GEOPHYSICAL RESEARCH LETTERS, VOL. 38, L21703, doi:10.1029/2011GL049380, 2011

Are secular correlations between sunspots, geomagnetic activity, and global temperature significant?

Jeffrey J. Love,[1] Kalevi Mursula,[2] Victor C. Tsai,[3] and David M. Perkins[4]

Received 19 August 2011; revised 12 October 2011; accepted 12 October 2011; published 11 November 2011.

[1] Recent studies have led to speculation that solar-terrestrial interaction, measured by sunspot number and geomagnetic activity, has played an important role in global temperature change over the past century or so. We treat this possibility as an hypothesis for testing. We examine the statistical significance of cross-correlations between sunspot number, geomagnetic activity, and global surface temperature for the years 1868–2008, solar cycles 11–23. The data contain substantial autocorrelation and nonstationarity, properties that are incompatible with standard measures of cross-correlational significance, but which can be largely removed by averaging over solar cycles and first-difference detrending. Treated data show an expected statistically-significant correlation between sunspot number and geomagnetic activity, Pearson $p < 10^{-4}$, but correlations between global temperature and sunspot number (geomagnetic activity) are not significant, $p = 0.9954$, ($p = 0.8171$). In other words, straightforward analysis does not support widely-cited suggestions that these data record a prominent role for solar-terrestrial interaction in global climate change. With respect to the sunspot-number, geomagnetic-activity, and global-temperature data, three alternative hypotheses remain difficult to reject: (1) the role of solar-terrestrial interaction in recent climate change is contained wholly in long-term trends and not in any shorter-term secular variation, or, (2) an anthropogenic signal is hiding correlation between solar-terrestrial variables and global temperature, or, (3) the null hypothesis, recent climate change has not been influenced by solar-terrestrial interaction. **Citation:** Love, J. J., K. Mursula, V. C. Tsai, and D. M. Perkins (2011), Are secular correlations between sunspots, geomagnetic activity, and global temperature significant?, *Geophys. Res. Lett.*, *38*, L21703, doi:10.1029/2011GL049380.

1. Introduction

[2] The secular increase in global surface temperature since the middle of the 20th century has been estimated to be mostly anthropogenic in origin [e.g., *Houghton*, 2004]. But there is also some evidence that driving part of the increase in global temperature, especially over timescales of multiple decades to centuries and longer, is the Sun [*Reid*, 2000; *Rind*, 2002]. Proposed causative mechanisms include: (1) change in solar irradiance, with nonlinear feedbacks this would result in warming of the Earth [e.g., *Fröhlich and Lean*, 2004], and (2) change in interplanetary magnetic field strength, which would result in a decrease in cosmic-ray flux, and, in turn, a lessening of atmospheric cloud production and a warming of the Earth [*Svensmark and Friis-Christensen*, 1997]. These theories seem to be supported by correlations between sunspot number, solar-activity proxies, and global temperature [*Hoyt and Schatten*, 1997; *Friis-Christensen*, 2001]. Recently, geomagnetic observatory data have been introduced into the discussion, with qualitative correlations reported between geomagnetic activity and temperature [*Bucha and Bucha*, 1998; *Cliver et al.*, 1998; *Kishcha et al.*, 1999; *Valev*, 2006; *Courtillot et al.*, 2007; *Le Mouël et al.*, 2008; *Mufti and Shah*, 2011].

[3] Are these correlations statistically significant? Ideally, this question would be objectively answered by comparing predictions of physics-based theories against future data. Unfortunately, theories relating the Sun, the geomagnetic field, and the Earth's climate require additional development before useful quantitative predictions can be made [e.g., *Bard and Frank*, 2006]. And even if such predictions were available, we would have to patiently wait for decades before enough data could be collected to provide meaningful tests of their accuracy. As a result, attempts to answer questions of correlational significance have been essentially empirical; the data used are those that are already available; and the inconsistency of results has led to controversy. *Laut* [2003] and *Pittock* [2009] have expressed profound reservations about the methods used to identify correlations between sunspots and global temperature. *Bard and Delaygue* [2008] and *Courtillot et al.* [2008] disagree on whether or not historical geomagnetic activity data are actually even correlated with global temperature.

[4] At least part of the difficulty in evaluating the significance of cross-correlations can be traced to the presence of autocorrelation and nonstationarity in the data. Specifically, the sunspot and geomagnetic time series contain significant solar cycle variation that occurs continuously over timescales that are short compared to global climate change, and all three data types record trends over timescales that are long compared to the total duration of each time series. Any and all of this can obscure cross-correlation of causal significance. In this context, and in order to make progress in assessing hypotheses of the causes of global climate change, we use simple methods to remove autocorrelation and nonstationarity in the sunspot-number, geomagnetic-activity, and global-temperature data so that reasonable estimates can be made of the statistical significance of secular cross-correlations.

2. Data

[5] We analyze 3 different standard data time series, collectively denoted as X, for the period 1868–2008, solar

[1]Geomagnetism Program, USGS, Denver, Colorado, USA.
[2]Department of Physics, University of Oulu, Oulu, Finland.
[3]Seismological Laboratory, California Institute of Technology, Pasadena, California, USA.
[4]Earthquake Hazards Program, USGS, Denver, Colorado, USA.

0094-8276/11/2011GL049380

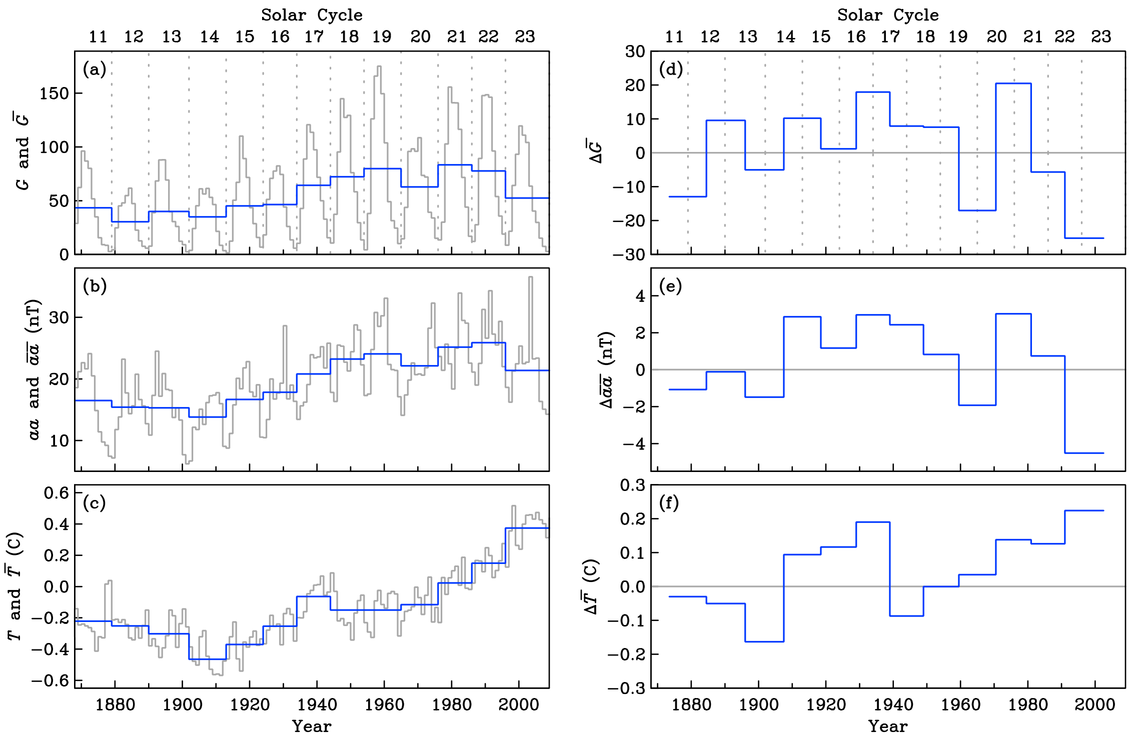

Figure 1. (a–c) Time series of annual-mean (gray) sunspot group number G, *aa* geomagnetic activity index, and global surface temperature anomaly T. Also shown are solar cycle averages (blue) $\overline{G}$, $\overline{aa}$, $\overline{T}$. (d–f) First-differences of solar cycle averages (blue) $\Delta\overline{G}$, $\Delta\overline{aa}$, $\Delta\overline{T}$.

cycles 11–23. (1) Sunspot number is often used as a proxy measure of either general solar activity or total irradiance. We use sunspot group numbers G [*Hoyt and Schatten*, 1998], which are generally considered to be an improvement over international numbers Z [e.g., *Hathaway et al.*, 2002]. (2) The three-hour *aa* geomagnetic activity index measures storms and lower-levels of general magnetic field disturbance driven by the interaction of the solar wind with the coupled magnetospheric-ionospheric system. The *aa* index starts at 1868; it is derived from K -index data from British and Australian observatories [*Mayaud*, 1980]. We checked the *aa* results presented here against separate results for K data; our conclusions were unaffected. (3) HadCRUT3 is a time series representing global-average anomalous surface temperature T [*Brohan et al.*, 2006], defined as the deviation from the 1961–1990 average. We checked the HadCRUT3 results against separate results using other prominent global-temperature time series, GISS and NCDC; our conclusions were unaffected. HadCRUT3 starts at 1850, and it covers the duration of *aa* time series.

3. Autocorrelation

[6] In Figures 1a–1c we show annual means of the X time series: sunspot number G, geomagnetic activity *aa*, and global temperature T. Note the prominent ~11-year solar cycle waxing and waning in both G and *aa*, and generally increasing trends in all three data sets of X over the 141-year timespan of solar cycles 11–23. A partial description of continuous variation in time can be made in terms of lag-one Pearson autocorrelation r^1 [*Press et al.*, 1992], which is high (low) if the values X_{j+1} are similar to (different from) the values X_j. For annual-mean data, "lag-one" corresponds to autocorrelation with a one-year lag. Results are listed in Table 1; these show substantial autocorrelation in all three data time series, for example, for G we have $r^1 = 0.82$. From the standpoint of statistics, the annual means are, in a sense, partially redundant. This can be qualitatively measured in terms of the "effective" number of independent data [*Priestley*, 1981, chapter 5.3.2],

$$N^e = N\frac{1 - r^1}{1 + r^1}, \tag{1}$$

where N is the number of data we actually have, and, following *Jones* [1975], we use the Pearson autocorrelation. Given high levels of autocorrelation, we see from Table 1 that the effective data numbers are much smaller than the number of annual means, $N^e \ll 141 = N$. Therefore, the significance of measured cross-correlations, which we will consider in section 5, might be artificially inflated [e.g., *von Storch and Zwiers*, 2002] – with fewer independent data, there is a higher probability that high measured values of cross-correlation are simply a statistical fluke. As a remedy, we make a simple two-step treatment of the data.

Table 1. Lag-One Autocorrelation r^1 and Effective Data Number N^e, Each for Annual Means X, Solar Cycle Averages $\overline{X}$, and First-Differences $\Delta\overline{X}$, Solar Cycles 11–23[a]

	X, N = 141		$\overline{X}$, N = 13		$\Delta\overline{X}$, N = 12	
	r^1	N^e	r^1	N^e	r^1	N^e
G	0.82	14	0.70	2	−0.29	22
aa	0.73	22	0.84	1	−0.03	13
T	0.88	8	0.87	1	0.30	6

[a]Also given are number of data N for each data type.

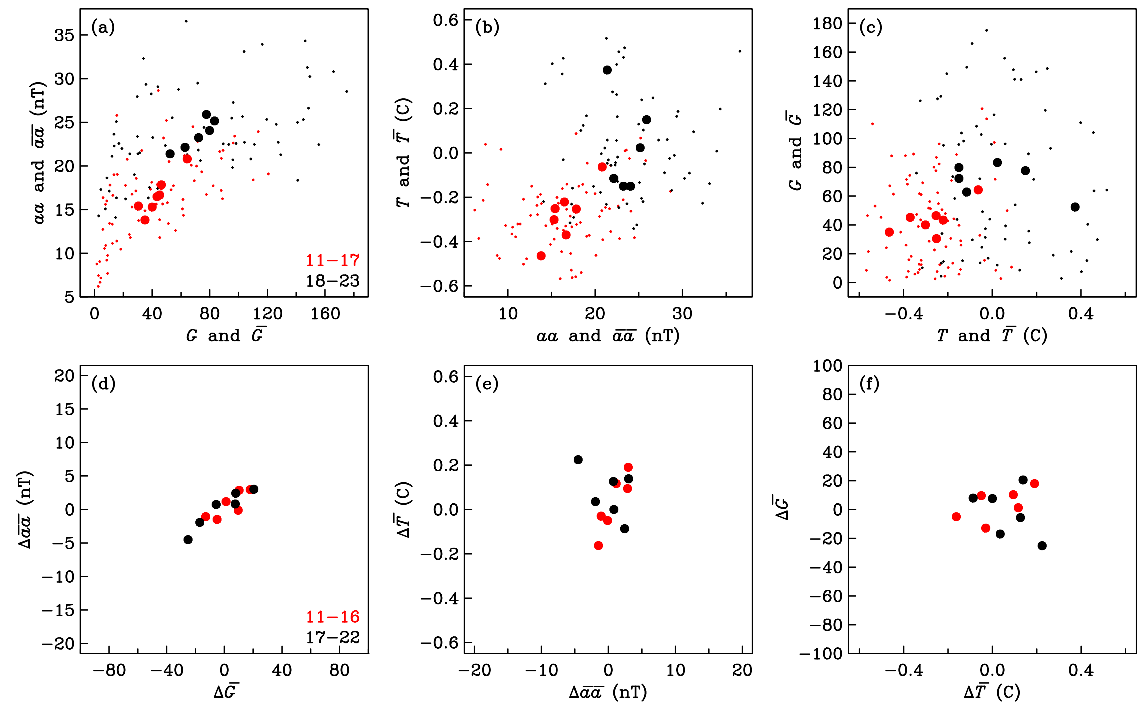

Figure 2. (a–c) Cross-correlation of annual-mean (small dots) sunspot group number G, aa geomagnetic activity index, and global surface temperature anomaly T. Also shown are solar cycle averages (large dots) $\overline{G}$, $\overline{aa}$, $\overline{T}$, for solar cycles 11–17 (red), 18–23 (black). (d–f) First-differences of solar cycle averages (black) $\Delta\overline{G}$, $\Delta\overline{aa}$, $\Delta\overline{T}$, for solar cycles 11–16 (red), 17–22 (black).

[7] First, consider solar cycle variation. Since our interest is in a possible secular relationship between solar-terrestrial interaction and global climate change, we choose to average over the amplitude of intra-solar cycle variation which dominates sunspot number G and geomagnetic activity aa. While this removes an important and interesting signal [e.g., *van Loon and Labitzke*, 2000], it is a signal that is very different from the longer-term secular variation that is the focus of our analysis. For consistency, we also average temperature T over solar cycles. We note that the 11-year timescale of a solar cycle is long compared to the 1–2 year lag of aa after G [e.g., *Richardson et al.*, 2000], and it is much longer than the ~3 month lag of T after solar irradiance [*Douglass and Clader*, 2002]. Averages are formed for bins defined from one sunspot minimum to the next; we denote these with an overbar, $\overline{x}$; for solar cycles 11–23, $N = 13$. The averages in Figures 1a–1c show that solar cycle variation is effectively removed, but the results listed in Table 1 show that substantial redundancy remains in the data as measured by autocorrelation and effective data number.

[8] Second, consider long-term trends. Many unrelated time series with similar trends appear to be cross-correlated, and this can sometimes be misinterpreted as being causal. A classic example of a "nonsense" correlation: from 1866–1911 the proportion of marriages in Britain performed by the Church of England declined, and simultaneously the mortality rate declined; Pearson cross-correlation $r^c = 0.95$ [*Yule*, 1926]. Obviously, there is no causal relationship between these two data sets, but a correlation is found because both data sets are dominated by trends of the same sign [e.g., *Aldrich*, 1995]. Acknowledging the need for caution, we would be motivated to investigate plausible hypothetical linkages if we had, for example, two time series that tracked each other in some nontrivial, nonmonotonic way. *Usoskin et al.* [2005] appreciated this, and in their analysis of sunspot number, cosmic rays, and global temperature, they detrended their data and then analyzed correlations between the remaining residuals. Here, we follow the simple advice of *Granger and Newbold* [1974] and take first-differences of the data,

$$\Delta\overline{x}_j = \overline{x}_{j+1} - \overline{x}_j. \tag{2}$$

Figures 1d–1f show that differencing removes most of the long-term trends in the data. From Table 1, we see that, in size, autocorrelations r^1 for $\Delta\overline{x}$ are small and effective data numbers N^e are the same order as the number of data we have $N = 12$; we note that with modest anti-autocorrelation, $r^1 < 0$, some of the effective data numbers are larger than the actual data number, $N^e > N$. The important point is that much of the redundancy in the data has now been removed.

4. Nonstationarity of Cross-Correlation

[9] Another property that makes it difficult to establish cross-correlational significance is nonstationarity. In Figures 2a–2c we see that the statistical distributions of data-set pairs of both X and $\overline{x}$ have changed over time. We illustrate this by breaking the data into two parts, cycles 11–17 (red) and cycles 18–23 (black). Since red is offset from black, it is clear that the relationships between the data are nonstationary, a property that renders correlational significance difficult to interpret – a reinforcement of the cautious assessments made in section 3. More generally, the presence

Table 2. Pearson r^c and Kendall k^c Cross-Correlation Coefficients and Their Corresponding Significance Levels p for Annual Means X, Solar Cycle Averages $\overline{x}$, and First-Differences $\Delta\overline{x}$[a]

	Pearson, Cycles 11–23						Kendall, 11–23		Kendall, 14–21	
	X		$\overline{x}$		$\Delta\overline{x}$		$\Delta\overline{x}$		$\Delta\overline{x}$	
	r^c	p	r^c	p	r^c	p	k^c	p	k^c	p
G-aa	0.58	0.0000	0.96	0.0000	0.90	0.0000	0.78	0.0003	0.90	0.0043
aa-T	0.40	0.0000	0.71	0.0062	0.07	0.8171	0.18	0.4105	0.42	0.1764
T-G	0.17	0.0348	0.54	0.0559	0.00	0.9954	0.03	0.8909	0.33	0.2931

[a]Results are indicated for solar cycles 11–23 and for the subset solar cycles 14–21.

of nonstationarity represents a serious difficulty for back-in-time extrapolation of proxy measures used for climate studies [e.g., *Bürger and Cubasch*, 2005]. The situation is different for first-differences of solar cycle averages $\Delta\overline{x}$, Figures 2d–2f; here the detrended data for cycles 11–17 (red) and cycles 18–23 (black) are more-or-less similarly distributed. There is apparently relatively little long-term nonstationarity in $\Delta\overline{x}$, they are what is sometimes called "trend stationary" [e.g., *DeJong et al.*, 1992]. We conclude that we are justified in using simple statistical measures in analyzing the significance of cross-correlations between the data sets of $\Delta\overline{x}$.

5. Cross-Correlational Significance

[10] To establish the significance of a Pearson cross-correlation r^c, we calculate the probability p that a random sampling of a normal distribution will yield an $|r^c|$ that is greater than that which is actually measured; results are listed in Table 2. For annual-mean data X, the correlation between sunspot number G and magnetic activity aa is r^c = 0.58, and this is an unlikely outcome of random data, $p < 10^{-4}$; the correlation between aa and global temperature T is almost as seemingly significant, $r^c = 0.40$, $p < 10^{-4}$; and even though the correlation between temperature and sunspot number seems modest $r^c = 0.17$, this appears to be reasonably significant as well, $p = 0.0348$. The problem with all of this, of course, is that which we discussed in sections 3 and 4, the annual-mean data X have autocorrelation and nonstationarity. Therefore, the measures of correlational significance are not meaningful. As for the averages $\overline{x}$, which have had solar cycle autocorrelation removed, Pearson correlations are higher than they are for X, but significances, estimated with fewer data, are lower.

[11] Of most interest, here, are the correlations between first-differences of solar cycle averages $\Delta\overline{x}$, Table 2, since these time series have less autocorrelation and nonstationarity than either X or $\overline{x}$. The well-known and physically well-established relationship between sunspot number and geomagnetic activity is seen as a significant correlation between $\Delta\overline{G}$ and $\Delta\overline{aa}$, $r^c = 0.90$, $p < 10^{-4}$. This simple fact reinforces the confidence we have in the validity of the averaging and differencing method used here. We get what we expected to get. On the other hand, correlations between global temperature $\Delta\overline{T}$ and either of geomagnetic activity or sunspot number are essentially insignificant; for $\Delta\overline{T}$ and $\Delta\overline{aa}$, $r^c = 0.07$, $p = 0.8171$; for $\Delta\overline{T}$ and $\Delta\overline{G}$, $r^c = 0.00$, $p = 0.9954$. From this, it is tempting to conclude that there is no causal connection between solar-terrestrial interaction and global temperature. This might be true. But in the spirit of statistical hypothesis testing, all we can really do is not reject the possibility that there is no causal connection, as measured by cross-correlations, between global temperature and either of sunspot number or geomagnetic activity.

6. Nonparametric Cross-Correlation

[12] In analyzing cross-correlation between two physically-distinct time series, it is common practice to develop a parameterization of the data: linear, quadratic, power-law, etc. Ideally, the parameterization would be motivated by a physical theory, otherwise the treatment can be considered to be ad hoc. In circumstances where we lack a quantitative theory, it is convenient to adopt a nonparametric approach for estimating correlations [e.g., *Chandler and Scott*, 2011]. For each of the 12 first-difference of solar cycle averages $\Delta\overline{x}$, an integer rank is assigned according to its size, with the largest of $\Delta\overline{x}$ being assigned the number 12, the next largest the number 11, etc. We represent this ranking by the mapping $\Delta\overline{x} \rightarrow R(\Delta\overline{x})$. Kendall measures of correlation k^c and corresponding significance p-levels [*Press et al.*, 1992] for the ranked data are listed in Table 2, cycles 11–23. As with the Pearson results, Kendall correlation between sunspot number and geomagnetic activity is both high and significant, but those for temperature and either of sunspot number or geomagnetic activity are neither.

7. A Recent Anthropogenic Signal?

[13] Of course, the present question of societal importance concerns the anthropogenic role in affecting global climate change. A seeming decrease, over the past few decades, in the correlation between solar-terrestrial data and global temperature [*Solanki and Krivova*, 2003; *Le Mouël et al.*, 2005; *Lockwood and Fröhlich*, 2007] might be interpreted as being anthropogenic. We see from Figure 1 that there is, in comparison to sunspot number $\overline{G}$ and geomagnetic activity $\overline{aa}$, an apparent divergence of $\overline{T}$ with the start of cycle 22. Whether or not we can confidently infer that this represents the emergence of anthropogenic warming depends, in part, on how confident we are that global temperature before cycle 22 was controlled by solar-terrestrial interaction. We choose to examine data from cycles 14–21 (a subset of the available data) because they appear to contain some visually-significant cross-correlation, but in choosing data this way, our tests for statistical significance lose their objectivity. Not surprisingly, the p-values for $\Delta\overline{T}$ from cycles 14–21 are smaller than for cycles 11–23; Kendall results are listed in Table 2. Despite this, the correlations for cycles 14–21 are still not compelling; for $\Delta\overline{T}$ and $\Delta\overline{aa}$, $p = 0.1764$; for $\Delta\overline{T}$ and $\Delta\overline{G}$, $p = 0.2931$. On the basis of our analysis of $\Delta\overline{x}$, we cannot confidently reject the null hypothesis that there is no causal relationship between solar-terrestrial interaction and global temperature for cycles 14–21, there-

fore, we cannot accept the hypothesis that an anthropogenic signal can be detected in the data from cycle 22 onwards. Furthermore, if future data of the same type record a superposition of natural and anthropogenically-driven global warming, then this would lead to a continued lack of significant correlation and the same agnostic conclusion. We are not convinced that the combination of sunspot-number, geomagnetic-activity, and global-temperature data can, with a purely phenomenological correlational analysis, be used to identify an anthropogenic affect on climate.

8. Conclusions

[14] One of the merits of using three separate data sets in a correlational analysis is that intercomparisons can be made. After treatment for removal of autocorrelation and nonstationarity through simple averaging and differencing, we find statistically-significant secular correlation between sunspot number and geomagnetic activity. This is expected, and it serves as important support for our analysis method. On the other hand, after making the same treatment to the global surface temperature, correlations between temperature and either sunspot number or geomagnetic activity are not significant. We have not, in this study, considered derived proxy metrics of relevance to climate change, such as reconstructed total-solar irradiance [e.g., *Fröhlich and Lean*, 2004] or interplanetary magnetic field [e.g., *Lockwood et al.*, 1999]. Still, we believe that our methods are general, that they could be used for other data sets, even though our analysis, here, is tightly focused on specific data sets.

[15] From analysis of sunspot-number, geomagnetic-activity, and global-temperature data, three hypotheses remain difficult to reject; we list them. (1) The role of solar-terrestrial interaction in recent climate change is wholly contained in the long-term trends we removed in order to reduce autocorrelation and nonstationarity. This possibility seems artificial, but we acknowledge that our method requires a nontrivial time-dependence in the data that is different from a simple trend. Still needed is a method for measuring the significance of correlation between data sets with trends. (2) An anthropogenic signal is hiding correlation between solar-terrestrial variables and global temperature. A phenomenological correlational analysis, such as that used here, is not effective for testing hypotheses when the data record a superposition of different signals. Physics is required to separate their sum. (3) Recent climate change has not been influenced by solar-terrestrial interaction. If this null hypothesis is to be confidently rejected, it will require data and/or methods that are different from those used here.

[16] **Acknowledgments.** We thank E. W. Cliver, V. Courtillot, C. A. Finn, J. L. Gannon, J. W. Godt, E. J. Rigler, and an anonymous reviewer for reviewing a draft manuscript. K. Mursula acknowledges financial support from the Academy of Finland, projects 128189 and 131350.

[17] The Editor thanks two anonymous reviewers for their assistance in evaluating this paper.

References

Aldrich, J. (1995), Correlations genuine and spurious in Pearson and Yule, *Stat. Sci.*, *10*, 364–376.

Bard, E., and G. Delaygue (2008), Comment on "Are there connections between the Earth's magnetic field and climate? by V. Courtillot, Y. Gallet, J. L. Le Mouël, F. Fluteau, A. Genevey Earth Planet. Sci. Lett., 253, 328–339, 2007," *Earth Planet. Sci. Lett.*, *265*, 302–307.

Bard, E., and M. Frank (2006), Climate change and solar variability: What's new under the Sun?, *Earth Planet. Sci. Lett.*, *248*, 1–14.

Brohan, P., J. J. Kennedy, I. Harris, S. F. B. Tett, and P. D. Jones (2006), Uncertainty estimates in regional and global observed temperature changes: A new data set from 1850, *J. Geophys. Res.*, *111*, D12106, doi:10.1029/2005JD006548.

Bucha, V., and V. Bucha Jr. (1998), Geomagnetic forcing of changes in climate and in the atmospheric circulation, *J. Atmos. Sol. Terr. Phys.*, *60*, 145–169.

Bürger, G., and U. Cubasch (2005), Are multiproxy climate reconstructions robust?, *Geophys. Res. Lett.*, *32*, L23711, doi:10.1029/2005GL024155.

Chandler, R. E., and E. M. Scott (2011), *Statistical Methods for Trend Detection and Analysis in the Environmental Sciences*, John Wiley, Chichester, U. K.

Cliver, E. W., V. Boriakoff, and J. Feynman (1998), Solar variability and climate change: Geomagnetic *aa* index and global surface temperature, *Geophys. Res. Lett.*, *25*, 1035–1038.

Courtillot, V., Y. Gallet, J. L. Le Mouël, F. Fluteau, and A. Genevey (2007), Are there connections between the Earth's magnetic field and climate?, *Earth Planet. Sci. Lett.*, *253*, 328–339.

Courtillot, V., Y. Gallet, J. L. Le Mouël, F. Fluteau, and A. Genevey (2008), Response to comment on "Are there connections between the Earth's magnetic field and climate?, Earth Planet. Sci. Lett., 253, 328–339, 2007" by Bard, E. and Delaygue, M., Earth Planet. Sci. Lett., in press, 2007, *Earth Planet. Sci. Lett.*, *265*, 308–311.

DeJong, D. N., J. C. Nankervis, N. E. Savin, and C. H. Whiteman (1992), Integration versus trend stationary in time series, *Econometrica*, *60*, 423–433.

Douglass, D. H., and B. D. Clader (2002), Climate sensitivity of the Earth to solar irradiance, *Geophys. Res. Lett.*, *29*(16), 1786, doi:10.1029/2002GL015345.

Friis-Christensen, E. (2001), Solar activity variations and possible effects on climate, in *Space Storms and Space Weather Hazards*, edited by I. A. Daglis, pp. 231–250, Kluwer Acad., Dordrecht, Netherlands.

Fröhlich, C., and J. Lean (2004), Solar radiative output and its variability: Evidence and mechanisms, *Astron. Astrophys. Rev.*, *12*, 273–320.

Granger, C. W. J., and P. Newbold (1974), Spurious regressions in econometrics, *J. Econometrics*, *2*, 111–120.

Hathaway, D. H., R. M. Wilson, and E. J. Reichmann (2002), Group sunspot number: Sunspot cycle characteristics, *Sol. Phys.*, *211*, 357–370.

Houghton, J. (2004), *Global Warming: The Complete Briefing*, Cambridge Univ. Press, Cambridge, U. K.

Hoyt, D. V., and K. H. Schatten (1997), *The Role of the Sun in Climate Change*, Oxford Univ. Press, London.

Hoyt, D. V., and K. H. Schatten (1998), Group sunspot numbers: A new solar activity reconstruction, *Sol. Phys.*, *181*, 491–512.

Jones, R. H. (1975), Estimating the variance of time series, *J. Appl. Meteorol.*, *14*, 159–163.

Kishcha, P. V., I. V. Dmitrieva, and V. N. Obridko (1999), Long-term variations of the solar-geomagnetic correlation, total solar irradiance, and Northern Hemispheric temperature (1868–1997), *J. Atmos. Sol. Terr. Phys.*, *61*, 799–808.

Laut, P. (2003), Solar activity and terrestrial climate: An analysis of some purported correlations, *J. Atmos. Sol. Terr. Phys.*, *65*, 801–812.

Le Mouël, J. L., V. Kossobokov, and V. Courtillot (2005), On long-term variations of simple geomagnetic indices and slow changes in magnetospheric currents: The emergence of anthropogenic global warming after 1990?, *Earth Planet. Sci. Lett.*, *232*, 273–286.

Le Mouël, J. L., V. Courtillot, E. Blanter, and M. Shnirman (2008), Evidence for a solar signature in 20th-century temperature data from the USA and Europe, *C. R. Geosci.*, *340*, 421–430.

Lockwood, M., and C. Fröhlich (2007), Recent oppositely directed trends in solar climate forcings and the global mean surface air temperature, *Proc. R. Soc. A*, *463*, 2447–2460.

Lockwood, M., R. Stamper, and M. N. Wild (1999), A doubling of the Sun's coronal magnetic field during the past 100 years, *Nature*, *399*, 437–439.

Mayaud, P. N. (Ed.) (1980), *Derivation, Meaning, and Use of Geomagnetic Indices*, *Geophys. Monogr. Ser.*, vol. 22, AGU, Washington, D. C.

Mufti, S., and G. N. Shah (2011), Solar-geomagnetic activity influence on Earth's climate, *J. Atmos. Sol. Terr. Phys.*, *73*, 1607–1615.

Pittock, B. (2009), Can solar variations explain variations in the Earth's climate?, *Clim. Change*, *96*, 483–487, doi:10.1007/s10584-009-9645-8.

Press, W. H., S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery (1992), *Numerical Recipes*, Cambridge Univ. Press, Cambridge, U. K.

Priestley, M. B. (1981), *Spectral Analysis and Time Series*, Academic, London.

Reid, G. C. (2000), Solar variability and the Earth's climate: Introduction and overview, *Space Sci. Rev.*, *94*, 1–11.

Richardson, I. G., E. W. Cliver, and H. V. Cane (2000), Sources of geomagnetic activity over the solar cycle: Relative importance of coronal

mass ejections, high-speed streams, and slow solar wind, *J. Geophys. Res.*, *105*, 18,203–18,213.
Rind, D. (2002), The Sun's role in climate variations, *Science*, *296*, 673–677.
Solanki, S. K., and N. A. Krivova (2003), Can solar variability explain global warming since 1970?, *J. Geophys. Res.*, *108*(A5), 1200, doi:10.1029/2002JA009753.
Svensmark, H., and E. Friis-Christensen (1997), Variation of cosmic ray flux and global cloud coverage—A missing link in solar-climate relationships, *J. Atmos. Sol. Terr. Phys.*, *59*, 1225–1232.
Usoskin, I. G., M. Schüssler, S. K. Solanki, and K. Mursula (2005), Solar activity, cosmic rays, and Earth's temperature: A millennium-scale comparison, *J. Geophys. Res.*, *110*, A10102, doi:10.1029/2004JA010946.
Valev, D. (2006), Statistical relationships between the surface air temperature anomalies and the solar and geomagnetic activity indices, *Phys. Chem. Earth*, *31*, 109–112.
van Loon, H., and K. Labitzke (2000), The influence of the 11-year solar cycle on the stratosphere below 30 km: Review, *Space Sci. Rev.*, *94*, 259–278.
von Storch, H., and F. W. Zwiers (2002), *Statistical Analysis in Climate Research*, Cambridge Univ. Press, Cambridge, U. K.
Yule, G. U. (1926), Why do we sometimes get nonsense-correlations between time-series?—A study in sampling and the nature of time-series, *J. R. Stat. Soc.*, *89*, 1–63.

J. J. Love, Geomagnetism Program, USGS, Box 25046, MS 966 DFC, Denver, CO 80225, USA. (jlove@usgs.gov)

K. Mursula, Department of Physics, University of Oulu, PO Box 3000, Oulu FIN-90014, Finland.

D. M. Perkins, Earthquake Hazards Program, USGS, Box 25046, MS 966 DFC, Denver, CO 80225, USA.

V. C. Tsai, Seismological Laboratory, California Institute of Technology, Pasadena, CA 91125, USA.