ORIGINAL ARTICLE

Higher quantiles of sea levels rise faster in Baltic Sea Climate projections

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Abstract

Absolute sea levels in the Baltic Sea will rise under the influence of climate warming, similar to those in the world ocean. For extreme sea levels, there are indications that they will rise even faster than mean sea levels, but that topic is still controversially discussed and existing studies point into different directions. We analyzed a regional climate model ensemble for the Baltic Sea for future sea level changes. We find that the rate of change differs between high sea levels and the average: In the eastern part of the Baltic Sea, the 99th percentile of sea level was predicted to rise faster than the median. In the south-western part, the relation was opposite. Thus, our simulations predict a change not only in the sea level mean, but also in its distribution. This pattern was almost consistent between the individual ensemble members. We investigated the 99th percentile as a proxy for extreme sea levels, since their partially stochastic nature limits the predictive skill of our 20-member ensemble. Our findings imply that adapting coastal protection to mean sea level change only may be regionally insufficient.

Plain Language Summary

We simulated sea level rise in the Baltic Sea with a regional model. We analysed whether high sea levels, as they occur during a storm, rise faster than the mean sea levels. Our model suggests that this happens in the eastern Baltic Sea, while in the south-western part the rise is less fast. This information might be useful for coastal protection against flooding.

1 Introduction

1.1 Mean sea level rise in the Baltic Sea

As the Baltic Sea is a marginal sea, its absolute sea level is controlled by three main factors. The first is the sea level in the world oceans, which propagates into the Baltic Sea via its connection to the North Sea. The second is its low salinity which causes an additional steric component, elevating absolute sea levels specifically in the innermost parts of the sea, where the lowest densities occur. A third major component

is local atmospheric forcing. Wind and air pressure create a dynamic component of the sea level signal. All three drivers, global sea level, Baltic Sea salinity and local atmospheric patterns, are predicted to change in a warming climate. For the period of 1960–2015, the influence of the global mean sea level was largest with about 75% of the variability, but not the only driver, also intensified westerly winds made the sea levels in the northernmost parts of the Baltic Sea rise faster than the global mean (Gräwe et al. 2019). Such trends in the past cannot easily be attributed to climate change though because of the considerable multidecadal variability (Weisse et al., 2021). Regional model projections for future climate scenarios show rising absolute sea levels throughout the Baltic Sea, similar to trends in the North Atlantic(Meier et al. 2022b).

For sea level changes relative to land, the vertical land movement needs to be taken into account, which is, in the Baltic Sea, dominated by glacial isostatic adjustment. The melting of the ice shield after the last glaciation removed weight from the Scandinavian peninsula, which still reacts to this with an uplift of up to 9.6 mm/year (Vestol et al. 2019). The southern coast of the Baltic Sea, in contrast,

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experiences a land subsidence as a compensating effect. This causes mean relative sea levels to rise in the south and fall in the north of the Baltic Sea, as can be seen from tide gauge records dating back to the 19th century. In the recent decades, an acceleration is seen in the long-term trends since the 1960s (Karimi et al. 2021), consistent with the global signal (Dangendorf et al. 2019).

1.2 Changes in sea level extremes

Extreme sea levels in the Baltic Sea are typically caused by storm surges, which can raise the local sea level by up to 3–4 m above the mean (Wolski and Wisnewski 2020). Additionally, the filling state of the Baltic Sea plays a role, westerlies over a period of several days can increase the water volume of the Baltic Sea and lead to a background sea level elevation of ~24 cm, on top of which even less strong cyclones can cause sea level extremes (Weisse and Weidemann 2017). Specifically meteotsunamis can locally produce large and fast local elevations (Pellikka et al. 2020). The Baltic Sea differs from other regions by the fact that the tidal signal is small and only marginally contributes to sea level elevations. While the coincidence of meteorological extremes with high tides is required for other seas, the extreme sea levels in the Baltic Sea are therefore only controlled by meteorological forcing and modified by ice conditions, which can reduce coastal sea level elevations.

There is a controversy in whether extreme sea levels rise or will rise faster than mean sea levels in the Baltic Sea. The quantile regression method, the same as we use in our study, has been applied to observational data before. Barbosa (2008) used it on monthly-mean sea level records at several stations around the Baltic Sea, which had been deseasonalized by subtracting a monthly climatology. She found that specifically in the northernmost part, the higher quantiles were rising systematically faster than the mean. However, these high quantiles refer to entire months with an extraordinarily high average sea level, rather than to individual extreme events. Ribeiro et al. (2014) analyzed daily time series at 7 stations along the Danish and Swedish coast for their extremes. From the quantile regression method, they found that extreme sea levels were rising faster than the mean sea levels at 6 out of these 7 stations, with highest discrepancies (up to 2 mm/year) in the northernmost part. A second method was fitting generalized extreme value distributions. Three out of seven of their time series were significantly better fitted when a trend in the location of the extreme value distribution was assumed, that is, assuming a change in the total distribution of sea levels. Meier et al. (2022), however, argue that the trend, that was clearly identified in the observations, cannot necessarily be attributed to a systematic change in climate, since also climate variability, and specifically a random occurrence of the strongest

individual storm surges in the latter part of the time series, could have as well caused the signal. The same is true for the study of Wolski and Wisnewski (2021), who investigated annual maximum surge levels and found a positive trend in 1960–2020 for stations all around the Baltic Sea.

Disentangling whether variability or a systematic trend is the reason for the observed changes is complicated by the limited length of the available time series, and correspondingly the few available data points that contribute to the trend in the higher percentiles. Also, simply adding more stations to the analysis will not necessarily help, since spatial covariance makes them not independent. Model studies could help in answering this question, since they can (a) simulate climate change in an ensemble of model runs with a different random signal, and (b) in the best case help to understand the dynamic cause for the changes in the higher percentiles and attribute it to a change in the forcing.

1.3 Extreme sea levels in Baltic Sea regional climate simulations

Extreme sea levels are influenced and determined by changes in the wind field. Atmospheric ensemble simulations show small changes in the wind field over the Baltic Sea region. Both mean and extreme 10-m wind speeds may change by a few percent, with an increase in winter and a decrease in summer, over the Baltic Sea region, but the signal has large uncertainties as the ensemble spread is much larger than the signal, even in the RCP8.5 scenario (Christensen et al., 2022). Climate simulations have also addressed extreme sea levels directly. An ensemble simulation by Vousdoukas et al. (2016) with 8 different climate scenarios confirmed the findings of Ribeiro et al. (2014): It projected larger trends for extreme sea levels, specifically sea levels with return periods of 5-100 years, relative to mean sea levels in the Baltic Sea. In its northern part, most ensemble members were consistent in predicting this trend in the shape of the sea level distribution. A shortcoming of the study was that the model was a shallow-water model which means that baroclinic effects such as the permanent halocline in the Baltic Sea could not be represented. It was directly driven by the atmospheric output of global climate models of the Coupled Model Intercomparison Project 5 (CMIP5).

Another study by Paprotny et al. (2016) used atmospheric downscalings of climate projections to drive a similar ocean model. Rather than applying the atmospheric forcing from a global simulation directly, they used a regional atmospheric model (RCA4 by the Swedish Meteorological and Hydrological Institute) which had been driven by lateral boundary conditions from a global climate model, ICHEC-EC-EARTH. Benefits are a finer resolution of atmospheric dynamics in the target region, specifically the use of a more realistic topography and land mask. Their study showed the

opposite result, declining storm surges in the Baltic Sea, in both an RCP4.5 and RCP8.5 climate scenario. A shortcoming of this study is the use of a single realization of each future climate scenario, instead of a model ensemble.

Our study investigates the same question with a dynamic regional downscaling simulation: Atmosphere and ocean are two-way coupled in our setup, which adds the ability of the system to represent interactions between ocean, ice and atmosphere. The ocean is represented by a full 3-dimensional model which includes baroclinic effects. Also, we use an ensemble of several climate scenarios driven by different global models to answer the question of changing extremes.

1.4 Outline

The article is structured as follows: In Sect. 2, we will describe the model system that we used and the statistical methods that we used for evaluating the model results. In Sect. 3, we describe the observational data we used, specifically for model validation. Section 4 shows our results, starting with a model skill assessment for the given purpose and then presenting our results on the changes in 99th percentile vs. 50th percentile sea levels. Section 5 ends with conclusions.

2 Materials and methods

2.1 Regional climate model simulations

We use a regional coupled model to do a downscaling of global climate simulations, which are used as boundary conditions. Our model system consists of an atmospheric and an ice-ocean component. The atmospheric model is the Rossby Centre regional atmospheric model (RCA4, Kjellström et al. 2016) in a resolution of 0.22° in the horizontal and 40 vertical layers. It is covering the EURO-CORDEX domain, i.e., a region including almost the entire European continent and parts of northern Africa. The ice-ocean model

is NEMO-Nordic (Hordoir et al. 2019), which is applied for the North Sea and Baltic Sea, with a horizontal resolution of approximately 2 nautical miles and 56 vertical z-levels. More details on the model setup can be found in Dieterich et al. (2019a, b).

An ensemble of runs is performed by this regional model, taking different global simulations as lateral forcing. The forcing data (see Table 1) include one hindcast simulation (the ERA-40 reanalysis) and eight climate models that were used in the coupled model intercomparison project CMIP5. Each of these models contributes one reference simulation for the historical period and two to three climate scenarios, which differ in their radiative forcing. Simulations for three reactive concentration pathways (RCPs) were chosen from the list of available model experiments, the RCP2.6, RCP4.5 and RCP8.5 scenarios, which represent an optimistic, a moderate and a strongly pessimistic development of atmospheric greenhouse gas concentrations during the 21st century. For each climate scenario, a transient simulation was performed starting in 1961–2005 with the historical reference and continued to including 2099 with the respective climate scenario. In total, this amounts to 20 transient simulations in addition to the 1961–2009 downscaling of the ERA-40 hindcast.

2.2 Contributions to the sea level signal

The local sea level change simulated by the model consists of different contributions. Global sea level rise enters the model via the open boundary conditions, since it is partly simulated by the global models. Our barotropic boundary conditions, prescribed as sea levels, are a sum of two signals: The tidal signal is defined by 11 constituents from a tidal model (Egbert et al. 2010), a non-tidal signal is added to these from a global simulation: In the hindcast simulation, we use the ORAS4 reanalysis (Balmaseda et al. 2013), in the climate scenarios we extract monthly mean sea level time series from the global models. These capture the thermal expansion of the ocean, a local steric contribution as well

Table 1 Boundary data used for the 20 + 1 simulations in the model ensemble

Global model	Number of simulations	Scenarios	Years
ERA-40	1	Reanalysis	1961–2009
CANESM2	2	Historical + RCP4.5/RCP8.5	1961–2099
CNRM-CM5	2	Historical + RCP4.5/RCP8.5	1961–2099
EC-EARTH	3	Historical + RCP2.6/RCP4.5/RCP8.5	1961–2099
GFDL-ESM2M	3	Historical + RCP2.6/RCP4.5/RCP8.5	1961–2099
IPSL-CM5A	2	Historical + RCP4.5/RCP8.5	1961–2099
MIROC5	2	Historical + RCP4.5/RCP8.5	1961–2099
MPI-ESM-LR	3	Historical + RCP2.6/RCP4.5/RCP8.5	1961–2099
NORESM1-M	3	Historical + RCP2.6/RCP4.5/RCP8.5	1961–2099

as dynamic changes induced by changes in the wind signal or the inverse barometric effect. These dynamic effects are also covered in the regional model. Missing in the model is the effect of the melting of inland ice, as well as the vertical land movement, which needs to be taken into account when considering relative sea level rise. These contributions were therefore added on top, after the simulations were finished. For the meltwater signal, we used global estimates from the IPCC fifth assessment report (IPCC, 2013), thereby neglecting regional effects of a change of the gravity field by the melting inland ice. Only in the reanalysis run, this mass signal did not have to be added, since it was contained in the global model already. For the vertical land movement, which is pronounced in the Baltic Sea area, we used estimates from the NKG2016LU model (Vestøl et al. 2019). Adding these contributions to the results only means that we have to assume a linear combination of the signals. A possible non-linear interaction of drivers, such as a change in the dynamic coastal sea level signal after a meltwater-induced global sea level rise, cannot be taken into account by our approach.

Daily maxima of hourly mean sea levels were stored by the model in all coastal grid cells, in order to assess the changes in sea level extremes. We only analyze the model output from 1971 onward, the first ten years of the simulation are considered as spin-up period.

2.3 The quantile regression method

Rather than looking at sea level extremes in the model, we analyse the development of the 99th percentile of sea levels as a proxy for changes in extremes. The reason for this is that climate-induced trends in sea level extremes are difficult to assess, since the occurrence of extremes has a stochastic component, which is driven by weather rather than climate. In reality as well as in model-generated sea level time series, this random component occurs on top of a systematic signal. In numerical models, it is in principle possible to eliminate this random part of the signal by running a large ensemble of simulations, each with perturbations, such that the stochastic component will be independent between the runs and disappear in the ensemble mean. The disadvantages of this approach from a regional modelling perspective are on the one hand the numerical effort and on the other hand its dependency on the existence of large enough global-model ensembles.It is, for our purpose, not helpful to generate regional ensembles by adding perturbations at the regional scale. This is because model runs driven by the same global boundary conditions, even if they may develop different internal variablity, would still share the stochastic components from the open-boundary forcing and thus not be independent realizations of a climate state. Treating them statistically

as independent members might thus lead to overconfidence and the misidentification of stochastic contributions as systematic trends.

While from a coastal engineering perspective, extreme sea levels are of interest, which means long return periods, their trend may show a strong stochastic component even in a model ensemble due to the limited number of events. It is therefore necessary to look at less extreme values which occur more frequently and give better statistics. A necessary condition for the model study to make sense would be that the regional model is able to reproduce the observed trends when being forced with realistic (hindcast) past boundary conditions. We will demonstrate that this is true for trends in the 99th percentile of sea levels in our model system.

We therefore use the quantile regression method (Koenker and Hallock 2001) to estimate trends in different percentiles of the sea level time series. It works similar to linear regression and estimates a linear fit through data points in a time series. In linear regression, the sum of the squared errors between model and data is minimised, this quadratic penalty function makes the trend line estimate the mean value. A penalty function using the absolute errors will, if minimized, make the trend line estimate the median (the 50th percentile). Lines that estimate trends in higher and lower percentiles can be obtained by using a suitably asymmetric penalty function. We use the software R (Core Team 2021) and the package quantreg (Koenker 2021) for the analysis and fit the 1st, 50th and the 99th percentile of the sea level time series.

2.4 Assessing model skill

Model skill is assessed by a comparison to selected tide gauge records in the Baltic Sea. The data were extracted from the GESLA database (Haigh et al. 2021) for the stations listed in Table 2 and were aggregated in the same way as the model data (daily maxima of hourly means). Observations were compared to the results of the ERA-40 downscaling simulation in terms of correlation and variance for an assessment of the overall model skill, and multidecadal trends in the percentiles of the sea level time series were analyzed to check the credibility of the model in predicting these percentile trends given the assumption that the boundary data are realistic. To compare these percentile trends, model data were extracted from the closest coastal grid points to the station locations in Table 2. At those points in time where observations had gaps, the model data were also set to missing values. Then, the trends for the three percentiles were calculated over different multidecadal periods and the modelled trends compared to the observed ones.

Table 2 Selected locations for sea level observations

Station name	Latitude (°N)	Longitude (°E)
Degerby	60.03190	20.384800
Furuogrund	64.91580	21.230600
Göteborg	57.68470	11.790600
Hanko	59.82290	22.976601
Helsinki	60.15360	24.956200
Klagshamn	55.52220	12.893600
Kungsholmsfort	56.10530	15.589400
Marviken	58.55360	16.837200
Raahe	64.66590	24.407101
Ratan	63.98610	20.895000
Rauma	61.13350	21.425800
Smögen	58.35360	11.217800
Spikarna	62.36330	17.531100
Travemünde	53.95802	10.872182
Turku	60.42830	22.100500
Visby	57.63920	18.284400

3 Results

3.1 Overall model skill on simulating sea level

To analyse whether the model is capable of reproducing observed sea levels, we compare observations at GESLA stations in the Baltic Sea to model results at the closest coastal points. We compare the daily maxima of hourly means. Figure 1a shows that the agreement between model

and observations depends on the region in the Baltic Sea: The model explains more than 70% of the variance east of 15°E, with the exception of the Raahe station where agreement is lower. Correlations are slightly lower but show the same spatial pattern if deseasonalized data are used. The low skill in the western part can be explained by a shortcoming in the choice of the boundary conditions for the model ensemble, see Sect. 4.1. The variance in the daily maxima of the sea levels is systematically underestimated in the model, see Fig. 1b. The underestimation however, only amounts to around 10–20% of the signal, and the spatial variability in the temporal variance is captured by the model. Exceptions are the westernmost stations Travemünde, Smögen and Göteborg where the underestimation is pronounced. The model correctly finds that the distribution of the daily-maxima sea levels is right-skewed for all stations. Its median is below the mean for all stations, and it's 97.5th percentile has a larger distance to the mean than the 2.5th percentile.

3.2 Model skill in simulating past changes in sea level percentiles

The trends in the 1st, 50th and 99th percentile of sea level were calculated for all six possible multidecadal periods with a starting or ending date of January 1st in 1970, 1980, 1990, 2000 or 2010. As these were six periods (partially overlapping), we got a vector of 18 trend values for the observed sea levels and another one for the reconstructed sea levels by the ERA-40 downscaling. Figure 2a and b illustrates how some modelled and observed trends
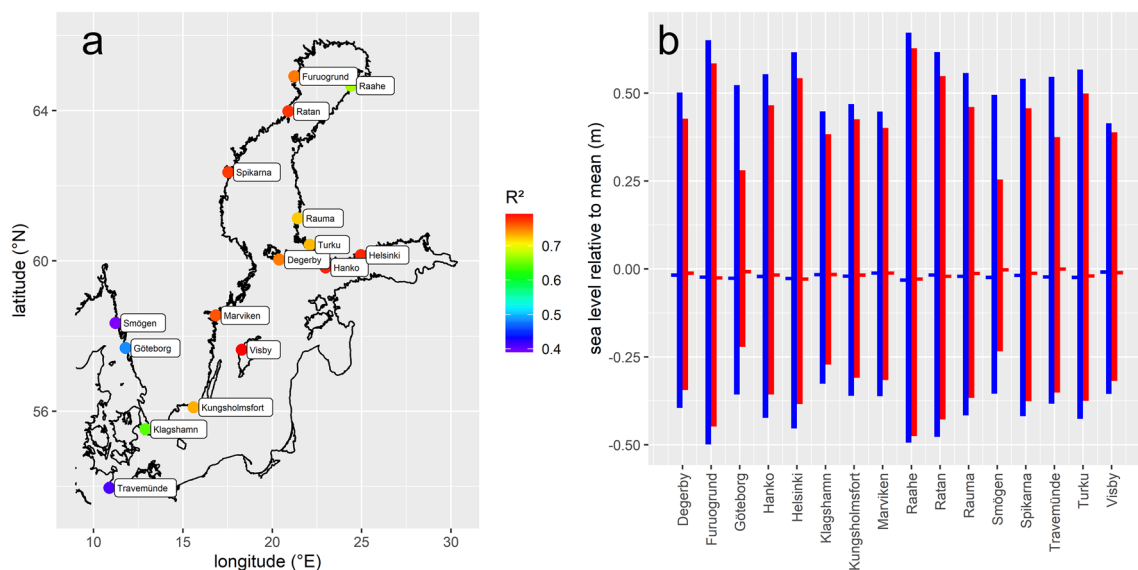

Fig. 1 **a** Squared correlation coefficient between modelled sea level time series and GESLA observation data. **b** Observed (blue) vs. modelled (red) spread in the daily maxima. Vertical bars denote the inter-val that contains 95% of the values. Horizontal ticks indicate the location of the median relative to the mean
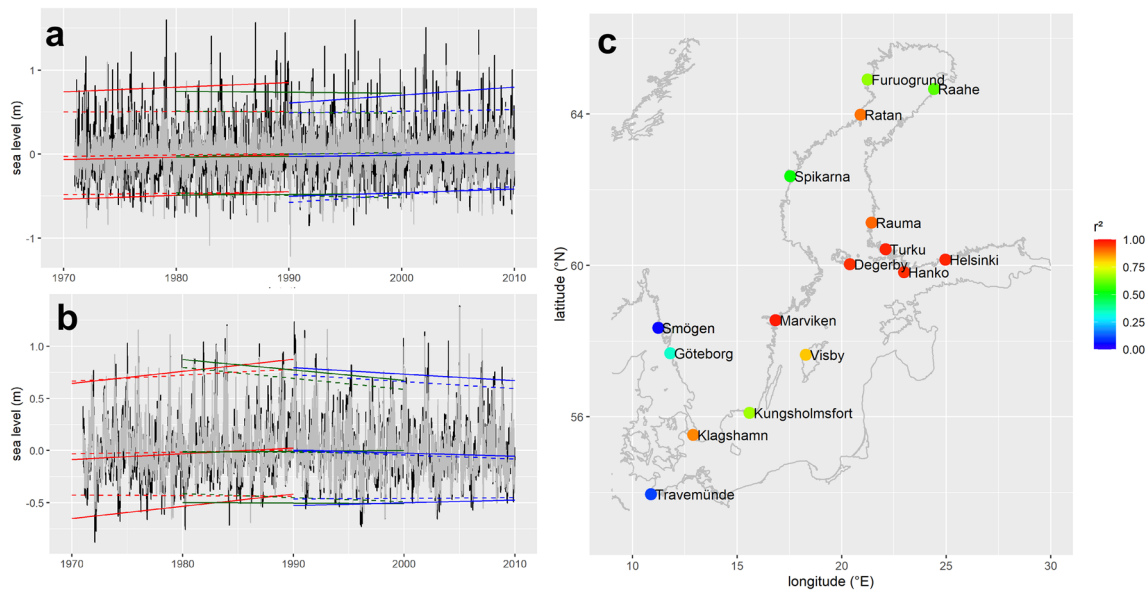
Fig. 2 Ability of the model to reproduce interdecadal trends in the sea level quantiles. (**a**-**b**) Trends at station Degerby / Kungsholmsfort for different two-decadal periods. The black and grey curves show observations and model results, respectively. The solid lines indicate the multidecadal trends in the observations and the dashed lines the corresponding trends in the model reconstruction. **c** Squared correlation coefficient between observed and simulated multidecadal trends in the 50th and 99th percentile for different stations

match for two stations, Degerby (with a good match) and Kungsholmfort (with a slightly worse match). Figure 2c shows the squared correlation coefficient between the observed and modelled trend vectors. While in the western part of the Baltic Sea (west of 15°E), the fraction of the variance in the observed trends that is explained by the model is less than half, these values improve in the eastern part where the model explains the majority of the variance in the multidecadal variations, with the exception of the Spikarna station. This gives us confidence that for this region, the downscaling model has skill in predicting the multidecadal trends in the selected sea level quantiles, given that the boundary data are realistic.

3.3 Projected changes in median sea level

For the 50th percentile of sea level, that is, the median value of daily maxima of hourly means, our model simulates a bipolar pattern in sea level change: Relative sea levels are predicted to rise with several millimeters per year at the southern part of the Baltic Sea, while we find a relative sea level drop of again several millimeters in Scandinavia (Fig. 3). This is a well-known pattern also observed today and a result of the pronounced vertical land movement caused by glacial isostatic adjustment. Sea level rise shifts the zero-line of mean sea level change northward, in our model scenarios for RCP2.6 and RCP4.5 it crosses the Swedish coast at the Öland and Gotland islands and the Estonian coast at the island of Saarema. In the more
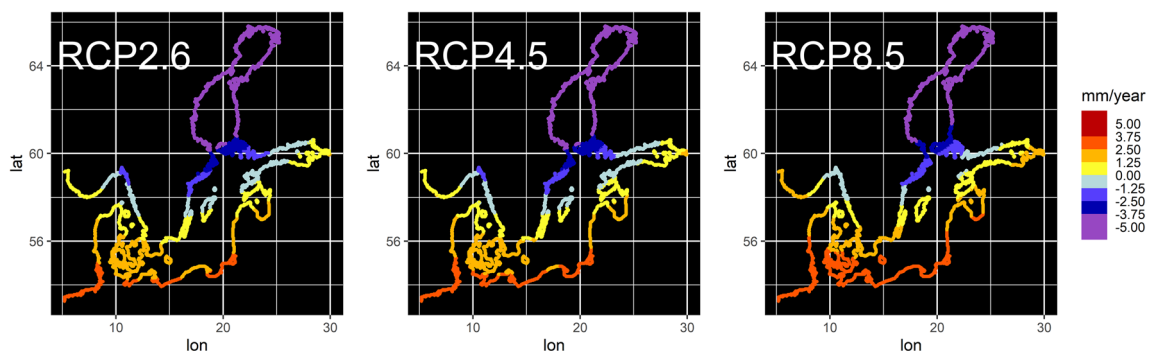

Fig. 3 Ensemble mean of the linear trend in the 50th percentile of sea level for 1971–2099

pessimistic RCP8.5 scenario, the isoline is shifted slightly northward and these islands experience a rise in relative sea level around their entire coast. Our model results are consistent with tide-gauge-based reconstructions for the period 1915–2014 which show a zero-trend-line a bit south of these mentioned islands (Madsen et al. 2019).

3.4 Projected changes in higher sea level quantiles

The 99th percentile shows similar, but not identical, trends as the 50th percentile. When looking at the ensemble mean of the difference between them (Fig. 4), the regional pattern is similar in all reactive concentration pathways: In the south-western part of the Baltic Sea, we see the 99th percentile sea levels rising more slowly than the 50th percentile, while in the northern and eastern part, extreme sea levels rise faster. In the Bothnian Bay in the very north, the signal depends on the chosen climate scenario, with faster rising 99th percentile, consistent with the adjacent Bothnian Sea, in the most pessimistic RCP8.5 scenario, and with 99th percentile sea levels rising more slowly in the other two scenarios. The magnitude of the relatively faster growth of the 99th percentile differs between the scenarios, with values below 0.25 mm/year in the optimistic and intermediate scenarios, but under RCP8.5 up to 0.75 mm/year are reached in the Gulf of Riga and Gulf of Finland. In the south-western part, the 99th percentile rise is slowed down by − 0.25 to − 0.5 mm/year in all climate scenarios.

Looking at the individual models rather than the ensemble mean (Fig. 5), we see that these trends are often consistent between the model runs forced with the different climate scenarios. We consider four stations, Travemünde in the southwestern Baltic Sea,Riga in the Gulf of Riga and Helsinki in the Gulf of Finland as reperesentatives of the eastern Baltic Sea region where the rise signal is most pronounced, and Raahe in the Bothnian Bay, the northernmost basin. For Travemünde, the agreement is largest, with 19 out of 20 scenario runs showing a decreasing trend in the 99th percentile minus the median, and only one scenario

showing the opposite trend. For the two eastern stations Riga and Helsinki, we see that the agreement between the models rises with the radiative forcing: 2 out of 4 (6 out of 8, 7–8 out of 8) models agree on the positive sign of the trend for the RCP2.6 (RCP4.5, RCP8.5) scenarios. For the station Raahe in the Bothnian Bay, models show agree on a negative trend in the RCP2.6 scenario but increasingly disagree on the direction of the trend in the warmer model scenarios.

Our last step is to investigate whether the trends are robust against interdecadal variablility. We want to check whether it is possible that a single strong storm could turn the trend around when it occurs in an early or in a late decade. To do so, we omit single decades from the modelled time series and repeat the trend calculation. The results are shown in Fig. 6. It can be seen that omitting single decades would change these trends by ~ 0.25 mm/year at most. Only few points occur in that graph in the second or fourth quadrant, where they indicate a switching of the sign in the signal. Only three situations occur where a positive trend turns negative by removing a decade from the time series, all of them for the Raahe station, so the positive trends at the Riga and Helsinki stations are systematic in a sense that they are not determined by extreme events in an individual decade of the simulation.

4 Discussion

4.1 Model applicability

The comparison of the modelled sea levels to observations shows that the model has skill in reproducing both daily maxima and also decadal trends of different quantiles of sea levels. The agreement is poor in the western Baltic Sea. This is probably due to the coarse resolution that does not resolve the topography in the Danish Straits, and due to the choice of the sea surface height boundary conditions at the borders between the North Sea and the Atlantic Ocean. Dieterich et al. (2019) showed that extreme sea levels in the
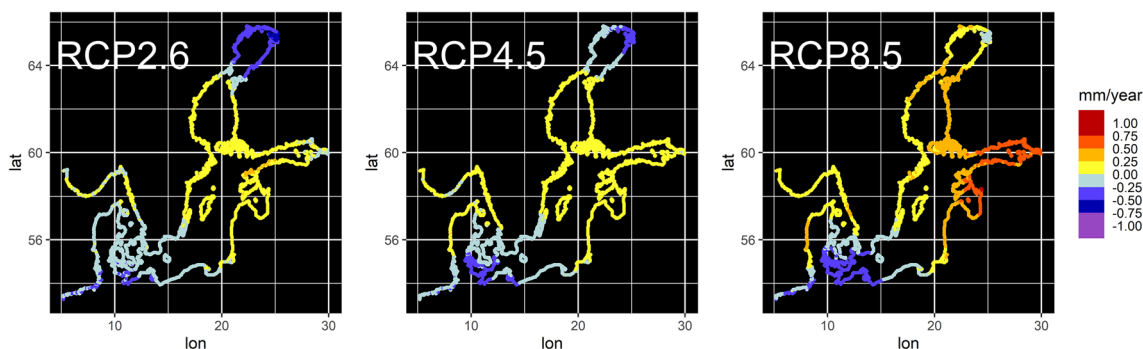

Fig. 4 Ensemble mean of the difference of linear trends, 99th minus 50th percentile, of sea level for 1971–2099
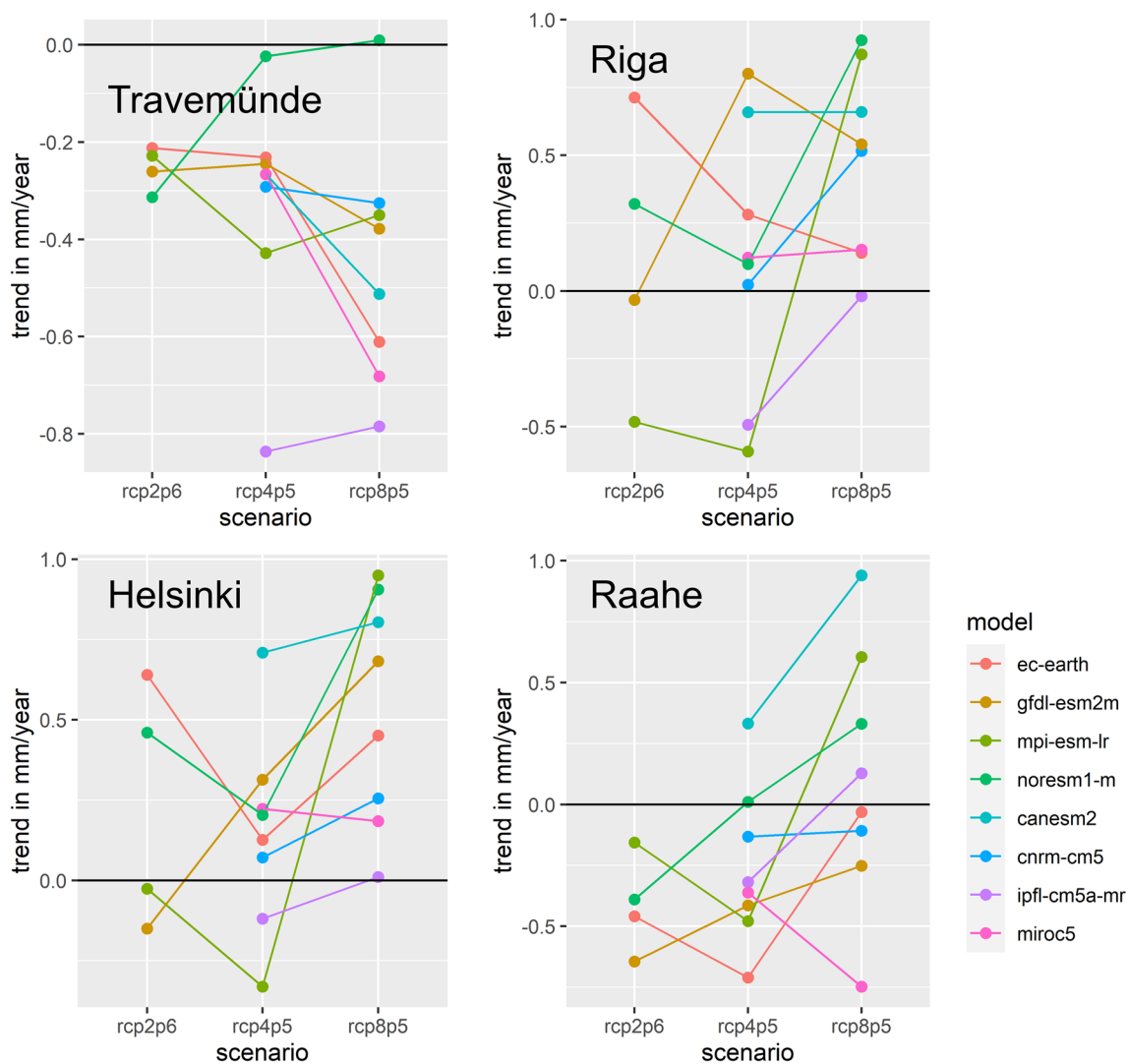
Fig. 5 The difference between 99th and 50th percentile trends for individual ensemble members for selected stations

model strongly depend on the specific choice, and Gröger et al. (2019) showed that the present choice of the boundary conditions causes unrealistic circulation patterns in the North Sea, which will likely affect the transition region in the Baltic Sea as well.

For the central and eastern part of the Baltic Sea, our model outperforms the barotropic models used in previous studies. Explained variance in the daily maxima is above 0.7, while Paprotny et al. (2016) states values around 0.6 for Northern European stations. Our root-mean-squared error values are 0.13 m as average over all Baltic Sea stations, here both Vousdoukas et al. (2016) and Paprotny et al. (2016) give a value of 0.15 m.

Our regional model has shown that it reproduces past multidecadal trends in the sea level quantiles, at least the majority of their variance, when driven by realistic historic atmospheric boundary conditions. So, if the global models

succeed in providing realistic projections of the atmospheric circulation over northern Europe in a changed climate, our regional model system should also be able to translate these to realistic future sea level distributions.

4.2 Discussion of model results

The results of our simulations suggest that in the eastern part of the Baltic Sea, climate change will cause a systematically increasing trend in the 99th percentile sea levels relative to the median sea level. This result of our simulations is not significant though; the use of different global climate models reflects our uncertainty in the global response to anthropogenically altered radiative forcing, and this uncertainty propagates into our projections for regional changes. Arriving at 95% confidence would thus only have been possible

Fig. 6 Robustness of the trend in the quantile difference against omitting individual decades from the time series, for selected stations
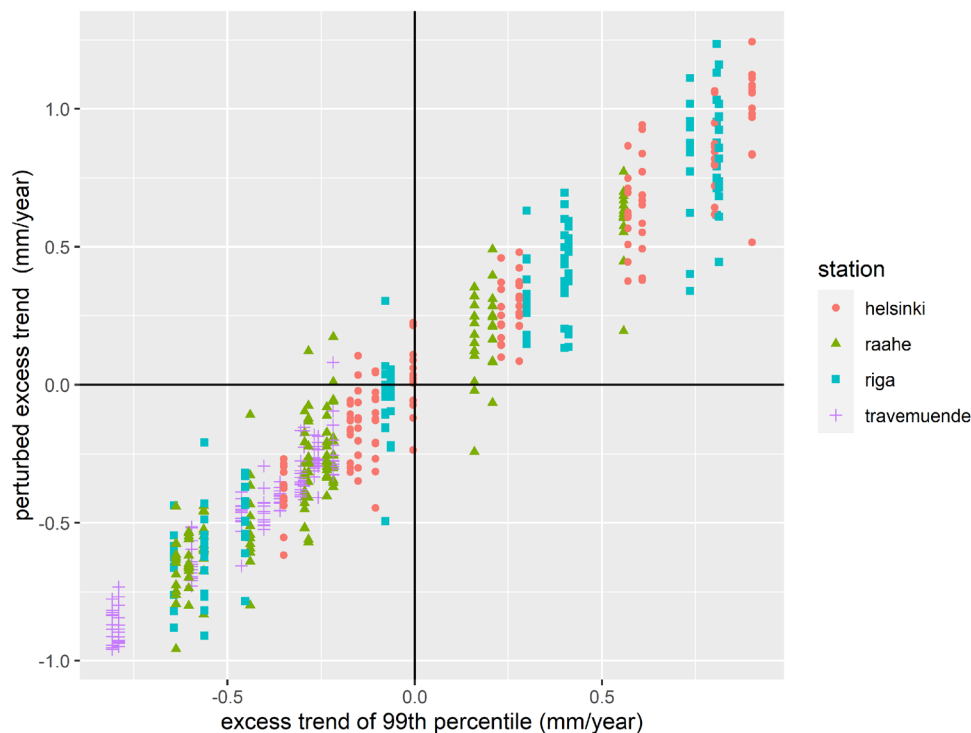
with a larger ensemble, or an agreement of all eight of the ensemble members for each scenario.

The results also suggest an opposite trend (declining 99th percentiles relative to the median) in the south-western part of the Baltic Sea. Even if the model agreement is even better here, this result is still less certain, since the model shows larger deviations from observational data in this region.

We did not look into higher percentiles, such as return periods of 100 years, since we could not prove from a comparison to observational data that our model has skill in predicting trends in those. The reason is that the larger the percentile, the more observations are needed to detect a systematic trend against variability. A transferability of our results to higher return periods therefore depends on the question whether these extreme sea levels have a similar generation mechanism as the 99th percentile sea levels for which our model suggested the change.

Seen in the light of the existing literature, our results give some support to the hypothesis of Ribeiro et al. (2014) that observed increases of extreme sea levels relative to the mean show a systematic effect or at least have a systematic component. There is a regional mismatch, though, between our study and those of Barbosa (2008) and Ribeiro (2014): The observed extreme sea level rises were maximal in the north-ermost part of the Baltic Sea, where our model shows such a signal only for the RCP8.5 scenario under much warmer conditions than at present. Our climate simulations are a complementary method to observations: By their nature, they differ in the random part of the signal. As they show

agreement beyond what would be expected in a random ensemble, this means the effect must be systematic. It is therefore likely that it may have occurred already in the past few decades which were influenced by climate warming. For the future scenarios, our study agrees with the projections of Vousdoukas et al. (2016) and questions the model results by Paprotny et al. (2016) which rely on a single realization of each future climate scenario.

5 Conclusions

Our study used a coupled regional atmosphere-ice-ocean model to do a downscaling of 20 CMIP5 global climate simulations for the North Sea and the Baltic Sea. We specifically looked into high sea levels (the 99th percentile of daily maxima) and found that they exhibit a change relative to the median. They rise faster in the eastern parts of the Baltic Sea and less fast in the south-western parts. The signal is almost consistent between the different climate models and increases in magnitude with the radiative forcing, even if this trend in the individual models is not linear with climate forcing.

Our model results are reliable for the Baltic Sea east of 15°E because here modelled and observed sea levels correlate well. Also we could show that our model was capable of reconstructing the changes in the 99th sea level quantiles that occurred in the past decades. The modelled trends are robust against removing single decades from the simulation.

The implications are that for coastal protection, it may not be sufficient to adapt the measures to changes in mean sea level, since the extremes could rise more rapidly. Fortunately, for large parts of the Baltic Sea, the land uplift due to glacial isostatic adjustment will still lead to a decline in relative sea levels. For the south-western Baltic Sea, where a land subsidence will add to the rise in absolute sea levels and increase its impact, the model predicts a slower rise of the extremes, but due to the poor model performance in this region, this remains uncertain.

The most relevant question that arises for future research is the attribution of the trends in the extremes. The explanation cannot be too simple, as the effect is opposite in single ensemble members. For example, the hypothesis that just the reduced ice cover leads to stronger sea level elevations in the eastern parts cannot give the full explanation, since a reduction of the ice cover also happens in those climate scenarios that show the opposite trend. A first look into changes in storminess and in the direction of strong winds also gave no clear indication of a difference between the outlier model with a negative trend and the other ensemble members. So, the physical mechanism remains an open question. Our existing and available data set, which contains the full hydrodynamic results of the model ensemble, should contain the answer. Investigating this and understanding what can cause an increased rise of sea level extremes might be of global relevance, since the yet unknown physical mechanism may as well act in other coastal seas and increase a flooding risk.

Data availability The modelled sea levels at grid points adjacent to the coast are available online under https://doi.org/10.12754/data-2023-0002. The full set of model results is available on request.

The sea level observations can be downloaded from https://www.gesla.org.

The code for the ocean model that is used in RCA4-NEMO is available at https://doi.org/10.5281/zenodo.2643477 (Dieterich and NEMO Team, 2019).

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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