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Climate Variability and Health:
Sweden 1751-2004

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Climate Variability and Health:
Sweden 1751-2004

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Abstract: Several studies have examined the link between climate and health, mainly focusing on the short term impacts of extreme temperatures. This paper analyzes instead the long term relation between climate variability and health using Swedish temperature and mortality data for the period 1751-2004 using different time scales. We find that periods with higher temperature are associated with lower mortality. The results indicate that long term climate variations in annual mean temperatures and not short term variations explain the connection between temperature and mortality. Considering annual extreme temperatures, we find that extreme low winter temperatures are correlated with higher short term mortality. We identify the impact of the 11-year solar cycle on crop yields as a possible explanation for our findings. The results have besides their economic-historical merits implications for modern day policy for developing countries, especially since the correlation with solar activity implies predictability.

Keywords: Mortality, Wavelet, Climate

JEL Code: I18, N53, N54, Q54

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1 Introduction

Due to the increasing attention focusing on climate change and its consequences it has also been considered that health can be affected by extreme temperatures or increased precipitation. There are several studies focusing on the relationship between temperature and mortality. Huynen (2001) finds that mortality and temperature are linked in Holland, with a higher mortality rate during periods of excessive heat or cold. The relationship is therefore v-shaped which means that it reverses at a certain temperature. Rocklöv et al (2003) have shown that hot waves cause higher mortality in the group of elderly and sick people in Stockholm. Average temperature might have another effect on health than extreme temperatures. Research from immunology shows that bacteria, viruses and parasites are less active in periods with higher temperature. Moreover, the adaptive immune system is more intense at higher temperatures. Recent research links indirectly temperature and psychological well being, for example the effect of sun light on depression disorders (Axelsson et. al., 2002; Pallos et. al, 2004). Research has furthermore shown that climate effects are dependent on latitude, as people are adversely affected by cold temperatures in southern areas and by warm temperatures in northern areas (Curriero et al 2003.)

In this paper we set out for an empirical test of temperature fluctuations and its impact on mortality in a longer time perspective, using mortality and temperature data for Sweden for the period 1751-2004. The analysis is facilitated by means of wavelet analysis. Wavelet methods transform a time series into several time series which reflect properties of the original time series at different time scales. Using different time scales is nothing new, since we can analyze relationships between variables using daily, monthly or yearly data. In wavelet analysis however, the information contained in one time scale is independent (orthogonal) from the information contained in the other time scales. The transformed time series can be added together in order to get the original time series, which implies that the transformed series essentially contain the same information as the original time series.

This paper is structured as follows. Since wavelets are a novel tool in the area of health economics we describe the methods used in section 2. The data used is described in section 3. The analysis and the results are shown in section 3. We find that the climate has a significant impact on mortality, especially the mean temperature during spring, which are the periods associated with shortages in food. Further, we use a harvest index for 1751-1912 and find that during warmer periods health status is better, as is the harvest quality. However, this link is strongest for the time period 1751-1890 and changes considerably during 1891-2004. Whereas the oscillations in mortality and temperature are countercyclical for dynamics with a period of at least 8-16 years and can be explained with the cyclic behaviour of crops, industrialization implies that climate has an impact on mortality on mostly short term fluctuations (2-4 years). The paper concludes with discussions in section 4.

2 Method: Wavelet decomposition

A time series is usually analyzed either in the time domain or in the frequency domain. The Fourier transform serves as a connection between time series analysis in the time domain and in the frequency domain. Fourier transformations use a sum of sine and cosine functions with different frequencies and amplitudes. Since sine and cosine functions have a repeating pattern of amplitudes along the time axis these Fourier transformations are not applicable to time series with structural breaks or sharp peaks. A Wavelet transformation is similar to Fourier transformation in that it converts the time series from the time domain to the frequency domain. In wavelet analysis however, the amplitude for a given frequency can change across time.

A wavelet is a mathematically defined function meeting certain requirements:

- Positive and negative deviations from zero cancel out
- The deviations from zero are limited to a relatively small interval in time

We therefore have a 'small wave', which is the literal meaning of "wavelet". There are several other properties a wavelet has to suffice in order to have any practical use, the most important the so called admissibility property (for details see Percival and Walden, 2000).

A discrete wavelet transformation (DWT) decomposes a time series into different frequency bands. In wavelet analysis each frequency band is called a scale. The first scale λ_1 covers the frequencies $\frac{1}{4}$ to $\frac{1}{2}$ and scale λ_j the frequencies $\frac{1}{2^{j+1}}$ to $\frac{1}{2^j}$, so that the width of each frequency band is scale dependent. A wavelet transformation with J-scales produces J sets of wavelet coefficients and one set of scaling coefficients. The wavelet coefficients can be interpreted as weighted differences on the physical scale $\lambda_j = 2^{j-1}\Delta t$, thus representing high frequency changes. Since the wavelet filter approximates an ideal band pass filter with pass band $[1/2^{j+1}, 1/2^j]$, the λ_j scale wavelet coefficients show variations with a period in the interval between $1/2^{j+1}$ and $1/2^j$ (Gallegati, 2007). The scaling coefficients can be interpreted as the sum of weighted averages, thus representing low frequency changes in local means. The different wavelet scales are an orthogonal transform of the original time series, meaning that we can easily reconstruct the time series from its transform. Thus, the 'information' in the transform is equivalent to the 'information' in the original series (Percival and Walden, 2000).

A practical shortcoming using DWT is that only 2^J, where J is an integer, observations can be included in the analysis. Further, the decomposition is dependent on both the specific choice of wavelet function and the starting point on the time axis. These deficiencies can be addressed by using a variant of DWT called the maximum overlap discrete wavelet transformation (MODWT) as described in Percival and Walden (2000). MODWT uses an overlapping window algorithm to circumvent the 2^J-restriction and decreases sensitivity with respect to choice of wavelet function and starting point.

One convenient property of a wavelet transform is the so called energy preservation across time scales. For a MODWT transform it can be shown that the following relationship holds:

$$\sum_t x_t^2 = \sum_{jt} w_{j,t}^2 + \sum_t v_t^2 \tag{1}$$

where x_t is the data value and $w_{j,t}$ and v_t are the wavelet coefficients and scaling coefficient, respectively. An unbiased estimator of the wavelet variance is:

$$\sigma_{\lambda_j}^2 = \frac{1}{n}\sum_t w_{j,t}^2 \tag{2}$$

Hence, the variance of the original time series can be decomposed into the sum of the variances over different time scales. Analogous, we can define the wavelet covariance for two time series, thus enabling us to decompose the relation between two variables on a scale by scale basis. Based on the wavelet decomposition outlined above, we can perform a multiresolution analysis (MRA) of the original time series, producing a series of wavelet details and a wavelet smooth. For a MRA based on MODWT the following relationship holds:

$$x_t = \sum_j d_{j,t} + s_t \tag{3}$$

where x_t is the value of the time series at time t and $d_{j,t}$ and s_t are the wavelet details and wavelet smooth, respectively. Hence, each data point can be decomposed as the sum of the wavelet details and the wavelet smooth over different time scales. The smooth coefficients mainly capture the underlying trend behaviour of the data at the coarsest scale while the details coefficients represent deviations from the trend behaviour for increasingly finer scales. MRA is therefore a convenient way for performing analysis based on levels rather than variances for different time scales.

3 Data

The analysis was conducted using annual and age adjusted mortality data in Sweden for the years 1751-2000 (Human Mortality Database, http://www.mortality.org/) and daily temperature data for Uppsala for the same period (Bergström/Moberg, 1998).

[Figure 1]

[Figure 2]

Table 1 summarizes descriptive properties of the data.

[Table 1]

In order to reveal the stochastic properties of temperature data we employ a battery of tests for the estimate of the long memory (fractional integration) parameter *d* of a time series, based on the log-periodogram regression (Phillips, 1999; Phillips, 2007) and the local Whittle estimation (Kuensch, 1987; Robinson, 1995; Shimotsu and Phillips, 2005; Shimotsu, 2006). If a series exhibits long memory it is a fractionally integrated process I(*d*) with *d* being a real number. Table 2 shows the results.

[Table 2]

We conclude that temperature for the sampled time interval and place is a long-memory process with stationary behavior since *d* lies between 0 and 0.5 (Percival and Walden, 2000). This has interesting implications: it implies that a shock in temperature has persistent effects resulting in non-periodic cycles which can be misinterpreted as local trends. The evidence for persistence in the time series of temperature indicates that it is hard to distinguish between trend and upturns in non-periodic long cycles.

In addition, we use a harvest index for the period 1751-1912 measuring the quality of crop yields on a scale ranging from 1 (worst) to 9 (best) obtained from Thomas (1941).

4 Analysis

We decompose the two transformed series into their timescale components using the maximum overlap discrete wavelet transform (MODWT), which is a variant of the classical discrete wavelet transform that. The wavelet filter used in the decomposition is the Daubechies least asymmetric wavelet filter with length L=8 (Daubechies, 1992) with periodic boundary conditions. The application of the wavelet transform with a number of scales $J = 4$ produces four sets of wavelet coefficients *w4,w3,w2,w1* and one set of scaling filter coefficients *v4*. Since we use yearly data scale 1 represents 2-4 yearly period dynamics, while scales 2, 3 and 4 correspond to 4-8, 8-16 and 16-32 year period dynamics respectively (Gallegati, 2007). Variations with periods longer than 32 years are captured in the set of scaling filter coefficients. With wavelet analysis we may examine the correlations on a scale by scale basis and determine which scales contributes to the overall relationship between two series.

In table 3 we report the MODWT-based wavelet correlation coefficients for different time scales, where each scale is associated with a particular time period. The findings indicate a significant negative relationship at all scales except scale 1 (short term fluctuations).[3]

[Table 3]

Using a multiresolution analysis (MRA) we test for causality in the Granger (1969) sense between temperature and mortality. That is, we want to test whether past values of one variable can contribute in predicting actual values of another variable. We estimate the following vector autoregressive model (VAR) for each of the wavelet details[4] separately using transformed mortality (MORT) and temperature (TEMP) data:

[3] It could be criticized that we correlate Swedish mortality with temperature data from Uppsala. However, temperatures are highly correlated between measuring places. Replicating the analysis with oxygen isotope contents in arctic ice cores as a proxy for northern hemisphere temperatures yields qualitatively the same results (results are available from the author on request).

[4] The so called wavelet-details d1,d2,d3 and d4 are the result of performing a MRA. Each of the details provides information about deviations from trend at increasingly coarser scales.

$$MORT_t = a_0 + \sum_{i=1}^{k} a_i MORT_{t-i} + \sum_{i=1}^{k} b_i TEMP_{t-i} + e_{1t} \tag{4}$$

$$TEMP_t = c_0 + \sum_{i=1}^{k} c_i MORT_{t-i} + \sum_{i=1}^{k} d_i TEMP_{t-i} + e_{2t} \tag{5}$$

The number of lags to include is decided using the Schwartz information criteria. Following Granger and Newbold (1986), we test for granger causality by constructing a joint F-test for the inclusion of lagged values of temperature and mortality. The null hypotheses is that the coefficients for temperature in equation41 and the coefficients for mortality in equation 5 are zero, that is, they do not contribute in reducing the variance in forecasts of temperature and mortality, respectively. If both null hypothesises are accepted we have a feedback mechanism between mortality and temperature. If both null hypothesises are rejected we have inclusive results regarding the causal relationship. In order to conclude that causality is unidirectional we must have that one null hypothesis is rejected and that one null hypothesis is accepted at conventional significance levels. We results of the granger causality test are presented in table 4.

[Table 4]

For the finest scales we have inclusive results with regard to the granger causality F-tests. One explanation for this might be that the contemporaneous effect dominates. On scale 3, corresponding to dynamics with a period of 8 to 16 years, we find that temperature granger causes mortality (at a significance level of 5 %). The same is true for scale 4, corresponding to dynamics with a period of 16 to 32 years.

Hence, the causality relationship between temperature and mortality is not straightforward, but is dependent on the time scale we analyze. Only time scale decomposition can shed light on the nature of causality between temperature and mortality.

For comparison, fitting a VAR-model on raw data for mortality and temperature, the granger causality test becomes inconclusive. Only time scale decomposition can therefore reveal the hidden relationship in the long term variations of temperature and mortality. The results of scale dependent temperature effects are well in line with research regarding the periodicity of solar activity, that finds cycles of on average 11 years (captured by scale 3).

Since we expect that the relationship has changed with time, we divide the hole period into two sub periods, the first ranging from 1751-1890 and the second from 1891-2004.

[Table 5]

[Table 6]

As can be seen from table 5 and table 6, the oscillations in mortality and temperature in the period 1751-1890 are significantly countercyclical for dynamics with a period of 8-16 years and 16-32 years, that can be explained with the long term cyclic behaviour of crops (see table 7 and table 8), which in turn depends on the solar cycle (results not shown here).[5]

[Table 7]

[Table 8]

Apparently industrialization changed the relationship for the period 1891-2004 so that climate instead has a significant impact on short term fluctuations in mortality (2-4 years). We expect that the results concerning the seasonal means give more detailed information on the relationship between annual mean temperature and mortality (see table 9). Winter temperature has no significant impact on mortality on the shorter scales (scale 1 and scale 2). However, long term fluctuations in winter temperature have a significant effect on mortality.

[Table 9]

[5] Using the same type of analysis for the number of sunspots we find that the crop yield quality is significantly positively correlated with solar activity for periods between 8-16 years. The 11-year solar sunspot cycle is not completely deterministic but varies between 9.8 to 12 years. Wavelet analysis is therefore an adequate tool for this type of analysis since it captures varying periodicities.

Considering spring temperature, we find a negative impact for the shortest time scale, corresponding to dynamics with a period of 2-4 years. Again, the correlation is significant for the longest scale, representing 32-64 year periodicity. The picture is quite different for the summer temperature. Both the magnitude of correlation coefficients and the lack of statistical significance indicate that summer temperature has no effect on mortality. The influence of the autumn temperature is only significant at the longest scale. The therefore can conclude that the relationship between seasonal means with regard to temperature and mortality is different from each other and, even more interesting, that it differs across time scales.

Using monthly data we construct a continentality index (CI). Usually this means calculating the range of temperature between the warmest and the coldest month and standardizing it with the latitude. Since the latitude in our case is constant we use only the difference between the warmest month in our sample (July) and the coldest month (January). The results are presented in table 6.

[Table 10]

Short term fluctuations in the CI have apparently no significant impact on mortality. However, the reverse is true for longer term fluctuations. For scales 2-4 we find that correlation increases with time scale and becomes highly statistical significant.

Next, we set out for a test of the impact of extreme temperatures on mortality. Since we have daily data we can easily obtain maximal and minimal temperatures for each year. Using annual mortality data we can perform however only a very rough test of the relationship between extreme temperatures and mortality. All things equal, we expect that extreme temperature both during summer and winter will increase mortality. However, it is very likely that extreme temperatures are correlated with temperatures during longer periods in respective year, so that it is hard to distinguish between the effect of extreme temperatures and temperatures during the weeks around the occurrence of the maximal or minimal temperature.

For minimal temperature the effect will be unambiguous, whereas extreme heat may kill old individuals but have a positive effect on younger people (since it is correlated with mean average temperatures). The results are presented in table 11 and table 12.

[Table 11]

[Table 12]

The coefficient for annual maximum temperatures although positive does not have any statistically significant short term impact on mortality. On the contrary, the coefficient for annual minimum temperature has a significant impact on mortality, more people dying because of cold spells. This could be compared to mean winter temperature which has no significant effect.

5 Conclusions

In this paper we investigate the impact of climate on health status. As a proxy for climate we use yearly and seasonal average temperatures plus a continentality index calculated from monthly data for Uppsala spanning 254 years beginning in 1751. For the same period we use age adjusted mortality as a proxy for health status. We show that the climate has a significant impact on mortality, especially the mean temperature during spring, which are the periods associated with shortages in food. Further, we use a harvest index for 1751-1912 and find that during warmer periods health status is better, as is the harvest quality. However, this link is strongest for the time period 1751-1890 and changes considerably during 1890-2006. Whereas the oscillations in mortality and temperature are contra cyclical for dynamics with a period of at least 8-16 years and can be explained with the cyclic behaviour of crops, industrialization implies that climate has an impact on mortality on mostly short term fluctuations (2-4 years). We results have besides their economic-historical merits some implications for modern day policy. Especially will this be the case for some developing countries, at least for those with similar climate characteristics as northern Europe. Moreover, the identification of the 11-year solar cycle as possible explanation might facilitate the timing of policy measures due to the predictability this implies. The approach used in this paper can easily be replicated since long temperature and mortality series are available from several places in Europe. This paper does not analyze climate change *per se*, instead it shows how natural climate variations have significant impact on peoples health status long before the temperature hike starting about 50 years ago. It questions statements claiming that modern day societies are more sensible to climate change effects; it depends on the length of the time scale we think about.

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Tables

Table 1: Descriptive statistics raw data

	Mean	Std. dev.	Min	Max
TEMP	5.51	0.98	2.95	8.46
MORT	3024.12	1090.28	1029.18	6981.25

Table 2: Estimate of fractional differencing parameter *d* for temperature

Method	Estimate of *d*
Modified Log-Periodogram Regression estimator	0.32
Local Whittle (LW) estimator	0.15
Exact LW (ELW) estimator	0.85
Feasible ELW estimator	0.25
Feasible ELW estimator (detrended)	0.16
2-step feasible ELW estimator	0.25
2-step feasible ELW estimator (detrended)	0.16

Table 3: Correlation temperature mortality 1751-2004

Scale	Correlation	90%-CI lower	90%-CI upper
W1	-0.0764	-0.1893	0.0385
W2	-0.1693*	-0.3243	-0.0055
W3	-0.3290*	-0.5255	-0.0992
W4	-0.5331*	-0.7463	-0.2208

Table 4: Granger causality tests for temperature (TEMP) and mortality (MORT)

Scale	Causality direction
D1	Inconclusive
D2	Inconclusive
D3	TEMP=>MORT
D4	TEMP=>MORT

Table 5: Correlation temperature mortality 1751-1890

Scale	Correlation	90%-CI lower	90%-CI upper
W1	-0.0574	-0.2108	0.0988
W2	-0.2052	-0.4092	0.0184
W3	-0.4188*	-0.6577	-0.1034
W4	-0.5987*	-0.8522	-0.1174

Table 6: Correlation temperature mortality 1891-2004

Scale	Correlation	90%-CI lower	90%-CI upper
W1	-0.1802*	-0.3422	-0.0078
W2	-0.1467	-0.3834	0.1082
W3	-0.2724	-0.5822	0.1066
W4	-0.4061	-0.7901	0.2069

Table 7: Correlation crop index mortality 1751-1912

Scale	Correlation	90%-CI lower	90%-CI upper
W1	0.0307	-0.1139	0.1741
W2	0.0298	-0.1790	0.2359
W3	-0.4197*	-0.6400	-0.1356
W4	0.0829	-0.3811	0.5135

Table 8: Correlation crop index temperature 1751-1912

Scale	Correlation	90%-CI lower	90%-CI upper
W1	-0.0624	-0.2038	0.0815
W2	0.1721	-0.0341	0.3642
W3	0.3630*	0.0694	0.5987
W4	0.3100	-0.1624	0.6668

Table 9: Correlation seasonal mean temperature and mortality 1751-2004

Scale	Spring	Summer	Autumn	Winter
W1	-0.2492**	-0.0983	-0.0945	-0.1121
W2	-0.1272	-0.0336	0.0153	-0.0880
W3	-0.1679	0.0125	-0.0484	-0.4385**
W4	-0.5865*	0.2216	-0.4073*	-0.5478**

Table 10: Correlation continantality index mortality 1751-2004

Scale	Correlation	90%-CI lower	90%-CI upper
W1	-0.0144	-0.1311	0.1027
W2	0.0763	-0.0916	0.2399
W3	0.3091*	0.0728	0.5126
W4	0.4448*	0.1079	0.6901

Table 11: Correlation minimum temperature and mortality

Scale	Correlation	90%-CI lower	90%-CI upper
W1	-0.1286*	-0.2397	-0.0142
W2	-0.0861	-0.2466	0.0790
W3	0.0978	-0.1431	0.3278
W4	0.2959	-0.0648	0.5883

Table 12: Correlation maximum temperature and mortality

Scale	Correlation	90%-CI lower	90%-CI upper
W1	0.0159	-0.0989	0.1303
W2	-0.0851	-0.2456	0.0800
W3	-0.2642*	-0.4721	-0.0284
W4	-0.2637	-0.5649	0.0995

Figures

Figure 1: Age adjusted mortality in Sweden 1751-2004

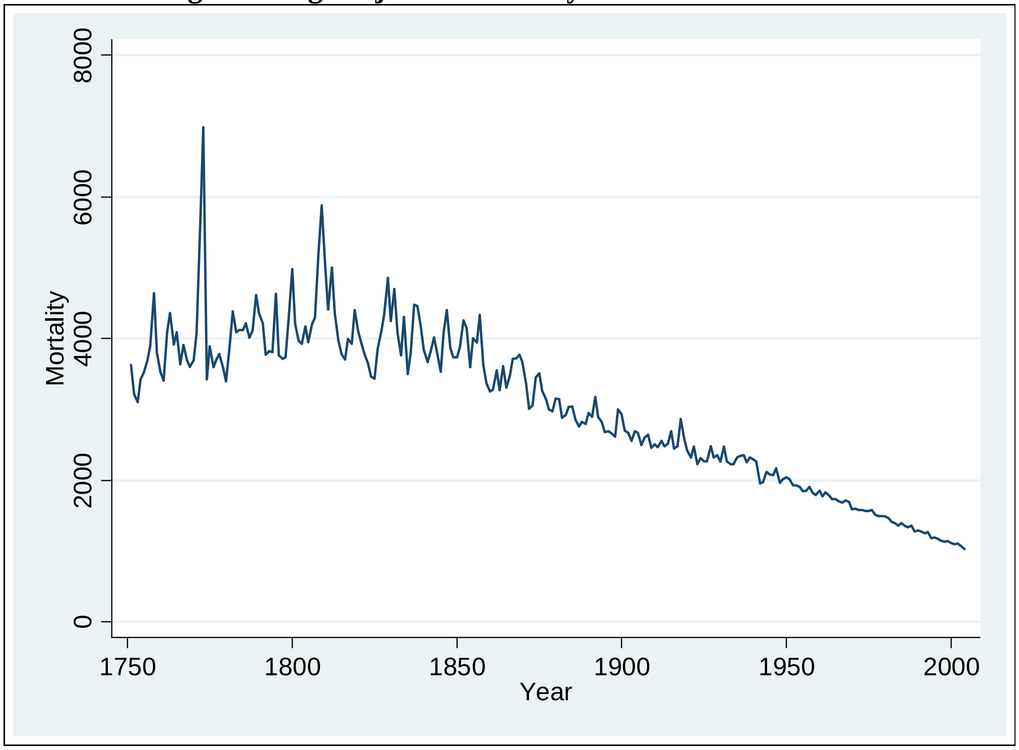

Figure 2: Annual average temperatures Uppsala 1751-2004