Applications of data science in coastal engineering

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MASCOT-NUM 2021
28TH-30TH April
How is the beach equilibrium planform?

Which is the block size of this breakwater?

How estimate the longitudinal sediment transport?

How many hours/year is the agitation of this port over 30 cm?
Propagation of wave climate to coastal areas

$X \xrightarrow{DD} Y_1 \xrightarrow{DD} Y_2 \xrightarrow{DD} Y_3$

- WIND
- WAVES at global scale
- WAVES at regional scale
- WAVES at local scale
Wave transformation processes in shallow water
Approaches to transfer regional wave climate to coastal areas

Dynamical Downscaling
Rusu et al., 2008

Statistical Downscaling
Kalra et al., 2005
Browne et al., 2007

Hybrid Downscaling
Groeneweg et al., 2006
Stansby et al., 2006
Breivik et al., 2009
Galiskova and Weisse, 2006
Herman et al. 2009
Hybrid downscaling approach to propagate wave climate to coastal areas

1. Data
2. Calibration
3. Selection
4. Propagation
5. Time series reconstruction
6. Marine climate
Hybrid downscaling approach to propagate wave climate to coastal areas

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Study domain
Deep water
Interpolation
Propagation
Hybrid downscaling approach to propagate wave climate to coastal areas

1. Data
2. Calibration
3. Selection
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Hybrid downscaling approach to propagate wave climate to coastal areas

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Hybrid downscaling approach to propagate wave climate to coastal areas

LIMITATIONS

(Holthuijsen, 2007)
Hybrid downscaling approach to propagate wave climate to coastal areas

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LIMITATIONS
Hybrid downscaling approach to propagate wave climate to coastal areas

LIMITATIONS

Wave variability along the coast
Selection and classification techniques

- Self-organizing maps (SOM)
- Kmeans algorithm (KMA)
- Maximum dissimilarity algorithm (MDA)
Selection and classification techniques

\[ \{ x_1, x_2, \ldots, x_N \} \quad N \text{ data} \]
\[ \{ v_1^0, \ldots, v_M^0 \} \quad M \text{ centroids or prototypes} \]
Bidimensional data sample
Goal: 16 groups – Random initialization

\[ \{ v_1^0, v_2^0, \ldots, v_M^0 \} \]
KMA

Iteration $k$

$x_i$  \hspace{1cm} \text{Belongs to the group } j \hspace{1cm} \text{The centroid } j \text{ is updated as the mean of data belongs to that group}

\[ j = \min \left\{ \| x_i - v_j \|, j = 1, \ldots, M \right\} \]

\[ v_j^{r+1} = \sum_{x_i \in C_j} x_i / n_j \]
SOM (self-organizing maps)

Bidimensional data sample
Goal: 16 groups – Initialization

\( \{v_1^0, v_2^0, \ldots, v_M^0\} \)
SOM (self-organizing maps)

Training in cycles:

$$x_i \rightarrow v_{w(i)} \rightarrow \min_j \{||v_j - x_i||, j = 1, \ldots, M\}$$

$$v_j = v_j + \alpha h(w(i), j)(x_i - v_j), j = 1, \ldots, M$$
Goal: subset of 16 elements
Initialization: the most different data

\[ D_i = \sum_{j=1}^{N-1} \| x_i - x_j \| ; j = 1, \ldots, N \quad \rightarrow \quad \max \{ D_i ; i = 1, \ldots, N \} \]
MDA (maximum dissimilarity algorithm)

Subset: \( \{v_1\} \)
New data of the subset: \( \{v_2\} \) \[\max \left\{ d_{i,subconjunto} = \|x_i - v_1\| ; i = 1, \ldots, N - 1 \right\}\]
MDA (maximum dissimilarity algorithm)

Subset: \( \{v_1, v_2\} \)

New data of the subset: \( \{v_3\} \)

\[
d_{ij} = \|x_i - v_j\|; i = 1, \ldots, N - 2; j = 1, \ldots, 2
\]

\[
d_{i,\text{subconjunto}} = \min \{\|x_i - v_j\|; j = 1, \ldots, 2\}; i = 1, \ldots, N - 2
\]

\[
\max \{d_{i,\text{subconjunto}}; i = 1, \ldots, N - 2\}
\]
Selection and classification techniques

Multidimensional characterization of Wave Climate
$H_s$, $T_m$, $\theta_m$
Multidimensional characterization of Wave Climate

SOM \( M = 529 \) (23x23)
Wave climate: \( \{ H_s, T_m, \theta_m \} \)

“Sea State types” in one location
Multidimensional characterization of Wave Climate

SOM  \( M = 529 \) (23x23)  Wave climate: \( \{H_s, T_m, \theta_m\} \)
Multidimensional characterization of Wave Climate

$H_s$, $T_m$, $\theta_m$, $H_s$, $T_m$, $\theta_m$
A global classification of coastal flood hazard climates associated with large-scale oceanographic forcing

GENERALIZED EXTREME VALUE ANALYSIS

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

\( \mu \rightarrow \text{location} \)

\( \psi \rightarrow \text{scale} \)

\( \xi \rightarrow \text{shape} \)

Rueda et al., 2017
A global classification of coastal flood hazard climates associated with large-scale oceanographic forcing

Rueda et al., 2017
Selection and classification techniques

Multidimensional Wave Climate
Hs, Tm, θm

MDA
Downscaled Ocean Waves (DOW) hindcast

- Reanalysis wave database
- Calibration
- Selection
- Propagation
- Time series reconstruction
- Validation
- Coastal wave climate characterization

Satellite and deep water buoy data

Bathymetry

Wave data from coastal buoys

Camus et al., 2013
Downscaled Ocean Waves (DOW) hindcast

Waves: GOW 1.0 – 1948-2008
Wind: NCEP

Historical data bases
Selection
Propagation
Reconstruction
Downscaled Ocean Waves (DOW) hindcast

- Historical databases
- Selection
- Propagation
- Reconstruction

Time series of boundary conditions

(1948-2008)
a) CALIBRATED DATA:
\[ X_i = \{ H_{x,i}, T_{x,i}, \theta_{x,i}, H_{y,i}, T_{y,i}, \theta_{y,i}, W_{x,i}, W_{y,i} \} \]

Standarization (the wave direction has been transformated to x and y components):
\[ X_i = \{ H_{x,i}, T_{x,i}, \theta_{x,i}, H_{y,i}, T_{y,i}, \theta_{y,i}, W_{x,i}, W_{y,i}, W_{x,i}, W_{y,i} \} \]

b) PCA to the calibrated data:
\[ EOF_x(x) \times PC_x(t) \]

\[ EOF_y(x) \times PC_y(t) \]

(c) MDA:
\[ D_{EOF}^{j} = \{ PC_{x,j}, PC_{y,j} \} \]
\[ D_{j} = \{ H_{x,i}^{D}, T_{x,i}^{D}, \theta_{x,i}^{D}, H_{y,i}^{D}, T_{y,i}^{D}, \theta_{y,i}^{D}, W_{x,i}^{D}, W_{y,i}^{D} \} \]
\[ j = 1, ..., M \]

Downscaled Ocean Waves (DOW) hindcast
Downscaled Ocean Waves (DOW) hindcast

Selected cases ($M=500$)

MDA

Historical data bases
Selection
Propagation
Reconstruction
Downscaled Ocean Waves (DOW) hindcast

Catalog of $M=500$ propagated cases

SWAN model
Variable boundaries: Directional wave spectra
RBF INTERPOLATION TECHNIQUE
(Radial Basis Function)
Rippa 1999

Radial Basis Functions

\[ RBF(X_i) = \rho(X_i) + \sum_{j=1}^{M} a_j \Phi(||X_i - D_j||) \]

\[ \rho(X_i) = b_0 + b_1 H_i + b_2 T_i + b_3 \theta_i + b_4 W_i + b_5 \beta_i \]

\[ \Phi(||X_i - D_j||) = \exp\left(-\frac{||X_i - D_j||^2}{2c^2}\right) \]

Camus et al., 2011
Downscaled Ocean Waves (DOW) hindcast

Propagated sea states parameters corresponding to $M$ selected cases

\[ D_{p,j}^* = \{ H_{sp}^D, T_{mp}^D, \theta_{mp}^D \} \quad j = 1, \ldots, M \]
Downscaled Ocean Waves (DOW) hindcast VALIDATION using instrumental data
Downscaled Ocean Waves (DOW) hindcast
ATLAS of Wave Energy Resources

Annual mean wave energy (kW/m)
Applications to determine loads for marine infrastructure design

Guanche et al., 2011
Selection and classification techniques

Statistical downscaling method to obtain climate change projections of waves
Statistical downscaling method

ATMOSPHERIC CIRCULATION
(predictor X: SLP)

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

Regional atmospheric climatology (X)

Local wave climatology (Y)
Statistical downscaling method

Predict multivariate wave climate (Y) at a particular location $S$ as a function of synoptic atmospheric circulation (X)
Statistical downscaling method based on weather types

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

$WT = \text{Weather-type (Circulation Type)}$
Statistical downscaling method based on weather types

\[ X = (WT_1, WT_2, WT_3, WT_4) \quad \Rightarrow \quad Y \]

\[ p_i = \text{occurrence probability of } WT_i \]

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

\[ f_S(H) = p_1 f_1(H) + p_2 f_2(H) + p_3 f_3(H) + p_4 f_4(H) \]
Statistical downscaling method based on weather types

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

$X' = $ new predictor

$Y = g(X')$

$p'_1 + p'_2 + p'_3 + p'_4 = 1$

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

$df(H) = f'_S(H) - f_S(H)$
Statistical downscaling method based on weather types

ATMOSPHERIC DATA (PREDICTOR)

\[ X = \text{SLP} \]

PREDICTOR PRE-PROCESS
(Spatial domain, temporal lag, gradients, ..)

WEATHER TYPES
(K-means clustering)

\[ WT_i \]

\[ p_i (WT_i) \]

NEW PROBABILITIES

\[ p_i ' (WT_i) \]

ASSOCIATED SEA-STATES

\[ f(Y) = \sum p_i f_i(Y) \]

INFERRED SEA-STATES

\[ f'(Y) = \sum p_i ' f_i(Y) \]

Camus et al., 2014
Statistical downscaling method based on weather types

WAVE PROJECTIONS over Europe

WEATHER TYPE CLASSIFICATION using KMA

Perez, J., Menendez, M., Camus, P., Mendez, F.J., Losada, I.J. Statistical multi-model climate projections of surface ocean waves in Europe (2015). Ocean Modelling, DOI: 10.1016/j.ocemod.2015.06.001
Statistical downscaling method based on weather types
WAVE PROJECTIONS over Europe

Relationship between the weather types and multivariate wave climate

*Predictor $X (WT)$*  $\rightarrow$  *Predictand $Y (hs, tm, FE, ...)$*

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Perez, J., Menendez, M., Camus, P., Mendez, F.J., Losada, I.J. Statistical multi-model climate projections of surface ocean waves in Europe (2015). Ocean Modelling, DOI: 10.1016/j.ocemod.2015.06.001
Statistical downscaling method based on weather types

Changes with respect to the control period (1975-2004)

Perez, J., Menendez, M., Camus, P., Mendez, F.J., Losada, I.J. Statistical multi-model climate projections of surface ocean waves in Europe (2015). Ocean Modelling, DOI: 10.1016/j.ocemod.2015.06.001
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Statistical downscaling method based on weather types

GLOBAL WAVE PROJECTIONS

1. PREDICTOR DEFINITION
   (Spatial domain, temporal, gradients...)

2. SEMI-GUIDED CLASSIFICATION
   1. Lineal Regression $\hat{Y} = XB$
   2. K-means $Z = \{(1-\alpha) \cdot X + \alpha \cdot \hat{Y}\}$

3. AT EACH GRID NODE AT GLOBAL SCALE
   - WEATHER TYPES
     - $p_1$, $p_2$, $p_3$, $p_4$
   - MEAN VALUE WAVE VARIABLE
     - (WT)
   - PROJECTED CLIMATE AT CERTAIN TIME SLICE
     - $p_1$, $p_2$, $p_3$, $p_4$

4. STATISTICAL DOWNSCALING AT GLOBAL SCALE
   - GLOBAL WAVE HINDCAST
     - Spatial resolution: 1.0° x 1.0°
   - INFERRED MEAN VALUE

More details in Camus et al., 2014; Pérez et al., 2015; Camus et al., 2017
Statistical downscaling method based on weather types

GLOBAL WAVE PROJECTIONS

Multi-model annual mean Hs (m) (1979-2005)

Regional Projections

PROJECTED CHANGES in Hs
Scenario RCP8.5
Multi-model Ensemble (40 GCMs)
For the period 2070-2099
Relative to the period 1979-2005

The first coordinated multivariate ensemble of 21st Century global wind-wave climate projections: COWCLIP 2.0
Morim et al., 2019, Morim et al., 2020
CLIMATE EMULATORS based on weather types
COASTAL FLOODING

OBJECTIVES:
- Increase the population of multivariate extremes multivariados
- Probabilistic characterization of the coastal flooding impact

1) Modelling the dependence between multiple variables (COPULAS models)
2) Linked to climate variability
CLIMATE EMULATORS based on weather types COASTAL FLOODING

Fitting

ATMOSPHERIC DATA (PREDICTOR)
\[ X = SLP, SLPG \]

PREDICTOR PRE-PROCESS
(Spatial domain, temporal lag, gradients...)

REGRESSION GUIDED CLUSTERING
1. Linear Regression \[ Y = KB \]
2. K-means \[ Z = \{1-a\} X + a \text{F} \]

WEATHER TYPES

EXTREMAL INDEX

ASSOCIATED DAILY EXTREMES DISTRIBUTIONS

GAUSSIAN COPULA

WAVE DATA (PREDICTAND)
\[ Y = Hs, Tm, SS \]

PREDICTAND PRE-PROCESS
Maximum daily Total Water Level and associated predictand values

Simulation

Step 1:
Weather Type simulation
Monte Carlo method
\[ W_{i} \]

Step 2:
Gaussian copula
Multivariate simulation
Monte Carlo method

Step 3:
Synthetic daily predictand
Transformation to original scales

Step 4:
Synthetic annual maxima
Selection of annual maximum
Total Water Level

Rueda et al., 2016
CLIMATE EMULATORS based on weather types
PORT OPERABILITY

HISTORICAL CLIMATE CONDITIONS
Waves: Hs, Tm, Dir
Sea Level: SS, AT

CLIMATE CHANGE
GCM Projections
RCP Scenarios
Regional SLR
RCP Scenarios

WEATHER GENERATOR
SYNTHETIC FORCING CONDITIONS
(Hs, Tm, Dir, Sea Level)

Simulated Data X

METAMODEL
SELECTION
(Hs, Tm, Dir, Sea Level)
Harbour Agitation MODELLING
(Hs inside the harbour)
Multidimensional INTERPOLATION Function

PROBABILISTIC ASSESSMENT OF PORT AGITATION
Reconstruction of Hs inside the port for present climate

PROBABILISTIC ASSESSMENT OF CLIMATE CHANGE IMPACT ON PORT AGITATION
Reconstruction of Hs inside the port for future climate

Camus et al., 2019
CLIMATE EMULATORS based on weather types
PORT OPERABILITY

WEATHER TYPES (WTs) (K-means)

1. WEATHER TYPES (WTs) (K-means)

2. MARGINAL DISTRIBUTIONS

3. MULTIVARIATE DISTRIBUTION
GAUSSIAN COPULAS

4. SYNTHETIC GENERATION
OF MULTIVARIATE DATA

Camus et al., 2019
METAMODEL – hybrid downscaling
PORT OPERABILITY

Synthetic Forcing Conditions
Waves: Hs, Tm, Dir
Sea Level: SS, AT

SELECTION
(Hs, Tm, Dir, Sea Level)

Harbour Agitation Model
(Hs inside the harbour)

Reconstruction of Hs inside the port
Probabilistic Assessment of Port Agitation

MSP: Díaz-Hernández et al., 2015
CLIMATE EMULATORS based on weather types
PORT OPERABILITY

PROBABILISTIC SEA LEVEL RISE SCENARIOS
Present Climate: 1960-2010
Future Climate: 2050-2100

Camus et al., 2019
CLIMATE CHANGE RISK TO GLOBAL PORT OPERATION

Figure SPM.1.
CLIMATE CHANGE RISK TO GLOBAL PORT OPERATION

Izaguirre et al., 2020
CLIMATE CHANGE RISK TO GLOBAL PORT OPERATION

Izaguirre et al., 2020
CLIMATE CHANGE RISK TO GLOBAL PORT OPERATION

Izaguirre et al., 2020
CLIMATE CHANGE RISK TO GLOBAL PORT OPERATION

Present risk CLUSTERS

Climate risk LEVELS

Izaguirre et al., 2020
Summary

Multidimensional INTERPOLATION Function

SELECTION
(Hs, Tm, Dir, Sea Level)

Harbour Agitation MODELLING
(Hs inside the harbour)

Multidimensional INTERPOLATION Function

WEATHER TYPES

EXTREMAL INDEX

ASSOCIATED DAILY EXTREMES DISTRIBUTIONS

GAUSSIAN COPULA
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