Statistical downscaling of multivariate wave climate using a weather type approach

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Objective #1

Predict multivariate wave climate (Y) at a particular location S as a function of synoptic atmospheric circulation (X)
Objective #1

ATMOSPHERIC CIRCULATION (predictor X: SLP)

MULTIVARIATE WAVE CLIMATE (predictand Y, H, T, Dir)

Regional atmospheric climatology (X)

Local wave climatology (Y)
Objective 1

Predict multivariate wave climate ($Y$) at a particular location $S$ as a function of **Synoptic Atmospheric Circulation patterns** ($X$)

$Y = f(H)$

$W T_i$ = Weather-type
Objective 1

Predict multivariate wave climate \((Y)\) at a particular location \(S\) as a function of synoptic atmospheric circulation patterns \((X)\)

\[ Y = f(H, T) \]
Objective 1

Predict multivariate wave climate (Y) at a particular location S as a function of synoptic atmospheric circulation patterns (X)

\[ Y = f(H, T, \text{Dir}) \] Camus et al 2011
\[ X = (\text{WT}_1, \text{WT}_2, \text{WT}_3, \text{WT}_4) \]

\[ Y = \text{g}(X) \]

**WT** = Weather-type

\[ p_i = \text{ocurrence probability of } \text{WT}_i \]

**Regression model / Stat. Downscaling:**

\[ Y = \text{g}(X) \]
\[ X = (W_{T1}, W_{T2}, W_{T3}, W_{T4}) \]

\[ Y \]

\[
\begin{align*}
    f_1(H) & \quad f_3(H) \\
    f_2(H) & \quad f_4(H)
\end{align*}
\]

\[ p_i=\text{occurrence probability of } W_{Ti} \]

\[ p_1 + p_2 + p_3 + p_4 = 1 \]

\[ f_S(H) = p_1 f_1(H) + p_2 f_2(H) + p_3 f_3(H) + p_4 f_4(H) \]
Objective #2

Project multivariate wave climate (Y) at a particular location S for a given GCM in a given time slice (X’)

\[ X' = \text{new predictor} \]

\[ Y = g(X') \]

\[ p'_1 + p'_2 + p'_3 + p'_4 = 1 \]

\[ f'_S(H) = p'_1 f_1(H) + p'_2 f_2(H) + p'_3 f_3(H) + p'_4 f_4(H) \]

\[ df(H) = f'_S(H) - f_S(H) \]
1. Synthesis of the work

2. Choosing the predictand Y

3. Choosing the predictor X

4. Statistical relationship: \( Y = g(X) \)

5. Wave climate projection

1. Conclusions
- GOW Wave reanalysis (IH Cantabria)
1. Synthesis of the work

2. Choosing the predictand Y

3. Choosing the predictor X

4. Statistical relationship: $Y = g(X)$

5. Wave climate projection

1. Conclusions
The predictor. Synoptic Atmospheric Circulation patterns

*Data: Sea Level Pressure fields (SLP)*
(from NCEP-NCAR Atmospheric reanalysis)
The predictor. Synoptic Atmospheric Circulation patterns

Data: Sea Level Pressure fields (SLP)  
(from NCEP-NCAR Atmospheric reanalysis)

Averaged 3-daily SLP fields

From: **2009-Jan-1st 00:00** to **2009-Jan-3rd 18:00 p.m**  
6 hourly SLP fields
The predictor. Synoptic Atmospheric Circulation patterns

Principal components analysis

\{PC_1, PC_2, \ldots, PC_M\}

Data mining algorithms

SELF ORGANIZING MAP (SOM)
The predictor. Synoptic Atmospheric Circulation patterns

$M=100 \ (10 \times 10)$

SELF ORGANIZING MAPS (SOM)
The predictor. Synoptic Atmospheric Circulation patterns
1. Synthesis of the work

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5. Wave climate projection

1. Conclusions
METHODOLOGY

❖ Selection of (H,T,Dir). The predictand.

3-day $H_s$
Selection of (H,T,Dir). The predictand.
Selection of (H,T,Dir). The predictand.
- 3-days directional energy flux (Fx, Fy)
3-days wave spectra
Surfing conditions at Mundaka
1. Synthesis of the work

2. Choosing the predictand Y

3. Choosing the predictor X

4. Statistical relationship: \( Y = g(X) \)

5. Wave climate Projection

1. Conclusions
GCM models analyzed (from AR4)

<table>
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<th>MODEL</th>
<th>Centre</th>
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25 Models
42 runs

Ensemble (multi-model)
Are the GCMs able to forecast the climate of the past?

Reanalysis (1961-1990)

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</table>
Projection from GCM

Reanalysis/20C3M

For a particular GCM...

Probability of occurrence

Predictand = X

Y' = g(X')

For a particular scenario...

Similar climate system (WT),
New Probability of occurrence!!

2010-2040

2040-2070

2070-2100

Predictand = X'
1. Synthesis of the work

2. Choosing the predictand Y

3. Choosing the predictor X

4. Statistical relationship: \( Y = g(X) \)

5. Wave climate Projection

1. Conclusions
• Statistical Downscaling of Multivariate Wave Climate
• Based on Weather Types approach + Data Mining Techniques
• Easy visualization of WTs and associated wave climate
• The projection is based on the occurrence probability of each weather type
• Low computational cost for study of ocean wave climate projections.
Statistical downscaling of multivariate wave climate using a weather type approach

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Other applications...

Wave energy flux
Extreme value model

The HsMAX sample of each cell is fitted to an extreme value distribution.

Option a) **GEV**

\[
F(x; \theta) = \exp \left\{ -\left[ 1 + \frac{x - \mu}{\psi} \right]^{\frac{-1}{\xi}} \right\}
\]

Option b) **Pareto-poisson**

\[
F(x; \theta) = 1 - \left( 1 + \frac{x}{\sigma} \frac{\xi}{\psi} \right)^{-\frac{1}{\xi}}
, \quad p(x; \theta) = e^{-\lambda} \frac{\lambda^x}{x!}
\]
METHODOLOGY

- Extreme value model

The composed extreme PDF can be obtained:

a) **GEV (annual maxima distribution)**

\[
F(H; \mu, \psi, \xi) = \prod_{i=1}^{M} F_i \left( H; \mu_i, \psi_i, \xi_i \right)^{p_i} 365 \over \Delta \text{days}
\]

b) **Pareto-poisson**

\[
F(H; \nu, \sigma, \xi) = \sum_{i=1}^{M} \nu_i F_i \left( H; \nu_i, \sigma_i, \xi_i \right)
\]

Occurrence rate:

\[
\nu = \nu_1 + \nu_2 + ... + \nu_n
\]