Absence of Correlation between the Solar Neutrino Flux and the Sunspot Number

Guenther Walther

Department of Statistics, Stanford University, Stanford, California 94305 (Received 23 July 1997)

There exists a considerable amount of research claiming a puzzling anticorrelation between the neutrino detection rate at the Homestake experiment and indicators of solar activity such as the sunspot number, giving rise to explanations involving the hypothesis of a neutrino magnetic moment. It is argued here that the claimed significant anticorrelation is due to a statistical fallacy. A proper test based on certain optimality criteria fails to detect a significant time variation of the neutrino flux in concert with the sunspot number, providing evidence that the observations are consistent with no correlation between the two series. [S0031-9007(97)04718-2]

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Solar neutrinos are the only known particles to reach Earth directly from the solar core and thus allow one to test directly the theories of stellar evolution and nuclear energy generation [1]. A perceived anticorrelation between the neutrino detection rate at the Homestake experiment [2] and indicators of solar activity such as the sunspot number has been the object of a considerable amount of research [2–12], yielding claims of statistically highly significant results. Such time variations of the solar neutrino flux are not possible in minimal standard electroweak theory and have motivated proposals for solutions of the solar neutrino problem based upon the hypothesis of a large neutrino magnetic moment [13–16].

However, the standard tests for correlation used in the research cited above require assumptions that are usually not met in a time-series context, where these tests may readily produce erroneous, highly significant results. Figure 1 illustrates one aspect of this fallacy, which is often ignored by statistics text books and therefore easily goes unrecognized in scientific work: The top scatterplot shows the first 100 of 109 typical independent observations $(X_1, Y_1), \dots, (X_{109}, Y_{109})$ from a standard bivariate normal distribution. The bottom scatterplot shows the 100 running means of length 10, $(\frac{1}{10}\sum_{i=k}^{k+9}X_i, \frac{1}{10}\sum_{i=k}^{k+9}Y_i), k = 1, \dots, 100.$ The correlation is visibly larger in the bottom plot. Indeed, Pearson's correlation coefficient r is 0.12 for the top plot, and 0.30 for the bottom plot. However, the probability of obtaining values of |r| of at least the observed size is *larger* for the situation of the bottom plot (27%) than for that of the top plot (24%), as can be verified by simulations. This example illustrates the fact that common tests for correlation between two series tend to give erroneous, highly significant results when there is dependence within each of the two series, e.g., when the series exhibit periodic behavior or are smoothed, a commonly employed procedure either implicitly in the data collection process or afterwards.

The sunspot numbers clearly have a strong dependence structure due to the 11 year period of the sunspot

cycle. Table I shows how easily one is led to an erroneous claim of a significant correlation between the sunspot numbers and an independent random series, this time using Spearman's rank correlation coefficient r_s , another popular measure of correlation: X is taken to be the series of the 100 monthly sunspot numbers starting January 1970. Y is a random walk with independent Gaussian increments in row 1, and a 2-point and 4-point running mean of

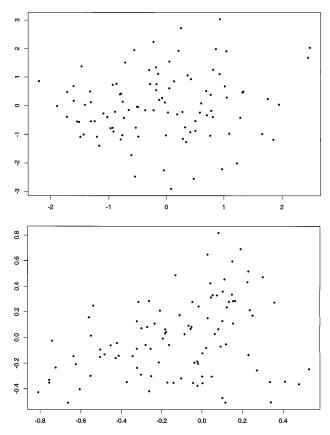


FIG. 1. Top: Typical scatterplot of 100 independent standard bivariate normal observations. Bottom: Running means of length 10. Pearson's correlation coefficient is 0.12 for the top plot and 0.30 for the bottom plot.

TABLE I. Relative frequencies of rejection of the null hypothesis of independence at various nominal significance levels in a Monte Carlo study using the nominal null distribution of Spearman's correlation coefficient. X is the series of the 100 monthly sunspot numbers starting in January 1970. The Z_i are independent standard normal random variables. T_i is the sum of the first i terms of a sequence of independent exponential random variables with mean 10 months.

		Relative frequency of rejection at nominal significance level		
	Time series	5%	1%	0.1%
1	X = sunspot numbers $Y_k = \sum_{i=1}^k Z_i, k = 1,, 100$	82.7%	77.3%	70.7%
2	X = sunspot numbers $Y_k = \sum_{i=k}^{k+1} Z_i, k = 1,, 100$	15.3%	6.1%	1.7%
3	X = sunspot numbers $Y_k = \sum_{i=k}^{k+3} Z_i, k = 1,, 100$	30.0%	17.5%	8.4%
4	X = sunspot numbers $Y_k = 1 + Z_k \text{ if } T_{2i} < k \le T_{2i+1},$ $Y_k = 3 + Z_k \text{ else}; k = 1,, 100$	35.7%	22.4%	11.7%

independent standard Gaussian random variables in rows 2 and 3, respectively. Y was simulated 10^5 times for each case, and the columns give the relative frequency of rejection of the null hypothesis of independence at nominal significance levels 5%, 1%, and 0.1%, using the null distribution of r_s given in [17]. For example, at the 1% significance level one is led to the conclusion that there is a correlation with the random walk about 77% of the time. A comparison of rows 2 and 3 shows that a larger degree of smoothing applied to one series makes the correlation seemingly more significant, a fact that will be of importance below. The effect described above is relevant quite generally for many tests of association or correlation, such as the χ^2 statistic for contingency tables, or Kendall's tau statistic. It applies directly to those published results on a perceived correlation between the sunspot number and the neutrino flux that employ a smoothing of the neutrino flux.

Furthermore, the assumptions of these tests can also be violated in other important ways. For example, tests for correlation using r_s or Kendall's tau require that the distribution of the components of at least one of the two series is invariant under permutations, which implies equal means and variances of the measurements in that series. Row 4 of Table I provides an important example that violates this requirement: The neutrino flux is taken to be constant equal to 1 for a random time which is distributed exponentially with mean 10 months, then the flux equals 3 for a random time with the same distribution, then it is set back to 1, etc. The flux is measured independently each month with a standard Gaussian measurement error. Incidentally, a typical simulation of this model looks even similar to the real neutrino data. Simulations of the flux from this model are uncorrelated with the sunspot number and have no connection to the solar cycle whatsoever. (There is nothing special about the exponential distribution chosen: Virtually any random or deterministic time will produce similar results to the ones quoted in the following.) Still, row 4 shows that r_s erroneously reports a correlation at the 1% level for 22.4% of the simulations. Clearly, this test misinterprets a change in the neutrino flux that is unrelated to the solar cycle as a correlation with the solar cycle. One can reproduce this effect with all the tests employed in [2–12]. This example makes clear that in this time-series context it is not correct to interpret significant results of these tests as significant evidence for a correlation with the solar cycle, even if no smoothing of the neutrino data is employed.

One may ask whether these tests are at least providing evidence for a time variation, not necessarily in concert with the solar cycle. However, due to the unequal uncertainties in the neutrino measurements, these tests are also not valid for testing whether the flux is constant: For an illustration, let x = (3, 2, 1, 5) be a vector of four observations, and Y_1, \ldots, Y_4 be four independent Gaussian random variables with mean 0 and standard deviations 1, 1, 1, and 4. The Y's represent observations of a constant quantity with measurement error. In 7.0% of 10⁵ simulations of the Y's, the correlation r_s between x and Y was equal to 1, whereas the table for the exact null distribution of r_s gives a value of 4.17% (see, e.g., Table VIII in [18]). Similar results obtain when the significance of the χ^2 and F statistics is evaluated by randomly shuffling the data [3,5], as the distributions of these statistics are not invariant under those permutations: The best correlation (smallest value of χ^2 , respectively, largest value of F) is obtained by exactly one of the 4! = 24 permutations of the data, yielding a significance level of 1/24 = 4.17%. However, this best correlation was obtained in 10.3% of the simulations. While this effect seems to become less severe with more data or more equal uncertainties, the example shows that these tests lack proper justification and can produce invalid results. More importantly, when a modified test is used that accounts for the uncertainties in a proper way, then the highly significant results reported for the neutrino data disappear:

The neutrino data that shall first be examined are the 108 estimates N_i of the neutrino flux provided by the Homestake experiment [2] up to run No. 133, so that $N_i = \text{flux}(t_i) + \sigma_i e_i, i = 1, ..., 108$. Here flux(t) denotes the neutrino flux at time t, which is possibly time varying. The uncertainties σ_i given by the Homestake experiment have recently been reanalyzed by the Homestake team, resulting in improved uncertainties that have generously been made available by Dr. Kenneth Lande (private communication). The standardized measurement errors e_i for the various runs are independent by the design of the experiment. A test for correlation can now be developed by examining how linear

functions $a + bs_i$ of the monthly sunspots numbers s_i explain flux (t_i) , i.e., using regression techniques. Under the null hypothesis of a constant neutrino flux, flux(t) = a, the distribution of the scaled differences $d_i = (N_i - a)/\sigma_i, i = 1, \dots, 108$, is invariant under permutations, which justifies the validity of a permutation test for the statistic $T = \sum_{i=1}^{108} s_i d_i$. This statistic is sensitive to trends in flux(t) that vary in concert with the s_i , and possesses certain optimality properties for this type of problem [19]. a was estimated by the standard estimate $(\sum_{i=1}^{108} N_i/\sigma_i^2)/\sum_{i=1}^{108} \sigma_i^{-2}$. The (improved) uncertainties provided by the Homestake experiment were used in the same way as in [3], i.e., the test was done using both "average errors" and "upper errors" for the σ_i . Using 10⁴ random permutations, the test resulted in a two-tailed significance probability of 16.3% for average errors, and 10.4% for upper errors.

As pointed out by a referee, it is informative to evaluate T for earlier stretches of the data, where highly significant correlations have been reported: One obtains only marginally significant results (significance around 2%) for the data up to run No. 108. The same significance obtains for the stretch from run No. 49 to run No. 104, after the result is adjusted by a factor of 10 due to favorable "fishing" for a significant stretch as suggested in [4].

A summary of these results also allows one to put together a coherent picture of the sometimes conflicting evidence reported in [2-12]: The data up to run No. 133 are clearly consistent with a constant neutrino flux when tested against the alternative of a time variation in concert with the solar cycle, according to a test with certain optimality properties for this problem. The previously reported highly significant results in earlier stretches of the data cannot be reproduced when the uncertainties and the permutation argument are employed correctly. Only marginal evidence for a time variation is found in these stretches. In any case, it would not be correct to interpret these results as evidence for a correlation with the solar cycle. This allows one to reconcile these findings with the periodogram analysis in [4], which shows no significant 11 yr component in the data. The reported improved correlation with smoother functions of the sunspot numbers [4,7,10,12] is not surprising in light of the artifact exhibited in the third paragraph.

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