Weather Effects on European Agricultural Output 1850-1913[1]

Solomos Solomou
Faculty of Economics, Cambridge
Weike Wu
Department of Applied Economics, Cambridge

July, 1999

Introduction

The sectoral structure of the leading industrial economies of Europe in the late 19th Century suggests that the agricultural sector was still central to macroeconomic performance. In Germany the agricultural sector accounted for approximately 40% of GDP in 1870, declining to 23% by 1913. In France the sector accounted for 43% of GDP in 1872, declining to 35% by 1909. In Britain the sector accounted for 15% of GDP in the early 1870s, declining to 6% by 1907. The existing historical business cycle literature has emphasised macroeconomic variables in accounting for economic fluctuations (Eichengreen, 1983; Solomou, 1994). The aim of this paper is to evaluate the importance of an independent cyclical effect on agricultural output arising from the impact of weather shocks to the sector. The accepted view of economic historians (more implicit than explicit) is that weather ceased to be a significant shock to industrial economies. Consequently, little *systematic* research has been undertaken in this area. The formulation and dismissal of simplistic theories about weather and economic cycles has not helped. For example, Jevons (1884, p.235) argued:

> ...after some further careful inquiry, I am perfectly convinced that these decennial crises do depend upon meteorological variations of like period, which again depend, in all probability, upon cosmical variations of which we have evidence in the frequency of sun-spot, auroras, and magnetic perturbations.

The evidence we have at present suggests that the impact of weather shocks on the economy needs to be carefully re-evaluated. Feinstein *et al.* (1983) show that in Britain agriculture accounted for most of the aggregate fluctuations in total factor productivity

[1] Acknowledgements: The research for this paper has been supported by the Economic and Social Research Council (Grant R000221237) and the Leverhulme Trust. The paper has benefited from the comments of Andrew Harvey.

during the inter-period comparisons of 1856-73 and 1873-82 and 1873-82 compared to 1882-89. Khatri *et al.* (1998) have shown that weather shocks account for over half the variations in British agricultural output, resulting in an *independent* effect from the agricultural sector to macroeconomic fluctuations. The aim of this paper is to compare the weather effects on British, French and German agriculture as a way of drawing more general inferences about the impact of weather shocks.

A number of cross-country differences should be noted, making such comparisons particularly interesting. First, the ratio of crop to animal production differed markedly across countries. In Germany the share of livestock production was relatively high and stable, averaging around 65% in the 1870s, and 67% in the early 20th Century (Weber, 1973, pp.54-5). In Britain the share of livestock production stood at 55% in 1867-9 and rose significantly to 75% by 1911-13 (O'Jala, 1958, pp.208-9). In France the share of livestock production stood at 45% as late as 1910 (O'Brien *et al.*, 1992, p.525). Consequently, the magnitude of weather effects across countries is likely to differ because of different sensitivities of crop and livestock production to weather extremes. Secondly, weather variables have different distributions across these three countries. For example, in Britain, the range of rainfall and temperature variations is much higher than those observed in France and Germany. Such differences are likely to get reflected in differential effects of weather shocks across different countries.

The importance of weather effects on the agricultural sector has long been recognised in the historical literature (Jones, 1964; Perry, 1973; Parry, 1981). However, although anecdotal evidence can be found in the historical literature, and in contemporary accounts, there has been little quantitative research. This is partly the result of the fact that the agricultural sector is obviously weather-sensitive. However, *quantifying* the nature of this relationship is not a simple exercise. In particular, since high and low extremes of weather conditions are likely to have adverse effects, the weather-production relationship is expected to be non-linear. A semiparametric time-series approach will be used to model output as a linear function of economic inputs and a non-linear function of weather variables.

The paper has the following structure. Section 1 outlines the semiparametric methodology, and uses it to estimate the effect of weather shocks on agricultural output in Britain, France and Germany. Section 2 uses a national income accounting framework to evaluate the magnitude of the macroeconomic effect of weather shocks.

1. Weather Effects on Agriculture

As noted above the effect of weather variations on production are likely to be non-linear. Semiparametric statistical models offer an effective way of modelling non-linearity (Engle *et al.,* 1986). Semiparametric models combine the partial linear specification in a subset of the explanatory variables **x**, with a nonparametric specification in the remaining variable(s) *z*:

$$y = \mathbf{x}b + g(z) + e \tag{1}$$

where y is the dependent variable; **x** is the $p\times1$ vector of linear explanatory variables; b is the coefficient matrix; $g(z)$ is the nonparametric function allowing for a non-linear relationship between y and z; and e is an iid disturbance term.

Denoting y_t as log of output, $\mathbf{x}_t$ as the vector of variables, b as the corresponding parameter vector for $\mathbf{x}_t$, and $\mathbf{z}_t$ as the vector of weather variables. Then, we can rewrite (1) as

$$\begin{aligned} y_t &= y_t^{\,e} + y_t^{\,w} \\ y_t^{\,e} &= \mathbf{x}_t b + h_t^e \\ y_t^{\,w} &= g(\mathbf{z}_t) + h_t^w \end{aligned} \tag{2}$$

where $y_t^{\,e}$ and $y_t^{\,w}$ are the effect of the changes in economic inputs and the effect of weather respectively.

The effect of weather on output, *g*, is expected to be non-linear, but of unknown form. An important property of the nonparametric estimation of weather effects is that the methodology does not assume an a priori form for the dependence of the response on the explanatory variables (a fuller outline of the methodology can be found in Khatri, Solomou and Wu, 1998).

Our aim is to estimate the magnitude of the effects of weather variations on agricultural output. Finding a relevant index for the weather conditions influencing the agricultural sector is not straightforward, partly because there does not exist a unique relationship between weather and agricultural production. The impact of weather on agricultural production depends on a number of factors including rainfall, temperature, sunshine hours, soil type and wind speed (Oury, 1959). Selecting only one element of weather might thus be considered an over-simplification. An index of agricultural drought that relates these different weather inputs may provide a good summary measure of relevant information. The effect of weather on soil moisture levels during the growing period is a key mechanism through which weather conditions affect output. A combination of precipitation and evapotranspiration (evaporation from the soil surface and transpiration from plants) will determine soil moisture levels. Evapotranspiration itself will depend on climate, soil moisture, plant cover and land management (Thornthwaite, 1948; Oury, 1959).

A useful practical index of weather is the soil moisture level during the growing season. Rodda *et al.* (1976) concludes that soil moisture deficits provide the best practical drought index. The most fundamental problem with this approach is the requirement of complex measurements needed to calculate the soil moisture level. Such data requirements limit the availability of soil moisture measurements over long-run time periods to a handful of areas. The index used in this study is the soil moisture deficit (SMD) level calculated by Wigley and Atkinson (1977) for Kew and updated by Atkinson (1992)[2]. Extreme deviations from mean SMD in either direction (high values implying drought and low values implying excess moisture) are thus predicted to have adverse effects on output. Wigley and Atkinson (1977) calculate growing season SMD values for Kew back to 1698. They find that there is a high correlation between precipitation in southeastern England and Kew (r = 0.89). In the case of Britain similar results are obtained using the SMD index, annual temperature and rainfall and growing period temperature and rainfall (Khatri, Solomou and Wu, 1998).

In the case of the European economies data limitations allowed us to undertake sensitivity analysis by comparing results using annual and growing period weather information. In general, the most effective explanatory variable depends on the structure of production in each country. When explaining crop yield variations we find that growing period weather information dominates annual weather information as an explanatory variable. However, when explaining aggregate production (which is a

[2] Tim Atkinson kindly provided the revised data.

weighted index of crop and animal production) annual weather information provides comparable or better explanatory power to the growing period weather information. In this paper, in order to achieve some comparability across countries, we chose to report the results using annual weather information.

The quality of the British data allows us to estimate the agro-weather relationship over the sample period 1867-1913. Our aim is to fit a sectoral production function to model the effects of weather variables on output. To avoid the problem of spurious regression, it is necessary to determine the order of integration of the data series to be analysed. Table 1(a-c) reports the results of ADF tests. While agricultural output and weather variables are stationary in levels, labour, capital and land inputs are not. The ADF tests suggest that capital stock and land might not be stationary even in first differences. However, within a fractional framework, Table 2 shows that the estimated fractional differencing orders of ∇logCapital and ∇logLand are not significantly different from zero using the approach of Sowell (1992). Thus, whereas the agricultural output and weather variables are $I(0)$, labour, capital stock and land are all $I(1)$.

To proceed to estimate a production function would be an inappropriate statistical exercise. Instead, we estimate the effects of weather on agricultural output, controlling for the growth of factor inputs, which are all stationary series. The procedure provides an appropriate statistical means for estimating the weather effects on production, even though we are unable to estimate a production function for the agricultural sector. Although this procedure leads to a loss of information, there are some gains in terms of data reliability. Given the methods by which historical data for factor inputs have been constructed (which mainly rely on methods of extrapolation and interpolation), it is likely that growth rates are measured more accurately than their levels (Solomou and Weale, 1993). We estimate the following model,

$$\log Q_t = b_0 + b_1 \nabla \log L_t + b_2 \nabla \log K_t + b_3 \nabla \log \Lambda + g(\mathbf{z}) + h_t \qquad (8)$$

where output is a linear function of the growth rates of labour, capital and land inputs and a non-linear function of weather variables.

Table 3 reports the results for the semiparametric model using annual temperature and rainfall as the weather variables. Both weather variables are statistically significant and are found to have non-linear effects on output. The economic input variables are insignificant (with the growth of labour marginally significant at 7 per cent). The model accounts for 65% of the variations in agricultural output, with the weather variables accounting for 59% of the variations of agricultural output. The impact of the weather variables on agricultural output is plotted in Figure 1. The worst combination of weather effects on production was high rainfall and low temperatures. Figure 2 shows the fit of the weather effect on agricultural output.

Given that weather data is cyclical and shows a high variance level at the annual frequency we also use the ‘wavelet’ decomposition methodology to decompose the series into a ‘random’ and a ‘cyclical’ component (an outline of this cyclical decomposition method is presented in Appendix 1). The main advantage of the wavelet decomposition over other approaches is that it does not require *a priori* knowledge to determine an appropriate model. In addition, the wavelet decomposition can capture the time-varying frequency in the observed cycles, which describes many processes, including the weather series. Table 4 presents the results using the decomposed weather data. The fit of the model improves marginally, accounting for 71% of the variation of agricultural output. As shown in Figures 3a-3c, the effects of the decomposed weather variables are captured as a mixture of linear and non-linear relationships. The effect of the sum of all weather effects on agricultural production is plotted in Figure 4.

Table 5 presents the results of stationarity tests for German agricultural output and weather series. German Agricultural output is trend stationary and all weather variables are level stationary. Although Weber (1973) presents some input data for the period 1880-1913, the time series aspects of the data prevented us from estimating a meaningful production function over the period. Instead we estimated the weather effects on the deviations from a linear trend (reflecting the trend-stationarity of output). Table 6 presents the results of estimating a semi-parametric model. Temperature and rainfall both have a significant effect on output variations, with temperature having a non-linear effect and rainfall a linear effect, as shown in Figure 5. The weather variables explain about 23% of output variations. The sum of the weather effects on agricultural production is plotted in Figure 6.

Table 7 presents the results of using the decomposed weather information. The fit of the overall model improves significantly from 40.8% to 50.4%. Figures 7a-c show that the rainfall effect remains linear and is mainly arising from the random variations. The temperature effects are non-linear with separable effects identified for the random and 'smoothing' component. The weather effects account for 33% of the variations in agricultural production deviations from trend. The effect of the sum of the weather effects on agricultural production is plotted in Figure 8.

The French data (see Appendix 2) allow us to model the agro-weather relationship over the period c.1850-1913. Figure 9 compares the agricultural output indices of Britain, France and Germany. Although Table 8 suggests that French agricultural production is trend-stationary this result is very sensitive to small changes in sample period. Instead, we estimate a Kalman filter stochastic level trend to the French output series[3], which yields more stable stationary deviations. Table 9 reports the results of estimating a semiparametric model. The best-fit model explains 42% of agricultural output variations. Although estimated in the semiparametric framework, the rainfall and temperature effects both have linear effects on output and explain about 22% of the variations in agricultural production over this period.

The fit of the model improves significantly with the use of decomposed weather indices (from 42.4% to 54.3%), with the weather variables accounting for 32% of the variations in agricultural production. The decomposed weather data allows us to separate a linear smoothing temperature effect and a non-linear random effect, improving the fit of the model significantly (see Figures 12a-c). The effect of the sum of the weather effects on agricultural production is plotted in Figure 13.

A pattern of results has emerged from a study of these three countries. Weather effects account for a large proportion of the variations in agricultural production, ranging from two thirds, in the case of Britain, to one third for France and Germany. In general, the weather effects are best modelled in a semi-parametric framework to capture the non-linear relationship between weather and production. The effect range of weather variations on agricultural production is found to be

[3] The stochastic trend is estimated with the assumption that there are two stochastic cycles using the Kalman Filter approach (Harvey, 1989).

greatest for Britain, reflecting the relatively high range of weather variables and the high share of crops in total agricultural output, at least in the early part of the period. The lowest effect range is observed for Germany, reflecting the relatively low range of weather variations and the dominant share of animal production in agricultural output. France falls between these two extremes. The relatively low range of weather variations makes it comparable to Germany, while the high ratio of crops in the share of agricultural production makes it comparable to Britain.

2. Aggregate Impact of Weather Shocks

The range of weather effects on agricultural production varied significantly across countries. The biggest range was observed for Britain (+3.9% and –13.9%), followed by France (+4.3% and –6.9%) and Germany (+3.3% and –3.6%). In order to evaluate the macroeconomic effect of these shocks we calculated the weighted impact of the weather effect on agricultural production using sectoral shares in GDP as weights.

The share of agriculture in GDP is plotted in Figure 14. In the case of Britain although the effect range of weather shocks on agricultural production was large the sector was relatively small in GDP. Hence, the weighted effect of weather shocks on GDP was relatively small, varying between ±0.5% of GDP for most of the pre-1890 period, and ±0.25% for most of the post 1890 period. The largest impact was observed in 1879 at –1.5% of GDP. In France the effect of weather shocks on GDP was mainly in the range of ±1.0% of GDP throughout the period 1870-1913, with an outlier effect of -2.5% of GDP in 1879. For Germany the effect of weather shocks on GDP varied around ±1.0% of GDP pre-1890 and ±0.5% in the post-1890 period. The largest effect was observed in 1879 at –1.3% of GDP. It is clear that in each case the variation of weather provided large sector-specific shocks to GDP over much of the pre-1913 period. In the context that aggregate business cycle fluctuations were of a relatively low amplitude in this period, the aggregate impact of such shocks accounts for a high proportion of macroeconomic fluctuations.

Two features of the aggregate impact of weather shocks stand out. First, the correlation of weather shocks across countries is relatively low, suggesting that the effects are mainly national-specific[4]. However some clusters are noteworthy, generating European-wide effects. For example, in 1879 adverse weather shocks to agriculture reduced GDP by 1.5% in Britain, 2.7% in France and 1.3% in Germany. The impact of such events needs careful consideration in future research. The evidence presented here suggests that these supply-side shocks had large effects on European fluctuations, which had major policy effects. The pressures towards increased agricultural protection in the late 1870s was a product of two unique and independent effects: international competition depressing agricultural prices and major adverse supply-side shocks in Europe depressing agricultural output. In the new world market conditions the adverse supply side shocks of the late 1870s were not compensating farmers income with favourable price adjustment[5].

Secondly, the effect of weather on GDP was highly cyclical, implying that weather shocks had an autocorrelated effect on macroeconomic business cycles. In the recent real business cycle literature it has become apparent that, to provide an empirically relevant role for real shocks in business cycle theory, shocks need to be autocorrelated, otherwise the effect of the shocks tends to be short lived. For the pre-1913 period weather shocks to the agricultural sector provide an empirically relevant supply-side shock: the orders of magnitude of the shocks are large and their pattern is autocorrelated. Weather shocks are an important and neglected component to pre-1913 fluctuations.

---

[4] The following correlation coefficients were calculated for the effects of weather shocks on production: Britain and France, r= 0.34; Britain and Germany, r=0.27; France and Germany, r=0.51.

[5] The timing of tariff changes was also conditioned by fixed duration of existing trade agreements.

Conclusions

Weather shocks had significant effects on agricultural output

Weather shocks had significant effects on agricultural output over the pre-1913 period. The effects are non-linear and account for approximately one third to two thirds of variations in agricultural production. The effect range of weather shocks were largest in Britain, partly reflecting the wider range of weather variations and the high share of crop production in the early part of the sample period.

Weather effects on output were cyclical

Weather variations generated both random and cyclical shocks to the sector. Because weather variables show significant autocorrelation, employing a decomposition model to separate the cycles from the noise in the data significantly improves the fit of the estimated models and allows us to identify the effects of random and cyclical shocks to agricultural output. In doing so we are able to derive better fitting models of output variations for agricultural output.

The macroeconomic effects of weather shocks

The sectoral structure of the leading industrial economies of Europe in the late 19th Century was such that the agricultural sector was still central to macroeconomic fluctuations. As a result, weather shocks to the agricultural sector had significant effects on macroeconomic fluctuations. This is not a restatement of Jevons' business cycle theory, but it is clear that to neglect the role of agriculture in macroeconomic fluctuations and, in turn, the role of weather, has no empirical foundation even in the peak of industrial maturity at the end of the 19th Century. The largest macroeconomic effects are observed in France and Germany, reflecting the very large agricultural sector in these economies. In Britain the macroeconomic impacts are large in the 1870s but decline significantly over time. An implication that arises from this study is that weather effects are likely to be even more important in accounting for fluctuations in the smaller European economies where agriculture accounted for 60-80% of GDP over the same period. It should also be emphasised that, to complete the macroeconomic analysis of weather effects, further research is needed in a multisectoral framework. A number of other sectors are known to be weather sensitive, including construction and energy demand. Considering a broader set of sectors can clarify to what extent shocks were sector-specific. However, it should be emphasised that, in the period being analysed, the size of the agricultural sector was significantly larger than the other sectors.

Appendix 1: Wavelet Analysis

The multiresolution analysis (MRA) is the decomposition of a process $f(t)$ into components of different "scales". For stationary series, such as rainfall and temperature in the sample period, the scales are analogous to cyclical frequencies. Following the MRA scheme by Mallat (1989), $f(t)$ can be produced as a lowpass component $s_{1,n}$ and a highpass component $d_{1,n}$ by two filters which have bandwidths of lower (upper) half of the $f(t)$. The former is the smoothed or approximation version of $f(t)$, and its resolution is half of $f(t)$; the latter contains the high frequency details of $f(t)$ that are not in $s_{1,n}$. This can be implemented recursively at different scales like the smoothing filters. In this study, we decompose the weather series at level 1 only. In terms of frequency, the two components can be thought of as smooth movement (i.e. the sum of various weather cycles) and the irregular (random) shocks respectively. One approach to approximating the MRA is so-called wavelet multiresolution representation.

Wavelet Transform

The Fourier transform is widely used to detect cycles in the frequency domain. However, traditional Fourier basis functions are localised in frequency but not in time. Empirical analysis suggests that time varying frequencies are common in many processes, including the weather series. To overcome this problem, the *wavelet* transform uses a two-parameter family of functions. One of the parameters is time location (parameter *t)*, the other parameter is a frequency/scale parameter l. Thus, the window-width of wavelet is frequency-dependent in that larger waves are used to measure lower frequency movements and shorter waves are used to measure higher frequency movements[6]. With continuous parameters l and t, the wavelet transform is defined as,

[6] Since higher frequency (or shorter wavelength) feature usually have smaller support, it would be desirable to have an analysing function such that its standard deviation is small when it characterises high frequency components and vice-versa.

$$CWT(l,t) = \frac{1}{\sqrt{l}} \int f(u) y\,(\frac{u-t}{l}) du$$

which has a parallel in the Fourier transform. If we choose discrete values $l = 2^m$ and $t = 2n$, then, the wavelet transform is

$$DPWT(m,n) = \frac{1}{\sqrt{2^m}} \int f(u) y\,(\frac{u-2n}{2^m}) du$$

where *m* and *n* are integer. The equivalent is the Fourier series, where only frequency is the discrete parameter.

The *wavelet* $y(t)$ above is defined to satisfy: a) sufficiently fast decay to obtain localisation in time; b) zero mean. Whereas the second property ensures that $y(t)$ has a wiggle, i.e. wave like, the first property ensures that it is not a sustaining wave. The wavelet $y(t)$ is not unique and may be selected based on *a priori* knowledge of the type of process variations when it is available. For example, if the process exhibits discontinuous jumps, the Haar wavelet may be best suited for describing this behaviour.

Given a wavelet $y(t)$, the corresponding *scaling function* $f(t)$ is defined to be orthogonal to the wavelet and have unit norm[7]. The wavelet can be obtained as a linear combination of dilates and translates of the scaling function. In some literature, $f(t)$ is called "father wavelet" whereas $y(t)$ is called "mother wavelet" (for the details see Bruce and Gao,1996).

MRA Wavelet Representation

At level 1, suppose $f_{1,k}(t)$ and $y_{1,k}(t)$ are a pair of discrete wavelet functions described above

$$y_{1,n}(t) = \frac{1}{\sqrt{2}} y\,(\frac{t-2n}{2})$$

$$f_{1,n}(t) = \frac{1}{\sqrt{2}} f(\frac{t-2n}{2})$$

It is proved that (see, for example, Chan 1995), for one level decomposition,

$$f(t) \approx \sum_k s_{1,k} f_{1,k}(t) + \sum_k d_{1,k} y_{1,k}(t)$$

$$s_{1,k} \approx \int f_{1,k}(t) f(t) dt$$

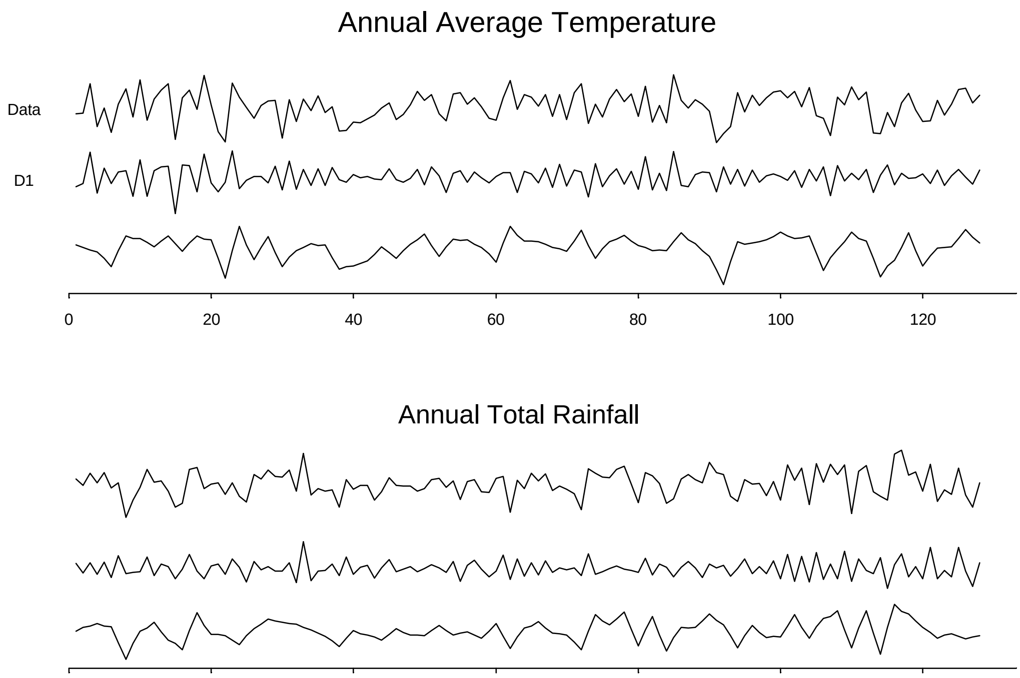
$$d_{1,k} \approx \int y_{1,k}(t) f(t) dt$$

where k ranges from 1 to the number of coefficients in the specified component. The coefficients $s_{1,k}$ and $d_{1,k}$ are the wavelet transform coefficients. They give a measure of the contribution of the corresponding wavelet function to the approximating sum. The $s_{1,k}$ is called smooth coefficient, and the $d_{1,k}$ is called detail coefficient respectively. The detail coefficient $d_{1,k}$ provide the coarse scale deviations from the smooth behaviour.

Due to the flexibility in choosing a wavelet, the wavelet multiresolution representation is not unique. The choice requires a trade-off between properties such as smoothness, temporal location, frequency location, orthogonality, and symmetry. In general, smoother wavelets have better frequency resolution but poorer temporal location. In this study we use the “c6” in the S+Wavelets package, which is a *Coiflets* transform function (for details see Bruce and Gao, 1996). As an example, Figure A1 illustrates a wavelet decomposition of German temperature and rainfall.

[7] $\int f(t)\, dt = 1$ and $\| f(t) \| = 1$.

Figure A1


Annual Average Temperature
Data
D1
0
20
40
60
80
100
120
Annual Total Rainfall

Appendix 2: Data Sources

Britain

Economic Data

British agricultural production data are from Lewis (1978, pp. 260-63); the Lewis index is an annual extension of O'jala's (1952) index which is given only for specific benchmark years. Labour input is expressed in man-years. An annual time-series is derived for the agricultural working population by assuming that the ratio of the agricultural labour force to the total working population changed on a linear path over the benchmark Census years. Adjusting the agricultural working population for the unemployment rate using Feinstein (1972) provides an estimate of the agricultural labour input series. Figures for capital stock are from Feinstein and Pollard (1988).

Weather Data

Annual average temperature data are from Parker e*t al.* (1992), which cover central England. Annual total rainfall data are reported by Wigley *et al.* (1984), which relate to Britain.

Germany

Economic Data

Data relating to German aggregate agricultural production are derived using Maddison (1991), Hoffmann (1965) and Sommariva and Tullio (1986). Hoffmann provides data for the share of agricultural production in GDP; Maddison provides a series for German NNP. Using the data from Sommariva and Tullio it is possible to make an adjustment for income flows from overseas investments to arrive at a figure for NDP. Input data for labour, land and fertiliser can be found in Weber (1973).

Weather Data

The temperature series are calculated from available station records in the file ADVANCE-10K, downloaded from the homepage of the Climate Research Unit at the

University of East Anglia. The ADVANCE-10K contains the station temperature data for the E.U. research project “Analysis of Dendrochronological Variability and Associated Natural Climates in Eurasia - the last 10,000 years” (ref. no. ENV4-CT95-0127). The following German stations contain the available data over the studied period:

1)	LEIPZIG	1840-1935 and 1951-1977;
2)	DRESDEN	1851-1930 and 1975-1977;
3)	JENA	1833-1935;
4)	ERFURT/BINDERSLEBEN	1848-1930 and 1951-1977;
5)	KIEL	1849-1926;
6)	HANNOVER	1856-1930 and 1951-1977;
7)	BERLIN	1756-1990;
8)	FRANKFURT A MAIN	1826-1961;
9)	DARMSTADT	1867-1930;
10)	BAYREUTH	1851-1930;
11)	KARLSRUHE	1855-1930;
12)	MUNCHEN/RIEM	1781-1990;
13)	FRIEDRICHSHAFEN	1866-1930;
14)	HOHENPEISSENBERG	1781-1970.

The rainfall series are calculated from the available records of the following German stations in the CD-ROM “World Climate Disc: Global Climate Change Data” produced by the Climate Research Unit at the University of East Anglia:

1)	Bamberg	1861-1974;
2)	Berlin-Dahlem	1844-1975;
3)	Emden-Hafen	1851-1991;
4)	Gutersloh	1837-1975;
5)	Halle	1851-1976;
6)	Husum	1861-1974;

7) Kalkar 1849-1976;
8) Lingelbach 1851-1974;
9) Loningen 1857-1975;
10) Mergentheim 1849-1974;
11) Regensburg 1861-1987;
12) Trier-Petrisberg 1849-1975.

France

Economic Data

French agricultural output data are from Levy-Leboyer and Bourguignon (1990).

Weather Data

The temperature and rainfall series are calculated from the corresponding averages of the available station records in CD-ROM of the "World Climate Disc: Global Climate Change Data" produced by the Climate Research Unit at the University of East Anglia.

The following stations contain the available temperature data over the studied period:

1) Marseille/Marignane (1847-1943);
2) Nantes (1851-1990);
3) Paris/Le Bourget (1764-1990);

The following stations contain the available rainfall data over the studied period:

1) Besancon (1845-1973);
2) Bordeaux/Merignac (1842-1990);
3) Cahors (1851-1973);
4) Dijon (1831-1990);
5) Grenoble (1845-1973);
6) La Rochelle (1810-1973);
7) Laval (1850-1973);
8) Le Puy (1849-1973);
9) Lille (1784-1988);

10) Lyon/Bron (1842-1990);
11) Marseille/Marignane (1749-1990);
12) Montbard (1831-1973);
13) Montpellier (1851-1973);
14) Nancy/Essey (1841-1990);
15) Nantes (1835-1990);
16) Orleans (1849-1973);
17) Paris/Le Bourget (1770-1990);
18) Perpignan (1850-1990);
19) Peyrehorade (1851-1973);
20) Pouilly (1831-1973);
21) Roanne (1851-1973);
22) Rouen (1845-1988);
23) Saint-Brieuc (1851-1973);
24) Strasbourg (1845-1990);
25) Toulouse/Blagnac (1809-1990);
26) Vendom (1851-1973).

References

Bruce A. and Gao, H.Y. (1996). *Applied Wavelet Analysis with S-Plus*, Springer, Berlin.

Chan, Y.T. (1995). *Wavelet Basics*, Kluwer Academic Publishers, London.

Climatic Research Unit at the University of East Anglia (1992). *World Climate Disc - Global Climatic Change Data*, Chadwyck-Healey, Cambridge.

Eichengreen, B.J. (1983). 'The Causes of British Business Cycles, 1833-1913', *Journal of European Economic History***,** 12(1), pp.145-161.

Engle, R. F., Granger, C.W., Rice, J. and Weiss, A. (1986). 'Semiparametric Estimates of the Relation Between Weather and Electricity Sales', *Journal of the American Statistical Association*, 81, pp.310-20.

Feinstein, C.H. (1972). *National Income, Expenditure and Output of the UK, 1856-1965*, Cambridge University Press, Cambridge.

Feinstein, C.H., Matthews, R.C.O. and Odling-Smee, J. (1983). 'The Timing of the Climacteric and its Sectoral Incidence in the UK 1873-1913', in Kindleberger and di Tella (eds), *Economics in The Long View: Essays in Honour of W.W. Rostow*, Vol. 3, London and Basingstoke.

Feinstein, C.H. and Pollard, S. (1988). *Studies in Capital Formation in the United Kingdom 1750-1920*, Oxford University Press, Oxford.

Granger, C.W.J. and Joyeux, R. (1980). 'An Introduction to Long-Memory Time Series Models and Fractional Differencing', *Journal of Time Series Analysis*, Vol. 1, No. 1, pp 15-29.

Härdle, W. (1990). *Applied Nonparametric Regression*, Econometric Monographs no.19, Cambridge University Press, Cambridge.

Harvey, A.C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, Cambridge.

Jevons, W.S. (1884). *Investigations in Currency and Finance*, London.

Jones, E.L. (1964). *Seasons and Prices*, George Allen and Unwin, London.

Khatri, Y.J. and S.N. Solomou and Wu, W (1998). 'The Impact of Weather on UK Agricultural Production, 1867-1913', *Research in Economic History*, 18, pp. 83-102.

Levy-Leboyer, M. and Bourguignon, F. (1990). *The French Economy in the Nineteenth Century*, Cambridge University Press, Cambridge.

Lewis, W.A. (1978). *Growth and Fluctuations 1870-1913*, George Allen and Unwin, London.

Maddison, A. (1991). *Dynamic Forces In Capitalist Development*, Oxford University Press ,Oxford .

Mallat, S.G. (1989). 'A Theory for Multiresolution Signal Decomposition:the Wavelet Representation', *IEEE Trans. Pattern Analysis, Machine Intelligence*, Vol. 11, No. 7, pp.674-693.

Manley, G. (1974). 'Central England Temperatures: Monthly means 1659 to 1973', *Quart. J. R. Met. Soc., Vol. 100, 389-405.*

Maunder, W.J. (1986). *The Uncertainty Business: Risks and Opportunities in Weather and Climate*, London.

O’Brien, P.K. and Prados de la Escasura, L (1992). ‘Agricultural Productivity and European Industrialisation, 1890-1980, *Economic History Review*, XLV, 3, pp.514-36.
O’jala, E.M. (1952). *Agriculture and Economic Progress*, Oxford University Press, London.
Oury, B. (1959). ‘Allowing for Weather in Crop Production Model Building’, *Journal of Farm Economics*, vol.41, pp.70-76.
Paker, D.E., Legg, T.P. and Folland, C.K. (1992). ‘A New Daily Central England Temperature Series, 1772-1991’, *International Journal of Climatology*, Vol. 12, pp. 317-342.
Parry, M.L. (1981*). Climatic Change, Agriculture and Settlement*, Dawson,Folkestone.
Perry, P.J. (1973). *British Agriculture 1875-1914*, Methuen & Co., London.
Rodda, J.C. , Downing, R.A. and Law, F.M. (1976). *Systematic Hydrology*, Butterworths, London.
Solomou, S.N. (1994). ‘Economic Fluctuations, 1870-1913’, in Floud, R. and McCloskey, D.N. (Eds.), *The Economic History of Britain Since 1700*, Volume 2, Second edition, Cambridge University Press, Cambridge.
Solomou, S.N. and Weale, M.R. (1993). `Balanced Estimates of National Accounts When Measurement Errors are Autocorrelated: The UK 1920-38', *Journal of The Royal Statistical Society*, Series. A, 156, Part 1, 89-105.
Sommariva, A. And Tullio, G. (1987). *German Macroeconomic History, 1880-1979*, Macmillan, London.
Sowell, F. (1992), ‘Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Methods’, *Econometrica*, Vol. 59, pp 165-188.
Thornthwatie, C. W. (1948). ‘An Approach Toward a Rational Classification of *Geographical Review*, January.
Weber, A. (1973). ‘Productivity Growth in German Agriculture: 1850 to 1970’, Department of Agricultural and Applied Economics Staff Paper, P73-1, University of Minnesita.
Wigley, T.M.L., Lough, J.M., and Jones, P.D. (1984). ‘Spatial Patterns of Precipitation in England and Wales and a Revised, Homogeneous England and Wales Precipitation Series’, *Journal of Climatology*, 4, 1-25.
Wigley, T.M.L., and Jones, P.D. (1987). ‘England and Wales Precipitation: A Discussion of Recent Changes in Variability and an Update to 1985’, *Journal of Climatology*, 7, 231-246.
Wigley, T. M. L. and Atkinson, T. C. (1977). ‘Dry Years in South-East England since 1698’, *Nature*, vol 265, No. 5593, pp.431-434.

Table 1.a: ADF tests of UK Series (1867-1913)

	(log)Output	Annual Temperature	Annual Rainfall	Critical Values
Without trend				
ADF(0)	-5.27*	-5.23*	-6.73	-2.93
ADF(1)	-3.57	-3.22	-5.45	-2.93
ADF(2)	-2.94	-3.04	-3.16*	-2.93
ADF(3)	-3.26	-2.48	-2.43	-2.93
ADF(4)	-3.04	-2.35	-1.80	-2.93
with trend				
ADF(0)	-5.26*	-5.35*	-7.16	-3.52
ADF(1)	-3.54	-3.34	-6.09*	-3.52
ADF(2)	-2.88	-3.13	-3.69	-3.52
ADF(3)	-3.29	-2.56	-2.94	-3.52
ADF(4)	-3.10	-2.42	-2.25	-3.52

Table 1.b: ADF tests of UK Series (1867-1913)

	(log)Labour	(log)Capital	(log)Land	Crit. Values
Without trend				
ADF(0)	-2.06	3.80	-3.53	-2.93
ADF(1)	-2.07	0.32	-3.09	-2.93
ADF(2)	-1.98	1.03*	-2.90	-2.93
ADF(3)	-1.94	1.08	-1.65*	-2.93
ADF(4)	-2.08*	0.57	-1.24	-2.93
with trend				
ADF(0)	-1.87	0.73	-0.76	-3.52
ADF(1)	-2.79	-0.86	-0.97	-3.52
ADF(2)	-2.38	-0.22*	-1.49*	-3.52
ADF(3)	-1.53	-0.08	-1.09	-3.52
ADF(4)	-0.73*	-0.33	-1.14	-3.52

(* suggested by the AIC)

Table 1.c: ADF tests of UK Series (1867-1913)

	∇(log)Labour	∇(log)Capital	∇ (log)Land	Crit. Values
Without trend				
ADF(0)	-4.87	-1.69	-4.57	-2.93
ADF(1)	-4.59	-2.22*	-3.32	-2.93
ADF(2)	-4.90	-1.89	-2.02*	-2.93
ADF(3)	-5.25*	-1.26	-2.07	-2.93
ADF(4)	-4.06	-0.87	-2.05	-2.93
with trend				
ADF(0)	-5.08	-2.82	-7.33	-3.52
ADF(1)	-4.88	-3.76*	-6.74	-3.52
ADF(2)	-5.30	-3.48	-3.75*	-3.52
ADF(3)	-5.83*	-2.72	-3.64	-3.52
ADF(4)	-4.73	-2.27	-3.69	-3.52

(* suggested by the AIC)

Table 2: Estimates of the fractional *d* in the suggested ARFIMA(*p*, *d*, 0) [8]

	∇(log)Capital	∇(log)Land
p	1	3
d	0.28 (1.45)	-0.14 (-0.86)

(t-statistics in parenthesis)

[8] The *p* is the suggested order by the AIC for each model.

Table 3: GAM of UK (log)Output Using Reported Weather Indices (1867-1913)

Parametric Part	t-ratio	Pr(>|t|)
Lagged (log)Output Fluct.	3.20	0.01
Gt. Labour	1.89	0.07
Nonparametric Part	Npar F	Pr(F)
s(Temperature, 4)	12.66	0.01
s(Rainfall, 4)	3.86	0.02

Figure 1.a

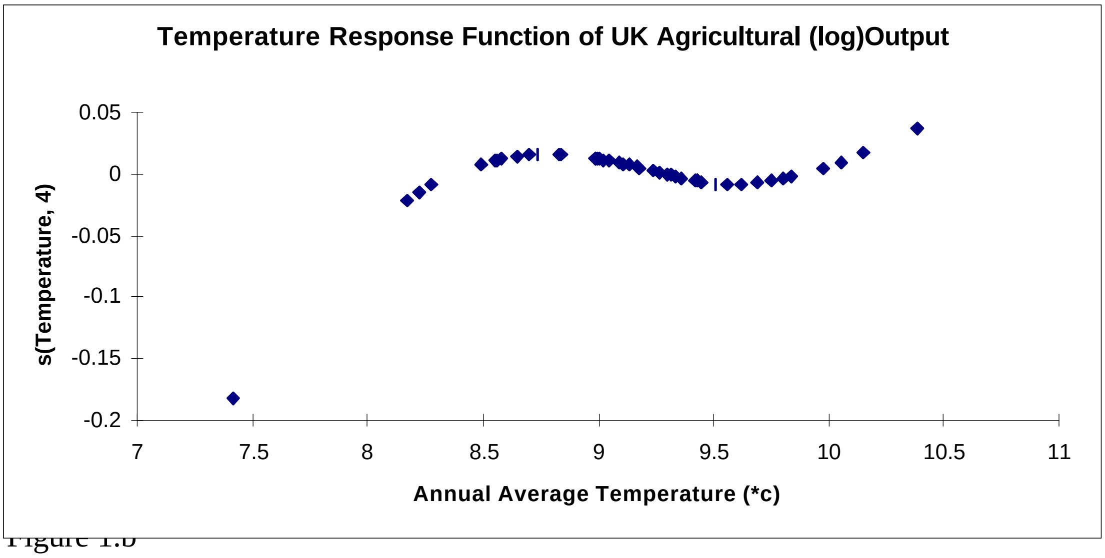


Figure 1.b

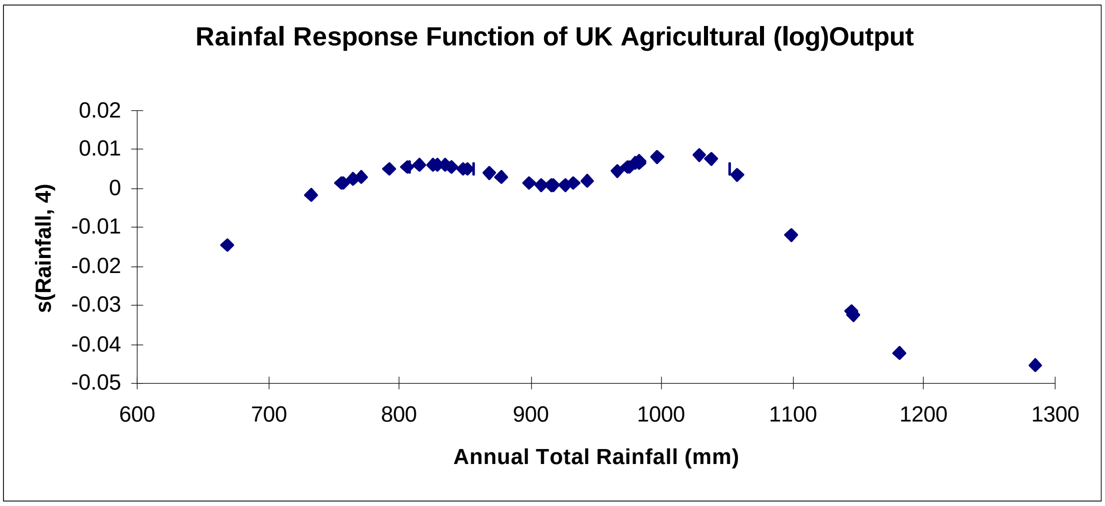


Figure 2

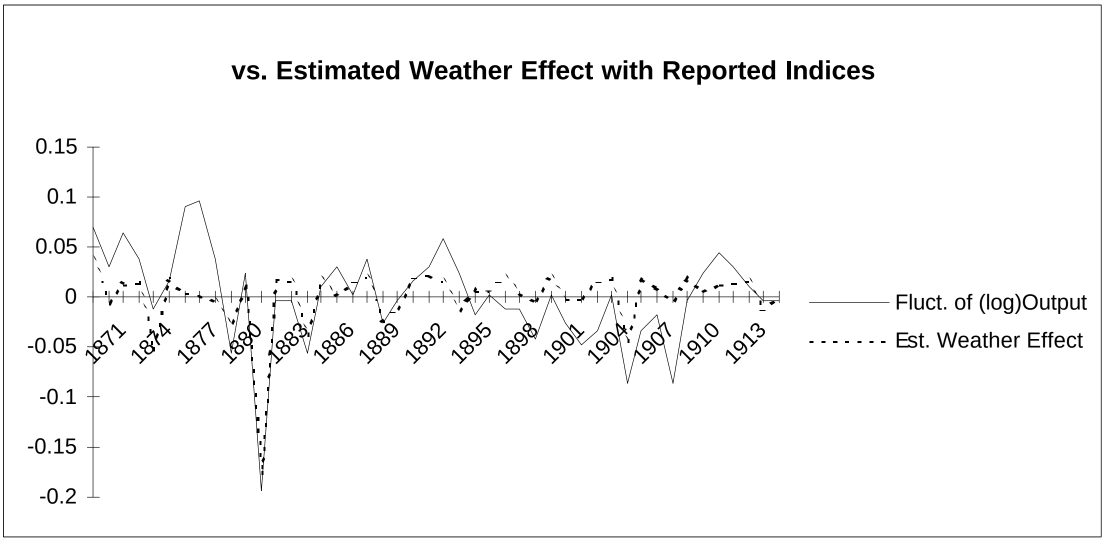
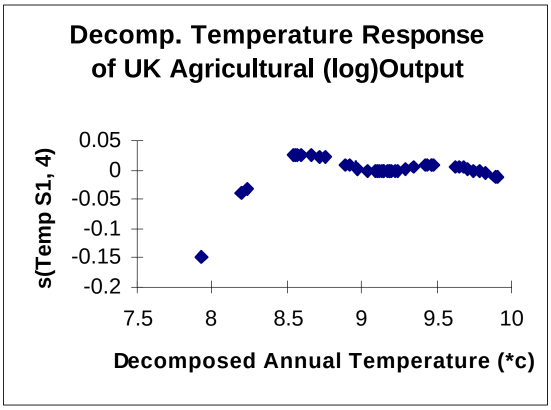
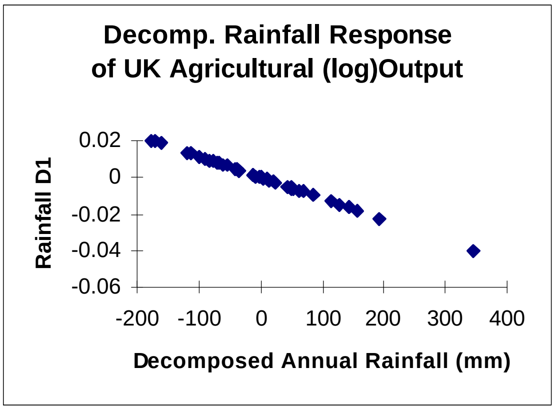


Table 4: GAM of UK (log)Output with Decomposed Weather Indices (1867-1913)

Parametric Part	t-ratio	Pr(>|t|)
Lagged (log)Output Fluct.	2.81	0.01
Gt. Land	2.70	0.01
Rainfall D1	-2.62	0.01
Nonparametric Part	Npar F	Pr(F)
s(Temperature S1, 4)	16.54	0.01
s(Rainfall S1, 3)	7.35	0.01

Figures 3.a – 3.c





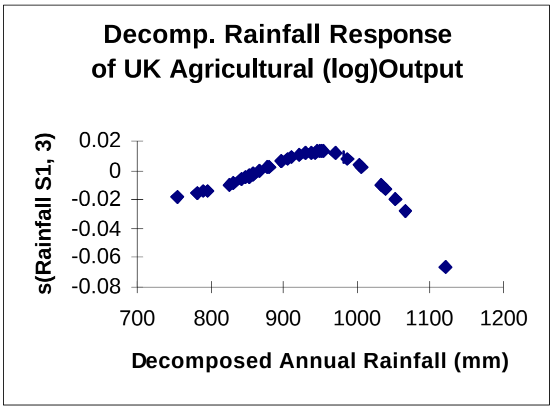


Figure 4

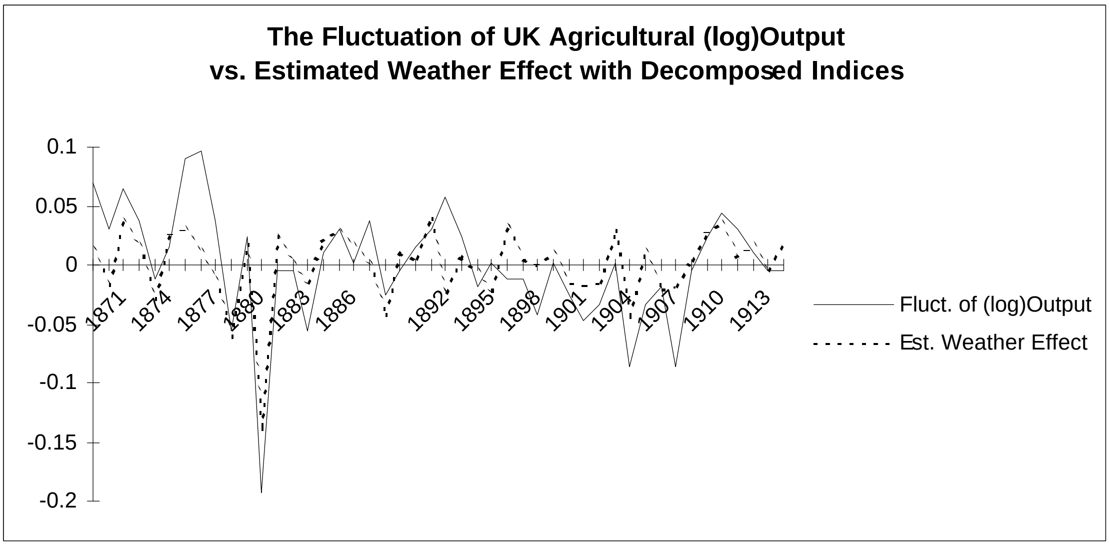


Table 5: ADF tests of German Series (1870-1913)

	(log)Output	Annual Temperature	Annual Rainfall	Critical Values
Without trend				
ADF(0)	-0.39*	-4.95*	-7.32*	-2.94
ADF(1)	-0.37	-3.36	-4.44	-2.94
ADF(2)	-0.44	-3.52	-3.24	-2.94
ADF(3)	-0.48	-2.23	-2.81	-2.94
ADF(4)	-0.48	-2.15	-2.86	-2.94
With trend				
ADF(0)	-3.87*	-5.39*	-7.88*	-3.53
ADF(1)	-3.44	-3.81	-4.96	-3.53
ADF(2)	-2.55	-3.92	-3.73	-3.53
ADF(3)	-2.17	-2.61	-3.27	-3.53
ADF(4)	-2.43	-2.60	-3.37	-3.53

(* suggested by the AIC)

Table 6: GAM of German (log)Output Fluctuation with Reported Indices (1870-1913)

Parametric Part	t-ratio	Pr(>|t|)
Lagged (log)Output Fluct.	3.83	0.01
Rainfall	-2.43	0.02
Nonparametric Part	Npar F	Pr(F)
s(Temperature, 3)	3.43	0.03

Figure 5.a

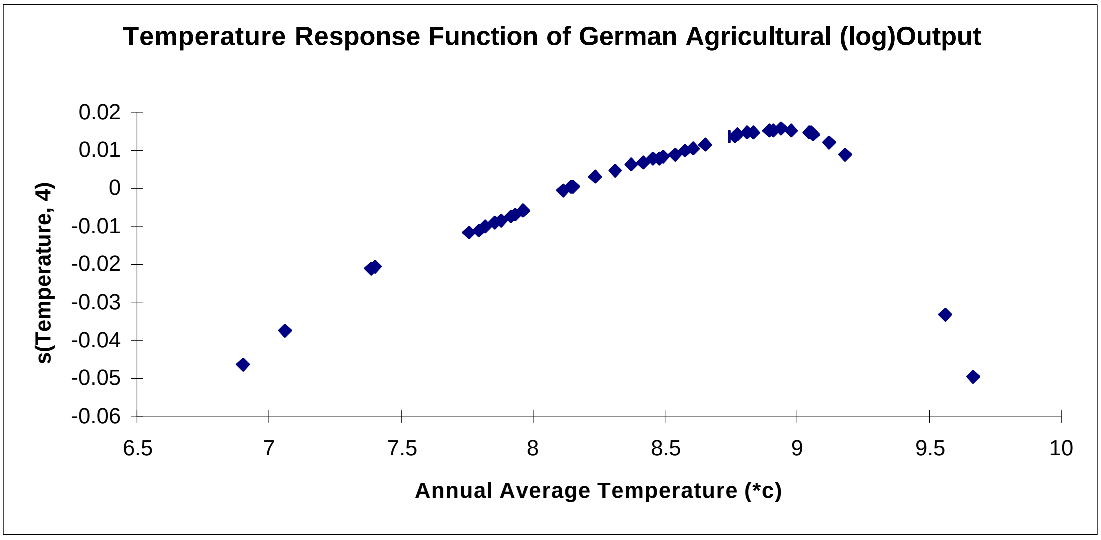


Figure 5.b

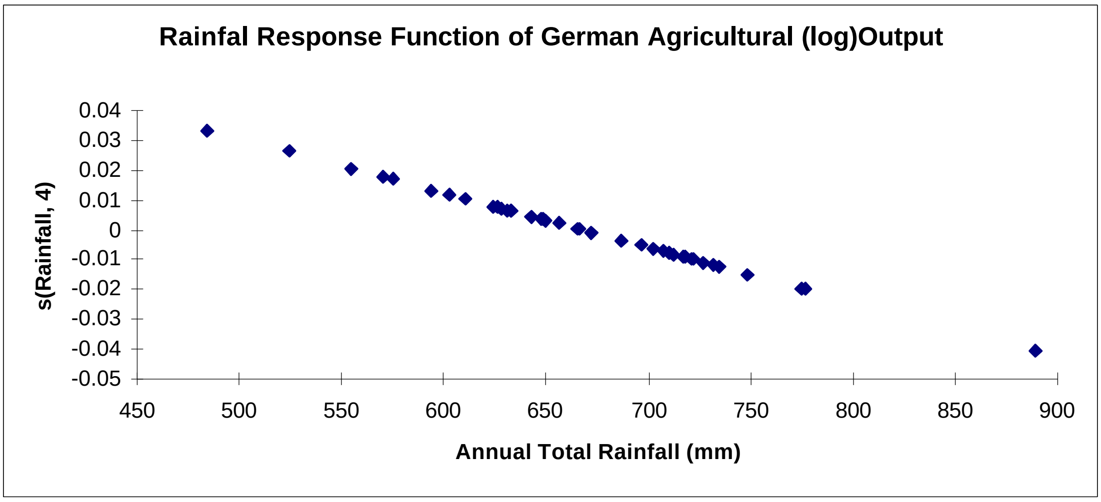


Figure 6

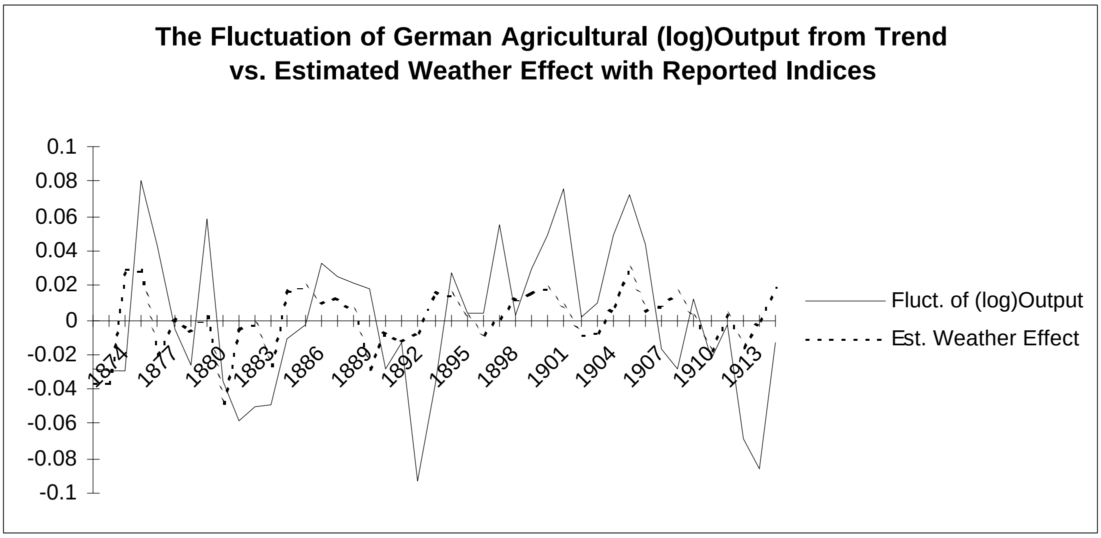
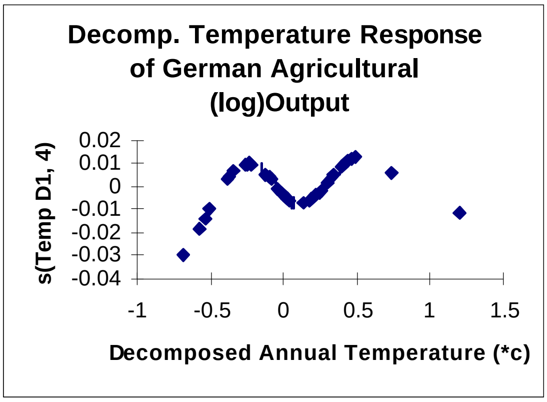
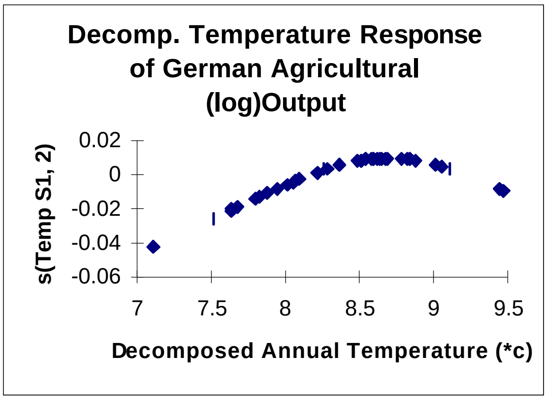


Table 7: GAM of German (log)Output with Decomposed Weather Indices (1870-1913)

Parametric Part	t-ratio	Pr(>|t|)
Lagged (log)Output Fluct.	3.87	0.01
Rainfall D1	-1.70	0.10
Nonparametric Part	Npar F	Pr(F)
s(Temperature D1, 4)	3.17	0.04
s(Temperature S1, 2)	6.77	0.01

Figure 7.a – 7.c





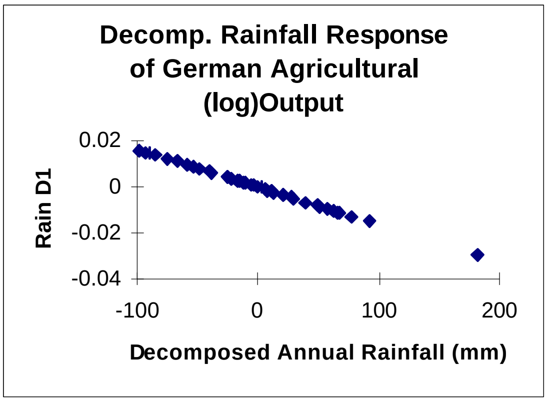


Figure 8

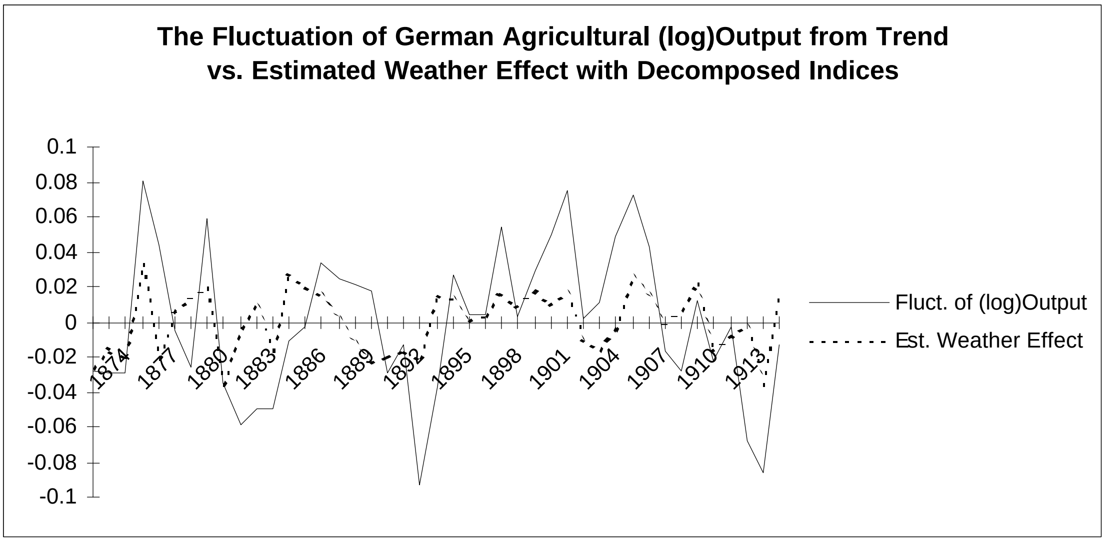


Figure 9

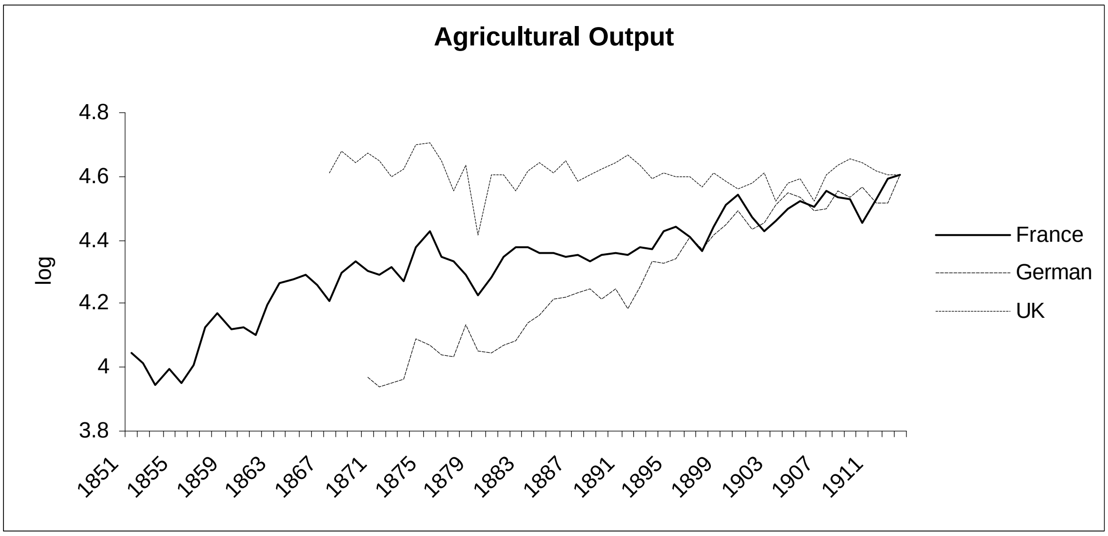


Table 8: ADF tests of France Series (1851-1913)

	(log)Output	Annual Temperature	Annual Rainfall	Critical Values
Without trend				
ADF(0)	-2.21	-6.55*	-7.40	-2.91
ADF(1)	-2.22	-4.60	-6.72*	-2.91
ADF(2)	-2.21	-4.21	-4.46	-2.91
ADF(3)	-2.26	-3.25	-3.72	-2.91
ADF(4)	-2.28*	-2.98	-3.23	-2.91
With trend				
ADF(0)	-4.74	-6.55*	-7.33	-3.49
ADF(1)	-5.45*	-4.61	-6.64*	-3.49
ADF(2)	-4.64	-4.24	-4.40	-3.49
ADF(3)	-3.90	-3.28	-3.61	-3.49
ADF(4)	-3.33	-3.02	-3.07	-3.49

(* suggested by the AIC)

Table 9: GAM of France (log)Output Fluctuation with Reported Indices (1851-1913)

Parametric Part	t-ratio	Pr(>|t|)
Lagged (log)Output Fluct.	4.51	0.01
Temperature	3.32	0.01
Rainfall	-3.13	0.01

Figure 10.a

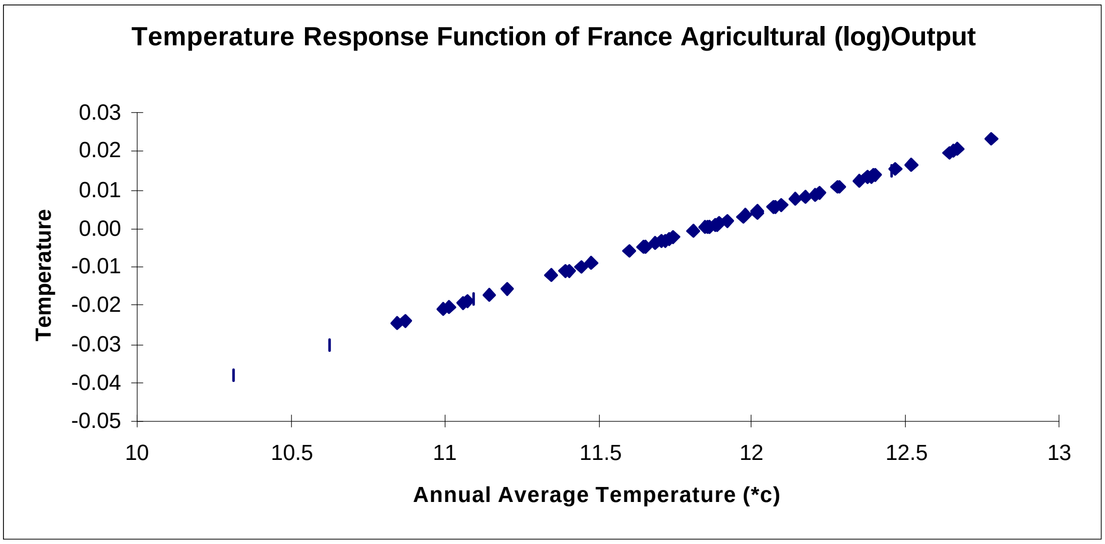


Figure 10.b

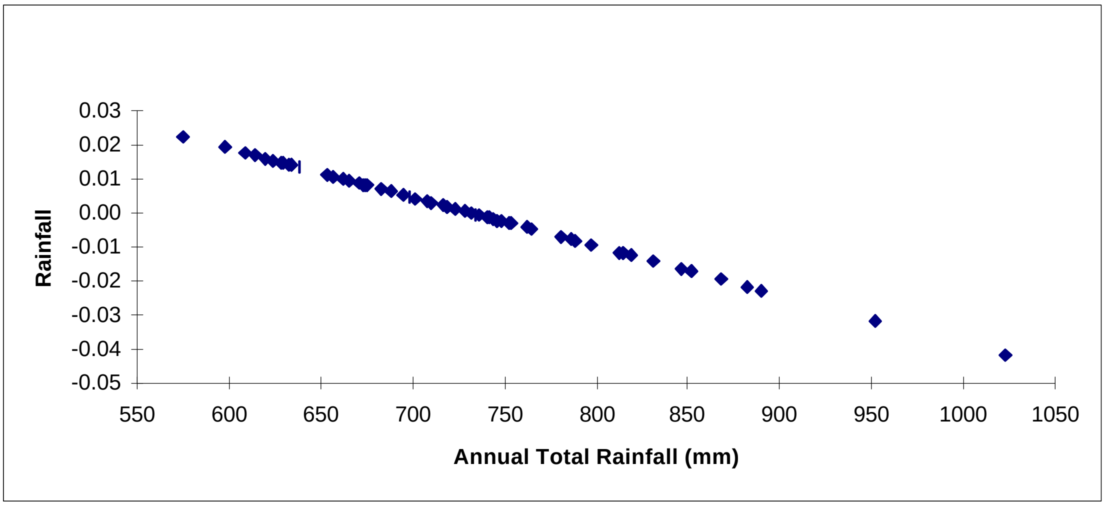


Figure 11

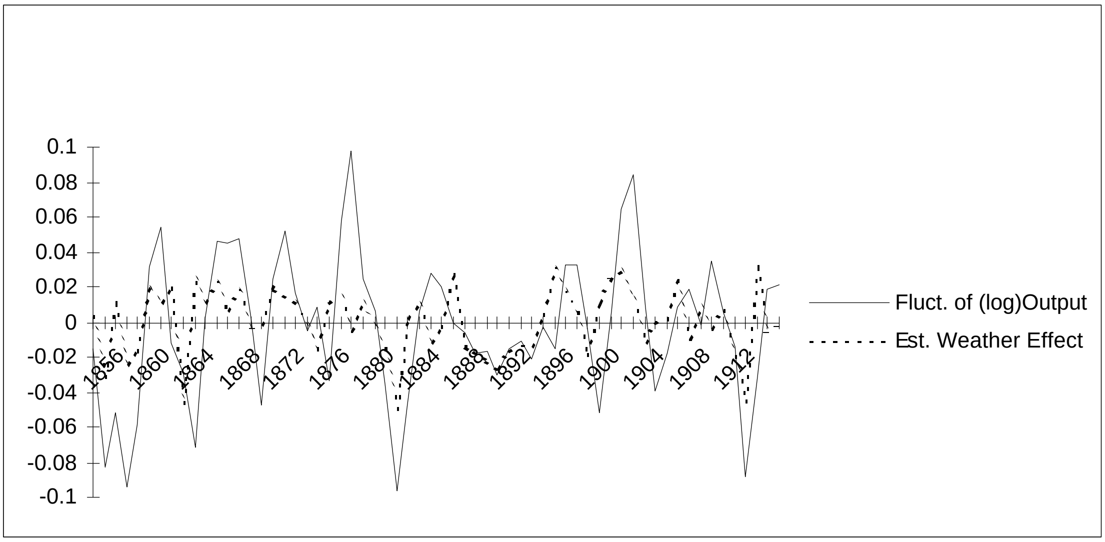
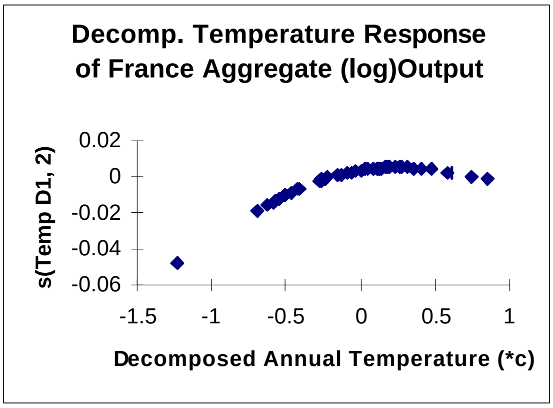
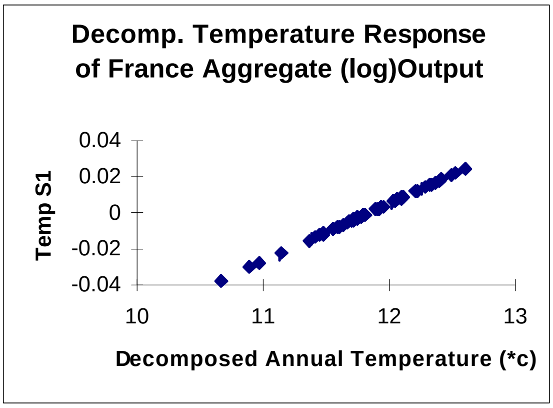


Table 10: GAM of France (log)Output with Decomposed Weather Indices (1851-1913)

Parametric Part	t-ratio	Pr(>|t|)
Lagged (log)Output Fluct.	4.11	0.01
Temperature S1	3.41	0.01
Rainfall S1	-4.28	0.01
Nonparametric Part	Npar F	Pr(F)
s(Temperature D1, 2)	4.61	0.04

Figure 12.a – 12.c





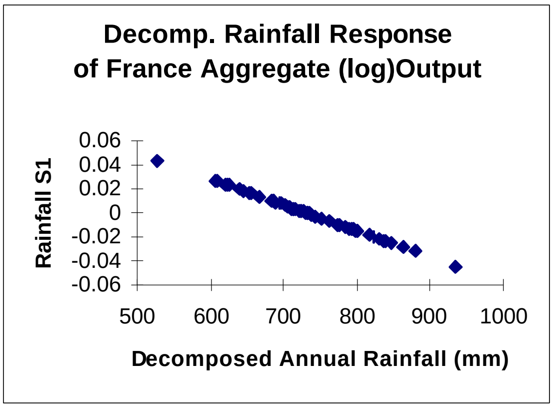


Figure 13

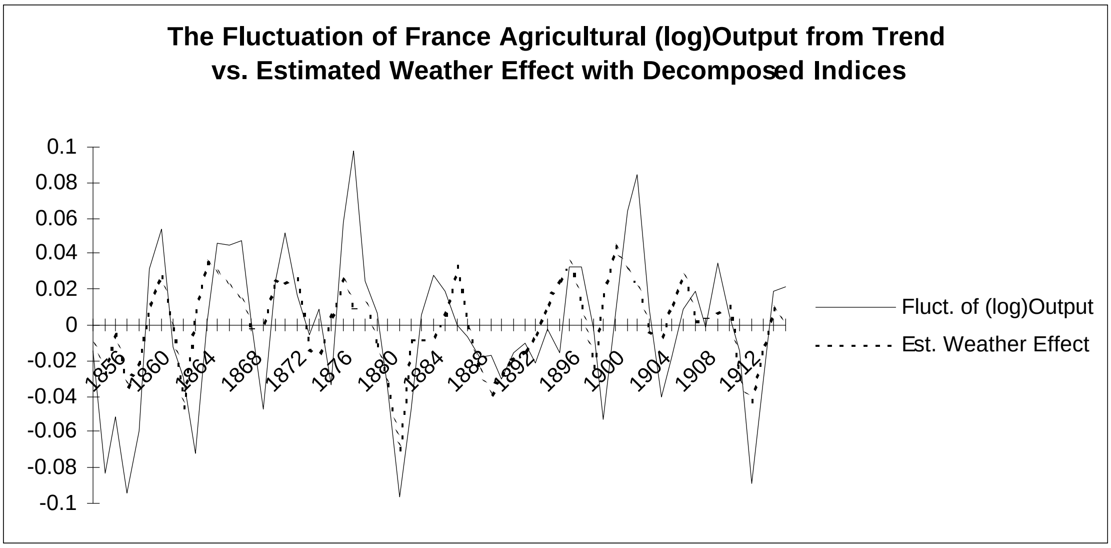


Figure 14