Skin Cancer and the Solar Cycle: An Application of Kolmogorov-Zurbenko Filters

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Abstract
Skin cancer is diagnosed in more than 2 million individuals annually in the United States. It is strongly associated with Ultraviolet exposure, with melanoma risk doubling after five or more sunburns. Solar activity, characterized by features such as irradiance and sunspots, undergoes an 11 year solar cycle. Strong random noise necessitates the analysis of long time scales, yet these account for relatively small variation when compared to shorter time scales such as daily and seasonal cycles. Kolmogorov-Zurbenko filters, applied to the solar cycle and skin cancer data, separate the components of different time scales to detect weaker long term signals and investigate the relationships between long term trends. Analyses of cross correlations reveal epidemiologically consistent latencies between variables which can then be used for regression analysis. This method reveals that strong numerical associations, with correlations >0.5, exist between these small but distinct long term trends in the solar cycle and skin cancer. This permits modeling and forecasting skin cancer trends on long time scales despite strong shorter time scale variation and the destructive presence of noise.

Key Words: Skin Cancer, Solar Cycle and Sunspots, Irradiation and Total Solar Irradiance, Kolmogorov-Zurbenko filter, Time Series Separation of Scales, Global Long Term Trend

1. Introduction

1.1 Skin Cancer
Caner is known to have genetic and environmental risk factors. Particular types of cancer can have greater association with one factor than others. One such example is that of skin cancer. Skin Cancer (SC) is an unregulated growth of abnormal skin cells named after the type of skin cell from which they arise, e.g. Basal, Squamous, and Melanoma. Skin cancer is the most common cancer in the United States, affecting over 2 million annually (Rogers, Weinstock, & Harris, 2010). Melanoma risk doubles with a history of more than five sunburns (Pfahlberg, Kolmel, & Gefeller, 2001). Risk likewise doubles after just one blistering sunburn during childhood (Lew, Sober, Cook, Marvell, & Fitzpatrick, 1983). For years the relationship between sunlight exposure, in particular that of the Ultraviolet portion of the electromagnetic spectrum, and the increased likelihood of developing skin cancer has been a frequent subject of study and research. Studies indicate that approximately 90% of non-melanoma skin cancer is associated with ultraviolet exposure (Koh, Geller, Miller, Grossbart, & Lew, 1996) while this value is approximately 86% for melanoma skin cancer (Parkin, Mesher, & Sasieni, 2011).

As the scientific community's understanding and the general public's awareness of the dangers and risks associated with overexposure to sunlight have changed throughout the years, there have been continual adjustments related to the prevention of skin cancer. This can be seen in awareness campaigns, public service messages, the availability and variety of methods of prevention and mitigation, consumer trends, legislative action, and behavioral and cultural norms. During this time, however, the impacts of each of the above on the incidence of skin cancer, both positive and negative, have not necessarily resulted in a well understood or clearly resolved representation of the underlying dynamics. The factors determining individual risk appear more convoluted than the risk relationship with the disease itself. One often overlooked group of risk factors in this relationship is the nature and characteristics of the sunlight. Solar intensity is the subject of little research with regard to diseases to which it is associated such as skin cancer and it is largely treated as invariant.

1.2 The Solar Cycle

The sun is an engine of nuclear fusion and as a result exhibits several measurable characteristics associated with solar nuclear activity. One defining feature is that solar activity is not constant across time. The intensity of solar activity undergoes an approximate 11 year cycle resulting in a naturally occurring pattern of maximums and minimums. Likewise, many characteristics associated with solar activity exhibit a strong cyclic nature with an approximate 11 year period (Wang, Lean, & Sheeley, 2005). This phenomenon is well documented and studied across various academic fields, such as astronomy, physics, the atmospheric and environmental sciences (Lean & Rind, 2009).

Some of the variables that exhibit the solar cycle include electromagnetic radiation, irradiation, luminosity, magnetic field strength, magnetic polarity, flares, sunspot number, and solar wind. Every characteristic variable has unique methods of measurement and measurement histories. Likewise, the relationship of each variable to the underlying solar cycle phenomenon is different and not automatically synchronous (Foukal & Lean, 1988). Though most exhibit their own 11 year cycle, each may have its own amplitude and phase shift (Sheeley, 1991). This makes each variable more or less suitable to the field or application of interest. In this study electromagnetic radiation, and Ultraviolet radiation in particular, is of clear interest and preference due to its known association with skin cancer risk.

Radiation is a type of transfer of energy by particles or waves with the ability to pass through the vacuum of space. Radiance is the measure of energy that is emitted from a surface into a particular solid angle. Irradiance, a focus of this study, is the power per unit surface area of electromagnetic radiation received by a body, and Solar Irradiance is that produced by the sun and received on the earth. Total Solar Irradiance (TSI) is the measure of the sum total power across the entire electromagnetic spectrum emitted by the sun and received per unit surface area of earth. This measure is of interest to the fields of physics, astronomy, meteorology, atmospheric and environmental sciences (Lean & Kopp, 2011). As such, it has long been an effort to accurately measure TSI.

Attempts to record TSI were first made at ground level (GTSI) elevations on the earth. This measurement is complicated by atmospheric, meteorological and geographic conditions that may screen some or all parts of the irradiation across the electromagnetic spectrum (Lean & Rind, 2009). Different layers of the atmosphere can reflect or absorb portions of the solar irradiance, such as cloud layers and visible light or ozone layers and ultraviolet light. With this consideration GTSI may best be suited as a regional

measurement rather than a global one. Orbital (OTSI) readings are not encumbered by these obstacles, however due to the historically brief satellite age, records of OTSI are shorter in duration (Mekaoui & Dewitte, 2008).

Another solar characteristic, sunspots, are patches on the surface of the sun characterized by locally diminished brightness and temperature and correspond to the changing magnetic field within the sun (Lean J. , Evolution of the Sun's Spectral Irradiance Since the Maunder Minimum, 2000). Like TSI and the other solar characteristics, sunspot number (SN) varies cyclically with an approximate 11 year period (Frohlich & Lean, 2004). Sunspots however have a far longer history of observation, with consistent historical records beginning in the early 18^{th} century (Wang, Lean, & Sheeley, 2005).

1.3 Separation of Time Scales

These time series data sets illustrate a difficulty when investigating long term trends and correlations between datasets in order to determine association structures and causative relationships. The relative strength of the components from one time scale can obscure those operating in a different time scale, interfering with the detection of a signal of interest. The separation of different time scales into constituent components allows for the proper unobstructed analysis. Kolmogorov-Zurbenko (KZ) filters are well suited to this task of separating and screening interfering time scales for signal detection. Analysis is further complicated by skin cancer, not unlike many cancers, having extensive periods of time between initiation, onset and detection (Nadler & Zurbenko, 2013). It has been shown that things such as a history of severe sun burns are a risk factor for skin cancer later in life. These are events that may have occurred decades earlier. Direct comparison of data without accounting for possible disease latencies may produce inconclusive results or erroneous effects.

There is a wealth of research into these individual datasets with regard to their roles in certain fields of study. There is scarce research into global effects of solar irradiation and intensity changes upon individual diseases and disease rates. The objective of this study is to examine the long term changes in TSI, SN, and SC, and investigate the solar cycle and skin cancer relationship. With limitations on what solar cycle variables are available this study evaluates each candidate in terms of suitability as a historical record to support an 11 year signal as well as their relation to each other. This study demonstrates KZ filtration of signals into different time scale components precisely because different time scales may result from different sources and may interfere in the analysis of each individual component (Tsakiri & Zurbenko, 2011). Cross correlations at all reasonable latencies are calculated to identify the latencies of peak correlation between time series datasets. These peak correlations and respective latencies enable regression analysis in an attempt to model the relationship. Finally, knowing the history of a predictor variable and the candidate latency, the model can be used to create better forecasting tools.

2. Methods

2.1 Data Sources

The sunspot number time series dataset comes from a record with dates spanning the years 1749 until the present consisting of monthly observed sunspot counts. This record is available from the Solar Influences Data Analysis Center (www.sidc.oma.be). Ground observations of Total Solar Irradiation, GTSI, for this study were recorded in New Mexico. There are recordings from throughout the geographic United States, but any site

selected will likely be inadequate as a global measure of TSI at the ground level. Each site is subject to the influence of latitude, geography and climate making it poorly suited as a global measure of GTSI. New Mexico was chosen simply for the length of the historical record and to minimize interference from weather upon TSI measurements recorded at the ground level. GTSI spans the years 1961-2010 and originated from the National Solar Radiation Data Base (rredc.nrel.gov). These are statistical summaries of solar data originally recorded hourly, compiled as averages of daily total solar energy for each given month. Orbital measurements of TSI were recorded from the ACRIM or Active Cavity Radiometer Irradiance Monitor, series of satellite instruments between the years 1974 and 2006 (Willson & Mordvinov, 2003). As a measure of power per unit surface area they are recorded as watts per meter squared (www.acrim.com).

Skin cancer records arise from case level data in the SEER or Surveillance, Epidemiology, and End Results database, 1973-2009[1]. The SEER sites included for this study are the states of Connecticut, Hawaii, New Mexico, Utah, and Iowa, and the cities of Oakland and Detroit. As retrospective observational records these sites were not purposefully selected but rather represent the earliest commencement and the longest continuous time series datasets in the SEER database. The cancer database includes all diagnoses at these sites of each cancer type. Here, all types of skin cancer are included in the analysis.

2.2 Transforming the data

For the analysis it is necessary to prepare the data and establish common unit time measures, in this case monthly observations. While several of the variables include measurements on shorter units of time, employing shorter units of measure becomes unnecessary when exploring long term trends, global scale changes and events with great periods of latency. The SN, GTSI and OTSI data sets have a time series representation with summarized monthly observations. To convert the SC case dataset to the same observational time scale we collapse cases into the count within each month.

Upon initial inspection, skin cancer case data exhibits a strong non-constant variance among the observations as well as a growth rate one would expect from changing population statistics across time (Figure 1). The natural logarithm transforms the case data and helps to stabilize the variance. Furthermore, natural logs provide a convenient interpretation that will be utilized later in the study by transforming differences of observations away from count or log count toward measures on the percentage scale. The other advantage of particular benefit with time dependent observations is the comparability of measures that previously were unique to populations of a certain specified time period.

[1]Surveillance, Epidemiology, and End Results (SEER) Program (www.seer.cancer.gov) Research Data (1973-2009), National Cancer Institute, DCCPS, Surveillance Research Program, Surveillance Systems Branch, released April 2012, based on the November 2011 submission.

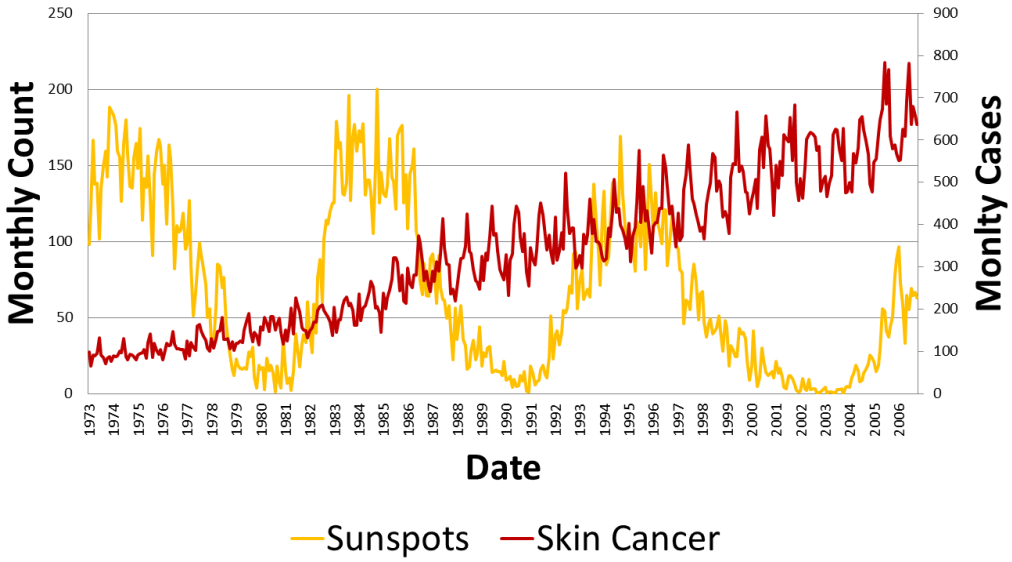

Figure 1: SN and SC monthly data

In time series analysis the linear trend must be removed from the natural logarithm transformed SC cases. The linear trend in log scale corresponds to an exponential growth in the original case data. After trend removal, the remaining deviations from the trend comprise our dataset for continued analysis.

The absence of long term linear trends throughout our time period of interest for SN and our other datasets representing solar activity makes a similar process of trend analysis and removal unnecessary (Figure 1). In fact, solar activity does exhibit even longer term patterns of fluctuation, patterns much greater than a period of 11 years (Lean, Beer, & Bradley, 1995), however the limits of the time frame of this study makes these even longer term fluctuations appear relatively trendless given the shorter window.

2.3 Spectral Analysis

Most visible when viewed in a frequency domain, different time scales are likely rooted in different physical processes and thus arise from different causes. Our datasets viewed in a time domain appear a compilation of the various influential time scales. Each dataset exhibits several strong features indicative of their respective time scales. The solar data most prominently exhibit a cyclic pattern with an approximate 11 year period. This is the solar cycle referenced. A periodogram displays a spike at the frequency corresponding to 11 years (Figure 2). In addition the data exhibits a great deal of random observation to observation fluctuation, relatively smaller in magnitude than the cyclic pattern but with overall variation that is plainly visible in a plot (Schrijver, 1998).

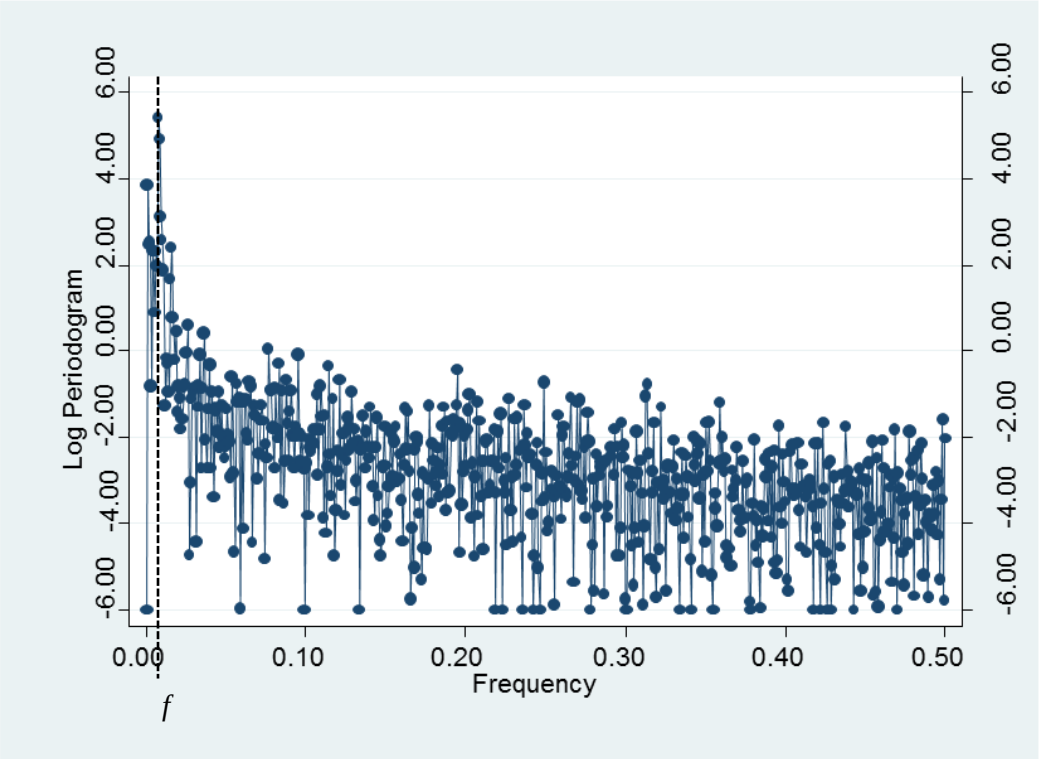

Figure 2: SN Log Periodogram with frequency *f* corresponding to 11 years

This is random noise with no one associated time scale. Rather it represents a base level of signal energy spread across all time scales. SC in the time domain however exhibited different characteristics. The first characteristic was the visible upward trend across time discussed previously. Second is a cyclic pattern that appears to repeat with an approximate one year period. A corresponding periodogram has a spike at a frequency corresponding to 1 year (Figure 3). Finally SC displays the random fluctuation between observations. These time scales represent the majority of the variation in skin cancer cases. Absent, at least visibly, is an apparent cycle at the frequency corresponding to the 11 year time scale.

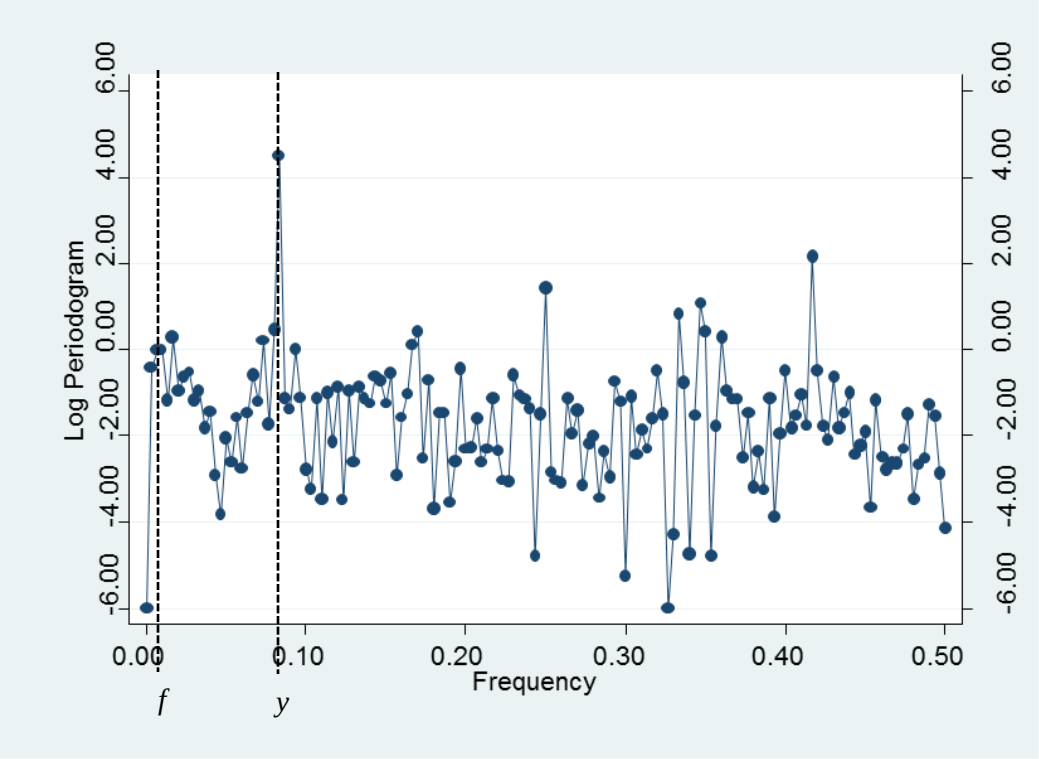

Figure 3: SC Log Periodogram after trend removed with frequencies *f* corresponding to 11 years and *y* corresponding to 1 year

2.4 Separation of Time Scales with KZ filters

Due to the strength of signals present throughout other time scales, a given time scale of with relatively less signal strength may be obscured. In order to investigate a particular time scale it is necessary to separate and remove those that are interfering. Kolmogorov-Zurbenko filters are low pass filters characterized by two parameters (Zurbenko I. , 1986). They are k iterations of a standard moving average filter of m points defining the moving average filter window. With interest in separating and filtering time scales, they are well suited in this study (Zurbenko & Cyr, 2011). The presence of strong yearly cycles in some of our datasets, as well as known naturally occurring annual processes associated with solar activity make a twelve month window the natural choice. Even numbered moving averages however do not preserve the observational center point. To accommodate, this study uses a modified 13 month moving average, preserving the center point of the filter, and weighting the first and last month of the window by one half. The first moving average iteration removes most signals with a period equal to or shorter than one year in each dataset. After the second moving average iteration, the KZ(13,2) filters have effectively removed all significant variation in this short term time scale, while leaving longer time scales unaffected (Close & Zurbenko, 2013). This eliminates the strong random noise and seasonal components as can be seen in the periodogram of SC (Figure 4). What remains is the long term >1 year time scale with the corresponding frequency associated with 11 years noted.

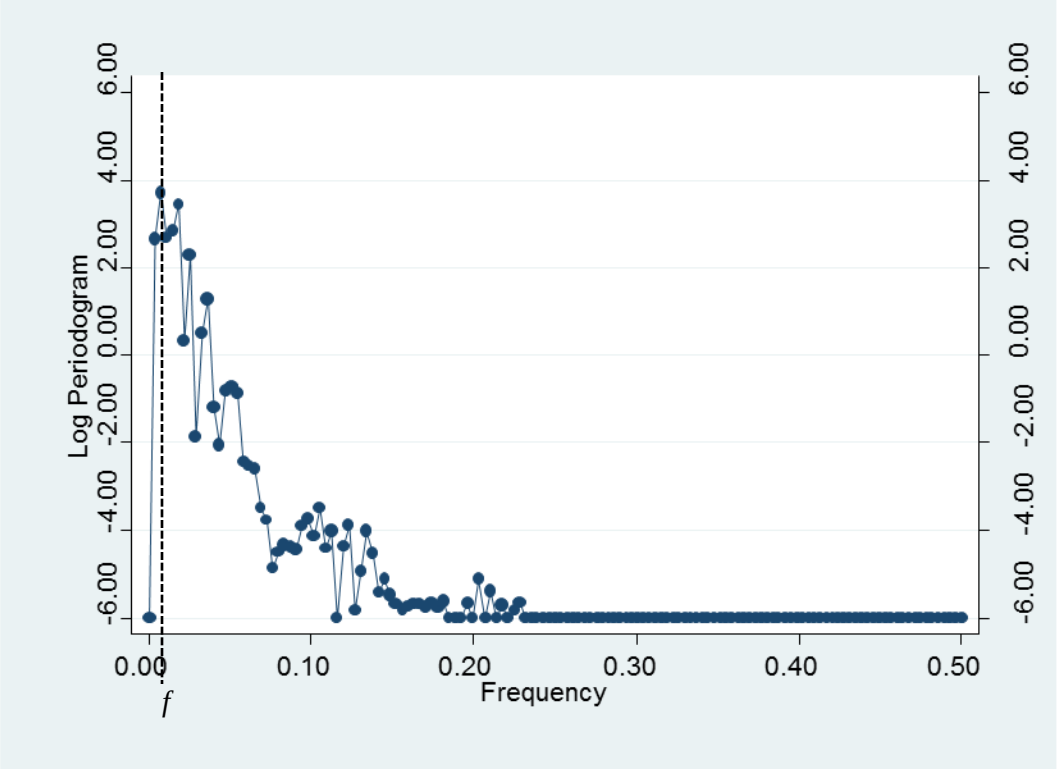

Figure 4: SC Log Periodogram after trend removed and KZ(13,2) filtration with frequency *f* corresponding to 11 years

2.5 Cross-Correlations

The data sets are then cross-correlated to better understand the relationship between them. Cross-correlation involves taking opposing pairs of data with one observation point from each dataset and correlating on the set of paired data. Note that for this study each pairwise cross-correlation between two datasets only utilizes observed points beginning with the latest commencement of any dataset timespan and likewise ending at the first termination of any dataset timespan. To account for possible latencies, or lags, in any possible causal relationship, data points from one variable are paired with opposing data points counted backward in time by t steps, or a lag t, prior to calculating the correlation. Cross-correlations are calculated first with lag t=0, or no latency, and then for all integers lags, up to some reasonably large value as compared to the number of points in the dataset. There are indications of several optimal lags for maximizing correlations. Two sinusoidal signals with a peak correlation occurring at lag t will also have peak correlations when the lag is an integer multiple of the signal period away from t. The choice of which lag is most appropriate can be guided by several factors, in this case maximization, but bounded within the lower limit of disease onset and the upper limit of human lifespan. A safe range might span from 0 to 70 years.

2.6 Regression Analysis

After cross-correlations are calculated for all possible latencies, the latencies associated with peak correlations are selected and used to perform regression analysis between the variables. Regression analysis, in this case linear regression, allows us to characterize the relationship and see how one variable is associated with the movement in another. Finally, the coefficient of explanation, R^2, created by squaring the correlation

coefficient at the chosen latency provides a measure to determine the fraction of variance of one variable explained by another. It should be noted that correlation is typically used in least squares estimation where observations should be independent. In time series analysis, particularly with the application of moving average filters, consecutive points are highly correlated. The use of correlation and subsequently the coefficient of explanation, R^2, in this analysis is a measure of the quality of fit. It uses identical calculations as the standard statistical correlation with an interpretation of the percentage of total variance explained by the fit of one variable to another.

3. Results

3.1 SN, OTSI, and GTSI

After KZ(13,2) filters are applied to the solar variables SN, OTSI, and GTSI, cross-correlation between paired datasets reveal that there exists strong correlations between each of these variables. The peak value in cross-correlation between SN and OTSI is r=0.80 (Figure 5). This peak occurs at zero latency. This is the anticipated result given it SN and TSI roughly move together, and it takes approximately 8 minutes for radiation to traverse the mean sun-earth distance. With the monthly scale used for these datasets, events delayed by this brief latency reasonably appear simultaneous. The correlations lessen between pairings of SN and GTSI (r=0.43), and OTSI and GTSI (r=0.56). Also, non-zero latencies are found in the peak cross-correlations with GTSI. This may be due to more complex atmospheric and geographical influences of ground level measurements and illustrates potential inadequacies of GTSI for analysis of global effects. Still, each of these pairings strongly exhibit 11 year solar cycle in cross-correlations.

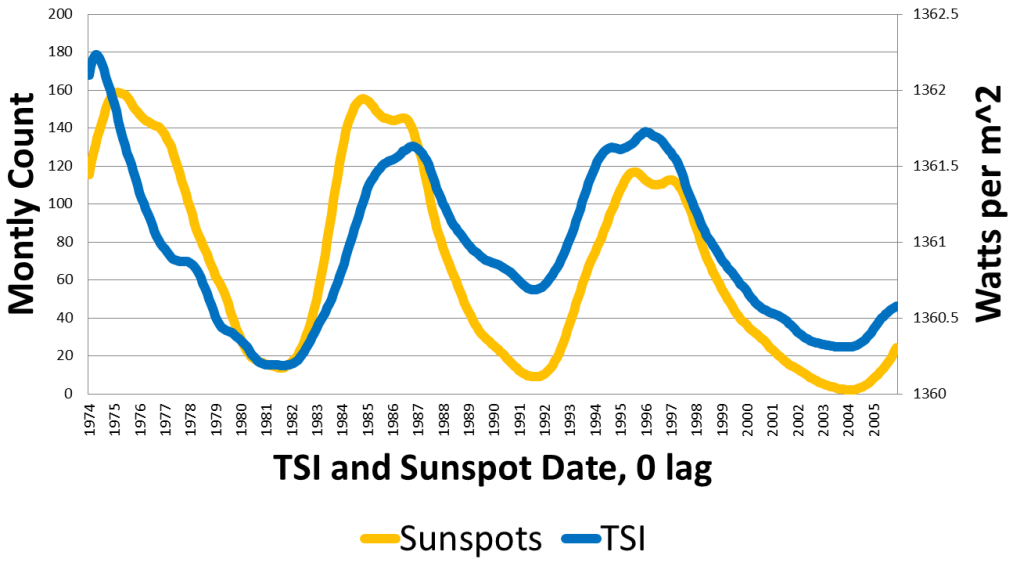

Figure 5: SN and OTSI long term (>1yr) time scale components

3.2 Skin Cancer

With SC it was necessary to transform the data prior to cross-correlation. First was the previously described natural logarithm transformation. Second was the removal of an upward trend. The construction of a linear trend using least squares estimation resulted in a slope coefficient of 0.0034. Given the natural log scale, 0.0034 corresponds to approximately 4.2% growth per year. Cross-correlations between SC cases reach

maximum correlation r=0.51 with GTSI, 0.58 with OTSI, and 0.63 with SN. Here GTSI and OTSI datasets have insufficient history to investigate latency with SC beyond a small number of years. While these datasets are too limited to fully examine the potential latency of skin cancer, their cyclic nature and strong correlation coefficient with both SN and SC are still supportive of the results observed between SC and SN. SN is the only solar cycle variable with a sufficient history to cross-correlate with SC approaching the mean individual lifespan, a sensible upper limit for cancer latency.

SC cross-correlations with SN peak at candidate latencies of 10.0, 19.9, 31.8, 42.2, 52.3 years, etc. Among these peaks, 42.2 years is maximal with a correlation of 0.68 (Figure 6). This correlation corresponds to a coefficient of explanation, R^2=0.39. The time series analysis of this study does not provide tools to indicate preference or likelihood of one candidate latency over another. However, given that the 42.2 year latency period is consistent with evidence of the delay between initiation and detection of skin cancer, and that cross-correlation maximizes at this latency, using 42.2 years is reasonable.

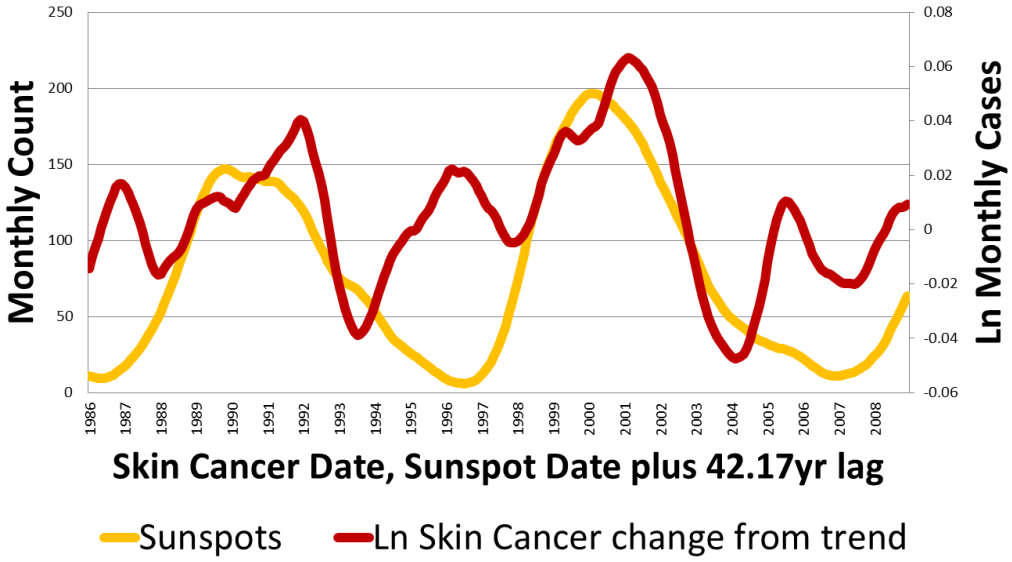

Figure 6: SN and Ln SC long term (>1yr) time scale components

With the peak in cross correlation at 42.2 years, we plot our transformed SC dataset, best described as the deviations from the natural log SC trend, against SN data that is lagged by 42.2 years (Figure 7). This plot helps us visualize the strong correlation at this latency. Recall using the calculated correlation of 0.63 to compute a coefficient of explanation, or R^2, we get 0.3911. Fitting a linear regression model to the lagged data produces a slope coefficient of 0.0003 (per one additional Sunspot), or more appropriately for the scale 0.03 per an increase in 100 SN. This corresponds to a 3.05% increase in skin cancers per 100 SN.

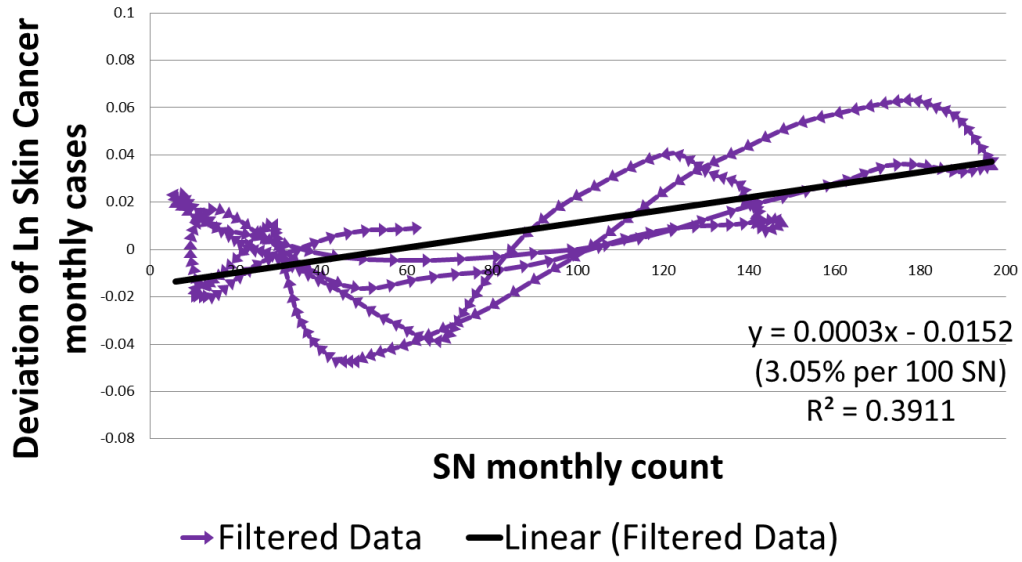

Figure 7: SC plot vs. SN with a 42.17 year latency.

4. Discussion

Evidence suggests there is a distinct solar cycle effect on long term SC case variation. The relative strength of SC variation from other time scales, such as long term trends, seasonal variation and noise cloak this long term effect. Kolmogorov-Zurbenko filters provide an effective tool to separate and screen interfering time scales. Cross-correlation at different latencies accounts for the unknown delay between risk exposure and cancer detection. The latency of peak cross-correlation is used to determine the magnitude of long term effect and characterize the relationship between variables.

TSI is a natural choice as a representative variable of the solar cycle effect on skin cancer. The known risk of ultraviolet light exposure on skin cancer is a compelling argument in favor of its use. Unfortunately at this time, without additional years of observation, the need for a sufficient history to both detect and 11 year cycle and account for a multi-decade latency make TSI unsuitable. These more accurate TSI records, though of or limited research potential here, are however supportive of the analysis that can be performed with SN. Although orbital TSI has the shortest history, and ground based TSI suffers from regional influences limiting its usefulness to study global effects, both produced results similar and compatible to that obtained using SN. Cross-correlations with SC in the long term time scale component gave evidence of the presence of the solar cycle effect. The extension of the cross-correlation analysis requires a far lengthier history to investigate reasonable cancer latencies. In the future, with several additional years' worth of data, extending this analysis using TSI measures may produce interesting and even more definitive results.

With SN as the only tenable solar cycle variable with sufficient history, the study proceeded by removing the linear trend from natural logarithm transformed SC case data. With a linear regression coefficient of 0.0034 on the log scale, this indicates that the rate of growth in skin cancer cases for several decades is approximately 4.2% per year. This outpaces the approximate population growth in the United States during a similar period

of approximately 1%. Clearly population growth can not alone account for the growth in skin cancer diagnoses, an interesting result and one worthy of continued investigation.

Cross-correlations between SN and SC displayed the cyclic patter with an approximate 11 year period when plotted at different latencies, further supporting the presence of a long term component. These cross-correlations attain a peak value of r=0.68 at the 42.2 year latency. The square of this correlation produces the coefficient of explanation, R^2=0.39. Recalling that the transformed SC was on a natural log scale and had a linear trend removed, and that both SC and SN data had the KZ filter applied to only retain the long term component we can properly interpret this coefficient. A suitable interpretation is that 39% of the long term (>1 year) variation in skin cancer (in log scale) deviation from the trend can be explained by the variation in SN that occurred 42.2 years prior.

After plotting at the 42.2 year latency, the association between the long term skin cancer and sunspot number datasets can be described by a linear relationship with a linear coefficient of 0.0003. Given the log skin cancer scale the coefficient of linear regression has a clear interpretation by differencing the natural logarithm transformed values resulting in a percentage scale. A typical solar cycle can decrease to near zero sunspots in a given month, and can peak at 150, 200 or even 250 sunspots during solar maximum (Solanki & Fligge, 1999). Using the derived linear coefficient and these typical solar cycle amplitudes, they represent associated increases in skin cancer cases of 4.6, 6.2 and 7.8 respectively. Therefore, a typical solar maximum with 200 monthly sunspots is associated with 6.2% more monthly SC cases 42.2 years later, when compared to a solar minimum. The close relationship between SN and TSI allows the extension of this result. During a typical solar cycle, orbital TSI indicates that irradiation varied by only 1.5 additional watts per m^2, an increase in TSI of only 0.1% (Frohlich & Lean, 2004). Even absent the data to directly cross-correlation TSI with SC at long latencies, the strong correlation between OTSI and SN makes it reasonable to similarly model the effect of small changes in TSI on SC cases. Thus, 1.5 additional watts per m^2 is associated with the 6.2% increase in monthly SC cases, 42.2 years following a solar maximum, as compared to a solar minimum.

Other than using current short term trends to forecast skin cancer cases, there is no long term forecast for skin cancer. The relationships and coefficients provided above, combined with the latency of skin cancer and the extensive historical record for sunspots provide a more accurate means of forecasting skin cancer prevalence in the near future as well as in the long term. There is the potential to forecasts decades into the future.
Knowing that associated skin cancer risk increases with increased solar activity during solar maximums and that this occurs in a well-known, predictable, cyclic pattern, there is opportunity to more effectively target education and prevention campaigns aimed at reducing skin cancer prevalence. The methods outlined in this analysis are equally applicable to similar research where the detection of a signal within a particular time scale is obscured by relatively stronger signals from different time scales, or by destructive noise. This research could be extended to the relationship between the solar cycle and other diseases that may have a long term hidden effect, or to other risk factors of disease.

Within the scope of this research project, the data was limited to records obtained within the United States although from a geographically diverse population given that constraint. With additional datasets, particularly those outside of the US, extending this research would better clarify results to more accurately determine true global long term effects of

the solar cycle. The Kolmogorov-Zurbenko filter has previously been extended and formalized in several useful applications including a spatial filter. With additional existing data elements it is possible to extend this research to include spatial data from the cancer database. Rather than pooling the data for a global effect it would then be possible to determine regional effects and develop regional models and forecasting. This could first be performed by banding latitudes to account for the effect of latitude on irradiation intensity. Secondly, the analysis could be refined to individual locations accounting for local variation in meteorology and geography.

These are just a few of the possible extensions and applications of the research methods and results outlined in this study. Modeling and forecasting are only likely to improve with improved data, additional years of observations and the inclusion of more accurate representative solar radiation variables as they become available. This study highlights the importance of investigating long term effects that may be hidden by short term noise, but that significantly contribute to the understanding of disease risk and prevention.

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