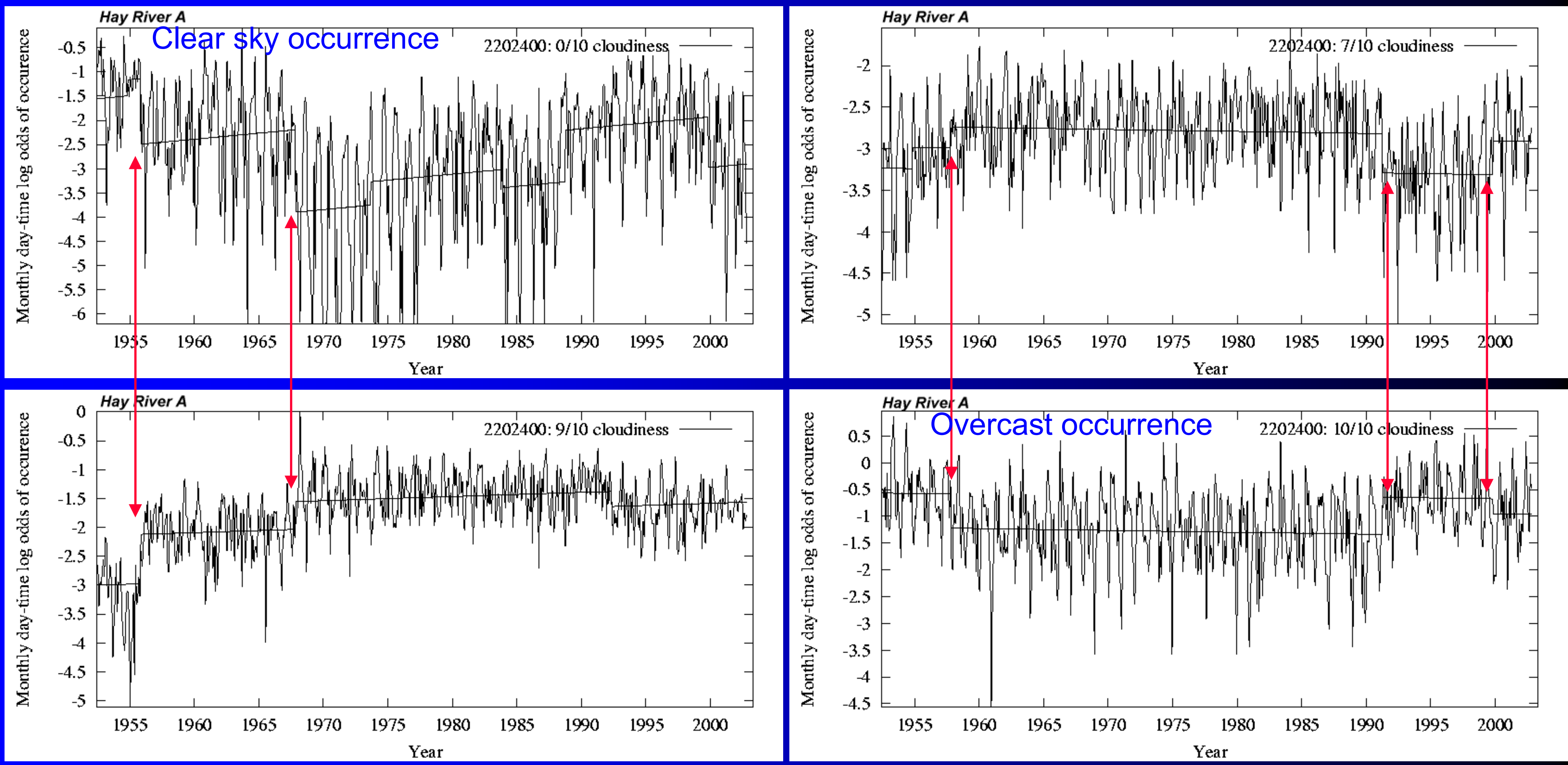
M_t is the number of observations in month t

S_t is the number of occurrences in month t

$f_t = \dfrac{S_t}{M_t}$ is the frequency of occurrence

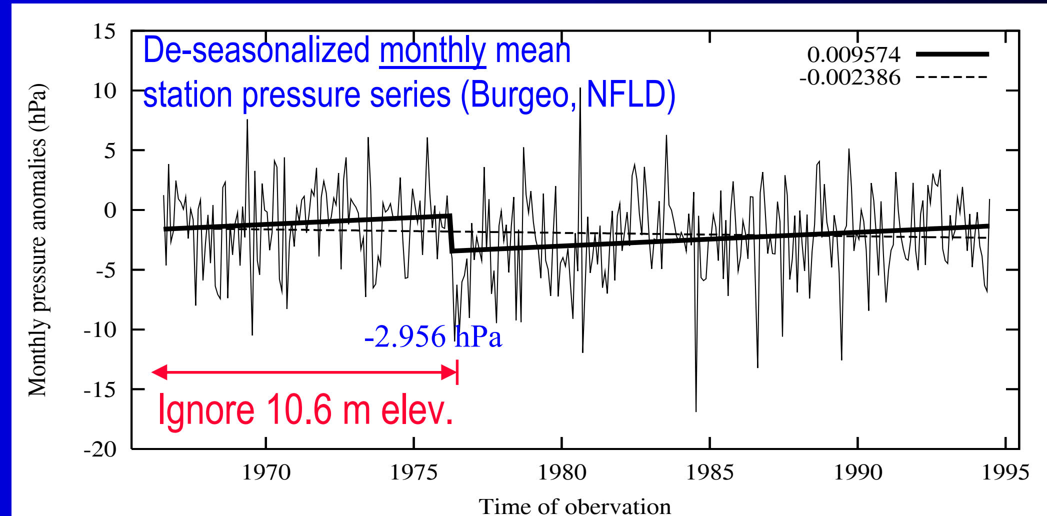


6. Cloudiness frequency data



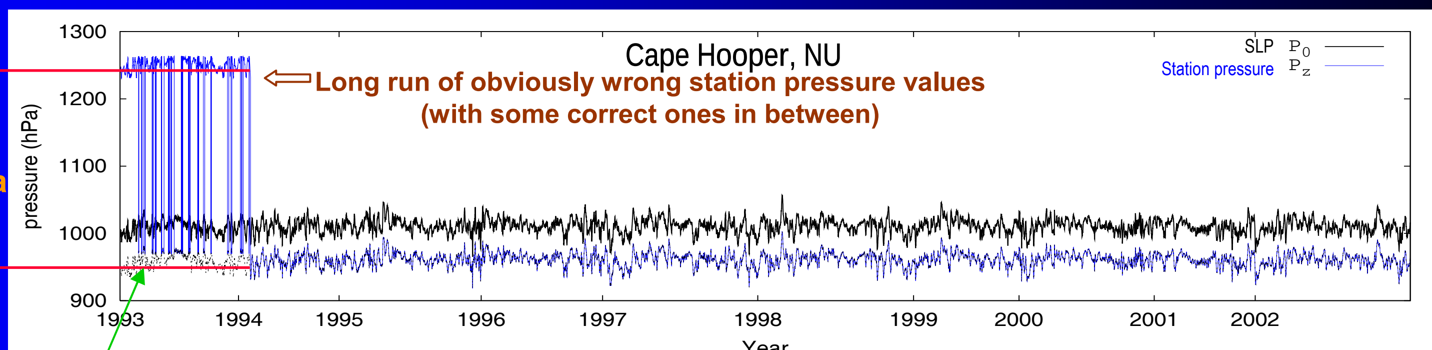
7. Pressure data:

Relatively small shift
but it changes the sign
of trend estimate



- examples of hourly station pressure values

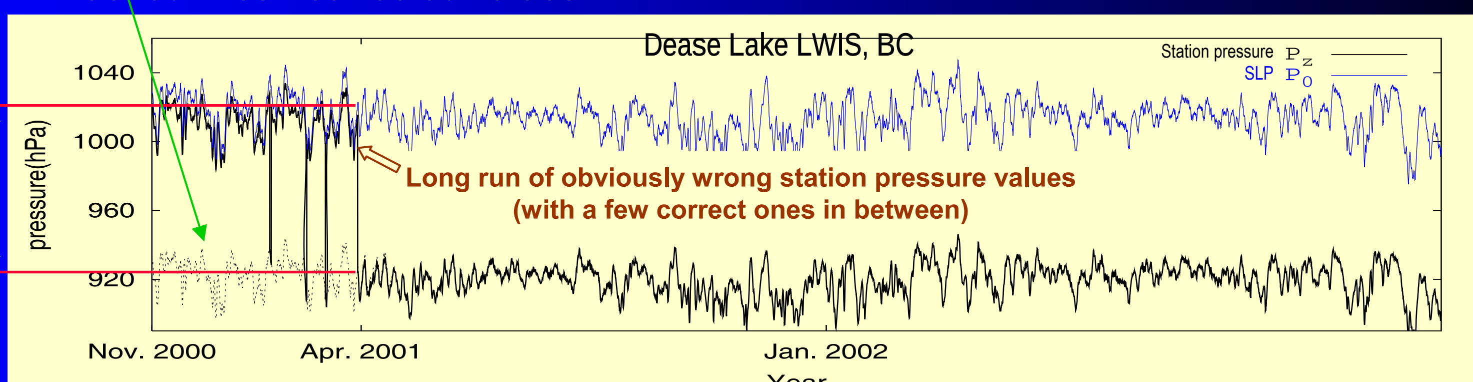
Δ = 294.6 hPa



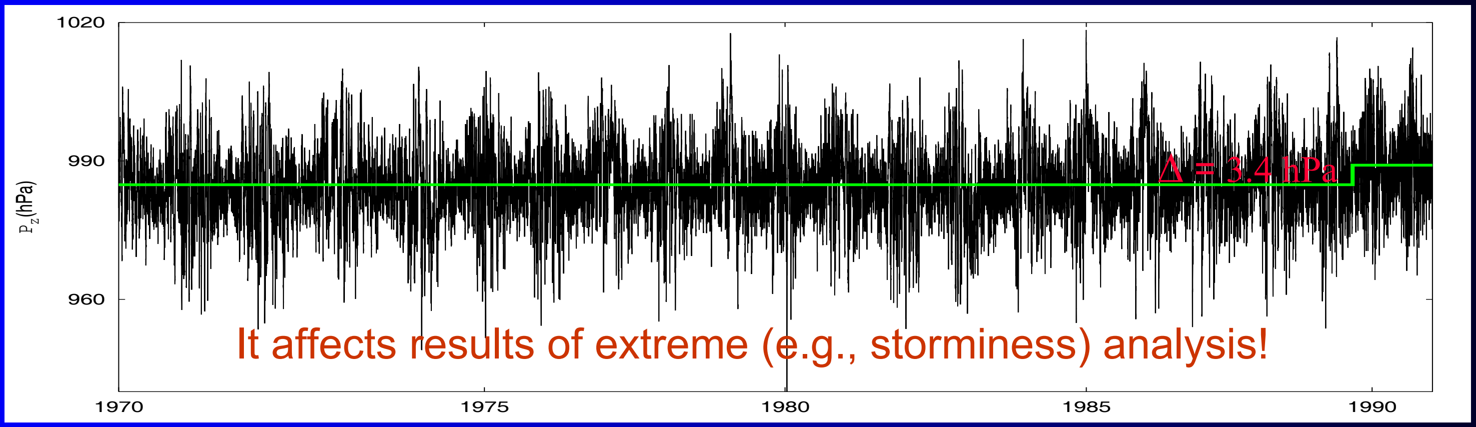
Huge errors!

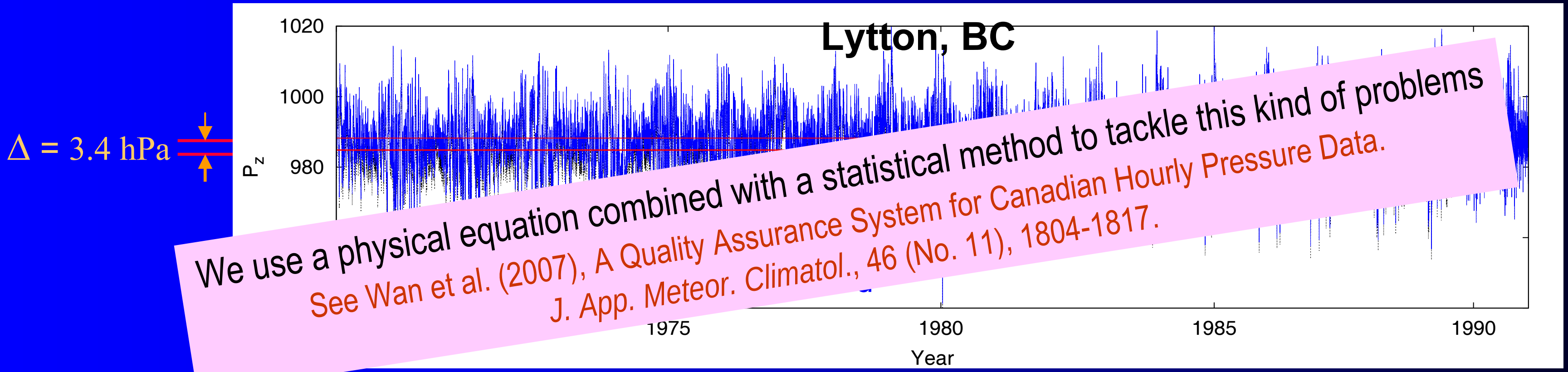
Dashed lines - corrected values

Δ = 91.4 hPa



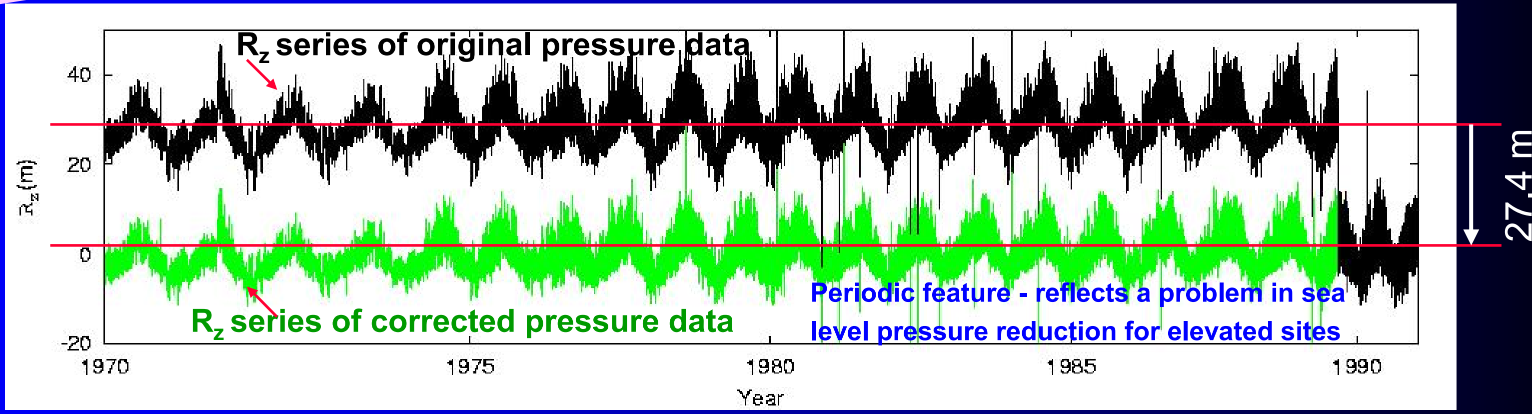
- Another problematic hourly pressure series (relocation with elev. drop of 27.4 m)





We use a physical equation combined with a statistical method to tackle this kind of problems

See Wan et al. (2007), A Quality Assurance System for Canadian Hourly Pressure Data. J. App. Meteor. Climatol., 46 (No. 11), 1804-1817.



Data discontinuities are inevitable due to inevitable changes in observing instrument/location/environment… and evolving technology

Such discontinuities not only affect trend assessment, but also affect

- *calibration of statistical relationships for use in statistical weather forecast,*
- *estimates of other statistics that are used to study climate variability and climate extremes, and to validate model simulations*
- *many other aspects of our study and understanding of the climate system*

Huge amount of $ spent on collecting climate data

→ big waste of $ if there were no effort to clean up the data

→ more and more effort devoted to climate data homogenization

Data Homogenization Tools:

e.g., hydrostatic equation to adjust pressure data for elevation changes, log wind profile for anemometer height adjustments for wind speeds

Metadata

1. Use physical relationships to correct some known shifts
2. Use statistical methods to detect shifts and estimate their magnitude

Most commonly used statistical methods include

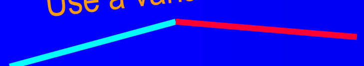
1) SNH test for detecting mean-shifts in zero-trend series (Alexandersson 1986):

2) TPR3 test for detecting mean-shifts in constant trend series (Wang 2003):

Special cases:

Use a variant of TPR3!

3) TPR4 test for detecting mean-shifts and/or trend-changes (Lund & Reeves 2002):



(a trend-change without an accompanying mean-shift)

Problems/drawbacks of these changepoint detection methods:

1. Uneven distribution of false alarm rate and detection power (details next)
2. Model errors are assumed IID Gaussian
3. For a series that contains at most one changepoint

Detection of a changepoint in a homogeneous series

Our recent studies

1. Propose two penalized tests to even out distribution of false alarm rate & detection power

2. Extend these penalized tests to account for the first order autocorrelation

3. Propose a stepwise testing algorithm for detecting multiple changepoints

Now, developing methods to deal with non-Gaussian data (e.g. daily precip.), and multi-categorical data (e.g., frequencies of cloudiness conditions)

The remainder of this presentation - outline

- The uneven distribution problem of the old methods
- The new methods and their detection power aspects (*vs*. those of the old methods)
- The RHtestV2 software package
- Examples of application

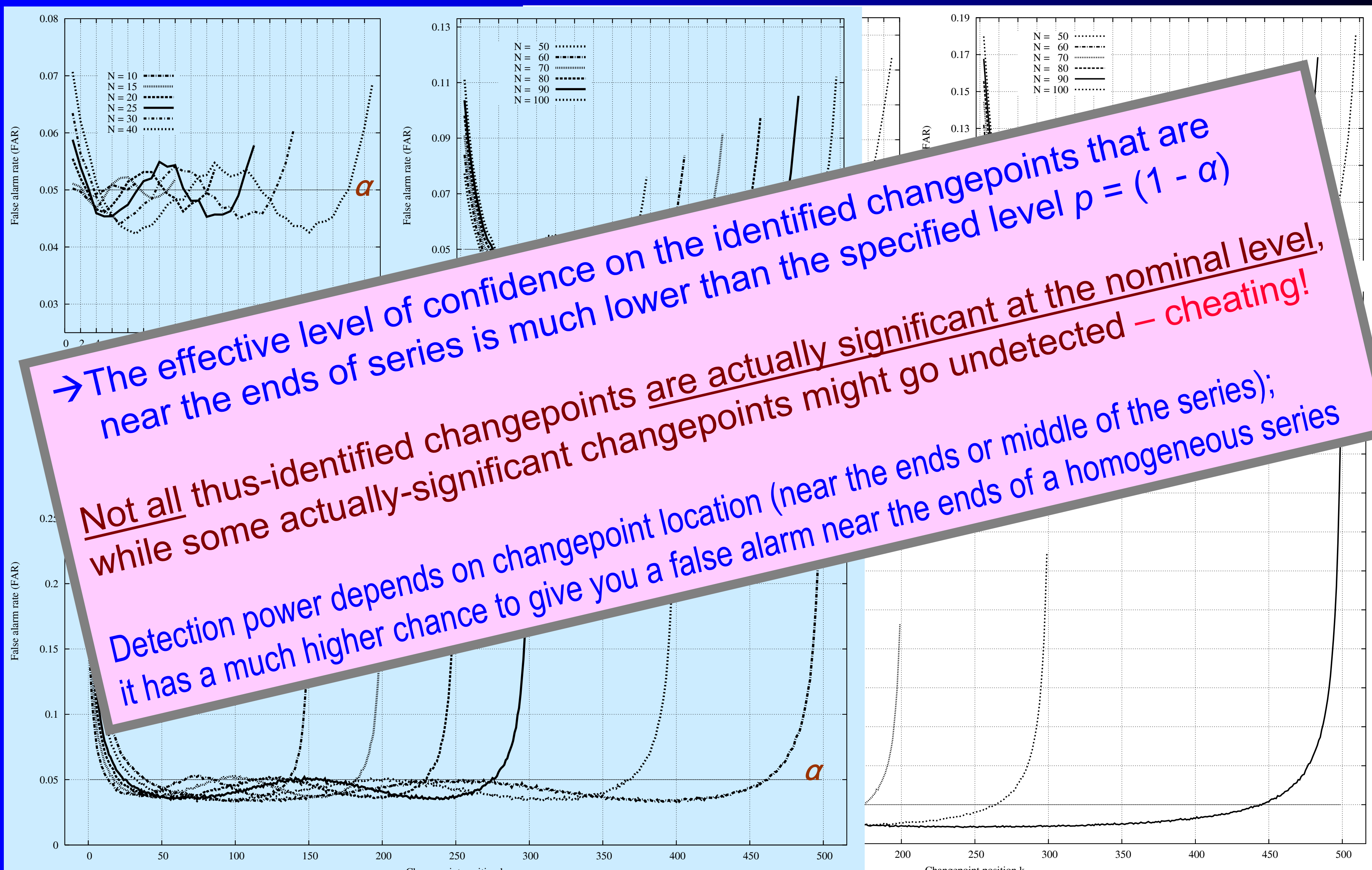
Problems!

SNH & TPR3 suffer from the effect of unequal sample sizes ($N_1 = k \neq N_2 = N\text{-}k$, generally)

→ FAR(k) = $\alpha_e(k) \neq \alpha$, $p_e(k) \neq p$!

TPR3: W-shape FAR(k) curves!

SNH test: U-shape FAR(k) curves!



→The effective level of confidence on the identified changepoints that are near the ends of series is much lower than the specified level $p = (1 - \alpha)$

Not all thus-identified changepoints are actually significant at the nominal level, while some actually-significant changepoints might go undetected – cheating!

Detection power depends on changepoint location (near the ends or middle of the series); it has a much higher chance to give you a false alarm near the ends of a homogeneous series

Wang et al. (2007) propose a Penalized Maximal *t* (PMT) test to even out the U-shaped FAR(*k*) curves of the SNH type tests:

∩-shape penalty *P*(*k*): (thick curves)

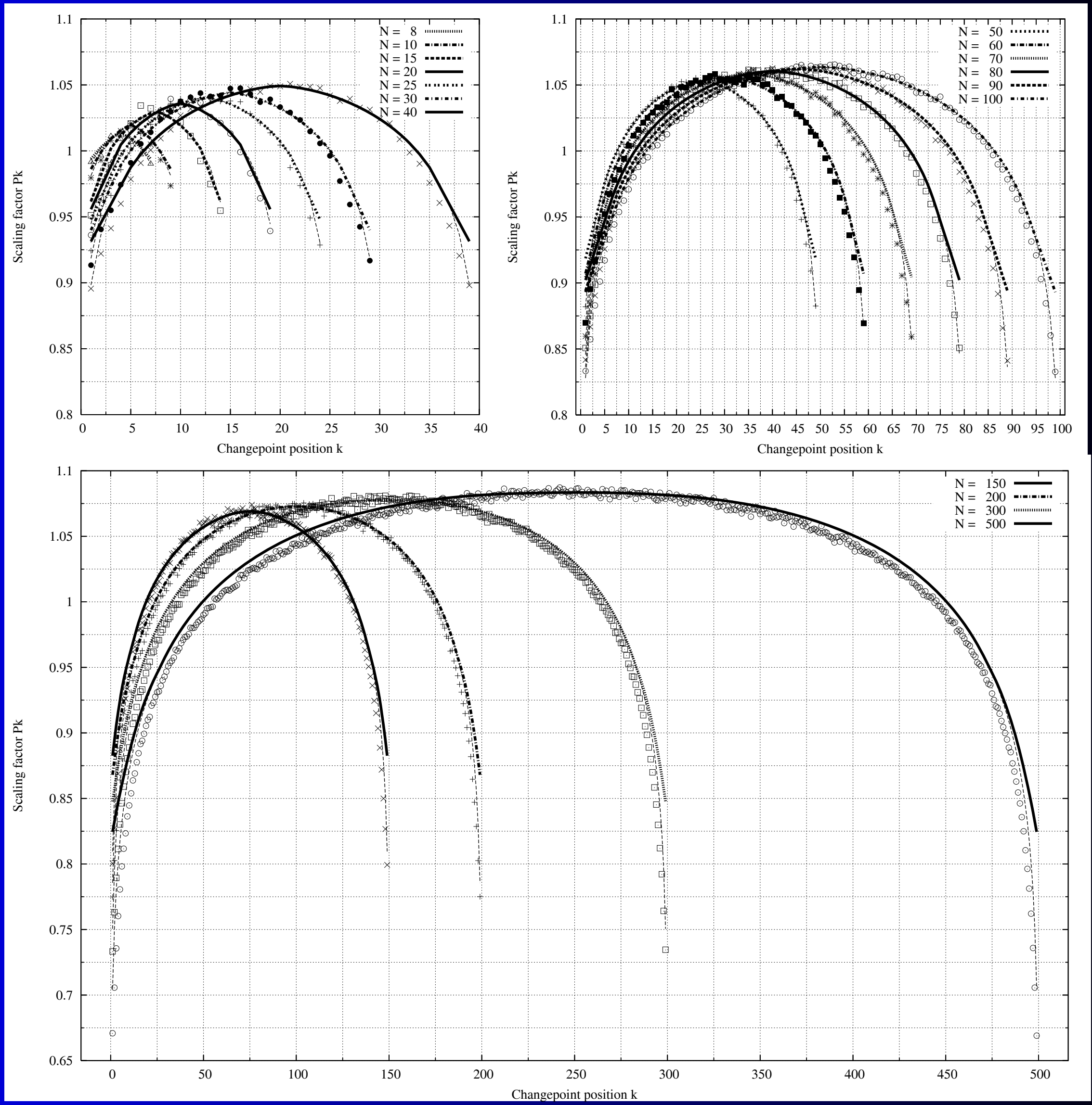
$$PT_{\max} = \max_{1 \le k \le N-1} \left[P(k)\ T(k) \right]$$

where $$T(k) = \frac{1}{\hat{\sigma}_k} \left(\frac{k(N-k)}{N} \right)^{\frac{1}{2}} \left| \overline{X}_1 - \overline{X}_2 \right|;$$

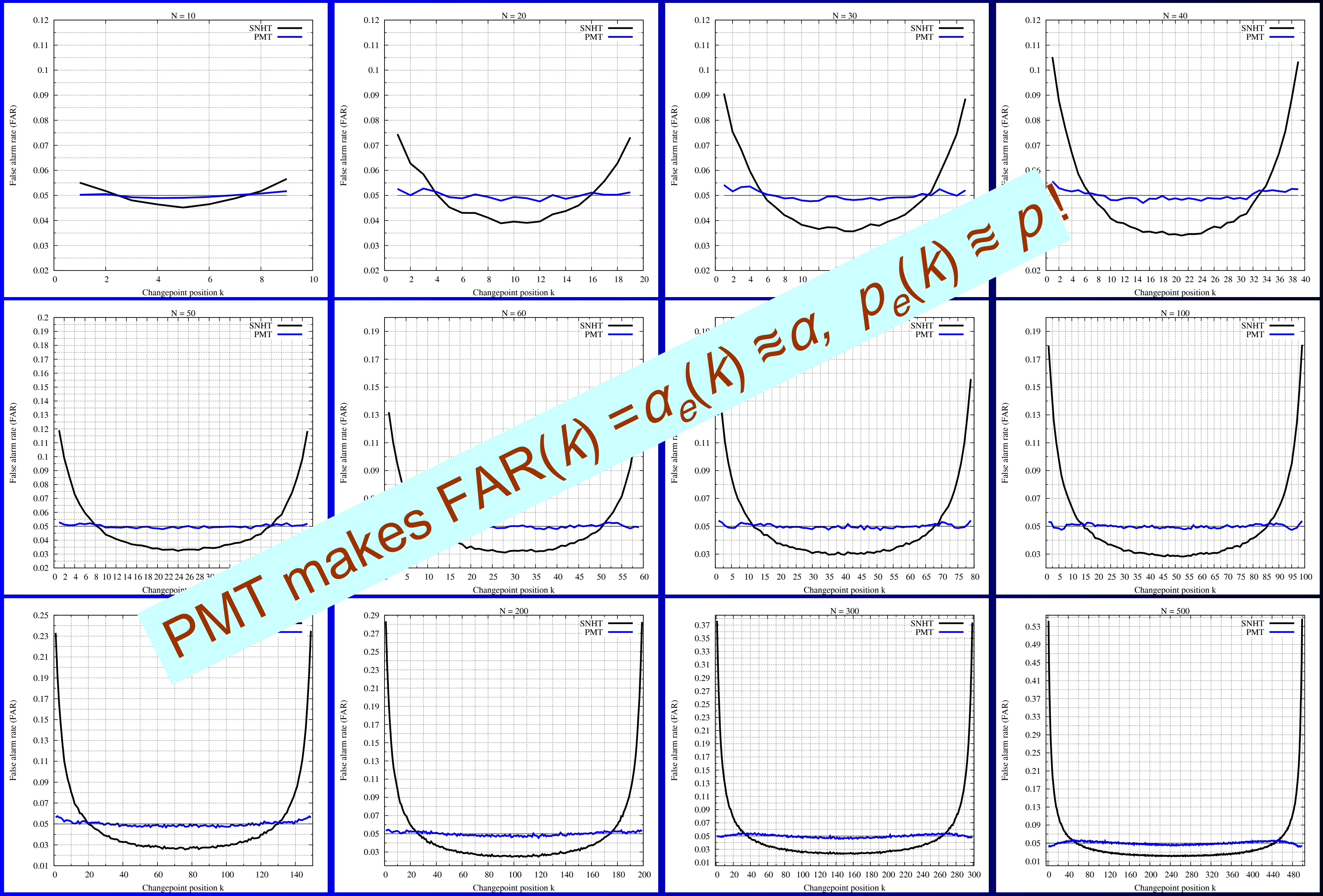
$$\overline{X}_1 = \frac{1}{k} \sum_{t=1}^{k} X_t; \qquad \overline{X}_2 = \frac{1}{N-k} \sum_{t=k+1}^{N} X_t$$

$$\hat{\sigma}_k^2 = \frac{1}{N-2} \left(\sum_{t=1}^{k} (X_t - \overline{X}_1)^2 + \sum_{t=k+1}^{N} (X_t - \overline{X}_2)^2 \right)$$

×, +, □, ○, …: $$R_k = \frac{T_{\max}(\alpha_e(k))}{T_{\max}(0.05)}$$



FAR(k): SNH test *vs* PMT test



PMT makes FAR(k) = $\alpha_e(k) \approxeq \alpha$, $p_e(k) \approxeq p$!

Power of detection: PMT *vs* SNH

(real mean-shift Δ at $t = k$)

$RSS = \Delta / \sigma$

averaged over $2 \le k \le N-2$

Mean Hit Rate: (PMT/SNH)

Detect it in [k-2, k+2] & with $p \geq 0.95$

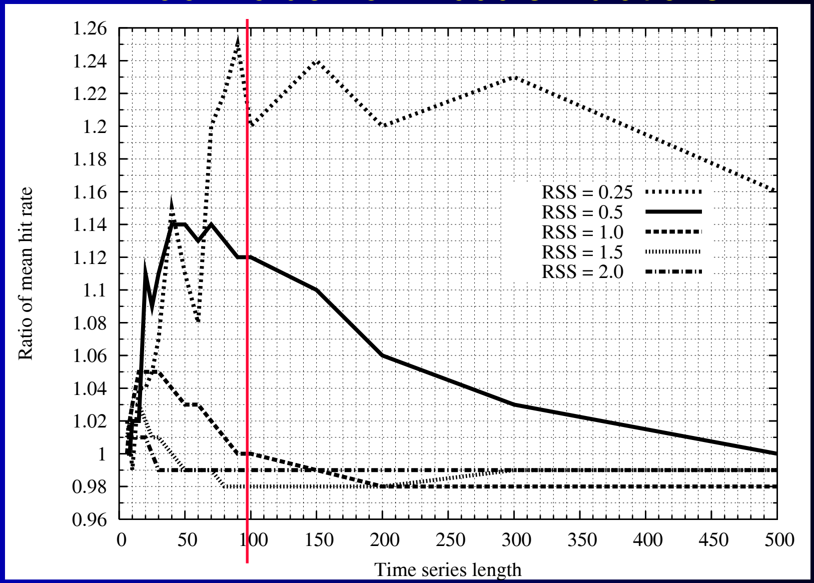
Mean Position Rate: (PMT/SNH)

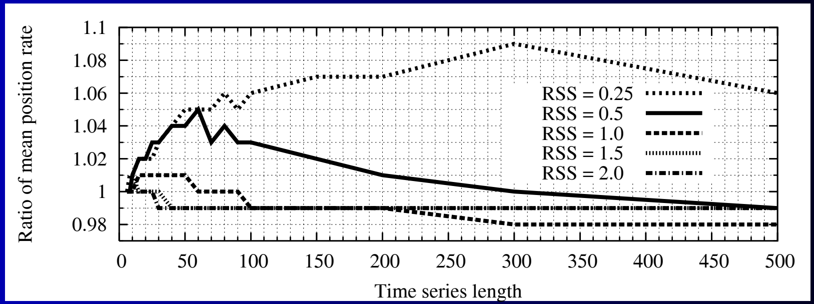
Detect it in [k-2, k+2] regardless of p

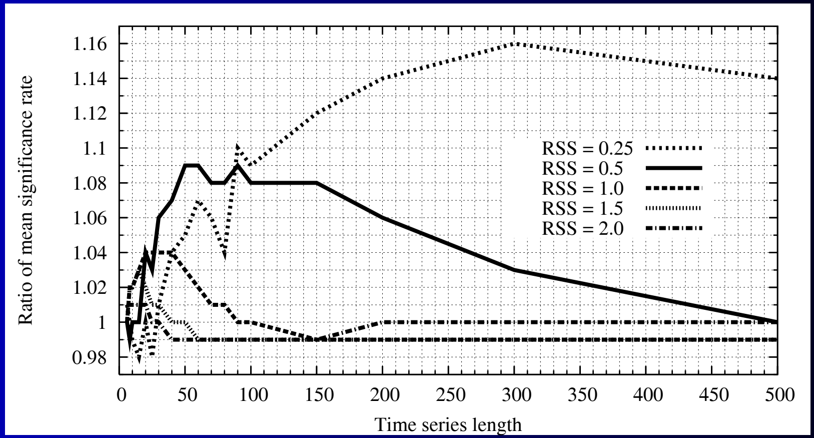
Mean Significance Rate: (PMT/SNH)

Detect it with $p \geq 0.95$ regardless of position

Each value from 1000 simulations







Wang (2008a) proposes a Penalized Maximal *F* test (PMF test) to even out the W-shaped FAR(k) curves of TPR3 test

M-shape penalty $P_f(k)$: (thick curves)

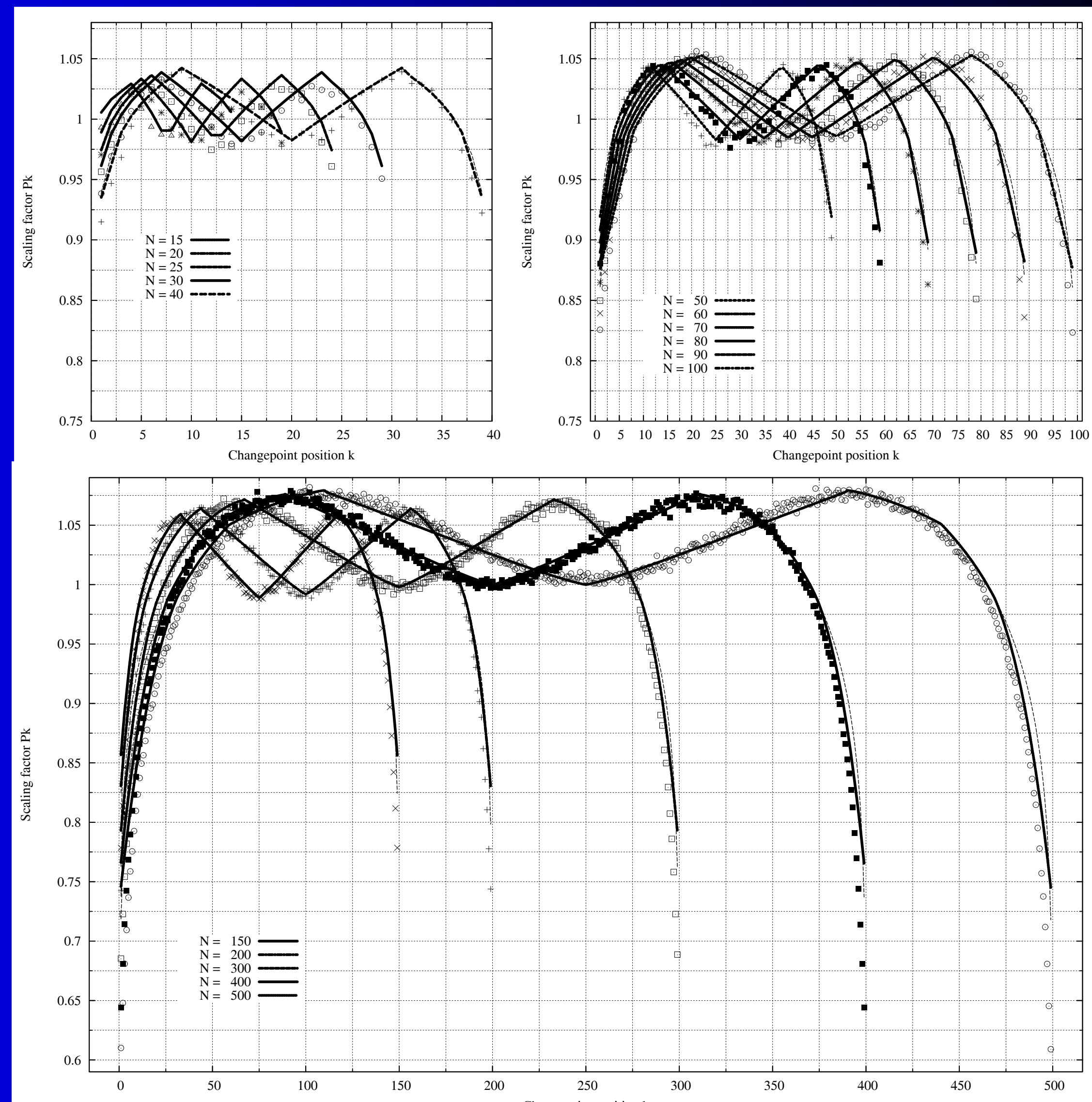
$$PF_{\max} = \max_{1 \le k \le N-1} \left[P_f(k)\ F(k) \right]$$

where $$F(k) = \frac{(SSE_0 - SSE_A)/1}{SSE_A/(N-3)};$$

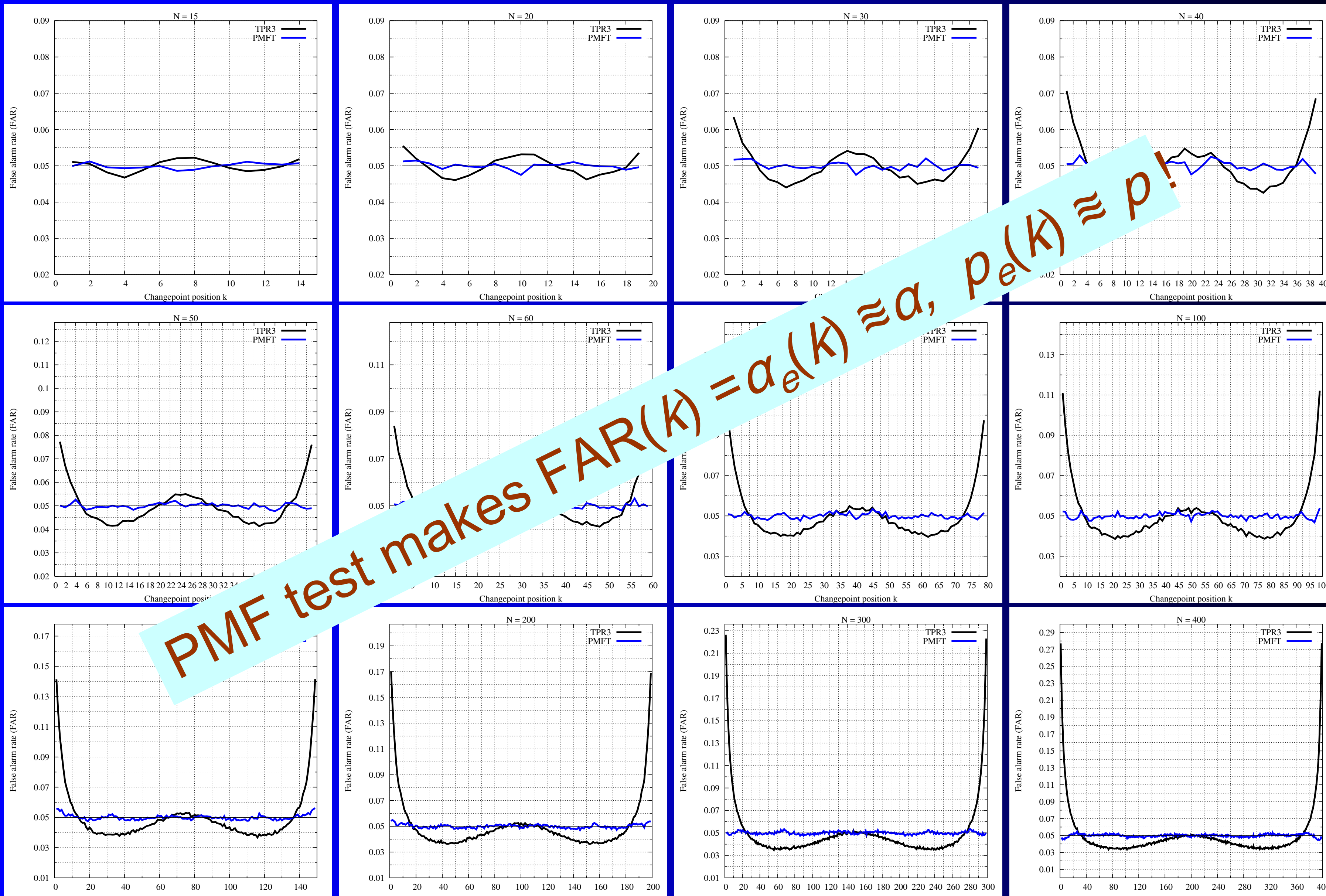
$$SSE_0 = \sum_{t=1}^{N} (X_t - \hat{\mu}_0 - \hat{\beta}_0 t)^2;$$

$$SSE_A = \sum_{t=1}^{k} (X_t - \hat{\mu}_1 - \hat{\beta} t)^2 + \sum_{t=k+1}^{N} (X_t - \hat{\mu}_2 - \hat{\beta} t)^2$$

×, +, □, ○, ...: $$R_k = \frac{F_{\max}(\alpha_e(k))}{F_{\max}(0.05)}$$



FAR(*k*): TPR3 *vs* PMF test



PMF test makes $FAR(k) = \alpha_e(k) \approxeq \alpha, \; p_e(k) \approxeq p$!

Power of detection: PMF *vs* TPR3

(real mean-shift Δ at $t = k$)

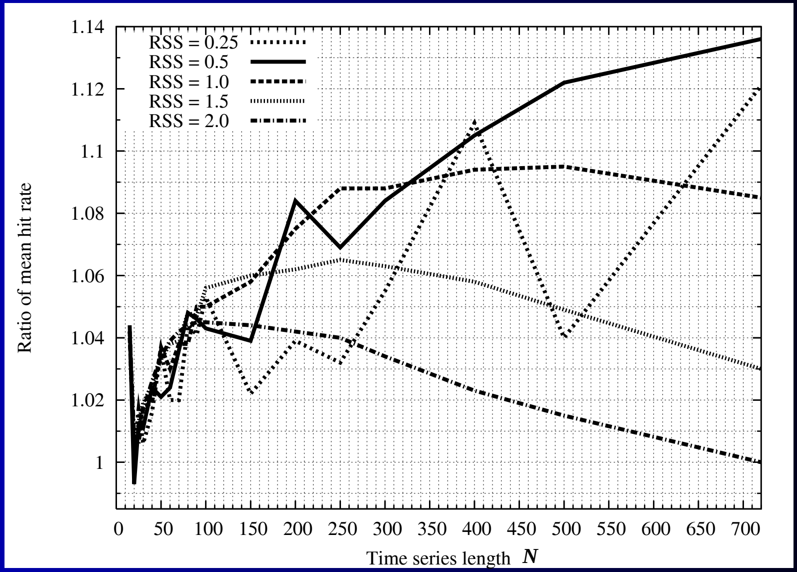
$RSS = \Delta / \sigma$

Each value from 10,000 simulations

averaged over
$2 \le k \le N-2$

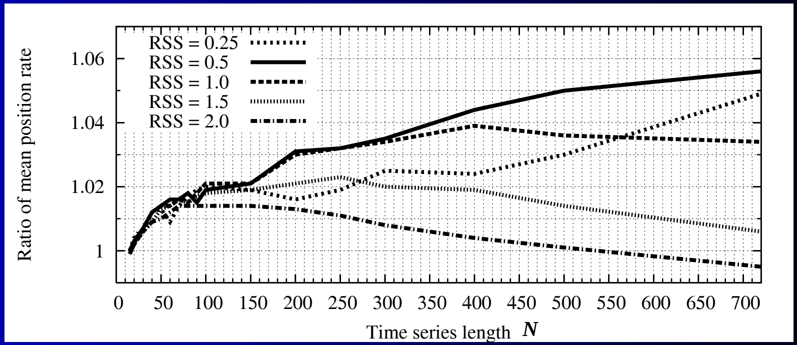
Mean Hit Rate: (PMF/TPR3)

Detect it in [k-3, k+3] & with $p \ge 0.95$



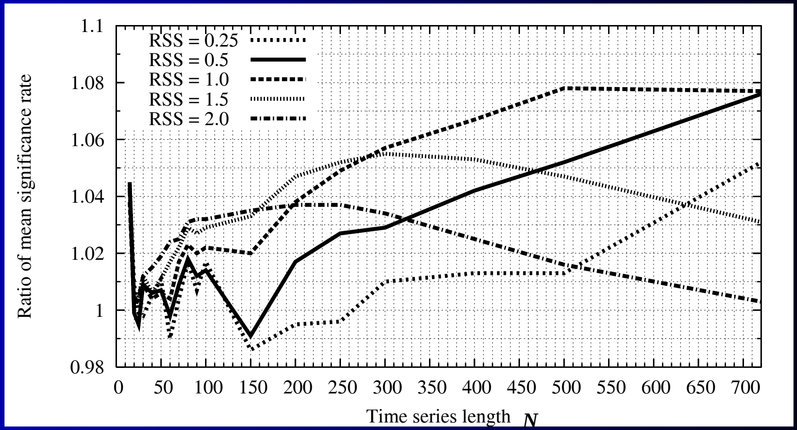
Mean Position Rate: (PMF/TPR3)

Detect it in [k-3, k+3] regardless of p



Mean Significance Rate: (PMF/TPR3)

Detect it with $p \ge 0.95$ regardless of position



PMT and PMF tests: still assume IID Gaussian errors!

Autocorrelation and Periodicity

- inherent features of most climate data series

Common practice:

- use ref series to diminish periodicity (and trend)

  > problem: ref series are not always available or homogeneous!

- apply tests to annual series to reduce autocorr.

  (usually autocorr. can not be diminished by using ref series! example)

  → sample size: only N/12

  → diff. shift-years identified in diff. month series for the same shift!

Some people ignore the effects, unaware of them

↓

Effects of autocor. *Φ* on PT_{max}

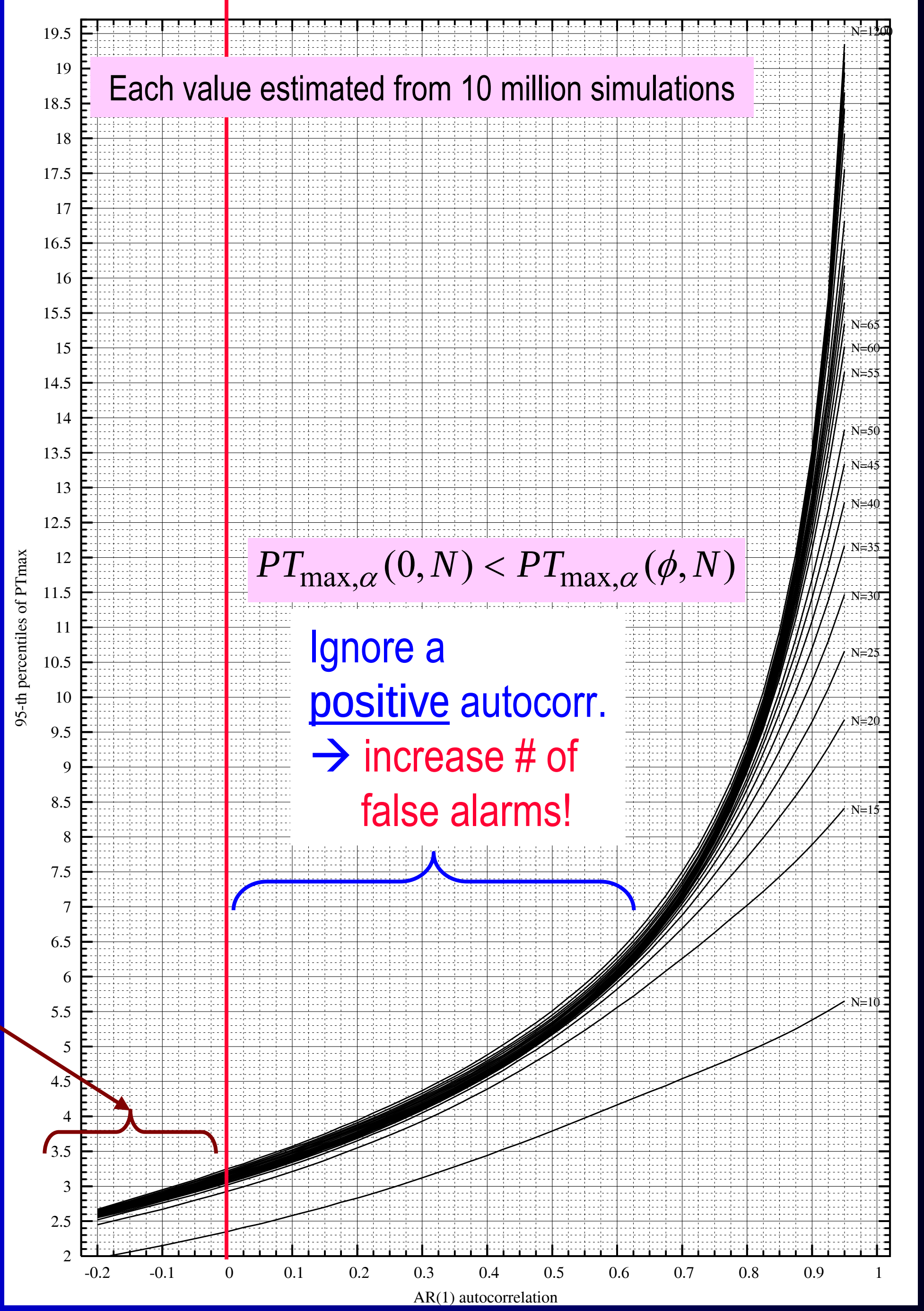
Consider AR(1) errors:

$$\varepsilon_t = \phi \varepsilon_{t-1} + z_t$$

IID Gaussian noise
(constant var.)

$$PT_{\max,\alpha}(0,N) > PT_{\max,\alpha}(\phi,N)$$

Ignore a negative autocorr.
→ let changepoints go undetected!

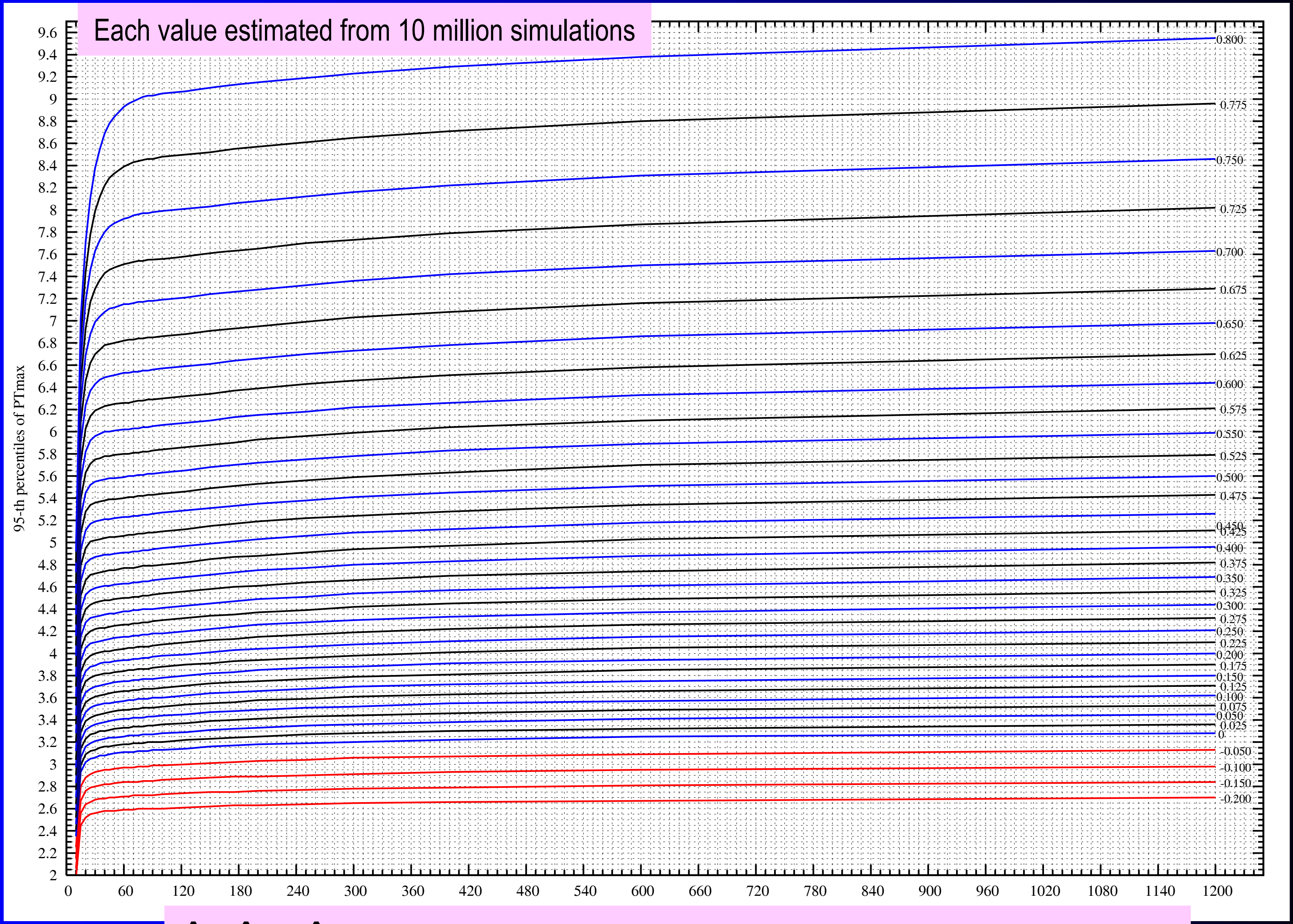


PT_{max} percentiles as a function of autocor. *Φ* for each *N*

Table of critical values

$PT_{\max,\alpha}(\phi, N)$

The PMTred algorithm (RHtestV2)



$\hat{\phi}\ [\hat{\phi}_L, \hat{\phi}_U]$ from the full model residual series

$\Rightarrow PT_{\max}(\hat{\phi}, N)\ \ [PT_{\max}(\hat{\phi}_L, N),\ PT_{\max}(\hat{\phi}_U, N)]$

n φ

Effects of autocor. Φ on PF_{max}

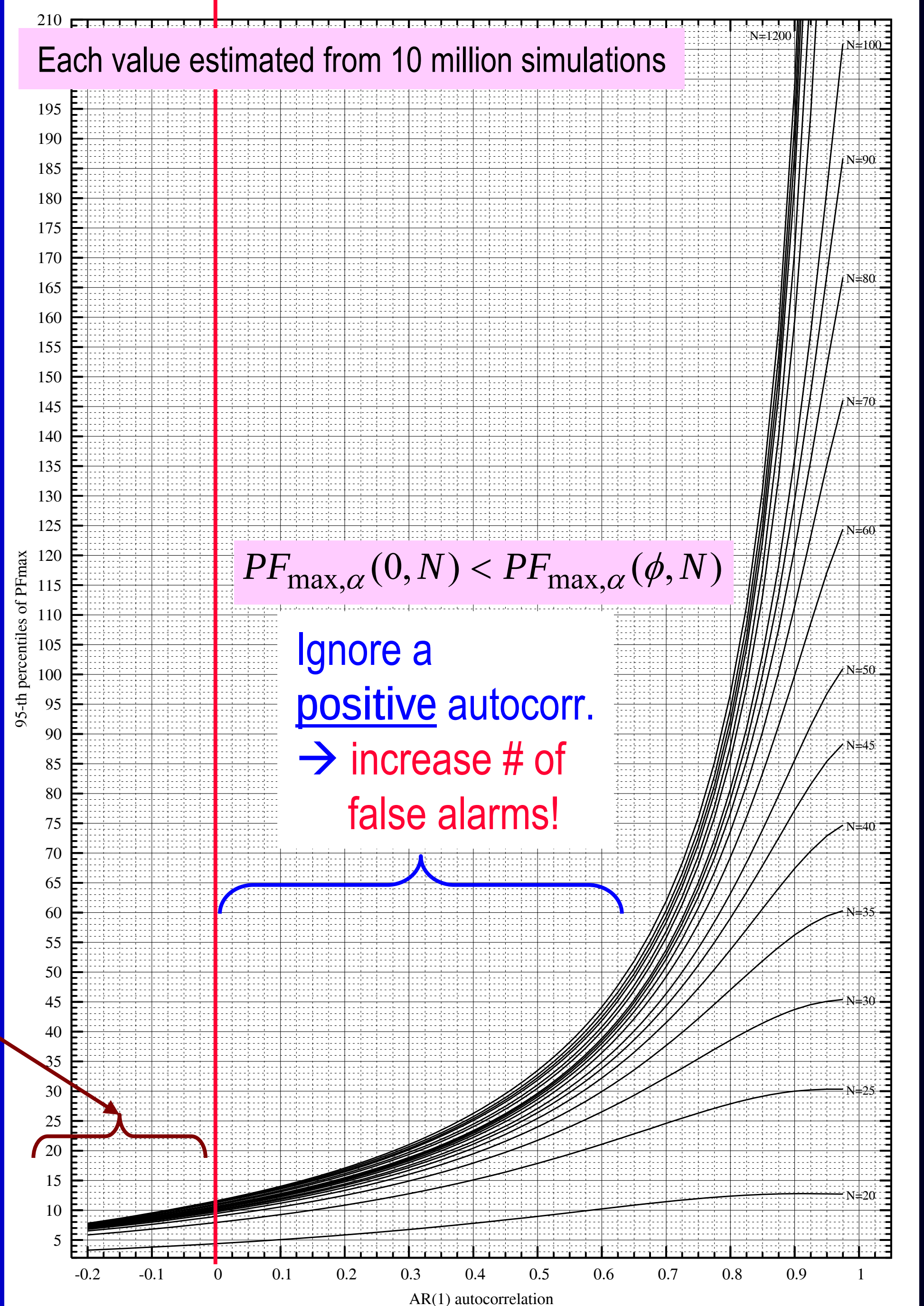
Consider AR(1) errors:

$$\varepsilon_t = \phi\varepsilon_{t-1} + z_t$$

IID Gaussian noise
(constant var.)

$$PF_{\max,\alpha}(0,N) > PF_{\max,\alpha}(\phi,N)$$

Ignore <u>negative</u> autocorr.
→ let changepoints
go undetected!

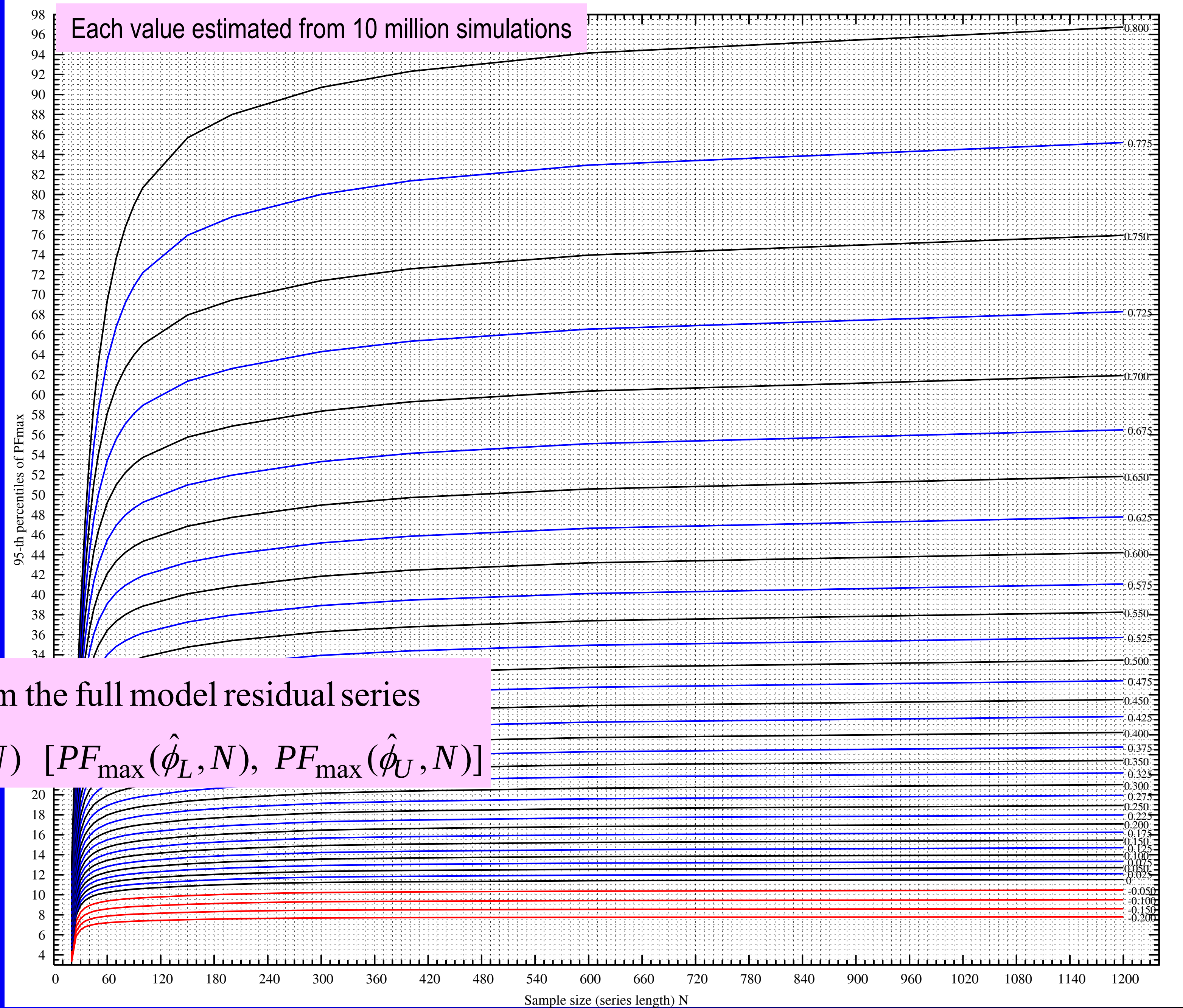


PF_{max} percentiles as a function of autocor. Φ

Table of critical values

$PF_{\max,\alpha}(\phi, N)$

The PMFred algorithm (RHtestV2)



$\hat{\phi}\,[\hat{\phi}_L, \hat{\phi}_U]$ from the full model residual series

$\Rightarrow PF_{\max}(\hat{\phi}, N)\ \ [PF_{\max}(\hat{\phi}_L, N),\ PF_{\max}(\hat{\phi}_U, N)]$

PF_{max} percentiles as a function of sample size N for each ϕ

Power aspects: False Alarm Rate (FAR) and Hit Rate (HR; k±18)

(Each value estimated from 10,000 simulations)

Power of accurate detection is satisfactory, $N_c = 1$ or $N_c > 1$!

FAR ≃α=0.05, regardless of ϕ value

Ignore positive ϕ → FAR » α

Power depends on shift magnitude & average segment length

A large sample size is needed for a reasonably accurate estimate of ϕ!

95% uncertainty range - uncertainty in $\hat{\phi}$

PMTred algorithm (for zero-trend series):

No shift (a–c); Single shift (d: IID; e: AR(1)); Multiple shifts; AR(1) errors (f–j). # of shifts = N_c; RO = Random order.

Case		FAR_L	FAR	FAR_U
a. $N_c = 0, N = 600, \phi = 0$, ($FAR_0 = 0.0526$)		0.0262	0.055[illegible]	[illegible]
b. $N_c = 0, N = 600, \phi = 0.1925$ ($FAR_0 = 0.2580$)		0.0269	0.055[illegible]	[illegible]
c. $N_c = 0, N = 1200, \phi = 0.1288$ ($FAR_0 = 0.1698$)		0.0298	0.052[illegible]	[illegible]
	$\lvert\Delta/\sigma\rvert$	HR_L	HR	HR_U
d. $N_c = 1$, $N = 600$, $\phi = 0$ (IID)	0.5	0.6555	0.6742	[illegible]
	1.0	0.9819	0.9858	[illegible]
	1.5	[illegible]	[illegible]	[illegible]
	2.0	1.0[illegible]	[illegible]	[illegible]
	2.5	1.0[illegible]	[illegible]	[illegible]
e. $N_c = 1$, $N = 600$, $\phi = 0.1925$ (AR(1))	0.5	0.5068	0.5266	0.5468
	1.0	0.9071	0.9141	0.9201
	1.5	0.9902	0.9913	0.9928
	2.0	0.9998	0.9999	0.9999
	2.5	1.0000	1.0000	1.0000
f. $N_c = 2$, $N = 600$, $\phi = 0.1925$	(1.0 1.0)	0.7601	0.7879	0.8174
	RO(0.5 1.0)	0.6614	0.6862	0.7107
	RO(1.0 1.5)	0.8860	0.9050	0.9210
	RO(1.5 2.5)	0.9711	0.9807	0.9872
	RO(1.0 2.5)	0.9222	0.9476	0.9579
g. $N_c = 3$, $N = 600$, $\phi = 0.1925$	(1.0 1.0 1.0)	0.6886	0.7245	0.7580
	RO(0.5 1.0 1.5)	0.6421	0.6720	0.7024
	RO(1.0 1.5 2.0)	0.8511	0.8750	[illegible]
	RO(1.5 2.5 3.5)	0.9628	0.9727	[illegible]
	RO(2.0 2.5 3.5)	0.9620	0.9745	[illegible]
h. $N_c = 3$, $N = 1200$, $\phi = 0.1288$	(1.0 1.0 1.0)	0.7977	0.8125	[illegible]
	RO(0.5 1.0 1.5)	0.7507	0.7638	[illegible]
	RO(1.0 1.5 2.0)	0.9214	0.9300	[illegible]
	RO(1.5 2.5 3.5)	0.9868	0.9898	0.9912
	RO(2.0 2.5 3.5)	0.9882	0.9902	0.9919
i. $N_c = 5$, $N = 600$, $\phi = 0.1925$	(1.0 1.0 1.0 1.0 1.0)	0.6084	0.6547	[illegible]
	RO(0.5 1.0 1.5 2.0 2.5)	0.7431	[illegible]	[illegible]
	RO(3.0 1.0 1.5 2.0 2.5)	0.8806	[illegible]	[illegible]
	RO(1.5 2.0 2.5 3.5 4.0)	[illegible]	[illegible]	[illegible]
	RO(3.0 2.0 2.5 3.5 4.0)	[illegible]	[illegible]	0.9772
j. $N_c = 5$, $N = 1200$, $\phi = 0.1288$	(1.0 1.0 1.0 1.0 1.0)	[illegible]	0.7816	0.8004
	RO(0.5 1.0 1.5 2.0 [illegible])	[illegible]	0.8307	0.8501
	RO(3.0 1.0 1.5 2.0 [illegible])	0.9451	0.9509	0.9581
	RO(1.5 2.0 2.5 3.5 4.0)	0.9794	0.9828	0.9854
	RO(3.0 2.0 2.5 3.5 4.0)	0.9898	0.9915	0.9921

[illegible]):

Case		[illegible]	FAR	FAR_U
[illegible]		[illegible]	[illegible].0503	0.1016
[illegible]		[illegible]	[illegible].0522	0.1057
[illegible]		[illegible]	[illegible].0498	0.0827
	[illegible]	[illegible]	HR	HR_U
d. [illegible] $N = 600$ [illegible]	0.5	[illegible]	0.3982	0.4454
	1.0	[illegible]	0.9317	0.9376
	1.5	0.9949	0.9959	0.9965
	2.0	0.9995	0.9998	0.9998
	2.5	1.0000	1.0000	1.0000
e. $N_c = 1$, $N = 600$, $\phi = 0.1925$	0.5	0.1836	0.2360	0.2822
	1.0	0.7965	0.8273	0.8480
	1.5	0.9506	0.9708	0.9811
	2.0	0.9895	0.9938	0.9972
	2.5	0.9995	0.9997	0.9998
f. $N_c = 2$, $N = 600$, $\phi = 0.1$[illegible]	[illegible]	[illegible]	0.7326	0.8182
	[illegible]	[illegible]	0.5113	0.5945
	[illegible]	0.8422	[illegible]	0.9314
	[illegible]	[illegible]	[illegible]	0.9965
	[illegible]	[illegible]	[illegible]	0.9872
[illegible]	[illegible] 1.0 1.0)	[illegible]	0.5924	0.6467
	RO(0.5 1.0 [illegible]	[illegible]	0.5597	0.5954
	RO(1[illegible]	0.7878	0.8428	0.8467
	[illegible]	0.9514	0.9646	0.9795
	[illegible].5)	0.9624	0.9771	0.9774
h. N_c [illegible]	[illegible] 1.0 1.0)	0.7805	0.7997	0.8154
	RO(0.5 1.0 1.5)	0.6895	0.7011	0.7215
	RO(1.0 1.5 2.0)	0.9092	0.9247	0.9363
	RO(1.5 2.5 3.5)	0.9811	0.9845	0.9924
	RO(2.0 2.5 3.5)	0.9842	0.9889	0.9906
i. $N_c = 5$, $N = 600$, $\phi = 0.1925$	(1.0 1.0 1.0 1.0 1.0)	0.4002	0.4520	0.5059
	RO(0.5 1.0 1.5 2.0 2.5)	0.6822	0.6911	0.7169
	RO(3.0 1.0 1.5 2.0 2.5)	0.8552	0.8800	0.8991
	RO(1.5 2.0 2.5 3.5 4.0)	0.9182	0.9225	0.9427
	RO(3.0 2.0 2.5 3.5 4.0)	0.9277	0.9499	0.9584
j. $N_c = 5$, $N = 1200$, $\phi = 0.140$	(1.0 1.0 1.0 1.0 1.0)	0.6762	0.7062	0.7226
	RO(0.5 1.0 1.5 2.0 2.5)	0.7785	0.7920	0.8022
	RO(3.0 1.0 1.5 2.0 2.5)	0.9528	0.9570	0.9606
	RO(1.5 2.0 2.5 3.5 4.0)	0.9752	0.9779	0.9802
	RO(3.0 2.0 2.5 3.5 4.0)	0.9799	0.9819	0.9836

The RHtestV2 software package

- recognized by WMO at COP-13 (Bali, Dec. 2007)

(R & FORTRAN)

1. PMTred algorithm
   - for zero-trend series with IID or AR(1) Gaussian errors
   - for use with reference series
   - *FindU.wRef*, *FindUD.wRef*, *StepSize.wRef*

2. PMFred algorithm
   - for constant trend series with IID or AR(1) Gaussian errors
   - can be used <u>without</u> reference series
   - *FindU*, *FindUD*, *StepSize*

Input data format for the RHtestV2

(Annual series) OR (Monthly series) OR (Daily series)

Annual series

YYYY	MM	DD	data
1974	00	00	-4.87
1975	00	00	-3.88
1976	00	00	-5.65
1977	00	00	-3.34
1978	00	00	-5.72
1979	00	00	-4.08
1980	00	00	-4.97
1981	00	00	-2.58
1982	00	00	-4.48
1983	00	00	-999. ← Missing Value code
1984	00	00	-3.40
1985	00	00	-4.58
1986	00	00	-4.25
1987	00	00	-2.25
1988	00	00	-3.94

Monthly series

YYYY	MM	DD	data
1967	7	00	1015.70
1967	8	00	1015.95
1967	9	00	1016.10
1967	10	00	-999.99 ← Missing Value code
1967	11	00	1010.71
1967	12	00	1011.58
1968	1	00	1009.37
1968	2	00	1003.07
1968	3	00	1011.94
1968	4	00	1014.74
1968	5	00	1009.59
1968	6	00	1011.77
1968	7	00	1014.35
1968	8	00	1010.87
1968	9	00	1016.45

Daily series

YYYY	MM	DD	data
1994	1	27	8.1
1994	1	28	5.3
1994	1	29	4.9
1994	1	30	4.9
1994	1	31	4.0
1994	2	1	3.9
1994	2	2	7.2
1994	2	3	8.7
1994	2	4	6.3
1994	2	5	-999.
1994	2	6	-999.
1994	2	7	-999.
1994	2	8	-999.
1994	2	9	9.0
1994	2	10	6.0

} Missing value code (rows 1994 2 5 – 1994 2 8)

A Ref series should be in a separate file of the same format!

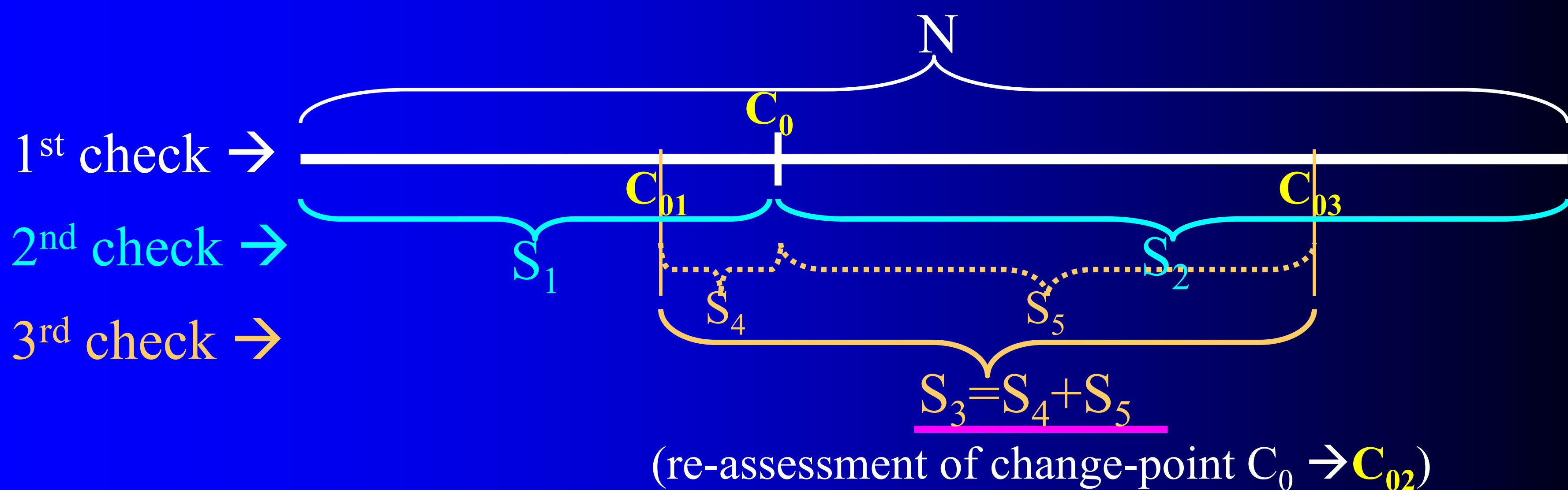
Base and Ref series can have data for different periods or missing values at different times, but they must have the same missing value code!

Stepwise testing algorithm

- Possible multiple change-points in one single time series
- Most methods developed assuming at most one change-point

→ 1st change-point: might be false or inaccurate ("contaminated")

[1] Find the most probable changepoint in the series being tested:



Is the largest among C_{01}, C_{02}, C_{03} significant at the nominal level α?

- No (End!)
- Yes, …

Stepwise testing algorithm for detecting multiple changepoints

[1] Find the most ... ed → C_1

[2] $M_c = N_c \geq 1$ chan ... → N_c+1 segments.
Identify the m ... $\{K_i\}$ (i=1,2,…N_c+1)

[3] Estimate ... in the presence of
$\{C_j\}$ (j=1 ... om the whitened series

[4] Find the ... N_c+1) .
Is it sig

Yes, repeat [2]-[4]

I ... =1,2,…N_c), and
$\{K_i\}$ (i=1,2,…N_c+1);
, & repeat [3]-[4]

Main points:

(1) Significant changepoints are added to the list of changepoints, one by one: the most significant, the next most…

2) Significance of a changepoint is always assessed in the presence of others listed, and re-assessed if the list changes.

(3) In the resulting list, each changepoint is significant in the presence of all others in the list.

(4) Final estimates ←(N_c+1)-phase model fit to de-seasonalized base series, and to the base-minus-reference series (β≡0) if a reference series is used

[5] Find the smallest among the N_c shifts, re-assess its significance in the presence of others. Is it significant at the nomial level α?

Yes

[6] output the list $\{C_j\}$ (j=1,2,…N_c) and obtain the final estimates of
- shift significance
- shift size ←(N_c+1)-phase model fit

No

Delete it from the list $\{C_j\}$ (j=1,2,…N_c), *set* $N_c = N_c$-1, re-assess significance of the remaining shifts, and repeat [5]

Examples of application

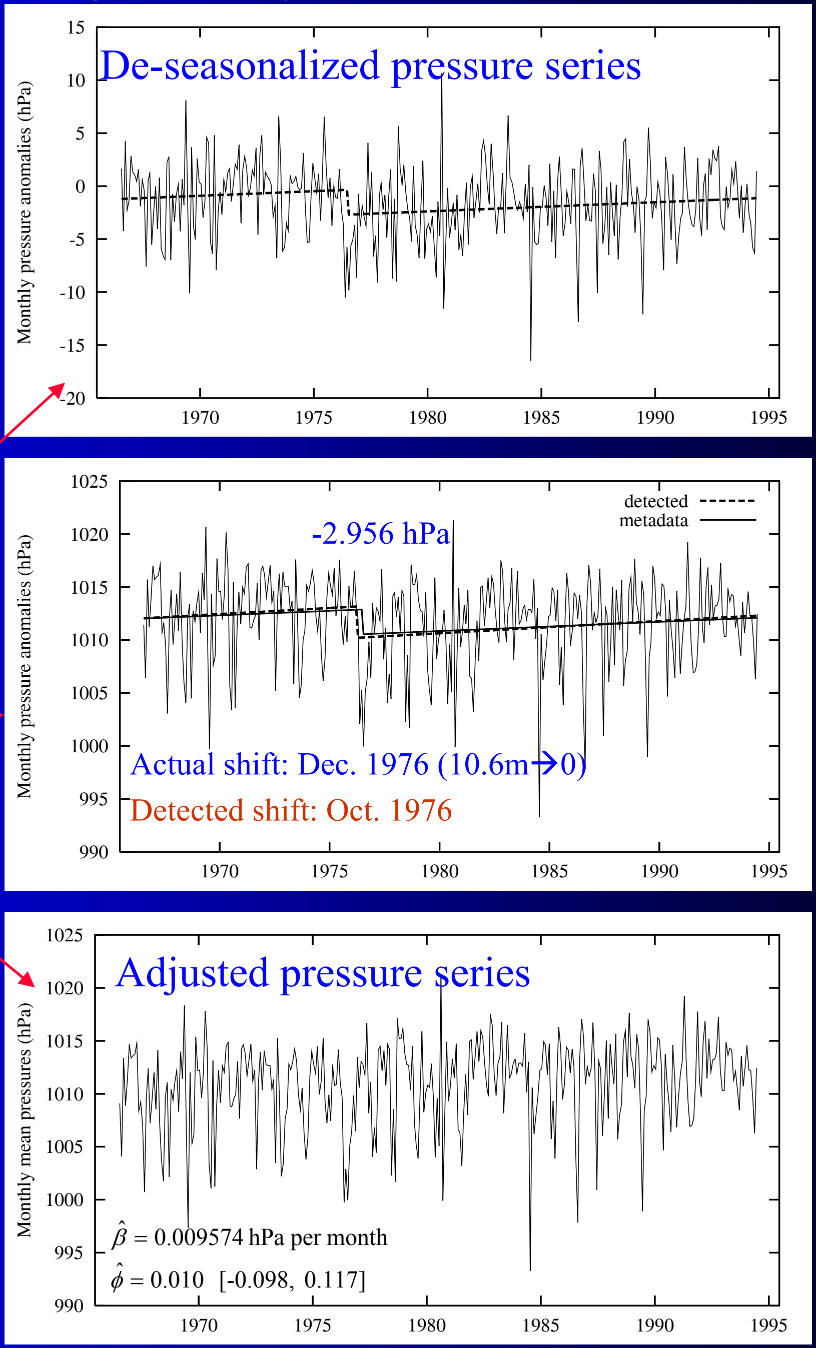
1. Single changepoint case

- PMTred → Base-Ref series

(Burgeo-Yarmouth)

Plots like these are included in the RHtestV2 output

Burgeo monthly station pressure series



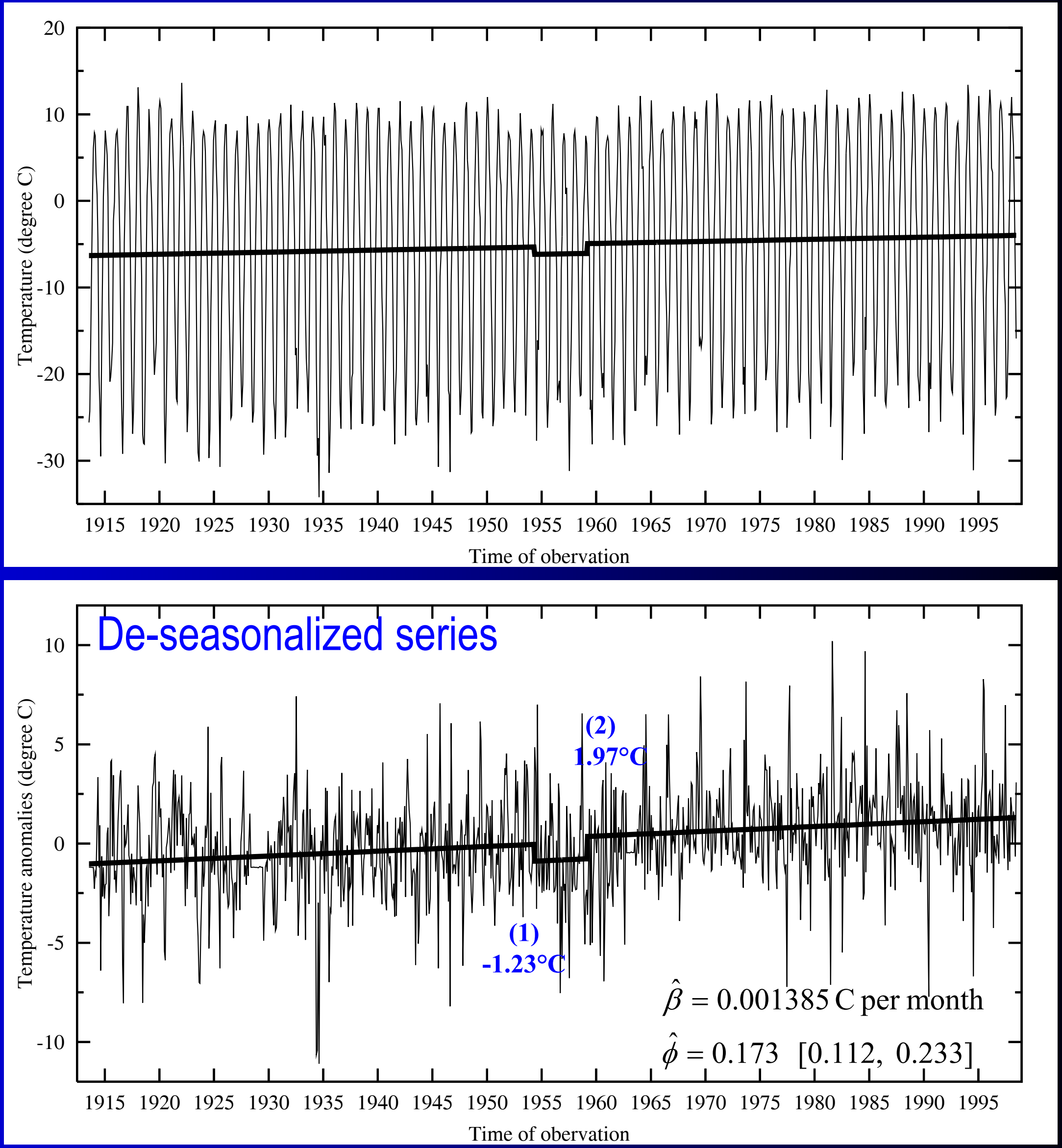
Examples of application

2. Two changepoints

- PMFred → de-seasonalized temp. series (shifts & seasonal means estimated via iteration)

Detected PMFred	Metadata
(1) Oct 1953	Aug 1948-Oct 1958: Stn elevation change (990 feet → 1002 feet)
(2) Aug 1958	Oct 1958: Thermometer screen & stand replaced

Amos monthly means of daily minimum temperatures



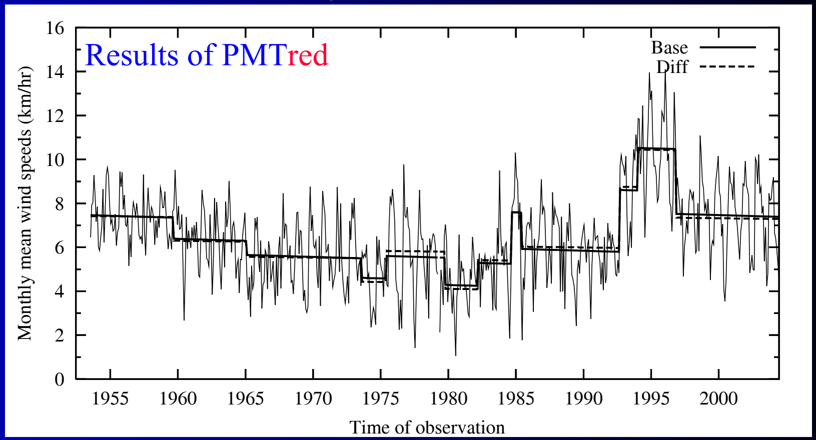
Examples of application

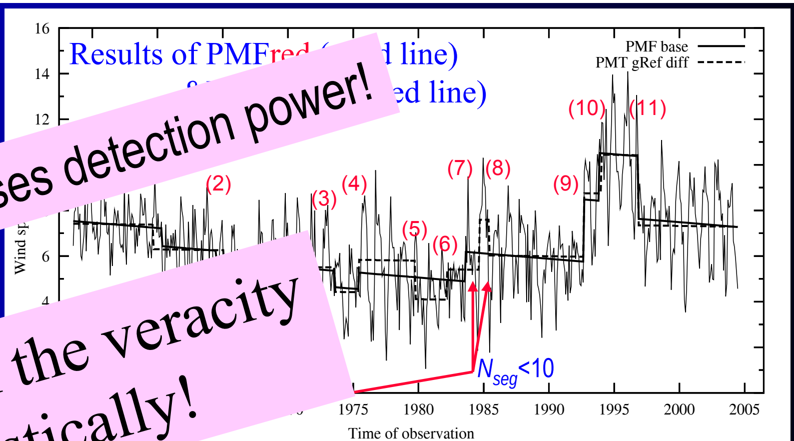
3. Multiple changepoints case

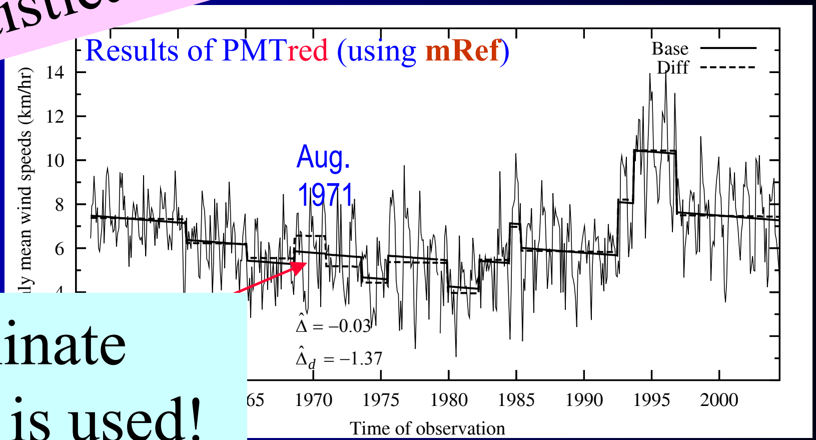
- PMTred → Base-Ref series

Two estimates of shift-size - Any notable inconsistency between them indicates …

Nanaimo monthly wind speed series







Detected PMTred_gRef	PMFred	Metadata
(1) Feb 1960	Oct 1960	May 1957-Feb 1961: anemometer 45B …
(2) Jul 1965	*Dec 1964*	Feb 1961-Mar 1967: Ane…
(3) *Feb 1974*	*Jan 1974*	Early 1974: WS… …usted U-arm
(4) *Jan 1976*	*Nov 1975*	Dec 1… …tor replaced
(5) Mar 1980	X	…U2A had bearing jam, wa…
(6) Aug 1982	Jan 1984	Jan 1984: WSD detector …
(7) Feb 1985	X	Mar 1985: Wi…
(8) Nov 1985	X	Ju… …ed
(9) Feb 1993	Feb…	…replaced
(10) Jun 1994	Ap…	…tor replaced, new tilt pole
(11) Apr 1997	Apr…	…ata from Jul. 1994 to Apr. 1997

$N_{min}=5$ $N_{min}=10$

Use of good reference series increases detection power!

It is **always necessary** to check the veracity of changepoints identified statistically!

Apply PMFred to a Ref series to eliminate large artificial shifts (if any) before it is used!

For more details about using the RHtestV2, please refer to

"Wang, X. L. and Y. Feng, 2007: *RHtestV2 User Manual.*"

Available at http://cccma.seos.uvic.ca/ETCCDMI/software.shtml,

along with the open source software

References:

Wang, X. L., 2008a: Penalized maximal *F* test for detecting undocumented mean-shift without trend change. *J. Atmos. Oceanic Technol.*, 25 (No. 3), 368-384. DOI:10.1175/2007/JTECHA982.1

Wang, X. L., 2008b: Accounting for autocorrelation in detecting mean-shifts in climate data series using the penalized maximal *t* or *F* test. *J. App. Meteor. Climatol*, 47, 2423–2444.

Wang, X. L., Q. H. Wen, and Y. Wu, 2007: Penalized Maximal t-test for Detecting Undocumented Mean Change in Climate Data Series. *J. App. Meteor. Climatol.*, 46 (No. 6), 916-931. DOI:10.1175/JAM2504.1

Wan, H., X. L. Wang, and V. R. Swail, 2007: A Quality Assurance System for Canadian Hourly Pressure Data. *J. App. Meteor. Climatol*., 46 (No. 11), 1804-1817.

Thank you very much!