

## MEDIATED AND DIRECT EFFECTS OF THE NORTH ATLANTIC OCEAN ON WINTER TEMPERATURES IN NORTHWEST EUROPE

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### ABSTRACT

This study has used a multiple regression model to quantify the importance of wintertime mean North Atlantic sea-surface temperatures (SSTs) for explaining (simultaneous) variations in wintertime mean temperatures in northwestern Europe. Although wintertime temperature variations are primarily determined by atmospheric flow patterns, it has been speculated that North Atlantic SSTs might also provide some additional information. To test this hypothesis, we have attempted to explain 1900–93 variations in wintertime mean central England temperature (CET) by using multiple regression with contemporaneous winter mean North Atlantic sea-level pressures (SLPs) and SSTs as explanatory variables. With no SST information, the leading SLP patterns (including the North Atlantic oscillation) explain 63% of the total variance in winter mean CET; however, SSTs alone are capable of explaining only 16% of the variance in winter mean CET. Much of the SST effect is ‘indirect’ in that it supplies no more significant information than already contained in the mean SLP; e.g. both SLP and SST together can only explain 68% of the variance. However, there is a small (5% variance) direct effect due to SST that is not mediated by mean SLP, which has a spatial pattern resembling the Newfoundland SST pattern identified by Ratcliffe and Murray (1970. *Quarterly Journal of the Royal Meteorological Society* **96**: 226–246). In predictive mode, however, using explanatory variables from preceding seasons, SSTs contain more information than SLP factors. On longer time scales, the variance explained by contemporaneous SST increases, but the SLP explanatory variables still provide a better model than the SST variables. Copyright © 2003 Royal Meteorological Society.

KEY WORDS: regression; North Atlantic; sea surface temperature (SST); North Atlantic oscillation (NAO); coupled processes; European climate; variability; predictability

### 1. INTRODUCTION

Wintertime surface temperatures in Europe are primarily determined by the ambient atmospheric flow. When the North Atlantic storm track extends over western Europe in winter, there are generally stronger southwesterly winds, more convection, and consequently warmer, more maritime, conditions. Strong responses in North Atlantic and European surface temperature are closely associated with large-scale modes of atmospheric variability. For example, the North Atlantic oscillation (NAO) produces a very clear signature in surface temperatures over the North Atlantic region and surrounding land masses (Stephenson *et al.*, 2000).

Because of its importance in transporting heat, it is tempting to speculate that the North Atlantic Ocean might also have some determining influence on European climate. For example, travel books and other popular articles often invoke the Gulf Stream to explain the milder winter conditions in western Europe compared with those at similar latitudes in North America. However, Seager *et al.* (in press) have recently dismissed this idea by showing that most of the *time-mean* temperature contrast is due to atmospheric stationary waves primarily generated by the orography of the Rocky Mountains. This does not exclude, however, the possibility that *variations* in North Atlantic sea surface temperatures (SSTs) might modulate European climate (Lau, 1997).

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Sutton and Allen (1997) and Rodwell *et al.* (1999) have speculated that variations in North Atlantic SST may determine part of the long-term (decadal) variability observed in European climate. However, the effects of North Atlantic SST variations on the overlying atmospheric flow are so small that optimal multivariate signal detection methods are required in order to isolate them (Sutton *et al.*, 2000).

Another complicating factor for attributing climate variations to SSTs is that there are significant ‘associations’ between SST and sea-level pressure (SLP) caused by the atmosphere forcing the ocean. The ‘associated’ patterns of variations in SLP and SST can result from one-way atmospheric forcing rather than being due to the ocean forcing the atmosphere, or the ocean and atmosphere being fully coupled with two-way interactions. Many previous studies into co-variability of oceanic and atmospheric fields in the extra-tropical climate system have identified ‘coupled’ (or, to be precise, associated) patterns of SST and SLP variability using descriptive multivariate techniques such as canonical correlation analysis, etc. (see Grötzner *et al.* (1998) and references therein), correlation maps and singular value decomposition (SVD) to explore the co-variability of different gridded fields (Bretherton *et al.*, 1992). Recently, Rodwell and Folland (2002) and Czaja and Frankignoul (2002) have used SVD to attempt to identify causal relationships in the SST and time-lagged 500 hPa geopotential height  $Z_{500}$  fields and found small yet significant covariances when North Atlantic SST leads winter  $Z_{500}$  by several months.

However, such multivariate descriptive methods identify co-varying patterns that only represent a fraction of the total variance ( $\sim 30\text{--}40\%$  in the  $Z_{500}$  case) and do not allow inferences to be tested about which are the most important factors in determining European climate. Other unexplained fractions of the variance might also be important for explaining variations in climate over Europe.

To quantify the relative importance of the co-varying SLP and SST factors, it is necessary to move away from descriptive methods and develop a model that specifies European temperature as a function of both those factors. In this study, we have developed a general linear multiple regression model that uses North Atlantic SLP and North Atlantic SST as explanatory variables to specify contemporaneous variations in European winter temperature. By using the wording ‘specify’ we emphasize that it is not our main concern to predict European temperature into the future but to try and quantify which parts of the contemporaneous SST and SLP fields contain the relevant information. In contrast to previous descriptive approaches, this allows us to test quantitatively the importance of different factors by including/removing them from the model. It also allows us to unravel direct effects of SST from indirect effects due to SST being correlated with SLP.

The rest of this paper is structured as follows. Section 2 introduces the general linear model; Section 3 explains the data sets used in this study; Section 4 presents model experiments and results; Section 5 investigates longer-term variations; and Section 6 concludes the article.

## 2. THE GENERAL LINEAR MODEL

One of the simplest assumptions for explaining European temperatures is that SLP and SST effects are additive; for example, a milder European winter can be due to the cumulative effect of stronger westerlies and warmer North Atlantic SSTs. This can be formulated mathematically in terms of the ‘general linear model’:

$$\mathbf{z} = \mathbf{X}\boldsymbol{\alpha} + \mathbf{Y}\boldsymbol{\beta} + \mathbf{e} \quad (1)$$

where  $\mathbf{z}$  is an  $(n \times 1)$  vector, containing the centred anomalies of  $n$  wintertime means of European temperature.  $\mathbf{z}$  is usually termed ‘response variable’ or — in older textbooks — ‘dependent variable’. In general, the ‘explanatory factors’  $\mathbf{X} = [x_1 x_2 \dots x_p]$  and  $\mathbf{Y} = [y_1 y_2 \dots y_q]$  are  $(n \times p)$  and  $(n \times q)$  data matrices that contain the centred time series (of length  $n$ ) of SLP ( $\mathbf{X}$ ) and SST ( $\mathbf{Y}$ ) of dimension  $p$  and  $q$  respectively.  $\mathbf{X}$  and  $\mathbf{Y}$  may represent observations at individual grid points, but may also be principal components (see Section 3). The model parameters,  $\boldsymbol{\alpha}$  and  $\boldsymbol{\beta}$ , are vectors of length  $p$  and  $q$  respectively and quantify the importance of the explanatory factors  $\mathbf{X}$  and  $\mathbf{Y}$ . The unknown random effects are represented by  $\mathbf{e}$ , which is an  $(n \times 1)$  vector of independent normally (Gaussian<sup>1</sup>) distributed noise.

The method of ordinary least squares is used to estimate the parameters  $\alpha$  and  $\beta$  (Draper and Smith, 1998) by minimizing the sum of squared errors (SSE):

$$\text{SSE} = \mathbf{e}'\mathbf{e} = (\mathbf{z} - \mathbf{X}\alpha - \mathbf{Y}\beta)'(\mathbf{z} - \mathbf{X}\alpha - \mathbf{Y}\beta) \quad (2)$$

where the prime symbol denotes the vector or matrix transpose.

The total sum of squares  $\text{TSS} = (1/n)\mathbf{z}'\mathbf{z}$  can be decomposed into  $\text{TSS} = \text{SSR} + \text{SSE}$ , where  $\text{SSR} = (\mathbf{X}\alpha + \mathbf{Y}\beta)'(\mathbf{X}\alpha + \mathbf{Y}\beta)$  is the part explained by the factors  $X$  and  $Y$  and SSE is the unexplained part.

The coefficient of multiple determination  $R^2 = \text{SSR}/\text{TSS}$  measures the fraction of variance in the response variable that can be explained by variations in the explanatory factors. However, a high value of  $R^2$  does not imply that a particular model is appropriate. In fitting this model, the assumption is made that the noise  $\mathbf{e}$  be a realization of an independent stochastic process with normal distribution, i.e. independent of the response variable and the explanatory variables. Examination of the validity of these assumptions about the error statistics is also necessary to make sure that the model is a good fit. We do not include a constant intercept  $\gamma$  in the model, because the model is based on centred anomalies of  $\mathbf{z}$ ,  $\mathbf{X}$  and  $\mathbf{Y}$ .

The estimation yields best estimates and confidence intervals for each of the parameters  $\alpha_i$  ( $i = 1, \dots, p$ ) and  $\beta_j$  ( $j = 1, \dots, q$ ). These parameter estimates will be used in the analysis, and can be tested for significance (e.g.  $\alpha_i = 0$ ).

### 3. DATA USED IN THIS STUDY

This study has used monthly mean central England temperature (CET) time series (Manley, 1974), monthly mean gridded SLP (Trenberth and Paolino, 1980), and monthly mean gridded SST from the COADS (Woodruff *et al.*, 1987)<sup>2</sup> from 1899 to 1993. For each of those data sets, centred anomalies have been derived by subtracting climatological means from monthly means for each calendar month. From these, winter means were obtained by averaging monthly anomalies over December, January, and February (DJF). Figure 1 shows the time evolution of CET DJF from 1900 to 1993. Its standard deviation is estimated as 1.23 K. The correlation of this time series with averaged temperatures for northwestern Europe (25–85°N, 25°W–45°E), derived from the Jones data set (Jones *et al.*, 1986) (not shown) is 0.67 (highly significant). Correlations with time series describing mean temperature in individual western European countries used in a study by Blender *et al.* (in press) are 0.88 (France), 0.61 (Germany). Further, analysis of surface temperatures (Stephenson *et al.*, 2000) shows that the main variance over Europe/North Atlantic is very well correlated between Britain, Scandinavia, and the northern regions of France, the Netherlands, Germany and Poland. So we consider CET as a proxy for temperature evolution over northwestern Europe.

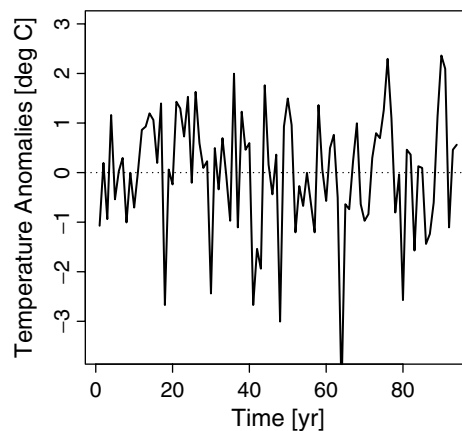


Figure 1. Wintertime (DJF) anomalies of CET (centigrade). DJF 1900 encompasses December 1899 and January, February 1900

Because of the large amount of grid points ( $p = 160$ ,  $q = 2295$ ), the sizes of the matrices SST and SLP present a huge estimation problem. To reduce the dimensionality of this problem, principal component analysis (PCA) is performed on the gridded SLP and SST data (Bretherton *et al.*, 1992), and only the first  $m = 5$  (or  $m = 10$ ) leading principal components (PCs) of each field are used in the regression model:

$$\text{SLP}(t, \lambda, \theta) \approx \sum_{k=1}^m X_k(t) e_k^X(\lambda, \theta) \quad (3)$$

$$\text{SST}(t, \lambda, \theta) \approx \sum_{k=1}^m Y_k(t) e_k^Y(\lambda, \theta) \quad (4)$$

where  $X_k$  and  $Y_k$  are the principal components for SLP and SST respectively.  $e_k(\lambda, \theta)$  are the spatial patterns associated with the PCs, and referred to as empirical orthogonal functions (EOFs).  $\lambda$  and  $\theta$  represent latitude and longitude.

The region for the PCA analysis of SLP (25–80°N, 70–0°W) was chosen in order to minimize the overlap of the region of the explanatory factors (SLP) and the response variable (CET). The analysis yields a leading north–south dipole SLP pattern with one centre of action to the southeast of Greenland and the second centre to the South of the Azores (Figure 2(a)). This NAO pattern, e.g. as identified by Wallace and Gutzler (1981) (their Figures 8 and 9), accounts for 44% of the unfiltered total variance in SLP. Since this dipole structure appears in many individual DJF anomaly maps (not shown), it represents a preferred mode of variation in the atmosphere over the North Atlantic.

The second SLP EOF (Figure 2(b)) describes a monopole over the North Atlantic centred on (50°N, 20°W), and accounts for 25% of the total variance. The first five (ten) EOFs represent 90% (97%) of the total variance of interannual variations in DJF means over the North Atlantic domain.

PCA analysis of SST has been applied to a sector encompassing the Northern Hemisphere from 100°W to 0°W, where data are available. The first EOF (Figure 2(f)) represents a basinwide (in fact global) centennial warming trend with highest amplitudes in the Gulf Stream region. The second EOF (Figure 2(g)) is the well-known SST tripole pattern described by Deser and Blackmon (1993). The explained variances are 21% and 8% respectively. The explained total variance of the first five (ten) EOFs (42% (52%)) is much less than for SLP, due to the small spatial scale of SST anomalies.

The standardized PC time series  $X_k$  and  $Y_k$  (not shown) are referred to as SLP1, SLP2, ... and SST1, SST2, ... These  $2 * m$  reduced variables are used as model factors in the following regression analysis. They result in an  $(n \times p) = (94 \times 5)$ -dimensional matrix  $X = (\text{SLP1}, \text{SLP2}, \dots, \text{SLP5})$  and  $(n \times q) = (94 \times 5)$ -dimensional matrix  $Y = (\text{SST1}, \text{SST2}, \dots, \text{SST5})$  in the 5PC case.

In fact, we perform the estimation using both five and ten PCs for each field respectively. The main results are already captured by the 5PC case, so, for clarity of representation, we restrict this to results of the latter case, unless mentioned otherwise.

#### 4. MODEL EXPERIMENTS AND RESULTS

The results of model fits on the interannual time scale are summarized in Table I. In the following, we discuss various models using oceanic factors only (Section 4.1), atmospheric factors only (Section 4.2), and then using all available factors (Section 4.3).

##### 4.1. Ocean-only model

To specify CET from the knowledge of SST fields, we set  $\alpha = 0$  in Equation (1) and estimate  $\hat{\beta}_j$ . This can only explain  $R^2 = 0.16$  of the CET variance (10 SST factors:  $R^2 = 0.2$ ). Figure 3(a1) shows the fitted time series and the observations used in the estimate. The fitted values are not a good representation of the observed values; in particular, the extremes are not captured at all. The standard deviation of the noise

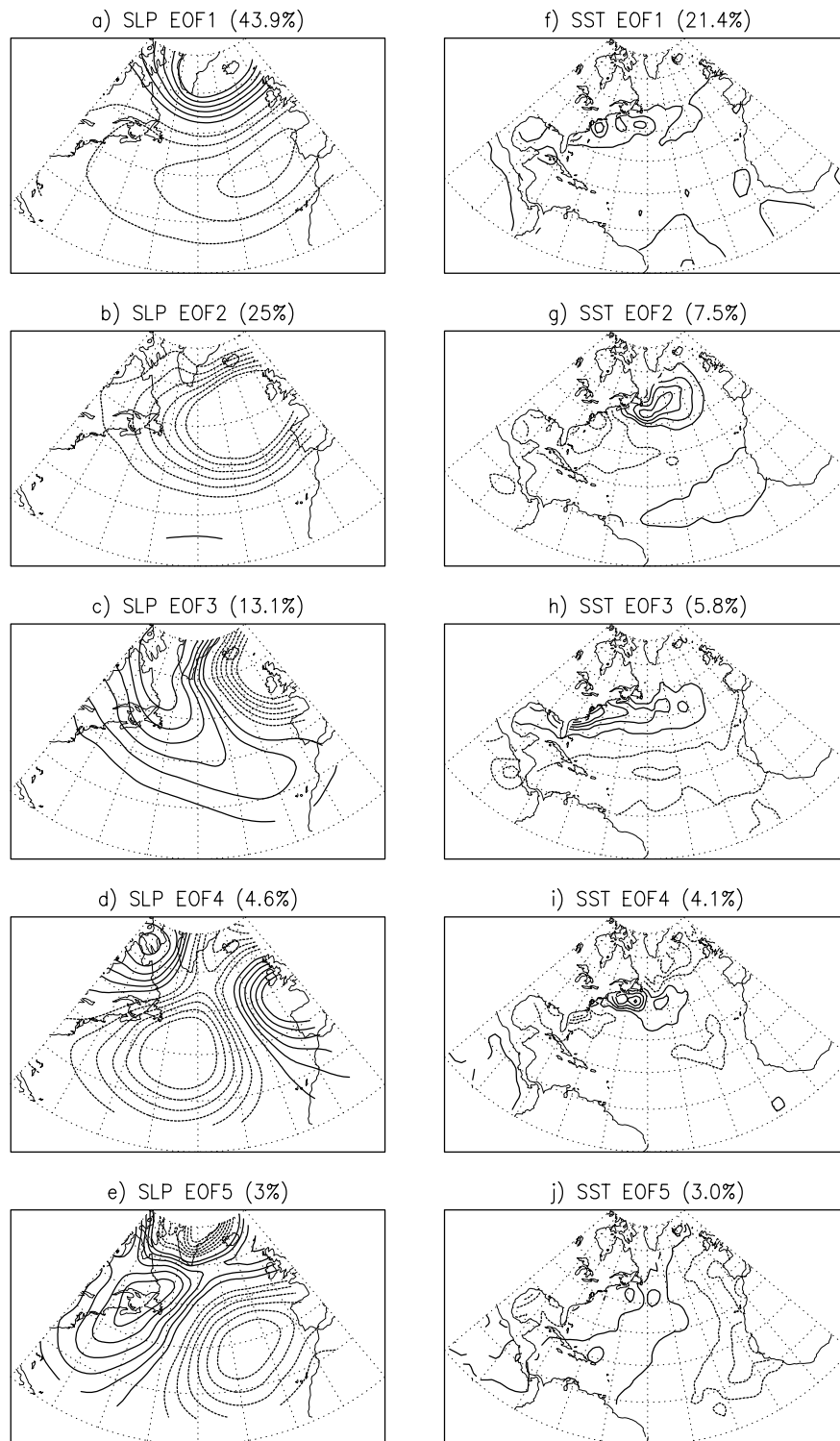


Figure 2. First five EOFs of wintertime (DJF) SLP fields (a)–(e) in the area 25–70°N, 80–5°W (contour interval: 2 hPa) and SST fields (f)–(j) (contour interval: 0.2 K). The corresponding PCs are normalized, so the values in the EOFs represent on standard deviation. The percentage of variance accounted for is shown at the top of each figure

Table I. Diagnostics of regression models for different models. The columns  $\alpha_i$  and  $\beta_j$  give the estimates of the respective parameters in each model. The first part of the table shows results from ocean-only models, the second part from atmosphere-only models and in the third part the models of combined SST and SLP factors are shown. The last row but one in the ocean–atmosphere section gives results from the bivariate model (See text for explanation, Section 4.3.2; the values here are given for a fit of non-scaled CET); the last row gives results for the optimal model. (See text for explanation; Section 4.3.3). Parameter estimates marked with an asterisk are significantly different from zero at the 1% level of significance

Atmosphere factors					Ocean factors					$R^2$ (%)	$\hat{\sigma}_E$
$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$		
					−0.14	−0.36*	0.19	0.0	−0.20	16	1.15
						−0.36*				9	1.17
−0.84*	0.23*	0.24*	0.43*	−0.06						63	0.75
−0.81*										44	0.91
−0.90*	0.20	0.30*	0.39*	−0.09	0.	0.02	−0.02	−0.22*	−0.14	68	0.73
−0.79*						−0.07				44	0.91
−0.87*	0.20*	0.29*	0.39*					−0.21*	−0.13	67	0.72

terms,  $1.15^\circ\text{C}$ , is of the order of the standard deviation of the CET itself. The scatter plot of the standardized residuals in Figure 3(a2) shows that outliers in the range of two to three standard deviations occur.

Ward and Folland (1991) have shown that variance inflation, where the model in Equation (1) is modified to  $\mathbf{z} = \mathbf{z}/r$ , where  $r = r(\text{CET}, \mathbf{z})$  is the correlation between the explanatory and the response variable, can result in a better presentation of extreme values by the model. In our test, this method did not prove to be substantially superior to the model in Equation (1).

To check the assumption of Gaussian distribution in the noise or error terms, the empirical quantiles of their distribution are plotted against the theoretical quantiles of the standard normal distribution. The quantile–quantile plot (Figure 3(a3)) shows a cosine-shaped deviation of the noise terms from the normal distribution. This suggests that the SST PCs alone do not provide a good model of CETs.

As all the standardized PCs have a variance of unity, the magnitudes of the estimated parameters  $\hat{\beta}_j$  give an indication as to which are contributing most to the regression relationship. The Student- $t$  distributed statistics,  $t_j = \hat{\beta}_j / \hat{\sigma}_{\beta_j} \sqrt{S_{Y_j Y_j}}$  ( $j = 1, \dots, 5$ ), where  $S_{Y_j Y_j}$  is the sum of squared variance of  $Y_j$ , can be used to test whether parameters are significantly different from zero.

The only SST PC that contributes significantly (at the 99% confidence level) is SST2 (see Table I), the tripole pattern, which has been identified in various model studies as correlated with wintertime temperature over Europe (e.g. Rodwell *et al.*, 1999).

In order to test the stability of these estimates, the parameters  $\hat{\beta}_j$  are re-estimated for the two time periods 1900–40 and 1945–93. The reason for this particular choice lies in the rapid variation of PC SST1 at the beginning of the 1940s (not shown). This basinwide warming shows up in all seasons as the first EOF, but the increase appears to be less rapid in the seasons March–May (MAM), June–August (JJA) and September–October (SON) (not shown). Results (Table II) show that the skill (defined by  $R^2$ ) of the model stems primarily from the first half of the century. The SSTs have no explanatory skill in the latter period.

These estimates suggest that North Atlantic SST fields alone contain very little information for specifying temperatures over northwestern Europe. However, there is some evidence that SSTs leading CET by several months may provide some predictive information (Czaja and Frankignoul, 2002; Rodwell and Folland, 2002). Using the preceding SST PCs in SON gives an  $R^2$  value considerably less than for contemporaneous winter SSTs (Table III). Using preceding JJA SSTs improves the specification of CET again, and with MAM SSTs the  $R^2$  value is of the same order as with DJF SSTs. The PC mostly accounting for the information in season MAM is associated with EOF2, a pattern very similar to the tripole of the DJF SST (not shown). These results are independent of the number of PCs (five or ten) chosen and the time period used. They are consistent with results presented in Czaja and Frankignoul (2002) and Rodwell and

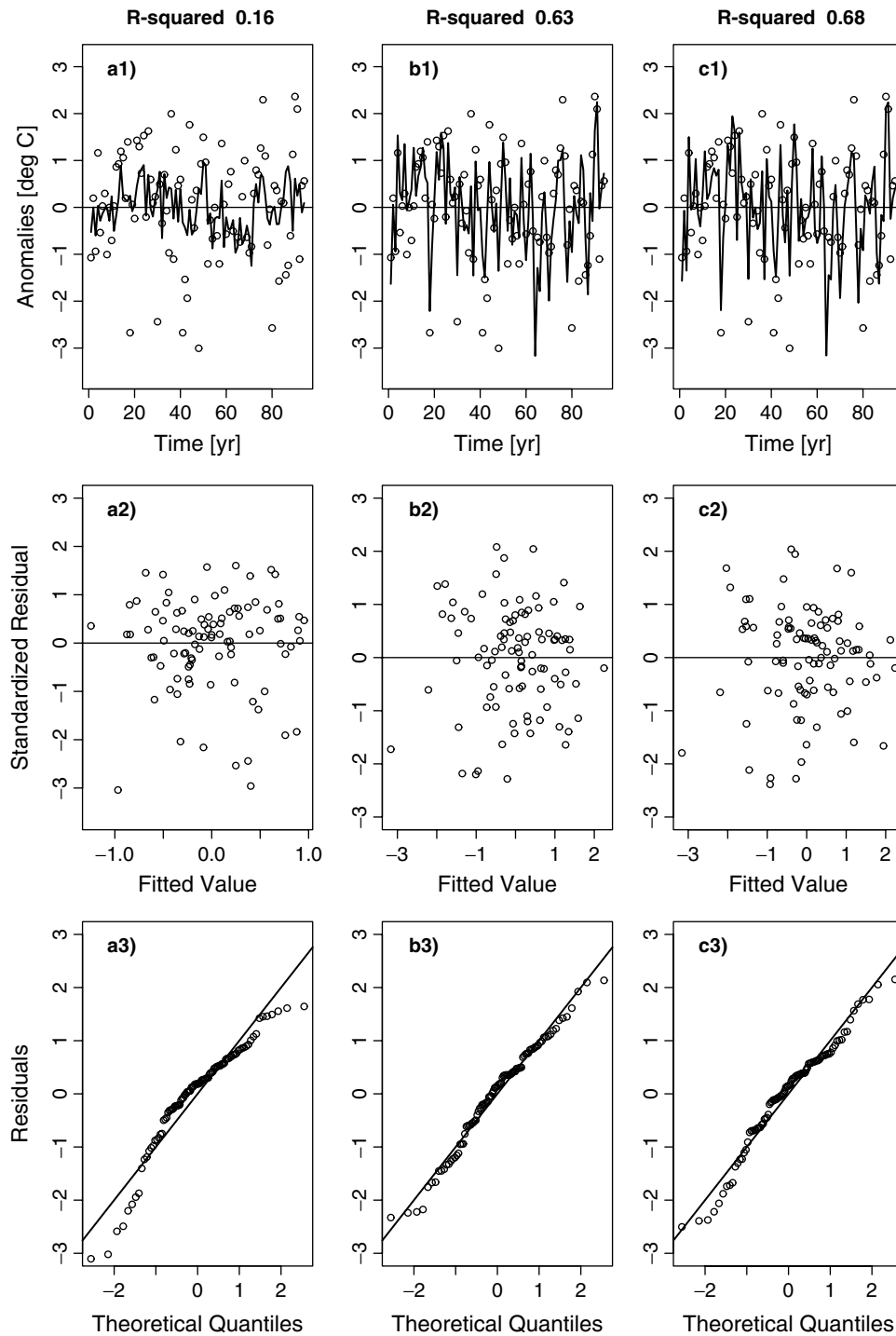


Figure 3. Three different models that fit CET: (a) only SST PCs are used as factors in the model; (b) SLP PCs only; (c) all SLP PCs and SST PCs. (a1), (b1) and (c1) show the respective fitted values (solid line) and the observations (CET) (open circles). Units are in deg.C. (a2), (b2) and (c2) show the standardized residuals against the fitted values. (a3), (b3) and (c3) show the ordered standardized residuals plotted against the  $[(i - 0.5)/n]$ -quantiles of the standard normal distribution

Table II. Diagnostics of regression models as in Table I for different time periods. The first part of the table shows results from ocean-only models, the second part from atmosphere-only models and in the third part the models of combined SST and SLP factors are shown. Parameter estimates marked with an asterisk are significantly different from zero at the 1% level of significance

Atmosphere factors					Ocean factors					Period <sup>a</sup>	$R^2(\%)$	$\hat{\sigma}_E$
$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$			
					-0.14	-0.36*	0.19	0.0	-0.20	c	16	1.15
					-0.05	-0.48	0.19	0.04	-0.22	f	22	1.06
					0.03	-0.31	0.16	0.02	-0.24	s	12	1.28
-0.84*	0.23*	0.24*	0.43*	-0.06						c	63	0.75
-0.75*	0.30*	0.19	0.36*	0.00						f	62	0.74
-0.87*	0.17	0.25	0.48*	-0.11						s	65	0.80
-0.90*	0.20	0.30*	0.39*	-0.09	0.0	0.02	-0.02	-0.22*	-0.14	c	68	0.73
-0.78*	0.32	0.30	0.38*	-0.11	0.16	0.04	0.17	-0.29	0.0	f	70	0.69
-1.08*	0.12	0.39*	0.49*	-0.09	-0.32	0.13	-0.09	-0.20	-0.03	s	73	0.75

<sup>a</sup> Period 'c' stands for 1900–94 (these are results already presented in Table I), 'f' for 1900–40, and 's' for 1945–94.

Table III. Diagnostics of regression models for predictive models. Two different predictands are used: DJF-SLP1 in the upper part of the table, DJF-CET in the lower part. For each model, five (ten) factors are used: SST factors (column 3), SLP factors (column 4). The predictive lag increases from zero (DJF) to three (MAM) seasons (column 2)

Predictand	Season	$R^2$	
		For 10 (5) SST factors	For 10 (5) SLP factors
DJF-SLP1	DJF	0.45 (0.39)	1.00 (1.00)
DJF-SLP1	SON	0.21 (0.19)	0.14 (0.07)
DJF-SLP1	JJA	0.37 (0.25)	0.24 (0.17)
DJF-SLP1	MAM	0.53 (0.48)	0.25 (0.09)
DJF-CET	DJF	0.20 (0.16)	0.70 (0.63)
DJF-CET	SON	0.12 (0.05)	0.08 (0.03)
DJF-CET	JJA	0.16 (0.12)	0.08 (0.05)
DJF-CET	MAM	0.22 (0.16)	0.14 (0.10)

Folland (2002) that show some skill in predicting  $Z_{500}$  in winter from late spring SSTs, but lower skill for summer SSTs.

#### 4.2. Atmosphere-only model

The linear model with only SLP factors ( $\beta = 0$  in Equation (1)) has a skill  $R^2 = 0.63$  (Table I) (ten SLP factors: 0.70). Though there is a wide spread of observations around the fitted graph (Figure 3(b1)), this model does much better than the SST-only model. The residual mean error is reduced to two-thirds of that of the latter model. The residuals are uncorrelated in time (not shown) and the comparison of its quantiles with those of the standard normal distribution is very close to a straight line, suggesting that the assumption of a normal distribution of these errors is valid (Figure 3(b3)).

An important question is which of the PCs are most important in the fit of the model. The single most important factor is SLP1, associated with the NAO pattern (compare Table I). SLP4 also plays an important role. When the associated EOF4 is in a positive phase its pattern suggests that relatively warm air from the African continent is transported around a high-pressure zone into the British Isles. Parameter estimates for all factors apart from SLP5 are all significantly different from zero at the 99% confidence level.

A model consisting of SLP1 as the only factor ( $\hat{\alpha}_1 = -0.81$ ) has a skill of 0.44, underlining the importance of this leading atmospheric mode for determining winter temperatures over Europe. However, modes other than the dominating NAO mode are also responsible for the actual manifestation of the climate over northwestern Europe. They increase the skill of the model by another 20%.

If we compare the values to those of Section 4.1, we find that the atmospheric SLP field is a considerably better specifier of CET on the interannual time scale than the oceanic field. These results also support the idea that variations in the atmosphere over the North Atlantic on the interannual time scale are more determined by internal atmospheric dynamics than by direct forcing from SSTs.

#### 4.3. Atmosphere and ocean model

*4.3.1. All predictors.* Using SST and SLP PCs from the whole 94 year period as factors gives a model with essentially the same  $R^2$  value and magnitude in the error terms as the atmosphere-only model (Table I). Figure 3(c1) shows the fitted time series and the observations used in the estimate. The visual impression is that the fit by the atmosphere–ocean model is only slightly improved compared with the fit by the atmosphere model. Again, to test the stability of this estimate the parameters  $\hat{\alpha}_i$  and  $\hat{\beta}_j$  are re-estimated for the two time periods 1900–40 and 1945–93 (Table II). It turns out that (as in the case of the atmosphere-only model) the fit is essentially insensitive to the chosen period. However, the errors are larger for the second half of the century. In summary, these results suggest that there is hardly any additional skill to be gained from using SST as well as SLP information.

This is confirmed by the analysis of the contributing factors. For both time periods the two most important factors are SLP1 and SLP4. SST factors are hardly significant and contribute very little, consistent with the minimal increase in the  $R^2$  values.

The fact that the SST tripole factor plays such a minor role in the regression model is, at first, surprising, as it was identified as the most important factor in the ocean-only model. The reason for this is that SST2 is significantly correlated with the SLP NAO factor (mutual correlation of 0.37), and so only one of the two factors remains important in the combined regression model.

We cross-validated our results by removing one year from the database, estimating the model parameters with the remaining years and then using the resulting model to predict CET of the omitted year. Going through all the years in this way we obtain a time series of predicted CET values that we can correlate with the observations of CET. The correlation values are  $r = 0.27$  for SST-only,  $r = 0.76$  for SLP only and  $r = 0.76$  for the model that includes both SST and SLP PCs. So, the  $R^2$  values presented give a good indication of the usefulness of the estimated models.

The inclusion of an  $XY$  in the general linear model of Equation (1) was not found to give estimates of  $\alpha$  and  $\beta$  significantly different to those quoted in Table I. This suggests that the atmosphere and ocean effects on European temperatures can be treated as purely additive, as one might expect for small effects such as those from the North Atlantic SSTs.

*4.3.2. A simple bivariate coupled example: the NAO–SST tripole model.* As with many multivariate methods, a good understanding can be obtained by considering the *bivariate* case of Equation (1) with two co-varying explanatory variables; for example,  $x_1$  (the NAO SLP pattern) and  $y_2$  (the SST tripole pattern)<sup>3</sup>.

To make matters even simpler, consider the unit scaled case in which  $x_1$  and  $y_2$  have been standardized (mean removed and divided by standard deviation) before performing the regression. By solving the two normal equations, the best estimates for the parameters can easily be shown to be given by

$$\alpha_1 = \frac{r_{1z} - r_{12}r_{2z}}{1 - r_{12}^2} \quad (5)$$

$$\beta_2 = \frac{r_{2z} - r_{12}r_{1z}}{1 - r_{12}^2} \quad (6)$$

where  $r_{12} = r(x_1, y_2) = 0.37$  is the mutual correlation between the two explanatory variables (NAO and the SST tripole),  $r_{1z} = r(x_1, z) = -0.66$  is the correlation between  $x_1$  (NAO) and  $z$  (CET), and  $r_{2z} =$

$r(y_2, z) = -0.30$  is the correlation between  $y_2$  (SST tripole) and  $z$ . By rewriting the correlations in terms of the parameters

$$r_{1z} = \alpha_1 + \beta_2 r_{12} \quad (7)$$

$$r_{2z} = \beta_2 + \alpha_1 r_{12} \quad (8)$$

it can be seen that the correlations with the response consist of the sum of two parts: a ‘direct effect’ (e.g.  $\alpha_1$ ) and an ‘indirect effect’ (e.g.  $\beta_2 r_{12}$ ) mediated by mutual correlation between the explanatory variables. Unlike descriptive correlation analysis, multiple regression is model based and so allows one to determine the relative contribution from these two parts. Progress can then be made in discriminating important direct factors from factors that are only indirectly correlated with the response. For the NAO–tripole example, the correlation of  $-0.66$  between NAO and CET is the sum of  $-0.64$  (direct effect) plus  $-0.02$  (indirect effect), whereas the correlation of  $-0.30$  between the SST tripole and CET is the sum of  $-0.06$  (direct effect) plus  $-0.24$  (indirect effect). In other words, the SST tripole is predominantly correlated with CET indirectly via the tripole’s correlation with NAO.

*4.3.3. Optimal choice of predictors.* Having determined that there is a significant regression relationship between the response variable  $\mathbf{z}$  and all explanatory variables and also that at least some of the SSTs are not important in this relationship, we want to find the most reductionist model having as few explanatory variables as possible and at the same time as high an  $R^2$  value as possible. There are a number of ways to determine such an ‘optimal’ model, and the method we use here is the stepwise forward inclusion and backward elimination (e.g. see section 8.5 in von Storch and Zwiers (2000)). It is worth mentioning that, having found an optimal model, this need not be unique, as we try to optimize two parameters and have 10 (20) degrees of freedom.

Figure 4 shows the residual mean squared  $RMS_k = SSE/(n - k)$  (Figure 4(e)) and the  $R_k^2$  (Figure 4(f)) as a function of the number  $k$  of factors included in the model. For a clearer presentation, the 20PC case is illustrated. The  $R_k^2$  curve shows a region where the increase in  $R_k^2$  becomes very small; in the same area, the  $RMS_k$  graph exhibits a minimum where the decrease in SSE by inclusion of more factors does not compensate for the loss of degrees of freedom: typically, this is the cut-off criterion for the inclusion of model factors.

The optimal model determined by the stepwise method includes nine factors in the 20PC case and six factors in the 10PC case. For the latter, they are SLP1, SLP4, SLP3, SST4, SLP2, and SST5, in this order. We see again that SST2 does not contain useful information in addition to the SLP PCs. The  $R^2$  value for this model is 0.67 (Table I), which is marginally smaller than for the full model, and the residual error is, in fact, smaller than for the full model.

The explanatory variables of this optimal model are almost independent of each other. Apart from the diagonal elements of the correlation matrix, only the relationship  $r(\text{SLP1}, \text{SST4}) = -0.25$  is significant at the 99% confidence level. All other correlations are less significant and, in fact, most of them are close to zero. Multicollinearity in the factors can result in instability of the estimates. To investigate this problem, the condition number of the matrix consisting of the six factors of the optimal model as its columns, defined as the ratio between the largest and the smallest singular value of this matrix, is computed. The condition number of 1.46 indicates that the parameter estimates are not very sensitive to small changes in the data. This is because SLP1 is much more important than SST4.

The optimal model for explaining winter CET can be written as

$$\hat{z} = \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \hat{\alpha}_3 x_3 + \hat{\alpha}_4 x_4 + \hat{\beta}_4 x_4 + \hat{\beta}_5 x_5 \quad (9)$$

where  $\hat{\alpha}_1 = -0.87$ ,  $\hat{\alpha}_2 = 0.2$ ,  $\hat{\alpha}_3 = 0.29$ ,  $\hat{\alpha}_4 = 0.39$ ,  $\hat{\beta}_4 = -0.21$ ,  $\hat{\beta}_5 = -0.13$  (compare with Table I). The corresponding spatial patterns  $O_X(\lambda, \theta)$  and  $O_Y(\lambda, \theta)$  can be reconstructed by using the estimated parameters  $\hat{\alpha}_k$  for SLP( $X$ ) and  $\hat{\beta}_k$  for SST ( $Y$ ):

$$O_X(\lambda, \theta) = \sum_{k=1-4} \hat{\alpha}_k e_k^X(\lambda, \theta) \quad (10)$$

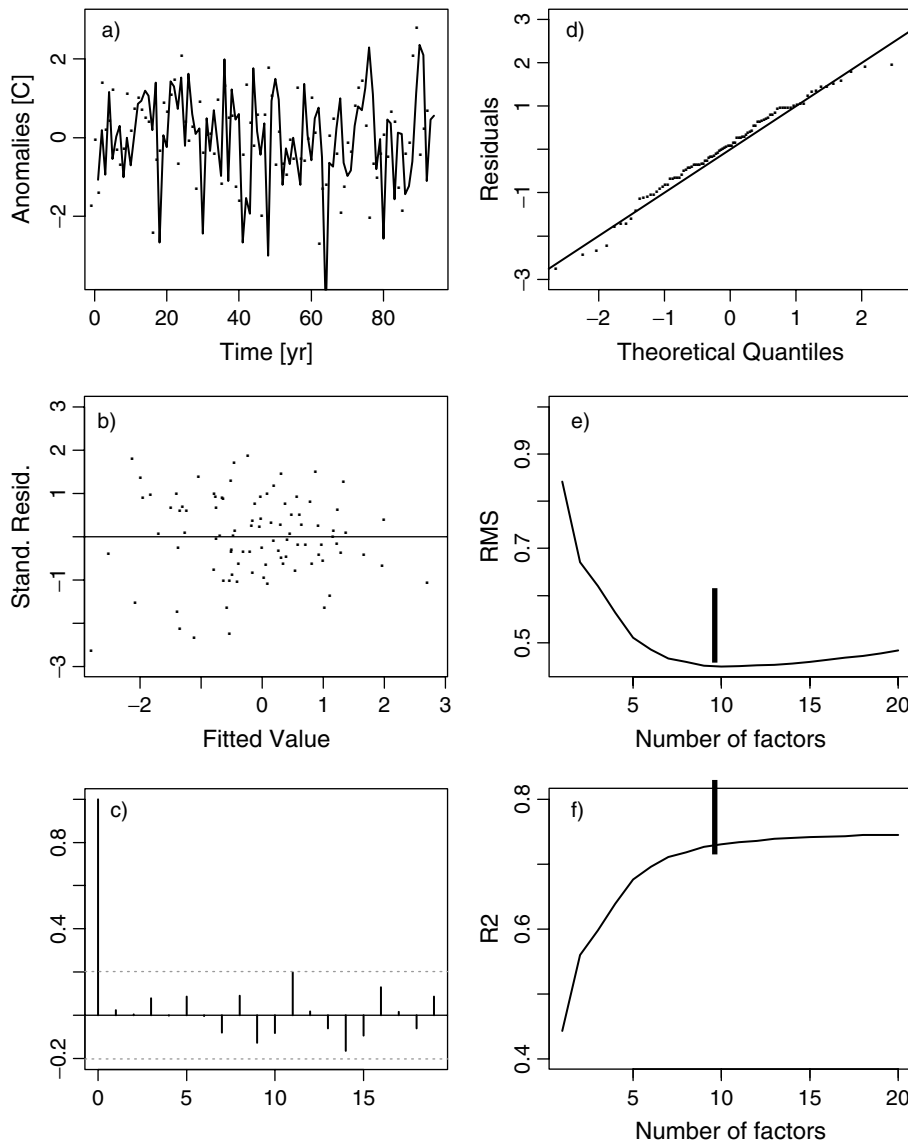


Figure 4. Fit and diagnostics of 20-PC ‘optimal model’: (a) fitted values (solid line) and CET (dots), (b) standardized residuals, (c) autocorrelation function of residuals, (e) residual mean squared  $RMS_k$  and (f)  $R_k^2$  as function of numbers of factors included. The cutoff for the optimal model is indicated by the black bar in (e) and (f)

$$O_Y(\lambda, \theta) = \sum_{k=4,5} \hat{\beta}_k e_k^Y(\lambda, \theta) \tag{11}$$

where  $e_k(\lambda, \theta)$  is the  $k$ th EOF of either  $X$  or  $Y$ . The ‘optimal SLP pattern’  $O_X$  (Figure 5(a)) constructed in this way is reminiscent of the NAO pattern (EOF1, Figure 2(a)), but is slightly shifted to the east. When CET exhibits a positive anomaly, the isobars run parallel and are tightly packed west of England. Physically, this is plausible, as, in this situation, mean westerly winds pass straight over the British Isles, carrying with them the relatively warm air that can give rise to a positive anomaly in CET.

The reconstructed SST-field  $O_Y$  (Figure 5(b)) has a large-scale structure, consisting of negative anomalies along the Gulf Stream where it has left the North American coast, and in the central North Atlantic between 30 and 50°N. These negative anomalies are surrounded by positive anomalies in the entire basin, with highest

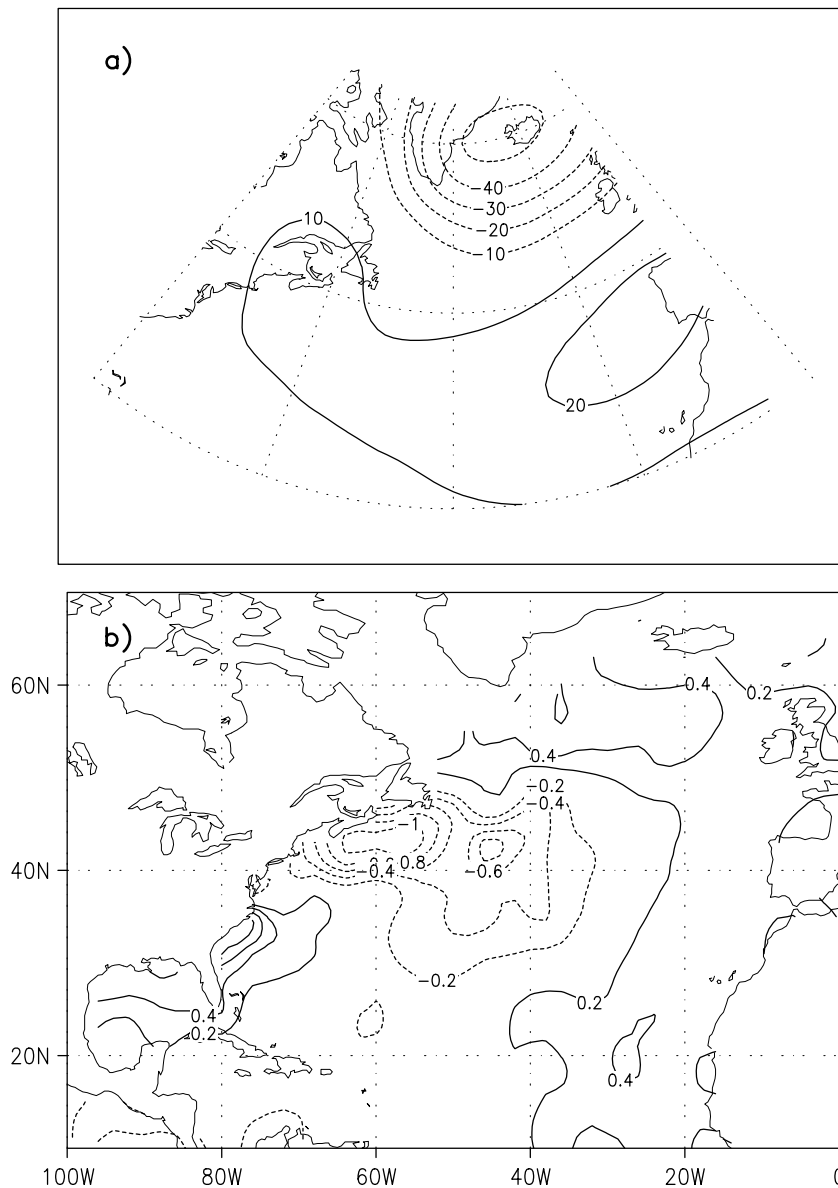


Figure 5. Reconstructed spatial fields for optimal model: (a) SLP (contour interval: 10 hPa); (b) SST (contour interval: 0.2 K) (see text for details)

amplitudes in the western part. The structure is reminiscent of the SST structure, discussed by Ratcliffe and Murray (1970), who argue that this can be used as a predictor of pressure over Europe on the monthly time scale. They show that colder (warmer) than usual ocean surfaces to the south of Newfoundland can be associated with blocked (more progressive synoptic) atmospheric patterns 1 month later. However, we are dealing with quasi-contemporaneous fields (seasonal means), whereas Ratcliffe and Murray (1970) considered monthly fields lagged in time by 1 or 2 months.

To test the results of Ratcliffe and Murray (1970), we re-did all our analysis by using the SST of the preceding seasonal mean SON instead of the DJF SSTs, but found no evidence that there is any more information or predictive skill contained in those preceding fields, as has already been discussed in the ocean-only case in Section 4.1.

Another explanation for  $O_Y$  would come from the fact that the reconstructed field shows warm (cold) anomalies to the west of the British Isles. These could result in positive (negative) anomalies of latent heat transfer that would warm (cool) the air that is carried over Britain by the atmospheric circulation, and hence increase surface temperatures there.

*4.3.4. Predictive models.* In the preceding sections it was demonstrated that the effect of North Atlantic SSTs onto winter CET is predominantly *indirect*, via the correlation with SLP–NAO. Therefore, it is of interest to ask if there is a quantifiable influence of SST (contemporaneous and preceding) onto the SLP1 factor (NAO), and which patterns are responsible. The results are summarized in Table III.

Contemporaneous SSTs provide a model for SLP1 (NAO pattern) with an  $R^2$  value of 0.39 (10PC case: 0.45). The most important factors are SST2 (tripole) and SST3, a dipolar pattern with the trough at 30°N. SSTs of the preceding autumn (SON) are only moderately useful ( $R^2 = 0.19/(0.21)$ ), greater values are obtained for summer ( $R^2 = 0.25/(0.37)$ ) and spring ( $R^2 = 0.48/(0.53)$ ) SSTs, the latter showing a more appropriate model than the contemporaneous SSTs. Here, the most important factors are SST3, SST1 and SST2 and the combined pattern is very similar to the winter tripole.

In contrast to the SSTs, the SLPs of all seasons prove less useful as predictors of the winter NAO. This is consistent with the rapid time scale of atmospheric adjustment.

Similarly, SSTs of preceding seasons also prove more useful than SLPs in predictive models of DJF–CET (Table III), though the predictive skill is very low for both variables. The time evolution, the autumn gap of small skill and an increase towards preceding summer and spring in particular seems to be a characteristic of the winter predictability.

Where does the relative high predictive skill provided by springtime SSTs come from? The notion of persistent SST anomalies that carry the signal from spring to winter is obliterated by the low values in particular for autumn. A possible mechanism that can function as a messenger is the re-emergence of SST anomalies: SSTs at the end of winter are sequestered into the main thermocline of the ocean, capped from the contact with the atmosphere by the developing shallow summer mixed layer, and re-entrained into the upper ocean layer when the mixed layer deepens again in late autumn and winter (Alexander and Deser, 1995; Junge and Haine, 2001). Thus, in this context, spring SSTs are not important through their *immediate* influence onto the atmosphere, but rather in a statistical sense as a *foreboding* of the winter SSTs that can have an impact on the winter atmosphere.

## 5. LONG-TERM VARIABILITY

In Section 4, it was shown that knowledge of contemporaneous SST conditions in the North Atlantic is not particularly crucial to deriving the simultaneous temperatures over England. The hope that these temperatures might be predictable on a multi-annual time scale, however, is based on the notions that (a) the evolution of SST is connected to the slowly varying and possibly predictable heat content of the ocean and (b) on longer time scales the SST has a quantifiable influence on the atmospheric circulation. We would, therefore, expect that SST becomes increasingly more important as a specifier as the considered time scale increases.

Figure 6 shows the  $R^2$  value as a function of the time scale for the three regression models: ocean-only, atmosphere-only and ocean–atmosphere. The time series of CET and the PCs are filtered prior to the estimation of the parameters by using a smoothing spline. In the 5PC case (Figure 6(a)), the atmosphere–ocean model yields a skill of about unity at a time scale of roughly 10 years. As expected, the skill to explain CET from the knowledge of SST increases with the time scale, but only at a time scale of about 20 years do the three models converge in their skill. It is interesting to note that the skill of the atmosphere-only model is always higher than that of the ocean-only model.

Considering the models with ten factors for each field (Figure 6(b)), we find considerably faster convergence of the  $R^2$  value in all three cases. This indicates, that higher order EOFs play a more prominent role on the longer multi-annual time scale. In particular, the considerably steeper rise of skill of the ocean-only model in the 10PC case, compared with the 5PC case, emphasizes that other patterns than the SST tripole

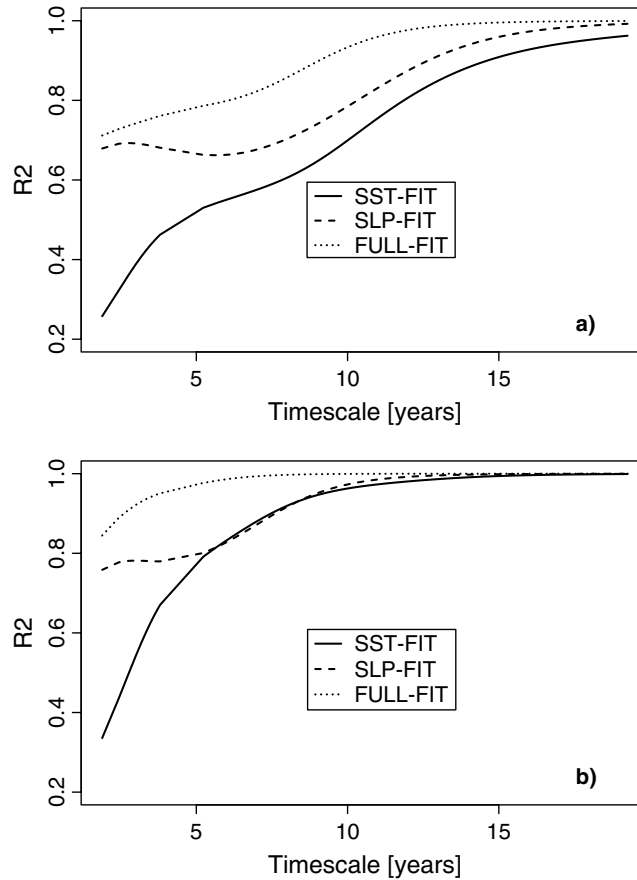


Figure 6.  $R^2$  as function of time scale used for the spline-fit: (a) models with five PCs for each field as factors; (b) models with ten PCs for each field as factors. Solid line: model consists of SST factors; dashed line: model consists of SLP factors; dotted line: model consists of SST and SLP factors

contain information that might be valuable for climate prediction. The fact that the  $R^2$  values of the ocean-only model and the atmosphere-only model are virtually identical from a time scale of 5 years onwards is particularly striking.

Figure 7 shows model fits of all three models, using ten PCs for each field, for a time scale of about 6 years, when the ocean-only and the atmosphere-only models provide approximately the same skill. Considering the fitted values against the observations (CET), there seem to be periods when the SST PCs yield the better fit (1920–30, 1940–50, 1970–80; Figure 7(a1)) and, alternately, when the SLP PCs yield a better model (1900–15, 1955–70, 1980–93; Figure 7(b1)). Using all PCs in the fit then consequently gives an  $R^2$  value close to unity (Table IV) and the fit (Figure 7(c1)) seems almost perfect. The misfit of the first two models is reflected in the wave-like deviation of the quantiles of the residuals from the straight line (Figure 7(a3) and (b3)). In comparison, the deviations for the full model are relatively small.

For the atmosphere-only fit, essentially the same PCs as in the interannual case determine the skill of the model, though the role of SLP1 is less dominant and SLP2 becomes almost as important. In the ocean–atmosphere model, however, some of the SST factors have gained a more important role than the SLP factors. Among them, SST2 is the second most important, confirming the more prominent role of the Atlantic tripole on the longer time scale. Among the SLP factors, the higher order PCs are also more important. This explains why the  $R^2$  value of the 20-factor model converges much more rapidly.

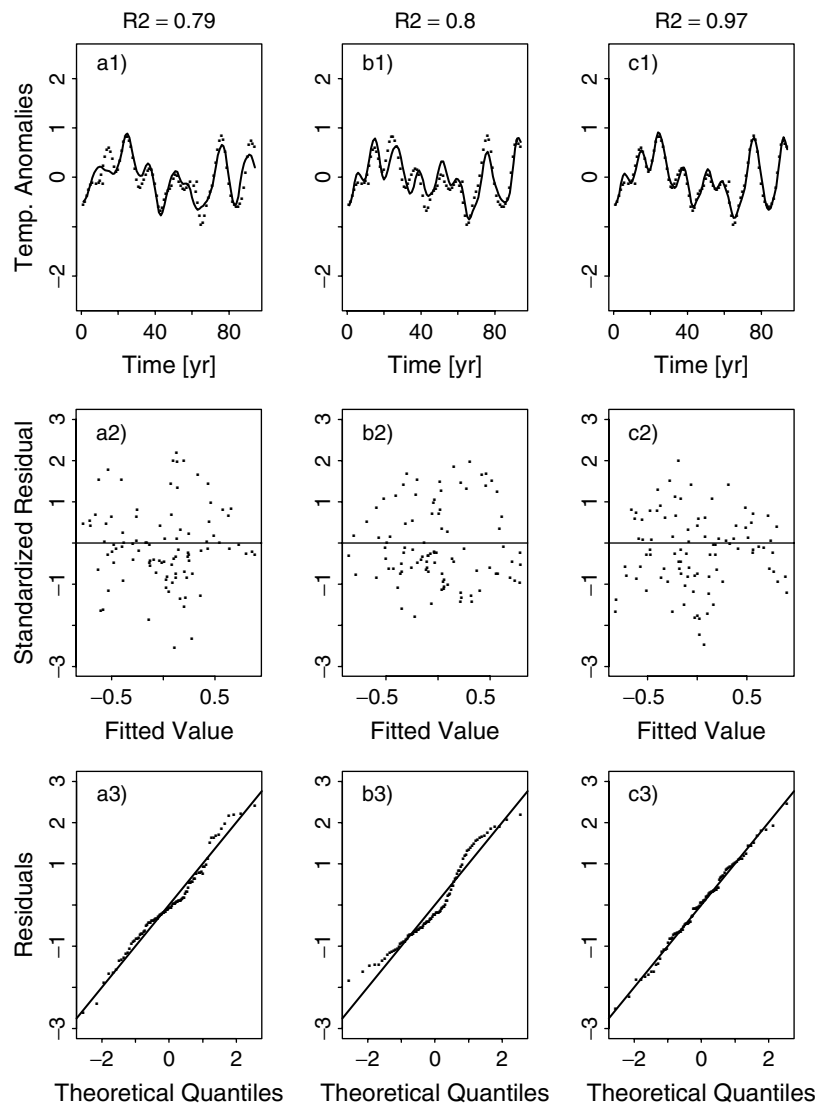


Figure 7. Three different models that fit CET: (a) only SST PCs are used as factors in the model; (b) SLP PCs only; (c) all SLP PCs and SST PCs. The time series of CET and the PC factors have been filtered with a smooth-spline and represent a smoothing time scale of about 6 years. (a1), (b1) and (c1) show the respective fitted values (solid line) and the observations (CET) (dotted line). Units are in centigrade (a2), (b2) and (c2) show the standardized residuals against the fitted values; (a3), (b3) and (c3) show the ordered standardized residuals plotted against the  $[(i - 0.5)/n]$ -quantiles of the standard normal distribution

## 6. CONCLUSIONS

This study has shown that mean SLP in the North Atlantic is capable of explaining a large fraction ( $R^2 = 0.63$ ) of the interannual variance in winter mean temperatures in central England. It is important to note that NAO alone ( $R^2 = 0.44$ ) is not a good model, and other factors of the SLP field play an important part. In contrast, the mean SSTs in the North Atlantic are only able to explain a small fraction of the variance ( $R^2 = 0.16$ ) of winter mean temperatures. Furthermore, most of the variance explained by winter mean SST is indirect via the correlation with winter mean SLP; in other words, the skill is mainly due to the SSTs acting as footprints (proxies) for the mean SLP variations — they contain little additional information to that contained in mean SLP.

Table IV. Diagnostics of regression models for different models at a time scale of 6.3 years. The columns  $\hat{\alpha}_i$  and  $\hat{\beta}_j$  give the estimates of the respective parameters in each model. Rows 1 contain results for ocean-only (compare Figure 7(a)) and atmosphere-only (compare Figure 7(b)) fits. The combination of rows 2 contains the estimates of the ocean–atmosphere model (compare Figure 7(c)). Parameter estimates marked with an asterisk are significantly different from zero at the 1% level of significance

	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$	$x_9$	$x_{10}$	$R^2(\%)$	$\hat{\sigma}_E$
<i>Ocean factors</i> ( $x = \hat{\beta}$ )												
1	−0.17*	−0.10*	0.27*	0.02	−0.17*	−0.07	−0.06	−0.07	−0.31*	0.07*	80	0.16
2	−0.19*	−0.28*	0.06	−0.17*	0.0	−0.30*	0.08*	0.01	−0.09	0.13*	98	0.05
<i>Atmosphere factors</i> ( $x = \hat{\alpha}$ )												
1	−0.36*	0.25*	0.08	0.03	0.0	−0.01	−0.16*	−0.04	−0.02	0.11*	81	0.16
2	−0.2*	0.18*	0.15*	−0.01	0.2*	−0.17*	−0.26*	0.21*	0.02	−0.11*	98	0.05

There is, however, a small yet significant direct effect from the SSTs not contained in mean SLP, which explains about  $R^2 = 0.05$  of the variance in CET. For it to influence European temperatures without being contained in the mean SLP field, the direct effect must somehow be mediated by something other than the time-mean atmospheric flow. The most likely suspect would be that it influences the variance (rather than the mean) of the atmospheric flow, e.g. the storm track transients. Alternatively, it could be mediated by non-diabatic processes, such as changes in humidity, that could then lead to more latent heat release over Europe. Intriguingly, the direct effect SST pattern closely resembles the Newfoundland pattern identified by Ratcliffe and Murray (1970).

Though SSTs are relatively weak specifiers of CET, they can be used more successfully to explain the NAO (SLP1) evolution. Even in predictive mode they provide useful information for DJF NAO three seasons ahead. The statistical gap of little predictive skill in autumn can be understood in terms of the re-emergence mechanism.

For longer time scales than interannual, the variance explained by SST factors increases, but the SLP factors still remain better specifiers than SST. In other words, on less than century time scales, variations in the North Atlantic Ocean related to phenomena such as the Gulf Stream do not have a large direct impact on winter temperatures in northwestern Europe. This generalizes the results found by Seager *et al.* (in press), who studied only the time-mean situation (not the variations). It should be noted, however, that the North Atlantic Ocean might still have an indirect effect by determining the mean atmospheric flow. Interestingly, this study shows that, on longer time scales, the NAO is no longer the dominant SLP pattern for determining CET — a blocking-like pattern becomes equally important. This has the implication for predictability of European climate that more than just NAO prediction will be required.

This study has used a general linear multiple regression model to diagnose and quantify the role of North Atlantic SLP and SST in determining European temperatures. It would be of interest in future work to apply the same methodology to output from long simulations of coupled ocean–atmosphere general circulation models. The general circulation models could also be used to perform mechanistic studies to test some of the results discovered in this study, e.g. the impact of the indirect effect SST pattern on both the time-mean SLP and the variance of the SLP.

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## NOTES

1. Although often referred to as the Gaussian distribution, in recognition of the work by K.F. Gauss in 1809, it was actually discovered earlier by De Moivre in 1714 to be a good approximation to the binomial distribution.
2. Available from <http://ingrid.lidgo.columbia.edu/SOURCES/COADS>.
3. All parameters except  $\alpha_1$  and  $\beta_2$  are set to zero.

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