CLIMATIC FORECASTING OF WIND AND WAVES USING FUZZY INFERENCE SYSTEMS

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Abstract

Wind and wave climatic simulations are of great interest in a number of different applications, including the design and operation of ships and offshore structures, marine energy generation, aquaculture and coastal installations. In a climate change perspective, projections of such simulations to a future climate are of great importance for risk management and adaptation purposes. This work investigates the applicability of FIS/ANFIS models for climatic simulations of wind and wave data. The models are coupled with a nonstationary time series modelling, which decomposes the initial time series into a seasonal mean value and a residual part multiplied by a seasonal standard deviation. In this way, the nonstationary character is first removed before starting the fuzzy forecasting procedure. Then, the FIS/ANFIS models are applied to the stationary residual part providing us with more unbiased climatic estimates. Two long-term datasets for an area in the North Atlantic Ocean are used in the present study, namely NORA10 (57 years) and ExWaCli (30 years in the present and 30 years in the future). Two distinct experiments have been performed to simulate future values of the time series in a climatic scale. The assessment of the simulations by means of the actual values kept for comparison purposes gives very good results.

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INTRODUCTION

The ocean wave climate is important for the design and operation of ships and other marine structures, which need to be designed, constructed and operated in a way that can withstand the environmental forces. In order to account for these forces, an understanding of the operating climate is of great importance. In particular, the highest values of certain environmental parameters such as wave heights impose structural stresses and responses and the structures need to be dimensioned accordingly. Historical measurements of the wave climate and long operational experience have resulted in the current understanding of the wave induced forces on marine structures.

However, in recent years it has become increasingly evident that the climate is changing [1]. Thus, knowledge and experience about the environmental forces and how to handle them must be supplemented with simulations of how the future climate will be. In particular, when structures are designed with an expected operational lifetime of several decades, the potential changes in the operating conditions due to climate change must be taken into account already in the design stage of the structure.

Thus, there is an increasing need for very long-term wind and wave data as climate projections require a baseline climatology against which to be compared, especially in future climate scenarios produced by coupled models. Third generation spectral wave models [2, 3] have been used for generating such kind of reanalysis data sets [4–6]. See also [7], where a number of climatologies based on regional models are cited.

In the present study, NORA10 [8] and ExWaCli [9] datasets are used. Especially the latter includes a number of future wave projections obtained by running a WAM implementation [2, 8] with wind input derived from several global circulation models [10]. A particular area in the North Atlantic Ocean is selected and the wave model has been run, in each case, for a 30-year historical period (1971-2000) and for a future period (2071-2100) assuming two different future climate scenarios, i.e. RCP 4.5 and RCP 8.5 [11, 12].

There are a number of sources of uncertainties in any climate projections into the future, and future projections of the wave climate is a result of several modelling steps. Different modelling choices introduce uncertainties in each modelling step. For example, to obtain future wave climate projections, one must first run global climate models to get large-scale climate projections related to atmospheric pressures, wind fields and ice pressures. However, such large-scale projections will be conditioned on projected external forcings, typically consistent with an emission scenario or a Representative Concentration Pathway (RCP). Hence, the choice of emission scenario, global climate model as well as initial conditions and exact parametrization of the climate model will affect the results and are sources of uncertainties of these climate projections. Moreover, to obtain wave climate projections one typically needs higher resolution regional climate projections of wind fields, and different downscaling methods may give different results. With regional wind projections, one may use numerical wave models to obtain wave projections and there are several

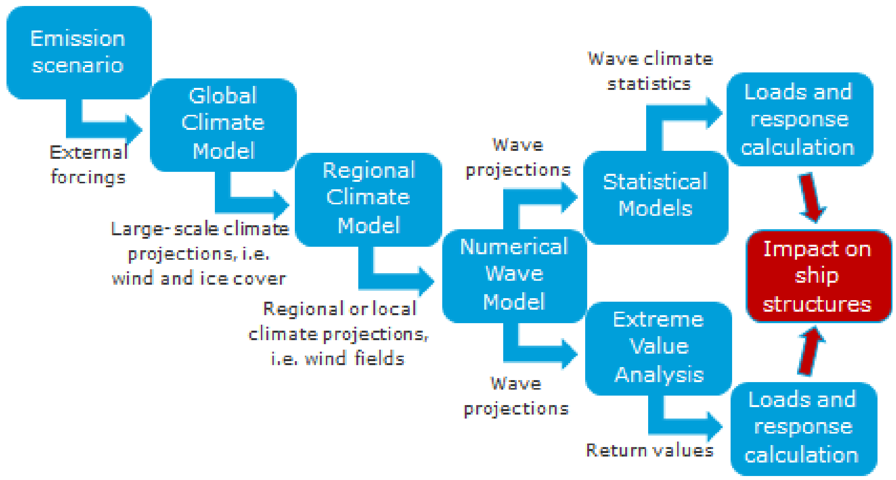

Figure 1: Main steps in future wave climate projections (different modelling choices introduce uncertainties in each modelling step)

different wave models that may give different results. All of this adds to the uncertainty of any wave climate projection leading to an overall large variability of future wave climate projections. See e.g. [13] for further discussions on the uncertainties of future wave climate projections. If one is interested in the extreme wave climate, extreme value analysis of the projected waves adds further to the overall uncertainty [14]. See also Fig. 1.

The Coupled Model Intercomparison Project phase 5 (CMIP5) promotes a set of coordinated global climate model experiments and forms the basis for the IPCCs fifth assessment report (AR5) [15, 1]. It was completed in 2014 and model output from a number of different climate models have been made available. The selection of model output to use in ExWaCli was partly pragmatic and partly based on an assessment of the individual merits of alternative models from the academic literature.

However, and because the numerical implementation of the wave models requires great computational power and high CPU time, there is an increasing interest for various soft computing techniques. Some researchers utilize Artificial Neural Networks (ANN); see, e.g., [16–18]. Some others use Fuzzy Inference Systems (FIS) in combination with Adaptive Neuro-Fuzzy Inference Systems (ANFIS); see, e.g., [19–24]. These techniques require less computational effort and they are easy to be applied.

In [25, 26], FIS/ANFIS models were applied for the first time to forecast future values of the whole wave field (North Atlantic and Pacific Oceans). Usually in Fuzzy Time Series (FTS) studies, the nonstationarity is neglected. In contrast, the authors in [27, 25, 26] consider that nonstationarity should be removed from the initial time series, before starting the fuzzy forecasting procedure; especially in time series of wind and wave parameters where the nonstationary character is inherent due to the seasonal effect. So, in these works, fuzzy techniques were combined with an existing nonstationary modelling of wind and wave parameters to improve the forecasting procedure.

According to this modelling, the initial nonstationary series is decomposed into a seasonal mean value, and a residual time series multiplied by a seasonal standard deviation. The seasonal components are estimated using mean monthly values, and the residual time series is modelled as stationary series; see, e.g., [28, 29]. Then, the FIS/ANFIS models are applied only to the stationary part.

In this way, the seasonal patterns, which contain all information concerning changing trends in the climate, are estimated separately from the FIS/ANFIS structure, which can be estimated by only a single point. This greatly decreases the computational time of the calculations without significant loss of the accuracy. Nonstationary modelling is finally used for the synthesis of the full simulated time series.

The present work follows the methodology presented in [25, 26] but for a significantly larger forecasting horizon; namely several years. Two distinct experiments with respect to very-long (climatic) forecasting are performed based on the two datasets mentioned above. Forecasting results are compared with existing model values intentionally kept for validation of the methodology.

METHODOLOGY

Data used

Two datasets have been used for this study, as also mentioned in Introduction, namely the NORA10 [8] and ExWaCli [9] datasets. The referred area is in the North-eastern Atlantic Ocean, west of British Isles, and the computational grids partially overlap; see Fig. 2. At each datapoint, three-hourly time series of significant wave height, wave period and wind speed are available. The NORA10 dataset covers the period 1957.09.01–2014.08.31, i.e. approximately 57 years, while ExWaCli dataset includes a historic period of 30 years (1971–2000) and two future wave projections of 30 years for the period 2071–2100 assuming two different future climate scenarios (RCP 4.5 and RCP 8.5). The span of the datasets is depicted in Fig. 3.

Model setup

The present work closely follows the methodology described in [25, 26], according to which the initial nonstationary time series of wind and wave parameters are first decomposed as follows

$$Y(t) = m(t) + s(t)\, W(t), \tag{1}$$

where $m(t)$ and $s(t)$ are deterministic periodic functions with a period of one year, and $W(t)$ is a zero-mean, stationary, stochastic process. The functions

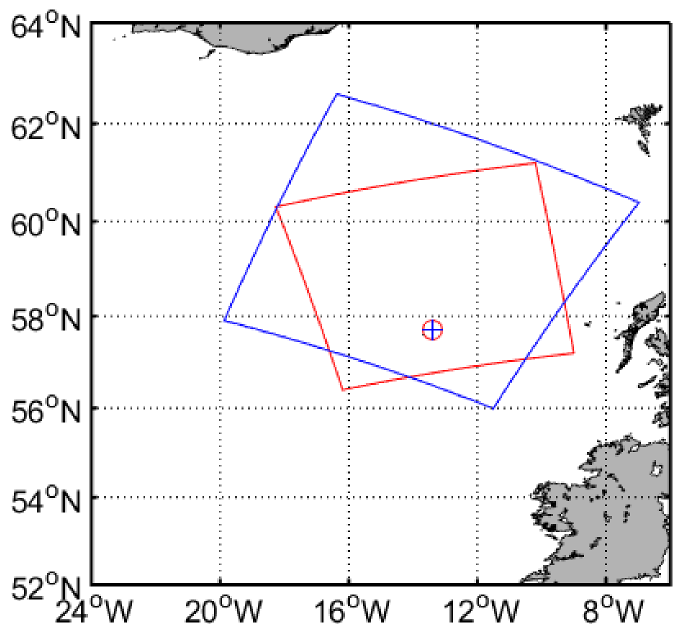

Figure 2: Data grid and points used (blue: NORA10, red: ExWaCli)

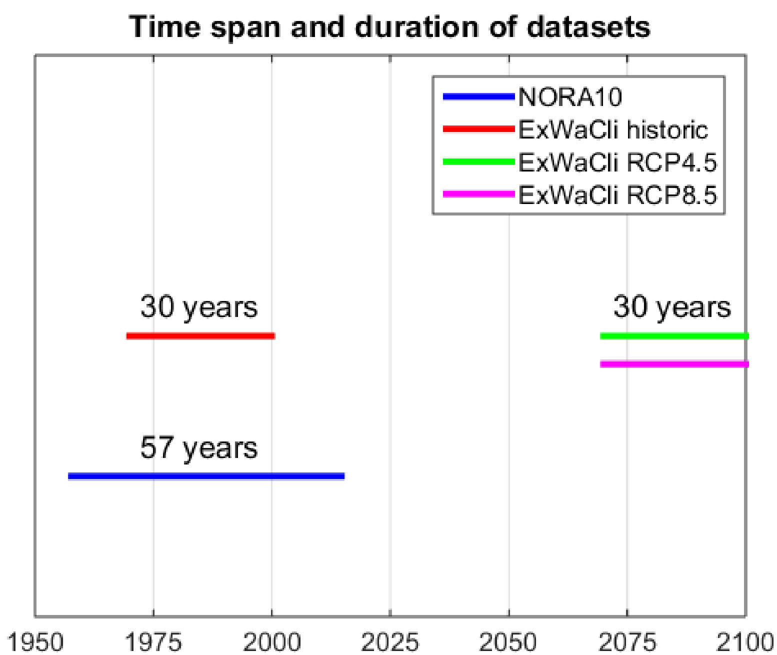

Figure 3: Time span and duration of datasets

$m(t)$ and $s(t)$ are seasonal mean value and seasonal standard deviation, respectively, and describe the exhibited seasonal patterns. The seasonal patterns (mean value and standard deviation) are obtained by means of:

$$\widetilde{\mu}_3(m) = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{K_m}\sum_{k=1}^{K_m} Y(j,m,\tau_k), \tag{2}$$

$$\widetilde{\sigma}_3(m) = \frac{1}{J}\sum_{j=1}^{J}\sqrt{\frac{1}{K_m}\sum_{k=1}^{K_m}\big[Y(j,m,\tau_k)-\mu_3(j,m)\big]^2}, \tag{3}$$

with m=1,2,...,12. Note that, $Y(j,m,\tau_k)$ is a re-parametrization of $Y(t)$, where j is the year index and m represents the monthly time, and $k = 1, 2, \ldots, K_m$. In [30, 25], it has been shown that, periodic extensions of quantities $\widetilde{\mu}_3(m)$ and $\widetilde{\sigma}_3(m)$ are good estimates of periodic functions $m(t)$ and $s(t)$.

In this way, the information contained in the time series $Y(t)$ is decomposed into two parts:

- one determinstic $[m(t),\ s(t)]$, containing info about features such as seasonal variability, interannual variability, climatic trends, and evolving more slowly in time, and
- one stochastic $[W(t)]$, containing info about the dependency (correlation) structure of the successive values of the series, and evolving more rapidly in time.

The simulation procedure is applied to the second one, as only this part has been modelled as a stochastic one. The first part (deterministic) is estimated by means of the existing values and is used in the end to reconstruct the simulated version $\widehat{Y}(t)$ of the initial nonstationary series.

Then, the FIS/ANFIS forecasting methodology described in [25], is applied to the stationary part $W(t)$. The membership functions to form the fuzzy input sets are simple linear functions and the FIS systems are established assuming the following IF-THEN rules:

(a) wind speed W_S:

$$W_S(t+1) = f_1\big(W_S(t)\big) \tag{4}$$

(b) significant wave height H_S:

$$H_S(t+1) = f_2\big(W_S(t), H_S(t)\big) \tag{5}$$

Finally, using Eq. (1), the simulated time series $\widehat{W}(t)$ is combined with the estimated seasonal components $m(t)$ and $s(t)$ to give a simulated version $\widehat{Y}(t)$ of the initial nonstationary series.

Measuring forecasting quality

To evaluate forecasting performance, the following error measures have been used:

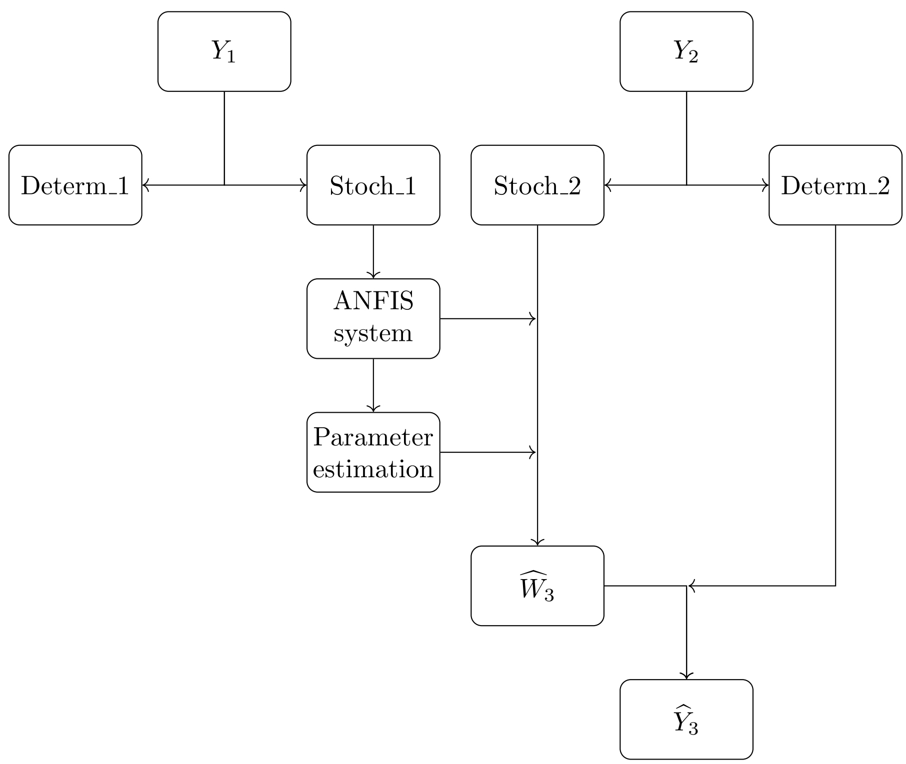

Figure 4: Sketch of the procedure followed in the two experiments (1: Training, 2: Input, 3: Simulated datasets)

(a) Root Mean Square Error (RMSE) defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{I}\sum_{i=1}^{I}|e(t_i)|^2} \tag{6}$$

(b) Mean Absolute Percentage Error (MAPE) defined as

$$\mathrm{MAPE} = \frac{1}{I}\sum_{i=1}^{I}\left|\frac{e(t_i)}{a(t_i)}\right|, \tag{7}$$

where

$$e(t_i) = a(t_i) - f(t_i) \tag{8}$$

denotes the forecasting error at time t_i between forecasts $f(t)$ and actual values $a(t)$.

(c) Mean Absolute Scaled Error (MASE) defined as

$$\mathrm{MASE} = \frac{1}{I}\sum_{i=1}^{I}\left|q(t_i)\right|, \tag{9}$$

where

$$q(t_i) = \frac{e(t_i)}{\frac{1}{N}\sum_{n=2}^{N}\left|X(t_n) - X(t_{n-1})\right|}, \tag{10}$$

where $\{X(t_n),\ n = 1, 2, \dots, N\}$ are the existing values, used for training of the fuzzy time series model.

(d) Root Mean Square Scaled Error (RMSSE) defined as

$$\mathrm{RMSSE} = \sqrt{\frac{1}{I}\sum_{i=1}^{I}|q(t_i)|^2} \tag{11}$$

(e) Bias:

$$\mathrm{Bias} = \frac{1}{I}\sum_{i=1}^{I}[-e(t_i)], \tag{12}$$

(f) Scatter Index (SI) in %:

$$\mathrm{SI} = \sqrt{\frac{RMSE}{\sum_{i=1}^{I} a(t_i)}} \times 100, \tag{13}$$

(g) Correlation coefficient R^2:

$$R^2 = \frac{\sum_{i=1}^{I}\Bigl(f(t_i) - \overline{a}\Bigr)\Bigl(a(t_i) - \overline{a}\Bigr)}{\sqrt{\sum_{i=1}^{I}\Bigl(f(t_i) - \overline{a}\Bigr)^2 \sum_{i=1}^{I}\Bigl(a(t_i) - \overline{a}\Bigr)^2}}, \tag{14}$$

where

$$\overline{a} = \frac{1}{I}\sum_{i=1}^{I} a(t_i). \tag{15}$$

Results from all error measures are calculated and given in the next section, showing the accuracy of the proposed forecasting methodology.

NUMERICAL RESULTS

In the present work, first results for a point-wise study are presented. Further results for the whole field, shown in Fig. 2, are under way and they will be published in due time. Two points from the two datasets have been chosen with neighbouring coordinates, so that the results could be directly comparable; see Fig. 2.

Two experiments have been designed. In both experiments the following simulation procedure has been applied:

1. A dataset Y_1 is chosen as the Training set.
2. Decomposition (1) is applied to Y_1.
3. Residual part W_1 is used as input for the estimation of the structure and the parameters of the FIS/ANFIS system.
4. A second dataset Y_2 is chosen as the Input dataset.
5. Step 2 is applied to Y_2.
6. Residual part W_2 is used as input for the simulation based on the FIS/ANFIS system estimated in Step 3.
7. Output $\widehat{W}_3$ of the simulation is combined with the deterministic part of Y_2 estimated in Step 5 and the final simulated time series $\widehat{Y}_3$ is obtained.

This procedure is also summarized in Fig. 4. Note that, although the deterministic part Determ_2 is estimated in the present work by means of the existing time series, it can be replaced in a later stage by other estimates that will be obtained concerning the future trends of that time period.

In Experiment 1, the first part of the NORA10 dataset (1957–1970) has been chosen as the Training set, based on which the FIS/ANFIS structure is estimated. Then, one simulation is obtained for the historic period (1971–2000) and two for the future one (2071–2100). See also Fig. 5 where the setup of Experiment 1 is shown. The results of the three simulations are compared with the three ExWaCli datasets (ExHist, ExR45, ExR85).

In Experiment 2, the historic part of ExWaCli dataset (1971–2000) has been chosen as the Training set for the estimation of the FIS/ANFIS structure. Then, one simulation is obtained for the historic period (2001–2014) and two for the future one (2071–2100). See also Fig. 6 where the setup of Experiment 2 is shown. The results of the three simulations are compared the first one with the last part of NORA10 dataset and the other two with the two future ExWaCli datasets (ExR45, ExR85).

In Tables 1 and 2, the error measures of wind speed and significant wave height, respectively, are given for Experiment 1. The corresponding measures for Experiment 2 are given in Tables 3 and 4.

In all cases, the results are very good. For example, there is a very good correlation between the simulations and the actual values of the order 91–95% (wind speed) and 98% (wave height). The bias is almost zero and the root-mean-square is of the order of magnitude of some centimetres for wave height and less than 2 m/s for wind speed. Experience with more data points will reveal if the slightly higher errors in the case of wind speed are significant or not.

Especially, by comparing the forecasting performance of the two experiments for the future scenarios RCP4.5 and 8.5, one can conclude that both are in a very good agreement with the actual values of the datasets, which means that both datasets (NORA10 and ExWaCli.historic) can be equally well used as Training dataset for the estimation of the parameters of the FIS/ANFIS procedure after the appropriate deseasonalization. As an example, the relative difference of the two estimates for the H_S as a percentage of the actual values is plotted for the two climatic scenarios in Figs. 7 and 8. In both cases, the relative difference is between -5% and 10%.

The estimation procedure for each experiment is very quick and takes 30 sec in a personal PC with Intel®Core™ i5-5200CPU @2.20 GHz and 4.0 GB RAM.

Finally, one can argue that the present results may not seem in line with other published work in the climate community [31, 32], where higher uncertainty levels are present. However, this is due to the fact that the present results are not directly comparable with the others, because the simulation procedure basically concerns only the stochastic part (containing the correlation structure) and not the deterministic one (containing among others the long-term trends). Thus, the present methodology can be combined in the future with other existing tools, such as the dynamical models and/or other statistical models, to enhance the accuracy of the existing predictions of the wave climate by decreasing the computational cost.

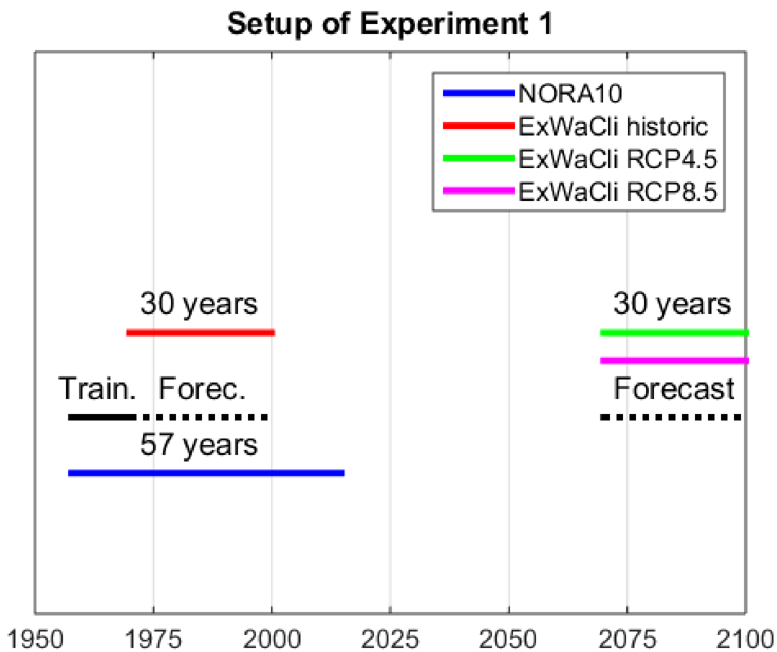

Figure 5: Setup of Experiment 1

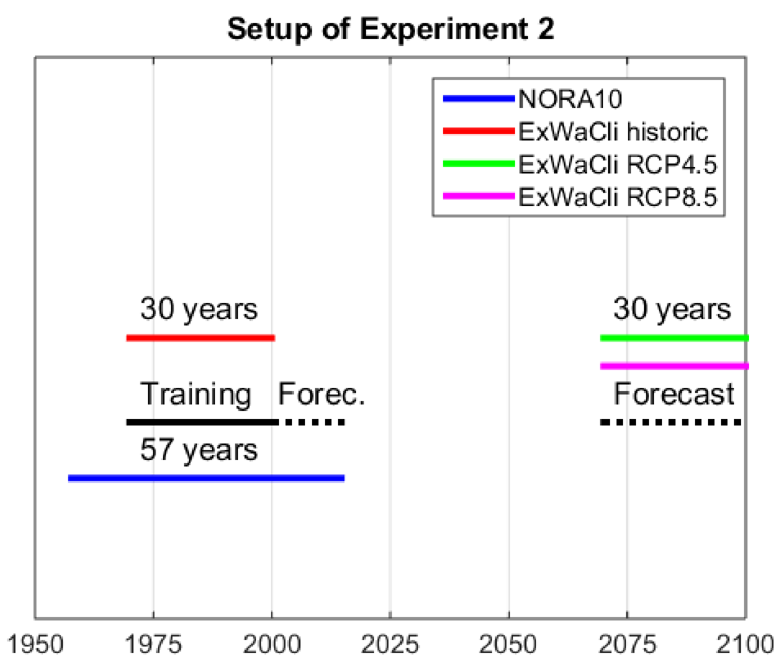

Figure 6: Setup of Experiment 2

Table 1: Error measures for wind speed, Experiment 1

dataset	ExHist	ExR45	ExR85
RMSE	1.341	1.296	1.314
MAPE	0.154	0.147	0.146
MASE	1.003	1.002	1.003
RMSSE	1.400	1.397	1.404
R^2	0.953	0.954	0.953
SI (%)	13.715	13.512	13.643
Bias	-0.005	-0.006	-0.005

Table 2: Error measures for wave height, Experiment 1

dataset	ExHist	ExR45	ExR85
RMSE	0.269	0.268	0.263
MAPE	0.047	0.046	0.046
MASE	0.843	0.833	0.811
RMSSE	1.321	1.364	1.324
R^2	0.990	0.989	0.990
SI (%)	7.785	8.126	7.986
Bias	-0.003	-0.003	-0.003

Table 3: Error measures for wind speed, Experiment 2

dataset	ExR45	ExR85	NORA10
RMSE	1.290	1.308	1.802
MAPE	0.140	0.139	0.187
MASE	0.991	0.992	0.984
RMSSE	1.391	1.398	1.389
R^2	0.954	0.954	0.913
SI (%)	13.453	13.584	18.383
Bias	0.000	0.001	-0.002

Table 4: Error measures for wave height, Experiment 2

dataset	ExR45	ExR85	NORA10
RMSE	0.258	0.254	0.308
MAPE	0.046	0.045	0.057
MASE	0.826	0.808	0.865
RMSSE	1.316	1.279	1.339
R^2	0.990	0.991	0.985
SI (%)	7.836	7.714	9.142
Bias	0.001	0.001	-0.008

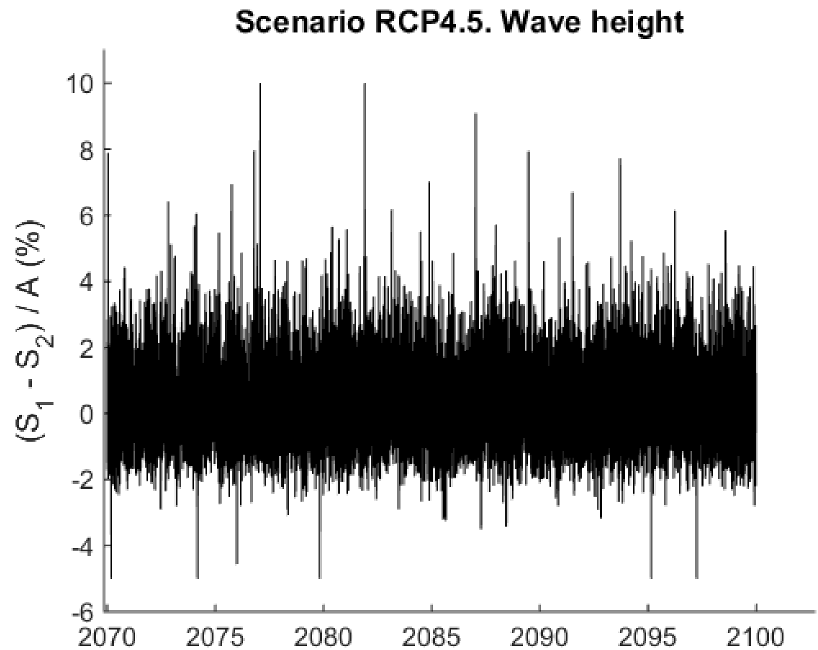

Figure 7: Relative difference of the two estimates with respect to actual values for scenario RCP4.5 (1: Exp1, 2: Exp2, A: actual values)

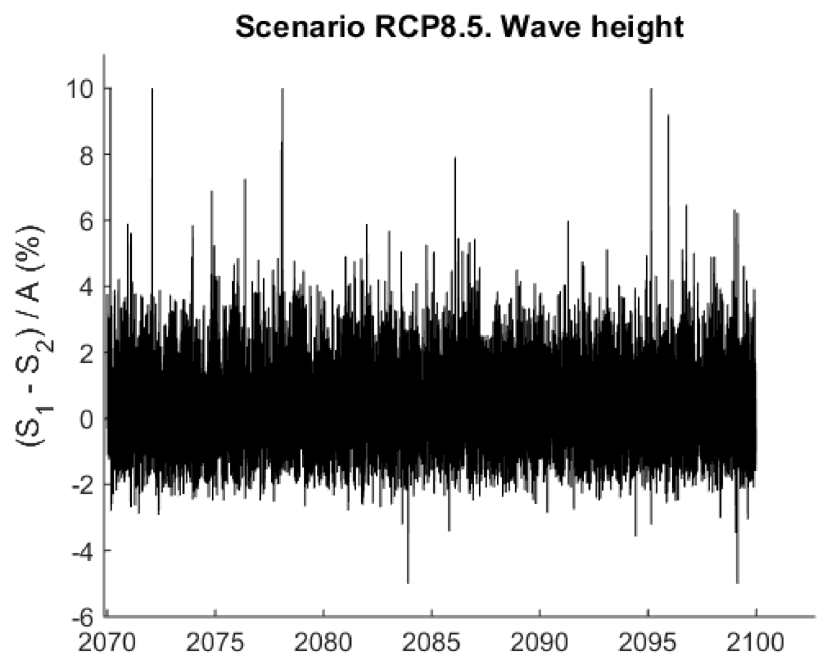

Figure 8: Relative difference of the two estimates with respect to actual values for scenario RCP8.5 (1: Exp1, 2: Exp2, A: actual values)

CONCLUDING REMARKS

Climatic simulations of significant wave height and wind speed have been obtained for the first time, based on a newly introduced procedure in [25, 26] where predictions were given for shorter periods. According to this, the well-known Fuzzy Inference Systems (FIS) in combination with Adaptive Neuro-Fuzzy Inference Systems (ANFIS), coupled with a nonstationary time series modelling, is applied to obtain the forecasts.

Two datasets have been used; namely NORA10 (1957–2014) and ExWaCli (1971–2000 and 2071–2100), covering an area of the North-eastern Atlantic Ocean, west of British Isles with partially overlapping computational grids.

Two forecasting experiments have been designed and performed. In the first one, the training set was the period 1957–1970 of the NORA10 dataset and the forecasts cover the periods 1971–2000 and 2071–2100. In the second one, the period 1971–2000 of ExWaCli dataset is the training set and the forecasts cover the periods 2001–2014 and 2071–2100.

The obtained forecasts are verified by means of actual values kept for comparison purposes. The calculated error measures show a very good performance demonstrating the feasibility of this methodology. In addition, the small amount of computational time needed makes it an attracting complementary tool in the process of obtaining future simulations in a climatic scale, which is in line with the current demand of using enhanced computational tools [33].

Acknowledgment

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