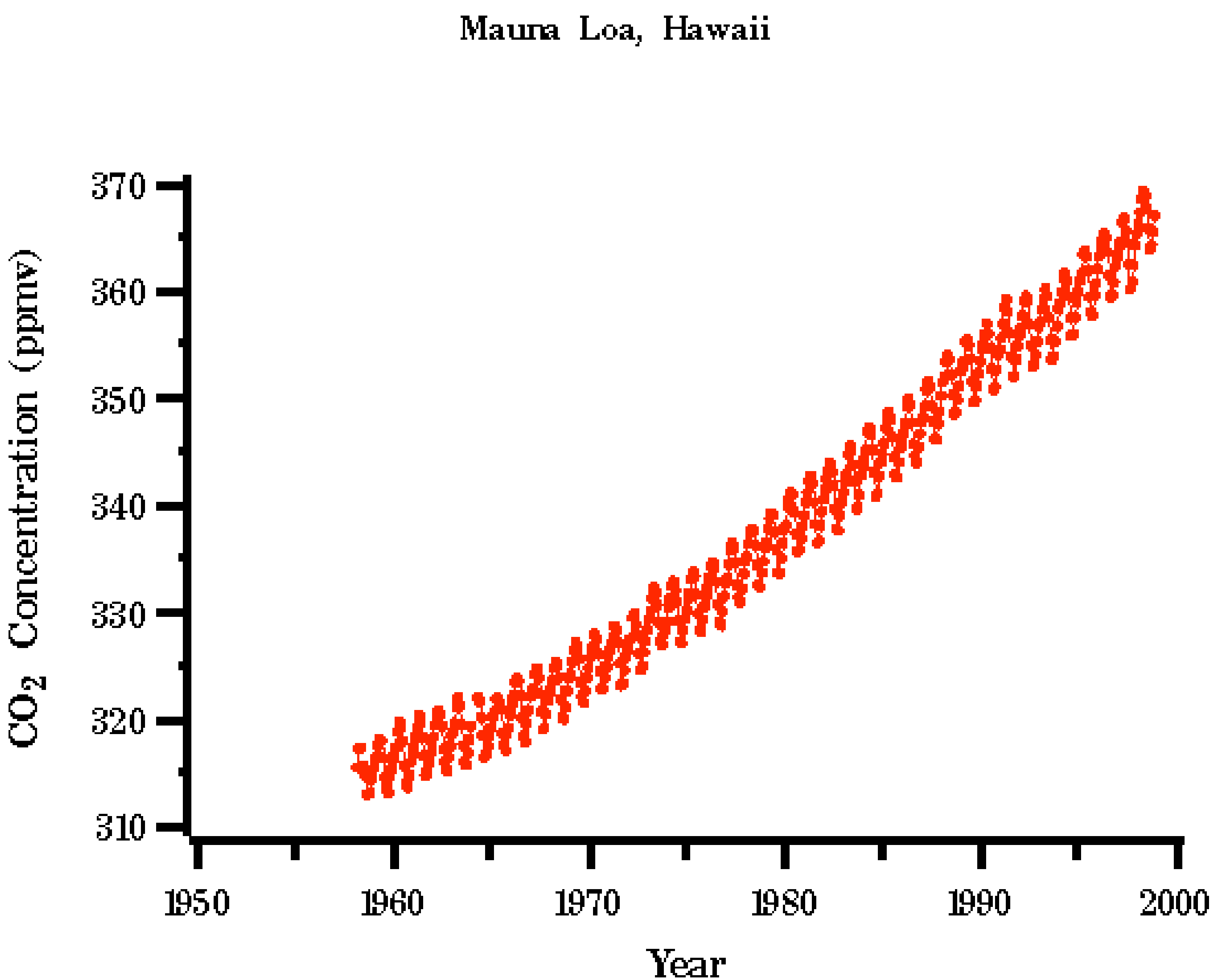
Analysis of Monthly Averaged Radiation Data to Determine Internal Structure Relevant to Trends

Betsy Weatherhead, Laura Hinkelman

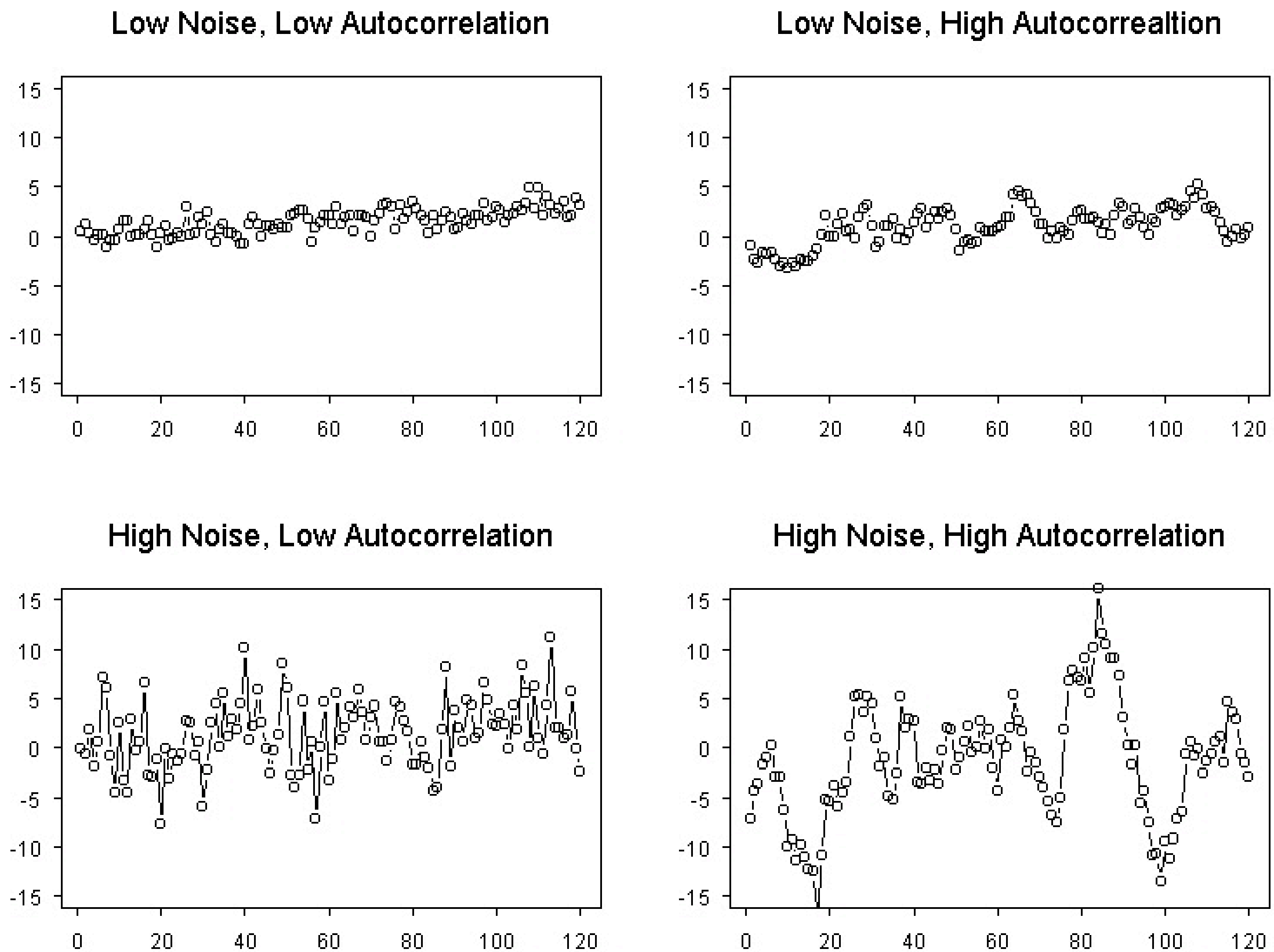
March 20, 2006

Trend Detection

- "Finding a change which is large relative to natural variability."
- Both the magnitude of variability and the memory hinder our ability to detect trends.
- Finding a change which is large relative to natural variability and instrument uncertainty.



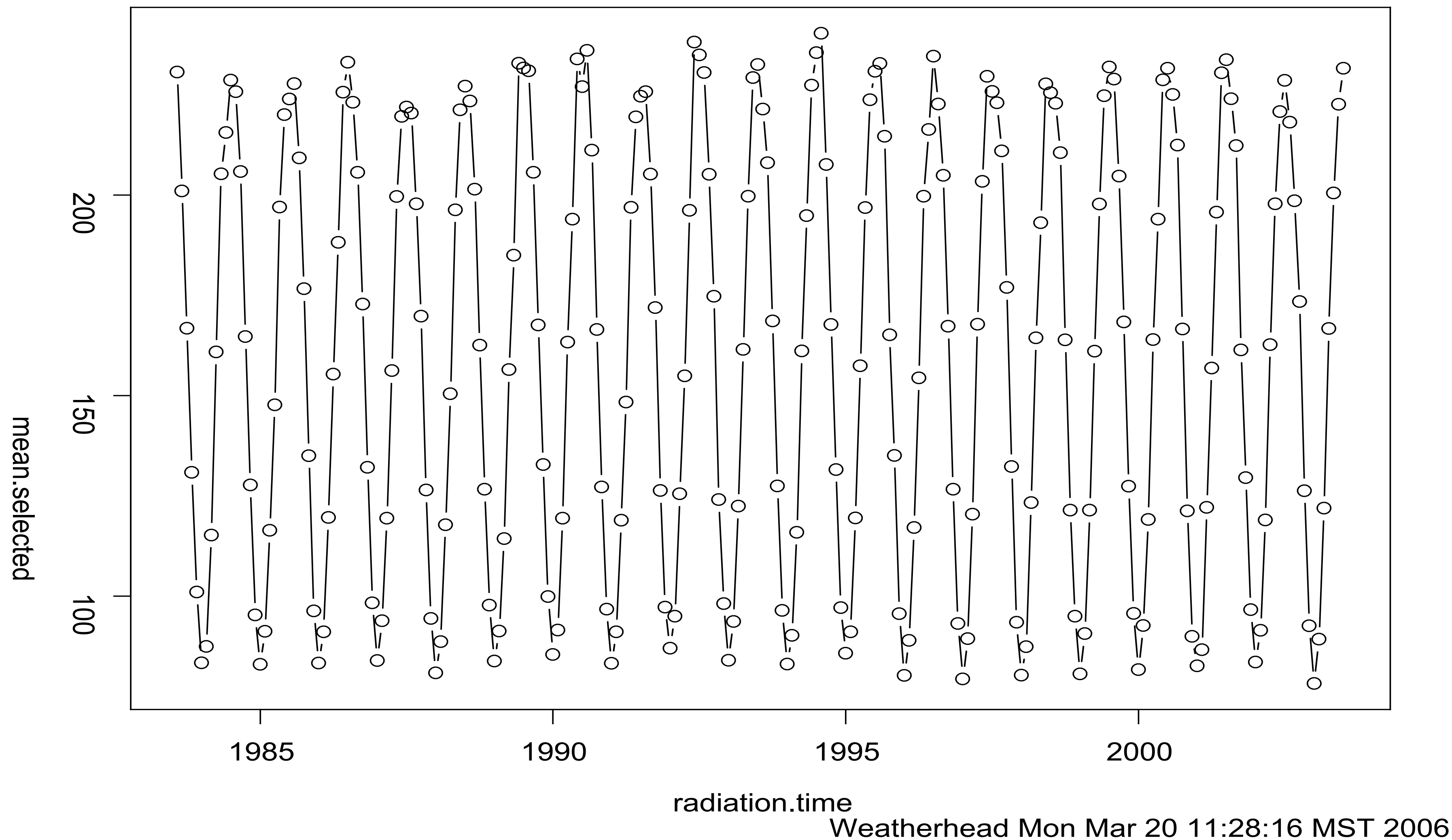
Mauna Loa, Hawaii
370
360
350
340
330
320
310
CO2 Concentration (ppmv)
1950
1960
1970
1980
1990
2000
Year


Low Noise, Low Autocorrelation
Low Noise, High Autocorrealtion
High Noise, Low Autocorrelation
High Noise, High Autocorrelation
15
10
5
0
-5
-10
-15
0
20
40
60
80
100
120

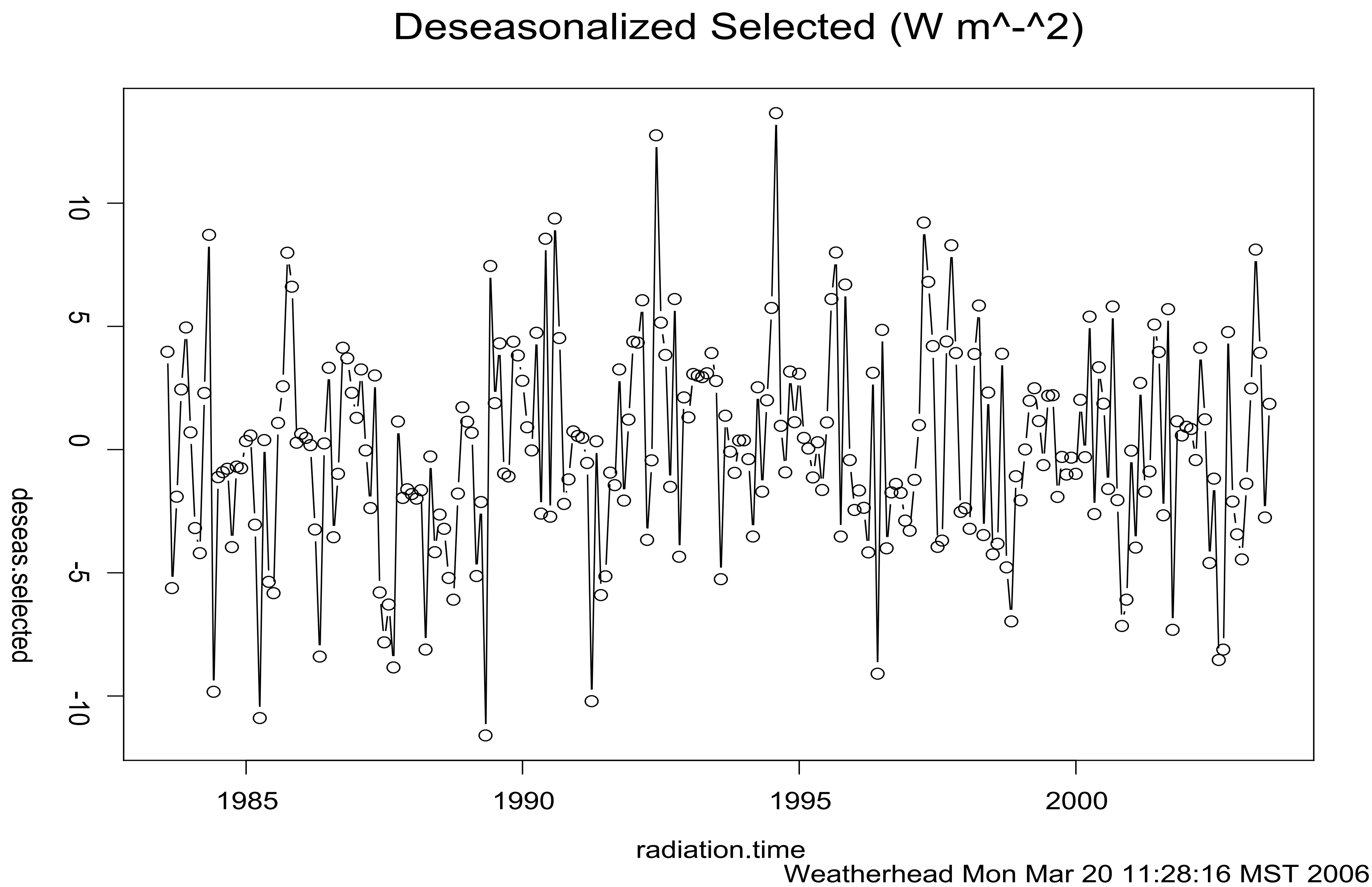
Brief and Incomplete Data Description

- Data were received from Laura Hinkelman on March 5, 2005 and were labeled as follows:
  - `(1)   "Time (Year)"`
  - `(2)   "SRB SWDW Mean Selected (W m^-^2)"`
  - `(3)   "SRB SWDW Mean Global (W m^-^2)"`
  - `(4)   "Deseasonalized Selected (W m^-^2)"`
  - `(5)   "Deseasonalized Global (W m^-^2)"`
- Plots of radiation versus time follow.

SRB SWDW Mean Selected (W m^-^2)



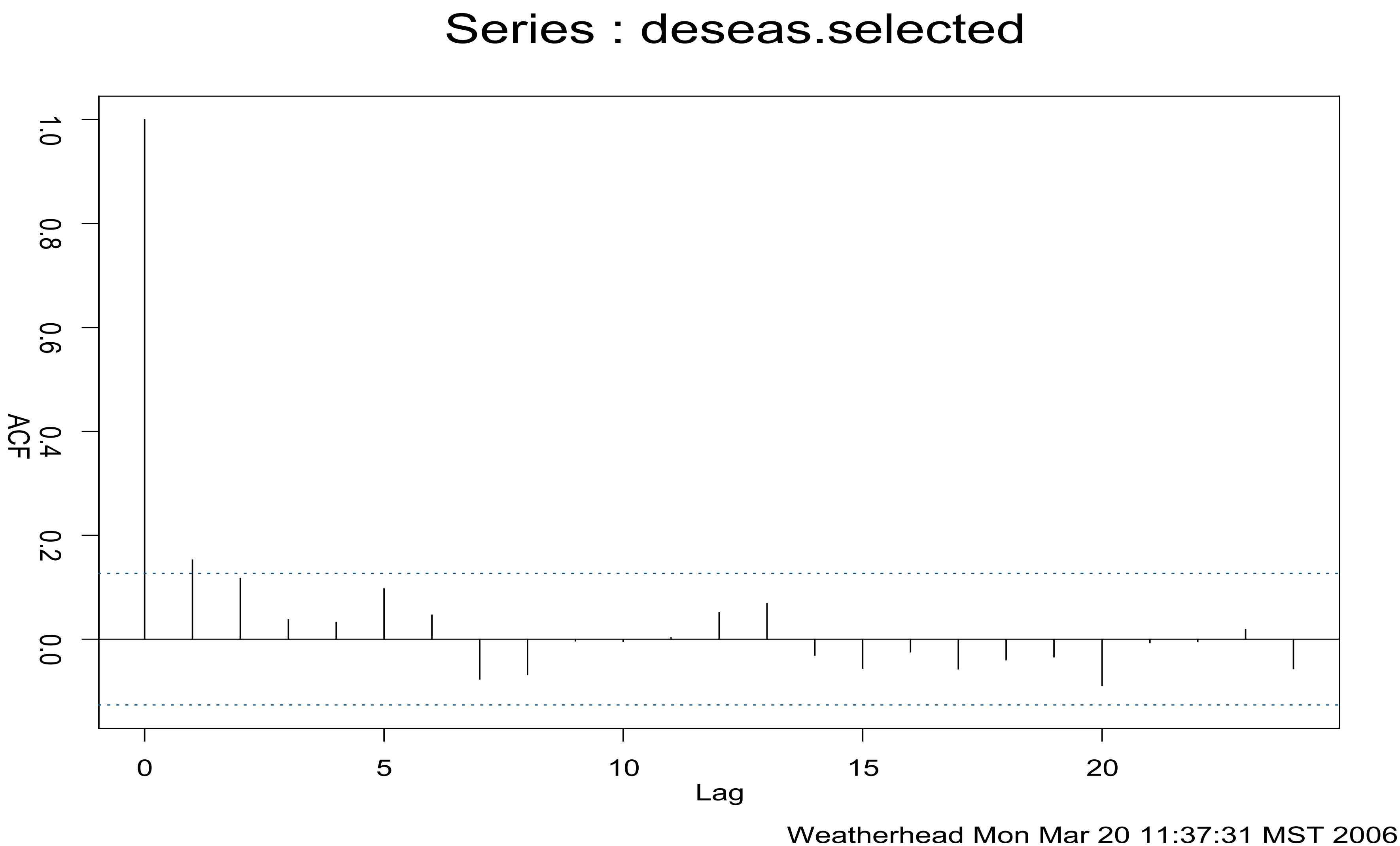
Note: Very stable looking time series. Perhaps more variability in the Peaks than the troughs?



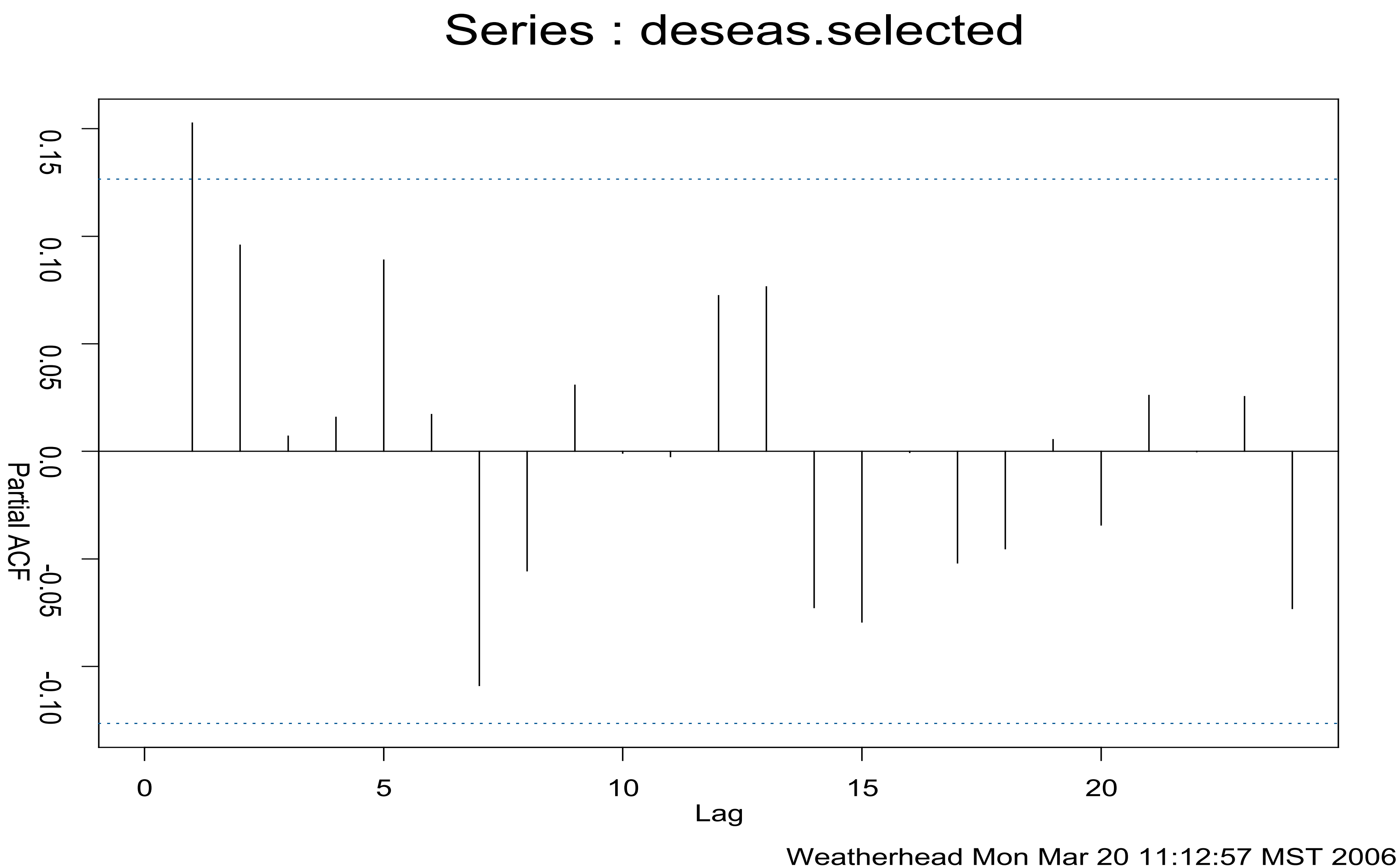
Note: Possible long-term, multi-year (possibly decadal) variability. This will be hard to account for statistically unless we can link it to Something else (QBO/solar/NAO).

Analysis of internal structure

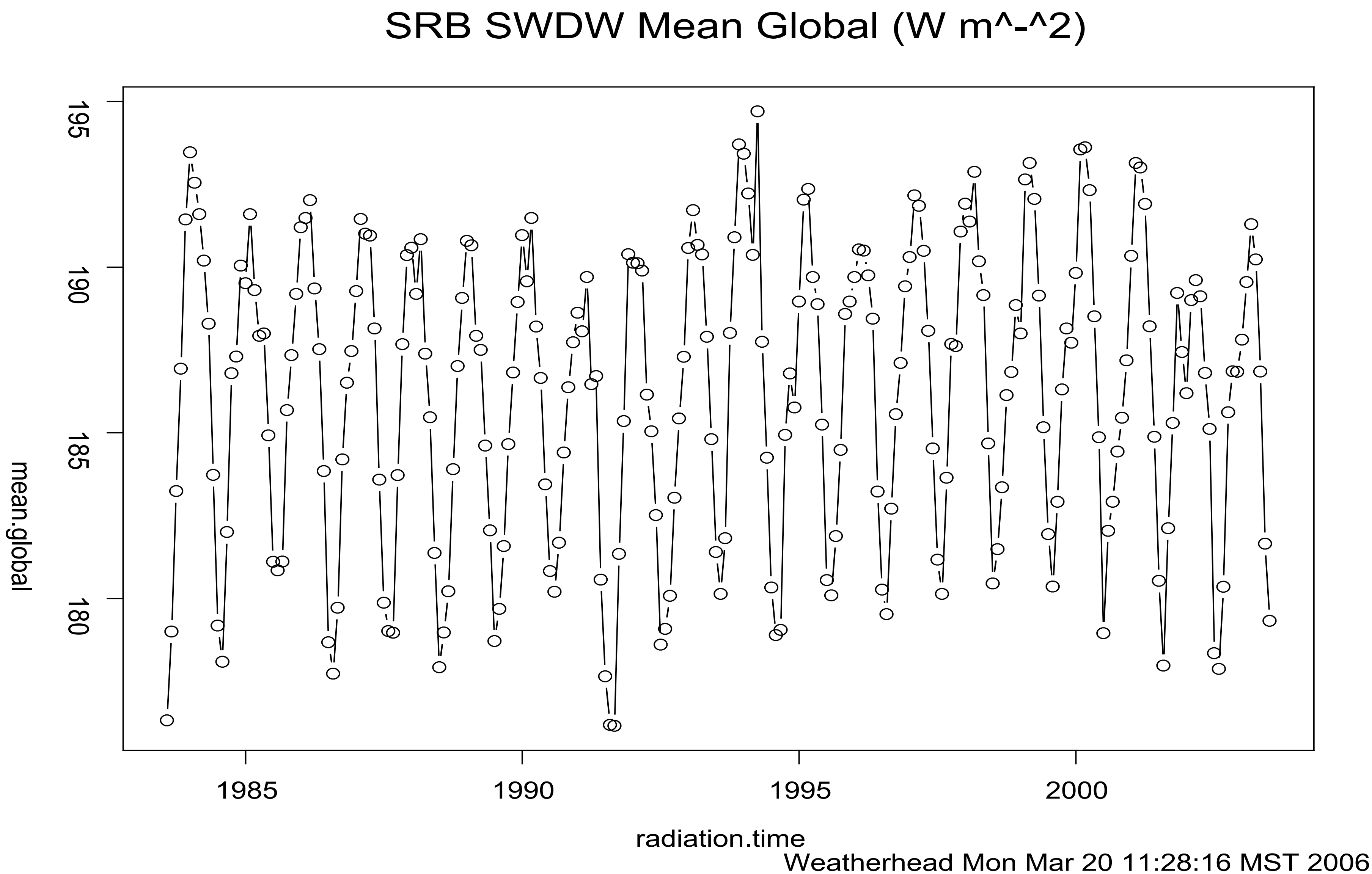
- Two types of plots follow:
  - ACF
    - Shows correlation of a month with one month prior; two months prior, etc.
    - Yule-Walker algorithm is used
  - PACF
    - Shows correlation of a month with one month prior; two months prior, etc. For two months and greater, the derived effect of the prior months is already removed.
    - Levinson-Durbin algorithm is used
- Time steps are one month
- Both sets of plots use the deseasonalized data provided.



Autocorrelation is always 1 for lag 0. This sets the scale. The horizontal dotted lines represent 2 sigma uncertainty on the fit, so the lag 1 term is barely significant. The lag 1 term is .1526; the lag 2 term is .1169; the lag 3 term is .0376.

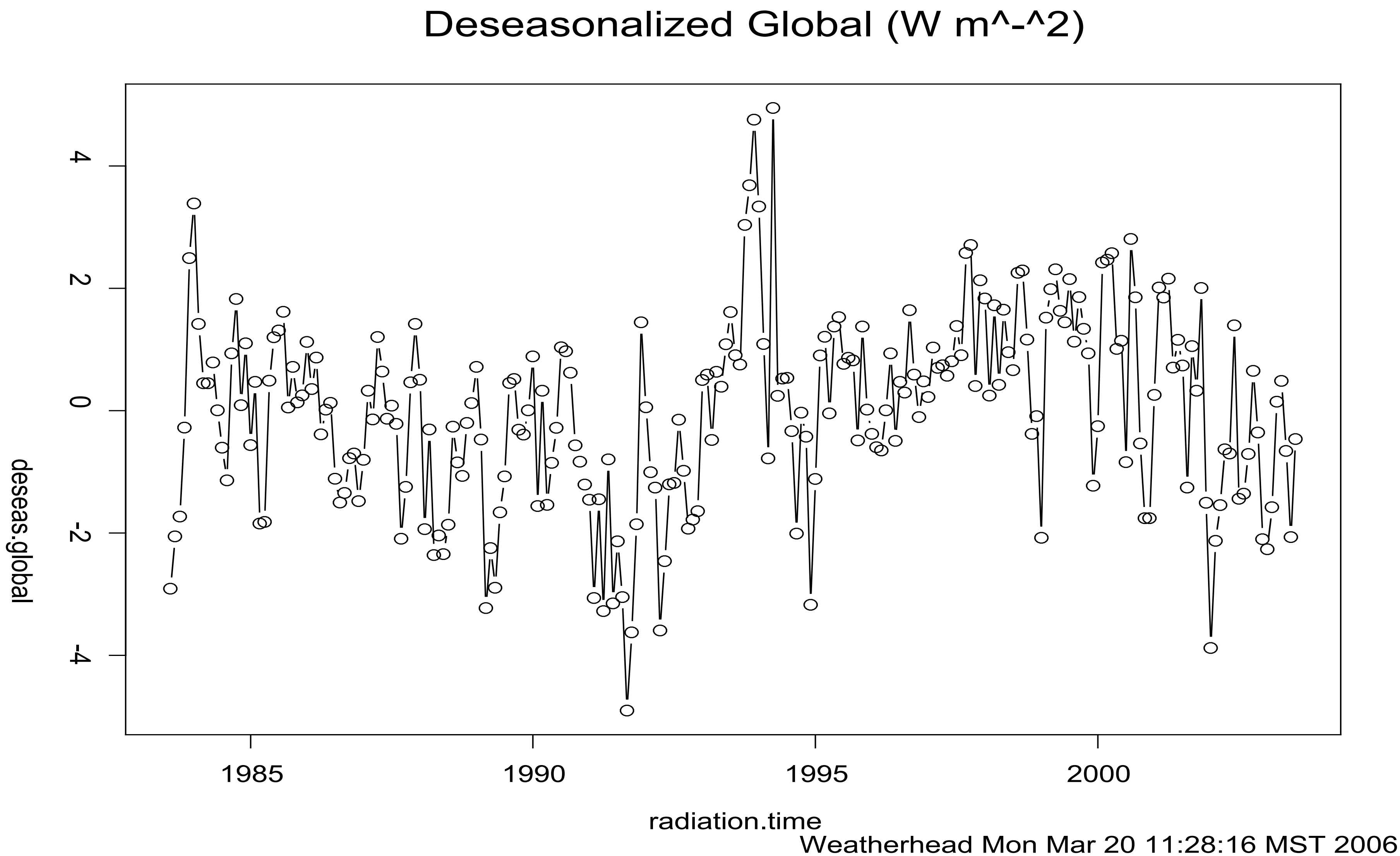


This Partial AC plot remove has the same lag 1 plot as the prior plot, but removes the expected Correlation for lags 2+, based on what we know about the earlier lags. Again, lag 1 is Small and only barely significant at the 2 sigma level. The rest of the lags are not Statistically significant. This implies an AR(1) is a sufficient model unless proven Otherwise.

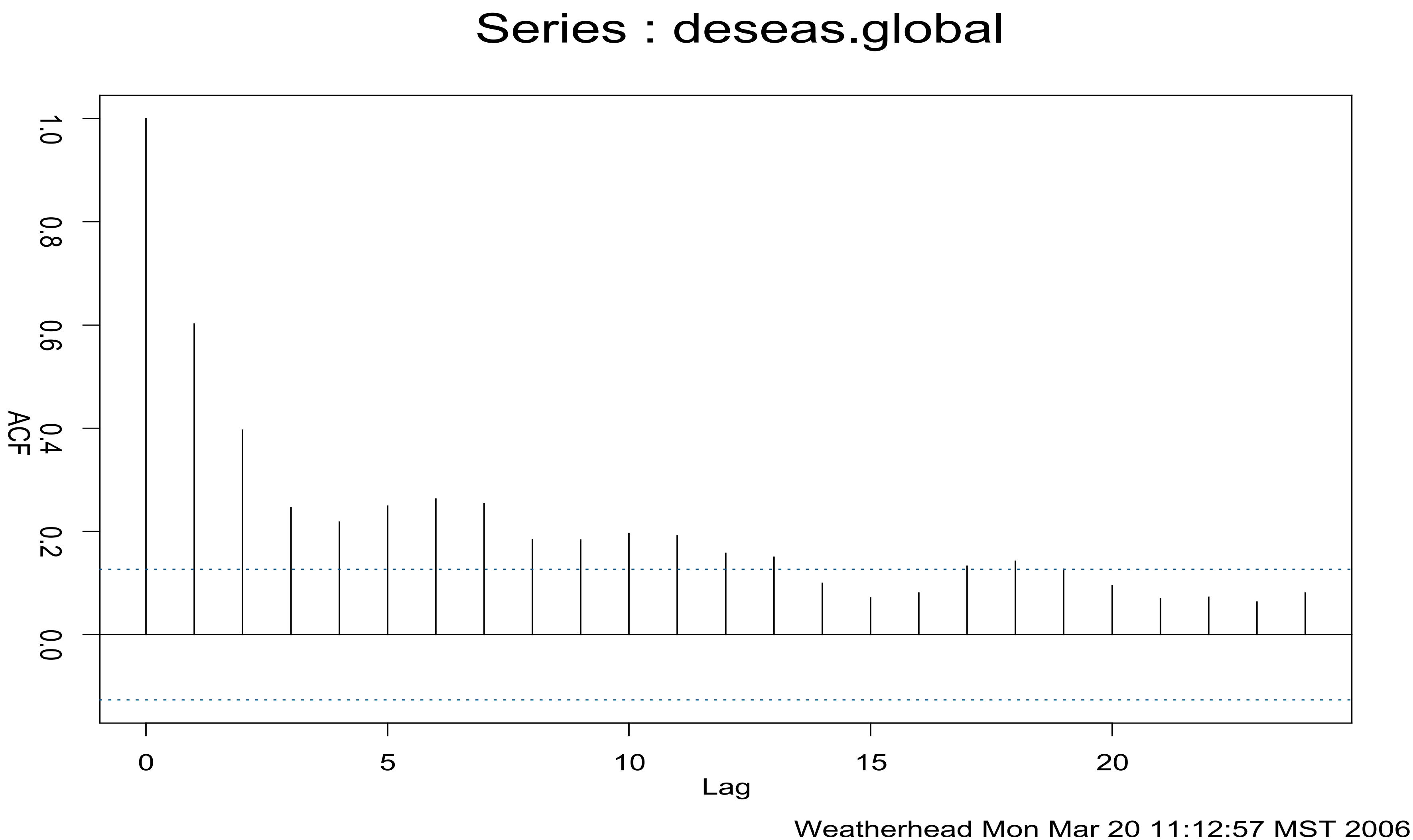


Note: Interesting 1994 event (Pinatubo delayed effect?)

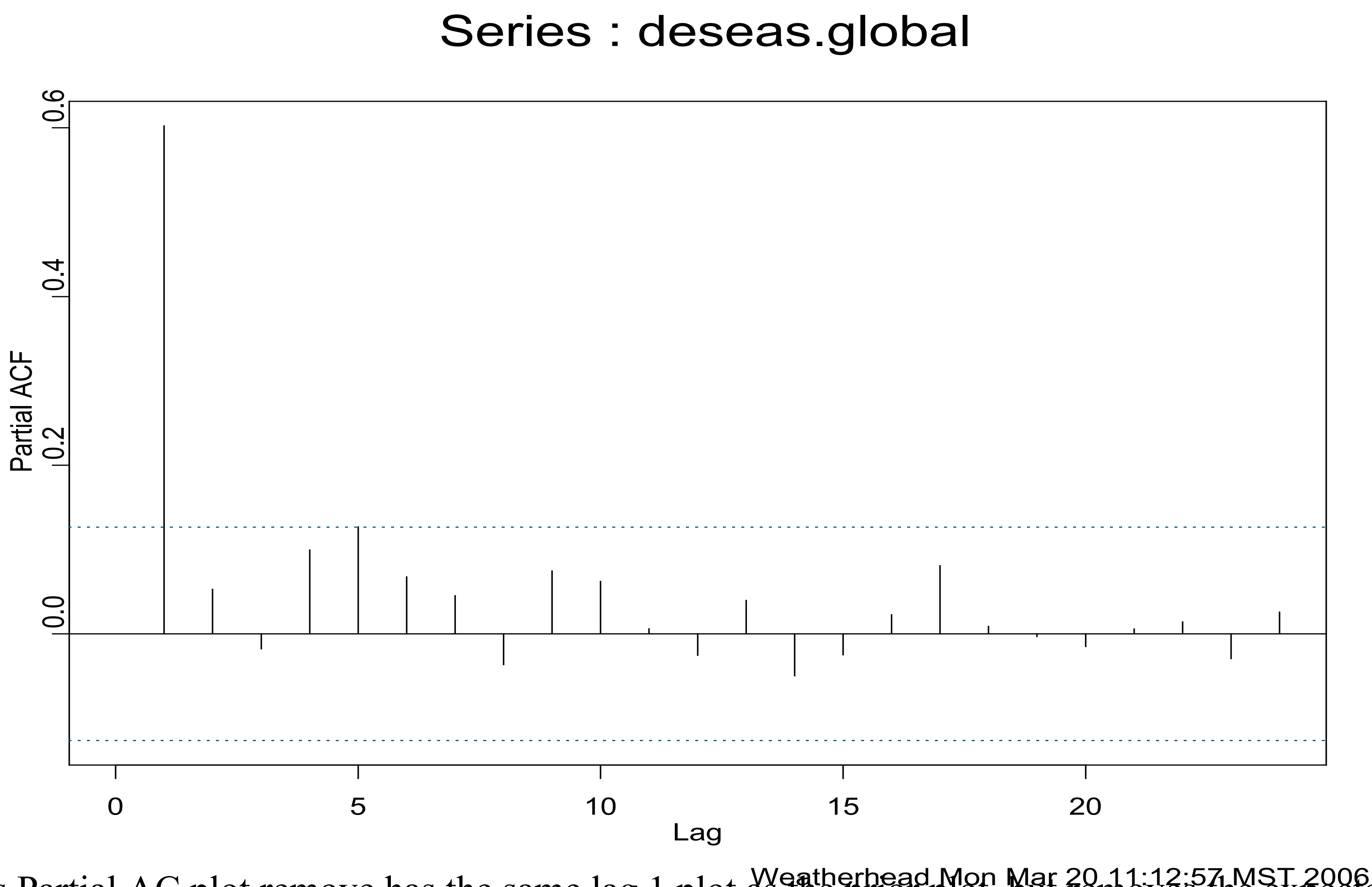
Note: Annual peaks and annual troughs seem related—very interesting!



Very clear decadal variability. This cannot be accounted for by a monthly model.
If there is any way to link this variability, that would be great. Without understanding
The long-term movement, trends and error bars will be misleading.



Again, autocorrelation is always 1 for lag 0. This sets the scale. The horizontal dotted lines represent 2 sigma uncertainty on the fit. The lag 1 term is .6022; the lag 2 term is .3964; the lag 3 term is .2467. This signature, with many statistically significant terms, can almost Be expected because the lag 1 term is so large. A large correlation between one month and Prior (0.6) almost dictates that there is a reasonable correlation between one month and two months prior.

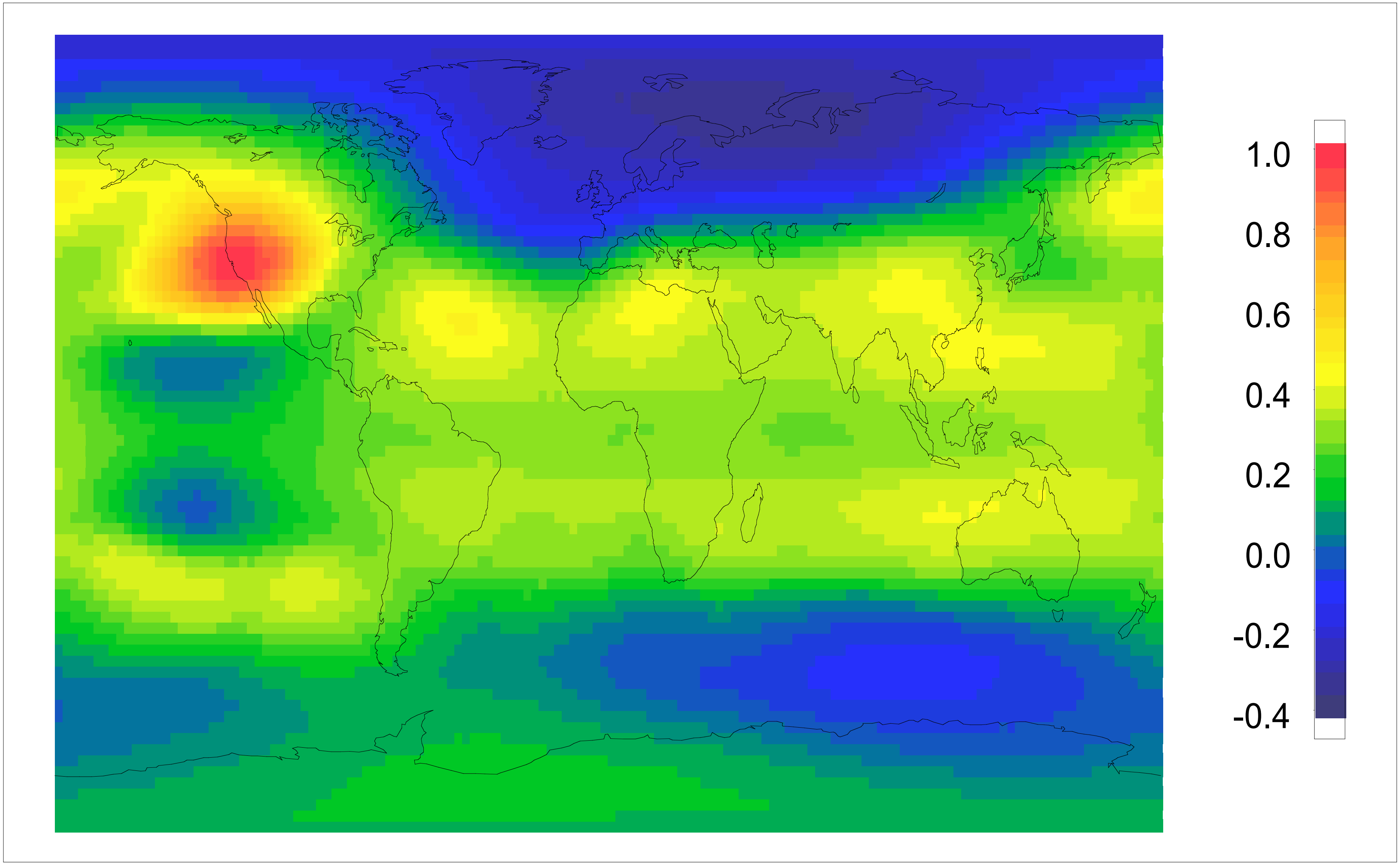


This Partial AC plot remove has the same lag 1 plot as the prior plot, but removes the expected Correlation for lags 2+, based on what we know about the earlier lags. Here, lag 1 is large and clearly significant at the 2 sigma level. The rest of the lags are not Statistically significant. This implies an AR(1) is a sufficient model unless proven Otherwise.

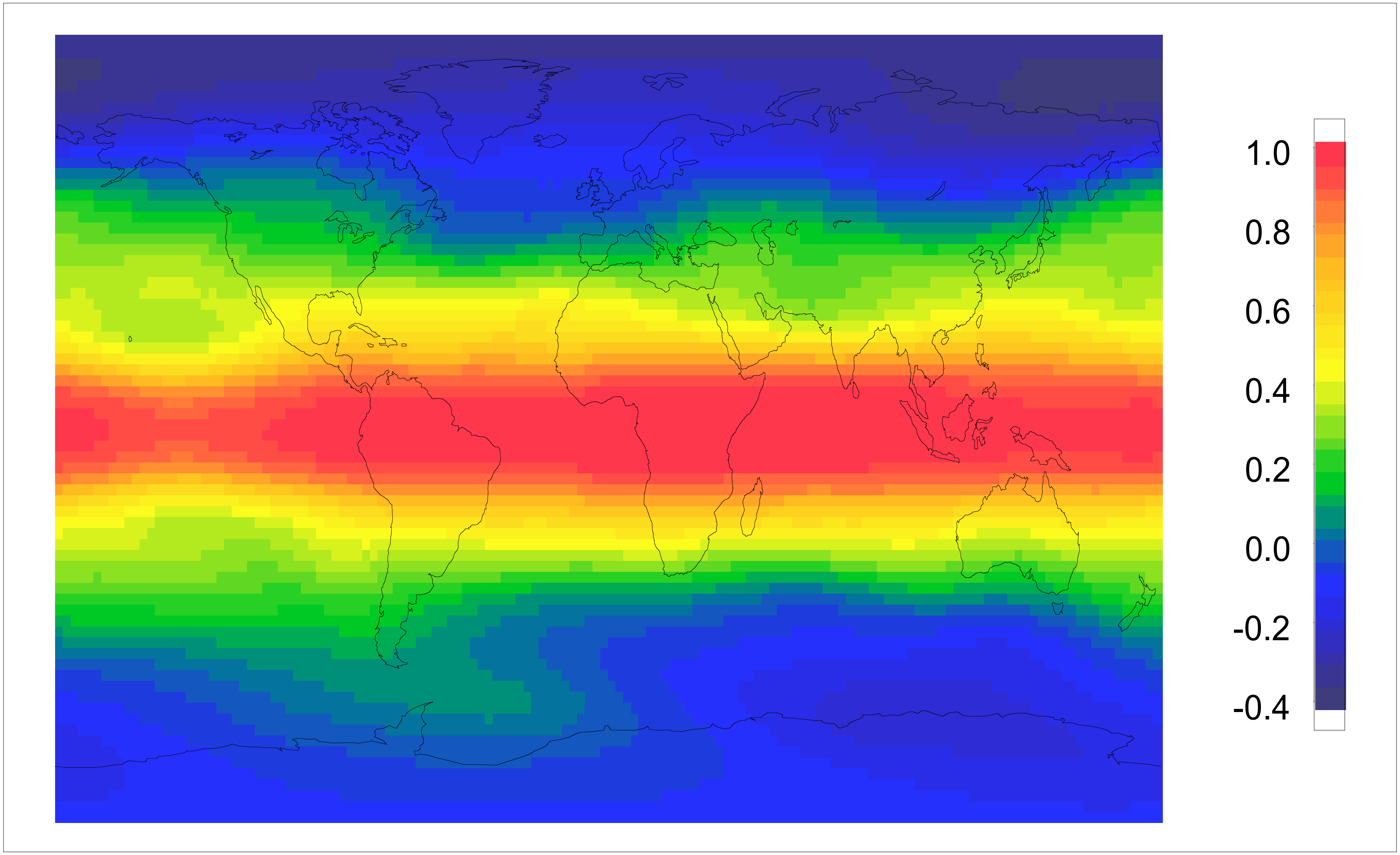
How many single stations do we need?

- Spatial coherence means that averaging many different locations does not always reduce error bars significantly.
- Spatial coherence can be estimated from past data.

MSU Channel 4
Correlation with S.F.



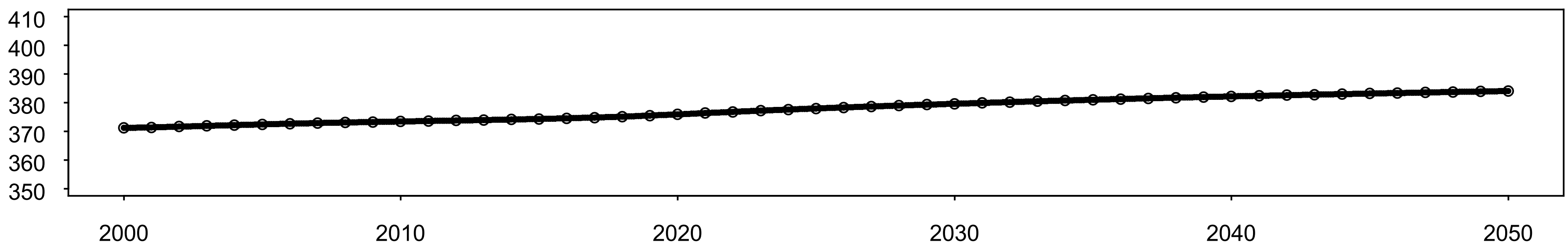
MSU Channel 4
Correlation with lat=0 and long=0



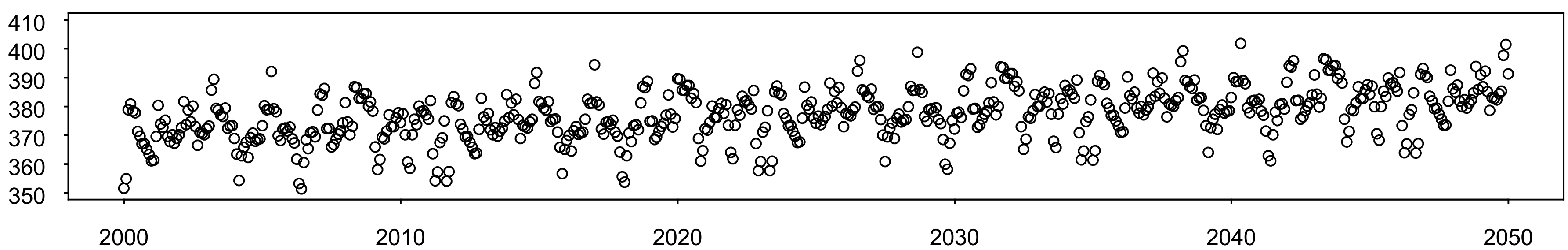
Number of Years needed to detect a trend

- Can we distinguish between cases where there are no trends and cases where we haven't monitored long enough?
- What can we improve in order to detect trends?

GSFC Predictions - without climate change

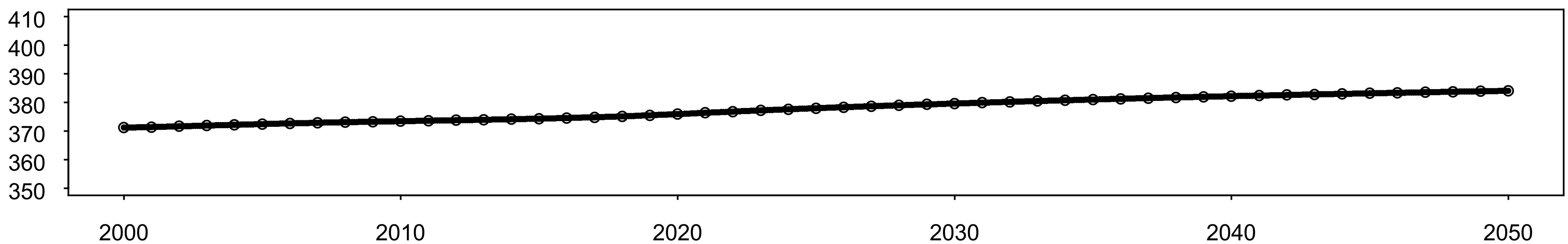


GSFC Predictions with SBUV Lowess Residuals

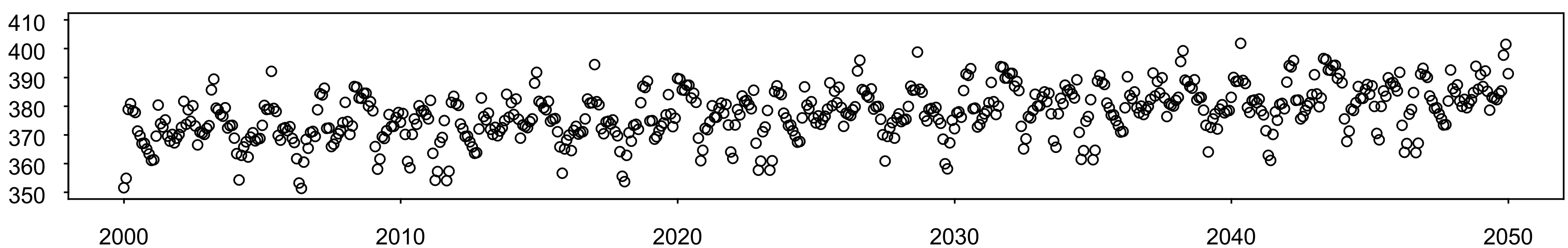


GSFC 2d Predictions with SBUV Residuals of Total Col. Ozone (d.u.) 40N

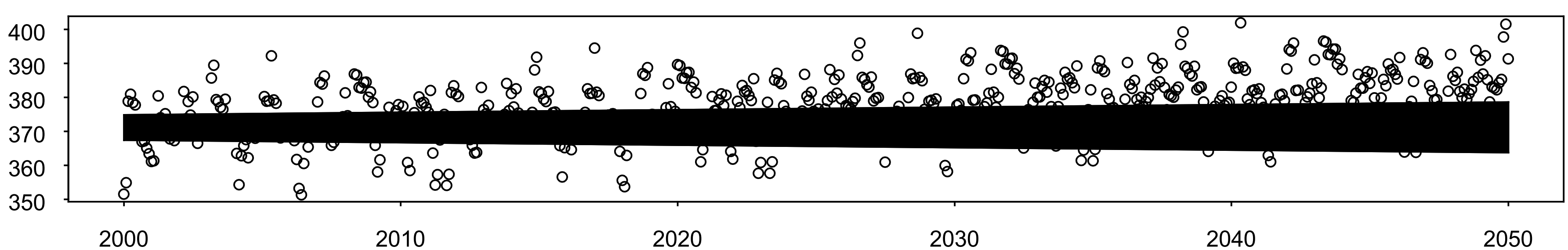
GSFC Predictions - without climate change



GSFC Predictions with SBUV Lowess Residuals



with +-1% error plus +-1% drift



Weatherhead Fri Nov 2 11:53:23 2001

Number of Years needed to detect a trend

- Approximately:

$$n = \left\{ \left(2 * \sigma_n / |\omega_o| \right) \text{ sqrt } (1+\phi)/(1-\phi) \right\}^{2/3}$$

  - Assuming that detection is declared at the 95% confidence level
  - This estimate allows for 50% likelihood of detection

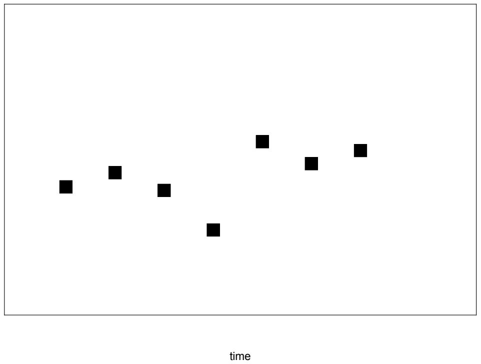
- What can we improve in order to detect trends?
  - Where we monitor
  - How frequently
  - How accurately
  - How well we understand the data

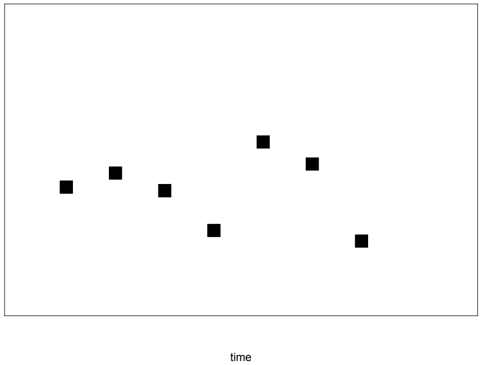
Anchor Point

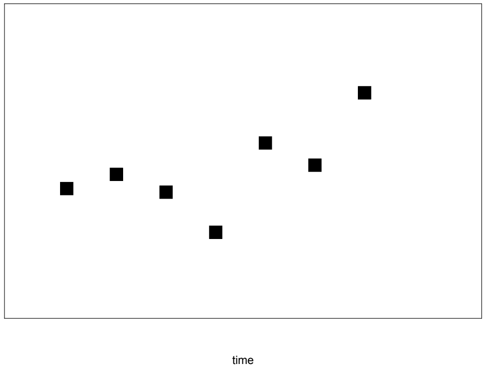
- One point can make a large difference on seven year trends.

- We can see it visually.

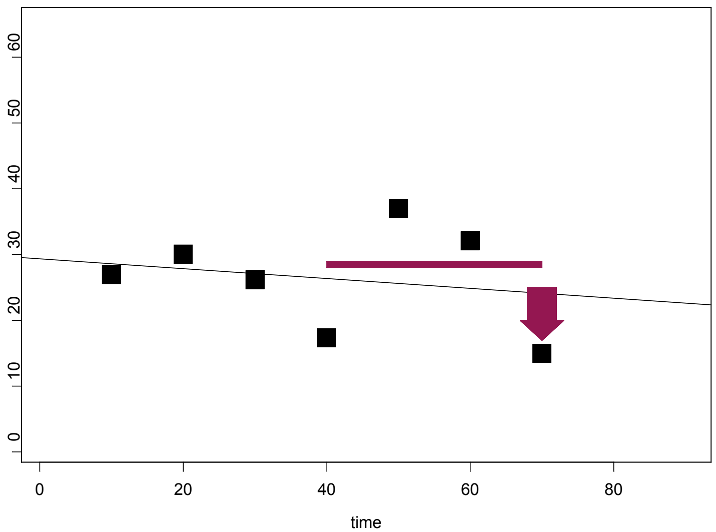
- This is reflected statistically.

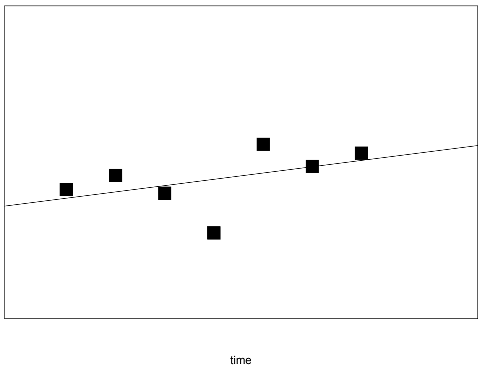


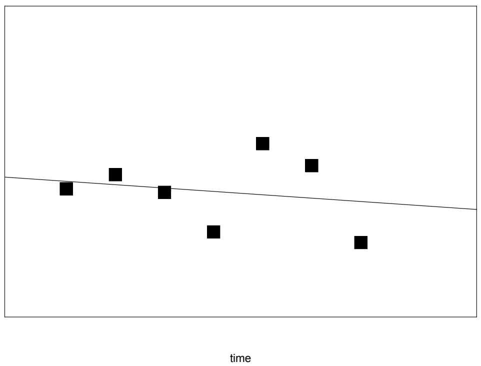


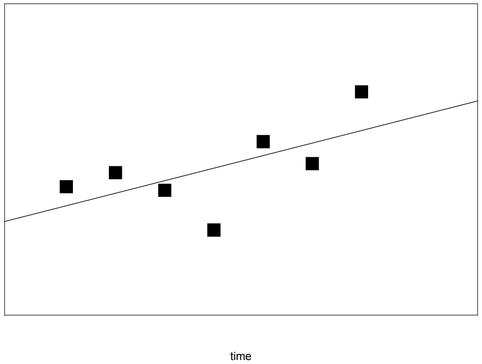


"Super Torque"









The power of a point to influence a trend line is proportional to:

the temporal distance from the center

x

the square of the distance of the point from the trend line.

Possible Questions?

Are the interventions normally distributed? Lack of normality could imply something very clear about positive or negative feedbacks—perhaps this will be most interesting when looking at regions of the world.

- Is the time correlation derived here independent of season? Is it possible that some months are more interconnected than others? This would be a good, independent way to help identify regimes.
- Are there some times of year better for detecting trends? Are there some places better for detecting trends?
- What explanatory variables can be pulled in to help explain long-term as well as short term variability? Once these variables have been brought in, what does that do to the internal structure of the data? Are they still AR(1) or are sub-exponential or super-exponential signals observed. Again, this could imply something about feedbacks on the station level or on the global level.
- Can the differences in variability be explained by the fact that one is an average over more areas, or is there a non-linear relationship which could imply tele-connections.
- How do the endpoints affect our trend results?

Summary Thoughts

The two time series have very different characteristics as can be seen by looking at the deseasonalized time series. The global time series has a more clear, decadal time scale associated with it.

- This initial analysis implies that an AR(1) is an appropriate model to use for both time series.