Global wave resource classification and application to marine energy deployments

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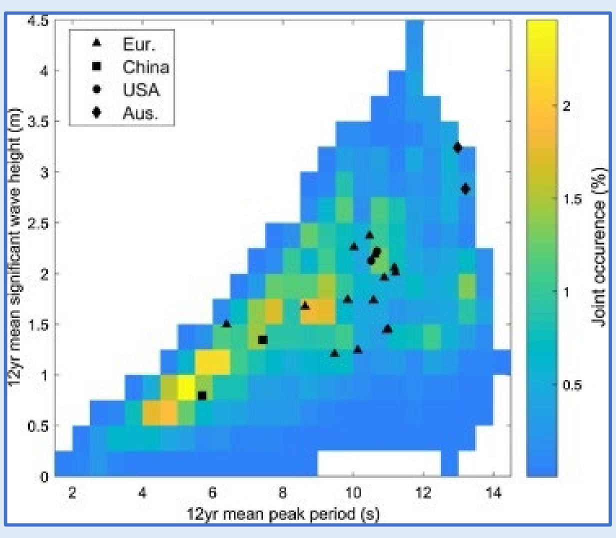
Details in Fairley et al., 2020. Open access: https://doi.org/10.1016/j.apenergy.2020.114515

Introduction

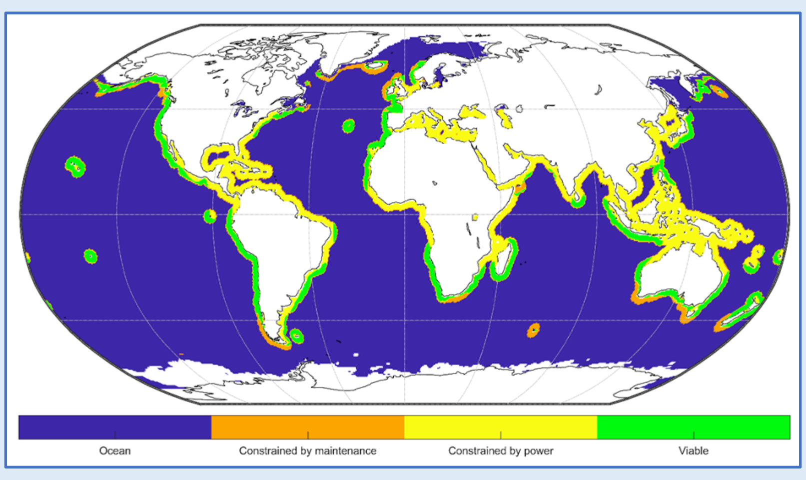
- Aim: Use k-means clustering to classify the global wave resource based on wave climate data and hence be device agnostic
- Motivation:
  - WEC development focussed largely in NW Europe – not representative of the global wave resource (see figure)
  - Resource classification would inform device development and global roll-out
- Classification of entire globe given in Fairley et al 2020.
- Discussion with device developers showed requirement for similar classification but with for a constrained area.
- Comparison between classifications given here



A joint occurrence matrix for mean H_s-T_p values over the coastal globe with the characteristics of wave energy test facilities marked in black (from Fairley et al, 2020).

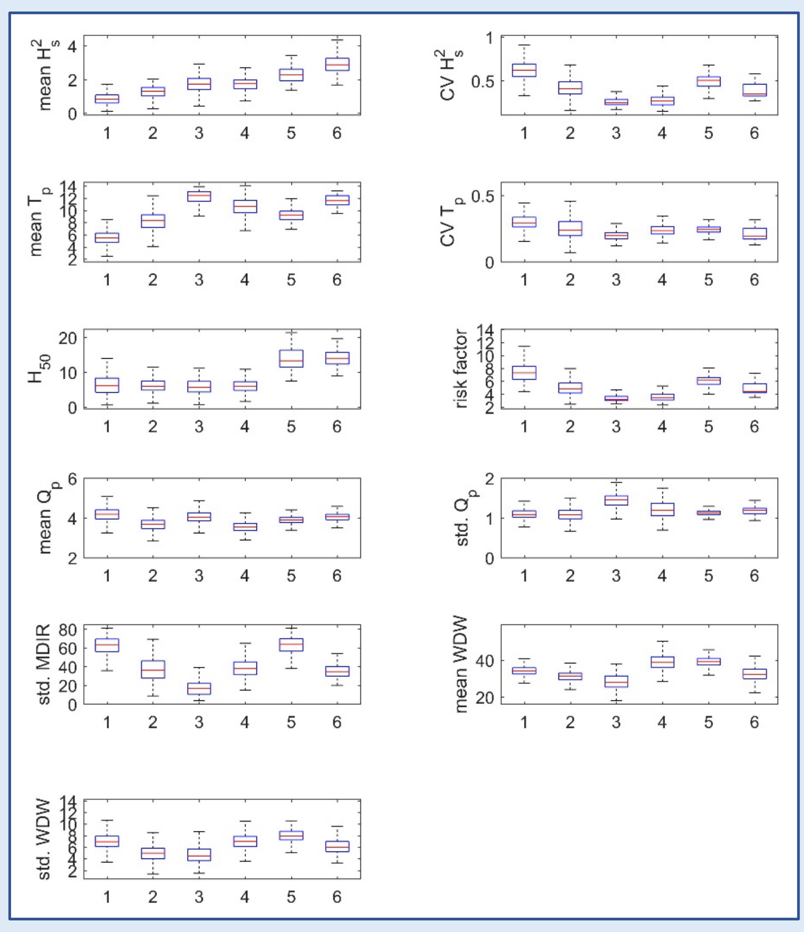
Methodology

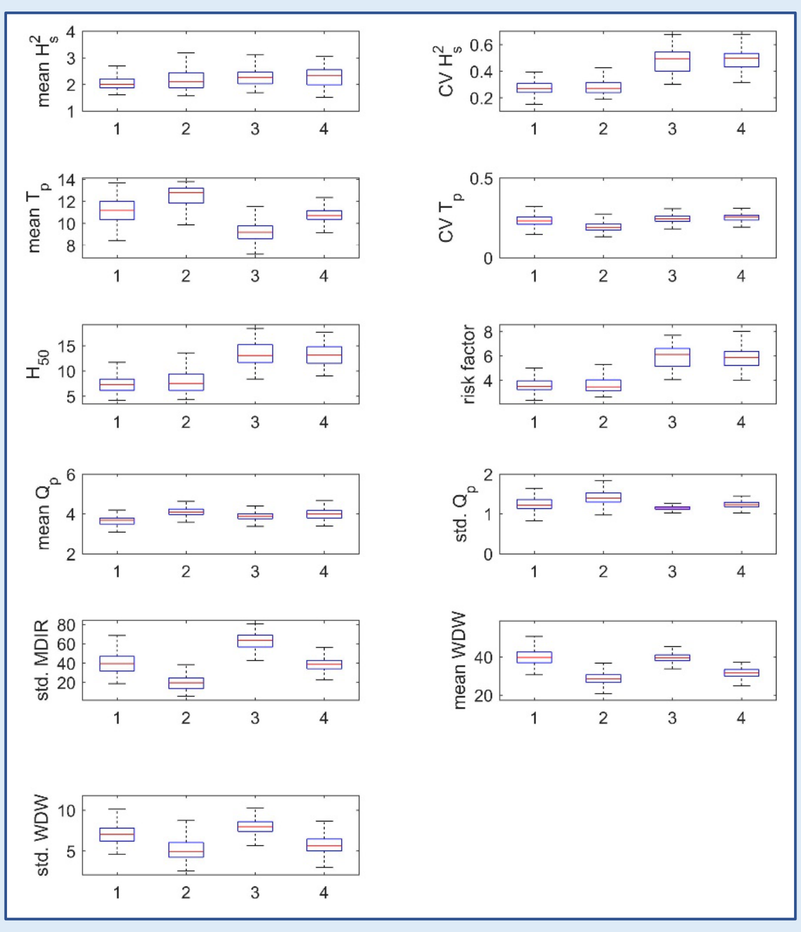
- K-means clustering of wave resource
- Data from ECMWF ERA5 between 2000-2011 at 3hrly intervals,
- Clustering conducted using:
  - Mean and variability of H_s^2, T_p,
  - Mean, variability of Goda's peakedness Q_p,
  - Mean and variability of wave directional width; standard deviation of mean wave direction
  - H_{50} and risk factor (mean H_s/H_{50})
- Parameters normalised so all parameters have equal weighting in classification (device agnostic)
- Two areas tested:
  - Coastal globe: all non- sea-ice areas within 3° of land (Fairley et al 2020)
  - Constrained area: constrained by power threshold and maintenance windows (see figure)
- Elbow / silhouette tests gave k=6 for tested area 1 and k=4 for tested area 2
- Returned clusters ranked using cluster mean H_s^2 (a proxy for energy)
  - from lowest cluster mean H_s^2 (class 1) to highest cluster mean H_s^2 (class 4/6)



Reduction in area tested between coastal globe and constrained area

Comparison of class parameter spaces

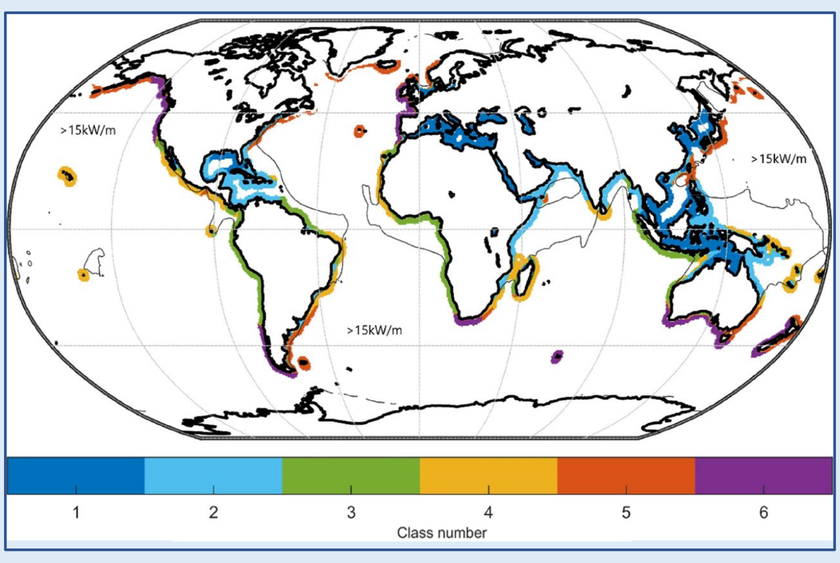


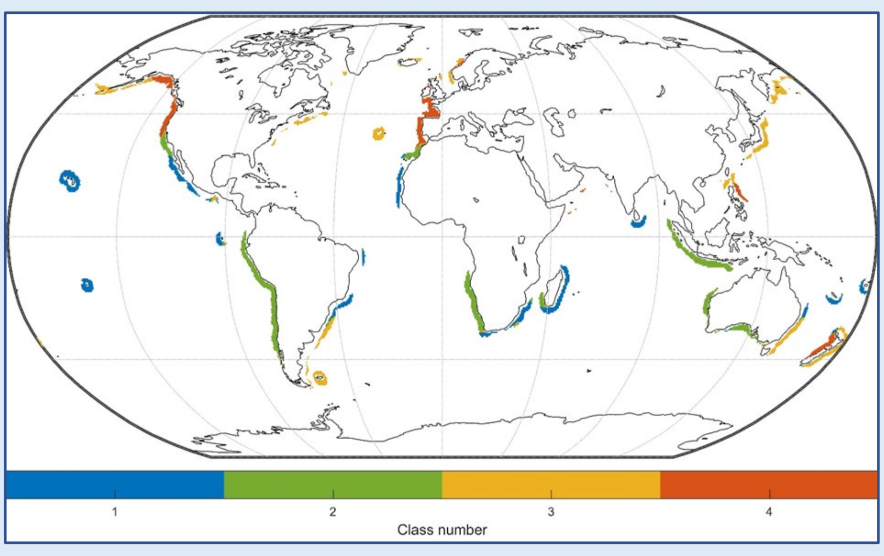


- Box and whisker plots show parameter spaces for the different classes (global classification on left, constrained area on right)
- Note similarity in mean H_s^2 between classes for constrained area compared to global

Comparison of geographic distribution

- Class order different for the constrained area but geographic spread similar for viable areas. Classes are equivalent to classes 3-6 in coastal globe classification





Geographic spread of classes: Global classification (left) and constrained area classification (right)

Conclusions

- Constraint reduces difference in mean H_s^2 between classes
  - Lower energy areas removed by power >15kw/m constraint and highest energy areas removed due to the weather window for maintenance constraint
- Geographic spread of class areas looks similar; although ranking changes
- For constrained area, classes equivalent to classes 3-6 in coastal globe classification.
- Therefore limited benefit in adding constraints to the analysis?

Fairley et al., 2020, A classification system for global wave energy resources based on multivariate clustering, Applied Energy. https://doi.org/10.1016/j.apenergy.2020.114515