Statistical downscaling of the significant wave height

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Abstract:

Future projections of sea state parameters, such as the significant wave height (Hs), are required for a wide number of maritime activities especially for designing ocean structures. General Circulation Models (GCMs) are the main tools that provide future projections of atmospheric variables taking into consideration the evolution of greenhouse gas emissions. However, in one hand, these models generally do not provide ocean sea state parameters. In the other hand, GCMs provide simulations with coarse spatial resolution, which makes them unsuitable for most of impact assessment applications that require local climate projections. Dynamical and statistical downscaling (SD) models are tools that bridge the gap between what GCMs provide and what industry and policy makers require for decision making. SD approaches are models that establish an empirical relationship between large scale atmospheric variables and local wave parameters or other variables. Besides their computational efficiency, statistical models are compared with dynamical models in various studies for ocean wave parameters ([3],[6]) and other climate variables.

In this study, a SD model that links the large scale wind and the local scale Hs parameter is presented. The location of interest is a coastal point situated in the Bay of Biscay at (25.4 N,1.6 W). The atmospheric data used in this work is extracted from the ERA5 reanalysis dataset of the ECMWF. The data consists of hourly zonal and meridional wind components with spatial resolution of 0.25*0.25. The historical wave data is the sea-state hindcast HOMERE [1]. To facilitate the analysis, the predictor spatial resolution is upscaled to 0.5*0.5 and the temporal resolution of both the predictor and the predictand is upscaled from hourly to 3 hourly resolution.

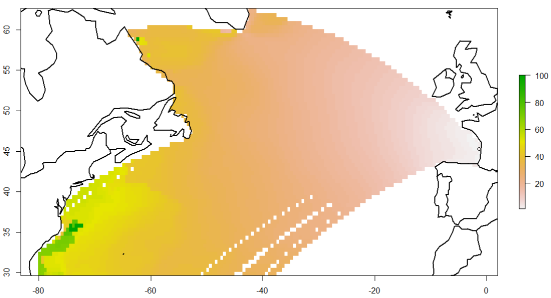

Figure 1: Travel time of waves $\hat{t}_j$ from each source point to the target point located in the Bay of Biscay in Mars-April-May.

At a given time, the sea state is characterized by a composition of a wind sea and swells. The wind sea is generated by the local wind whereas swells are generated and propagated over large distances. SD models have to take into consideration both wave systems. Therefore, given the non instantaneous and non local relationship between wind and waves, more attention has to be given to the spatiotemporal definition of the predictor([2]).

At first, the local and the global predictors are defined. The local predictor X_t^L is defined based on the wind speed and the fetch at the point of interest and the global predictor is defined as follows. Based on the assumption that waves travel along a great circle path[4], the wind components at each grid point are projected into the bearing of the target point in a great circle path and the spatial coverage of the global predictor is defined based on the same assumption. Subsequently, its temporal coverage is defined by two parameters, called waves travel time and time window size, using a fully data driven approach. The global predictor X_t^G at time t is then defined as the mean of the lagged squared projected wind in a time window, so that

$$\mathrm{X}_t^G = \{(\bar{W_j^2})_{t-\hat{t}_1-\alpha_1:t-\hat{t}_1+\alpha_1}, ..., (\bar{W_j^2})_{t-\hat{t}_j-\alpha_j:t-\hat{t}_j+\alpha_j}, ..., (\bar{W_j^2})_{t-\hat{t}_m-\alpha_m:t-\hat{t}_m+\alpha_m}\}$$

where $(\bar{W_j^2})_{t-\hat{t}_j-\alpha_j:t-\hat{t}_j+\alpha_j}$ is the mean of the squared projected wind at time window $[t-\hat{t}_j-\alpha_j, t-\hat{t}_j+\alpha_j]$ at location j, α_j controls the length of the time window, m the total number of grid points, and $\hat{t}_j$ is the waves travel time. The two parameters $\hat{t}_j$ and α_j are selected using the maximum correlation between Hs and the global predictor.

After defining the predictors, we consider the linear regression model $Hs_t = X_t^L\beta^L + X_t^G\beta^G + \epsilon_t$ which links the predictors and the local Hs. Given the multicollinearity of the high-dimensional input space, variable selection is performed with various methods: Forward selection, LASSO, Ridge, and generalized Ridge [5]. These methods and the resulting models are compared in terms of prediction error, computational time, and interpretability. In this work, we seek coefficients β^G that are smooth, meaning that close locations should have close coefficients. Furthermore, given the nature of the relationship between the predcitand and the predictors, we seek model coefficients that are positive.

The results show that the prediction error of most of the methods are close to each other ($RMSE \simeq 0.35m$). Therefore, the choice of the model should be based on the physical interpretation of the model coefficients. The generalized ridge is the only method that has the smoothness propriety of coefficients. However, none of the four methods has the ability to provide smooth and positive coefficients at the same time.

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Short biography – I have a bachelor degree in applied mathematics and a master degree in statistics and econometrics. My PhD subject is about climate change and statistical downscaling of ocean waves in coastal zones funded by the university of Rennes 1 and the Ifremer. The goal of the PhD is to provide future characterization of sea state parameters with a focus in its impact in ocean structures.