Chapter 2

Climate Variability

2.1 introduction

Climate variability embraces not only the range of conditions over the course of a year but the ranges on many time scales, from hours to decades. Variability arises from the dynamics of fluids in motion on a rotating sphere with with an uneven surface shape (Earth’s continents and ocean basins), and from the thermodynamics of interaction between the atmosphere and ocean. Patterns of variability recognized in statistical analyses of climate data as distinct from expected seasonal cycles are called climate modes. Patterns that can be mapped from one data set to another (say from sea level pressure to precipitation) and can be understood according to principles from climate dynamics, are useful to understanding how the coupled climate system behaves and to interpreting short-term climate trends.

The dominant decadal-scale climate modes are the Northern Annular Mode centered about the Arctic; the Southern Annular Mode (SAM) centered about the Antarctic; the tropical El Niño Southern Oscillation (ENSO), which dominates the Pacific on interannual scales; and the Pacific North American (PNA) pattern forced by the Tibetan Plateau and Rocky Mountains. Here in Oregon we are familiar with the relatively longer time scale Pacific Decadal Oscillation (PDO), a manifestation of ENSO. The North Atlantic Oscillation (NAO), a manifestation of the NAM is a familiar feature in eastern North America and Europe. Enough acronyms yet? It is important to recognize these modes of variability because they are essential features of the coupled climate system and because we cannot interpret observations of climate variables like air temperature or sea ice concentration if we cannot distinguish between climate variability and climate change.

In this lab you will examine time series of climate variables collected at weather stations in the northern and southern hemisphere. These records are the raw data used by various authors to produce global climatologies like the ones we used in the first lab. We start by plotting several temperature time series, compute anomalies and simple linear trends, and introduce the idea of spectral analysis.
2.2 the data

2.2.1 temperature time series

Temperature time series for a set of high-latituide weather recording stations are organized for you in the MATLAB file Trecords.mat. Each record contains mean monthly temperature, in degrees Celsius, as well as seasonal and annual mean values. The seasonal groupings are December-January-February, March-April-May, June-July-August, and September-October-November, as used by climatologists. It should be noted that ecologists may use different definitions of seasons, depending on processes in action in a particular geographic region.

Record length varies from site to site. “Modern” instrumental records have been kept since the middle of the 17th century, although very few are continuous before the 18th century. By the start of the 19th century, reliable and continuous records were being kept in Europe and East Asia. More widely available and reliable records pick up the mid 19th century. In North America, reliable climate records begin in the late 19th century. The longest Antarctic record, from the Argentine Orcadas Base on Laurie Island, began in 1903 (the first year of occupation was by the Scottish National Antarctic Expedition).

Time series have been prepared for the following locations:

<table>
<thead>
<tr>
<th>Location</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Elevation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barrow, AK</td>
<td>71.3 N</td>
<td>156.8 W</td>
<td>13 m a.s.l.</td>
</tr>
<tr>
<td>Verhojansk, Russia</td>
<td>67.5 N</td>
<td>133.4 E</td>
<td>137 m</td>
</tr>
<tr>
<td>Murmansk, Russia</td>
<td>69.0 N</td>
<td>33.0 E</td>
<td>50 m</td>
</tr>
<tr>
<td>Akureyri, Iceland</td>
<td>65.7 N</td>
<td>18.1 W</td>
<td>27 m</td>
</tr>
<tr>
<td>Orcadas, South Orkney Islands</td>
<td>60.8 S</td>
<td>44.7 W</td>
<td>4 m</td>
</tr>
<tr>
<td>Halley Station, Antarctica</td>
<td>75.5 S</td>
<td>26.6 W</td>
<td>30 m</td>
</tr>
<tr>
<td>South Pole Station, Antarctica</td>
<td>90 S</td>
<td>0</td>
<td>2835 m</td>
</tr>
</tbody>
</table>

The data were retrieved from the NASA Goddard Institute for Space Studies temperature data archive, GISTEMP, http://data.giss.nasa.gov/gistemp/.

2.2.2 climate modes

Most simply, annular modes are oscillations of atmospheric mass between high and middle latitudes centered around the poles. These oscillations produce distinct patterns of change in sea level pressure, which in turn moderate atmospheric circulation and thereby drive variations in temperature, storm tracks, and other weather phenomena. The annular modes about the poles account for between 20 and 30% of the total variance in the sea level pressure field.

The Northern Annular Mode (NAM), or Arctic Oscillation (AO), is a non-seasonal pattern of sea level pressure variation north of 20 N latitude in which high-latitude pressure anomalies of one sign co-vary with mid-latitude anomalies of the opposite sign. Several indexes have been used to generate time series representations of the AO. A simple index can be made using the normalized pressure difference between lower and higher latitude weather stations, for example between the...
Figure 2.1: Composite maps of Jan-Feb-Mar surface air temperature (color map) and sea level pressure (contours) for high and low index states from Thompson and Wallace, *Science*, 2001. The contour intervals are 5°C (blue indicates temperature below -10°C) and 3 mbar.
Azores and Iceland. More complete statistical representations of the variability may be created using the leading empirical orthogonal function (EOF) of the sea level pressure field (or 1000 mbar height) north of 20 N. EOF analysis is like a principal component analysis but it embraces variance in both time and space. EOFs are basis functions chosen to minimize residual variance (that is, eigenvectors). Don’t panic. What you really need to know is that the analysis identifies persistent patterns in the non-seasonal variance of the sea level pressure field and we call the leading pattern, the one that embraces the largest amount of the variance, the AO or NAM.

The positive (or high index) phase of the AO is characterized by relatively lower pressure over the Arctic and relatively higher pressure at mid-latitudes (Figure 2.1). The strong pressure gradient results in relative strengthening of subpolar westerly winds between about 55 and 60 N (the “polar vortex”). A relatively cold low is confined over the pole; relatively warm, higher pressure conditions prevail between 35 and 55 N (the extratropics); and cool anomalies appear in the tropics. Cold temperatures prevail over eastern Canada and Greenland while warm conditions prevail over Siberia and the subpolar United States (Figures 2.2 and 2.3, from John Wallace, http://www.jisao.washington.edu/wallace/ncar_notes/). Storm tracks take a relatively northerly route across the north Pacific and Atlantic, bringing relatively more precipitation to Alaska and northern Europe while leaving the Mediterranean anomalously dry (Figure 2.4, from J. Wallace).

Motion of the Arctic sea ice is also affected by AO state. A positive state, sea ice spends less time than usual in the Beaufort gyre, open water appears on the Russian side of the Arctic Basin, and passage of relatively young and thin ice out of the basin through Fram Strait is promoted. Together, these effects result in anomalously young and thin sea ice under high AO index conditions.

The negative (or low index) phase of the AO is characterized by relatively higher pressure over the Arctic, relatively lower pressure in the extratropics, and relatively weaker subpolar westerlies. This allows cold polar air to extend relatively farther south over the northern United States and Siberia than in the positive state. Sea ice spends relatively more time recirculating in the in the Beaufort gyre. The long residence time yields older, thicker ice.

The southern hemisphere experiences its own annular mode of variability, the Southern Annular Mode (SAM), or Antarctic Oscillation (AAO). The AAO index is calculated as the leading EOF of sea level pressure or the 850 mbar height south of 20 S and has features similar to its northern counterpart. In the positive index state, pressure is relatively low over the pole, relatively high over mid-latitudes, and subpolar westerlies between 55 to 60 N are relatively strong. As in the north, the positive phase is associated with relatively cool temperatures in the interior of Antarctica and relatively warm temperatures north of the westerlies. Relatively strong divergence in the shallow ocean under the relatively stronger westerlies moves sea ice north, exposing more ocean water to the cold atmosphere and promoting additional sea ice formation. Thus, the positive phase of the AAO is associated with an expansion of winter sea ice extend around Antarctica.

Monthly mean and winter (D-J-F) mean AO and AAO indexes are provided for you with this lab. The indexes were computed by National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center and were retrieved from their archive at http://www.cpc.noaa.gov/products/precip/CWlink/daily_ao_index/teleconnections.shtml. The AO index begins in 1950 and the AAO index begins with the dawn of the Earth-observing satellite era in 1979.
2.2. THE DATA

AO surface temperature anomalies (C) 1950-96

Figure 2.2: Terrestrial surface air temperature anomaly pattern associated with the AO computed using Global Historical Climatology Network (GHCN data). Figure from J. Wallace.
AO surface temperature anomalies (C) 1960-96

Figure 2.3: Oceanic surface air temperature anomaly pattern associated with the AO computed using the Comprehensive Ocean-Atmosphere Data Set. Figure from J. Wallace.
AO precipitation anomalies (cm/month) 1950-96

Figure 2.4: Precipitation anomaly pattern associate with the AO computed using GHCN data. Figure from J. Wallace.
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2.3 time series analysis

A time series is a sequence of observations made of some quantity, ideally at uniform intervals of time. The data, then, are a discontinuous sample of the quantity in which we have interest and the samples have an explicit ordering that is important to their analysis. Time series analysis is used to develop statistical and other descriptions of the data that lead to deeper understanding of the time series and the system component it represents. Analyses may be made in either the time or the frequency domain. We could devote an entire term to time series analysis and only scratch the surface.

A good place to start with time series data is just to have a look at it, either in a big data table or a graph of the function $Y(t)$. Is the data set complete or are there missing intervals? What is the total duration of the record and how frequently have the measurements been made? How do those metrics compare with time scales you might expect to be important to $Y(t)$? These are the types of questions you need to answer before you begin any kind of analysis. Next, we may wish to compute some simple metrics like the mean or standard deviation.

Changes over time in climate data can be thought of as having two components, seasonal (or longer) cycles and a trend. Both are systematic, but the trend does not repeat through the series while cycles do. The trend may be zero (but this is unlikely). The amplitude of the seasonal cycle may be the same from year to year or may change, either in another, larger cycle, or monotonically. Cycles may also arise in seasonal or annual mean conditions. When we are looking for cycles, we must first remove the trend from the time series.

Often we are interested in differences from the mean state, anomalies, of particular quantities. The anomaly is the difference between individual values and the mean value some range of years. The standard range used to define the mean in climate studies is 1951 to 1980.

2.3.1 preliminaries

In the following discussion, the function $Y(t)$ is used to represent some climate variable $Y$ measured at a set of times $t$ at a particular location. As a first step, we may wish to simply graph $Y(t)$, for example, as a line or scatter plot. This may give us a handle on the mean value and standard deviation. It easy enough to calculate these quantities as well,

$$\nu = \frac{1}{N} \sum_{n=1}^{N} Y_n \quad (2.1)$$

and

$$s = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} (Y_n - \nu)^2} \quad (2.2)$$

The subscript $n$ indicates a particular sample in a set containing $N$ total samples. Recognizing that our time series is only a sample of all possible temperatures at the location, equation 2.2 yields the
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sample standard deviation. If we have some confidence that our sample is normally distributed, we can use the standard deviation of the sample instead, in which case $\frac{1}{N}$ is used.

Trend detection is, unfortunately, less simple than it may seem. Suppose we simply want to know the mean rate of warming in McMinnville, Oregon over the last fifty years. The easiest thing we can do is fit a line through a set of mean temperatures for the years of record. The slope of the line would be the trend over the interval. Is this approach valid? To answer that question, we must consider whether or not our temperature samples conform to the statistical model underlying our chosen technique. Do we have enough samples to ensure that we are working with a normal distribution? We must use different analysis methods when our data are drawn from a normal distribution and when they are not. Next, we should consider that trends may take many forms, from linear to exponential, may have cycles superimposed upon them, or may include step changes. While simple linear trends are convenient and capture overall change in a variable, they rarely reveal all there is to be learned in some cases may be misleading. With that caveat in mind, we will forge ahead. Be careful.

The model for a linear trend is

\[ y(t) = b + mt + u(t) \]  

in which $t$ represents the independent variable time, $y(t)$ is the value of a the dependent variable $y$ at a particular value of $t$, $m$ represents the slope of the linear regression, $b$ is the intercept $y(0)$, and $u$ represents a random error in the measurements. In an ordinary least squares regression (described below), we assume that the errors are uncorrelated and have a mean of zero. The slope $m$ is the linear trend in the data series. The most common trouble with this approach is that the data values are probably not independent, that is, the data are autocorrelated. Indeed, cycles are an interesting attribute of climate time series, but they do complicate our trend analysis.

Matlab provides functions for several least squares algorithms. The resulting trends may be similar but the standard errors can be very different for different methods. A trend that appears significant using ordinary least squares (OLS) may not appear significant when a more appropriate method is used. We use an OLS procedure here because it is most likely to be familiar but please be aware of its limitations.

2.3.2 data visualization using Matlab

The raw temperature data can be plotted for individual stations using the function f_Ttrends.m, provided for you at the class website. f_Ttrends uses a second function, f_Tanom.m to compute a temperature anomaly and a linear trend through the anomaly. You must load the data file T_records.mat into the workspace before using the function. It is also important to note that the function does not clear the figure window, so that several records can be plotted together in the same set of axes. This makes it important to clear out old figures manually if you want to use them again.

Several values are passed to the function to guide its behavior. These include the column number for the mean you wish to plot (individual months, seasons, etc.), the “no data” value of 999.9 (indicates missing station data), a flag to indicate whether or nor you want some statistics written in the figure window (0 for no and 1 for yes; more on this below), and a flag to indicate whether
or not you want to plot both the temperature and anomaly series or just the anomaly (0 for both; 1 for just the anomaly). You must tell the function which years are to be used in computing the mean. The standard range is 1951 to 1980 (this range will not work for all of the time series prepared for you in this lab).

The function returns the slope of the linear trend, along with the coefficient of determination and the goodness of the fit. These values may be returned to either the command window or stored in a set of variables if you wish.

The trend is calculated using a built-in MATLAB function `polyfit`. The function finds a set of model data \( \hat{Y}_n \), given a set of original data \( Y_n \), such that the quantity

\[
\sum_{n=1}^{N} (\hat{Y}_n - Y_n)^2
\]

is minimized for a proposed model. In this case, we enforce a linear relationship.

The coefficient of determination \( R^2 \) is computed using sums of squares:

\[
R^2 = 1 - \frac{\sum_{n=1}^{N} (\hat{Y}_n - Y_n)^2}{\sum_{n=1}^{N} (Y_n - \bar{Y})^2}
\]

in which the overbar indicates a mean.

The goodness of the fit of the linear model is evaluated using means:

\[
S = \frac{\sum_{n=1}^{N} (\hat{Y}_n - Y_n)^2}{\sum_{n=1}^{N} (Y_n - \bar{Y})^2}
\]

in which, of course, the number of data points \( N \) cancels. You have noticed, of course, that we use metrics consistent with the assumption of a normal distribution.

An example using the function at the command line in the command window to plot the December-January-February mean temperature and anomaly at Verhojansk in which the trend statistics are returned to a variable named `S_Verho14`:

```matlab
>> load T_records.mat
>> ttl='Verhojansk mean winter temperature';
>> yv=[1951 1980];
>> S_Verho14=f_Ttrends(15, T_verhojansk, 14, yv, 999.9, 0,0, ttl);
```

An example plotting anomalies only for summer and winter at Verhojansk:

```matlab
>> load T_records.mat
>> ttl='Verhojansk mean summer (r) and winter (b) temperature anomalies';
>> yv=[1951 1980];
```
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2.3.3 a simple search for cycles

Our analysis thus far has been for the most part an exercise in data visualization. A more rigorous analysis method is needed, for example some type of harmonic analysis, if our goal is to develop an understanding of the physical processes underlying the measured values. A number of methodologies are available, depending on the nature of the data set. How long is the time series? Do we have just one point or gridded data covering a geographic region? Next, we need to think about what we want to learn. Are we interested in statistical comparisons among different locations, identifying patterns at different stations, or something else?

A straightforward place to start is to look for cycles, or autocorrelation, within individual time series. We might also be interested in correlation among time series from different locations. If we know something about variability in the coupled climate system, such information may help us place individual time series in that context. Here, simple statistical measures of similarity are introduced for the purpose of identifying cycles in individual time series.

Covariance is a measure of the mutual variation among two or more data sets about their common mean. Correlation is the covariance normalized using the standard deviations of the data sets. Thus, correlation is dimensionless. The variance in a single data set, where this all begins, is average squared deviation of all the data from the mean

$$
\sigma^2 = \frac{\sum_{n=1}^{N} (X_i - \mu)^2}{n}
$$

in which $N$ is the number of observations in the data set and $\mu$ is their mean value. The covariance for two data sets is computed in a similar way but using values and means of the two sets, $X$ and $Y$ and $\mu$ and $\nu$, respectively

$$
\text{COV}(X,Y) = \frac{\sum_{n=1}^{N} [(X_i - \mu)(Y_i - \nu)]}{n - 1}
$$

The correlation is computed by normalizing the covariance

$$
r = \frac{\text{COV}(X,Y)}{\sigma_X \sigma_Y}
$$

in which the standard deviations $\sigma$ are computed following equation (2.6).

Repetition in a time series may be found by computing its autocorrelation, that is, its correlation with itself or self-similarity across successive points in the sequence. You can imagine this as lining up two exact copies of the time series and then shifting one relative to the other and looking for shifts at which patterns in the replicates line up. The sampling interval must be uniform for this analysis. If $\delta$ is that interval, the total length of the series is $\delta(n - 1)$. The data set must be
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Figure 2.5: Mean annual temperature at McMinneville, Oregon: original time series and replicas shifted at lags $\tau = 1$ and $\tau = 10$.

Figure 2.6: Spectral power in the McMinneville mean annual temperature record shown in Figure 2.1, computed using a fast fourier transform. Two maxima, at about 10 years and 3 years may represent the influence of the Pacific Decadal Oscillation and ENSO, respectively.
complete, that is, there can be no missing values. If missing values exist, they must be replaced using a carefully selected interpolation scheme.

The separation between any two points in the series, called a lag, has a length \( \tau \) that is the number of intervals \( \delta \) between the points. It is the separation as we shift the replica of our time series past the original. The autocovariance for lag \( \tau \) is

\[
\text{COV}_\tau = \frac{1}{n - \tau} \sum_{t=1+\tau}^{n} [X_tX_{t-\tau} - \mu_t\mu_{t-\tau}]
\]

(2.9)

The autocovariance at \( \tau = 0 \) must of course be the variance of the time series.

As with the correlation, the autocorrelation is the covariance normalized using the variance of the series. The autocorrelation at lag \( \tau \) is

\[
r_\tau = \frac{\sum_{t=1+\tau}^{n} [X_tX_{t-\tau} - \mu_t\mu_{t-\tau}]}{\sum_{t=1}^{n} (X_t - \mu)^2}
\]

(2.10)

The autocorrelation at \( \tau = 0 \) is thus one. The autocovariance (and autocorrelation) is usually calculated for lags from 0 to about \( n/4 \). When you plot covariance (or correlation) as a function of lag in an autocovariogram (or autocorrelogram), the maximum covariance will be at \( \tau = 0 \). The covariance (or correlation) will drop with increasing \( \tau \) and then rise again if a correlation is found at some lag 0. The plot will be two-sided, with a negative part that is a mirror of the positive part. There are more analyses to be performed with the results of correlation calculations but making it this far is a good start.

A MATLAB script and two functions have been written to perform a simple autocorrelation analysis on a data set of your choosing. You may use the time series as in the example here but will need to adapt the script to perform the analysis on an additional time series (or perhaps for your term project). The script you will run is called Tautocorr.m. The function fautocorr.m performs an autocorrelation analysis for a time series passed to it and the function fpowerspec.m uses a Fourier transform to evaluate the “power” at different frequencies in the autocorrelation. The autocorrelation is interesting on its own but the spectral analysis gives us a cleaner view of overall variation in the series. MATLAB’s built-in \texttt{fft} function is used to perform the discrete-time Fourier transform. If you look in Tautocorr.m you will see equation (2.10) written out using variable names specified in the function declaration. The \texttt{for} statement is used to systematically repeat the correlation calculation for lags of increasing size. You may also use \texttt{fpowerspec.m} on its own to look for dominant frequencies in the temperature time series but this is not required and may be problematic with short time series.

2.3.4 function listing: temperature trend

\begin{verbatim}
function [stats]=f_Ttrends(fn, T, N, myrs, ND, SF, AF, ttxt)
% plot temperature data and trends
% fn
\end{verbatim}
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% T  temperature record to plot
% N  column number to plot
% myrs [2 x 1] containing start and end years for average
% ND  no data value
% SF  flag, write stats on figure or not, 0 for no, 1 for yes
% AF  flag to plot anomaly only, 0 for no, 1 for yes
% ttxt title text, a string of characters

% define colors and line types to draw
switch N
    case 14
        ls=['.b--'; 'b--'];
    case 15
        ls=['.g--'; 'g--'];
    case 16
        ls=['.r--'; 'r--'];
    case 17
        ls=['.c--'; 'c--'];
    case 18
        ls=['.m--'; 'm--'];
    otherwise
        ls=['.k--'; 'k--'];
end

% use function to compute anomaly and trend
[anom, fep, stats]=f_Tanom(T(:,1), T(:,N), myrs);

figure(fn)
if ~AF
    subplot(2,1,1)
    gds=find(T(:,N)==ND);  % find missing data locations
    plot(T(gds,1), T(gds,N), ls(1,:))
    hold on
    ylabel('(C)')
end
    title(tttxt)

if ~AF
    subplot(2,1,2)
end
plot(T(:,1), anom, ls(1,:))
hold on
plot(fep(:,1), fep(:,2), ls(2,:))
ylabel('anomaly (C)')
xlabel('year')
if SF
    text(max(T(:,1))-10, min(anom)/1.5, num2str(stats(1)))
    text(max(T(:,1))-10, min(anom)/1.1, num2str(stats(3)))
end
f_Ttrends calls a second function

```matlab
function [ranom, fep, sts]=f_Tanom(Ty, Tr, vargin)

% function f_Tanomplot(fn, Ty, Tr, vargin)
% compute anomaly and best fit linear trend
% assumes 999.9 is missing data
%
% Ty     years for temperature record
% Tr     temperature record to plot
% vargin start year for mean, 1951 default
% vargin end year for mean, 1980 default
%
% return values
% anom  temperature anomaly to plot
% fep   best fit endpoints for graphing
% p(1)  slope of trend line
% rsq   coefficient of determination ("r–squared")

% compute anomalies
goodies=find(Tr˜=999.9);

if length(vargin)==2
    mstart=find(Ty==vargin(1));
    mend=find(Ty==vargin(2));
else
    mstart=find(Ty==1951);
    mend=find(Ty==1980);
end

Tm=mean(Tr(mstart:mend));
anom=Tr(goodies)−Tm;

% linear trend
[p, S] = polyfit(Ty(goodies),anom,1);
f=p(1)+Ty(goodies)+p(2);

fep=[Ty(min(goodies)) f(1);Ty(max(goodies)) f(length(f))];

% coefficient of determination
ssr=sum((f−anom).^2);
ssd=sum((anom−mean(anom)).^2);
rsq=1−ssr/ssd;

% significance of trend (goodness of fit of linear model)
msr=mean((f−anom).^2);
msd=mean((anom−mean(anom)).^2);
S=msr/msd;
```
sts=[p(1); rsq; S];

% pad anomaly with NaNs for missing data
ranom=NaN(size(Tr));
ranom(goodies)=anom;

2.3.5 script listing: Tautocorr.m

%** create plots of power spectra for paleoclimate data sets
% with UNIFORM sample interval
%
% this script uses quick and easy function f_powerspec
% [freq, pow]=f_powerspec(SDATA, SF)
% SDATA: equally-spaced (in time) samples
% SF: sample frequency
% freq: frequency spectrum
% pow: signal power at those frequencies
%
% this script uses function f_autocorr
% R=f_autocorr(SDATA, SF)
% R: level of correlation at a range of lags
% 1: lag in time units
% 2: correlation
%
% detrend the data to clean up the analysis
% built-in Matlab detrend takes flags 'constant' and 'linear'
%
% select time series
ts=detrend(T_akureyri(2:128,2), 'linear'); % dependent variable, detrended
tst=T_akureyri(2:128,1); % independent variable (time)
sf=tst(2)-tst(1);

ttl='Akureyri January temperature';
f=100; % figure number

% compute correlation and plot the result
autoC=f_autocorr(ts,sf);
[fSPAC, pSPAC]=f_powerspec(autoC(:,2), sf);

figure(f)
subplot(3,1,1)
plot(tst,ts, '.m-')
ylabel('data')
xlabel('time')
title(ttl)

subplot(3,1,2)
plot(autoC(:,1), autoC(:,2), 'm-')
grid on
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```matlab
ylabel('correlation'), xlabel('lag')

subplot(3,1,3)
plot(fSPAC(2:length(fSPAC)), pSPAC(2:length(fSPAC)))
grid on
ylabel('power')
xlabel('frequency spectrum of autocorrelation (cycles/a)')
```
2.4 Questions

Please use the MATLAB programs at the course website to answer the following questions. Short paragraphs are sufficient. You may wish to print a coastline map to use as a reference. You may email electronic documents or hand in paper copies.

everybody

1. In which season is the linear trend in temperature largest at each station? Do all the stations exhibit similar seasonal trends?

2. At which stations are the temperature trends the largest?

3. Identify northern hemisphere sites with relatively large and relatively small temperature trends and compare the geographic settings of sites in those groups. How does geographic setting influence the trends you have calculated for different sites?

4. Repeat the comparison of question 3 for the southern hemisphere records.

5. Are variations in the temperature series provided here better correlated with the AO in summer or winter? It is not necessary to conduct a covariance analysis (the AO index provided here is relatively short) but please do discuss how you arrived at an answer for this question.

gradient students

6. Compare your answers for 3 and 4. What other data might you use to expand the analysis and identify the physical processes underlying the patterns you identify?

7. Climate time series are relatively short at many high latitude locations but several of the series here were chosen for their length and should be suitable for autocorrelation. Choose at least two time series with which to perform an autocorrelation. Describe and discuss your result. Are there any dominant cycles? Are there differences or similarities between the sites and time of year you chose?

2.5 References