Extremes, Patterns, and Other Structures in Oceanographic and Climate Records

C. Wunsch

Massachusetts Institute of Technology, Cambridge, Ma 02140

Abstract. The human eye and brain are powerful pattern detection instruments. Coupled with the clear human need to perceive the world as deterministic and understandable, and the often counter-intuitive results of probability theory, it is easy to go astray in making inferences. In particular, many examples exist where attention was called to apparent extreme behavior, whether in time or space series, or in the appearance of unusual patterns, that are just happenstance. Used carefully, and with a residual open-mindedness, it is possible to employ some simple statistical tests to avoid the outcomes of inferring unusual behavior where none is present, nor in rejecting a major finding as being insignificant.

Introduction

> "My eye is better than any statistical test."
> Well-known paleoceanographer, circa 2001.

Many of the most important inferences that are made about the climate system and its changes are based upon statistical or probabilistic inferences. These inferences include the deduction of occurrence of extreme events in a general sense (including e.g., exceptionally large El Niño events, stronger than expected trends, covariances beyond that expected between disparate records, unusual "runs"). Probability and statistics are, however, among the least intuitively accessible of all mental constructs, and a very large literature now exists (e.g., Kahneman et al., 1982; Gilovich et al., 2002) showing how counter-intuitive many important statistical inferences are—with serious implications not only for science, but for economics and public policy generally. Kahneman, although a psychologist, won the Nobel Prize in economics because his discussions of how people make decisions in the presence of uncertainty captured so much of their real (as opposed to ideal) behavior. A classic discussion of economic behavior is Mackay (1852); a more recent one is Malkiel (1999). Coupled with a very powerful human instinct that the world must be deterministic (predictable)[1], the scientific literature too, is riddled with misguided or mistaken conclusions. A number of authors (e.g., Diaconis and Mosteller, 1989) have noted the very great difficulties people, including scientists, have in dealing with apparently amazing, but expectable, coincidences.

This paper has a primarily pedagogical intention—there are no original results; rather it arises out of attempts to teach students some of the most basic of statistical inference skills, while simultaneously cautioning them to remain open-minded and skeptical.

Most of what follows is nothing more than a series of examples where some statistical or probabilistic inference was made of a remarkable event that is less clear-cut than the authors' seemed to believe, and/or where a certain skepticism would have been better retained despite the temptation to make an exciting inference. The possible connection with the widespread wish for attention in the popular media will be obvious. An earlier more limited version of these examples was discussed by Wunsch (1999).

Single Time Series Examples

Time Domain

Consider Fig. 1 showing the negative of the anomaly of atmospheric pressure in Darwin, Australia and used by Trenberth and Hoar (1997) as a measure of the strength of the Walker circulation. Fig. 2 displays the sea surface temperature (SST) Niño3.4 index commonly used as a measure of the strength of El Niño. Trenberth and Hoar (1997) infer that ENSO behavior shifted after about 1970 to more frequent and larger El Niño events. (The change was interpreted as the result of global warming and to be "unprecedented" in the

[1] "Human nature likes order; people find it hard to accept the notion of randomness. No matter what the laws of chance tell us, we search for patterns among random events wherever they might occur..." (Malkiel, 1999).

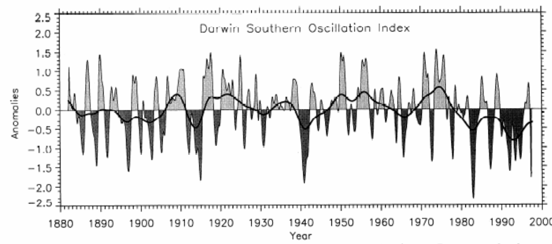

Figure 1. Negative of the anomaly of atmospheric surface pressure at Darwin, Australia (Trenberth and Hoar, 1997) and used by them as a measure of the Walker circulation strength. Curve is normalized to be dimensionless An 11-year low-passed version is plotted as the heavy curve.

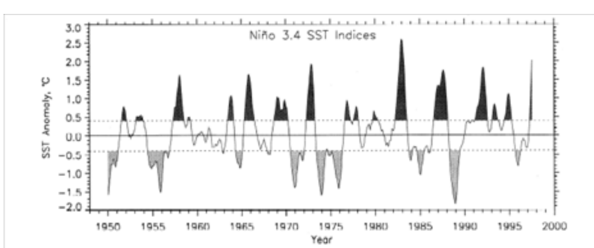

Figure 2. Time series of the Niño-3 index (from Trenberth and Hoar, 1997). A baseline of the first 30 years sets the zero and El Niño and La Niña identified events are indicated by the black and gray areas.

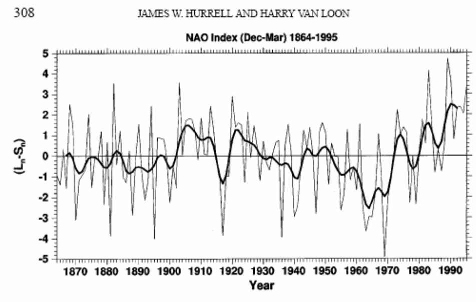

Figure 3. Thin line shows the so-called winter North Atlantic Oscillation (NAO) Index from Hurrell and van Loon (1997). Thick line is a low-pass filtered version. The subject of discussion is the apparent trend beginning about 1960, and inferred to represent a climate change.

historical record.) Solow (2006), however, noted that their anomalous test period, 1992-mid-1995, in Fig. 1 was not independent of the earlier interval of supposedly normal behavior; he used the subsequently longer record to recalculate the probability that the nature of ENSO had changed in some significant way. His conclusion was, in contrast, that while the test period appears different from the earlier one, subsequently there was essentially no evidence that the nature of the physics had changed. The comparatively dramatic story of the original authors is thus replaced by a much more ambiguous and unexciting, but presumably more soundly-based, description of the nature of ENSO.

Another example of simple pitfalls can be seen in Fig. 3. Hurrell and van Loon (1997) inferred that the apparent trend at the end of this record represented another unprecedented shift in a climatologically important index that of the so-called North Atlantic Oscillation (NAO). Wunsch (1999) showed, however, that such *apparent* trends were characteristic of ordinary red noise processes and *did not necessarily* have any significance beyond that of a random walk. Subsequently, Percival and Rothrock (2005) noted that the statistical significance of such a trend, if calculated using ordinary least-squares fits over the interval from 1965 to the record end, could produce results differing by an order of magnitude from the correct inference. The gist of their argument was that the conventional tests do not permit one to choose the interval for the test by visual examination—that has the effect of using posterior knowledge (the region with an apparent trend) with a statistical test that assumes no such knowledge. These debates are related to those about "regime changes" (Rudnick and Davis, 2003; Overland et al., 2006 and

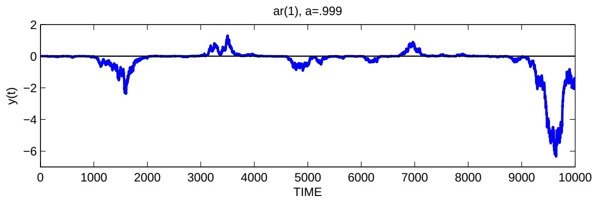

Figure 4. Example of a record that might be inferred by visual inspection to have non-stationary behavior. In practice, it is simply the cube of a stationary AR(1) process, $x(n) = 0.999x(n-1) + \theta(n-1)$, where $\theta(n)$ are iid Gaussian pseudo-random. Small sample determination of non-normal (which this is) as distinguished from non-stationary behavior is difficult.

subsequent comments) and non-stationarity. For the latter, consider Fig. 4 showing a record that many would probably visually declare to be non-stationary, the major event near time 1300 appearing out of character with the previous and later intervals. This record is in fact stationary, having been generated as the cube of an AR(1) process (Wunsch, 1999). Visual inspection is quite misleading, and one would need to attempt to distinguish the hypothesis of non-stationarity from non-normal behavior of an autocorrelated process—a very difficult problem with small sample sizes.

How Significant Must a Signal Be?

For most of the history of physical oceanography and climate studies generally, the results were primarily of interest world-wide to a handful of mainly academic scientists. The stakes, from the point of view of the wider community, were low, and no dire effects arose from mistaken inferences. A commonly accepted measure of significance was beyond one standard deviation (a 65% confidence interval for Gaussian distributions), or 95% confidence intervals or levels for Fourier analyses. One might contrast that situation with e.g., a drug trial, where one would like to be confident at the 99.9% level, that a new drug does not generate excess mortality in its users. In a world troubled by climate shifts, and the tendency of the latest scientific results to make headline news, the impact of erroneous inferences in climate and oceanography now can have enormous social consequences (see e.g., Kerr, 2006; Chylek, 2007). Much of the comfortable scientific obscurity has vanished.

A level-of-significance of 95% implies the expectation of about 5% false positives. With one million independent samples, there will be 50,000 false signals (large sample fluctuation extremes become an issue e.g., in David Thomson's tests for true periodicities in geophysical records; see Percival and Walden, 1993, P. 513, who quote him as suggesting confidence levels above $1-1/N$ where N is the number of samples.) In an interesting paper, Seife (2000) discusses numerous physics signals apparently significant at the five and six standard deviation level that ultimately proved ephemeral or simply incorrectly interpreted. The astronomer John Bahcall is quoted as observing "Half of all three-sigma results are wrong." As discussed by Seife (2000), sometimes the context is the wish to call a press conference so as to forestall a competing high energy physics team from announcing first and thus winning a Nobel Prize for a new particle discovery. One can be desperately torn between being cautious, wanting a tighter error bar, and the need to announce first—a trade-off between possibly appearing quite foolish, and losing fame and fortune. Earth sciences, fortunately, rarely demands such fraught statistical decisions!

In contrast, and in a different but related problem worth mentioning, Lanzante (2005) makes note of the tendency to compare overlaps of ordinary error bars as a test of consistency of data sets. He notes that such a comparison can be quite misleading—and overly conservative. Where feasible, one needs to use two-sample rather than one-sample tests.

Being overly conservative is thus a major problem as well—leading to rejection of a important new conclusions. A conspicuous public example of such failure was the rejection by NASA scientists of observations demonstrating the ozone hole—the values seen by a spacecraft were deemed so low as to be erroneous. It was only later, with the detection of the ozone hole by ground-based measurements, that the NASA data were resurrected, and it was clear that the ozone hole could have been discovered much earlier (see references in Solomon, 1999). Fortunately, someone had the good sense to retain the data. The history of science is filled with missed discoveries with conclusions rejected on the grounds that they were "outliers." One nice example is the failure of optical astronomers to realize that Mercury rotated 2/3 of a revolution per orbit, not once/orbit as stated by all the textbooks before about 1965, when a radar pulse was bounced off the planet. Hindsight showed ample observations inconsistent with once/orbit revolution, but that were not taken seriously.

Fourier Methods

Spectra

Fourier spectral density estimates are very powerful analysis tools in many contexts. As a combination, however, of Fourier analysis and statistics, they are perhaps unrivaled in the literature in giving rise to elementary misconceptions. Consider for example, the spectral densities displayed in Fig. 5 for the purpose of conveying

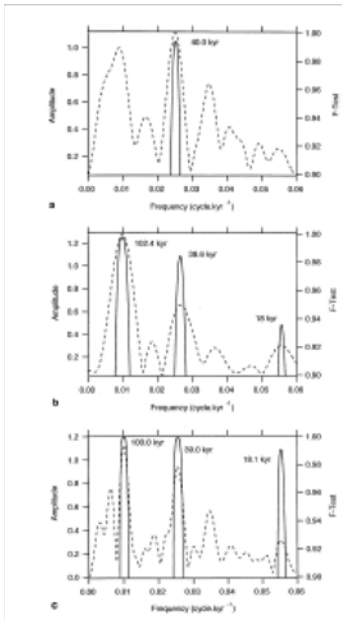

Figure 5. From Vimieux et al. (2001) showing spectral peaks in a proxy measured in an Antarctic ice core and analyzed over different time intervals. Note the linear power scale and the small frequency interval displayed.

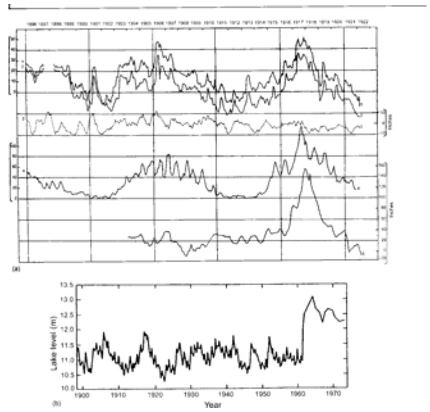

Figure 6. Upper panel is from Brooks (1923) showing the apparent correlation of Wolf sunspot numbers with central African lake levels. Lower panel shows the disappearance of the apparent sunspot cycle in the lake levels (reproduced from Pittock, 1978).

the importance of the so-called Milankovitch cycles in ice core records. The peaks (here considered "extreme events") strongly suggest record dominance by the astronomical forcing periods lying in the vicinity of 100, 41 and 21 thousand years. (Notice the absence of any uncertainty estimates in these figures).

If one plots the power density spectral estimate over the entire frequency band, not just that restricted part visible in Fig. 5, and uses a logarithmic power scale (so that the displayed 95% confidence interval is constant with power), one infers a completely different picture of the underlying time series: one in which the record is described at zero-order as nearly red-noise, and in which the apparent peaks at the astronomical frequencies, while likely real, contain only a very small fraction of the record variance (see Wunsch, 2004). Hundreds of examples of such exaggerated display of "peaks" can be found in the literature. Often the energy fraction in the peak is so slight as to be of truly questionable importance. (For example, see Wagner et al., 2001, for the so-called solar DeVries cycle.)

Bivariate and Multivariate Correlation and Coherence

Perhaps the most insidious issues lie with inferences that two or more records are correlated. Indeed, much of the paleoclimate literature indulges in what is candidly labelled "wiggle matching". In that method, two spatially distant records with uncertain time bases are assumed to be related, the time axes being then shifted to align the events in the records. Sometimes after shifting, correlations are calculated and proclaimed to be statistically significant (e.g., Bond et al., 1991). Fig. 6 displays a classical example of records apparently showing compelling visual correlation, but that disappeared when the record became long enough (see Pittock, 1978)

The possibility of excursions of any stationary Gaussian time series far from the apparent mean value can be considered in several ways, including the use of extreme value statistics. Alternatively, the approach of Rice (1945), summarized e.g. by Cartwright and Longuet-Higgins (1956) or Vanmarcke (1983), provides considerable insight. In that approach, it is shown that for any time series with a known power spectral density $\Phi(\omega)$, that the rate of threshold crossings (upward or downward) depends only upon the low order spectral moments,

$$\lambda_n = \int_0^{\pi/2\Delta t} \omega^n \Phi(\omega)\, d\omega,$$

where Δt is the sampling interval. Unless one can show that some particular excursion is exceptional, no claim can be made that anything unusual has transpired.

In other examples (e.g., Chapman and Shackleton, 1999), coherences between records are computed, sometimes properly, but at such low levels of no significance (in that example, 80%) that the number of frequency bands apparently related in the two records is so large

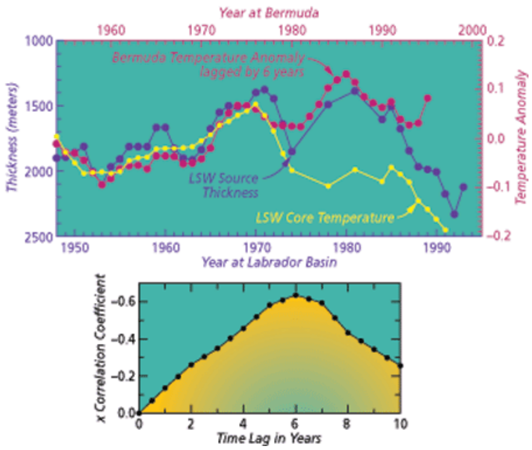

Figure 7. Curry and McCartney (1996) in which the red and blue curves are inferred to be causally related. Note that the red curve has been shifted by six years relative to the blue one. The number of statistical degrees of freedom here is very small.

as to vitiate the entire test. Another example, shown in Fig. 7, was clearly intended to convince the reader by visual inspection that the two records were causally related,.and that the time-lag of six years introduced in the time shift was justified by the crosscorrelation also displayed. It is left to the reader to judge whether these two records are convincingly connected. A few more examples are discussed by Wunsch (2006).

A common practice in the geophysical sciences is to combine theory with empiricism and to relax even the usual weak tests of statistical significance. One example, in which I was directly involved, concerns the so-called pole tide. The Earth's rotation axis wobbles about the geographical north pole with a period of approximately 14 months (see Munk and Macdonald, 1960). This motion induces a changing centrifugal force at all locations, and which acts dynamically as a broadband tide.

Analysis of periodograms and spectral density estimates of long tide gauge records showed (see Fig. 8) excess energy in this band only in the North Sea region, increasing eastward into the Baltic Sea. The apparent amplitude was several times that expected for so-called "equilibrium tide". A formal analytical theory explaining this phenomenon was offered (Wunsch, 1986). Subsequently, attempts to reproduce the phenomenon with numerical models proved negative; furthermore, as the record length subsequently grew, the apparent pole tide strongly diminished with time. It now appears (Wunsch, 2001 and the references there) that the signal was nothing but the random fluctuation

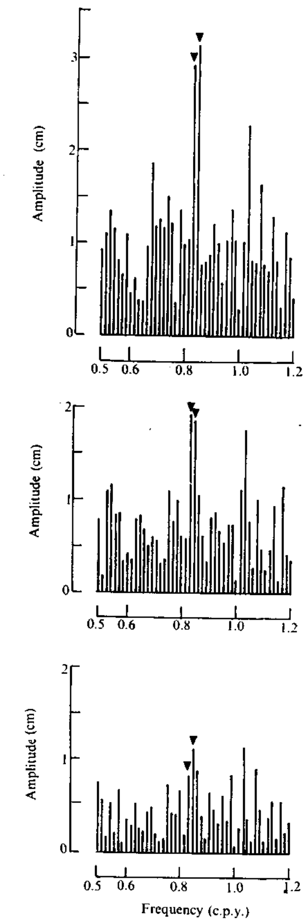

Figure 8. From Miller and Wunsch (1973) showing the growth of periodogram amplitudes with distance into the North Sea. The period of excess energy coincides with that known from the Chandler Wobble and was inferred to represent a non-equilibrium "pole tide". With hindsight, the simplest explanation is just a random fluctuation in the periodograms in this region.

of energy in the meteorological forcing, coincidentally in the pole tide frequency band, and that the entire oceanographic literature on this subject was directed at a will-o'-the-wisp. As this topic has been of interest to a tiny scientific community, no great harm was done. It does strongly suggest, however, that one should use more formal Bayesian methods (e.g., Gauch, 2003) in combining a priori theoretical knowledge with observations (although precisely what was prior and what was posterior in such situations is not completely obvious).

Patterns and Formulas

The so-called Titius-Bode Law, providing a formula for the spacing of the planets (including Pluto), has been known for hundreds of years. It says, in one form, that the spacing (in astronomical units) is $d = 0.4 + 0.3 \times 2^j$ where j is the j-th planet (see Fig. 9 and Murray and Dermott, 1999). Work over hundreds of years has been devoted by physicists and astronomers to the derivation of this formula as a physical law—to no avail. The futility leads to the question of whether it is not simply a statistical accident, as convincing as the results in the Table might be. The statistician Good (1969) concluded that there was only one chance in 130 that it was a statistical fluke. But another well-known statistician (Efron, 1971) inferred that the probability was about 50% that it was indeed a statistical accident. Without attempting to analyze the remarkable difference between these two conclusions (it appears to lie with differing null-hypotheses—see Huybers, 2004), it stands as an example both of the treachery of certain kinds of statistical inference, but also the ability of nature to provide intriguing patterns that are indistinguishable from chance.

A somewhat different form of pattern was the focus of attention by the well-known British physicist A. Eddington whose book (1946) described a number of seemingly important expressions for the fundamental constants of nature. For example, Lenz (1951) noted that the ratio of the proton to electron mass ratio was nearly $\mu_p/\mu_e = 6\pi^5$. Or (Wyler, 1969), the fine structure constant by observation is $\alpha^{-1} = 137.03611 \pm 0.00021$. One then finds,

$$\alpha^{-1} = \left(9/8\pi^4\right)\left(\pi^5/2^4 5!\right) = 137.03608245, \qquad (1)$$

which appears to call for explanation. But it turns out (e.g. Roskies, 1971) that there exists an infinite number of such formulae in small integers and π, e, and expressions such as Eq. (1) have no apparent physical significance, intriguing as they are.

Planet	j	Semi-Major Axis (AU)	Titius-Bode Law (AU)
Mercury	-∞	0.39	0.4
Venus	0	0.72	0.7
Earth	1	1	1
Mars	2	1.52	1.6
Ceres	3	2.77	2.8
Jupiter	4	5.2	5.2
Saturn	5	9.54	10
Uranus	6	19.18	19.6
Neptune	7	30.06	38.8
Pluto	8	39.44	77.2

Figure 9. The Titius-Bode Law of planetary separation in AU (Murray and Dermott, 1999) where j is the planet number. Is the rule coincidence?

Interesting Classroom Examples

In teaching it helps to suggest some of the pitfalls of superficial, non-objective, inference. Here are some examples intended to make a class think a bit.

- Consider Fig. 10 which resembles many star charts. Are these dots structured? From the earliest days of astronomy, people have been finding patterns in such pictures (viz., the constellations). The particular pattern shown is completely random, but one's eye is attracted to various clusters and one might even generate a theory of these patterns. Ability to recognize patterns has a clear evolutionary advantage, with false positives commonly being less dire than false negatives (failure to detect the tiger in the jungle). For this reason, astronomers have long been concerned about the inference of spurious patterns (see Julesz, 1981; Barrow and Bhavsavar, 1987; Newman et al., 1994). Fig. 11 compares the patterns seen by eye on Mars in the late nineteenth and early twentieth centuries, with a Hubble telescope image of the same part of the planet.

- A couple has two children. One of them is a girl. What is the probability that the other child is a boy?[2]

- Consider the game of Peter and Paul in which a true coin is flipped sequentially. Every time the

[2] Two-thirds. See Gauch (2003).

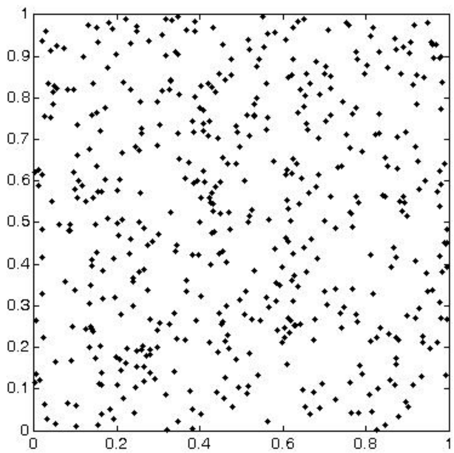

Figure 10. A "star-chart" generated by determining horizontal and vertical positions by drawing two numbers from uniform distributions in $[0,1]$. The eye seeks non-existent patterns.

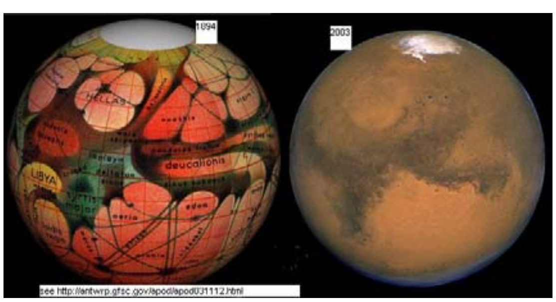

Figure 11. On the left is a view of Mars drawn in 1894 by Giovanni Virginio Schiaparelli and on the right is from the Hubbell Telescope (from NASA website).

coin comes up heads, Peter pays Paul \$1, and Paul pays Peter the same amount if the coin is tails. Draw a picture example of Paul's winnings through time.[3]

- In a game, 20 marbles are distributed randomly among 5 players. Two example outcomes are:

Player: A B C D E

Game 1: 4 4 5 4 3 Type I outcome (non-uniform)

Game 2: 4 4 4 4 4 Type II outcome (uniform)

Which is more probable in the long run?[4] (Related to the so-called law of small numbers—the common expectation that small samples should display the statistical properties of a large-sample.).

- Basketball player A tends on average to make 30% of his shots. Player B averages 35%. Player A has just made 8 shots in a row. Player B has missed his last two. Should you bet on player A or player B?[5]

- Cause and effect inference confounded by tendency of regression toward the mean: Anecdote of pilot school—instructors find that when giving praise for a good landing, the next time out, the student seems often to do worse. But when, instead, a bad performance is harshly criticized, the next time out, the student does better. Pedagogical conclusion is that one should not praise, only criticize! A statistical test shows the difference is no greater than expected from chance.[6]

- A population of women is known to have a probability of 1 in 100 of having breast cancer. One woman has a mammogram which shows a lump, believed malignant. It is known that when a tumor is present, the test has an 80% accuracy (that is, shows as malignant). When no tumor is present, the test shows a false positive 10% of the time. What is the probability that the woman has cancer?[7]

- The Monte Hall Game—more formally known as Bertrand's (1889) paradox. Named for the host

[3] Feller (1957)

[4] The second is more probable. Kahneman et al., (1982) P. 36

[5] A run of eight shots in a row *must* occur by chance. Empirically, the idea of a "hot hand" in basketball cannot be distinguished from happenstance and on average one is advised to nonetheless bet on player B.

[6] Kahneman et al. (1982). It was suggested at the Aha that one should criticize successful landings and applaud bad ones. Presumably that experiment has not been conducted.

[7] Eddy (1992). From Bayes's theorem, the correct answer is 8%.

of the television quiz show "Let's Make a Deal." Contestant is faced with three doors. She is told that behind one door is a car, and behind the other two doors are goats. Contestant is asked to pick a door—which is not opened. Host (who knows where the car is) then opens one of the two remaining doors to show a goat. Contestant is then asked if she wishes to switch her original choice to the remaining closed door. Should she switch?[8]

Discussion

I have omitted here discussion of the interesting phenomenon of "pathological science" (see Park, 2000). Misuse or misinterpretation of statistics and probability is only one way for scientists to get into trouble. Wishful thinking and general self-delusion are not unknown. The moral of the story is that statistical and probabilistic inference needs to be done carefully, with as many of the assumptions the investigator is aware of being made plain and explicit (National Research Council, 2006). There are many ways to go astray, but in general, careful use of existing statistical methods, transparency, and lingering skepticism are safe harbors for the scientific investigator. Statisticians sometimes remind people of the words of Oliver Cromwell to the Church of Scotland (J. Kadane, private communication, 2007): "I beseech you, in the bowels of Christ, think it possible you may be wrong" (Bartlett, 1968). Locale aside, it seems like good advice for scientists.

Acknowledgments. Supported in part by the National Ocean Partnership Program (NOPP) and the National Aeronautics and Space Administration through the ECCO-GODAE consortium. Comments at the Aha Huliko'a were very helpful in formulating this written version of my remarks.

[8] She should switch, assuming the contestant prefers a car to a goat, as there is a 2/3 chance that the car is behind the other door, as opposed to the 1/3 probability that it is behind the first choice. See http://math.ucsd.edu/~crypto/Monty/montybg.html. Also Wikipedia which has an extended discussion.

References

Barrow, J. D. and S. P. Bhavasar, 1987: Filaments: what the astronomer's eye tells the astronomer's brain. *Q. J. Royal Astronom. Soc.*, 28, 109-128.

Bartlett, J., 1968: *Familiar Quotations*, 14th Ed., E. M. Beck, Ed. Little, Brown Boston, 1750pp.

Bertrand, J., 1889: *Calcul des Probabilities*. Gauthier-Villars, Paris 1907 (3rd edition reprinted by Chelsea, New York, 1972), 332 pp.

Bond, G., B. Kromer, J. Beer, R. Muscheler, M. N. Evans, W. Showers, S. Hoffman, R. Lotti-Bond, I. Hajdas, and G. Bonnani, 2001: Persistent solar influence on North Atlantic climate during the Holocene. *Science*, 294, 2130-2136.

Brooks, C. E. P., 1923: Variations in the levels of the central African lakes Victoria and Albert. Geophys. Mem. London, 2, 337-344.

Cartwright, D. E. and M. S. Longuet-Higgins, 1956: The statistical distributions of the maxima of a random function. *Proc. Roy. Soc., A*, 237, 212-232.

Chapman, M. R. and N. J. Schackleton, 1999: Evidence of 550-year and 1000-year cyclicities in North Atlantic circulation patterns during the Holocene. *The Holocene*, 10, 287-291.

Chylek, P., 2007: Uncertainty over weakening circulation. *Physics Today,* March 2007, 14.

Curry, R. G., and M. S. McCartney, 1996: Labrador Sea Water carries northern climate signal south. *Oceanus*, 39(2), online edition.

Diaconis, P. and F. Mosteller, 1989: Methods for studying coincidences. *J. Am. Stat. Assoc.*, 84, 853-861.

Eddington, S. A., 1946: *Fundamental Theory*. Cambridge Un. Press, Cambridge, 292pp.

Eddy, D. M., 1992: Probabilistic reasoning in clinical medecine: Problems and opportunities. in *Judgment Under Uncertainty: Heuristics and Biases*, D. Kahneman, P. Slovic, A. Tversky, Eds., Cambridge Un. Press, Cambridge, 249-267.

Efron, B., 1971: Does an observed sequence of numbers follow a simple rule? (Another look at Bode's Law). *J. Am. Stat. Assoc.*, 66, 552-559.

Feller, W., 1957: *An Introduction to Probability Theory and Its Applications*, Second Ed. Wiley, New York, 461pp.

Gauch, H. G., 2003: *Scientific Method in Practice*. Cambridge Un. Press, 435 pp.

Gilovch, T., D. Griffin, and D. Kahneman, 2002: *Heuristics and Biases: The Psychology of Intuitive Judgement*. Cambridge Un. Press, Cambridge, 857 pp.

Good, I. J., 1969: A subjective evaluation of Bode's Law and an objective test for approximate numerical rationality. *J. Am. Stat. Ass.*, 64, 23-.

Hurrell, J. W. and H. van Loon, 1997: Decadal variations in climate associated with the North Atlantic Oscillation. *Clim Change*, 36, 301-326.

Huybers, P., 2004: *The Origins of Ice Ages: Insolation Forcing, Age Models, and Nonlinear Climate Change*. PhD Thesis, MIT, 245pp.

Julesz, B., 1981: Textons, The elements of texture-perception and their interactions. *Nature*, 290, 91-97.

Kahneman, D., P. Slovic, A. Tversky, 1982: *Judgment Under Uncertainty: Heuristics and Biases*. Cambridge Un. Press, Cambridge, 555pp.

Kerr, R. E., 2006: False alarm: Atlantic conveyor belt hasn't slowed down after all. *Science*, 314, 1065.

Lanzante, J. R., 2005: A cautionary note on the use of error bars. *J. Clim.*, 18, 3769-3703.

Lenz, F., 1951: The ratio of proton and electron masses. *Phys. Rev.*, 82, 554.

Mackay,, 1852: *Memoirs of Extraordinary Illusions and the Madness of Crowds*. L. C. Page, Boston Also:http://onlinebooks.library.upenn.edu, 724 pp.

Malkiel, B. G., 1999: *A Random Walk Down Wall Street*. Norton, New York (Also, later editions), 461pp.

Miller, S. and C. Wunsch, 1973: The pole tide. *Nature, Physical Science*, 246, 98-102.

Munk, W. H. and G. J. F. MacDonald , 1960: *The Rotation of the Earth: A Geophysical* Discussion. Cambridge University Press, Cambridge, 323pp.

Murray, C. D. and S. F. Dermott, 1999: *Solar System Dynamics*. Cambridge Un. Press, Cambridge, 592pp.

National Research Council, 2006: *Surface Temperature Reconstructions for the Last 2,000 Years*. National Academies Press, Washington, 146 pp.

Newman, W. I., M. P. Haynes and Y. Terzian, 1994: Redshift data and statistical inference. *Ap. J.*, 431, 147-155.

Overland, J. E., D. B. Percival and H. O. Mofjeld, 2006: Regime shifts and red noise in the North Pacific. *Deep-Sea. Res.,*, 53, 582-588.

Park, R. 2000: *Voodoo Science. The Road from Foolishness to Fraud.* Oxford Un. Press, Oxford, 230pp.

Percival, D. B. and D. A. Rothrock, 2005: "Eyeballing" trends in climate time series: a cautionary note. *J. Clim.*, 18, 886-891.

Pittock, A. B., 1978: A critical look at long-term sun-weather relations. *Revs. Geophys. and Space Phys.*, 16, 400-420.

Rice, S. O., 1945: Mathematical analysis of random noise. *Bell Sys. Tech. J.,* 25, 46-.

Roskies, R., 1971: New pastime—calculating alpha to one part in a million. *Phys. Today*, 24, 9-.

Rudnick, D. L. and R. E. Davis, 2003: Red noise and regime shifts. *Deep-Sea Res.*, 50,, 691-699.

Seife, C., 2000: CERN's gamble shows perils, rewards of playing the odds. *Science*, 289, 2260-2262.

Solomon, S., 1999: Stratospheric ozone depletion: A review of concepts and history. *Revs, Geophys.,* 37, 275-316.

Solow, A. R., 2006: An ENSO shift revisited. *Geophys. Res. Letts.*, 33 (22): Art. No. L22602 NOV 21 2006.

Takahahsi, T., S. C. Sutherland, C. Seeney, A. Poisson, N. Metzl, B. Tilbrook, N. Bates, R. Wanninhkhof, R. A. Feely, C. Sabine, J. Olafsson, Y. Nojiri, 2002: Global sea-air CO2 flux based on climatological surface pCO2, and seasonal biological and temperature effects. *Deep-Sea Res., II*, 49, 1601-1622.

Trenberth, K. E. and T. J. Hoar, 1997: El Niño and climate change. *Geophys. Res. Letts.*, 24, 3057-3060.

Vanmarcke, E., 1983: *Random Fields: Analysis and Synthesis*. The MIT Press, Cambridge, 382 pp.

Vimeux, F., V. Masson, G. Delaygue, J. Jouzel, J. R. Petit and M. Stievenard, 2001: A 420,000 year deuterium excess record from East Antarctica: information on past changes in the origin of precipitation at Vostok. *J. Geophys. Res.*, 106, 31,863-31,873.

Wagner, G., J. Beer, J. Masarik, R. Muscheler, P. W. Kubik, W. Mende, C. Laj, G. M. Raisbeck and F. Yiou, 2001: Presence of the solar de Vries cycle (205 years) during the last ice age. *Geophys. Res. Letts.*, 28, 303-306.

Wunsch, C., 1986: Dynamics of the North Sea pole tide revisited. *Geophys. J. Roy. Astron. Soc.*, 87, 869-884.

Wunsch, C., 1999: The interpretation of short climate records, with comments on the North Atlantic and Southern Oscillations. *Bull. Am. Met. Soc.*, 80, 245-255.

Wunsch, C., 2001: Comments on "Windstress forcing of the North Sea pole tide" by W. P. O'Connor et al. *Geophys. J. Int.*, 146, 264-265.

Wunsch, C. , 2004: Quantitative estimate of the Milankovitch-forced contribution to observed quaternary climate change. *Quaternary Sci. Rev.*, 23/9-10, 1001-10012.

Wunsch, C., 2006: Abrupt climate change: an alternative view. *Quat. Res.*, 65, 191-203.

Wyler, A., 1969: . *Comptes Rendus Acad. Sci. Paris A, 271*, 186.