Statistical Downscaling of Seasonal Wave Forecasts

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Key words:
Seasonal forecast; statistical downscaling; significant wave height; Western Pacific; Atlantic Ocean
Abstract

In spite of the potential application of seasonal forecasting for decision making in construction, maintenance and operations of coastal and off-shore infrastructures, tailored climate services in the marine sector are yet to be developed. In this work we explore the potential of state-of-the-art seasonal forecast systems to predict wave conditions, in particular significant wave height. Since this information is not directly provided by models, a statistical downscaling method is applied to infer significant wave height based on some model outputs like sea level pressure, which drive waves along time over large wave generation areas beyond the target location. This may be beneficial for seasonal forecasting since skill from wide generation areas can be propagated to wave conditions into (distant and smaller) target regions. We consider one month ahead seasonal predictions from the CFSv2 hindcast in two regions: the Western Pacific around Indonesia during the season June-July-August (JJA) and the North Atlantic Ocean during the season January-February-March (JFM). In the former case, skillful predictions are found, higher during decay years after ENSO warm phases when a negative anomaly of the significant wave height is expected. Statistical downscaling in the North Atlantic Ocean captures only the low predictive signal of the predictor, but no extra added value is found in this case.

1 Introduction

Seasonal forecasting has a great potential for a wide range of planning and maintenance activities which strongly depend on seasonal to interannual climate variations. Global predictions at this time scale are routinely produced using ocean-atmosphere coupled models by a few centers around the world, due both to the specialized knowledge and the computational resources required. Although seasonal predictability over most extratropical regions is still limited (Doblas-Reyes et al., 2013), more skillful predictions are expected in the near future due to the recent advances in new potential sources of predictability (Dunstone et al., 2016, Clark et al., 2017). The recent adoption of climate services (Hewitt et al., 2013, Bruno Soares et al., 2018) has boosted the development of tailored products for decision-making in different sectors (see, e.g. the COPERNICUS Sectoral Information System over Europe, https://climate.copernicus.eu/sectoral-information-system). Sectoral applications of seasonal forecasting are now being established in a number of sectors, such as agriculture, energy and water management (Bruno Soares et al., 2018). Other recent applications are emerging including, among others, early-warning systems for heat wave-related mortality (Lowe et al., 2016), and for fire danger (Bedia et al., 2018). However, the development of climate services is yet to be developed in other areas, such as the marine sector, with a number of potential applications based on seasonal wave predictions (significant wave height, etc.) for planning construction, maintenance and operations of coastal (e.g. ports) and offshore (e.g. wind farms) infrastructures. Two recent studies investigate the skill of significant wave height predictions from global models, focusing on tropical regions (the West Pacific and Indian Oceans) where moderate-to-high skill is expected (Lopez and Kirtman, 2016 and Shukla and Kinter, 2016). In the case of the North Atlantic region, wintertime mean wind and wave conditions are known to be largely driven by atmospheric circulation patterns such as the North Atlantic Oscillation (NAO), the East
Atlantic (EA) and the Scandinavian (SCAND) patterns. The moderate skill of global models for predicting these large-scale patterns has motivated the development of alternative empirical techniques relying on lagged relationships between slowly-varying components of the climate system and the predictand of interest. Colman et al. (2011) predicted winter ocean wave heights in the North Sea based on North Atlantic sea surface temperatures (SSTs) for the preceding month of May. As an alternative to this classical predictor, October Eurasian snow cover increase was recently found to highly correlate with the DJF mean Arctic Oscillation (AO) (Cohen and Jones 2011). Based on this hypothesis, Brands (2016) proposed a statistical technique for forecasting DJF mean wind and wave conditions in the North Atlantic from Eurasian snow cover increase in October.

The potential added value of dynamical and statistical downscaling methods to improve the skill of global forecasts over particular regions of interest has been recently explored in a number of intercomparison studies. Manzanas et al. (2018a) assessed the added value of dynamical and statistical downscaling for seasonal temperature predictions in Europe. Nikulin et al. (2018) performed a similar study for precipitation in East Africa. The added value of dynamical downscaling was shown to be quite limited, whereas statistical downscaling methods (building on the link between large-scale atmospheric predictors and the local predictand of interest) could yield significant skill improvement in those cases where the large-scale predictor variables used as predictors are better predicted by the global model than the local variable of interest (see Manzanas et al. 2018b). These methods are also suitable to predict variables which are not directly provided by the model, but which can be statistically connected to some model variables.

The potential predictability of wave climate is largely linked to the predictability of the wind or sea level pressure fields, a common predictor in statistical downscaling approaches (Wang et al., 2014). On the other hand, the global wave field is found to be dominated by swell, even along the extratropical storm areas, where the relative weight of the wind-sea part of the wave spectra is highest (Semedo et al., 2011). Swells are generated remotely and are not directly coupled to the local wind field. Therefore, the local target waves are strongly connected with large-scale predictors from global model simulations. Statistical downscaling methods could in principle take advantage of atmospheric teleconnections by extending the predictor region well beyond the target region. Therefore, there is the potential of improving the skill of the wave seasonal forecast as a result of aggregating predictability of distant wave generation areas. In this paper we explore this possibility by adapting a statistical downscaling method for waves recently introduced by Camus et al. (2017), and assessing its added value for seasonal forecasting using the retrospective seasonal forecasts provided by the publicly available CFSv2 seasonal hindcast (Saha et al., 2011). We focus in two regions: 1) The Western Pacific around Indonesia during the season June-August (JJA) due to the forecast skill of wave climate associated with ENSO variability –this was previously analyzed in Lopez and Kirtman (2016) and Shukla and Kinter (2016); 2) The North Atlantic Ocean during the season January-March (JFM), the period during which severe wave climate can cause more disruptions in marine operations. The relationship between the NAO Index and the winter wave conditions is analyzed because it represents major climatic features in this region. The experiments are limited to the predictions corresponding to lead month 1 (May/December initializations) for season JJA/JFM in the Western Pacific and North Atlantic, respectively.

The paper is organized as follows. Section 2 introduces the data used for both predictand and predictors, and the characterization of the wave climate in the two regions under study. The
statistical downscaling methodology applied and the validation of the statistical model are described in Section 3. Verification of the forecast quality is presented in Section 4. Finally, the most important conclusions are summarised in Section 5.

2 Data

Historical information of the predictand (waves) and predictor (sea level pressure) is required to calibrate the (perfect prog) statistical downscaling model. Besides, a retrospective forecast dataset is also used to verify the performance of the seasonal forecast of wave heights. The historical wave database is also used to assess the forecast quality of the downscaled wave heights. Historical information from El Niño and NAO indices is also used to analyze their connection to the summer or winter wave conditions in the Western Pacific and the North Atlantic, respectively.

2.1 Historical data

2.1.1 Historical Wave Data

The wave hindcast GOW2 developed by Perez et al. (2017) provides historical wave data (significant wave height, $H_s$, peak wave period, $T_m$, mean wave direction, $\theta$; $m$) with hourly resolution and 0.5° spatial resolution at a global scale and 0.25° in the continental shelf along the coast worldwide from 1979 onwards. This hindcast uses the wave model, named WaveWatch III (version 4.18, Tolman, 2014) in a multigrid configuration and considering winds and ice coverage fields interpolated from the historical CFSR and CFSv2 data (Saha et al., 2014).

Figure 1 shows the mean, and 95th percentiles for the JJA $H_s$ in the Western Pacific (upper panels) and for the JFM $H_s$ in the North Atlantic (lower panels). In the case of the Western Pacific, differences in spatial patterns reflect that the amount of increment of wave energy is not proportional between different statistics due to differences in wave generation. Mean conditions reflect only wave generation due to local winds (Indonesia) or far extratropical storms (Eastern Australia, Eastern Asia), with the highest mean wave height around 2.0 m in the Eastern Australia, or 1.6 m in the Northwest Pacific Ocean. The extreme wave conditions concentrated in the area of the China Sea are explained due to the larger frequency and intensity of Tropical Cyclones (TCs) in this region, reaching values around 4.0 m and 6.0-7.0 m for the 95th and 99th percentile (not shown), respectively. The tracks of the extratropical storms in the North Atlantic determined the wave spatial patterns. Patterns of the three wave statistics (mean, 95th and 99th percentiles) are similar in the North Atlantic, with highest waves around 20°N and 60°N with values reaching 5.0, 9.0 and 11.0 for the mean, 95th and 99th percentile conditions, respectively.
2.1.2 Historical Atmospheric Data

Historical sea level pressure (SLP) is obtained from the Climate Forecast System Reanalysis (CFSR and CFSRv2, Saha et al., 2014), which is the corresponding reanalysis of the seasonal forecasting systems which will be considered in this study (see Sec. 2.3). The temporal coverage spans from 1979 to 2015 with hourly temporal resolution and 0.5° spatial resolution.

2.1.3 Climate Indices

The definition of the warm (El Niño) and cool (La Niña) ENSO events in this paper are based on the SST anomalies in El Niño 3.4 region (5°N-5°S, 120°W-170°W). This is the standard index used by the National Ocean and Atmospheric Administration of the United States (NOAA). The 18-month period spanning from the spring on the onset year (MMA-1) to the summer of the decay year (JJA), is centered in SON-1 and DJF, when SST anomalies reach their maximum (minimum) value. El Niño events for the period 1982-2010 are: 1983, 1987, 1988, 1992, 1995, 1997, 1998, 2003, and 2007.

The North Atlantic Oscillation (NAO) is traditionally defined as the normalized pressure difference between two stations, one in the Azores and the other in Iceland. An extended version
has been used in this study based on one station in the SW part of the Iberian Peninsula (Hurrell, 1995), Gibraltar, and the other one in SW Iceland (Jones et al., 1997), derived for the winter half of the year and calculated by the Climatic Research Unit (CRU) of the University of East Anglia.

Wave severity in the Indian and Pacific Oceans is mainly due to TCs. The ENSO inter-annual cycles have a strong impact on the wave climate of this region (Stopa and Cheung, 2014) and on TC genesis: in warm ENSO phases the cyclones have a tendency to have longer lifetimes, to be more intense and to form in greater numbers over the central Pacific region (Camargo et al., 2007).

The correlation of the wave climate in JJA in the Western Pacific with the DJF (December-January-February) Niño 3.4 Index is showed in the upper panels of Figure 2. The spatial patterns of the correlation with wave statistics parameters (mean, 95th and 99th percentiles; the first two ones only shown) are quite similar. High positive correlation is found in almost the whole area, while significant negative correlation is found around New Guinea. The correlation between
JFM Hs and the NAO Index is shown in the lower panels of Figure 2. A positive correlation at highest latitudes and negative correlation in the lowest latitudes can be observed.

Figure 2. Correlation between Western Pacific JJA $H_s$ and DJF Niño3.4 Index: a1) Mean; a2) 95th Percentile of the JJA $H_s$. Correlation between North Atlantic JFM $H_s$ and NAO Index: b1) Mean; b2) Percentile 95th of JFM $H_s$.

2.2 Seasonal forecast data (hindcast)

The NCEP CFSv2 seasonal forecasting system is used in this study to evaluate the predictability of wave climate at seasonal scale. The 28-year (1982–2009) ensemble retrospective forecast, known as hindcast, data set from CFSv2 with 24 members is provided by NCEP (Saha et al., 2011). The CFSv2 used in the reforecast consists of the NCEP Global Forecast System at T126 (~0.937°) resolution, the Geophysical Fluid Dynamics Laboratory Modular Ocean Model
version 4.0 at 0.25–0.5° grid spacing coupled with a two-layer sea ice model, and the four-layer NOAH land surface model.

The NCEP-CFSv2 forecast database is coherent with the reanalysis atmospheric database (NCEP Global Forecast System) used to calibrate the statistical downscaling model. It is the forcing used to generate the GOW2 database and is publicly available.

This information is retrieved from the ECOMS User Data Gateway (ECOMS-UDG), developed by the Meteorology Group of the Universidad de Cantabria (Cofiño et al., 2018), in the framework of the European Climate Observations, Modelling and Services initiative (ECOMS) projects. ECOMS coordinates the activities of three on-going European projects (EUPORIAS, SPECS and NACLIM) focusing on seasonal to decadal predictions. The ECOMS-UDG facilitates harmonized multi-model seasonal forecast data. This information can be obtained directly from the data providers, but this is an error-prone and time-consuming activity due to the fact that resulting formats, temporal aggregations and vocabularies may not be homogeneous across datasets.

Historical reanalysis and retrospective CFSR SLP data are converted to a common 2.0ºx2.0º latitude-longitude grid. Daily predictor fields are standardized to avoid biased results due to differences in climate model climatology and variability. In the case of GCMs, standardization is applied using the simulated seasonal climatological mean and seasonal standard deviation for the historical period covered (1982-2009) by the retrospective seasonal forecast database.

3. Seasonal Forecast Downscaling Methodology

3.1. Statistical downscaling approach

In this work we build on the Statistical Downscaling (SD) method developed by Camus et al. (2017) based on weather types (WTs), adapting it to the particularities of seasonal forecasting. In particular, the following steps of the methodology were reviewed:

1) Following Manzanas (2016) that obtains a more skillful statistical downscaling model for seasonal precipitation forecast using season-specific data in the model calibration, a particular regression-guided classification is performed at every wave GOW2 grid node at 1.0° resolution taking into account multivariate wave conditions ($H_s$, $T_p$, $\theta$) as predictand in each seasonal period, independently. 100 WTs of the SLP fields are obtained for every GOW2 grid node;

2) The seasonal empirical distribution of hourly wave parameters at every grid node of the GOW2 wave database is calculated for each WT;

3) The seasonal empirical distribution of the wave variables is obtained for each grid node using the probability of WTs at the target season. Different statistical parameters can be obtained from the empirical distribution. The seasonal forecast quality is assessed in terms of the mean seasonal wave height and the 95th and 99th percentiles.

Daily SLP and daily squared SLP gradients (SLPG) are usually taken as the atmospheric variables to define the wave predictor, since SLPG fields are proved to improve the statistical relationship with waves (Wang et al., 2014). A verification of the performance of the
retrospective seasonal forecast of the SLP and SLPG has been carried out (not shown) before establishing the final version of the predictor for the statistical downscaling model at seasonal scale. A low predictability of SLPG is found, which could deteriorate the quality of the forecast of the seasonal wave climate. Therefore, this variable is eliminated as predictor in the statistical downscaling model.

The predictor is defined as the \( m \)-daily mean SLP, with \( m=7 \) days for Western Pacific (subdomain 3) and \( m=3 \) days for North Atlantic (subdomain 9), i.e., the predictor at each specific day is calculated as the average of the SLP at the same day and the previous \( m-1 \) days through the historical time period. The predictor is defined by the leading principal components (PCs) explaining 95% of the entire predictor variance. PCs are calculated for the seasonal forecast by projecting the corresponding standardized fields onto the empirical orthogonal functions obtained from the reanalysis, which were computed simultaneously from the combination of the weighted predictor and predictand. Each \( m \)-daily mean SLP field from the CFSRv2-NCEP hindcast database, adding the predictand estimation component from the regression model, is associated with the most similar semi-guided WT, obtained from the reanalysis CFSR atmospheric database.

### 3.2 Statistical model cross-validation

A \( k \)-fold cross-validation of the SD model is performed with the criterion of an optimal selection of \( k \) based on a calibration period covering 80% of the full period (Casanueva, 2016). In this work, in which 35 years (1979 – 2015) of predictor and predictand data are available, \( k=5 \) stratified folds (7/8 years each) have been defined. Stratified folds are subsampled by selecting 1 per 5 years, i.e., the first fold would be formed by years 1979, 1984, 1989, 1994, 1998, 2004, 2009 and 2014. Using this option, the same distributions/climatologies are sampled for all folds and each fold covers a more representative range of years (Gutiérrez et al., 2013).

The estimates from the statistical downscaling model are compared against the parameters obtained from the observations (GOW wave data) at monthly scale during the JJA season in the Western Pacific and during the JFM season in the North Atlantic. The monthly mean, 95\(^{th}\) and 99\(^{th}\) percentiles of \( H_s \) are validated using the corresponding sea-state parameter distribution associated with each WT during the calibration period of each \( k=5 \) test subsets. The single correlation coefficient, the normalized root mean square error (NRMSE, expressed in %), scatter index (a measured of dispersion between the estimated and observed value, defined as the root mean square error divided by the mean observed value) and bias are computed for each \( H_s \) parameter using the full available period 1979-2015, by joining the test subsets together into a single prediction.

#### 3.2.1 Western Pacific

The validation scores are shown in Figure 3 for the mean (left column) and the 95\(^{th}\) percentile (right column) of the significant wave height (mean in the left column, percentile 95\(^{th}\) in the right column). The skill of the SD model is considerably high, worsening for higher \( H_s \) percentiles. Correlation coefficients are about 0.8-0.95 for the mean \( H_s \) for almost the whole area, except in
the most shelter part, as in the coast of the China Sea and north of New Guinea where it decreases to 0.5. The correlation decreases for extreme wave heights, with restricted areas with coefficients around 0.8. Regarding NRMSE, the values increase from about 10% for the mean Hs to 20% for the 95th percentile and 30%, even 50% for the 99th percentile (not shown) in the area with highest extreme waves generated by TCs. The scatter index (not shown) presents a similar pattern as the NRMSE. This score increases with wave height, with maximum values around 0.4-0.5 in the area of extreme waves. Bias (not shown) is almost negligible for the mean significant wave height and slight for extreme percentiles.

3.2.2 North Atlantic

Figure 4 shows the correlation coefficient, the NRMSE, scatter index and bias, computed for the two statistics of JFM $H_s$ (in columns) for the full available period 1979-2015 using a 5-fold cross-validation. The skill of the SD model is considerably high for the mean conditions, worsening as the $H_s$ percentile gets higher. Correlation coefficients are around 0.9-0.95 for almost the whole area (decreasing to values around 0.5 in the western part of the Mediterranean Sea and the Caribbean Sea). Regarding NRMSE, the values increase from about 5% for the mean Hs to 10% for the 99th percentile. The scatter index (not shown) reaches values around 0.1 for the
percentile 99th in the whole North Atlantic. Bias (not shown) does not inform about a clear trend to over- or underestimate Hs.

Figure 4. Validation of SD model in the JFM season for the monthly mean (left column) and the 95th percentile (right column) of $H_s$ in the North Atlantic by means of the correlation coefficient (upper panel) and normalized root square mean error (lower panel).

4. Seasonal Forecast quality

4.1. Verification metrics

The assessment of quality based on past performance is required to give value to the prediction itself (Doblas-Reyes et al., 2013). A range of additional verification measures are applied to provide a complete description of different quality aspects relevant to users (Jolliffe and Stephenson, 2003). In this work, the correlation coefficient and the bias are used for a deterministic verification (ensemble mean). The Ranked Probability Score (RPS), the Ranked Probability Skill Score (RPSS) and the Relative Operating Characteristic Skill Score (ROCSS) are used for the probabilistic verification.

Bias is a metric of the mean deviation of the forecast from observations and, thus, informs about systematic biases. On the other hand, the correlation coefficient measures the temporal correspondence between the forecast and the observational reference, being insensitive to linear transformations of the data and, thus, complementary to bias. Besides, a tercile-based approach is used for the probabilistic verification of the prediction quality. Interannual series of seasonal prediction of the mean, percentiles 95th and 99th of the significant wave height are classified into
three categories (above-, near- or below-normal), according to its respective climatological terciles.

The ranked probability score (RPS) is a measure of forecast quality based on the squared forecast probability error, cumulative across the three forecast categories from lowest to highest. The error (see equation 1) is the squared difference between the cumulative categorical forecast probability \( (P_{cumfct}, \text{fraction of ensemble members in the corresponding category}) \) and the corresponding cumulative observed “probability” \( (P_{cumobs}) \), in which 1 is assigned to the observed category and 0 is assigned to the other categories. Note that higher RPS indicates greater forecast probability error. The ranked probability score (RPSS) is a skill score based on a comparison of the ranked probability score (RPS) for an actual set of forecasts with the RPS corresponding to constant climatology \((0.333/0.333/0.333)\) forecasts. Positive RPSS implies that the RPS is lower for the forecasts than it is for climatology forecasts. Higher scores indicate forecasts having higher skill levels. RPS is defined as:

\[
RPS = \frac{1}{ncat-1} \sum_{icat=1}^{ncat}(P_{cumfct_{icat}} - P_{cumobs_{icat}})^2
\]  

where \( icat \) is the category number (1 for below normal, 2 for near normal, 3 for above normal), \( ncat \) is the number of categories (3 in a tercile-based system).

The Relative operating characteristic (ROC) curve measures forecast quality in terms of discrimination ability. ROC is constructed by plotting the hit rate against the false alarm rate using a set of increasing probability thresholds (e.g., 0.05, 0.15, 0.25, etc). A hit implies the accurate forecast (true positive) of a particular event, such as below normal wave severity, while a false alarm implies a false positive for the non-occurrence of such an event. The ROC skill score (ROCSS, the area under the ROC curves) characterizes the system’s ability to anticipate correctly the occurrence or non-occurrence of pre-defined events. ROCSS above 0.5 reflects positive discrimination skill, 1.0 representing a perfect forecast system. A value zero indicates no skill with respect to a climatological prediction. This skill measure is independent of the model bias.

4.2. Forecast verification

4.2.1 Western Pacific

The correlation coefficient is a simple metric to assess the ability of the downscaled 24-member ensemble JJA wave height to reproduce the observed interannual variability of the 28 years (1982-2009) of the JJA significant wave height. The correlation coefficient is shown in the upper panels of Figure 5 for the JJA mean and 95th percentile significant wave height. In general, significant correlation coefficients are found (values around 0.4-0.6). The correlation is higher for the 95th and 99th percentiles (not shown), especially in the area around 150°E due to a higher TC activity during warm ENSO phases (Camargo et al., 2007). The TCs frequency is related with the ENSO and, therefore, the JJA interannual variability in terms of higher wave heights, increasing the predictability of these extremes. The bias of the JJA climatology of the mean and
the 95th percentile wave height is depicted in the lower panels of Figure 5. The bias is negligible for the mean $H_s$, slightly negative (5%) for the percentile 95th, and almost limited to TCs region.

![Figure 5. Upper panels: Correlation coefficient between observed and predicted JJA $H_s$ in the Western Pacific Ocean: a1) mean; a2) 95th percentile. Lower panels: Bias (in %) of the predicted JJA significant wave height climatology: b1) mean; b2) 95th percentile.](image)

As an illustrative example of the tercile-based probabilistic validation approach, Figure 6 shows the 1982-2009 standardized historical time series of the 95th percentile of JJA $H_s$ observations and Niño3.4 Index with its correlation coefficient and the binary occurrence/non-occurrence for the three terciles in several grid points with different wave climate and forecast skills (see Frías et al., 2018 for a detailed description of a tercile validation plot). The standardized JJA $H_s$ time series informs about the high interannual variability of the seasonal wave climate in this area. Higher waves during strong warm ENSO phases (high values of the DJF Niño 3.4 Index) and a wave height decrease the following JJA season can be observed.

The highest relationship with Niño3.4 is found in location $[\text{Lon}=132.0^\circ; \text{Lat}=9.0^\circ]$ (panel a) with lowest JJA waves usually in El Niño years (1983, 1988, 1992, 1995, 1998, 2003, 2007, marked with green points in Figure 6 panel 2) after highest values of the DJF index. The forecast
resolution increases in general in El Niño years (see lower tercile with the observed one in green), especially in the strongest El Niño events (1988, 1998). These results suggest that the predictability signal in this region and season is linked to this mode of variability. Other non-El Niño years with observed upper terciles (i.e., 1994, 1997, 2001, 2002, 2004 and 2006 in blue points) are well predicted, indicating a certain predictability of the SLP fields transferred to downscaled wave heights. Several of this non-El Niño years (i.e., 1994, 1997, 2002, 2006) are associated with the JJA season of the onset year of El Niño events (1995, 1998, 2003 and 2007).

Correlation with Niño3.4 Index is smaller for the location [Lon=114.0°; Lat=9.0°] (see panel b). However, the relation between high index value and small waves (below tercile) can still be detected, with significant forecast skill in El Niño years (1982, 1988, 1995 and 1998). Regarding the upper tercile (above-normal), the forecast predictions achieved values around 0.5-0.6, especially in the period between 1999-2002, negatively linked to the ENSO (La Niña events: 1999, 2000, 2001). In the case of location [Lon=129.0°; Lat=9.0°], shown in panel c of Figure 6, almost no skill (ROCSS near to zero) is found. This grid is located in the area with high differences between spatial patterns of the mean and high percentiles, because of high extreme waves due to TC generation. Therefore, the lack of forecast quality in this location might be related to errors in GCMs in simulating TCs. Despite the general insignificant skill through the historical years (1982-2009), the observed below-normal terciles during the strongest El Niño events are well predicted (1988, 1995, 1998).

Figure 7 shows the ROCSS for the mean (upper panels) and the 95th percentile (lower panels) for the three categories: below-normal in the left column, normal in the middle columns and above-normal in the right column. ROCSS scores around 0.4-0.6 suggests skillful predictions for the
The lack of skill for the normal category is in agreement with previous studies (Manzanas, 2016).

Figure 7. ROC Skill Score of the seasonal JJA wave height predictions in the Western Pacific Ocean (mean in the upper panels and the 95th percentile in the lower panels) for the below normal, normal and above-normal terciles (left, middle and right column, respectively).

Figure 8 shows the maps of ROCSS for El Niño events for the below-normal category. Negative anomalies are expected after the peak phase of DJF Niño Index, as a result of reduced atmospheric synoptic activity associated with an anomalous anticyclone which strengthens the West Pacific subtropical high (Lopez and Kirtman, 2016). An increase of the skill of these wave predictions, ROCSS close to 1 over a wider area is obtained, which confirms that the warm phase
of ENSO during DJF (El Niño events) is a source of skill of JJA Hs anomalies (Lopez and Kirtman, 2016).

4.2.2 North Atlantic

The correlation coefficient is shown in the left column of Figure 9 for the mean and 95\textsuperscript{th} percentile of the JFM $H_s$. In general, correlation coefficients are smaller than 0.4 with an analogous spatial pattern for the different wave statistics. The bias (not shown) is negligible for the mean $H_s$ and the 95\textsuperscript{th} percentile and slightly positive (<5\%) for the 99\textsuperscript{th} percentile. The forecast probability error, quantified by means of the RPS, is shown in the middle column of Figure 9. RPS value is around 0.2-0.3, indicating a small probability error for the two wave height statistics. This could mean that the JFM forecast is able to discriminate among outcomes. However, the RPS is sensitive not only to the forecast probability given to the observed category, but also to the probabilities given to the other categories. The forecast error is more limited when a high probability is forecast for an adjacent category than when a category on the opposite extreme is predicted or the probability of each category is quite similar. Thus, the RPS could be relatively smaller (a better forecast) when the near normal category has a high forecast probability than when the below or above normal categories are observed. RPSS compared the actual forecasts to the constant climatology forecasts. RPSS is reversed from that of RPS, where now higher scores mean forecasts having higher skill levels. RPSS is presented in the left panels of Figure 9. Values obtained are not significant, ranging between -0.2 to 0.2 for almost the whole North Atlantic Ocean, except in the western part where this verification score presents a higher negative value, indicating the unsuccessful ability of the forecasts to differentiate among
dissimilar observed outcomes, as compared to constant climatology forecasts (0.333/0.333/0.333).

**Figure 9.** Verification of the JFM $H_s$: (a) mean; (b) 95th percentile in the North Atlantic Ocean using the metrics: 1) Correlation coefficient; 2) RPS; 3) RPSS.

Spatial maps of ROCSS of the mean of JFM $H_s$ are shown in Figure 10 for the below-normal, the normal and the above-normal categories (left, central and right columns, respectively). It can be observed that the area [40°W - 20°W; 20°N - 40°N] shows the highest predictability, especially for the lower tercile. Also other locations in the North Sea and the Western Mediterranean Sea show a high predictability. Similar ROCSS spatial distribution is obtained for the 95th percentile and almost disappearing for the 99th percentile (not shown). The analysis of the ROCSS of the JFM SLP predictions (input variable) detects a skillful area centered between the latitudes 35°N and 55°N and the longitudes 15°W and 55°W which is reflected in the areas with higher skill of the JFM $H_s$ predictions.

**Figure 10.** ROC Skill Score of the seasonal mean of JFM $H_s$ predictions in the North Atlantic Ocean for the below normal, normal and above-normal terciles (left, central and right column, respectively).
5 Conclusions

The marine sector has not yet made use of the potential of climate services, in spite of the broad range of potential applications in this sector. This includes but is not limited to applications of seasonal wave predictions. In this work, we have adapted the statistical downscaling framework proposed by Camus et al. 2017 for its application to seasonal forecast. The downscaled wave is obtained from the seasonal CFSv2 hindcast which was analyzed and verified using the quasi-observational GOW2 wave database and a variety of deterministic and probabilistic metrics.

First, the suitability of statistical downscaling approach to generate wave seasonal forecast of mean and 95th and 99th percentiles for JJA season in the Western Pacific Ocean and for JFM season in the Northern Atlantic Ocean has been tested. To this aim, the quality of the NCEP-CFSv2 ensemble retrospective forecast (1982–2009) has been assessed validating the performance of wave seasonal forecast in the past, issued one month before beginning of the validation period.

The statistical downscaling model in the Western Pacific presents certain lack of skill itself due to differences in wave generation in this tropical area. This model configuration is defined to be as representative as possible for the main wave characteristics (swell component generated from distant storms which determine the spatial domain of the predictor). The downscaled wave estimates in this region can be improved locally using particularized predictors to represent wave generation by local winds or distant storms. Despite these limitations, downscaled seasonal JJA wave predictions in the Western Pacific show some predictability skill assessed by the ROCSS probabilistic metric. The skill is higher during decay years after ENSO warm phases when a negative anomaly of the significant wave height is expected. Although years with high wave heights are related with ENSO due to the increase in TCs, restricted performance of the statistical relationship due to scarce extreme events associated to TCs and the intrinsic limitations of GCMs to reproduce the intensity of these atmospheric conditions leads to predictions failure to detect these positive wave height anomalies during these ENSO phases.

The statistical downscaling in the North Atlantic Ocean can capture the predictive signal in the global hindcast CFSR but not relevant added value is found in terms of aggregating predictability of the input atmospheric variable. JFM wave forecast quality shows a similar performance of the SLP predictor. The low skill in this area is conditioned to the limited seasonal predictability over Europe in the retrospective database used. The skill pattern (evaluated by means of the ROC Skill Score) of the wave seasonal forecast resembles the skill pattern of the SLP seasonal predictions. The application of the statistical downscaling model does not lose the (low) predictor predictive skill.

Although the skill found by the results in the North Atlantic was low to moderate, this experimental development opens new potential application in the marine sectors. The new seasonal forecast system from the UK Met Office, GloSea5, has shown a promising skill in predicting the NAO due to a considerable increase in resolution. This improvement joined with access facilitation to seasonal forecast data, as the emerging Copernicus Climate Change Service which is expected to provide reliable and credible source of free climate information in Europe.
in the coming years (EC, 2015), may lead to the application of this climate products within an operational framework in the near future.

Conclusions obtained from this work is only for summer wave heights in the Western Pacific and winter wave heights in the North Atlantic and may not be not extensible to other regions of the global ocean and seasons. Further investigation is still needed to provide a more conclusive overview on the merits and limitations of statistical downscaled wave seasonal predictions.

Acknowledgments
P.C. acknowledges the support of the Spanish Ministerio de Economía y Competitividad (MINECO) and European Regional Development Fund (FEDER) under Grant BIA2015-70644-R (MINECO/FEDER, UE). The authors acknowledge funding from the ERANET ERA4CS (ECLISEA project) and the government of Cantabria and FEDER under the project CLISMO.

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