European Research Area for Climate Services

# ECLISEA

## European advances on CLImate Services for Coasts and SEAs

# Potential skill of decadal predictions for wind waves and storm surges.

Work Package 3 - Deliverable 3.C

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# 1. Introduction

The need to provide climate information to society has been recognized for many decades of years. For example, the first World Climate Conference held in 1979 by the World Meteorological Organization called for establishing a World Climate Programme to improve our understanding of the climate system and its impacts on society (Vaughan and Dessai 2014). Generally, climate change information is provided in the form of *scenarios* conditioned upon different levels of greenhouse gas emissions. Mostly such information is available for the end of the 21st century and less often for the coming about 10-30 years, in the following referred to as the decadal time scale. As time-dependent climate change is unfolding, there is however an increasing need among policy and decision-makers, both for climate services and for climate information to support adaptation (Weisse et al. 2015; Weisse et al. 2009) especially on the decadal time scale (Pulwarty 2003).

The evolution of the climate in the coming decades will be the result of an interplay between contributions from anthropogenically forced climate change, intrinsic natural climate variability, and externally forced climate variations (e.g. solar or volcanic forcing) (Meehl et al. 2009). Mostly, information on such decadal changes is presently obtained from ensemble-averaged forced climate simulations driven by different greenhouse gas emission scenarios (Meehl et al. 2009). Using this technique, intrinsic climate variability is typically averaged out and information is lost. Meehl et al. (2009) suggested that retaining this information by using initialized predictions may foster better quantification of the uncertainty in the decadal range. This suggestion is further based on the fact, that over time different sources provide different contributions to the overall uncertainty. While uncertainty caused by choosing a particular climate model or a set of such models is expected to represent the dominant source of uncertainty in the coming decades, its relevance is expected to decrease over time, as climate change is unfolding. On the other hand, uncertainty arising from the choice of a particular emission scenario or a range of such scenarios is small in the near future but becoming increasingly more important and larger over time. From these points, Meehl et al. (2009) concluded that relative to other time scales there may exist a minimum of uncertainty in the decadal range.

However, even if uncertainty is low in the decadal range, the signal-to-noise-ratio may vary substantially by region and for different variables. Here, the *signal-to-noise ratio* refers to the extent to which the magnitude of predictable climate variations exceeds noise from uncertainties in forced simulations and unpredictable aspects of intrinsic climate variability (Barnett et al. 2008). Generally, a forecast is referred to as *skillful* when the signal-to-noise ratio is sufficiently large. What exactly *sufficiently large* means represents a matter of definition, expectation, and the reference against which skill is measured.

Using several different approaches and techniques, in this report the extent to which skill can be detected in decadal predictions of storms, waves and storm surges along the German North Sea coast is assessed. Approaches and techniques are briefly described in section 2. Moreover, data and methods are shortly introduced. Results are presented in section 3, and a summary and some conclusions are provided in section 4.

# 2. Approach, Methods, and Data

## *2.1 Approach*

A double-track approach was taken to assess the skill of decadal predictions for storms, waves, and storm surges along the German North Sea coast. On the one hand, the skill existing in climate model simulations available from the CMIP5 coordinated decadal predictability experiment (Taylor et al. 2012) was explored. As waves and storm surges are not directly available from these simulations, indices of storm activity (Krueger et al. 2019) over the North Atlantic together with statistical downscaling between observed (hindcast) large-scale atmospheric patterns and waves and storm surges were used. Also and on the other hand, the inherent predictability that may arise from autocorrelations or, in other words, the slow decay of existing anomalies towards the mean was explored and compared to results obtained from the CMIP5 decadal predictability experiment.

## *2.2 Methods*

Geostrophic wind speeds calculated from mean sea level pressure readings were used to derive time series of northeast Atlantic storminess. The technique was originally developed by Schmidt and Storch (1993) and subsequently used widely for studies of changes and variability of extra-tropical storm activity (Alexandersson et al. 1998; Alexandersson et al. 2000; Matulla et al. 2008; Krueger and Storch 2011; Krueger et al. 2019; Krieger et al. 2020). It provides relatively homogeneous, large-scale, and long-term information on storm activity and is thus well suited for statistical analyses. We use both, *observed* indices computed from historical air pressure data available from the International Surface Pressure Databank (ISPD) complemented with data from the Danish and Norwegian Meteorological Institutes and from hindcast met-ocean data (Weisse et al. 2015) and *predicted* indices derived from the pressure data from simulations of the CMIP5 decadal predictability experiment (Taylor et al. 2012).

Both, linear and logistic regression as well as canonical correlation analyses (Storch and Zwiers 1999) were used to downscale large-scale atmospheric patterns onto the local wave and storm surge changes along the German North Sea coastline. Naiive Bayesian pattern recognition (Bishop 2009) and spectral analysis were used to assess predictability potentially inherent in the storm index time series and to compare it to estimates derived from the CMIP5 decadal predictability experiment.

## *2.3 Data*

For the calculation of time series of observed northeast Atlantic and German Bight storm activity, we used sea level pressure data from the International Surface Pressure Databank ISPD (Compo et al. 2015; Cram et al. 2015), which is a vast collection of historical surface pressure observations ordered in time and space with WMO station codes being used as identifiers. For more details, see Krueger et al. (2019) and Krieger et al. (2020). We further used high-resolution hindcast met-ocean data (Geyer 2014; Weisse et al. 2014) available for the North Sea to derive additional storm-index time series and to train statistical downscaling models for waves and storm surges. For the latter, additionally observed hourly water level data available from responsible German authorities (https://pegelonline.wsv.de/) were used.

To explore potential predictability on decadal time scales corresponding atmospheric data from the CMIP5 decadal predictability experiment (Taylor et al. 2012) were used. In this experiment, a series of 10-year hindcasts (re-forecasts) with initial observed climate states was made every five years starting around 1960 using a variety of different models. Comparing results from these hindcasts with the climate eventually observed allows an assessment of the potential skill and limits of decadal predictability for different variables and regions, in our case for storms, waves, and surges over the northeast Atlantic and along the German North Sea coastline.

## 3. Results

### *3.1 Inherent predictability of northeast Atlantic storm activity*

Figure 1 shows two indices for observed North Atlantic storm variability based on annual 95th and 99th percentiles of geostrophic wind speeds. While the low-pass filtered time series show pronounced decadal variability that may imply some potential decadal predictability, the annual time series exhibit substantially stronger fluctuations resulting in weak signal-to-noise ratios. This is supported by spectral analysis of the time series (Figure 2) which shows that time series are predominantly white indicating only limited predictability.

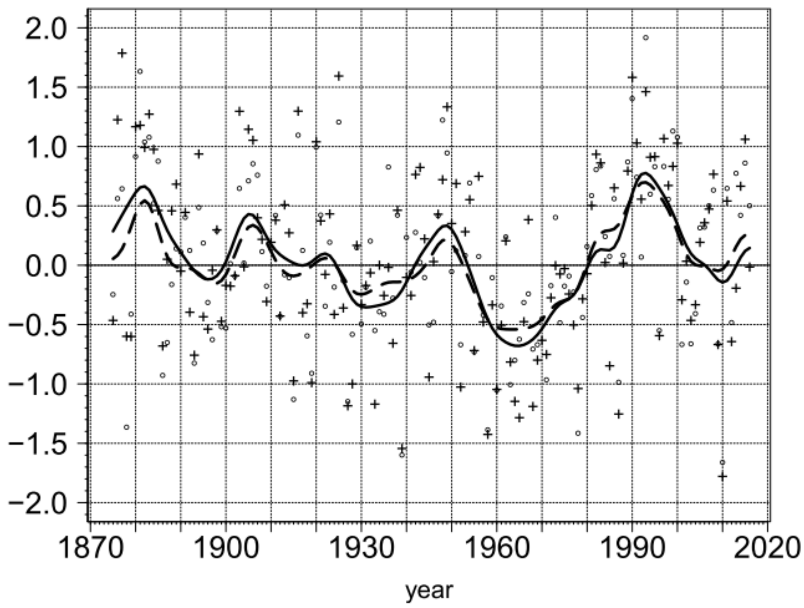


FIGURE 1. STANDARDIZED TIME SERIES OF ANNUAL 95TH (PLUS-SIGNS) AND 99TH (CIRCLES) PERCENTILES OF GEOSTROPHIC WIND SPEEDS AVERAGED OVER 10 TRIANGLES IN THE NORTHEAST ATLANTIC. BOLD AND DASHED LINES DENOTE LOW-PASS FILTERED TIME SERIES (SOURCE: KRUEGER ET AL. 2019).

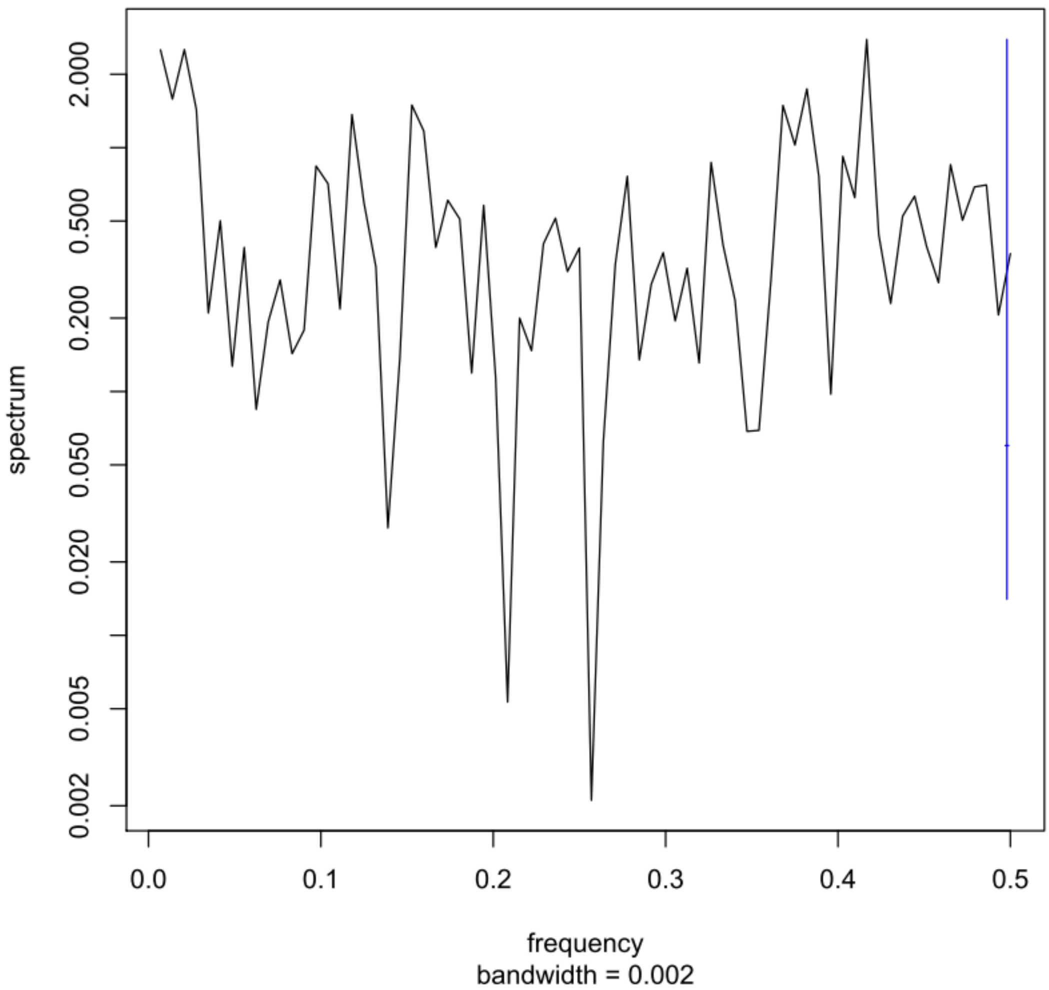


*FIGURE 2. THE SPECTRUM OF THE STANDARDIZED ANNUAL 95TH PERCENTILES OF GEOSTROPHIC WIND SPEEDS AVERAGED OVER 10 TRIANGLES IN THE NORTHEAST ATLANTIC. FREQUENCY IS GIVEN IN CYCLES PER YEAR. THE VERTICAL BLUE LINE INDICATES THE 95% CONFIDENCE INTERVAL.*

To assess potential predictability in more detail, two different simple approaches were tested. First, we tried to "predict" storm activity of the next year conditioned upon the values of the previous years by fitting models of different complexity ranging from simple persistence and autoregressive models (AR(1), e.g. Storch and Zwiers 1999) to naïve Bayesian pattern recognition (Bishop 2009). Second and using the same models, predictability of the categorical forecast (storm activity will rise or fall) was analyzed. In the latter case and for the Bayesian pattern recognition, the probability that storm activity will increase is given by:

$$P_t(\text{rise}|x_{t-1,\ldots,t-n}) = \frac{P(\text{rise})P(x_{t-1,\ldots,t-n}|\text{rise})}{P(\text{rise})P(x_{t-1,\ldots,t-n}|\text{rise}) + P(\text{fall})P(x_{t-1,\ldots,t-n}|\text{fall})}$$

where t determines the predicted time step, and (t-1),…,(t-n) denote the length of blocks of prior time steps used in the naïve Bayesian pattern recognition approach.

The results of these analyses are shown in Figure 3. For the categorical forecast, the skill is measured by the hit ratio (Wilks 2009). In a Bayesian framework and for the raw and unfiltered data, the categorical forecast of storm tendency (increase or decrease; Figure 3, left) shows skill comparable to that of a simple AR(1) model; both exceeding that of persistence. For increasingly low-pass filtered time data persistence becomes the dominant approach. The situation is different for the continuous case (Figure 3, right). Here skill is measured by the correlation. For both, raw and increasingly low-pass filtered data persistence and the AR(1) model have the largest skill exceeding that of the Bayesian approach in all cases.

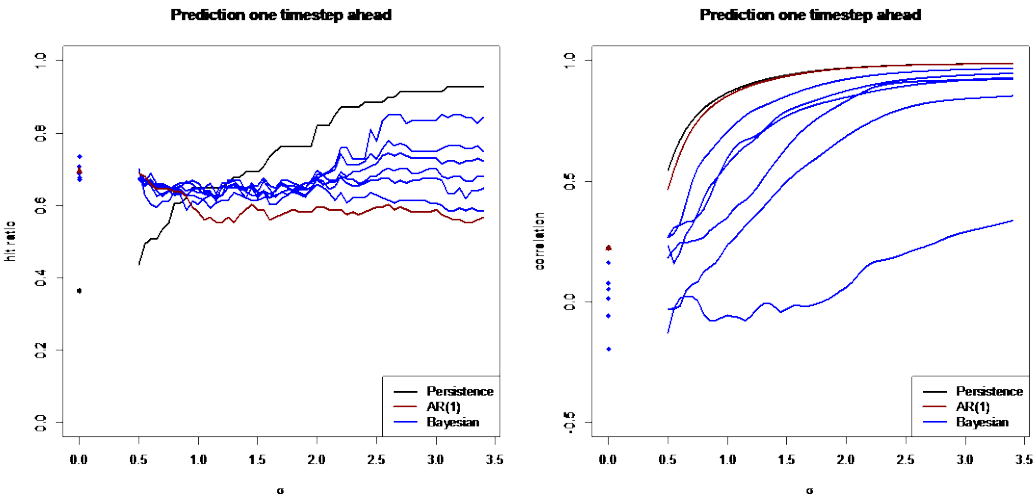


FIGURE 3. LEFT: HIT RATIO OF THE CATEGORICAL FORECAST OF THE ONE-YEAR-AHEAD STORM TENDENCY OVER THE NORTHEAST ATLANTIC FOR AN AR(1)-PROCESS (RED LINE), PERSISTENCE (BLACK LINE), AND VARIOUS NAÏVE BAYESIAN FORECAST SETUPS (BLUE LINES). RIGHT: CORRELATION SKILL SCORE FOR THE SAME MODELS USED, BUT FOR ONE-YEAR-AHEAD PREDICTIONS OF ACTUAL VALUES OF STORMINESS. THE SKILL IN BOTH FIGURES ONE YEAR AHEAD IS SHOWN DEPENDING ON THE AMOUNT OF LOW-PASS FILTERING APPLIED, WHERE THE AMOUNT OF FILTERING DEPENDS ON THE PARAMETER σ OF A GAUSSIAN FILTER. NOTE THAT THE BLUE LINES SHOW DIFFERENT CONFIGURATIONS OF THE BAYESIAN METHOD APPLIED, WHICH DIFFER IN THE LENGTH OF BLOCKS USED, I.E. THE PARAMETER N IN THE EQUATION ABOVE, WHICH IS SHOWN FOR THE CASES N=3,…,7, AND 22 YEARS. SKILL IS OBTAINED FOR HIGHER VALUES OF N AND σ.

### *3.2 Downscaling of storm activity*

To make inferences for storm surges or waves, some downscaling of large-scale atmospheric circulation on local wave or storm surge statistics is needed. Different approaches were tested. In the first approach information about the state of the atmosphere was taken from a high-resolution met-ocean hindcast (Geyer 2014; Weisse et al. 2014) in which the atmospheric state is a dynamically and spectrally nudged downscaled version of the NCEP/NCAR reanalyses (Kalnay et al. 1996; Kistler et al. 2001). From this hindcast, annual 1st and 95th percentiles of mean sea level pressure, annual standard deviations of 24h-pressure tendencies, and annual 95th percentile of near-surface (10 m height) marine wind speed were taken as predictors characterizing the state of the atmosphere. The annual number of storm surges along the German North Sea coast was derived from tide gauge data as the number of cases in which water levels exceeded the official storm surge-warning threshold of 1.50 m above mean tidal high water. Using data for the period 1949-2016 a canonical correlation analysis was performed and the model was subsequently used to reconstruct (predict) the number of surges conditioned upon projections of linear combinations of the atmospheric variables. In a second approach, only time series of northeast Atlantic storminess (section 3.1) was used as a predictor.

For both cases, again the skill of a simple categorical forecast scheme was tested, in particular, whether or not the number of storm surges in a season will exceed the long-term average depending on the given (predicted) state of the large-scale atmospheric circulation or northeast Atlantic storm activity. For this, a logistic regression model was fitted in which the probability that more/fewer storm surges than on average will occur is given by

$$\mathrm{f}(\mathrm{p_t}) = \log\left(\frac{\mathrm{p_t}}{1-\mathrm{p_t}}\right) = \sum \alpha_\mathrm{i} \mathrm{x_t} + \epsilon_\mathrm{t}$$

$$\mathrm{p_t} = \mathrm{f}^{-1}(\mathrm{p_t}) = \frac{1}{1+\mathrm{e}^{-\mathrm{f}(\mathrm{p_t})}}$$

where x represents the large scale atmospheric canonical covariates from the canonical correlation analysis or the northeast Atlantic storm activity time series.

The analysis was carried out for five tide gauges (Husum, Cuxhaven, Büsum, Dagebüll, List) along the German North Sea coast. As an example, Figure 4 shows the results for the tide gauge in Husum located at the North Frisian mainland coast. Figure 4 (left) shows the fitted logistic regression (black); that is, the probability that the number of surges will exceed the long-term average given the non-dimensional state of the large-scale atmospheric covariate (x-axis). The red/blue points indicate whether the observed number was finally above (red) or below (blue) average given the large-scale atmospheric state. It can be inferred that the medians of both distributions (blue and red vertical lines) are well separated indicating that there is some potential skill in the prediction. Figure 4 (right) presents the same information in the form of a time series. Again, the black line indicates the predicted probability that the number of surges will be above/below the long-term average while the blue and red crosses indicate the observations. While some misses occurred, there were successful periods, for example between about 1980-2000. Similar analyses were carried out for additional tide gauges along the German coastline producing comparable results (not shown).

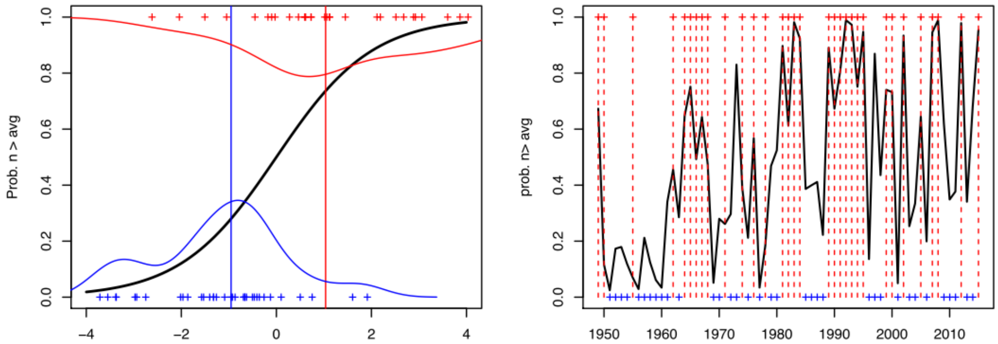


FIGURE 4. LEFT: PROBABILITY DISTRIBUTION OF THE MODELED INSTANTANEOUS PROBABILITIES THAT THE NUMBER OF STORM SURGES EXCEEDS THE LONG-TERM AVERAGE OF STORM SURGES AT HUSUM FOR THE CASES OF EXCEEDANCE (RED) AND NON-EXCEEDANCE (BLUE). RED (BLUE) CROSSES DENOTE THE OBSERVED CASES OF EXCEEDANCE (NON-EXCEEDANCE). MEDIANS OF RESPECTIVE DISTRIBUTIONS ARE GIVEN AS VERTICAL LINES. RIGHT: TIME SERIES OF THE MODELED INSTANTANEOUS PROBABILITY THAT THE NUMBER OF STORM SURGES EXCEEDS ITS LONG-TERM AVERAGE AT HUSUM. FOR ILLUSTRATIVE PURPOSES, CROSSES DENOTE THE ACTUALLY OBSERVED OCCURRENCES OF EXCEEDANCES (RED) OR NON-EXCEEDANCES (BLUE).

A comparison of the performance of the different downscaling models (predictors from canonical correlation analysis and northeast Atlantic storminess only) is shown in Figure 5 in terms of a Brier score. The Brier score (BS) is defined as

$$\mathrm{BS} = \frac{1}{\mathrm{N}} \sum (\mathrm{p_{true}} - \mathrm{p_{mod}})^2$$

and measures the accuracy of probabilistic predictions for categorical variables where $p_{mod}$ represents the probability that was forecasted and $p_{true}$ (either zero or one) that of the actual outcome. For three out of the five tide gauges it can be inferred, that using the canonical correlation model as a downscaling approach provides better skill metrics than using only the northeast Atlantic storminess as an independent variable. However, in all cases, the distribution of the scores is wider in the case of the canonical correlation analysis which indicates that the model is less reliable. In the following, therefore, we limit ourselves to cases in which only the northeast Atlantic storminess time series was used as the predictor variable.

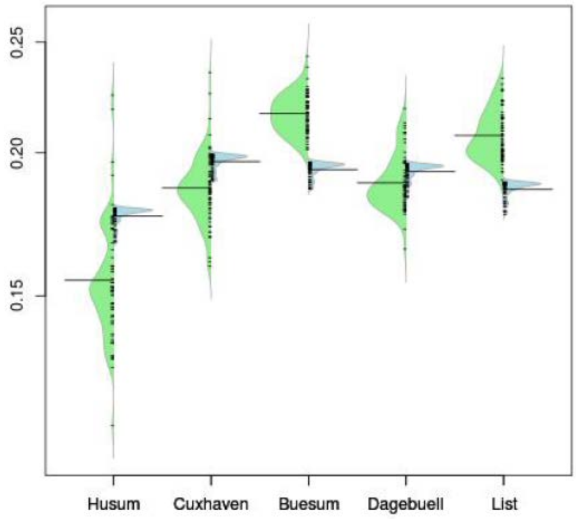


FIGURE 5. PROBABILITY DISTRIBUTION OF THE CROSS-VALIDATED BRIER SCORE FOR TWO APPROACHES AT VARIOUS SITES. GREEN CURVES DENOTE THE DISTRIBUTION FOR THE LOGISTIC REGRESSION THAT DEPENDS ON THE LINEAR COMBINATION OF CANONICAL VARIABLES DERIVED FROM CANONICAL CORRELATION ANALYSIS OF LARGE-SCALE FIELDS OF THE 95TH ANNUAL PERCENTILE OF WIND SPEED AT 10 M HEIGHT, THE 1ST ANNUAL PERCENTILE OF MEAN SEA LEVEL PRESSURE, AND THE 95TH PERCENTILE OF 24-H PRESSURE TENDENCIES. THE BLUE CURVES DENOTE THE DISTRIBUTION OF THE BRIER SCORE OF THE LOGISTIC REGRESSION, FOR WHICH THE ANNUAL NORTHEAST ATLANTIC STORMINESS TIME SERIES FROM KRUEGER ET AL. (2019) IS UTILIZED AS AN INDEPENDENT VARIABLE. BLACK LINES DENOTE THE MEDIAN BRIER SCORES OF RESPECTIVE DISTRIBUTIONS; BLACK CROSSES SHOW THE ACTUAL VALUES OF OBTAINED BRIER SCORES.

### *3.3 Analysis of predictability in the CMIP5 predictability experiment*

Using sea level pressure data from the decadal hindcast experiments available from CMIP5 (Taylor et al. 2012), time series of Northeast Atlantic storm activity (section 3.1) were calculated. This was done using all available models and 10-yr hindcast simulations. Both, a linear and a logistic regression model (section 3.2) were subsequently used to make categorical predictions about the probability of the number of storm surges at the five tide gauges along the German North Sea coast. Here the categorical variable predicted was whether or not more storm surges than on average will be expected in the coming years. In the logistic regression case, the predicted probability was taken directly from the model. For the case of the linear regression, a probabilistic approach was taken in which the probability was derived from the number of ensemble members that predicted more surges divided by the overall number of ensemble members.

The result of this exercise for different lead times is shown in Figure 6, again exemplarily for the tide gauge Husum. Again, skill is measured by the Brier score. It can be inferred that the skill of the probabilistic approach is substantially better than that of the logistic regression approach. This may be a consequence of the fact that the logistic regression model is substantially more complicated, contains more degrees of freedom, and thus more variability and uncertainty while the probabilistic approach based on linear regression only is simpler and more likely to produce robust results.

However, we also need to compare the skill with that of very generic approaches. For example, if the forecast is always 50%, regardless of whether more or fewer surges will occur, the Brier score would be 0.25 indicated by the red line in Figure 6. It can be inferred, that the skill of the probabilistic decadal prediction based on linear regression is only close to this generic case. There may in principle two reasons for that: Either the skill of our downscaling approach is limited or there is already only limited skill for the predictor variable in the downscaling model, in our case the northeast Atlantic storminess.

To check the latter, we assessed the skill of the CMIP5 decadal predictions to re-forecast our storm index time series (Figure 7). Again, we tested the skill to re-forecast whether storm activity will be above/below the long-term average for different lead times. It can be inferred that the skill is best for the probabilistic approach. It is, however, only close to random. This indicates that the skill to predict large-scale northeast Atlantic storm activity in the CMIP5 ensemble is small and intrinsic climate variability substantially exceeds potential signals.

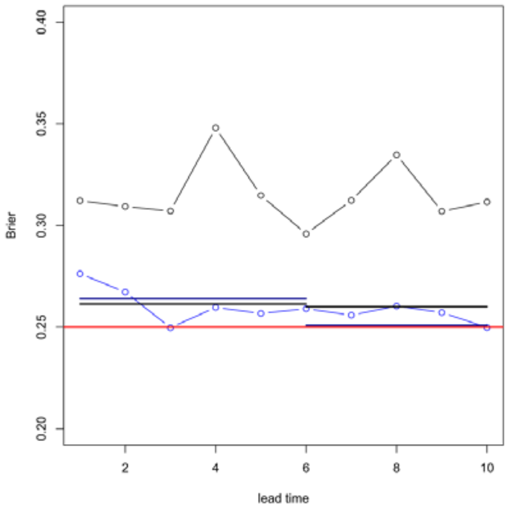


FIGURE 6. BRIER SCORE OF VARIOUS APPROACHES TO MODEL THE PROBABILITY OF EXCEEDANCES OF THE NUMBER OF SURGES BEING GREATER THAN ITS LONG-TERM AVERAGE AT HUSUM FOR LEAD TIMES OF 1 TO 10 YEARS IN CMIP5. THE BLACK LINE INCLUDING DOTS DENOTES THE BRIER SCORE OF THE LOGISTIC MODEL, THE BLUE AND DOTTED LINE THE BRIER SCORE OF THE PROBABILISTIC APPROACH. HORIZONTAL LINES IN RESPECTIVE COLORS SHOW THE SKILL OF THE AVERAGES OF PREDICTIONS FOR LEAD TIMES 1-5 YEARS AND 6-10 YEARS. FOR COMPARISON, THE RED HORIZONTAL LINE DEPICTS THE BRIER SCORE OF A PROBABILITY OF 0.5 (RANDOM CHANCE).

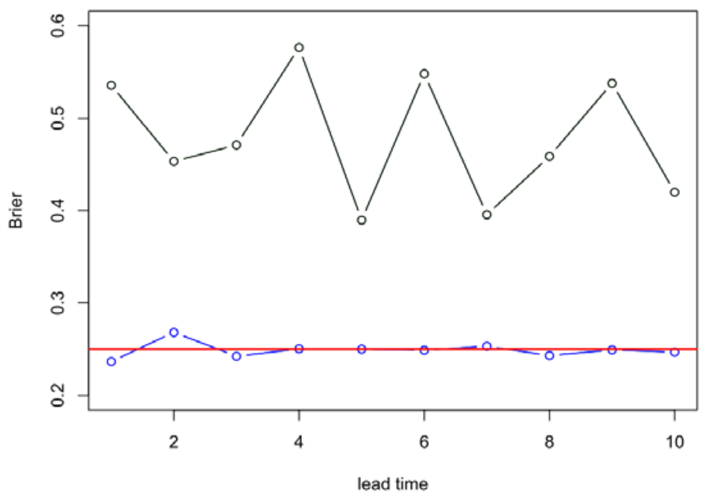


FIGURE 6. BRIER SCORES OF RE-FORECASTING NORTHEAST ATLANTIC STORM ACTIVITY FOR LEAD TIMES 1-10 YEARS. THE BLUE LINE DENOTES THE BRIER SCORE OF PROBABILITIES OF STORMINESS BEING HIGHER THAN AVERAGE DERIVED IN A PROBABILISTIC APPROACH IN CMIP5. THE BLACK LINE SHOWS THE BRIER SCORE OF THE SAME PROBABILITY, BUT FOR MODELING STORMINESS AS AN AUTOREGRESSIVE PROCESS OF ORDER 1 BASED ON THE OBSERVED TIME SERIES GIVEN IN KRUEGER ET AL. (2019). AS A REFERENCE, THE BRIER SCORE FOR P=0.5 (RANDOM CHANCE) IS GIVEN BY THE RED LINE. NOTE THAT RESULTS FOR THE AR(1) MODEL ARE NOT DIRECTLY COMPARABLE TO THE LEFT PANEL IN FIGURE 3, AS FIGURE 3 (LEFT) HANDLES STORMINESS TENDENCIES, WHEREAS THIS FIGURE RELATES TO STORMINESS EXCEEDING ITS LONG-TERM AVERAGE.

## 4. Summary and Conclusion

Decadal predictability of northeast Atlantic storm activity and statistically downscaled waves and storm surges at the German North Sea coast were analyzed. Both, predictability inherent in time series derived from observations and the CMIP5 decadal predictability experiment were explored. Skill in decadal predictions was assessed for quantitative forecasts and simpler categorical schemes. Generally, some skill could be identified for the training data of the downscaling approaches. However, when re-forecasts were assessed the skill of the various approaches was very limited hardly exceeding that of random chance. There are several possible explanations for these results: First, the storm index time series derived as a predictor from the CMIP5 ensemble is already characterized by a low signal-to-noise-ratio and an almost white spectrum which points to already low potential decadal predictability of the predictor. The signal-to-noise-ratio is further reduced when additional downscaling for waves and storm surges is introduced. Second, metrics used to describe storm activity, downscaling approaches, or forecast schemes and variables may have been suboptimal. It cannot be excluded that other approaches, metrics, or schemes may provide better results.

## 5. REFERENCES


*Alexandersson, H.; Schmith, T.; Iden, K.; Tuomenvirta, H. (1998): Long-term variations of the storm climate over NW Europe. In Gobal Atmos. Ocean Syst (6), pp. 97–120.*

*Alexandersson, H.; Tuomenvirta, H.; Schmith, T.; Iden, K. (2000): Trends of storms in NW Europe derived from an updated pressure data set. In Clim. Res. 14, pp. 71–73. DOI: 10.3354/cr014071.*

*Barnett, T. P.; Pierce, D. W.; Hidalgo, H. G.; Bonfils, C.; Santer, B. D.; Das, T. et al. (2008): Human-Induced Changes in the Hydrology of the Western United States. In Science 319 (5866), pp. 1080–1083. DOI: 10.1126/science.1152538.*

*Bishop, Christopher M. (2009): Pattern recognition and machine learning. Corrected at 8th printing 2009. New York, NY: Springer (Information science and statistics).*

*Compo, G. P.; Whitaker, J. S.; Sardeshmukh, P. D.; Allan, R. J.; McColl, C.; Yin, X. et al. (2015): The International Surface Pressure Databank version 3. Edited by Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. Dataset., checked on 6/3/2020.*

*Cram, Thomas A.; Compo, Gilbert P.; Yin, Xungang; Allan, Robert J.; McColl, Chesley; Vose, Russell S. et al. (2015): The International Surface Pressure Databank version 2. In Geosci. Data J. 2 (1), pp. 31–46. DOI: 10.1002/gdj3.25.*

*Geyer, B. (2014): High-resolution atmospheric reconstruction for Europe 1948–2012. CoastDat2. In Earth Syst. Sci. Data 6 (1), pp. 147–164. DOI: 10.5194/essd-6-147-2014.*

*Kalnay, E.; Kanamitsu, M.; Kistler, R.; Collins, W.; Deaven, D.; Gandin, L. et al. (1996): The NCEP/NCAR 40-Year Reanalysis Project. In Bull. Amer. Meteor. Soc. 77 (3), pp. 437–471. DOI: 10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2.*

*Kistler, Robert; Collins, William; Saha, Suranjana; White, Glenn; Woollen, John; Kalnay, Eugenia et al. (2001): The NCEP–NCAR 50–Year Reanalysis. Monthly Means CD–ROM and Documentation. In Bull. Amer. Meteor. Soc. 82 (2), pp. 247–267. DOI: 10.1175/1520-0477(2001)082<0247:TNNYRM>2.3.CO;2.*

*Krieger, Daniel; Krueger, Oliver; Feser, Frauke; Weiße, Ralf; Tinz, Birger; Storch, Hans von (2020): German Bight storminess revisited. In Int. J. Climatol., under revision.*

*Krueger, Oliver; Feser, Frauke; Weisse, Ralf (2019): Northeast Atlantic Storm Activity and Its Uncertainty from the Late Nineteenth to the Twenty-First Century. In J. Climate 32 (6), pp. 1919–1931. DOI: 10.1175/JCLI-D-18-0505.1.*

*Krueger, Oliver; Storch, Hans von (2011): Evaluation of an Air Pressure–Based Proxy for Storm Activity. In J. Climate 24 (10), pp. 2612–2619. DOI: 10.1175/2011JCLI3913.1.*

*Matulla, C.; Schöner, W.; Alexandersson, H.; Storch, H. von; Wang, X. L. (2008): European storminess. Late nineteenth century to present. In Clim Dyn 31 (2-3), pp. 125–130. DOI: 10.1007/s00382-007-0333-y.*

*Meehl, Gerald A.; Goddard, Lisa; Murphy, James; Stouffer, Ronald J.; Boer, George; Danabasoglu, Gokhan et al. (2009): Decadal Prediction. In Bull. Amer. Meteor. Soc. 90 (10), pp. 1467–1486. DOI: 10.1175/2009BAMS2778.1.*

*Pulwarty, R. S. (2003): Climate and water in the West: Science, information and decisionmaking. In Journal of Contemporary Water Reserach and Education 124, pp. 4–12.*

*Schmidt, Heiner; Storch, Hans von (1993): German Bight storms analysed. In Nature 365 (6449), p. 791. DOI: 10.1038/365791a0.*

*Storch, Hans von; Zwiers, Francis W. (1999): Statistical Analysis in Climate Research. Cambridge: Cambridge University Press.*

*Taylor, Karl E.; Stouffer, Ronald J.; Meehl, Gerald A. (2012): An Overview of CMIP5 and the Experiment Design. In Bull. Amer. Meteor. Soc. 93 (4), pp. 485–498. DOI: 10.1175/BAMS-D-11-00094.1.*

*Vaughan, Catherine; Dessai, Suraje (2014): Climate services for society. Origins, institutional arrangements, and design elements for an evaluation framework. In Wiley interdisciplinary reviews. Climate change 5 (5), pp. 587–603. DOI: 10.1002/wcc.290.*

*Weisse, Ralf; Bisling, Peter; Gaslikova, Lidia; Geyer, Beate; Groll, Nikolaus; Hortamani, Mahboubeh et al. (2015): Climate services for marine applications in Europe. In Earth Perspectives 2 (1), p. 3887. DOI: 10.1186/s40322-015-0029-0.*

*Weisse, Ralf; Gaslikova, Lidia; Geyer, B.; Groll, Nikolaus; Meyer, Elke M. I. (2014): coastDat – Model Data for Science and Industry. In Die Küste 81, pp. 5–18. Available online at https://hdl.handle.net/20.500.11970/101679.*

*Weisse, Ralf; Storch, Hans von; Callies, Ulrich; Chrastansky, Alena; Feser, Frauke; Grabemann, Iris et al. (2009): Regional Meteorological–Marine Reanalyses and Climate Change Projections. In Bull. Amer. Meteor. Soc. 90 (6), pp. 849–860. DOI: 10.1175/2008BAMS2713.1.*

*Wilks, Daniel S. (2009): Statistical methods in the atmospheric sciences. 2. ed., [Nachdr.]. Amsterdam: Elsevier (International geophysics series, 91).*