Modelling trends in the ocean wave climate for dimensioning of ships

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Motivation and background
Ocean waves and maritime safety

- Ships and other marine structures are continuously exposed to environmental forces from wave and wind
  - Ocean waves obviously important to ship stability, ship manoeuvrability, hull strength, ship operation, sloshing in tanks, fatigue, handling operations etc.

- Ocean wave climate important to maritime safety
  - Bad weather account for a great number of ship losses and accidents
  - Severe sea state conditions taken into account in design and operation of ships and marine structures
  - Need a description of the variability of various sea state parameters – Significant Wave Height
Some failure modes related to ocean waves

- Extreme loads – breaking in two
  - Sagging (1) and hogging conditions (2)
- Fatigue
- Parametric roll
- Capsize
- Breaking of windows
- Sloshing of tanks/cargo shift
- Loss of containers
  - 10,000 containers lost at sea each year!
Why a statistical description?

- The sea surface changes constantly in space and time
  - Not practical (possible) to describe the sea surface elevation deterministically as a continuous function in space and time

- Significant wave height ($H_S$):
  - Average of the 1/3 largest waves over a time period (over which the sea states is assumed stationary)
  - Measure of sea state – not describing individual waves
  - May assume a distribution of individual wave height conditional on significant wave height to give probabilities of extreme waves in a certain sea state (Often, the Rayleigh distribution is used)

- Other integrated wave parameters:
  - Mean wave period, mean wave direction, etc.
Deterministic vs. Statistical wave models

Deterministic models:
- Based on physical laws
- Typically, $H_S$ a function of wind speed, wind duration and fetch
- Typically used for short-term forecast
- Important in ship operation
  - operational windows
  - weather routing

Statistical models:
- Using statistics and stochastic dependences
- Probabilistic description of sea states
  - Return periods, exceedance probabilities
- Typically used for long-term description
- Important for design of ships
  - What environmental loads is a ship expected to encounter throughout its lifetime?
What about long-term trends?

- There is increasing evidence of a global climate change.
- How will such a climate change affect the ocean wave climate?
- Possible trends in the wave climate may need to be taken into account in dimensioning of ships
  - To make sure ships are safe in a future environment.

- A stochastic model for significant wave height in space and time is developed
  - Including a component for long-term trends
  - Fitted to data in the North Atlantic Ocean from 1958 – 2002
A Bayesian hierarchical space-time model for significant wave height
Methodology – brief summary

- Bayesian hierarchical space-time model
  - Bayesian framework to incorporate prior knowledge
  - Hierarchical model to describe complex dependence structures in space and time

- Observation model and different levels of state models
  - Split temporal and spatial dependence into separate components
  - The various components are described conditionally on other components
Data and area description

- Corrected ERA-40 data of significant wave height(*)
  - Spatial resolution: 1.5° × 1.5° globally
  - Temporal resolution: 6 hourly from Jan. 1958 to Feb. 2002 (44 years and 2 months = 64 520 points in time)

- Ocean area between 51° - 63°N and 324° - 348°E
  
(*) Data kindly provided by Royal Netherlands Meteorological Institute (KNMI), Dr. Andreas Sterl.
Model description – Main model

- Significant wave height at location \( x \), time \( t \): \( Z(x, t) \)

- Observation model:

\[
Z(x, t) = H(x, t) + \varepsilon_Z(x, t)
\]

With

\[
H(x, t) = \mu(x) + \theta(x, t) + M(t) + T(t)
\]

and

\[
\varepsilon_Z(x, t) \sim N(0, \sigma_Z^2), \text{ i.i.d}
\]

- All noise terms in the model assumed independent in space and time and also independent of all other stochastic terms
Time independent, spatial component

- 1st order Markov Random Field

\[
\mu(x) = \mu_0(x) + a_\varphi \{ \mu(x^N) - \mu_0(x^N) + \mu(x^S) - \mu_0(x^S) \} \\
+ a_\lambda \{ \mu(x^E) - \mu_0(x^E) + \mu(x^W) - \mu_0(x^W) \} + \varepsilon_\mu(x)
\]
Short-term spatio-temporal model

- 1\textsuperscript{st} order vector autoregressive model

\[
\theta(x, t) = b_0 \theta(x, t-1) + b_N \theta(x^N, t-1) + b_E \theta(x^E, t-1) \\
+ b_S \theta(x^S, t-1) + b_W \theta(x^W, t-1) + \varepsilon_\theta(x, t)
\]
Spatially independent seasonal model

- Modelled as an annual cyclic Gaussian process

\[ M(t) = c \cos(\omega t) + d \sin(\omega t) + \epsilon m(t) \]
Long-term trend model

- Gaussian process with quadratic trend

\[ T(t) = \gamma t + \eta t^2 + \varepsilon_T(t) \]

- Model alternatives:

Model 1: \( T(t) = \gamma t + \eta t^2 + \varepsilon_T(t) \) (quadratic trend model)

Model 2: \( T(t) = \gamma t + \varepsilon_T(t) \) (linear trend model)

Model 3: \( T(t) = 0 \) (no trend model)

Model 4: \( M(t) = c \cos(\omega t) + d \sin(\omega t) + \gamma t + \eta t^2 + \varepsilon_m(t); \ T(t) = 0 \)

Model 5: \( M(t) = c \cos(\omega t) + d \sin(\omega t) + \gamma t + \varepsilon_m(t); \ T(t) = 0 \)
MCMC simulations

- MCMC techniques used to simulate from the model
  - Gibbs sampler with Metropolis-Hastings steps
  - 1000 samples of the parameter vector with 20,000 burn-in iterations and batch size 25 (monthly data) or 5 (daily data)
  - Convergence likely by visual inspection of trace plots, control runs with longer burn-in and different starting values
  - Plot of the residuals indicate that model assumptions are reasonable

Normal probability plot of the residuals:
Simulation results

- Spatial, space-time dynamic and seasonal models perform well, with contributions (monthly data)
  - $\mu(x) \sim 2.7 - 3.3$ meters
  - $\theta(x, t) \sim \pm 1.5$ meters
  - $M(t) \sim \pm 1.4$ meters

- $\theta(x, t)$ becomes more important for daily data

- Figures show spatial field and seasonal component (monthly data)
Results – Example of estimated trends

- Quadratic and linear model, monthly data
### Results – estimated expected trends

<table>
<thead>
<tr>
<th></th>
<th>Normal conditions ((H_s \approx 3.5) m)</th>
<th>Severe conditions ((H_s \approx 7.5) m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Monthly data</td>
<td>Daily data</td>
</tr>
<tr>
<td>Model 1</td>
<td>35 cm</td>
<td>23 cm</td>
</tr>
<tr>
<td>Model 2</td>
<td>28 cm</td>
<td>22 cm</td>
</tr>
<tr>
<td>Model 4</td>
<td>38 cm</td>
<td>23 cm</td>
</tr>
<tr>
<td>Model 5</td>
<td>37 cm</td>
<td>23 cm</td>
</tr>
</tbody>
</table>
Future projections – 100 year trends

- Future projections made by extrapolating the linear trends (somewhat speculative)
- Critical assumption – estimated trend will continue into the future

<table>
<thead>
<tr>
<th>Normal conditions (mean $H_S \approx 3.5$ m)</th>
<th>Severe conditions (mean $H_S \approx 7.5$ m)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Monthly data</strong></td>
<td><strong>Monthly maximum data</strong></td>
</tr>
<tr>
<td>Model 2</td>
<td>1.6 m</td>
</tr>
<tr>
<td>64 cm</td>
<td></td>
</tr>
<tr>
<td>51 cm</td>
<td></td>
</tr>
<tr>
<td>Model 5</td>
<td></td>
</tr>
<tr>
<td>84 cm</td>
<td></td>
</tr>
<tr>
<td>53 cm</td>
<td></td>
</tr>
<tr>
<td>1.6 m</td>
<td></td>
</tr>
</tbody>
</table>
Simulations on 6-hourly data

- Extremely time-consuming and computationally intensive
  - One set of simulations run for 1 month on TITAN cluster

- Model failed to perform on 6-hourly data
  - Does not mix well - lack of convergence?
  - Non-linear dynamic effects which are not accounted for?
  - $\theta(x, t)$ increasingly important. Could it absorb long-term trends?
Log-transform of the data

- Performing a log-transform might account for:
  - Stronger trends for extreme conditions
  - Heteroscedastic features in the data
  - Avoid predicting negative significant wave heights
Revised model

- Logarithmic transform: $Y(x, t) = \ln Z(x, t)$
- Observation model:

$$Y(x, t) = H(x, t) + \varepsilon_Y(x, t)$$

With

$$H(x, t) = \mu(x) + \theta(x, t) + M(t) + T(t); \quad \varepsilon_Y(x, t) \sim N(0, \sigma_Y^2), \text{ i.i.d.}$$

- Alternative representation on original scale

$$Z(x, t) = e^{\mu(x)} e^{\theta(x, t)} e^M(t) e^T(t) e^{\varepsilon_Y(x, t)}$$

- Various components represents multiplicative factors on the original scale
  - Stronger trends for extreme conditions
Including a CO$_2$ regression component for future projections

- Previous models used linear extrapolation to predict future projections
  - Somewhat speculative
  - Improve projections by including covariates for which there exist reliable future projections

- Extend the model with a CO$_2$-regression component for the long-term trends
  - Exploit the stochastic relationship between atmospheric levels of CO$_2$ and significant wave height
  - Critical assumption: Stochastic dependence between CO$_2$ and SWH remains unchanged
  - Historical CO$_2$ data for model fitting
  - Future projections of wave climate based on two future CO$_2$ scenarios: A2 and B1 scenarios from IPCC
Historic CO₂ data

- CO₂ data from Mauna Loa Observatory covering the period 1959 - present
CO\textsubscript{2} data – future scenarios

- Use two of four IPCC marker scenarios – A2 and B1
  - A2 is an extreme scenario – worst case
  - B1 is more conservative

![Historic and projected CO2 concentrations](image-url)
Model extension – long-term trend, \( T(t) \)

\[
T(t) = \gamma G(t) + \eta \ln G(t) + \varepsilon_T(t)
\]

- \( G(t) = \) average level of CO\(_2\) in the atmosphere at time \( t \)
- \( \varepsilon_T(t) \sim N(0, \sigma_T^2) \), i.i.d.

- Model alternatives:

  - Model 1: \( T(t) = \gamma G(t) + \eta \ln G(t) + \varepsilon_T(t) \) (linear-log model)
  - Model 2: \( T(t) = \gamma G(t) + \varepsilon_T(t) \) (linear model)
  - Model 3: \( T(t) = \eta \ln G(t) + \varepsilon_T(t) \) (log model)
  - Model 4: \( T(t) = 0 \) (No trend model)

- The linear-log and linear models performed best.
Projections from the linear-log model

Yearly trend - future projections

A2 scenario

B1 scenario

Projected trends, A2 scenario

Projected trends, B1 scenario

Year (since 1958)

Trend (m)

Projected trend (m)

Projected trend (m)

With mean and 90% credible interval

With mean and 90% credible interval
Results – trends and future projections towards 2100

- Trends and projections of monthly maximum significant wave height
  - Trends from 1958 – 2001
  - Projections: Increase from 2001 - 2100

<table>
<thead>
<tr>
<th>Estimated trend</th>
<th>Projections; A2 scenario</th>
<th>Projections; B1 scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear-log model</td>
<td>59 cm</td>
<td>5.4 m</td>
</tr>
<tr>
<td>Linear model</td>
<td>49 cm</td>
<td>4.3 m</td>
</tr>
</tbody>
</table>
Summary and preliminary conclusions

- Bayesian hierarchical space-time model has been developed for significant wave height data in North Atlantic
  - With and without log-transform of the data
  - With and without regression on CO₂

- Different components seem to perform well for monthly, daily and monthly maximum data. Fails to perform on 6-hourly data

- Difficult to evaluate model alternatives
  - Does the log-transform represent an improvement?
  - Original data: Larger trends for monthly maximum data suggest that some sensible data-transformation might be reasonable.
  - Log-transformed data: monthly maxima gives smaller trend factors – indicates that the logarithmic transform might not be the optimal transformation
  - Including CO₂ regression seems to be an improvement
Estimated centurial projections

- Original model:
  - Increase of 50 – 80 cm for monthly and daily data; 1.6 m for monthly maximum data

- Log-transformed model:
  - Increase of 53 – 90 cm for moderate conditions ($H_S = 3m$);
    1.8 – 3.0 m for extreme conditions ($H_S > 10m$)
  - Comparable to trends estimated without the log-transform

- CO$_2$ regression model:
  - Increase of 1.6 – 1.9 m for B1 scenario;
    4.3 – 5.4 m for A2 scenario (monthly maximum)
  - Corresponds to 25% - 72% increase in monthly maximum $H_S$

- B1 projections agrees well with extrapolated linear trends, but A2 gives much larger projections – worst case scenario
Impact on ship structural loads
Introduction

- Estimated long-term trends and future projections should be included in load calculations for ships

- A joint environmental model is needed for load calculations
  - Lack of full correlation between met-ocean parameters
  - Significant wave height ($H_s$) and mean wave period ($T_z$)
  - Use Conditional Modelling Approach
Joint distribution of $H_S$ and $T_Z$

- Conditional Modelling Approach:
  \[
f_{H, T}(h, t) = f_H(h)f_{T|H}(t|h)
  \]

- Marginal distribution of $H_S$: 3-parameter Weibull

- Conditional distribution of $T_Z$: log-normal

- Assumption: Trend in significant wave height give modified marginal distribution for $H_S$, but does not change the conditional distribution of $T_Z$
Effect of the long-term trend on $f(H_S)$

<table>
<thead>
<tr>
<th></th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$E[h]$</th>
<th>$sd[h]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitted distribution</td>
<td>2.776</td>
<td>1.471</td>
<td>0.8888</td>
<td>3.408</td>
<td>1.741</td>
</tr>
<tr>
<td>Modified parameters</td>
<td>2.846</td>
<td>1.471</td>
<td>2.457</td>
<td>5.033</td>
<td>1.781</td>
</tr>
</tbody>
</table>
Effect on joint distribution of $H_S$ and $T_Z$

Contour plots of the joint distribution of $(H_S, T_Z)$ with and without the climatic trend
Example: Load assessment of oil tanker

- Design criteria specified by environmental contours
  - Define contours in the environmental parameter space, in this case \((H_s, T_z)\), within which extreme responses with a given return period should lie
Extreme load characteristics

- The 25-year stress amplitude for the example oil tanker has been calculated, with and without the 100-year trend
  - 25-year stress amplitude increased by 7-10%
  - Extreme response period increased by 2%
- 3-hour sea state duration and Rayleigh stress process assumed

### 25-year extreme load characteristics of example oil tanker

<table>
<thead>
<tr>
<th></th>
<th>Stress amplitude (MPa)</th>
<th>Response period (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Modified fit - Basic model</td>
<td>1.07</td>
<td>1.02</td>
</tr>
<tr>
<td>Modified fit - B1 scenario</td>
<td>1.10</td>
<td>1.02</td>
</tr>
</tbody>
</table>
Effect of the long-term trend on $f(H_S)$ – Estimate from CO$_2$ regression model
Summary and preliminary conclusions

- Climatic trends in significant wave height can be related to loads and response calculations of ships

- The effect of the trend on an oil tanker has been assessed
  - Extreme stresses increase notably in both amplitude and response period
  - Effect of climatic trends is not negligible
  - Should be considered in design
Final remarks and open issues

- The model seems to work reasonably well in describing the spatial and temporal variability of $H_S$

- Different long-term trends have been identified
  - Estimates differ, but all are increasing!

- Future projections (100 years) are notable and may affect structural ship loads – should be considered in design

- Some open issues and possible model extensions
  - Model fails to perform for 6-hourly data
  - Reliable model selection
  - Include other relevant covariates, e.g. sea level pressure or wind fields
  - Different trends for different seasons; spring, summer, autumn, winter
  - Model a trend in the variance
References


References


- **Identifying trends in the ocean wave climate by time series analyses of significant wave height data.** Erik Vanem, Sam-Erik Walker. *Ocean Engineering* vol. 61, pp. 148-160, 2013


- **Bayesian hierarchical space-time models with application to significant wave height.** Erik Vanem. In press. In series: Ocean Engineering and Oceanography, Springer, 2013
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