Exploring spectral wave climate variability using a weather type approach

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1. INTRODUCTION- Motivation

Traditional approaches for determining wave climate variability have been broadly focused on aggregated or statistical parameters ($H_s, T_m, \theta_m$...)

- The overall complexity of the wind-wave fields is contained in the wave spectra, $S(f, \theta)$

- Future wave climate is addressed usually by changes in $H_s$, changes in $T_m$, and changes in $\theta_m$, but not by changes in $pdf(H_s, T_m, \theta_m)$ or $S(f, \theta)$

-- Many coastal impacts depend on $H_s, T_m$ and $\theta_m$: wave run-up, overtopping, vertical breakwater stability, harbor agitation, ...

-- Wave propagation in shallow water areas can sometimes be erroneous calculated using spectral parameters ($H_s, T_m, \theta_m$...)
1. INTRODUCTION - Objectives/Summary

- To propose a framework to model the seasonal-to-interannual variability of directional spectra at a given location.
- The framework is based on data mining – clustering techniques.
- A statistical downscaling model is proposed to obtain a probabilistic relationship between a large-scale predictor ($X$) and a local predictand ($Y$).
- The framework is able to deal with another temporal scales and predictors and predictands (ENSO and Tropical Cyclone activity).

![Diagram](image)

**Large-scale met-ocean predictor**

**Local directional spectra**
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1. Motivation and Summary

2. Clustering Techniques

3. Statistical downscaling of an univariate variable

4. Statistical downscaling of a trivariate variable

5. Statistical downscaling of directional spectra

6. Other applications of SD

7. Conclusions
PRINCIPAL COMPONENT ANALYSIS

{PC1(t), PC2(t), PC3(t), PC4(t),...}
\begin{align*}
\{x_1, x_2, \ldots, x_N\} & \quad \text{N data} \\
\{v_1^0, \ldots, v_M^0\} & \quad \text{M centroids or prototypes}
\end{align*}
Data mining algorithms

**K-means**
$SLP^*(x) = EOF_1(x)PC_1^* + EOF_2(x)PC_2^* + ...$
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2. Clustering Techniques
3. **Statistical downscaling of an univariate variable**
4. Statistical downscaling of a trivariate variable
5. Statistical downscaling of directional spectra
6. Other applications of SD
7. Conclusions
Occurrence probability, $p_i$

Histograms, $f_i(y)$

$p_1 + p_2 + \ldots + p_N = 1$

$f_S(y) = p_1 f_1(y) + p_2 f_2(y) + \ldots + p_N f_N(y)$

Ocurrence probabilities, $p_i$
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Sea state types
Sea state types, STs

Circulation (weather) types, CTs

Look-up table of occurrence probabilities of ST types /conditioned to CT

\[ X_d \xrightarrow{SD} Y_d \]
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2. DATA

Buoys from Puertos del Estado (Spanish Ministry of Public Works & Infrastructures)
2. DATA

Sea level pressure (SLP): is the geophysical variable used to explain the state of the atmosphere. It is also our predictor to investigate the wave climate and its inter-annual variability.

NCEP Climate Forecast System Reanalysis (CFSR)

31 years (1979 to 2009)
6-hourly fields
0.5° longitude x 0.5° latitude (grid)
Conventional and satellite observations included
3. METHODOLOGY- The discrete wave spectrum

- Wave spectra provide significantly more information, being possible to differentiate between distant and local wave generation areas (Bromirski et al., 2004).

- When grouped by bins or packages the wave energy distribution becomes Gaussian, which is a precondition when a PCA analysis is conducted.

- More easily interpretable by visual inspection.

\[
m_{oi,j} = \int_{f_i}^{f_{i+1}} \int_{\theta_j}^{\theta_{j+1}} S(f, \theta) \, df \, d\theta
\]

\[
h_{i,j} = 4.004 \sqrt{m_{oi,j}}
\]

\[
H_s^2 = \sum_i \sum_j h_{i,j}^2
\]
3. METHODOLOGY- Clustering

a) Dimension reduction: EOFs of daily averaged wave spectra
b) Classification: K-means of the temporal modes
3. METHODOLOGY- Spectral types analysis

Villano

Cádiz

- Westerly swells
- Easterly windseas
- Mixed seas
- Calms
3. METHODOLOGY - Circulation types analysis

- a) Dimension reduction: EOFs of the 3-days running averages of SLP squared gradients
- b) Classification: K-means of the temporal modes
3. METHODOLOGY - Exploring relations
3. METHODOLOGY - Validation
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7. CONCLUSIONS

• An useful **descriptive graphical tool that helps understanding the effect of the atmosphere circulation pattern on the directional wave spectra** has been presented.

• The method is based on the **combination of instrumental wave data** of two deep waters buoys and the CFSR atmospheric reanalysis, that by mean of clustering statistical methods allows to **define a probabilistic relationship between the CTs and the STs**.

• **K-means algorithm** has demonstrated **excellent skills when working with the wave spectra**. It provides more information about the wave conditions than the traditional used aggregated or statistical wave parameters.

• This approach can be applied to different time scales and to different predictors and predictands (ENSO, TCs)
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3. METHODOLOGY- Validation
4. RESULTS - Seasonality

Villano

Annual

DJF  MAM  JJA  SON

Cádiz

Annual

DJF  MAM  JJA  SON
4. RESULTS - Inter-annual variability

(Thompson and Wallace, 1998) (Barnston and Livezey, 1987) (Charles et al., 2011; Le Cozannet et al., 2011)
4. RESULTS - Long-term trends

(Charles et al., 2011; Le Cozannet et al., 2011; Wang and Swail, 2002; Woolf et al., 2002; and Dupuis et al., 2006)
Sea Surface Temperature Index por TC activity

\[ SST \rightarrow I_{SST}(SST) \]
$X = (ET_1, ET_2, \ldots, ET_9)$

$p_i = \text{occurrence probability of } ET_i$

$p_1 + p_2 + \ldots + p_9 = 1$

$f_s(y) = p_1 f_1(y) + p_2 f_2(y) + \ldots + p_9 f_9(y)$
ENSO types

SLA composites (cm)
Church et al 2004
3. METHODOLOGY - Validation
5. CONCLUSIONS

• **Seasonal variations** of the discrete wave spectra gather up the Iceland low and Azores high winter-summer dominance.

• **Inter-annual variability** results go further revealing much more aspects than traditional approaches based on aggregated or statistical wave parameters, as for example enclosing frequencies and directions in which the analyzed climate pattern have significant effects.

• **Long-term trends** results show increased summer medium period westerly energy at Villano and a decrease of the easterly short period waves at both locations. No significant trends have been found in other seasons.