Modelling trends in the ocean wave climate for dimensioning of ships

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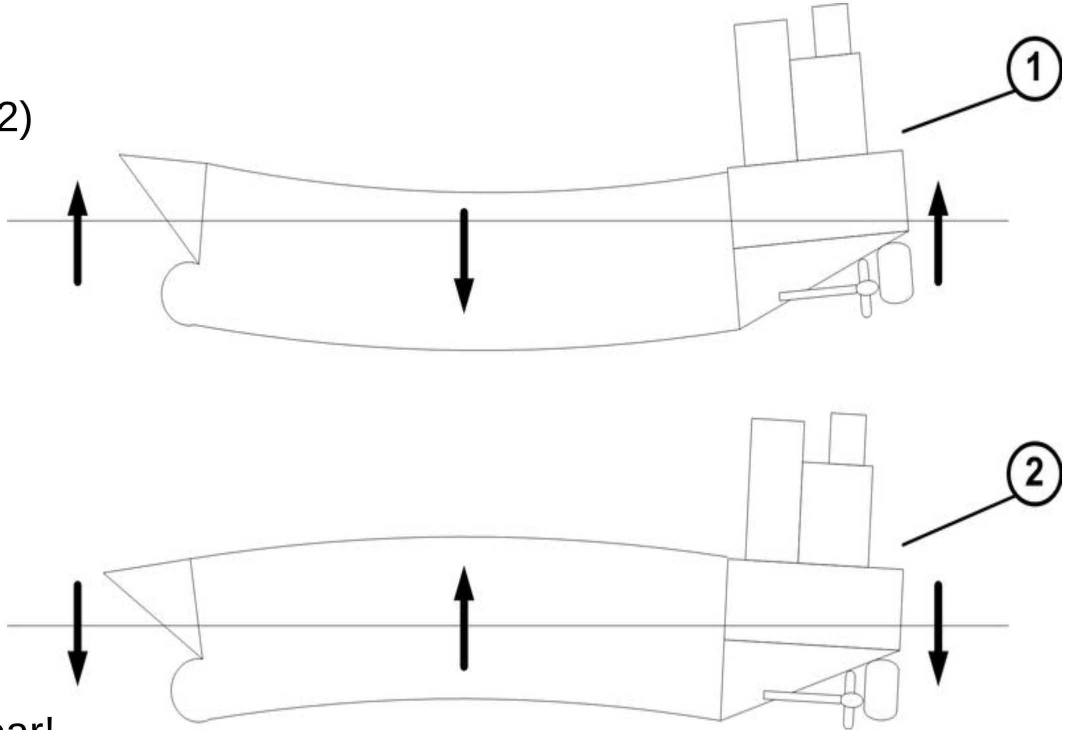
Motivation and background

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 <u>conditional</u> 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

<u>Deterministic models:</u>

- 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

<u>Statistical models:</u>

- 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

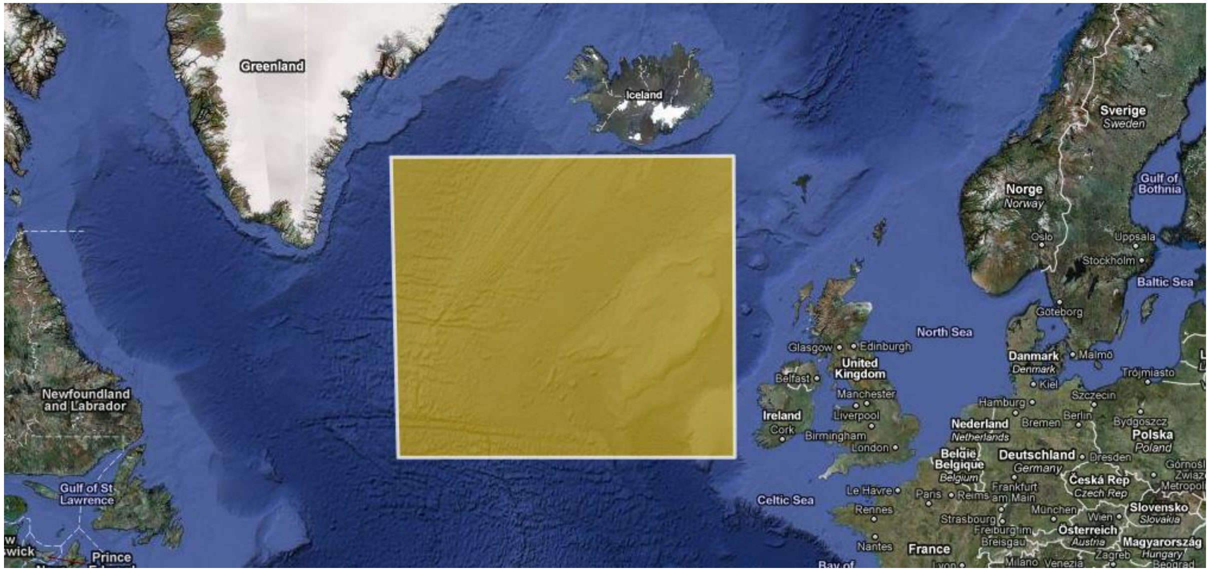
A Bayesian hierarchical space-time model for significant wave height

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.

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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^{st} order vector autoregressive model

$$\theta(x, t) = b_0\theta(x, t\text{-}1) + b_N\theta(x^N, t\text{-}1) + b_E\theta(x^E, t\text{-}1)$$
$$+ b_S\theta(x^S, t\text{-}1) + b_W\,\theta(x^W, t\text{-}1) + \varepsilon_\theta(x, t)$$

Spatially independent seasonal model

- Modelled as an annual cyclic Gaussian process

$$M(t) = c\cos(\omega t) + d\sin(\omega t) + \varepsilon_m(t)$$

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) = γt + ηt2 + εT(t)	(quadratic trend model)
Model 2: T(t) = γt + εT(t)	(linear trend model)
Model 3: T(t) = 0	(no trend model)

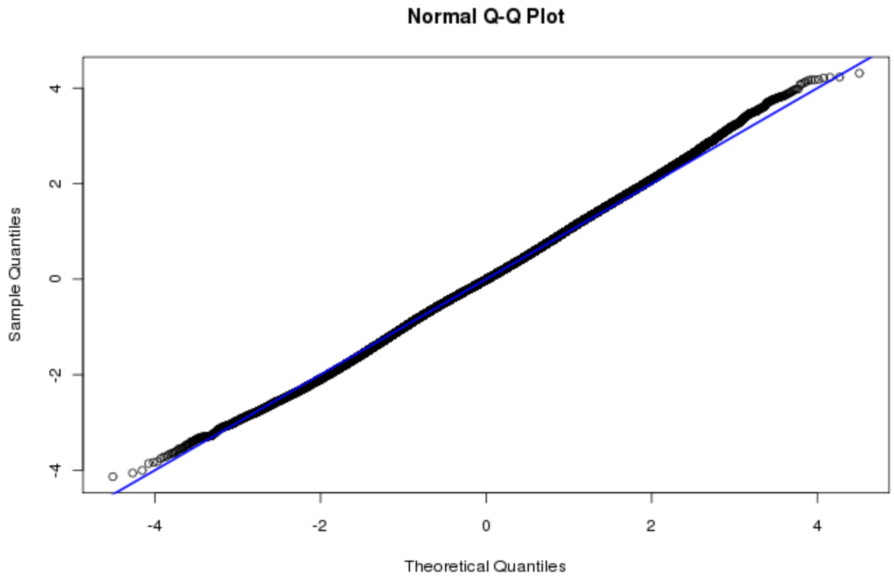
Model 4: M(t) = c cos(ωt) + d sin(ωt) + γt + ηt2 + εm(t); T(t) = 0

Model 5: M(t) = c cos(ωt) + d sin(ωt) + γt + εm(t); T(t) = 0

MCMC simulations

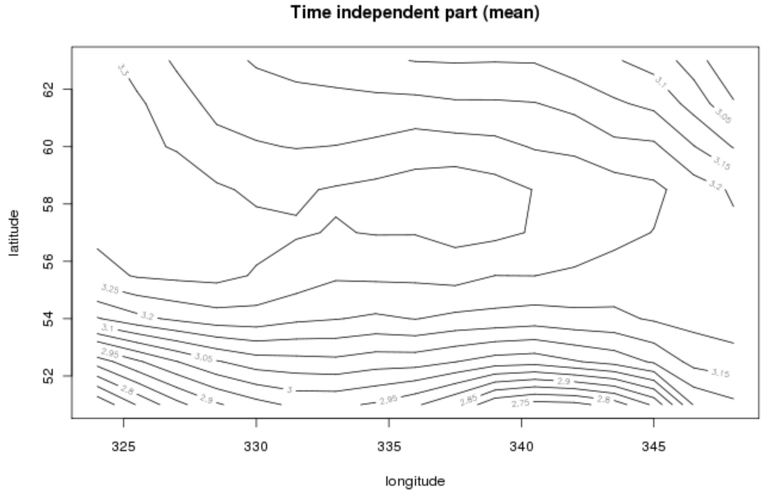
- MCMC techniques used to simulate from the model
  - Gibbs sampler with Metropolis-Hastings steps
  - 1000 samples of the parameter vector with 20,000 burn-in iterations and batch size 25 (monthly data) or 5 (daily data)
  - Convergence likely by visual inspection of trace plots, control runs with longer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

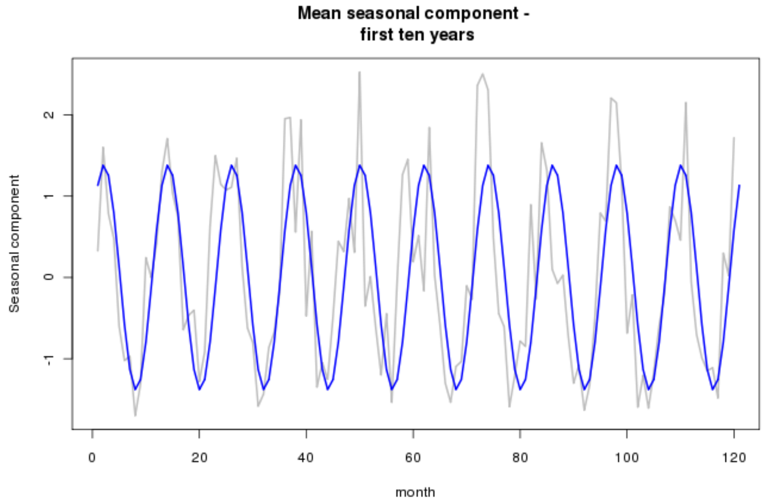
Normal probability plot of the residuals:



Simulation results

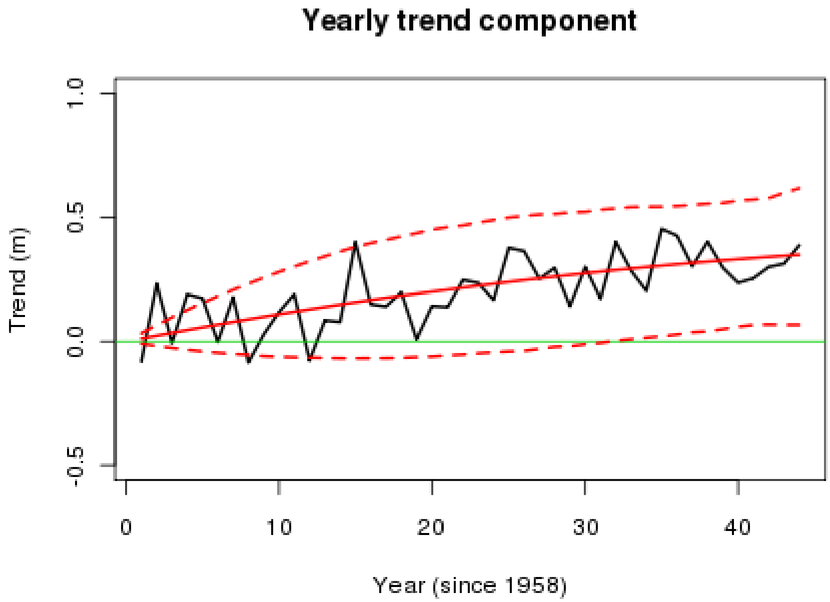
- Spatial, space-time dynamic and seasonal models perform well, with contributions (monthly data)
  - $\mu(x)$ ~ 2.7 – 3.3 meters
  - $\theta(x, t)$ ~ ± 1.5 meters
  - $M(t)$ ~ ± 1.4 meters
- $\theta(x, t)$ becomes more important for daily data
- Figures show spatial field and seasonal component (monthly data)

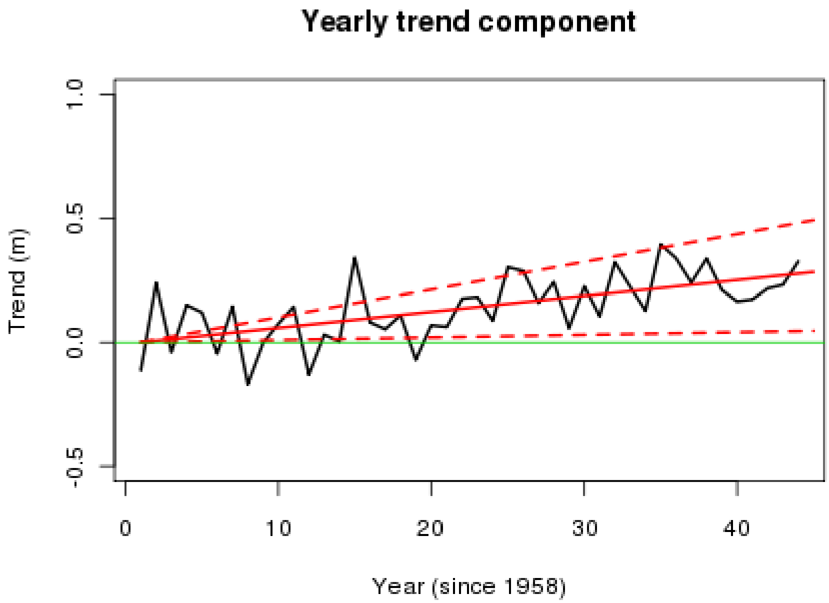




Results – Example of estimated trends

- Quadratic and linear model, monthly data





Results – estimated expected trends

	Normal conditions ($H_S \approx 3.5$ m)		Severe conditions ($H_S \approx 7.5$ m)
	Monthly data	Daily data	Monthly maximum data
Model 1	35 cm	23 cm	70 cm
Model 2	28 cm	22 cm	69 cm
Model 4	38 cm	23 cm	68 cm
Model 5	37 cm	23 cm	69 cm

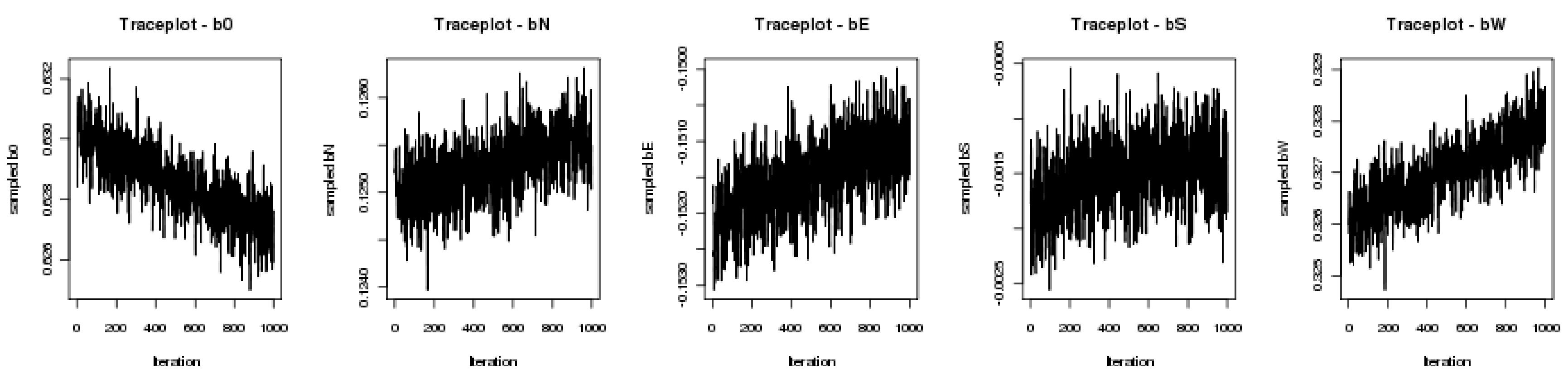
Future projections – 100 year trends

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

	Normal conditions (mean $H_S \approx 3.5$ m)		Severe conditions (mean $H_S \approx 7.5$ m)
	Monthly data	Daily data	Monthly maximum data
Model 2	64 cm	51 cm	1.6 m
Model 5	84 cm	53 cm	1.6 m

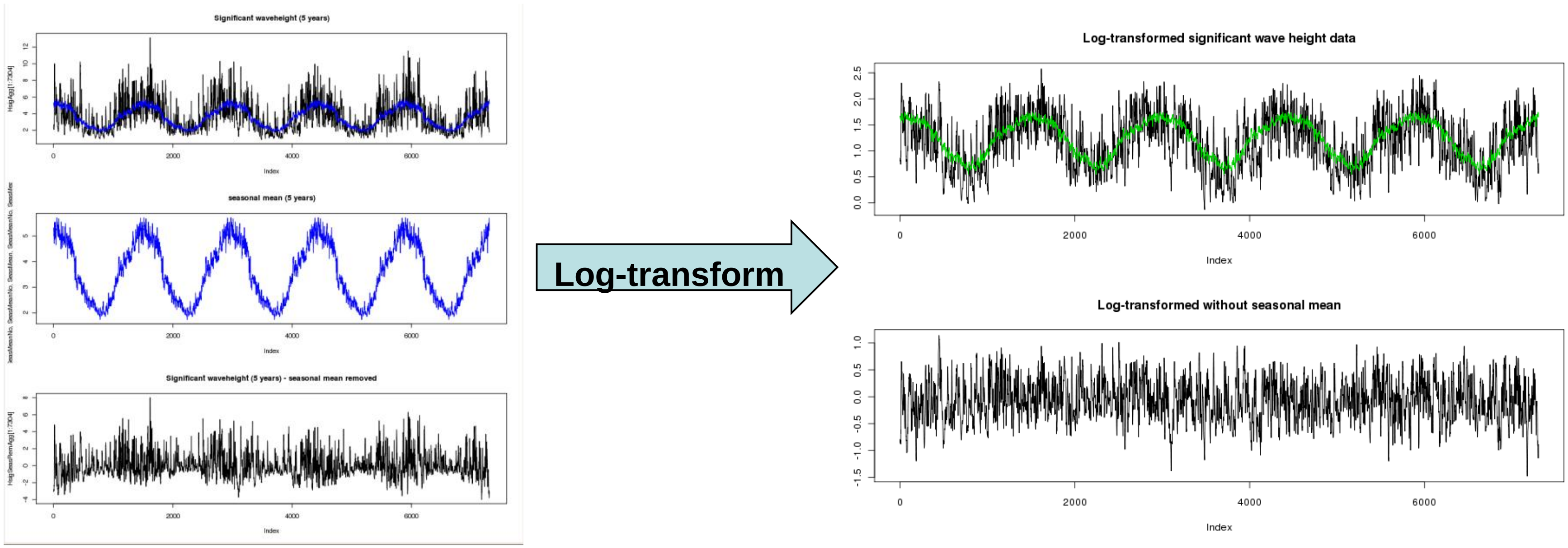
Simulations on 6-hourly data

- 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?
  - θ(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

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

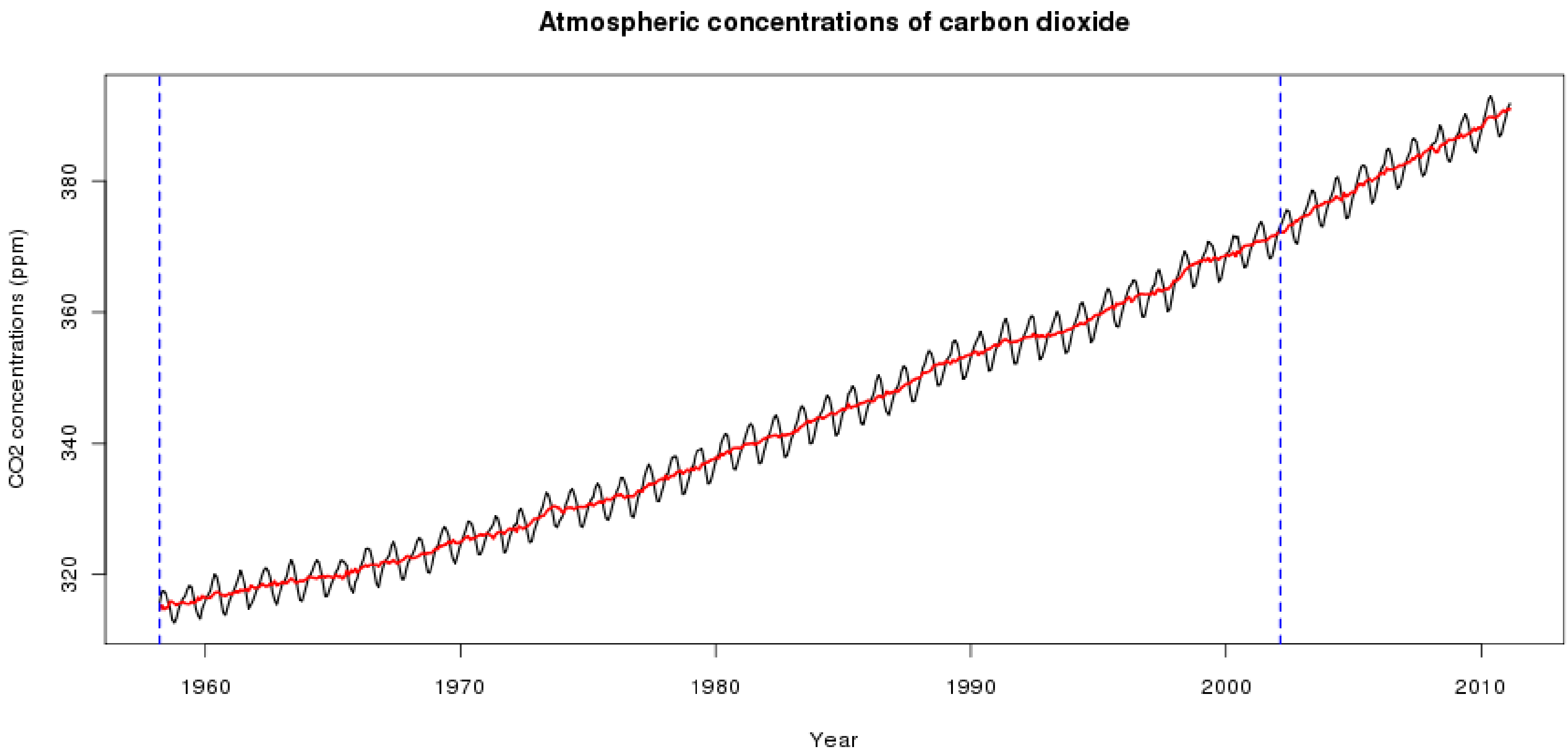
- Various components represents multiplicative factors on the original scale
  - Stronger trends for extreme conditions

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

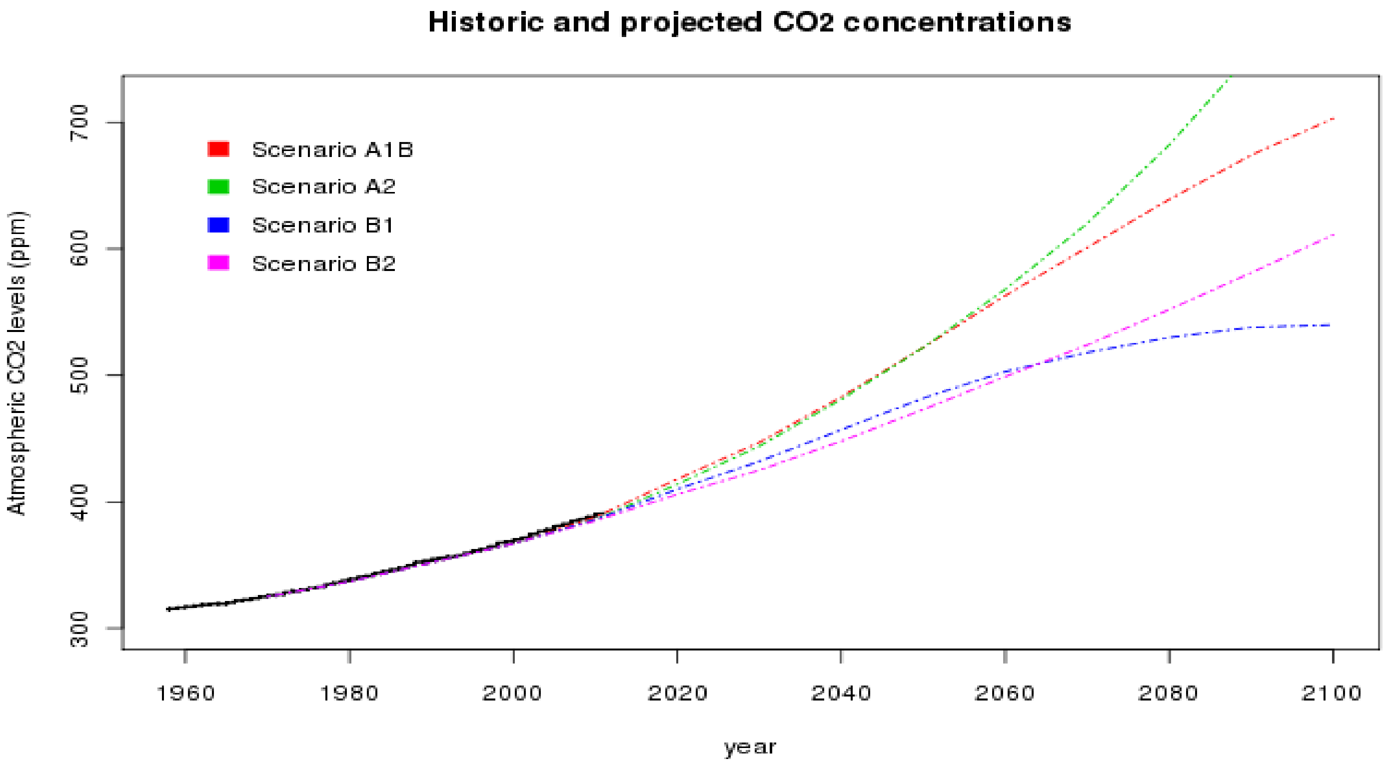
Historic CO_2 data

- CO_2 data from Mauna Loa Observatory covering the period 1959 - present



CO_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



Model extension – long-term trend, T(t)

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

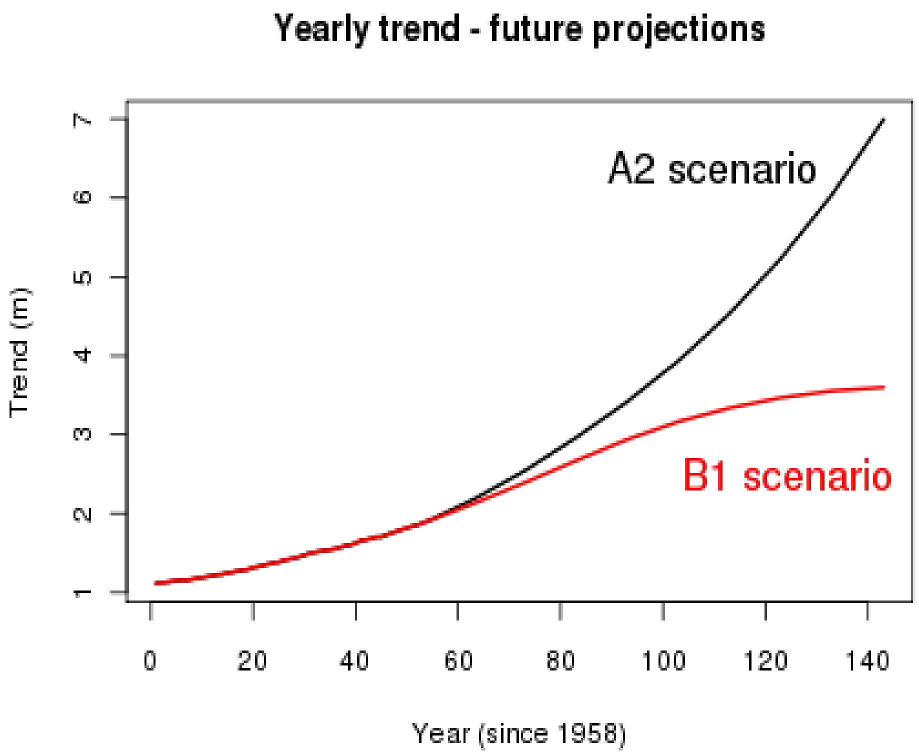
- G(t) = average level of CO_2 in the atmosphere at time t
- $\varepsilon_T(t) \sim N(0, \sigma_T^2)$, i.i.d.

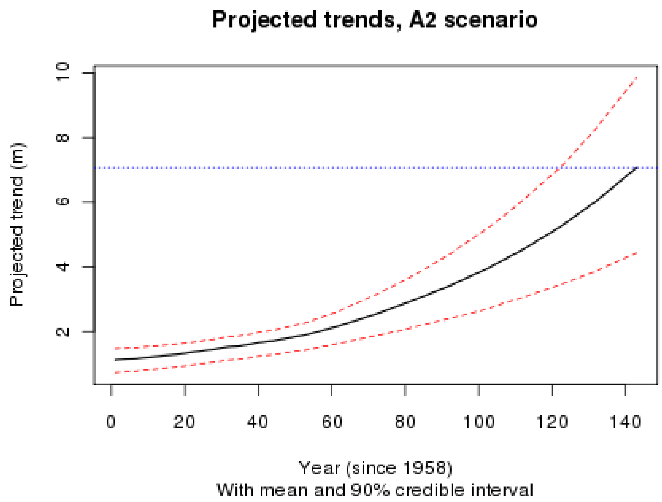
- Model alternatives:

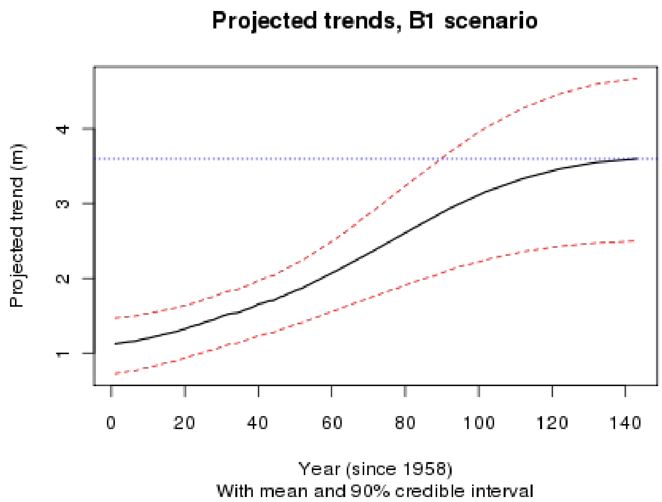
Model 1: $T(t) = \gamma G(t) + \eta \ln G(t) + \varepsilon_T(t)$	(linear-log model)
Model 2: $T(t) = \gamma G(t) + \varepsilon_T(t)$	(linear model)
Model 3: $T(t) = \eta \ln G(t) + \varepsilon_T(t)$	(log model)
Model 4: $T(t) = 0$	(No trend model)

- The linear-log and linear models performed best.

Projections from the linear-log model







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

	Estimated trend	Projections; A2 scenario	Projections; B1 scenario
Linear-log model	59 cm	5.4 m	1.9 m
Linear model	49 cm	4.3 m	1.6 m

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 CO_2
- 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 CO_2 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

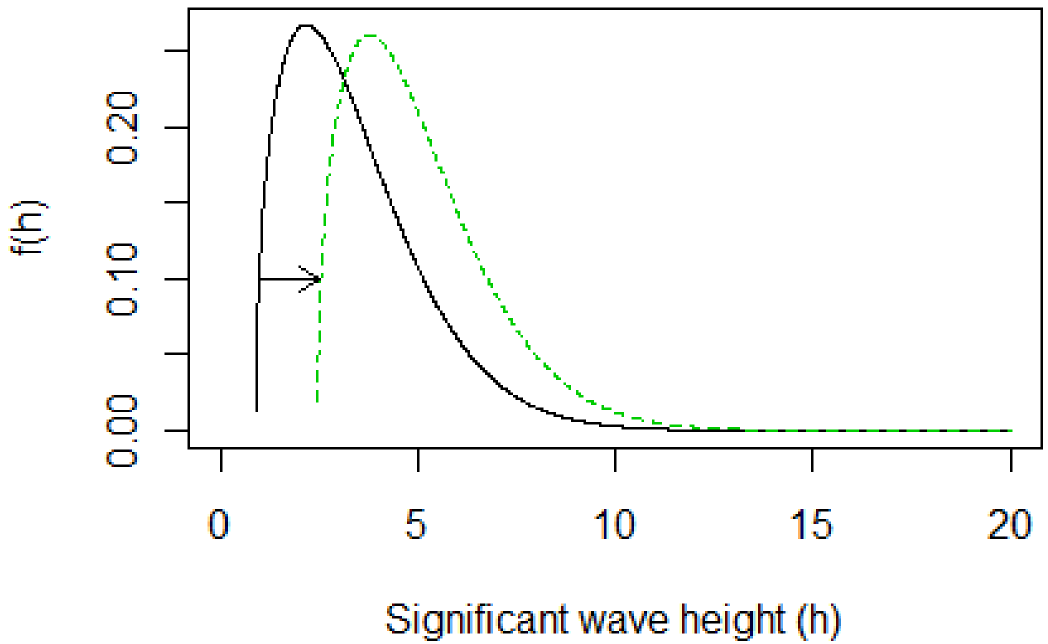
Joint distribution of H_S and T_Z

- 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

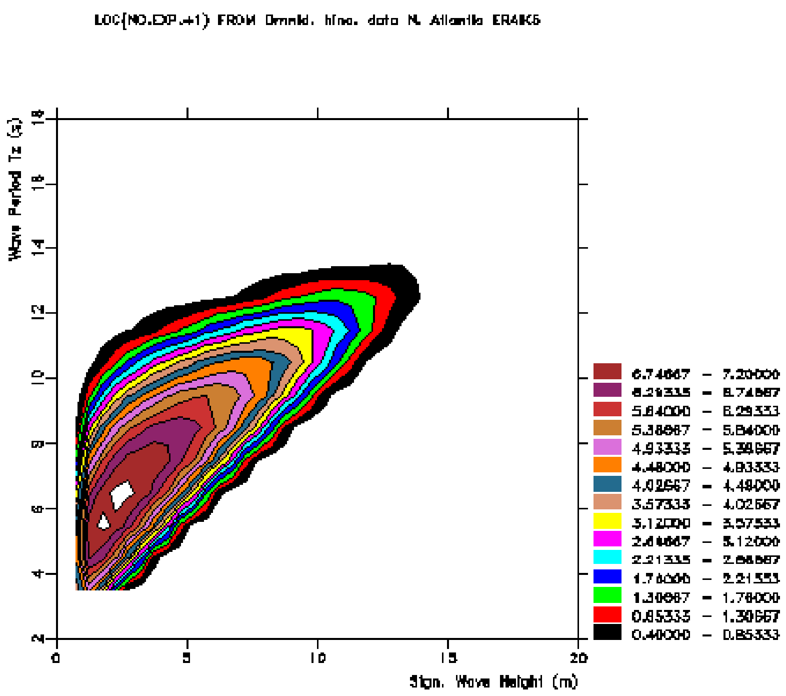
Effect of the long-term trend on $f(H_S)$

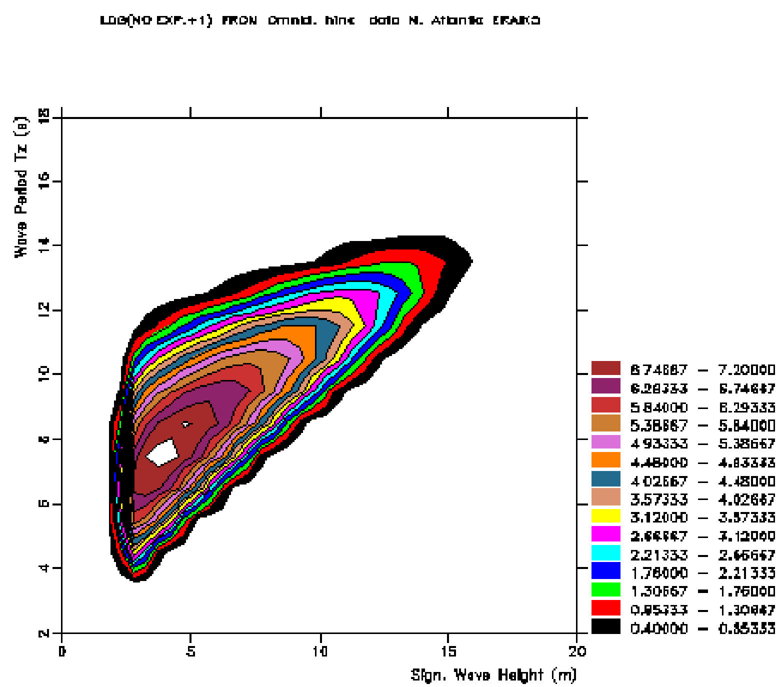


	α	β	γ	E[h]	sd[h]
Fitted distribution	2.776	1.471	0.8888	3.408	1.741
Modified parameters	2.846	1.471	2.457	5.033	1.781

Effect on joint distribution of H_S and T_Z

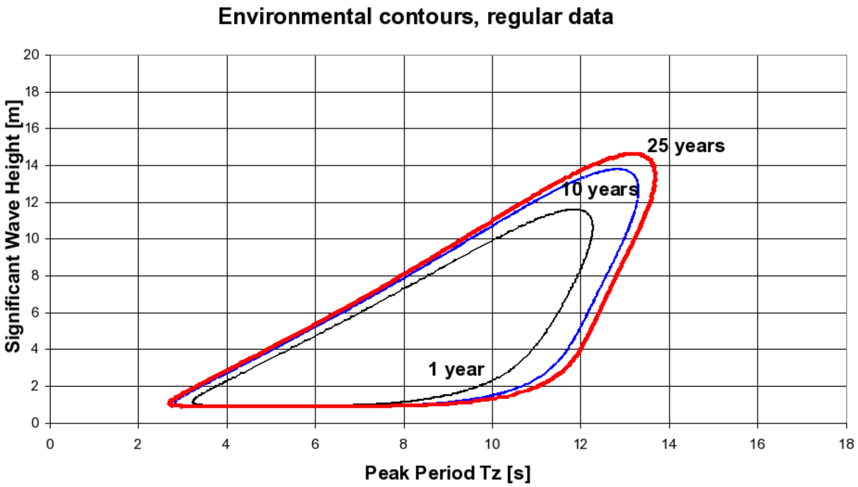
Contour plots of the joint distribution of (H_S, T_Z) with and without the climatic trend

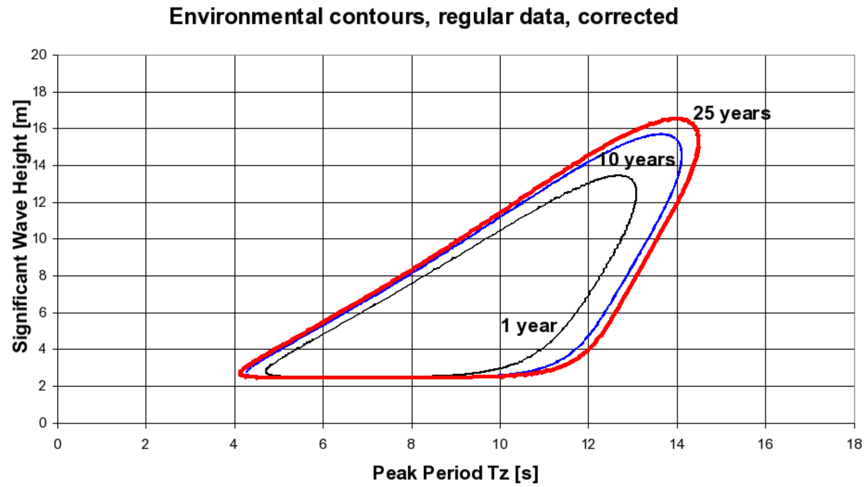




Example: Load assessment of oil tanker

- 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





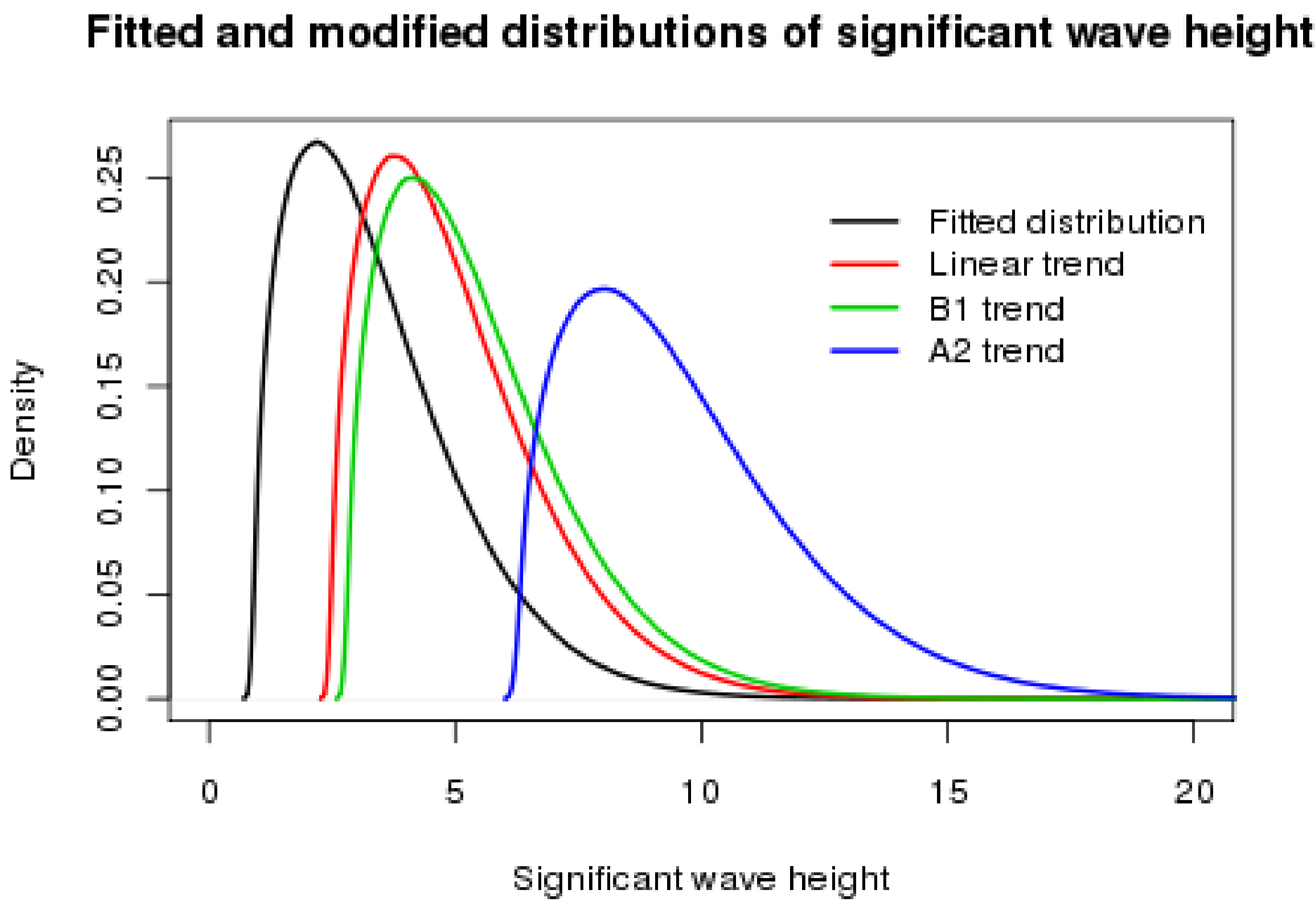
Extreme load characteristics

- 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

<u>25-year extreme load characteristics of example oil tanker</u>

	Stress amplitude (MPa)	Response period (s)
Base case	1.0	1.0
Modified fit - Basic model	1.07	1.02
Modified fit - B1 scenario	1.10	1.02

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

- **Long-term time-dependent stochastic modelling of extreme waves**. Erik Vanem. *Stochastic Environmental Research and Risk Assessment* vol. 25/2, pp.185-209, 2011
- **A Bayesian-Hierarchical Spatio-Temporal Model for Significant Wave Height in the North Atlantic**. Erik Vanem, Arne Bang Huseby, Bent Natvig. *Stochastic Environmental Research and Risk Assessment* vol 26/5, pp. 609-632, 2012
- **Modeling Ocean Wave Climate with a Bayesian Hierarchical Space-Time Model and a Log-Transform**. Erik Vanem, Arne Bang Huseby, Bent Natvig. *Ocean Dynamics* vol 62/3, pp. 355-375, 2012
- **Stochastic modelling of long-term trends in the wave climate and its potential impact on ship structural loads**. Erik Vanem and Elzbieta M. Bitner-Gregersen. *Applied Ocean Research* vol. 37, pp. 355-375, 2012
- **Bayesian Hierarchical Spatio-Temporal Modelling of Trends and Future Projections in the Ocean Wave Climate with a CO_2 Regression Component**. Erik Vanem, Arne Bang Huseby, Bent Natvig. *Environmental and Ecological Statistics*, in press, 2013

References

- **Modelling the effect of climate change on the wave climate of the world's oceans**. Erik Vanem, Bent Natvig, Arne Bang Huseby. *Ocean Science Journal* vol 47/2, pp. 123-145, 2012
- **A new approach to environmental contours for ocean engineering applications based on direct Monte Carlo simulations**. Arne Bang Huseby, Erik Vanem, Bent Natvig. *Ocean Engineering* vol 60, pp. 124-135, 2013
- **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 modelling of North Atlantic windiness**. Erik Vanem and Olav Nikolai Breivik. *Natural Hazards and Earth System Sciences* vol. 13, pp. 545-557, 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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