An Opinion Born of Years of Observing Timeseries Observations

by Skip McKinnell

It is common practice in our business to present an idea to an audience with a graphic that features a time-ordered sequence of observations, a timeseries. It is argued frequently that some pattern of temporal variation in one particular timeseries is caused by variation in some other timeseries of observations, based on real or imagined interconnections between them. Likewise, it may be argued that two timeseries share a similar history as a consequence of variation caused by some third timeseries. Regardless of the argument made, its evaluation and interpretation rests squarely on the similarity of the timeseries under consideration. The methods used to make such comparisons are the subject of this opinion.

Most of us can recognize a typical timeseries (**Fig. 1**). Time appears on the abscissa, while some variable of greater interest appears on the ordinate. Each value is plotted at a time that corresponds to when the observation was made; often a line is drawn to connect them in sequence. Less often, variable magnitudes are represented by the heights of vertical bars. Trends, cycles, periodicity, or step shifts reveal themselves if they are the dominant features of a timeseries.

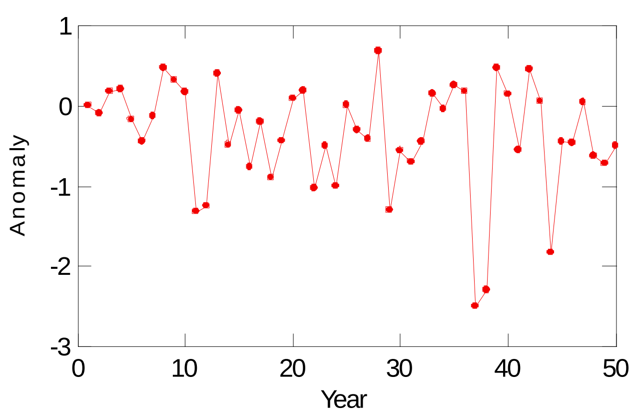

Fig. 1 A timeseries of 50 years duration.

At issue, however, is the best way to compare two (or more) timeseries that may have one or more of these characteristic patterns. Unfortunately, the most common practice for displaying variation in one timeseries has been adopted as common practice for displaying variation in two or more, by superimposing all on one abscissa. It is this practice that I hope will become less common in future for the reasons that I will describe in more detail.

In the simple case of comparing two timeseries, four outcomes are possible when two variables are measured at the same time. The two values may diverge (one increases while the other decreases), or they may converge (one value increases and one decreases), or both can increase, or both can decrease. In climate or ecological timeseries plots, where longer is almost always better, a 50-year series of annual values is not uncommon nor is a 50-years series of monthly values (n = 600).

In a 15 or 20 minute oral presentation most graphics can stay on the screen for only 45–60 seconds. How is it possible for an observer to make an assessment of the pattern of co-variation, if four outcomes are possible at each time step? One's ability to understand some argument is based on one's ability to interpret the pattern co-variation across 50–600 observations, each one having at least 4 potential outcomes. Furthermore, the similarity of two timeseries is based not only on how often they both do the same thing (in phase), but also how often they do the opposite (out of phase). In a 50-year timeseries of annual values, for example, there are 50 comparisons with 4 possible outcomes at each step. Should their variances be unequal, the problem is compounded by one series occupying more of the "visual real estate" on a graph than another.

Perhaps I am slowing, but I cannot make this judgment in the 45 seconds allowed by most speakers. At best, I might notice that a couple of outliers in the two series occurred at the same time and perhaps with similar magnitude. I may also notice that both share some low-frequency pattern that may or may not be offset by some lag. Regardless, the main point is that my eye must make 50–600 comparisons in a very short period of time, and my brain is simply not up to the challenge of processing anything but the gross-level co-variation in the two series. It is not, or should not be, a practice of science to give a speaker the "benefit of the doubt." It is our job to be critical of what is being presented. Fortunately, there is a better way to minimize the demands on those of us who are perceptively challenged—scatterplots!

Whether in phase or out of phase, timeseries observations that are in perfect synchrony (at zero lag) will, as a bivariate scatterplot, lie exactly along a diagonal line. Some might argue that two identical timeseries, when superimposed, will be indistinguishable. The difference in the two approaches becomes evident when the correspondence is less than exact. In a scatterplot, if two timeseries are highly correlated, the scatter of points forms a narrow diagonal ellipse. As two timeseries become less correlated, the shape and orientation of this ellipse changes; with no diagonal ellipse, there is no association. The extent to which they are correlated is immediately apparent by the extent of dispersion from a diagonal and the rotation off diagonal. The only demand on the brain to fully understand the degree of correspondence between two timeseries is to

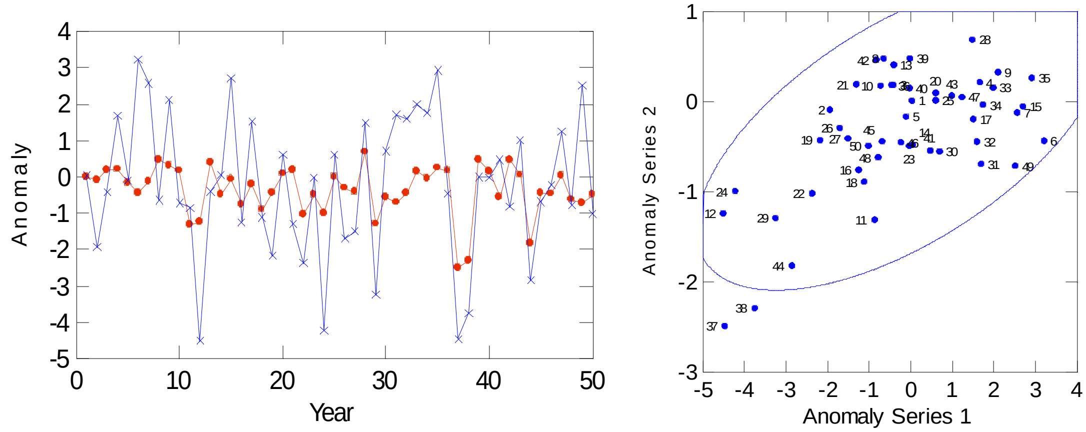

Fig. 2 Two arbitrary timeseries with a correlation of 0.61.

assess the nature of the dispersion pattern. Should there be additional value in showing the temporal order in a scatterplot, plot point labels can be added to indicate time. If the temporal evolution is also important, the points can be interconnected in sequence by a line.

The ability to assess a force and response of nature is particularly important if the arguments being made are causal in nature. In such cases, it is the outliers that become important. If you argue that it is colder when the wind blows by presenting timeseries observations of wind and temperature, most will judge the strength of your argument based on the presence or absence of departures from that model. A scatterplot immediately shows where the outliers can be found against the foundation of your argument—the diagonal running from upper left to lower right. If, in some years it is warm when the wind blows, these values will appear in the upper right quadrant of the figure. In timeseries plots, these outliers tend to be buried in the chatter of temporal variation so you need to look for them. This cannot be done easily in 45 seconds.

So, if you cannot completely give up on the concept of timeseries plots for inter-comparisons, please add a scatterplot on the side so that viewers are not left wondering about hidden outliers. The example in **Figure 2** shows that the relatively high correlation between these two timeseries is a consequence only of about 6 strong negative anomalies out of 50 points. There is no correlation between these timeseries in the other 44 points. This pattern is not revealed by the timeseries comparisons alone, particularly in the 45 seconds normally provided to make a judgment.

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New Bering Sea publication

A special volume of *Deep-Sea Research II*, "The Marine Ecosystem of the Pribilof Domain, Southeastern Bering Sea" edited by S.A. Macklin, Sharon Smith, Sue Moore and James Schumacher, was recently published (August 2008, Vol. 55, Nos. 16-17). The issue contains original research articles on aspects of ocean ecology from physics to halibut, seabirds and pinnipeds. An overview paper concludes the volume and integrates recent work from the southeastern shelf and updates our understanding about how a warmer Bering Sea might affect the abundance of zooplankton and the recruitment of fish, including walleye pollock.

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