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Pressure effects on past regional sea level trends and variability in the German Bight

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Abstract

The impact on a large-scale sea level pressure field to the regional mean sea level changes of the German Bight is analysed. A multiple linear regression together with an EOF analysis is used to describe the relationship between the sea level pressure and the regional mean sea level considering the time period 1924–2001. Both, the part of the variability and of the long term trend that can be associated with changes in the sea level pressure are investigated. Considering the whole time period, this regression explains 58% of the variance and 33% of the long term trend of the regional mean sea level. The index of agreement between the regression result and the observed time series is 0.82. As a proxy for large-scale mean sea level changes the mean sea level of the North East Atlantic is subsequently introduced as an additional predictor. This further improves the results. For that case the regression explains 74% of the variance and 87% of the linear trend. The index of agreement rises to 0.92. These results suggest that the sea level pressure mainly accounts for the inter-annual variability and parts of the long-term trend of regional mean sea level in the German Bight while large-scale sea level changes in the North East Atlantic account for another considerable fraction of the observed long-term trend. Sea level pressure effects and the mean sea level of the North East Atlantic provide thus significant contributions to regional sea level rise and variability. When future developments are considered their scenarios for their future long-term trends thus need to be comprised in order to provide reliable estimates of potential future long-term changes of mean sea level in the German Bight.

Keywords: German Bight, wind and pressure effects, regional mean sea level variability, regional mean sea level trends

1 Introduction

For the assessment of ongoing and potential future changes in mean sea level (MSL) research into the observed variability and its causes remains a central challenge. In principal there are two sources of data from which MSL changes and variability can be analysed. Satellite data from altimeters provide nearly global coverage but are concentrated over the open ocean and are available only from 1993 onwards. The altimetry data, in particular provides the possibility of analysing sea level variations of different regions from a grid of observations which is continous in time and regularily in space. Many different areas have been analysed using this data. For example Cheng and Qi (2007) used altimetry data to analyse sea level in the South China Sea. They found a long-term trend with a rise of 11.3 mm/yr for the period 1993 – 2000, followed by a decreasing of 11.8 mm/yr for the period 2001 –2005. Trends of the tropical Pacific and the Indian Ocean Islands where analysed by Church et al. (2006) using altimetry and tide gauge data. The authors found a rise of up to 30 mm/yr in the western Pacific and the eastern Indian Ocean for the period 1993 – 2001. Simultaneously a fall of up to 10 mm/yr was found in the eastern Pacific and the western Indian Ocean. Data from tide gauges are available for much longer periods but are mostly concentrated in coastal areas in the Northern Hemisphere. Often, data are also in-homogeneous because of relocation of tide gauges, water level changes due to local water works etc..

The longest records from tide gauges dating back until the 18^{th} century are available from e.g. Amsterdam (The Netherlands), Liverpool (UK) or Brest (France). While the record of Amsterdam ends in 1925 the other two tide gauges are still active. The tide gauge of Amsterdam was analysed in van Veen (1945) and the analysis was updated in Spencer et al. (1988). Analyses of the Liverpool data can be found in Woodworth (1999a, 1999b) and for Brest analyses are provided in Wöppelmann (2006). Over time, data from more and more tide gauges became available. Using observations from globally distributed tide gauges, Jevrejeva et al. (2006) constructed an index time series of global mean sea level (GMSL) dating back until 1850. A similar time series was constructed by Church and White (2006) using the approach described in Church et al. (2004). However, contrary to the time series derived in Jevrejeva et al. (2006) data from both, tide gauges and satellites were used to construct the GMSL time series. Church et al. (2006) come to the conclusion that a significant acceleration occured in the 20^{th} century. Jevrejeva et al. (2006) found a trend of 2.4 ± 1.0 mm/yr for the GMSL in the period 1993 – 2000, but showed that trends of similar height have occured in earlier periods. Thus, they do not assume a significant acceleration in the last decades. Several authors used a modified version of the method introduced by Church and White (2004). For example Ray and Douglas (2011) reconstructed a time series for 1900 – 2006 and a linear long-term trend of 1.70 ± 0.24 mm/yr is computed. The linear trend for the period of altimetry data is higher than 3 mm/yr, but the authors state that such a high trend was possibly also reached between 1935 and 1950. The reconstruction of Ray and Douglas (2011) shows higher values than the one of Church and White (2006) until about 1955. Differences are especially visible when comparing decadal trends. Considering 15-year running trends the reconstruction of Ray and Douglas (2011) suggests extraordinary high trends in the recent past, the one of Church and White (2006) does not. Another reconstruction, based on a modified method of Church and White (2006), is shown in Hamlington et al. (2011). They reconstructed a time series for the GMSL for the period

1950 – 2009. The authors found a long-term trend of 1.97 mm/yr for this time period and for the period 1993 – 2009 they computed a trend of 3.22 mm/yr. The latter reconstruction is in good agreement with satellite data for the period from 1993 on, however the spacial distribution of the sea level reconstruction shows regional discrepancies compared to other reconstrutions, especially for longer time periods. The number of analysis and results concerning this topic shows its difficulty. The main problem remains that decreasingly data is available when going back in time. The approach of Church and White (2006) and its modified versions act on the assumption that this drawback can be balanced with the nearly globally available altimetry data for a much shorter time period.

Despite of some potential issues related with such reconstructions such as the limited spatial coverage of tide gauge data in the earlier years or introduction of potential in-homogeneities when satellite data are taken into account, GMSL index time series provide a valuable tool for assessing long-term changes and variability of MSL on a global scale. On a regional scale, their explanatory power is however limited, as large deviations from the global mean may occur (e.g. Church et al. 2008). Such deviations may, for example, result from regional differences in ocean temperature changes and corresponding differences in ocean thermal expansion (e.g. Church et al. 2008), self-gravitational effects from melting ice sheets and glaciers (e.g. Mitrovica et al. 2001), or regional sea level changes resulting from long-term and large-scale changes in ocean and/or atmospheric circulation. The latter is associated with large-scale changes in atmospheric wind and pressure fields that will leave the GMSL unaffected but that may play an important role in explaining regional deviations from the global mean and regional sea level variability.

There are a number of studies analysing the effects of changes in atmospheric circulation on regional mean sea level (RMSL) and variability. For example, Heyen et al. (1996) and Hünecke and Zorita (2007) analysed detrended time series of winter MSL in the Baltic Sea and found that a large part of the observed variability could be explained with corresponding variations in mean sea level pressure (SLP). Yan et al. (2004) analysed the connection between the North Atlantic Oscillation (NAO) and MSL from several tide gauges along the North and Baltic Sea coast. Again, the authors found a considerable part of the sea level variability explained by changes in the atmospheric circulation, but further concluded that the correlation in winter is better compared to the rest of the year. Considering the area of the North Sea and the European Atlantic coast Jevrejeva et al. (2005) analysed the connection between the winter MSL of different tide gauges and the winter NAO-index for the last 150 years. They found that from 10% to 35% of the variance of the winter MSL can be explained with the NAO. They found a spatial pattern in the correlations with the highest values in the northeast part of the North Sea. The same pattern was found by Wakelin et al. (2003) for the period 1955 – 2000 for both, observed and modeled MSL data. Woolf et al. (2003) included satellite data in their analysis. They found a high correlation between the winter NAO Index and the winter sea level of the North Sea, especially the German Bight. However, the considered time period is short, consistig of only 9 years. Kolker and Hameed (2007) analysed the contribution of the NAO to MSL variability at 5 tide gauges around the North Atlantic. The strongest relation was found for

Cascais, Portugal. Here variations in the NAO account for about 80% of the annual variability and about 80% of the observed long-term trend 1905–1993. The relationship between the NAO and MSL of the German Bight are analysed in Dangendorf et al. (2012). Analysing the period 1937 – 2008, the authors found that the NAO strongly influence the MSL in the month January to March aswell in the varability as in the long term trend.

In this paper we concentrate on RMSL variability in the German Bight (the most southeastern Bight of the North Sea, Fig. 1) caused by large-scale changes in the atmospheric circulation. There are a number of studies analysing past sea level changes in the North Sea and a fewer those in the German Bight. Based on UK tide gauge data Woodworth et al. (1999; 2009) as well as Haigh et al. (2009) analysed MSL changes along the UK coast. Both used the same approach namely defining a so called 'sea level index' based on the long available records. Woodworth et al. (2009) calculated a linear trend of 1.4 ± 0.2 mm/yr for the UK and Haigh at al. (2009) found that the trends in the English Channel vary between 0.8–2.3 mm/yr, both for the 20^{th} century. Woodworth et al. (2009) further showed that the estimated linear trends were consistent with other locations in the North Sea area. For the Netherlands a constant rise of 2.5 ± 0.6 mm/yr for the 20^{th} century is documented in Katsman et al. (2008). In none of the cases an acceleration in MSL could be found. For the German Bight, index time series of RMSL were provided by Wahl et al. (2010; 2011) and Albrecht et al. (2011). While the details of the approaches differ, both authors report mainly consistent results with respect to RMSL variability and long-term change. For the time period 1924 – 2008 a linear trend of 1.7 mm/yr was calculated. The authors found an accelerating rise in the recent past, however they found similar rises in earlier decades and thus do not assume an extraordinary acceleration in RMSL.

In this paper we use the most recent RMSL time series for the German Bight provided in Albrecht et al. (2011) to investigate to what extent observed variability and long-term changes may be associated with corresponding changes in large-scale atmospheric pressure fields. In contrast to previous studies we do not use data from individual tide gauges, but rely on a reconstructed index time series in which in-homogenities are filtered out to a large extent (Albrecht et al. 2011). We also consider the effects of SLP by using the full information available without the limitations arising from preselecting certain atmospheric pressure patterns (such as NAO) which might be suboptimal in describing regional sea level responses. Moreover, we focus not solely on interannual variability but also investigate the extent to which the observed long-term trend in RMSL in the German Bight might be associated with corresponding changes in atmospheric circulation. To include other factors like thermal expansion or the effect of land-ice melting, the MSL of the North East Atlantic (NEA) is included as a proxy for large scale MSL changes as a second predictor.

The structure of the paper is as follows. In section 2 we will briefly introduce the data and methods used for our analysis. We will then derive an empirical relation between RMSL and the large-scale SLP field that will be used to analyse the extent to which observed RMSL variability and trend can be explained from corresponding variations in the SLP field (section 3.1). In section 3.2 the empirical model will be extended by additionally using the MSL from the North

East Atlantic as a predictor. In doing so, we additionally account for effects that may arise from any large-scale changes in MSL caused by e.g. ocean thermal expansion or halosteric changes. In section 3.3 both models will be analysed regarding their robustness while a summary and discussion is presented in section 4.

2 Data and Methods

Data

The time series of RMSL in the German Bight we use was derived in Albrecht et al. (2011). In that work a time series representing annual RMSL was constructed from the tide gauge data at 15 different locations (Fig. 1) using two different methods. We will here use the reconstruction derived from the so called "EOF-approach" covering the time period 1924 – 2008. No correction for glacial isostatic adjustment (GIA) was applied, that is only relative sea level is considered. Some tide gauges cover a longer time period, the longest data available is from Cuxhaven ranging back until 1843. The usage of the shorter time period 1924 – 2008 is a result of the applied method ("EOF-approach") to reconstruct the RMSL. A detailled description of the data and construction method can be found in Albrecht et al. (2011).

For SLP we use the HadSLP2r data which is a near-real-time update of the HadSLP2 data from the Met Office Hadley Center for Climate Change. It contains monthly means of SLP for the period 1850 – 2009.[1] Observations from 2228 stations were interpolated on a $5° \times 5°$ grid. The data can be downloaded at http://www.metoffice.gov.uk/hadobs/hadslp2/data/download.html. A detailled description of the dataset can be found in Allan and Ansell (2006). Here we computed annual means from that data and used the grid points from 30°N to 75°N and 70°W to 20°E covering large parts of the North Atlantic.

For MSL in the NEA we use the data described in Jevrejeva et al. (2006). That is a sea-level reconstruction based on data from tide gauges in the NEA, downloaded from the Permanent Service for Mean Sea Level (PSMSL, www.psmsl.org). No inverted barometer correction was applied. The tide gauge data was corrected for local datum shifts and GIA. More details can be found in Jevrejeva et al. (2006). The time series consists of monthly means for the period 1850 – 2001. An update of this time series is in progress but was unavailable to us. In this paper only annual means are used.

Methods

An *EOF-analysis* was used to find the dominant patterns and corresponding time series of the SLP data. In an EOF-analysis the data is decomposed in a number of spatial patterns such

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[1] Note that the update from 2005 on is not homogenous with the time series from 1850 – 2004, but a comparison for our special use of the data (EOF-analysis, see section 3.1) showed no differences in the first three patterns and principal components of the EOF-Analysis.

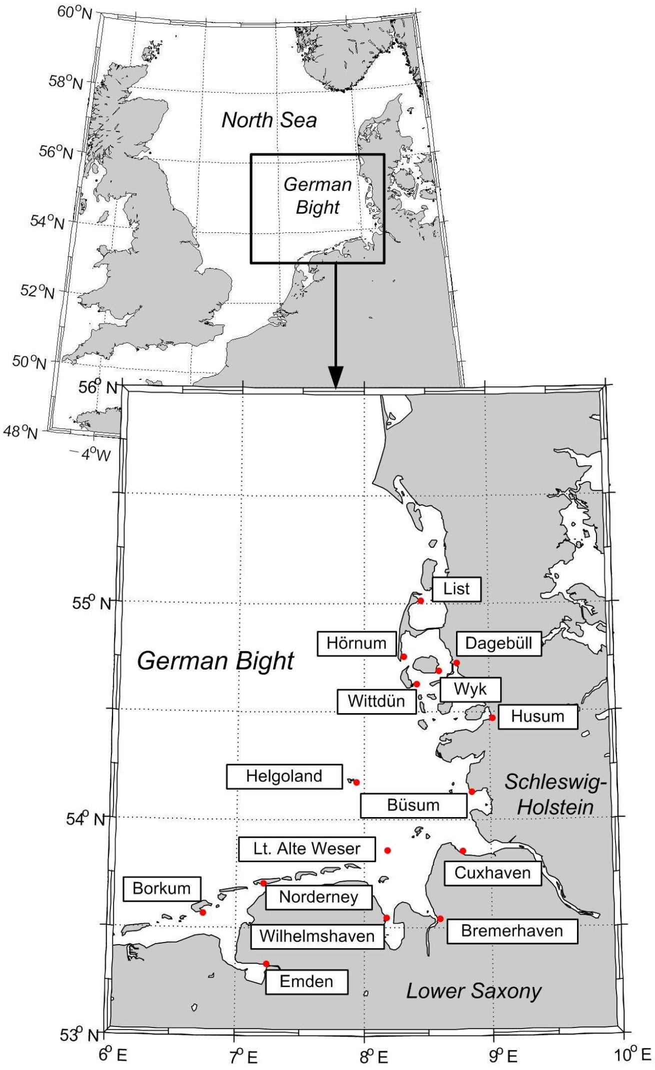

Fig. 1 Study area and locations of the tide gauges considered for the RMSL time series of the German Bight

that they are ordered by their explained variance. We start from our data vector $X \in \mathbb{R}^n$, $n \in \mathbb{N}$ that is multiplied with a rotational matrix $R \in \mathbb{R}^{n \times n}$. This multiplication results in a new vector $Y \in \mathbb{R}^n$, carrying the same information as the original vector X, but displayed with respect to a new basis. The matrix R is chosen such that its columns consist of the eigenvectors $(e_1, e_2, \dots, e_n)$ of the covariance matrix of X. These eigenvectors are also referred to as patterns of X. They are orthonormal and ordered by the absolute values of the eigenvalues starting from the highest one. As described in von Storch and Zwiers (1998) the subspace spanned by multiplying X with the first eigenvector e_1 is the one representing the largest part of the variance of the data X, e_2 the second largest and so on. Thus the data X can be reduced representing a large part of the variance by using only the most important patterns $e_1, \dots, e_k$ with $k \in \mathbb{N}$, $k < n$. In the following EOF-analysis is used to find the dominant modes of SLP variability over the North Atlantic and their temporal behaviour. The latter is described by the corresponding principal components (PCs) obtained from the EOF analysis.

The second concept we use is *linear regression*. Both simple and multiple linear regressions are used. As the simple linear regression is a special case of the multiple linear regression we will not explain it seperately. Details about its concept can be found in von Storch and Zwiers (1998). The intention of a linear regression is to describe a random vector $y = (y_1, \dots y_n)$, $n \in \mathbb{N}$ with one or more other random vectors $x_1 = (x_{11} \dots, x_{1n}), \dots, x_k = (x_{k1} \dots, x_{kn})$, $k \in \mathbb{N}$. This relationship is supposed to be linear in $x_1, \dots x_k$. That is

$$y_i = a_0 + a_1 x_{1i} + \cdots + a_k x_{ki} + \epsilon_i,$$

for all $i = 1, \dots n$. Here a_j, $j = 0, \dots k$ are appropriate coefficients such that the residuals ϵ_i are minimised. In our case we use least squares for error minimisation. As we only use anomalies of our time series a_0 is equal to zero. If we use matrix notation, we thus solve the minimisation problem

$$||Xa - y|| \rightarrow min,$$

with $|| \cdot ||$ denoting the euclidian norm, $X = (x_1, \dots x_k)$ and $a = (a_1, \dots, a_k)$. The solution of this problem is - as we are only considering real variables - the solution of the normal equation

$$X^T X a = X^T y. \tag{1}$$

This solution is unique if X is a regular matrix. We are aware that there are algorithms testing for each variable whether the regression error is reduced statistical significantly (e.g. stepwise regression). Details for these concepts can also be found in von Storch and Zwiers (1998). We anyhow use the direct solution of (1) as we have some a priori information about physical relations. In section 3.2 we use a simple linear regression build up on the residuals of another regression. The mathematical correct solution would be to use a multiple linear regression with all variables instead of using two independent regressions. As above the reason for that is physically motivated. We assume that the additional parameter should not change the relationship of the ones before but just bring some additional information.

To measure the quality of our regression result compared to the original time series we use *correlation coefficients* and *explained variances*. As the correlation coefficient is not able to show systematic errors in constant additive differences and differences in proportionality the *index of agreement* is additionally calculated. This index and its properties are discribed in detail in Willmott (1981). It takes values between 0 and 1 and measures to what extent a model is free of error, where 1 connotes total agreement between model and observations and 0 total disagreement. For the case, where the long term trend is included we will also use the magnitude of the long term trends of both time series to evaluate the regression results. We mainly focus on the percentage of the explained trends, but consider the absolute deviation of the trends at the end of section 3.3. Throughout the whole paper 90% confidence levels are given with the linear trends.

3 Results

3.1 Relation between large-scale SLP and the RMSL in the German Bight

Changes in large scale atmospheric pressure fields are associated with corresponding changes in ocean water levels. There are several effects: Increasing/decreasing atmospheric pressure will lower/rise the sea surface by about 1 cm per 1 hPa atmospheric pressure change (e.g. Weisse and von Storch, 2009). This effect is generally known as inverse barometric effect. Moreover, the atmospheric pressure gradients are directly linked to wind speed and direction and any change in large-scale atmospheric pressure patterns will be associated with corresponding changes in the wind climate. Eventually, changes in the prevailing wind direction may set up changes in prevailing ocean circulation with corresponding changes in sea surface height while higher/lower wind speed may be associated with increasing/decreasing coastal water levels.

Any long-term change in large-scale atmospheric pressure fields may thus be associated with different regional changes in the MSL. In the following we elaborate on these effects for the German Bight. SLP fields from 30°N to 75°N and from 70°W to 20°E are used to represent the large scale atmospheric pressure fields over the North Atlantic. To identify the dominant modes of variability an EOF-analysis is performed (Figs. 2, 3 and 4). The leading three modes explain about 51%, 17%, and 11% of the observed variability. For higher EOFs explained variances are generally smaller than 6%. The first EOF pattern closely resembles the pattern of the so-called NAO; that is, a dipole with one pole centred over the eastern part of Greenland and the other pole located in the southern part of the analysis domain at about 20° longitude west of the Azores. Depending on sign, such a pattern is generally associated with westerly/easterly wind anomalies over the North Atlantic. The second and third EOF both resemble mono poles with either northerly/southerly wind anomalies or enhanced cyclonic/anticyclonic circulation over the North Sea respectively.

A multiple linear regression is used (section 2) to derive a statistical relation between the RMSL in the German Bight and the corresponding SLP fields. Let $z(t)$ be the time series of the

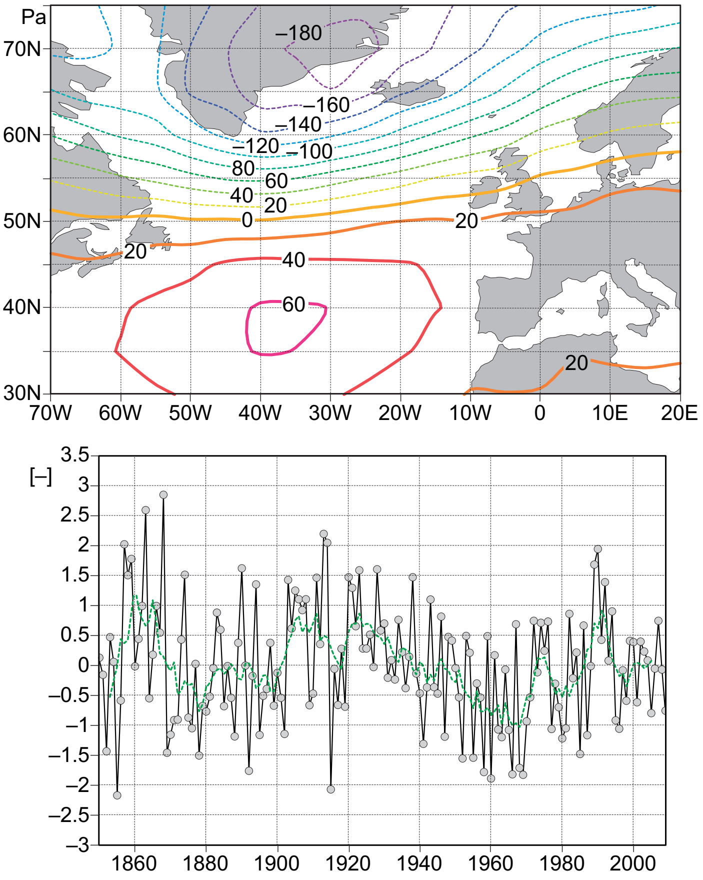

Fig. 2 First EOF (top) and PC (bottom, black) for SLP data of the North Atlantic for the time period 1850 – 2009 (explained variance: 50.6%). The green curve in the lower panel is a 5-year running mean.

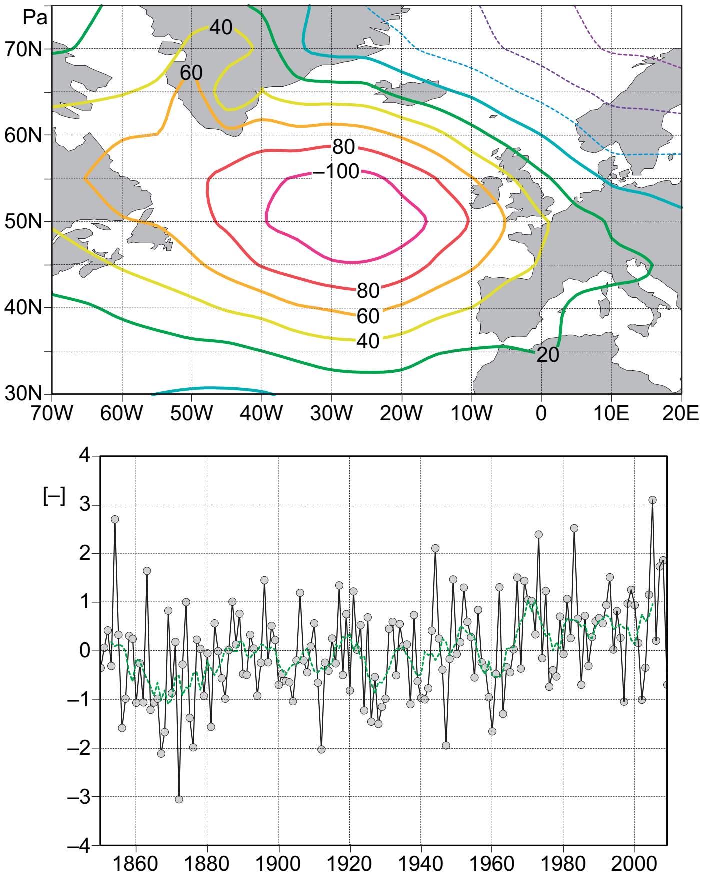

Fig. 3 Second EOF (top) and PC (bottom, black) for SLP data of the North Atlantic for the time period 1850 – 2009 (explained variance: 16.75%). The green curve in the lower panel is a 5-year running mean.

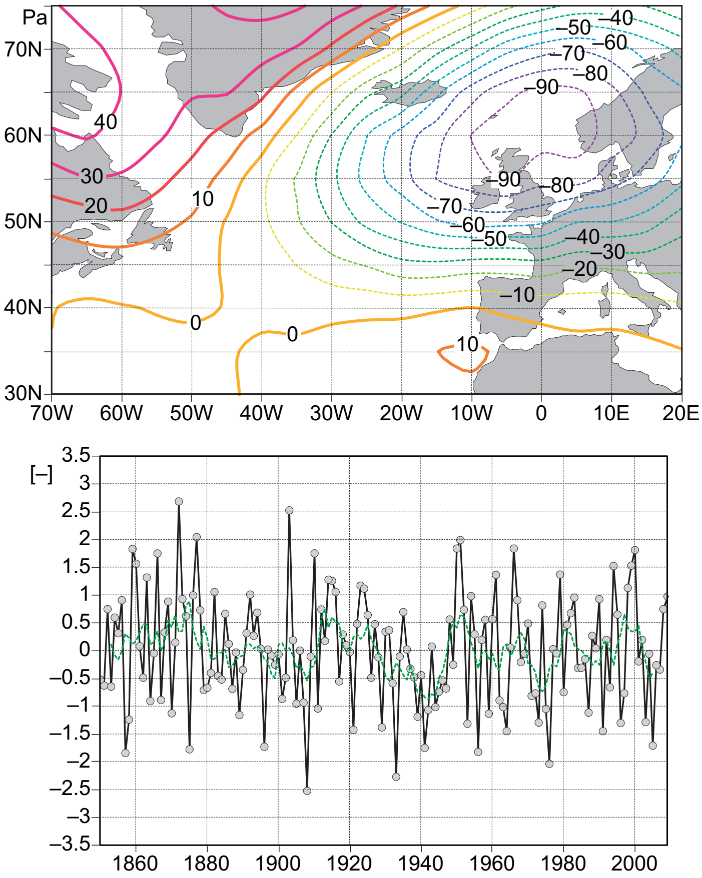

Fig. 4 Third EOF (top) and PC (bottom, black) for SLP data of the North Atlantic for the time period 1850 – 2009 (explained variance: 10.88%). The green curve in the lower panel is a 5-year running mean.

RMSL and $\alpha_1(t)$, $\alpha_2(t)$, $\alpha_3(t)$ be the PCs of the three leading EOFs of SLP, with t being the time from 1924 – 2001. The index "d" is used to denote the cases when detrended time series were used. In the following the regression is generally established for the detrended time series. This is done to ensure that the statistical relation not only reflects common long term trends in the time series but resembles the inter-annual and decadal variability. Subsequently the regression is applied to both the complete and the detrended time series as well. The latter shows how much of the variability in RMSL can be explained by corresponding SLP fluctuations while the other reveals how much of the observed trend in RMSL can be accounted for by corresponding long-term changes in atmospheric pressure fields. The regression can then be written as

$$z_d(t) = a_1\alpha_{1d}(t) + a_2\alpha_{2d}(t) + a_3\alpha_{3d}(t) + \epsilon_1(t), \tag{2}$$

with a_1, a_2 and a_3 associated coefficients such that the error ϵ_1 is minimised (see section 2). Here RMSL is denoted in meters and while the PCs are dimensionless the coefficients a_1, a_2, a_3 are carrying the units.

Fitting this multiple regression model for the time period 1924 – 2001 results in coefficients of $a_1 = 0.0123$ m, $a_2 = 0.0227$ m and $a_3 = 0.0264$ m. This suggests that the second and the third EOF generally have more power in explaining sea level variations in the German Bight, a result that is consistent with wind field anomalies associated to the EOF patterns.

The RMSL from applying this model to the detrended time series is referred to as $\tilde{z}_d(t)$. A comparison of $\tilde{z}_d(t)$ and $z_d(t)$ and the associated residuals $z_d(t) - \tilde{z}_d(t)$ is shown in Fig. 5.

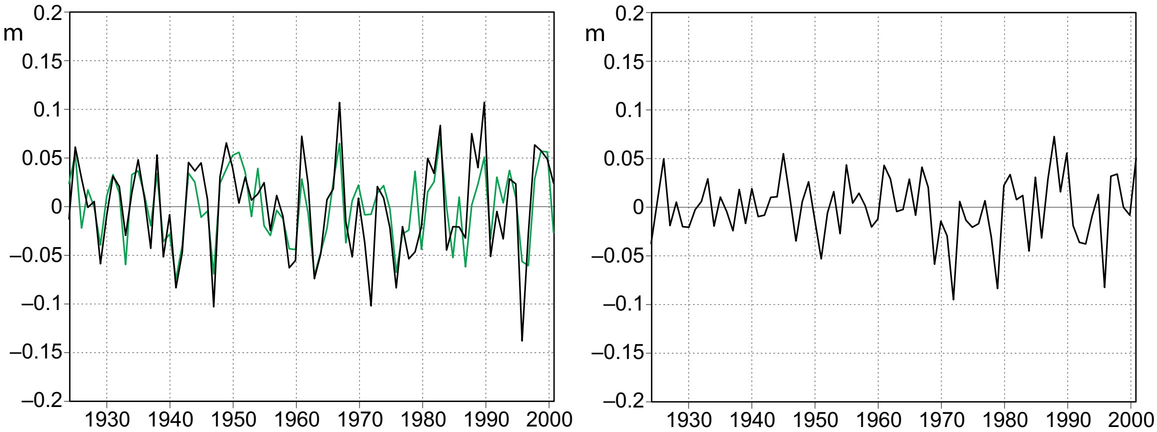

Fig. 5 Left: Comparison of the RMSL of the German Bight without long term trend ($z_d(t)$, black) and the regression result of (2) applied to detrended data ($\tilde{z}_d(t)$, green). Right: Residuals of the RMSL and the regression result ($z_d(t) - \tilde{z}_d(t)$).

The correlation coefficient between the two time series is 0.73 corresponding to an explained variance of 53%. The index of agreement has a value of 0.85. While in general a reasonable

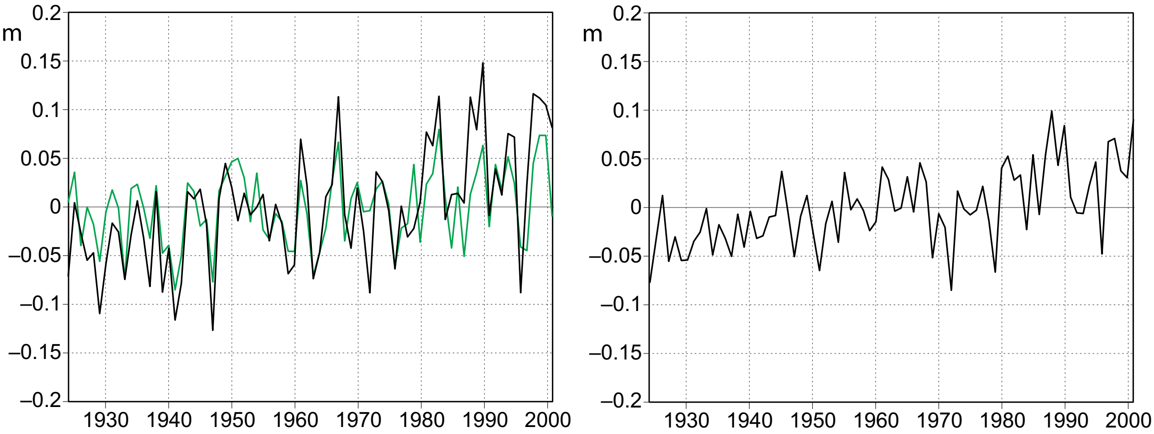

Fig. 6 Left: Comparison of the RMSL of the German Bight ($z(t)$, black) and the regression result of (2) applied to data with long term trend included ($\tilde{z}(t)$, green). Right: Residuals of the RMSL and the regression result ($z(t) - \tilde{z}(t)$).

aggreement is infered, some problems are obvious in reproducing the observed RMSL in the 1970s. Here the residuals show relatively high values of up to -0.09 m. The RMSL time series declines in 1971 and rises extraordinary high in the following 20 years. The linear trend from 1971 to 1990 is about 6.7 mm/yr which is high above the average of all 20-year trends of 1.6 mm/yr. This exceptionally high decadal trend is also visible in the time series of the RMSL with the long term trend subtracted and is obviously not associated with changes in the atmospheric pressure fields.

We now apply the regression model to the full time series of the PCs from SLP EOFs; that is, with the long term trend included. We call the resulting time series $\tilde{z}(t)$. A comparison of $\tilde{z}(t)$ and $z(t)$ and their residuals $z(t) - \tilde{z}(t)$ is shown in Fig. 6. The correlation coefficient between the two time series is 0.76 for the time period 1924 to 2001 corresponding to an explained variance of 58% rather comparable to that obtained from applying the model to the detrended data. The index of agreement has a value of 0.82 in this case. The long term trend of $\tilde{z}(t)$ has a value of 0.5 ± 0.2 mm/yr for the time period 1924 to 2001 compared to 1.5 ± 0.3 mm/yr which is the linear trend of $z(t)$. That is about 33% of the linear trend in RMSL in the German Bight can be accounted for by corresponding long-term changes in the large-scale SLP field. As for the comparison of $\tilde{z}_d(t)$ and $z_d(t)$, the high decadal trend from 1971 to 1990 is obvious and not associated with corresponding variations in SLP.

3.2 Extension of the Regression

The results from our regression analysis suggest that long-term changes in large scale atmospheric pressure fields had a substantial effect on observed changes in RMSL. However, there are other factors influencing the RMSL, e.g. thermal expansion or the effect of land-ice melting. The latter will have influences on large scale sea levels as well. In the following we use MSL from the NEA as a proxy for such effects. The data used for NEA MSL are described in section 2 and the time series is shown in Fig. 7.

The regression model is extended the following way: As we aim at improving the regression derived in the previous section, in the following only the residuals $z(t) - \tilde{z}(t)$ are considered[2]. The time series for NEA MSL is referred to as $z_{na}(t)$. As in section 3.1 detrended time series are denoted with the index "*d*" and t is again the time from 1924 to 2001. We thus conduct the simple linear regression

$$(z(t) - \tilde{z}_d(t)) = a_4 z_{nad}(t) + \epsilon_2(t). \tag{3}$$

The coefficient a_4 is chosen such that the error ϵ_2 is minimised (see section 2). In this regression $(z(t) - \tilde{z}_d(t))$ and $z_{nad}(t)$ both have the units meters and the regression coefficient a_4 is thus dimensionless.

Fitting the model to the data yields a regression coefficient of 0.48. As an indication on whether or not this regression is reasonable we computed the correlation coefficient between $(z(t) - \tilde{z}_d(t))$ and $z_{nad}(t)$ which is about 0.3. The latter is significantly different from zero at the 99% confidence level when using a t-test statistics.

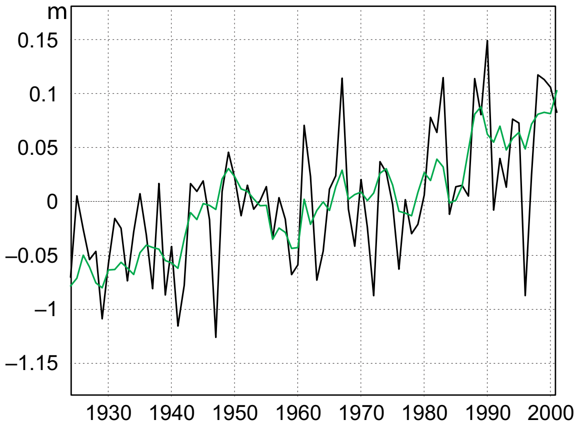

Fig. 7 Time series of the RMSL of the German Bight (black) and the MSL of the NEA (green) for the time period 1924 – 2001.

Our new approximation of the RMSL in the German Bight $\tilde{\tilde{z}}(t)$ is thus the sum from both regressions (2) and (3)

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[2] The linear trend is calculated as the slope of the linear regression between the time series and the time. Re-sorting of the sums shows that it does not matter whether we consider the detrended residuals $(z_d(t) - \tilde{z}_d(t))$ or the residuals with trend and subtract the trend afterwards $((z(t) - \tilde{z}_d(t)))$.

$$\tilde{\tilde{z}}_d(t) = \tilde{z}_d(t) + a_4 z_{nad}(t) = a_1\alpha_{1d}(t) + a_2\alpha_{2d}(t) + a_3\alpha_{3d}(t) + a_4 z_{nad}(t). \tag{4}$$

As in the previous section we first apply our model to the detrended time series (Fig. 8). A correlation coefficient of 0.79 is obtained corresponding to an explained variance of about 62% which means that by including MSL changes from NEA the explained variance of detrended RMSL changes in the German Bight increased by about 9%. The index of agreement is 0.88 and thus slightly higher than without the NEA time series.

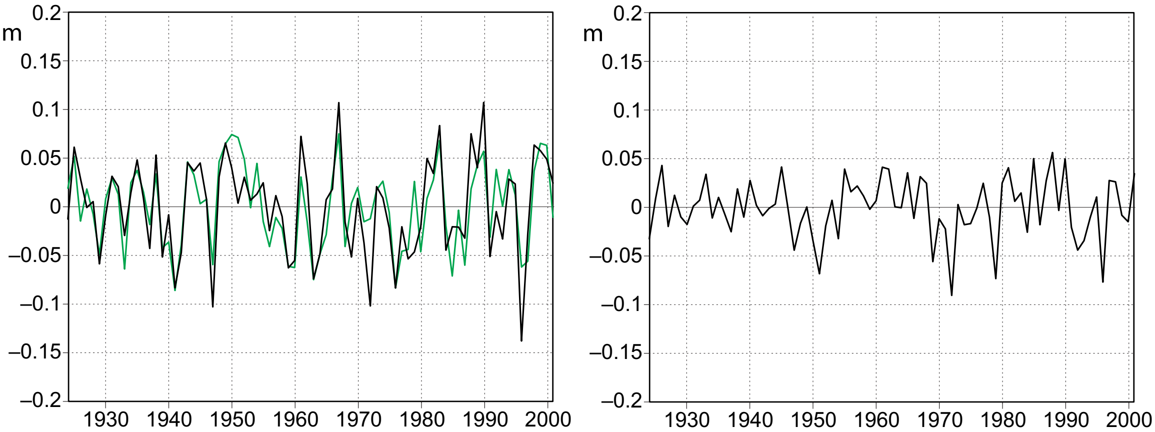

Fig. 8 Left: Comparison of the RMSL of the German Bight without long term trend ($z_d(t)$, black) and the regression result of (4) applied to detrended data ($\tilde{\tilde{z}}_d(t)$, green). Right: Residuals of the RMSL and the regression result ($z_d(t) - \tilde{\tilde{z}}_d(t)$).

Next we again applied the model fitted to detrended data to the full data set including the trend. This way inferences about the models capability in reproducing the observed trend in RMSL in the German Bight can be obtained. Results are shown in Fig. 9. The time series obtained from our simple statistical approach and that for the RMSL in the German Bight share a correlation coefficient of 0.86 corresponding to an explained variance of 74%. This corresponds to an increase in explained variance of about 16% compared to the regression model in which sea level effects from the NEA were excluded. The index of agreement increases to a value of 0.92 indicating a reduction in systematic errors. For the period 1924 – 2001 the linear trend obtained from the regression based on SLP fields and NEA MSL is about 1.3 ± 0.3 mm/yr compared to about 1.5 ± 0.3 mm/yr obtained directly from the RMSL time series of the German Bight for the same period. In other words, about 87% of the observed long-term trend in German Bight RMSL can be associated with corresponding changes in the large-scale SLP and MSL fields in the NEA. Compared to the model that only uses SLP as predictor, the latter represents an improvement of about 53%.

From introducing MSL of the NEA as an additional predictor, our model further improves the

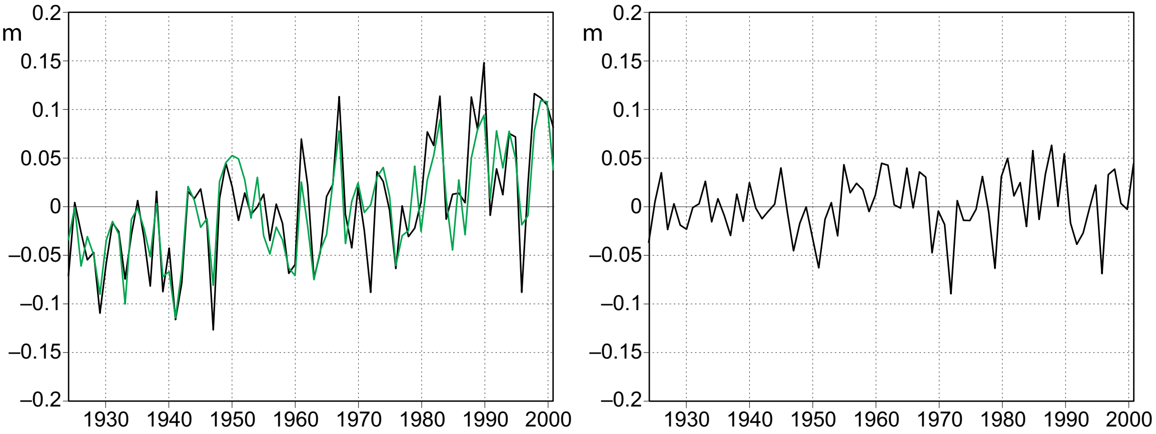

Fig. 9 Left: Comparison of the RMSL of the German Bight ($z(t)$, black) and the regression result of (4) applied to data with long term trend included ($\tilde{\tilde{z}}(t)$, green). Right: Residuals of the RMSL and the regression result ($z(t) - \tilde{\tilde{z}}(t)$).

representation of annual and decadal variability. We thus tested the predictive skill of a similar regression model using only NEA as predictor. That is to conduct a simple linear regression with the RMSL of the German Bight on the one side and the MSL of the NEA on the other side. Again the linear trend was subtracted before the regression coefficient was computed and then this coefficient was applied to the MSL of the NEA with long term trend included. For the reconstruction from 1924 to 2001 the explained variance is 50% and the linear long term trend is 2.2 ± 0.2 mm/yr compared to 1.5 ± 0.3 mm/yr of the RMSL, that is the model overestimates the trend by about 47%. The index of agreement is 0.84 and thus somewhat smaller compared to the model that uses both, SLP and NEA as predictors.

While there is considerable improvement in reconstructing observed long-term trends in RMSL when sea level variations in the NEA are taken into account, the problems in reconstructing decadal variations in the 1970s remain. Several other factors potentially being responsible for theses changes were investigated: Indices for global mean sea level (GMSL) (Church and White 2006; Jevrejeva et al. 2006) do not show pronounced decadal variations around the 1970s. Similarly, anomalies in local thermal expansion can be excluded as a long-term temperature time-series from Helgoland (the central island in the German Bight, see Fig. 1, Wiltshire and Manley 2004) does not show a corresponding behaviour either. Potential effects caused by changes in the ocean circulation were analysed using data from a high-resolution tide-surge hindcast for the North Sea driven by observed (reanalysed) wind and pressure patterns for the period 1948 – 2004 (Weisse and Pluess 2006). As the sea level data obtained from this hindcast do not show a corresponding high trend from 1971-1990 changes in the wind driven ocean circulation might be excluded as well. Eventually, data inhomogeneities can not fully be excluded but remain highly unlikely to be responsible for the strong decadal changes in the 1970s as the signal is visible not only in German but also in Danish (e.g. Esbjerg) or Dutch (e.g. Delfzijl, Den Helder) tide gauges. A convincing explanation is missing so far.

3.3 Cross Validation

So far the regression models considered were fitted to the entire detrended data set. In the following we elaborate on the robustness of these regression models by using a two-fold cross validation approach: The 78 years of data were splitted into two parts (1924 – 1962 and 1962 – 2001) of equal size. The models were then both fitted to one part of the data and compared to the other.

We first performed the cross-validation for the regression model using only SLP as predictor (equation (2), in the following referred to as SLP model). The coefficients are $a_1 = 0.0146$ m, $a_2 = 0.0285$ m and $a_3 = 0.0199$ m and $a_1 = 0.0104$ m, $a_2 = 0.0143$ m and $a_3 = 0.0339$ m when fitted to the first and the second part of the detrended data, respectively. These coefficients are rather similar to those obtained from fitting the regression model to the detrended data over the entire period. They retain the relative weigths of each SLP pattern in the regression with the second and third patterns providing larger contributions than the first pattern.

Time series and residuals obtained from applying the model to the detrended data are shown in Fig. 10. The correlation coefficients of the cross validation are 0.72 for the time period 1924 – 1962 using the regression fitted to the period 1963 – 2001 and 0.68 for the time period 1963 – 2001 using the regression fitted to the period 1924 – 1962. Thus the explained variance is 52% in the first case and 46% in the second. The index of agreement for the period 1924 – 1962 is 0.84 and for 1963 – 2001 it is 0.79. In both periods the numbers are generally slightly smaller than for the entire period 1924 – 2001, where the correlation coefficient is 0.73 and the index of agreement 0.85.

We subsequently applied the SLP regression model to the data including the long-term trend using the cross validation approach described above. Time series and residuals are shown in Fig. 11. In this case the correlations of the cross validation are 0.69 for the time period 1924 – 1962 using the regression fitted to the period 1963 – 2001 and 0.70 for the time period 1963 – 2001 using the regression fitted to the period 1924 – 1962. Here, in both cases the correlations are slightly lower than 0.76, which is the value for the entire time period, but comparable for both validation periods. The explained variances for the validation periods are 48% for 1924 to 1962 and 49% for 1963 to 2001. The index of agreement for the period 1924 – 1962 is 0.82 and 0.79 for the period 1963 – 2001. These values are close to or even equal 0.82, which is the index of agreement for the whole time period 1924 – 2001.

Considering the data including trends, for the period 1924 to 1962 the regression result has a trend of 0.1 ± 0.7 mm/yr compared to 1.5 ± 0.8 mm/yr of the RMSL. Thus, the regression explains only 7% of the observed long term trend. For the time period 1963 to 2001 the regression result has a trend of 1.1 ± 0.7 mm/yr compared to 2.6 ± 1.0 mm/yr derived from the observations,

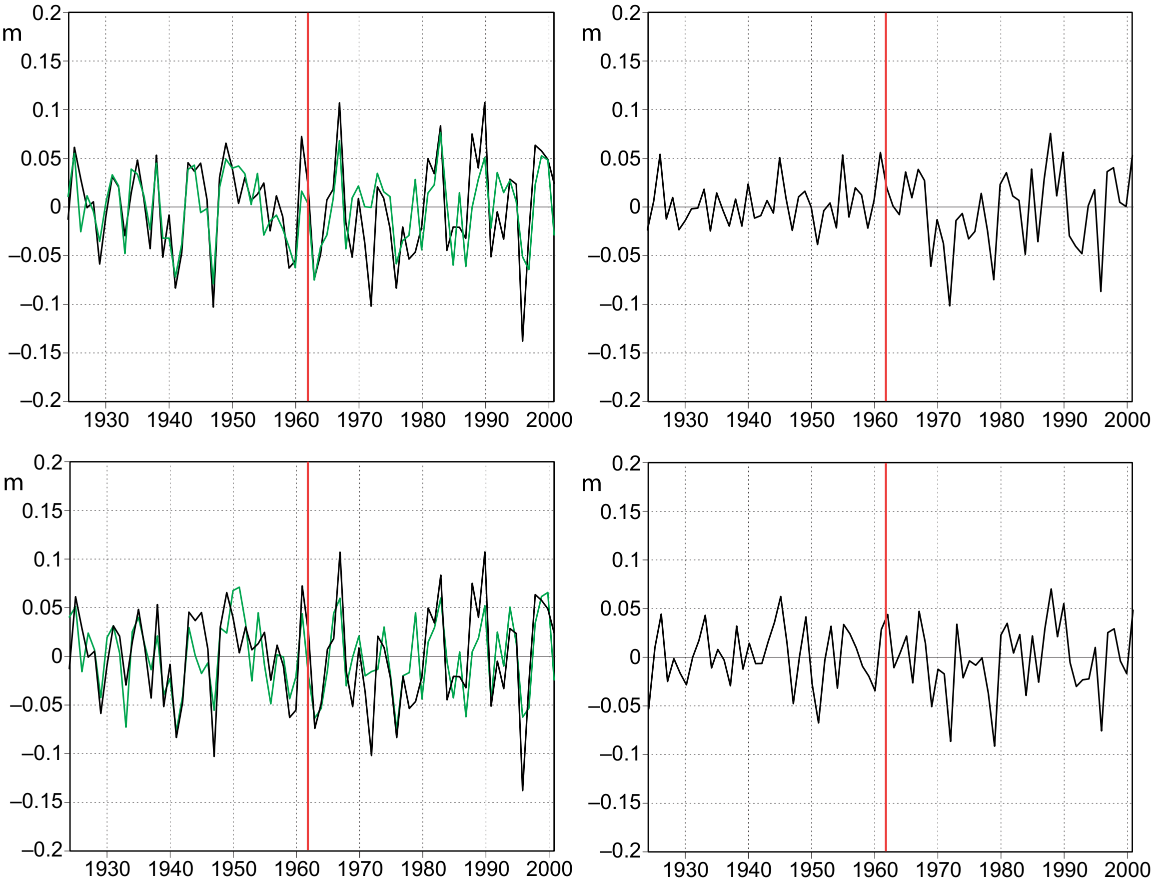

Fig. 10 Top [left]: Comparison of the RMSL of the German Bight without long term trend ($z_d(t)$, black) and the regression result of (2) from 1924 – 1962 applied to detrended data ($\tilde{z}_d(t)$, green) and [right] their residuals ($z_d(t) - \tilde{z}_d(t)$). Bottom: Analogue for the regression result from 1963 – 2001.

which corresponds to 42%. The ability of the statistical model in reproducing the observed long term trend thus depends on the time period, which calls for a limited skill in using the model for prediction. However, the 90% confidence levels overlap in both cases. It should be noted that long term trend estimates of a time series can change substantially when in- or excluding the first/last time step. If we e.g. consider the time period 1925 – 1961 the linear trend of the observed RMSL is 1.3 ± 0.9 mm/yr and the one of the regression result 0.4 ± 0.8 mm/yr - this complies with 31%. Further, the index of agreement for this time period takes the same value as for the whole time period. That is the systematic error for this period is not higher than for the whole time period.

The ability of the model to predict observed trends seems to depend strongly on the considered time period. However, we can conclude that there are time periods where the SLP contributes a non-negligible part to the long term trend of the RMSL.

We now consider the model including both predictors: SLP and MSL of the NEA (equation (3), in the following referred to as SLP-NEA model). We conduct a second cross-validation using the residuals of the regressions with only SLP as described in section 3.2 (Fig. 10, note footnote 2). The statistical relevance of the additional parameter (i.e. MSL of the NEA) is analysed by considering the correlation coefficients of the residuals of the SLP model and the MSL of the NEA for both cases. The correlation coefficients are significantly different from zero at the 99% confidence level. The regression coefficients are $a_4 = 0.16$ for 1924 to 1962 and $a_4 = 0.86$ for 1963 to 2001 and thus differ substantially for the different time periods.

We again first apply the coefficients to the detrended time series. The results are shown in Fig. 12. The correlation coefficients are 0.74 for the time period 1924 – 1962 using the regression fit for 1963 – 2001 and 0.70 for the time period 1963 – 2001 using the regression fit for 1924 – 1962. An improvement compared to the SLP model in the explained variance can be seen for the validation period 1924 to 1962, which is 55%. Whereas it is slightly reduced for the period 1963 to 2001 to the value of 49%.[3] The index of agreement is 0.85 for the period 1924 – 1962 and 0.80 for 1963 – 2001. These numbers are very close to those of the SLP model, that is the systematic error does not change substantially including the MSL of the NEA. Considering the numbers above, the conclusion that the contribution of the MSL of the NEA to the annual variability is small compared to the contribution of the SLP remains for the cross validation.

Next, we apply the coefficients to the data with trends included. The results can be seen in Fig. 13. The correlation coefficient for the period 1924 – 1962 resulting from the model fit to 1963 – 2001 is 0.78 and for the period 1963 – 2001 resulting from the fit from 1924 – 1962 is 0.74. In this case the explained variances in the validation periods are 61% for 1924 to 1962 and 55% for 1963 to 2001 which is an improvement in both cases compared to the SLP model. The index of agreement for the period 1924 – 1962 is 0.87 and for 1963 – 2001 it is 0.83. These

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[3] This reduction is a result of the decission to use a physical motivated model. If we would e.g. use stepwise regression the correlation coefficient would of course always be higher adding an additional statistical significant variable.

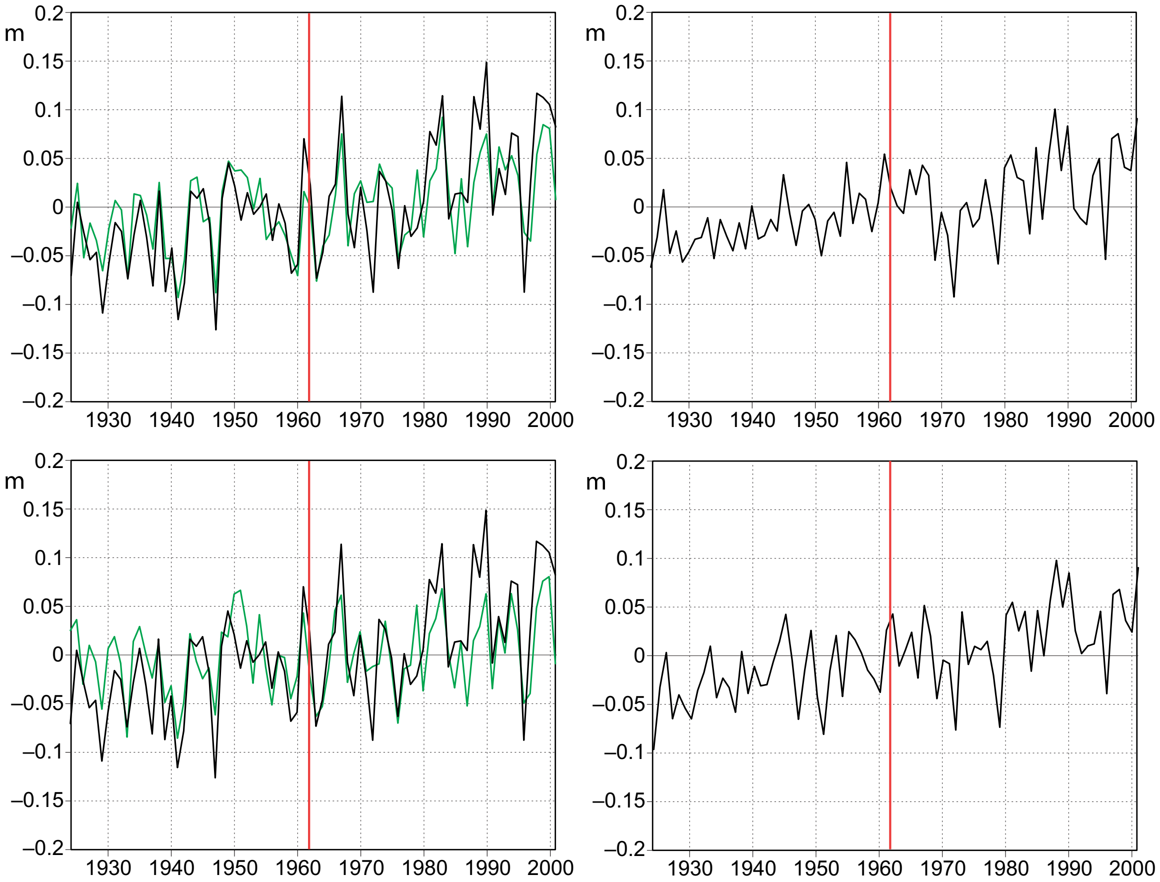

Fig. 11 Top [left]: Comparison of the RMSL of the German Bight ($z(t)$, black) and the regression result of (2) from 1924 – 1962 ($\tilde{z}_d(t)$, green) and [right] their residuals ($z(t) - \tilde{z}(t)$). Bottom: Analogue for the regression result from 1963 – 2001.

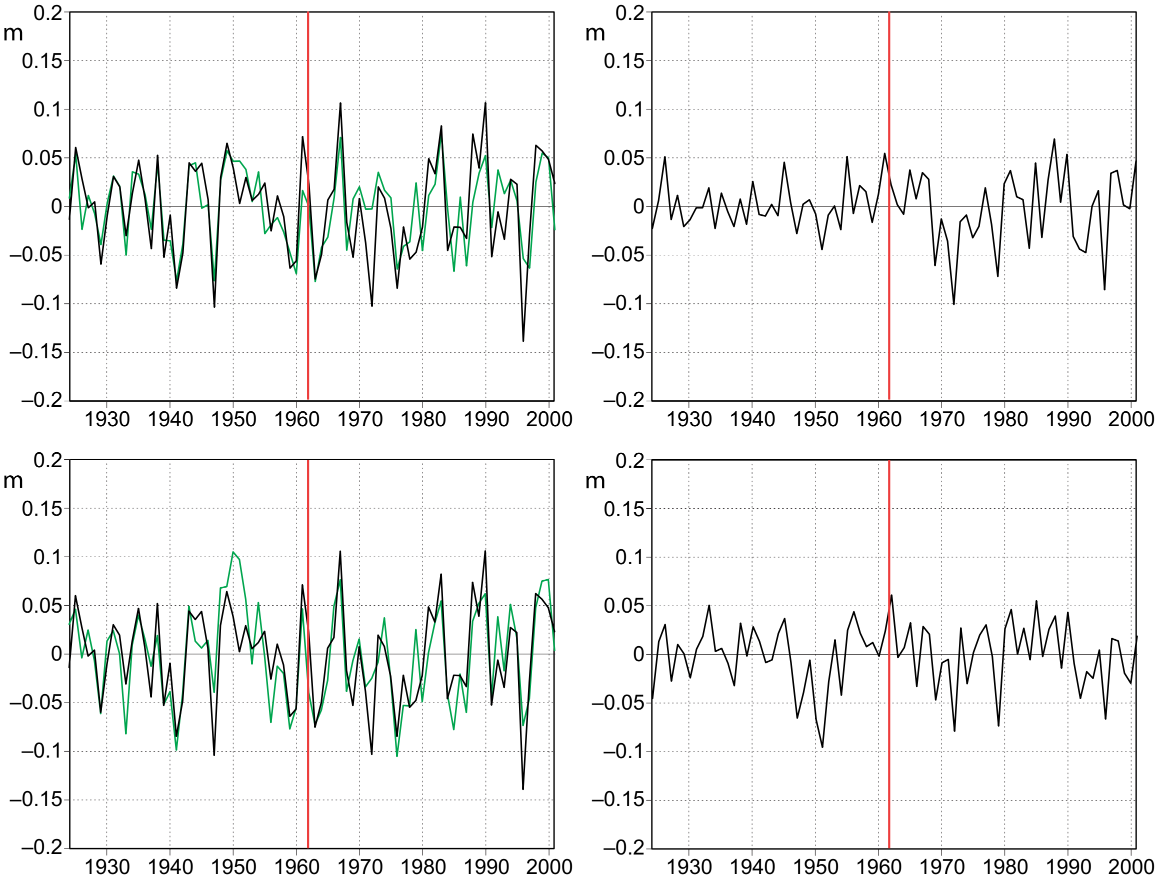

Fig. 12 Top [left]: Comparison of the RMSL of the German Bight without long term trend ($z_d(t)$, black) and the regression result of (4) from 1924 – 1962 applied to detrended data ($\tilde{\tilde{z}}_d(t)$, green) and [right] their residuals ($z_d(t) - \tilde{\tilde{z}}_d(t)$). Bottom: Analogue for the regression result from 1963 – 2001.

values are not as high as 0.92, which is the index of agreement for the whole time period, but in both cases the values are higher than in the SLP model.

For the period 1924 to 1962 the model resulting from the reression period 1963 to 2001 leads to a trend of 1.8 ± 0.9 mm/yr and the RMSL has a trend of 1.5 ± 0.8 mm/yr. That is the model overestimates the trend by about 20%. For the time period 1963 to 2001 the regression model for the period 1924 to 1962 shows a a trend of 1.5 ± 0.8 mm/yr compared to the observed trend of 2.6 ± 1.0 mm/yr. That is about 58% of the observed long-term trend in RMSL in the German Bight are associated with corresponding changes in the large-scale atmospheric pressure fields and sea level changes in the NEA. As with the SLP model the explained trends are very different for the two time periods. However, again the 90% confidence levels overlap. These results show that the MSL of the NEA certainly explains a great part of the long term trend. Especially in the time period 1924 to 1962 the MSL of the NEA clearly is the main predictor of the long term trend. Likewise, as in the SLP model a stability can be seen in the explained variances. They are about 50% to 60% in all cases and thus have only few variability for the different time periods.

As in the SLP model the values of the explained variances are certainly lower than for the whole time period. However, there is only a small reduction in the SLP contribution to the explained variances. It can be seen that the SLP is accountable for about 50% of the annual variability in all considered validations. The index of agreement is also somewhat lower for the validation periods than for the whole time period. However, the values of 0.83 and 0.87 are still high and show that the systematical errors in the validation periods do not predominate. The predicted long term trends also show larger differences compared to the observed values as when taking the entire time period into account. We still conclude that the MSL of the NEA is the main contributer to the linear long term trend. However, the percentage of the predicted trend varies considerably within the validation periods.

A special issue of our work is to analyse the ability of trend prediction with the above model. So far, we analysed to what magnitude SLP and the MSL of the NEA influence the long term trend of the RMSL. Our analysis showed that both factors contribute an important part to the linear trend, with the MSL of the NEA explaining the main part. Next, we want to analyse the magnitude of the errors for trend prediction using the SLP model and the SLP-NEA model. In the cross-validation used, two different regressions were performed and analysed. It is difficult to estimate the error made in trend prediction from these two regressions. For that reason we conduct another cross-validation. We cut 39 years of the time series of the RMSL - starting with the first 39 values and then incrementing the starting year by one in each step. That is, first 1924 – 1962 are cutted off, then 1925 – 1963, and so on. The regression of section 3.1 and section 3.2 is then performed with the 39 years left in each case. That is for 1963 – 2001 in the first case, for 1924 and 1964 – 2001 in the second and so on. This result is then applied to the cutted off 39 years. This leads to a pool of 40 prediction periods of the same length with the two predictions considered above contained within this set. In each case we can compare the 39-year trend of the computed RMSL, with the predicted trend of the SLP model or the SLP-NEA model

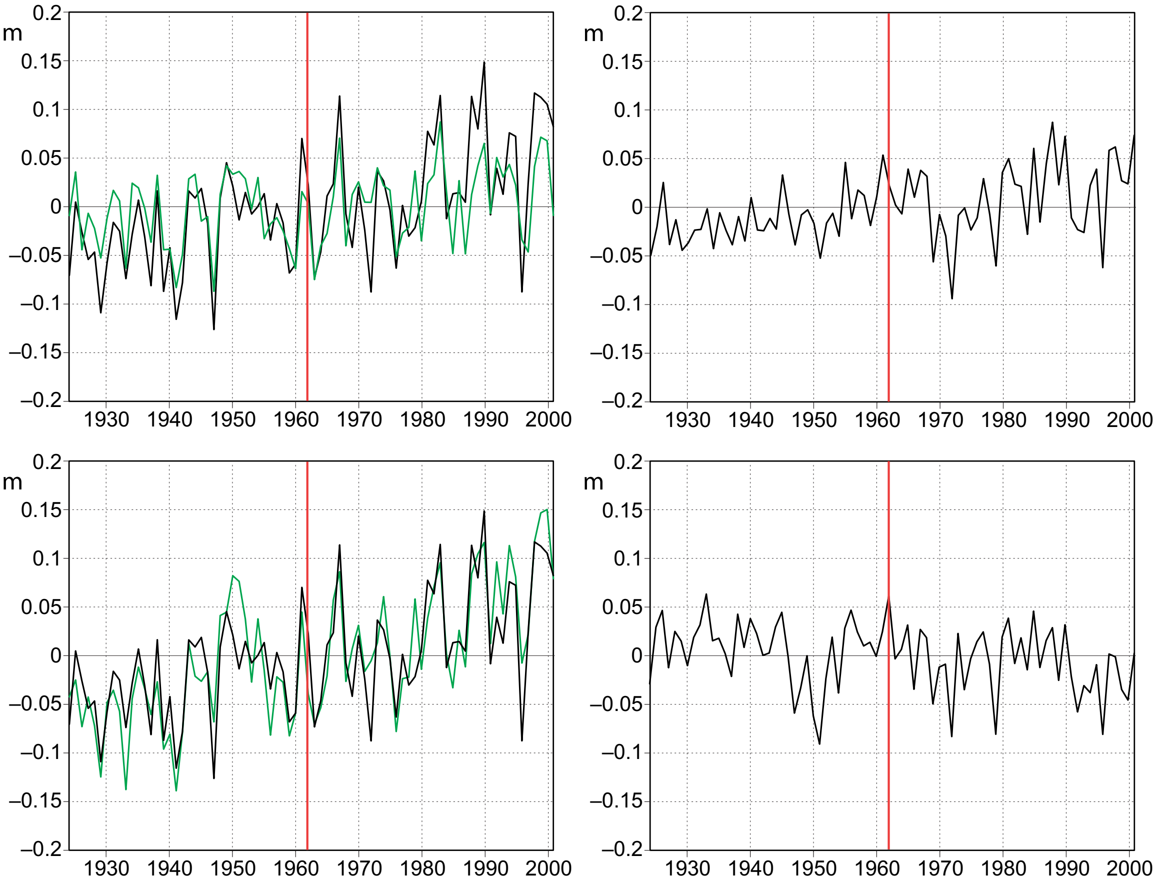

Fig. 13 Top [left]: Comparison of the RMSL of the German Bight ($z(t)$, black) and the regression result of (4) from 1924 – 1962 ($\tilde{\tilde{z}}(t)$, green) and [right] their residuals ($z(t) - \tilde{\tilde{z}}(t)$). Bottom: Analogue for the regression result from 1963 – 2001.

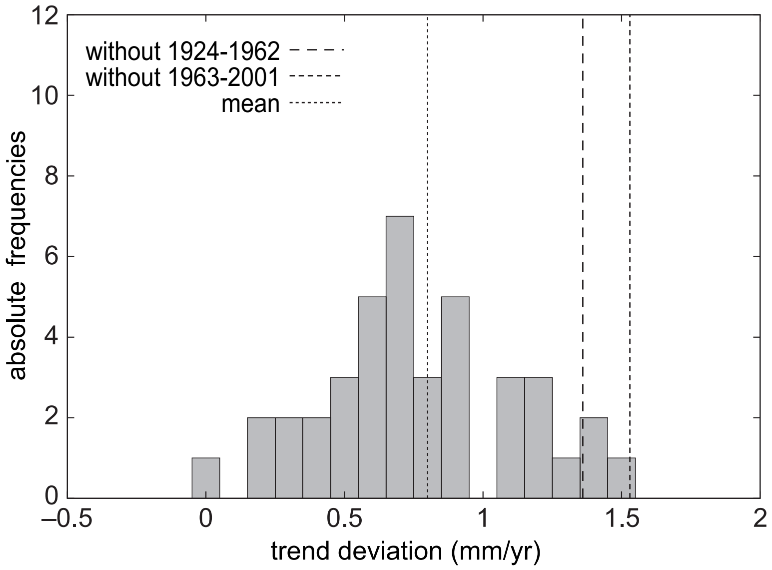

Fig. 14 Distribution of the deviations of the 39-year SLP-model trends and the observed trends of the computed RMSL $(abs(tr(\tilde{z}(t)) - tr(z(t))))$.

respectively. The distributions of the deviations can be seen in Fig. 14 and Fig. 15. We consider only absolute deviations, thus do not distinguish between under- and overestimation of the trend. However, we should mention that all projected trends underestimate the observed value in the SLP model, whereas in the SLP-NEA model both, under- and overestimation occur. The mean deviation to the observed trend is 0.8 mm/yr using the SLP model and 0.5 mm/yr with the SLP-NEA model. That is the additional variable is reducing the mean deviation. In Fig. 14 and Fig. 15 the two above considered cases are specially marked. They are both at the margin of the distribution in the SLP model. In the SLP-NEA model the deviation of 1.1 mm/yr for the projection of the period 1963 to 2001 is at the margin of the distribution. Only one deviation has a higher value. That is the deviations in the above considered cross-validation seem not to be represantative in most cases, but they are in general expected to be smaller.

4 Discussion

In this study, we developed an empirical model for predicting regional sea level changes associated with corresponding changes in large-scale atmospheric pressure and sea level fields. The results show that the SLP is the main factor to reconstruct and predict annual variability, whereas the NEA time series is mostly accountable for trend reconstruction and prediction. However, the SLP also makes an important contribution to the long term trend, but the contribution varies

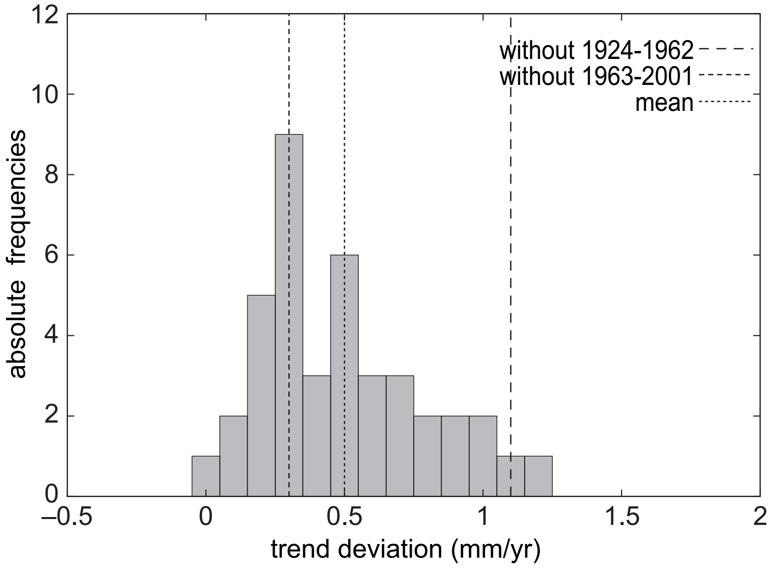

Fig. 15 Distribution of the deviations of the 39-year SLP-NEA-model trends and the observed trends of the computed RMSL $(abs(tr(\tilde{z}(t)) - tr(z(t))))$.

with time. For the time period 1924 to 2001 SLP explains 58% of the annual variability and 33% of the long term trend. The MSL of the NEA adds another 16% to the annual variability and 53% to the long term trend, such that using both variables 74% of the annual variability are explained and 87% of the long term trend. The index of agreement rises from 0.82 to 0.92 including the MSL of the NEA, thus also the systematic errors are reduced. Cross-validating the regression model approves that the SLP is mainly responsable for annual variability and MSL of the NEA for the long term trend. The explained variances are about 50% to 60% in all considered cases, whereas the main part comes from the SLP. The index of agreement varies from 0.79 to 0.87, that is systematic errors do not predominate. The relative contribution of the explained trends is quite different for both prediction periods. The SLP-NEA model overestimates the observed trend by about 20% for the period 1924 to 1962 and explains 58% for the period 1963 to 2001. However, the statement that an important part of the trend of the RMSL can be determined by the SLP and the MSL of the NEA remains valid. It is difficult to estimate the error made in trend prediction from these two numbers. For that reason we addressed this topic separately. An analysis of 40 different projections - all of the length of 39 years - leads to a mean deviation of 0.8 mm/yr of the linear trend of the RMSL using the SLP model and of 0.5 mm/yr using the SLP-NEA model. In this trend analysis the possible effect of GIA is not taken into account. During the last glacial maximum the ice depressed the earth crust and with the melting process this has been reversed. This process of land uplift is still going on and is called GIA. It is especially strong in high latitudes as in Scandinavia or

Canada. However, it might also have influence in the German Bight. Subtracting the effect of GIA might change the linear long term trend of our RMSL time series. That part of the linear trend determined by GIA can of course not be reproduced by the statistical model. Part of the differences in the trends of the observed RMSL and the model result might thus be explained by GIA. The estimations of vertical land movement resulting from a GIA model at different tide gauges in the German Bight are shown in Wahl et al. (2011). An interesting fact is, that the magnitude of the rise is about -0.5 mm/yr at all tide gauges. This complies with the mean trend difference the SLP-NEA model shows to the observed values.

As already discussed, in all reconstructed and predicted time series problems occur in the 1970s. The reason is an extraordinary high decadal trend in the RMSL of the German Bight. This high trend is also visible at the Danish and Dutch coast and cannot be explained with the two factors we use here. As mentioned in section 3.2 we tried to include other factors in the regression model in order to overcome these problems. We used time series of the GMSL and local temperature data, but neither of these time series could abolish the trend. We also could not find an indicator for a change in the ocean circulation. These problems can thus not be solved with our methods. There is thus either another factor influencing the RMSL of the German Bight which we could not constitute or the problems are due to the simplicity of the model.

As concluded above we think that the devolped model can be used as an approach for projecting those parts of future regional sea level change associated with large-scale changes in atmospheric pressure and sea level. In particular, the above results suggest that pressure effects need to be considered when potential future changes in RMSL are trying to be quantified. So far, such effects are usually not accounted for in regional sea level projections (e.g. Katsman et al. 2008, Katsman et al. 2011). For future work it would thus be interesting to apply the developed model to future projections of the SLP to estimate the potential effect of wind and pressure effects to RMSL rise in the German Bight.

Acknowledgment

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