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Temporal Investigation of Flow Variability in Scottish Rivers Using Wavelet Analysis

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Abstract

River flow records form the basis of flood risk estimates. In Scotland, the Flood Risk Management Act (2009) has the objective of improving flood risk management by improved modelling of river flows taking into account potential future climate change. Wavelet analysis is presented here as a possible method for detecting and comparing trends, investigating spatial heterogeneity and periods of significant variability in non-stationary environmental time series. The results from a wavelet analysis of a set of 9 Scottish rivers confirm a difference in river flow maxima between the East and the West that has been pointed out in previous studies, along with changes in the seasonal patterns that may be linked to external climatic drivers, including the North Atlantic Oscillation and the Atlantic Multidecadal Oscillation. Such influences (which act on several time scales, the principal one being annual) are not constant and vary both temporally (being stronger from 1987 onwards) and spatially, with a possible catchment size effect, highlighting the importance of assessing flood risk at a regional level. The study is currently being extended to a further 26 rivers to gain a better understanding of the spatial dependence in extreme river flows, which will contribute to the improvement of flood risk management.

Keywords: discrete wavelet transform, stationarity, variability, river flow data.

1. Introduction

Understanding the pattern of flows and its relationship to flooding is critical to flood planning and risk management. In particular in Scotland the Flood Risk Management Act (2009) was passed with the aim of introducing "... a more sustainable and modern approach to flood risk management" (Government (2010)). To do so, new and improved estimates of flood risk which take into account the impact of climate change and possible spatial heterogeneity are needed.

Records of river flows are widely used to predict flood and low flow levels, in water resource allocation, and form an important basis for assessing the impacts of climate change. Data records are often short (a few decades or less) and a range of classical time-series and extreme value methods have been used as a basis for making predictions. Much flood-risk management is based on the concept of a return period for an event of given magnitude and, despite ongoing debate about the utility of the return period approach (White (2001); Young and Davies (1989)), considerable effort continues to be made to refine predictions of the 1 in 100 year event. Current changes in environmental conditions, specifically those driven by climate change, have led investigators to look for new statistical models which account for non-stationarity and seasonal variations. Climate change impacts are also expected to vary spatially (Jenkins *et al.* (2009)) and thus would be expected to result in spatially variable changes in river flows. In addition, there is continuing evidence for spatial relationships, e.g. in Scotland, evidence of an East West difference in terms of rainfall and river flow is apparent over the last 30 years (Black (1996); Black and Burns (2002); Werritty (2002); Mayes (1996)). The attention drawn to this topic over the last few years coupled with the greater availability of data as a result of the recent development of climate models has led researchers to try to relate patterns in rainfall and river flow to various climate signals. In Europe, the main influence comes from the North Atlantic Ocean, for which two main indices have been identified, the North Atlantic Oscillation (NAO) and the Atlantic Multidecadal Oscillation (AMO).

The NAO is a large-scale signal of natural climate variability, calculated as the normalized atmospheric pressure difference (at sea level) between the Azores and Iceland (Hurrell (1995)). The resulting index is positive when the pressure is high in the Azores and low in Iceland, and negative when the situation is reversed. A high index is associated with strong westerly winds, cool summers, mild winters and frequent rain in the north of Europe, while a low index is linked to scarce winds, extreme temperatures and dry conditions (with localized storms) (Macklin and Rumsby (2007); Bouwer *et al.* (2008)).

A less well known and less studied index is the Atlantic Multidecadal Oscillation (AMO) (Kerr (2000); Delworth and Mann (2000)), a further signal of climatic variability, related to anomalies in the sea surface temperature (SST) and sea level pressure (Delworth and Mann (2000)) and calculated based on the former. Similarly to the NAO, the resulting index can be either positive (warm phase) or negative (cold phase). It has been attributed with an oscillation period of about 60 years and it is thought to be correlated to air temperatures and rainfall over much of the Norther Hemisphere, in particular affecting European summer climate (Knight *et al.* (2006); Sutton and Hodson (2005)).

Time series analysis can be approached from two different perspectives: the time domain (classical time series analysis) or the frequency domain. In hydrology, Fourier analysis (also called spectral analysis) has traditionally been used for the latter. However, it assumes that the time series is stationary and that it can be expressed as a "... linear superposition of linear, independent and non-evolving cycles" (Labat (2005)), conditions rarely met by hydrologic series. Having found clear evidence of non-stationarity by means of traditional time series analysis, newer statistical methodology, namely wavelets are presented here and applied to river flow data to investigate changes in river flow maxima patterns and evidence of spatial differences. Wavelet analysis is a useful tool for analysing non-stationary time series to capture the local behaviour at different frequencies (Percival and Walden (2006); Torrence and Compo (1998); Labat (2005)). By subsequently filtering the original series, we obtain sequences of results which relate to variations at different scales (frequencies). The result is a time-scale decomposition of the original time series that provides an alternative way of looking at the time series, showing features that would not be visible in, say, a plot of the time series versus time (Percival and Walden (2006); Torrence and Compo (1998)). All the information contained in the original time series is also preserved in its wavelet transform. Examples of wavelet analysis applied to hydrologic series can be found in Smith *et al.* (1998); Percival and Mofjeld (1997); Labat *et al.* (2005); Rossi *et al.* (2009) and Sen (2009).

In this paper, the trend and seasonal components of flows in 9 Scottish rivers are identified by means of wavelet analysis and compared for Western and Eastern rivers, and the influence that external climatic drivers such as the AMO and the NAO might have had on them is investigated. All the analysis was carried out using the software packages **sowas** and **wmtsa** in R (version 2.8.1).

1.1. Data

Given the country's geographical situation, Scotland's weather is subject to both continental and Artic influences, combined with a dominant Atlantic signal. There is also a strong West-East rainfall gradient; in particular, three precipitation regions have been defined, the South West, the North West and the East (Gregory *et al.* (1991)), with the North West being the wettest region and the East the driest. Apart from these three broad groups, local conditions vary from catchment to catchment within the same precipitation region. Nine rivers of different catchment sizes across Scotland (Figure 1) were selected based on data quality and spatial location. Since the main interest lies in the extreme values the (logged) series of monthly maxima were calculated. The resulting time series for one of the rivers is shown in Figure 2. Data (gauged daily flow (m^3/s)) were provided by the National River Flow Archive (NRFA) and the Scottish Environment Protection Agency (SEPA) (Table 1).

The NAO data were downloaded from *http://www.cdc.noaa.gov/data/climateindices/List/* and consists of a monthly series covering 51 years (January 1950-December 2008). Data for the AMO were downloaded from *http://www.esrl.noaa.gov/psd/data/timeseries/AMO/* and consists of a monthly series running from January 1856 to April 2009.

2. Methods - wavelet analysis

One way of identifying the local behaviour of non-stationary time series is by wavelet analysis. By subsequently filtering the original series, we obtain sequences of results which relate to variations at different scales (frequencies). The result is a time-frequency representation of the data (Percival and Walden (2006); Torrence and Compo (1998)). The discrete wavelet transform (DWT) coefficients $\{W_n : n = 1,\ldots,N\}$ of a time series X of length N are calculated as $\mathbf{W} = \mathcal{F}\mathbf{X}$, where $\mathcal{F}$ is an N×N matrix constructed using the chosen filter. The original time series can then be reconstructed as the sum of a number of wavelet detail components D_j and a smooth component S_J :

$$X = \mathcal{F}^T\mathbf{W} = \sum_{j=1}^{J} D_j + S_J \tag{1}$$

where J is the level of decomposition. D_j (wavelet detail) is a time series related to variations in X at scale τ_j=2^{j-1}, j=1,...,J, and S_J (wavelet smooth) is a time series associated with scales $\lambda_J = 2^J$ and higher and can be interpreted as the trend. The DWT has a number of constraints; first, the sample size of the time series has to be a power of two, and second, both the filter choice and the starting point of the time series might have an influence on the resulting wavelet transform. These constraints are due to the algorithm underlying the construction of the discrete wavelet transform, in which the filtered series is downsampled at each stage (Percival and Walden (2006)). The maximum overlap discrete wavelet transform (MODWT) provides a decomposition of the time series without the constraints of the DWT. The algorithm of the DWT is modified so that no downsampling is involved; as a result, it is no longer an orthogonal transformation and the computational cost is higher (Percival and Walden (2006)). Similarly to the DWT, the original series can be expressed as the sum of a number of wavelet details components plus a smooth component. By investigating the wavelet decomposition of a time series, one can identify the scale(s) responsible for the major part of the variability. The time-dependent wavelet variability at a particular scale τ_j ($\hat{\upsilon}_{X,t}(\tau_j)$) describes the behaviour of the variability at that scale over time, and can be estimated as:

$$\hat{\upsilon}_{X,t}(\tau_j) = \frac{1}{N_S} \sum_{u=-(N_S-1)/2}^{(N_S-1)/2} W_{j,t+|\nu_j^{(H)}|+umodN} \tag{2}$$

where umodN is the remainder of u/N, N_S is the width of the smoothing window and $W_{j,t+|\nu_j^{(H)}|+umodN}$ is the wavelet coefficient $W_{j,t}$ circularly shifted so that it is aligned in time with the original time series (Percival and Walden (2006)). In particular, we chose N_S=12 given the monthly resolution of the data.

A continuous version of the wavelet transform is also available. When the interest is to study how two time series are related, continuous wavelet analysis offers a wavelet-based version of the usual cross-correlation, to investigate the relationship between two time series not only across time but also for different time scales. The cross-wavelet spectrum of two time series X and Y is defined as:

$$W_n^{XY}(s) = W_n^X(s) W_n^{Y*}(s) \tag{3}$$

where $W_n(s)$ is the continuous wavelet transform (Torrence and Compo (1998)) at time n and scale s and * indicates the complex conjugate. However, defined this way it is not a reliable tool, for peaks of high correlation can appear even when the two series are independent, reflecting just peaks of high variability of the individual series (Maraun and Kurths (2004)). The alternative is to use a normalized version of the cross-wavelet spectrum, the wavelet coherency. The wavelet cross spectrum is a complex number, so it can be re-written as $W_n^{XY}(s) = |W_n^{XY}(s)|e^{n\phi_n(s)}$. The wavelet coherency (Grinsted *et al.* (2004); Torrence and

Webster (1999)) is then defined as:

$$WCO_n^{XY}(s) = \frac{|\langle s^{-1}W_n^{XY}(s)\rangle|^2}{\langle s^{-1}|W_n^X(s)|^2\rangle\langle s^{-1}|W_n^Y(s)|^2\rangle} \tag{4}$$

Its value ranges from 0 to 1. The symbol $\langle\cdot\rangle$ indicates smoothing. The smoothing, which can be done in time or/and scale direction, is necessary because otherwise the wavelet coherency would always be equal to 1, for every time point and scale (Torrence and Compo (1998)).

The wavelet coherency provides information about how strong the association between the two time series is, but it does not carry information about the time lag at which the two series are correlated. The phase function $\phi_n(s)$ provides a measure of the lag difference between the two time series at time n, scale s, and it can be calculated as:

$$\phi_n(s) = \tan^{-1}\left(\frac{Im\{\langle s^{-1}W_n^{XY}(s)\rangle\}}{Re\{\langle s^{-1}W_n^{XY}(s)\rangle\}}\right) \tag{5}$$

where $s^{-1}W_n^{XY}(s)$ has been smoothed.

A significance test for the wavelet coherency was proposed by Maraun and Kurths (2004) and Grinsted *et al.* (2004), the null hypothesis being that the processes are not significantly correlated. However, the fact that neighboring times and scales are correlated is problematic for deriving the distribution of the test-statistic under the null hypothesis. To overcome this problem, Maraun and Kurths (2004) and Grinsted *et al.* (2004) make use of Monte Carlo simulation to generate 10000 realizations of two independent Gaussian white noise processes or AR(1) processes. The simulated sample can be used to derive the empirical distribution of the test-statistic under H_0, from which a critical value for the chosen significance level can be obtained. Critical values depend on the amount of smoothing and appear to be scale dependent (Grinsted *et al.* (2004)) even though Maraun and Kurths (2004) suggests that the ideal is to find the right amount of smoothing so that they are scale independent.

3. Results

3.1. Trends and seasonality

MODWT (based on an LA(8) filter (Figure 3) (Percival and Walden (2006)) with 4 levels of decomposition was applied to the monthly maxima series (normalized to the overall mean). LA (or least asymmetric) filters are a special class of filters proposed by Daubechies (1992). LA filters are appropriate for calculating the DWT because their phase function is very close to the phase function a linear phase filter. This means that the filtered series can be easily aligned in time with the original series (Percival and Walden (2006)). An alternative to Daubechies filters are Coiflet filters, but the use of the latter is not as common as they are likely to introduce artifacts in the wavelet transform (Percival and Walden (2006)). Since it is of interest to align in time the original series with its wavelet transform, an LA filter was considered appropriate. The number 8 here represents the width of the filter. Following Percival and Walden (2006), who suggest the width of the filter to be as small as possible, this value was chosen comparing a series of wavelet transforms calculated for a range of filter width values. The wavelet transform corresponding to filter width equal to 8 provided a good smooth representation of the corresponding time series; smaller width values resulted in sharp peaks in the individual elements of the time series decomposition, while greater width values did not make any difference. Each of the 9 river series was decomposed as $\sum_{j=1}^{4} D_j + S_4$. Components D_1, ..., D_4 reflect changes over the scales 1, 2, 4 and 8 months respectively. The smooth component S_4 reflects changes over a scale of 16 months (and higher) and can be regarded as the trend. Results are presented in Figures 4 and 5.

Figure 4 confirms that the seasonal component varies over the years. Component D_3 is of special interest, as it reflects changes over a scale of 4 months and therefore can be regarded as the seasonal component. Also, D_3 is the main contributor to the sample variance for all 9 rivers.

The trend series (component S_4 from wavelet decomposition), plotted on Figure 5, suggest some differences between the East (Figure 5(a)) and the West (Figure 5(b)). There is a sharp decrease in the East around 1973 that, even though present in the West series, is not as low as for the latter. There is a second decrease around 1996 although in this case it is more prominent in the West than in the East. It is difficult to say whether there is an overall increasing or decreasing trend as the trend series are not linear; however, there appears to have been a slight increase in the West towards the end of the record that is not found in the East.

The time dependent wavelet variability (Equation 2) was calculated to get a measure of fluctuations in the yearly cycle variability. The resulting series are plotted on Figure 5. Overall, the variability is higher in the West (Figure 5(d)) than in the East (Figure 5(c)). There is a clear indication of non-stationarity with periods of high variability alternating with periods of very low variability. In particular, there is a clear change point around mid 1986 for both eastern and western rivers, when the variability is minimum.

3.2. Relationship with climatological covariates

Having found strong indication of changes in the seasonality of flow in these rivers, it is of interest to investigate the potential drivers of these changes as well as whether different regions of the country might be affected in different ways. Black (1996) compared Scotland with the rest of Europe, finding similar results in terms of increases in annual maximum flood in Norway, southern Finland and Estonia over the last 30-50 years, suggesting that there might be a common climate cause. The North Atlantic Oscillation (NAO) and the Atlantic Multidecadal Oscillation (AMO) are two potential causes of some of the changes.

The time series plot of the NAO series is shown in Figure 6(a), along with a long-term trend (S_4) estimated from wavelet analysis. The trend series shows that the NAO was mainly in negative phase up to the beginning of the 1970s and in positive phase during the 1980s and the first half of the 1990s.

Similarly, the AMO series is plotted in Figure 6(b), with the corresponding wavelet estimated long-term trend. Even though it has been less explored in the literature, it is of great interest to investigate how this index relates to river flow, and maxima in particular. The reason for this is that it is less variable than the NAO, with a fairly well established cyclic component and hence is more predictable. It is clear from the plot that the AMO was in its warm phase until the beginning of the 1960s and then again since the mid 1990s onwards, with a cold phase of about 30 years in between. During this cold phase there seems to be a period just before 1990 with anomalously high AMO values.

Even though some authors restrict the NAO influence to winter months, NAO has been shown to be significantly correlated to precipitation over Northern Europe outside the winter months (Marković and Koch (2005)). The results presented here are based on the whole NAO series. The length of the data record varies from river to river; for comparison purposes, only values from October 1975 onwards have been used. The wavelet coherence (top) and phase difference (bottom) (smoothed in time and scale direction) between NAO and each of the rivers is shown on Figure 7. Only the graphs for 4 of the rivers are shown here for reasons of space. In general, the correlation takes values between 0.4 and 0.6 for most of the time and most scales. The thick black contour lines denote regions of statistically significant correlation. Critical values were calculated as the 95^{th} percentile of the empirical distribution of the simulated wavelet coherencies following Grinsted *et al.* (2004) and Maraun and Kurths (2004).

Amongst the Western rivers (Figures 7(a), 7(b)) the coherency for the rivers Nith, Kelvin and Clyde has a similar structure, with statistically significant correlation around 1987-1990 and then again during 1998-2001 on the 1 year band, plus a period of high correlation between scales 4-6 years towards the end of the record in the River Kelvin. In terms of the phase difference, river flow and NAO seem to be out of phase, but this relationship is not constant over time. For the 1 year band, the phase difference changes from about the mid 1980s onwards, while for the 2 year band, it looks as if the phase difference can be divided into 3 different stages. The River Ewe, on the other hand, shows a correlation structure quite different from the rest of the Western rivers, with statistically significant correlation around 1987-1990 and around 1998-2001 (although the latter now extends up to 2004) in the 1 year band plus statistically significant correlation at higher scales (2-4 years band). The phase difference for this river is similar to the previous ones on the 1 year band, but considerably different at higher scales.

Amongst the rivers in the East (Figures 7 (c), 7(d)), the rivers Tweed, Water of Leith and Tay also show high correlation on the 1 year band around 1987-1990 and 1998-2001, plus a period of significant correlation on the 4 year band that can also be seen for the River Tay. The River Lossie seems to have a different pattern, with patches of high correlation along the 1 year band around 1991-1994 and 2002, ie, with a delay of about 1 year with respect to the rest of the rivers. All five Eastern rivers show intermittent periods of high correlation at higher scales. As was the case for the rivers in the West, NAO and river flow maxima are out of phase but the phase difference is not constant for every scale and time point.

To gain a better understanding of the phase difference, the 1 year band filtered NAO series was added to Figure 4. It is clear, for example from the plot for the River Nith, that the NAO series slowly shifted from being completely out of phase around 1976-1977 to being completely in phase at the beginning of the 1990s. A similar plot was produced for the AMO series, but the variability for the 1 year band filtered series was too small compared to the variability of the river maxima series to be informative and hence the plot is not shown here.

The correlation structure between river flow and AMO (Figure 8) resembles that of the NAO, although the relationship seems to be stronger than for the NAO. As before, there is moderate correlation for most of the time and scales, but it is not constant. The highest correlation is concentrated on the 1 year band, suggesting that AMO has a strong influence on the seasonal cycle of river maxima. A peak of high, significant correlation can be found for most of the rivers around 1987-1990, independently of whether they are in the East or West of the country. It is interesting that the AMO influence appears to be stronger in the second half of the record (from 1987 onwards) than it is in the first. Among the Western rivers (Figures 8(a), 8(b)), the Nith and Clyde present a patch of high correlation between 2000 and 2005, a feature that is also present on the Eastern rivers Dee, Tay and Tweed. The catchment area of these five rivers is much larger than that of the remaining four rivers, suggesting that the AMO influence might depend on the size of the catchment. Two rivers show slightly different patterns; these are the River Lossie, for which the correlation in the 1 year band appears to be higher (and significant) around 1993 and at the end of the record and at the beginning on the 2 year band, and the Water of Leith, which still shows high correlation in 1987-1990 but does not appear to be influenced by AMO as much as the rest of the rivers at the end of the record.

Peaks of significant correlation following Maraun and Kurths (2004) and Grinsted *et al.* (2004) have been identified at localized time periods and scales. While the correlation structures (as in coherency plots) between river maxima and AMO and NAO have common features (meaning that they are mainly concentrated on the 1 year band and that they are not constant over time) the phase difference plots are distinct. Even though river flow and AMO are also out of phase and the phase difference is not constant, such difference along the 1 year band appears to be nearly the opposite of what was observed for the NAO (Kerr (2000)).

4. Discussion and Future Work

Wavelet analysis is presented here as a powerful tool for exploring the variability and cross-correlation of non-stationary time series as well as comparing rivers at different locations. The results suggest differences between the East and the West in terms of long term trends and seasonal variability, the latter being higher for rivers in the West of Scotland. A clear indication of non-stationarity was found for for both eastern and western rivers. 1986 was detected as a "change point", when the seasonal variability is minimum. This is in agreement with Black (1996), who suggest a shift towards a "flood rich" period in the late 1980s. The 'cluster' of high variability just before that (from about 1977 to 1986), especially in the West, would correspond to the wettest period on record for the UK (Marsh (1995)). Figure 5(c) also suggest a North to South difference, as the rivers Water of Leith and Tweed, situated in the Southeast of Scotland, seem to have higher variability than those in the Northeast (Lossie, Dee and Tay).

Relationships between NAO and river flow have been reported in previous studies, either on a worldwide scale or restricted to Europe, while literature relating AMO to river flow or rainfall is less abundant. The relationship between NAO and river flow is not a simple one. In Europe, results from a cross-wavelet analysis suggested strong correlation with river flow during 1900-1950 on a scale band of 8-15 years (Labat (2010)). Shorthouse and Arnell (1997) investigated such a relationship during the period 1961-1990 looking at 744 river basins across Europe, finding spatial and temporal patterns in the NAO influence. However, their results, despite being indicative of what the relationship might be, must be interpreted carefully, for the conclusions are based on the results of a Pearson correlation analysis, which assumes independence of observations (something that is rarely the case when dealing with time series) and a linear relationship between the two series. Wavelet based cross-correlation appears to be a good alternative to traditional correlation, even though some authors (Torrence and Compo (1998)) argue that smoothing is somehow contrary to the purpose of using wavelets, which is that of improving the localization of events, as localization is decreased by smoothing. Nonetheless, cross-correlation is highly informative and allows exploration of relationships in a broader time frame, with the assumption of independence no longer being made. With respect to the linearity of the relationship, the interpretation is less clear. While some authors define coherency as the strength of the linear relationship between two series, it has been suggested that the phase difference might be interpreted not only as the time lag but also the degree of linearity (Velasco and Mendoza (2008)); a value close to the extremes -π and π would suggest a (negative/positive)linear relationship, while values in between would mean that the relationship is not linear.

In an effort to investigate how current climate change might impact on the frequency of extreme events, relationships between NAO and AMO and river maxima were explored. The results from the wavelet coherency analysis suggest that the influence of NAO varies slightly from catchment to catchment, with Eastern rivers showing periods of correlation at scales higher than the 1 year band, the latter being common to most of the rivers in both the East and West. The relationship between the AMO and river maxima also changes slightly from catchment to catchment, but the influence appears to be stronger than that of the NAO, especially at the end of the 1980s. During this period of high correlation, the AMO has been said to be in negative or cold phase, although unusually high values (to be in a cold phase) were recorded, regarded as a period of 'transition' between the cold and warm phase. From that point onwards, the correlation with river maxima is higher, suggesting that rivers might be more affected when AMO is in its warm phase. At this point, this results should be interpreted as merely indicative, and further research is needed to draw definite conclusions. The AMO has an oscillation period of about 60 years and here we are looking at possible relationships over 30 years. It would be useful to extend the length of the records to see how this oscillation has influenced river flow in the long term, to investigate whether the effect has always been similar or has changed through time. Further, AMO is claimed to be linked to summer rather than winter climate (Knight *et al.* (2006); Sutton and Hodson (2005)). A seasonal analysis to gain a better understanding of the relationship would be informative.

The NAO is now "... well recognized to have an important influence on European climate and its variability" (Marković and Koch (2005)) particulary in the winter months (Marković and Koch (2005); Shorthouse and Arnell (1997)). Since the NAO has such a strong influence on rainfall, the expectation is that this influence will extend to river flow too. Previous studies have linked it to winter river discharge globally (Dettinger and Diaz (2000); Labat (2010)) and in Europe (Shorthouse and Arnell (1997); Kingston *et al.* (2009); Bouwer *et al.* (2008)). Macklin and Rumsby (2007) investigated the relationship between NAO and floods in upland catchments in the UK over the last 250 years, arguing that "... the non-stationarity of the flood series was related to decadal and multi decadal scale climatic fluctuations" (Macklin and Rumsby (2007)). They claim that the relationship changes both spatially and temporally, with the NAO influence over Scotland being different to that in England and Wales (Macklin and Rumsby (2007)) and within Scotland itself, where 3 upland regions were studied, Glencoe, An Teallach, in the West of Scotland and the Cairngorms, in the East. Their results suggest an increase in the frequency of floods in the second part of the 19th century and again in the 1980s, the latter associated with high rainfall (autumn) and positive NAO (Macklin and Rumsby (2007)) (Figure 6(a)), contrary to data from England, which suggest higher frequency floods when NAO is negative (Macklin and Rumsby (2007)). In agreement with the findings of Macklin and Rumsby (2007), Shorthouse and Arnell (1997) report strong positive correlation between regional runoff and NAO in Scotland, especially in winter (December,January,February), although the strength of the correlation varies across the country.

Even though the AMO has only been defined recently, its oscillatory nature was observed in the early 1970s (Kerr (2000)), when researchers noticed an increase in the North Atlantic sea surface temperature during 1910-1940 that was accompanied with an increase in global air temperature, after which a phase of cooling down began, both in sea surface and global air temperature, to then warm up again in the 1980s. Phases of warm/cold AMO index have been related to anomalous regional climate, particularly in the North West of Europe. This dependence seems to vary seasonally, with the highest impact during the summer months (June, July and August) (Knight *et al.* (2006); Sutton and Hodson (2005)).

The rivers Lossie and Ewe seem to be affected differently from the rest of the rivers investigated in this study; they are both in the North of Scotland and have relatively small catchments. This might be an indication of a North to South differentiation that had already been suggested by Kingston *et al.* (2009) and possibly a catchment size effect, reinforcing the importance of carrying studies on a regional level (Government (2010)).

Differences between the East and the West of Scotland have been identified in river flow maxima over the last 40 years, both in the long term trend and seasonal pattern. The latter appears to be subject to great variability, being slightly higher in the West than in the East, with a common time point around 1986 for all the rivers, when the variability is minimum. Periods of greater seasonal variability (and hence a more pronounced seasonal pattern) coincide with flood rich periods. Some of these changes might be explained through the influence of external climatic drivers such as the AMO and the NAO. The correlation strength between river maxima and these two indices varies temporally, appearing to be stronger, specially for the AMO, in the second half of the record (from about 1987 onwards). The influence of AMO and NAO not only changes through time but also the phase difference is highly variable, and is different depending on location (East/West) but also on the size of the catchment. This analysis could be extended wider to cover Europe, in order to gain a better understanding of the spatial dependence in extreme river flows, which will contribute to the improvement of flood risk management.

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Table 1: Data set.

River	Catchment area (km^2)	Mean discharge (m^3/s)	Location	Coordinates	Data record
Nith(Friars Carse)	799	27.38	West	3^o 41.4' W,55^o 08.9' N	1/10/57 - 1/10/08
Dee(Woodend)	1370	36.95	East	2^o 36.1' W,57^o 03.0' N	1/10/29 - 30/9/08
Tweed(Norham)	4390	79.59	East	2^o 09.7' W,55^o 43.4' N	1/10/62 - 31/10/08
Ewe(Poolewe)	441	29.91	West	5^o 36.0' W,57^o 45.7' N	19/10/70 - 31/12/08
Lossie(Sheriffmills)	216	2.70	East	3^o 21.0' W,57^o 38.8' N	1/10/63 - 31/10/07
Tay(Ballathie)	4857	169.22	East	3^o 23.7' W,56^o 45.4' N	1/10/52 - 31/10/08
Water of Leith(Murrayfield)	107	1.49	East	3^o 14.2' W,55^o 56.7' N	1/1/63 - 31/12/05
Clyde(Blairston)	1704	42.80	West	4^o 04.1' W,55^o 47.8' N	1/10/58 - 5/11/08
Kelvin(Killermont)	335	8.41	West	4^o 18.4' W, 55^o 54.4' N	1/10/48 - 31/12/07

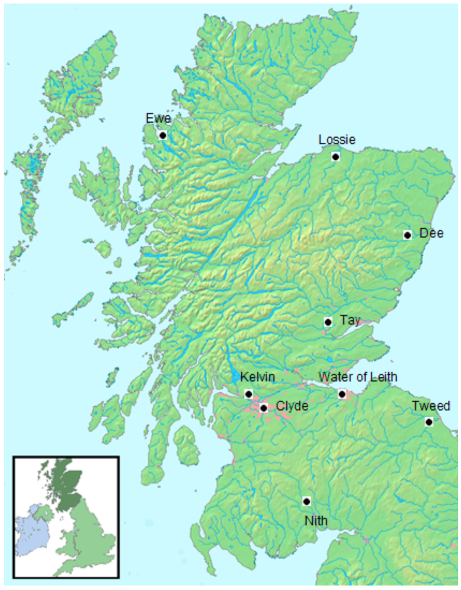

Figure 1: Map of Scotland showing the gauging stations used in the analysis. Source: *map-soft.net*

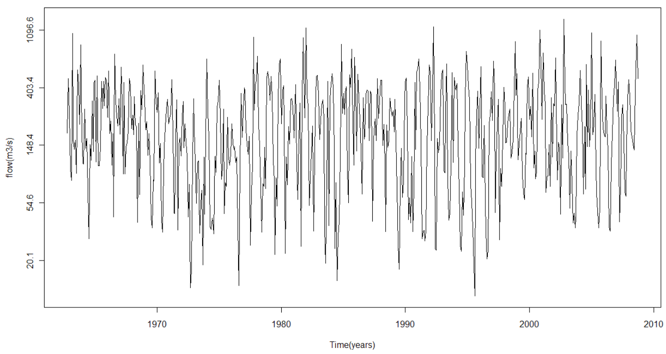

Figure 2: Time series of logged monthly maxima (River Tweed).

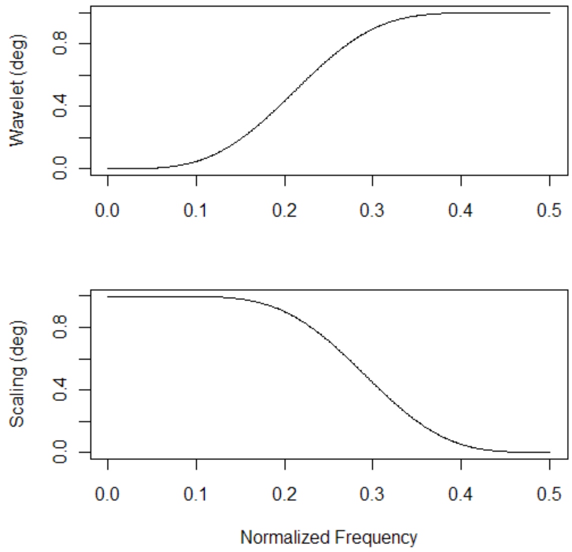

Figure 3: Wavelet and scaling filters for the LA(8).

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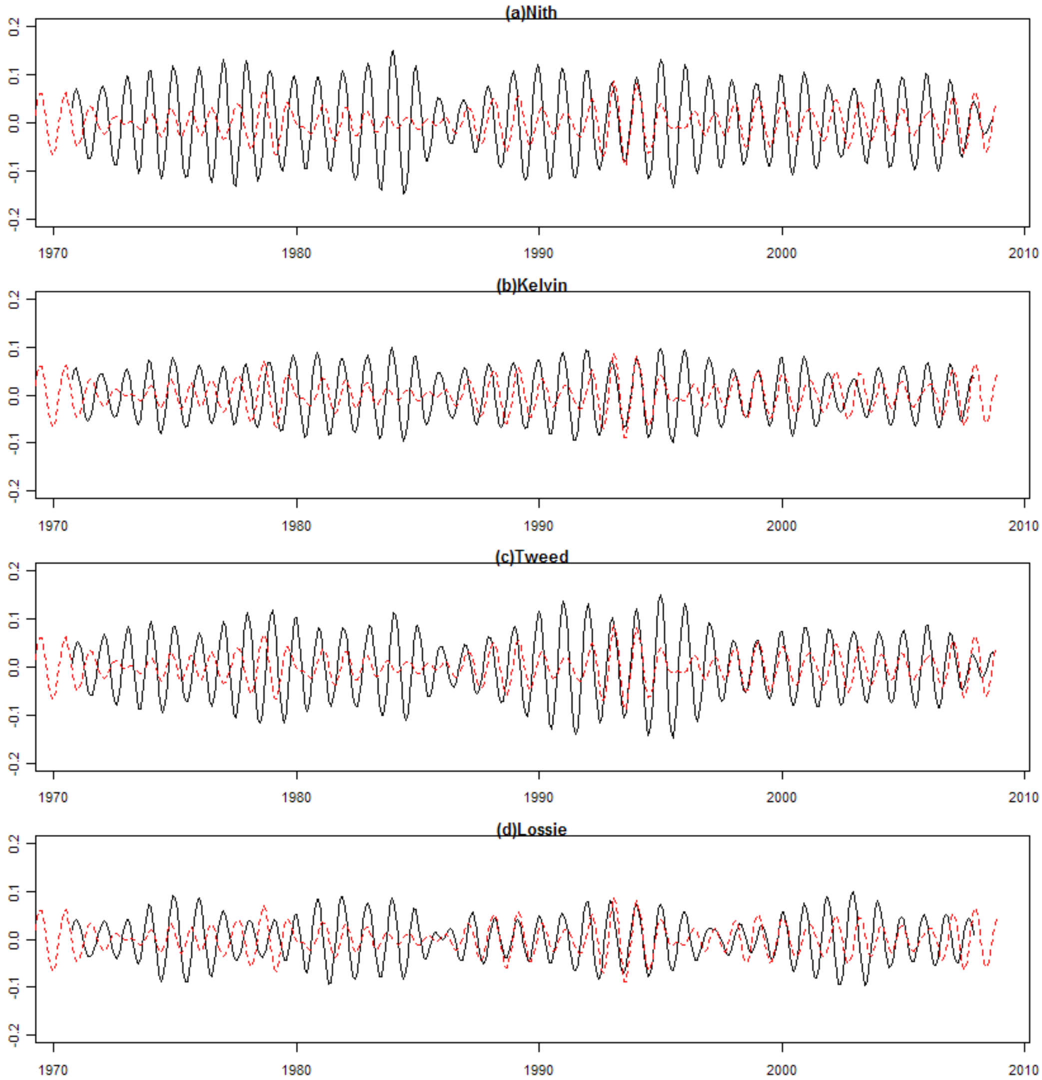

Figure 4: Seasonal component (D_3) for rivers (a)Nith, (b)Kelvin (West) and (c)Tweed and (d)Lossie (East). For reasons of space, only 4 rivers are plotted. The dashed red line represents the seasonal component for the NAO (see page 12).

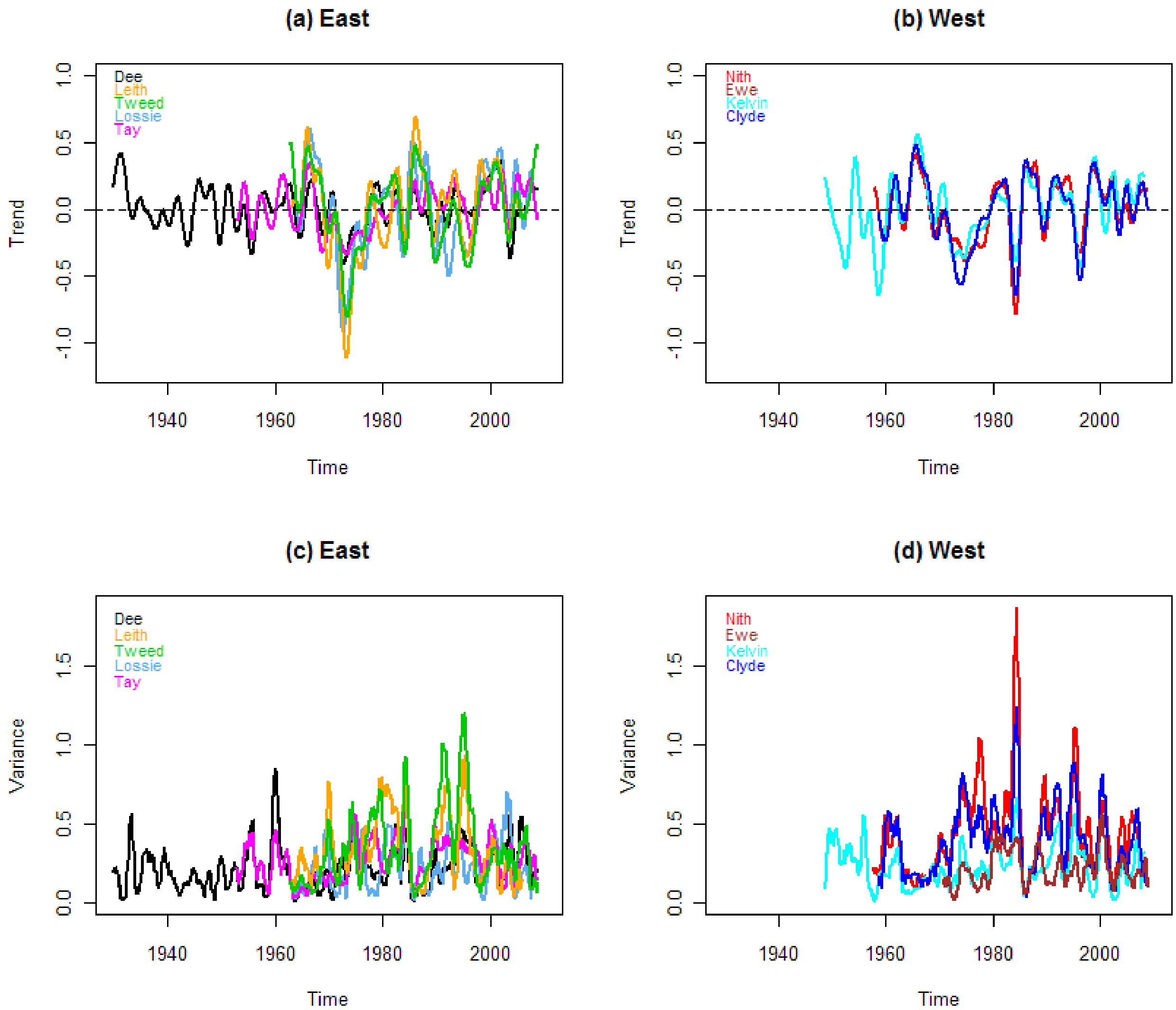

Figure 5: Trend (S_4) from wavelet decomposition for (a)Eastern and (b)Western rivers and seasonal time dependent variability based on component D_3 for (c)Eastern and (d)Western rivers.

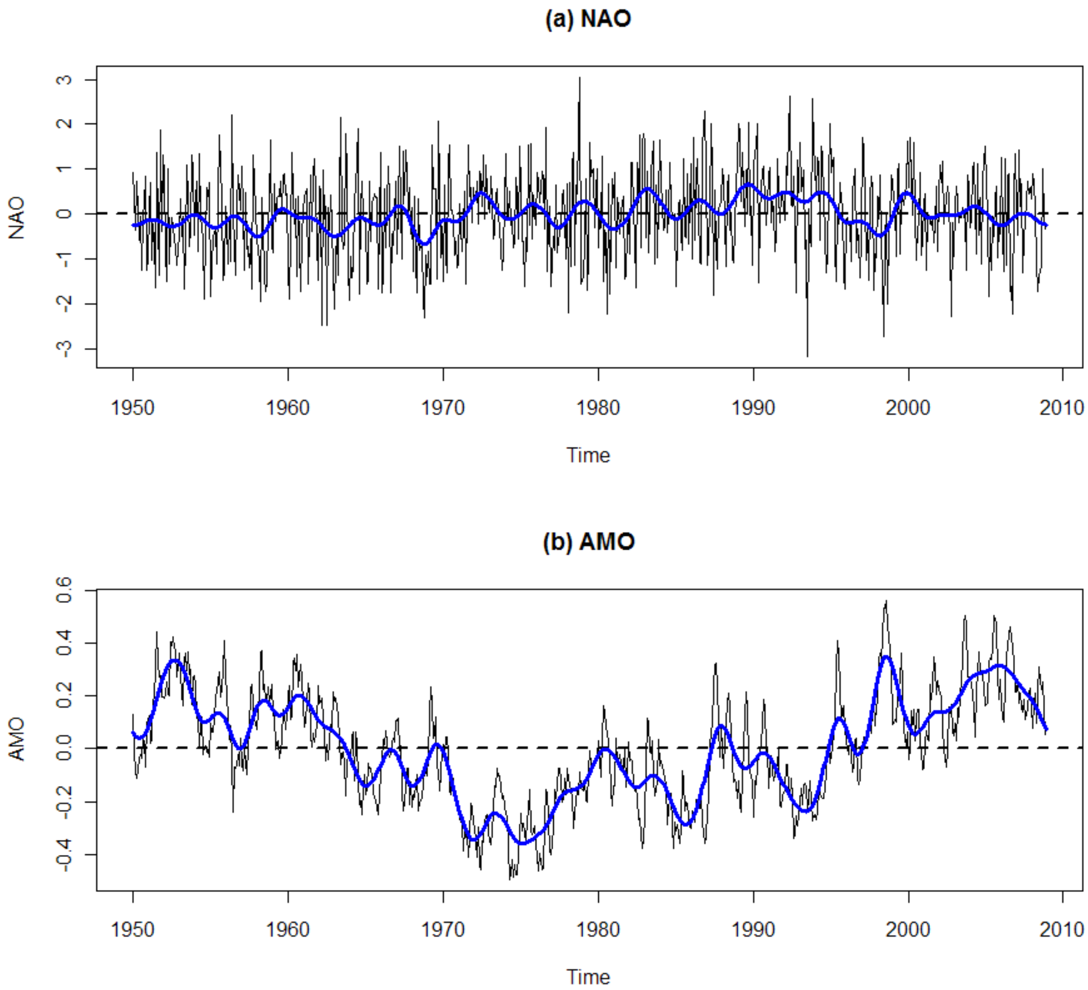

Figure 6: (a)NAO and (b)AMO time series. The blue line is the trend as estimated from wavelet analysis. Data were downloaded from *http://www.cdc.noaa.gov/data/climateindices/List/* and *http://www.esrl.noaa.gov/psd/data/timeseries/AMO/*

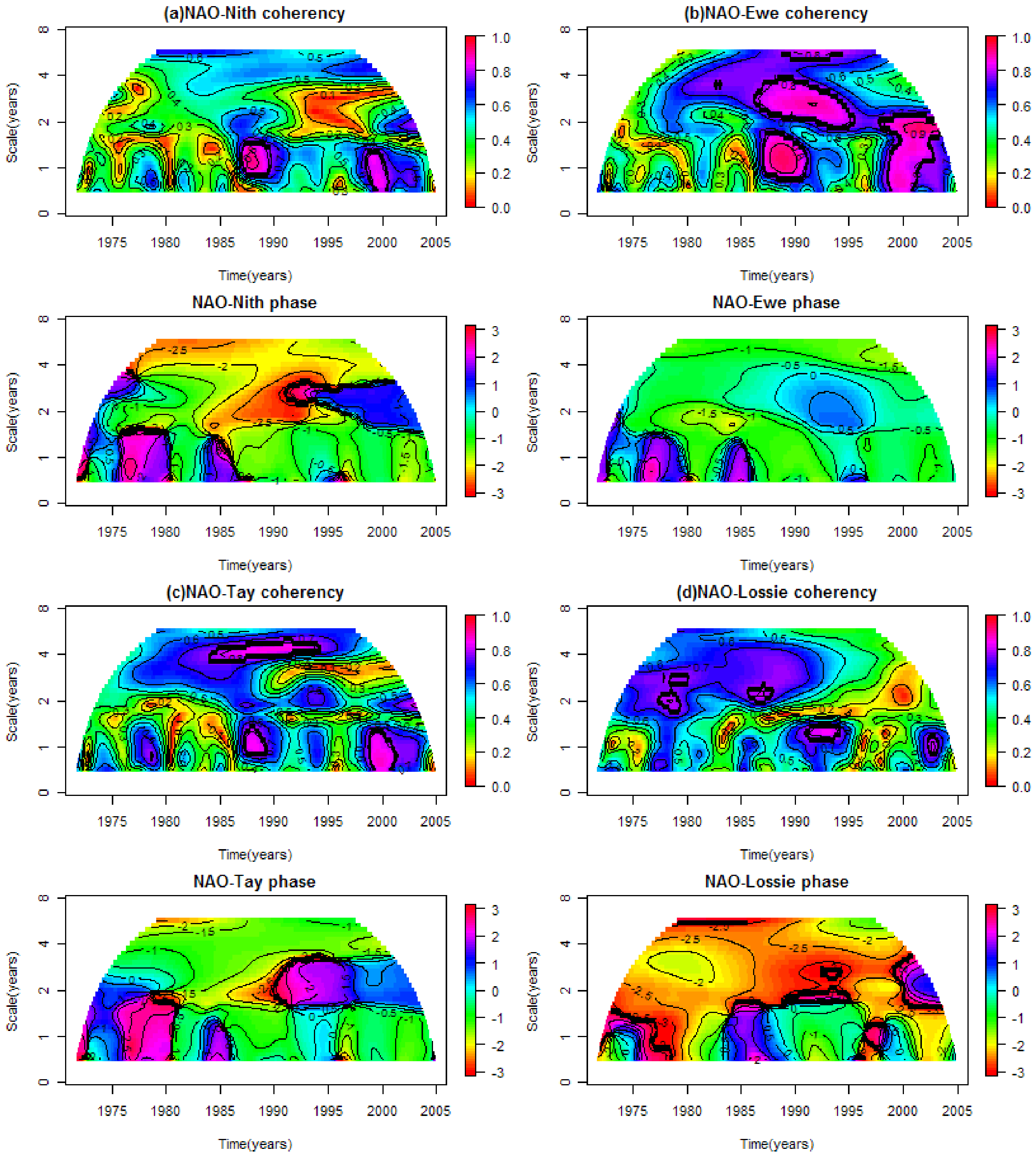

Figure 7: Wavelet coherency (top) and phase (bottom) between NAO and rivers (a)Nith, (b)Ewe, (c)Tay and (d)Lossie. The thick black contour lines on the wavelet coherency plots denote regions of statistically significant correlation.

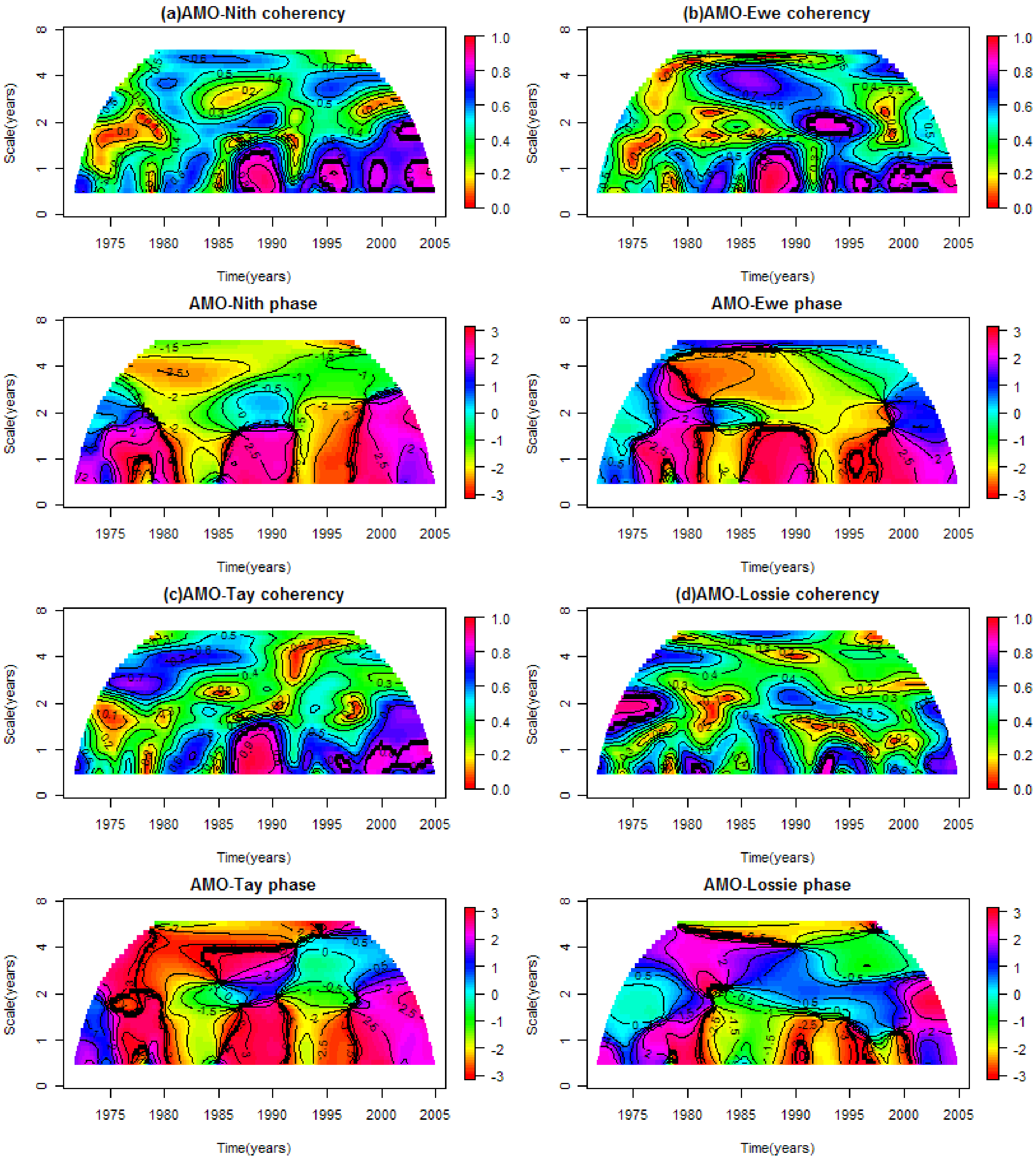

Figure 8: Wavelet coherency (top) and phase (bottom) between AMO and rivers (a)Nith, (b)Ewe, (c)Tay and (d)Lossie. The thick black contour lines on the wavelet coherency plots denote regions of statistically significant correlation.