Wave climate projections using statistical downscaling for the Gold Coast (Australia)

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INTRODUCTION

MOTIVATION

Gold coast beaches are periodically affected by large wave events originating erosion and flooding episodes. The willing to develop adaptation strategies for coastal communities for the future has motivated this study, since it would be necessary to analyze the changes in ocean wave heights. However, this variable is not directly available from the output of global climate models. Useful projections of future wave height climate need to be produce through dynamical or statistical ‘downscaling’ approaches.

OBJECTIVES

To generate high resolution shallow water sea state time series.
To develop and validate a statistical downscaling model to relate an atmospheric field with deep water or local sea states
To provide wave climate projections for different scenarios of the Access 1.0 CIMP5model.

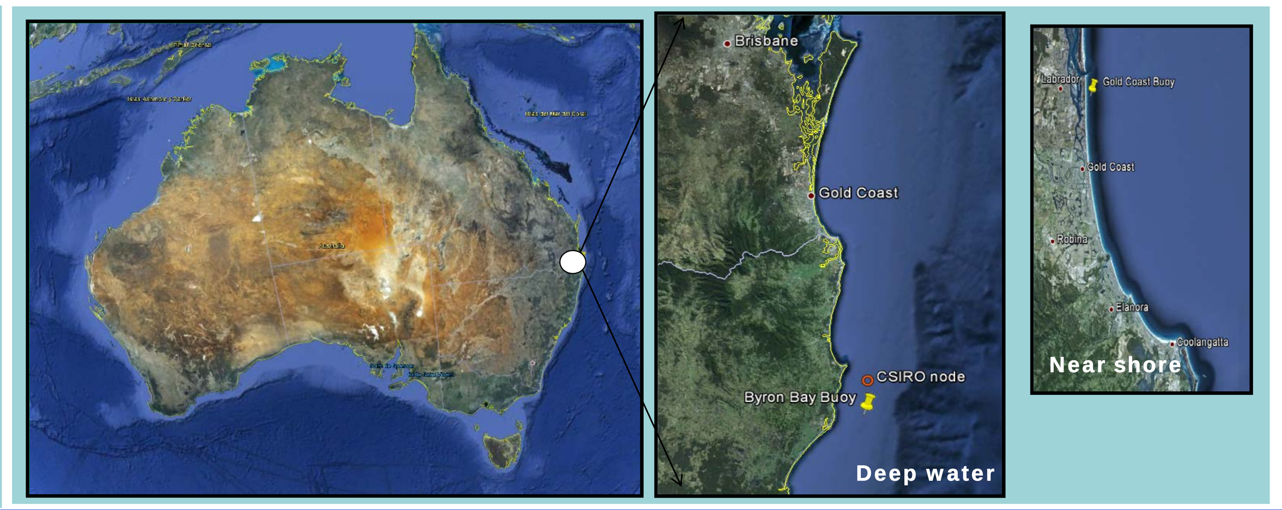
DATA BASES

ATMOSPHERIC REANALYSIS DATA **from the US National Center for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (NCFSR; Saha et al., 2010). This reanalysis spans from 1979 to 2009 with an hourly temporal resolution and 0.5°x0.5° spatial resolution.**

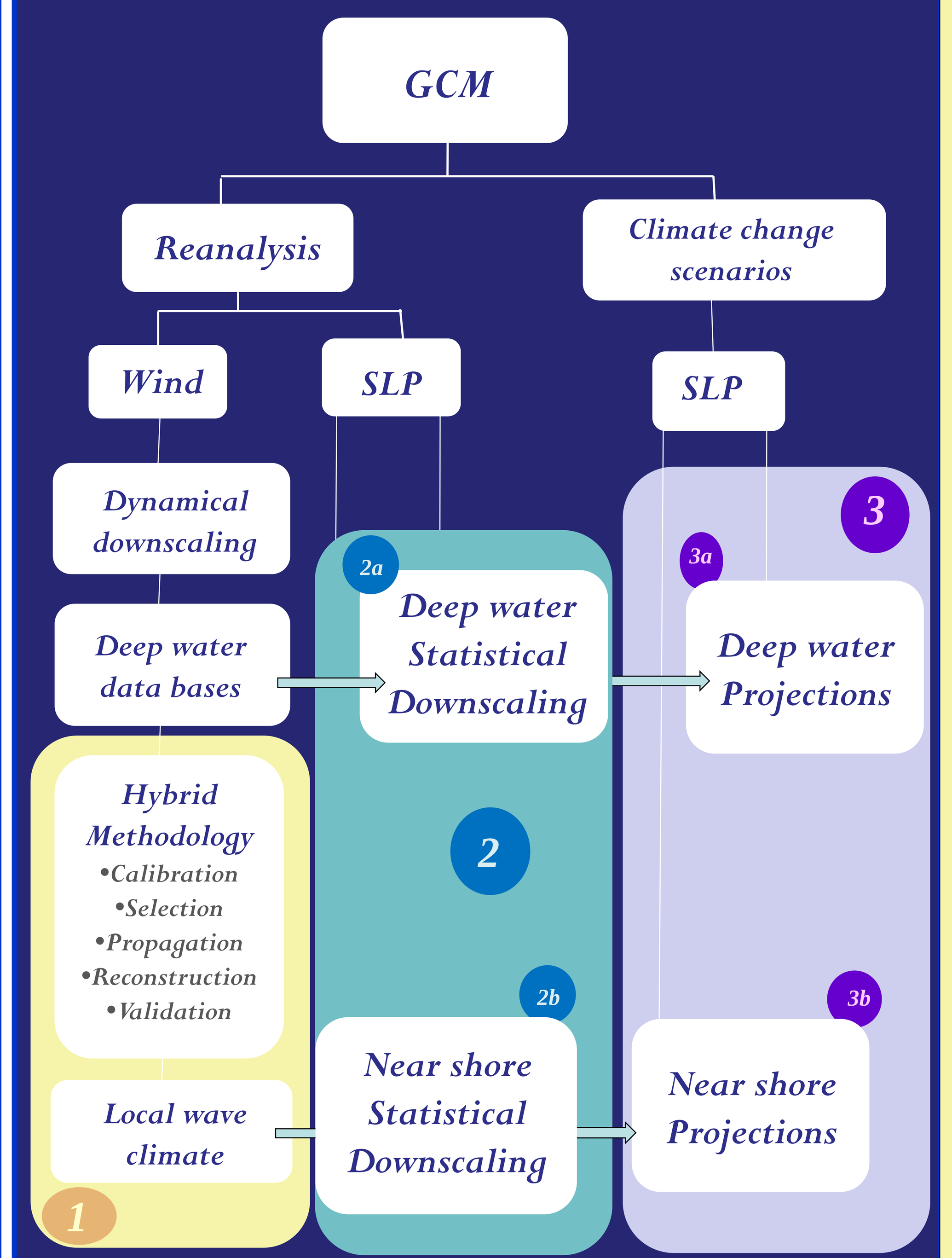
WAVE REANALYSIS DATA **kindly provided by Dr. Hemer. This model hindcast was forced using the NCFSR winds and sea-ice concentrations. The output is an hourly wave spectra defined by a directional resolution of 15° (24 directions) and 32 frequency bands for the 30 years of data (1979-2009).**

INSTRUMENTAL DATA **Byron bay buoy which spans from 1976 to 2010. Gold Coast buoy year 2008.**

AREA OF STUDY



METHODOLOGY



HYBRID METHODOLOGY TO TRANSFER WAVE CLIMATE TO COASTAL AREAS

CALIBRATION

Directional calibration with the instrumental data, by fitting the parameters of a potential function that relates the wave instrumental data to the simultaneous reanalysis data for each directional bin (Mínguez et al., 2011).

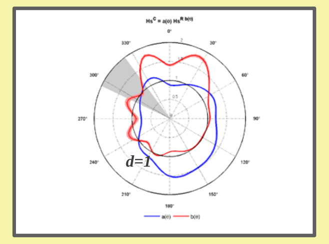


Fig. 1. Calibration parameters

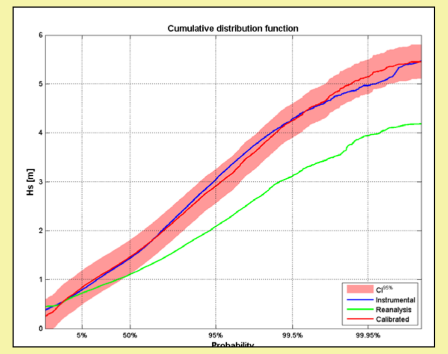


Fig. 2. Cumulative distribution function of Hs, original (green), instrumental (blue) and calibrated (red) series.

SELECTION

Data dimension reduction - PCA

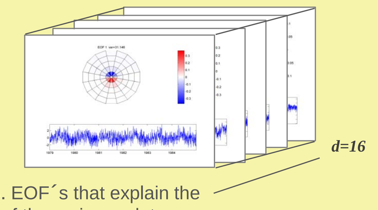


Fig.3. EOF´s that explain the 95% of the variance data.

Selection - KMA

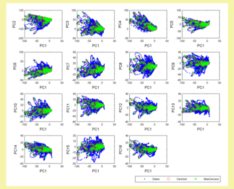


Fig.4. KMA selection

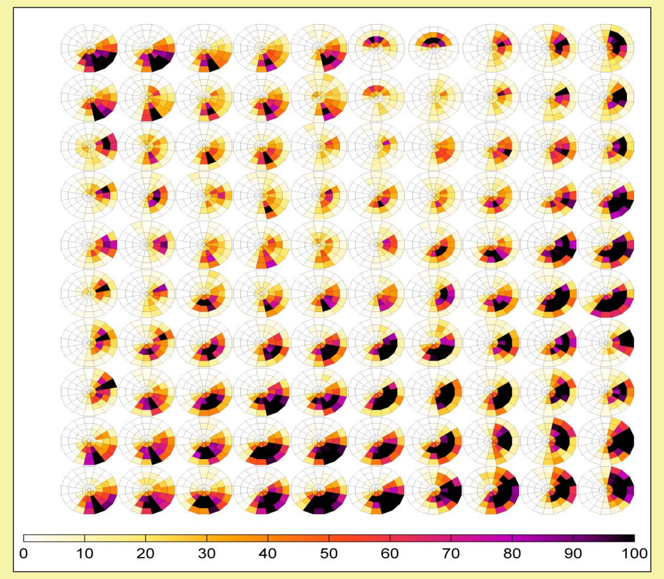


Fig.5. 10x10 representative spectral patterns of deep water wave climate using KMeans classification. [units: cm]

PROPAGATION

Local wave propagation of the 100 cases selected using SWAN model

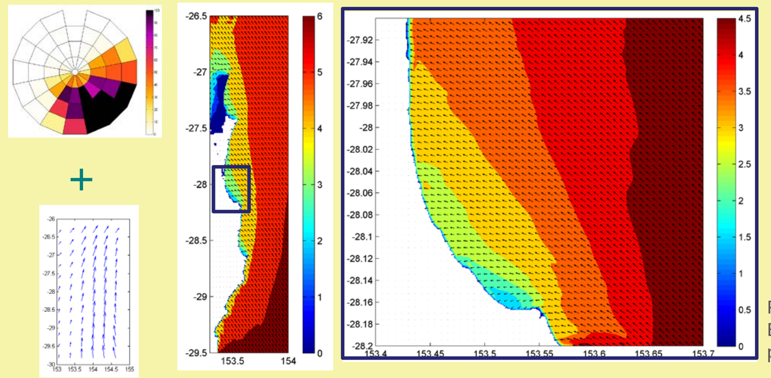


Fig. 6. Example of propagation

RECONSTRUCTION

RBF interpolation technique

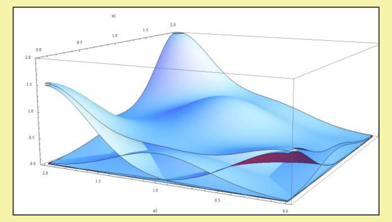


Fig. 7. RBF sketch

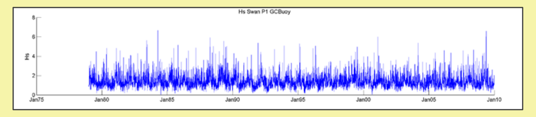


Fig. 8. Time serie reconstruction on P1, located in the position of the Gold Coast Buoy

VALIDATION

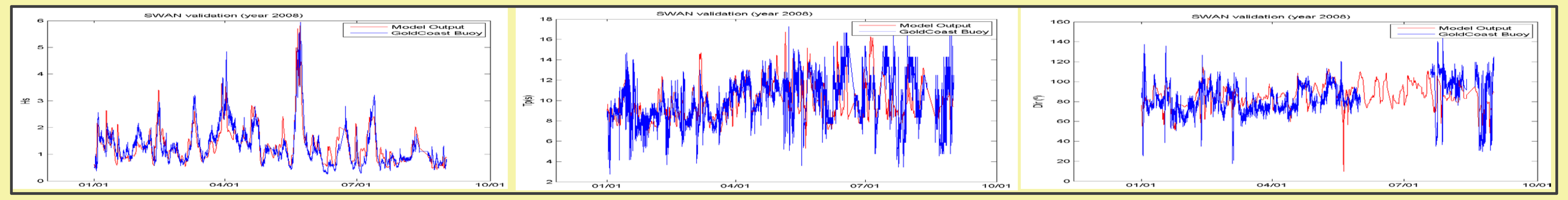


Fig. 9. Validation of propagation procedure with the statistical parameters Hs, Tp and Dir on the Gold Coast buoy position

STATISTICAL DOWNSCALING

STEP 1. PREDICTOR

Effective fetch analysis

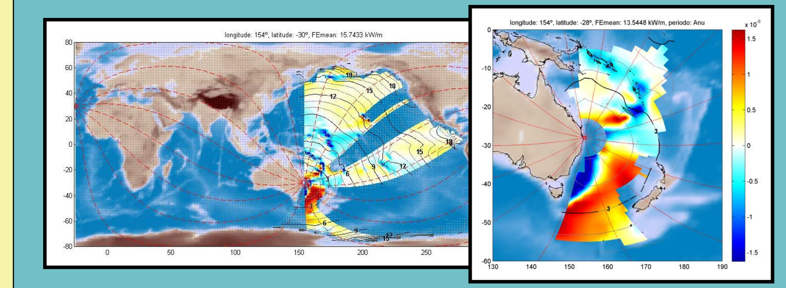


Fig.10. Influence area of storm generation Gold Coast, Australia

Squared SLP gradient (i.e. sum of the squared zonal and squared meridional SLP gradients) are defined as atmospheric predictors due to its physical meaning such they are proportional to the squared wind speed, and consequently roughly proportional to wave height.
In order to reproduce the swell and sea components of waves, the spatial atmospheric pattern introduced as predictor in the statistical model is defined by the previous 3-days-averaged of squared SLP gradient field in the large area and daily averaged of the square SLP gradient field in the small one (local area). This predictor is calculated daily for the 30 years of data.

Predictor area

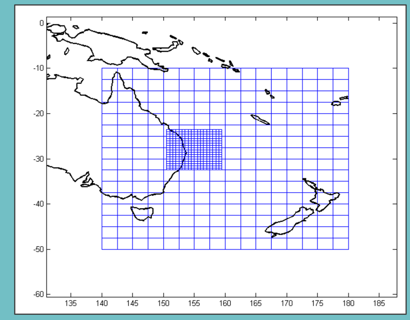


Fig.11. Areas and resolution of the predictor, taking into consideration the sea and swell components.

In order to reduce the dimensionality a PCA analysis is done. We have used the standardized signal of the squared SLP gradient to reduce the model climate biases. Afterwards, we have done the KMA classification in a lattice of 15x15 synoptic patterns to be able to represent properly the different atmospheric situations due to the large atmospheric variability in the study area.

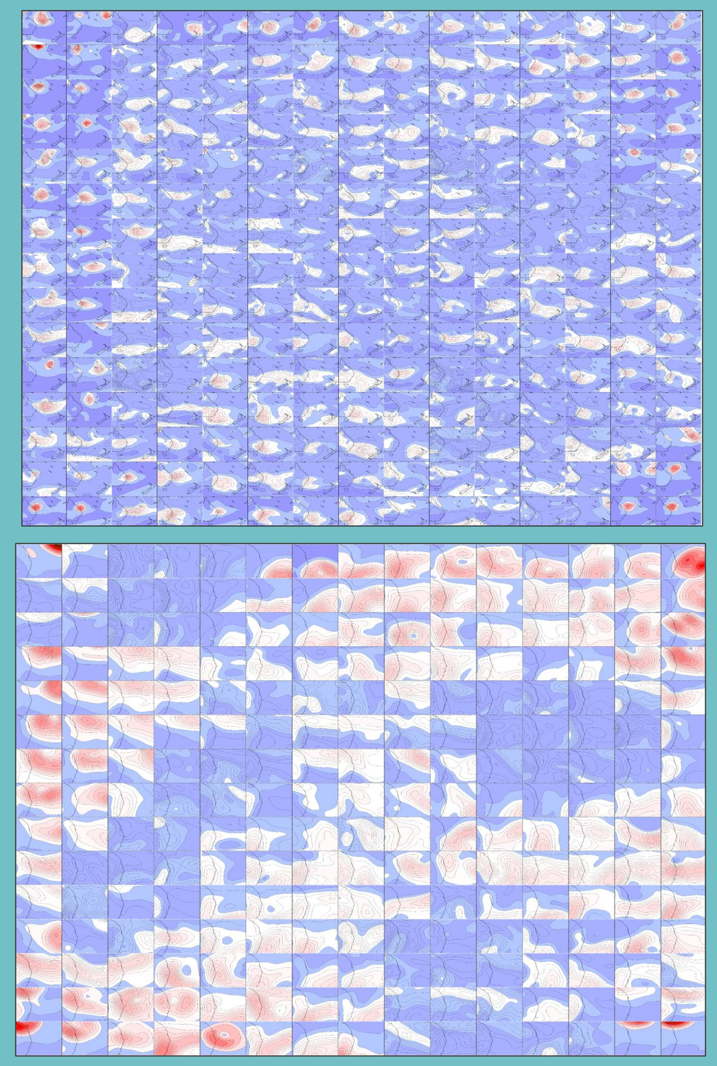


Fig.12. Synoptic patterns (anomalies of squared SLP gradients). Upper panel: large scale predictor. Lower panel: local predictor.

STEP 2. PREDICTAND

The predictand is defined by the corresponding sea states of each synoptic pattern on the target point during the calibration period (1979-1999).

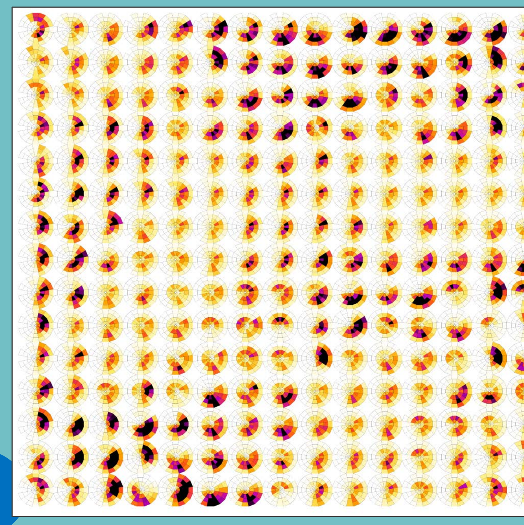


Fig.13. Deep water mean spectra for each weather type.

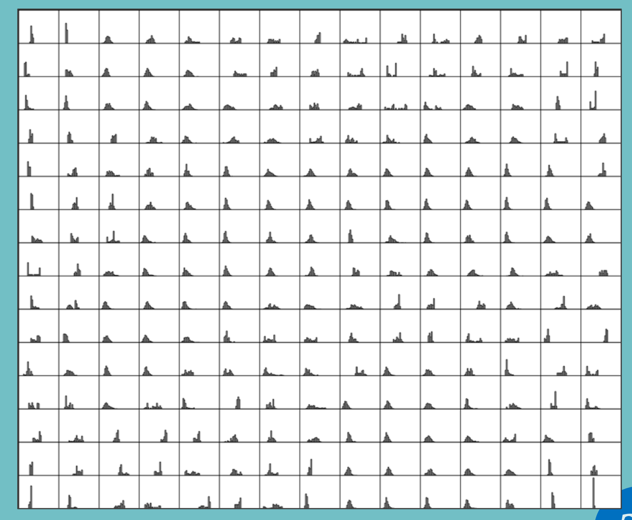


Fig.14. Near shore wave height histogram for each weather type.

STEP 3. STATISTICAL MODEL (WEATHER TYPES)

The model is based on the idea that for a certain period of time knowing the occurrence probability of each weather type, it is possible to estimate the predictand.

$$Y=f(H)= \sum fi(H)\ \ pi$$

During the calibration period the predictor as much as the predictand are considered known and the weather type classification is made. Therefore, the results are the classification of the predictor (X, figure 12) and the corresponding significant wave height distribution for each one (Y=f(H), figures 13 and 14).
For any other timeframe the appearance probability (pi’) of each weather type would change but the wave height distribution associated is considered constant. Consequently, it would be possible to define the predictand based on the new occurrence probabilities.

$$f(H)'=\sum fi(H)\ \ pi'$$

STEP 4. VALIDATION

Monthly

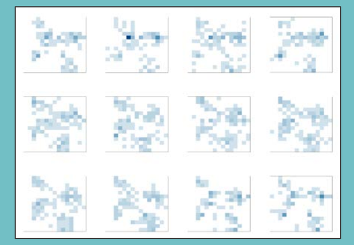


Fig.15. Monthly probability of each weather type (atmospheric conditions). Validation period.

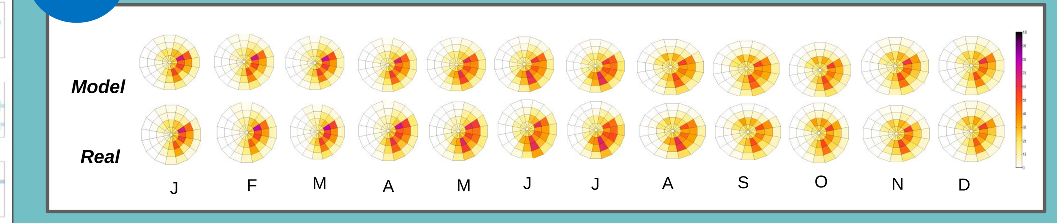


Fig.16. Monthly deep water spectral comparison

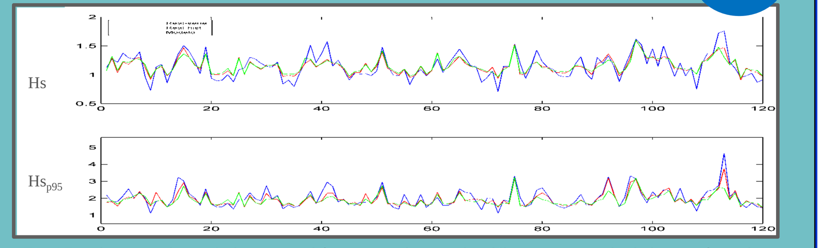


Fig.17. Time series of the monthly near shore significant wave height real and modeled. The upper graph is the mean wave height and bottom graph is the 95 percentile wave height.

PROJECTIONS

MODEL Access 1.0 Csiro-Bom CIMP5

Scenarios

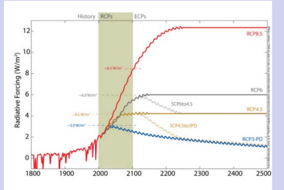


Fig. 18. Global Anthropogenic Radiative Forcing for the high RCP8.5, the medium-high RCP6, the medium-low RCP4.5 and the low RCP3-PD.
Source: Meinshausen (2011)

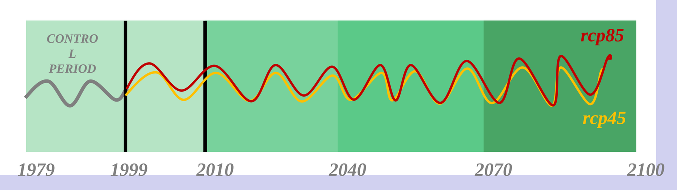


Fig. 19. Sketch with the different periods and scenarios of projections

For a certain period of time, we must know the variation on the occurrence probability of each weather type.

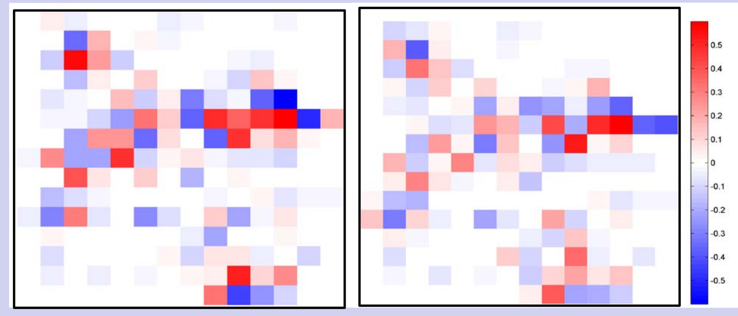


Fig. 20. Variation on the occurrence probability of each weather type for the different scenarios during the years 2070-2099. Left panel: rcp45 scenario, right panel:rcp85 scenario

DEEP WATER

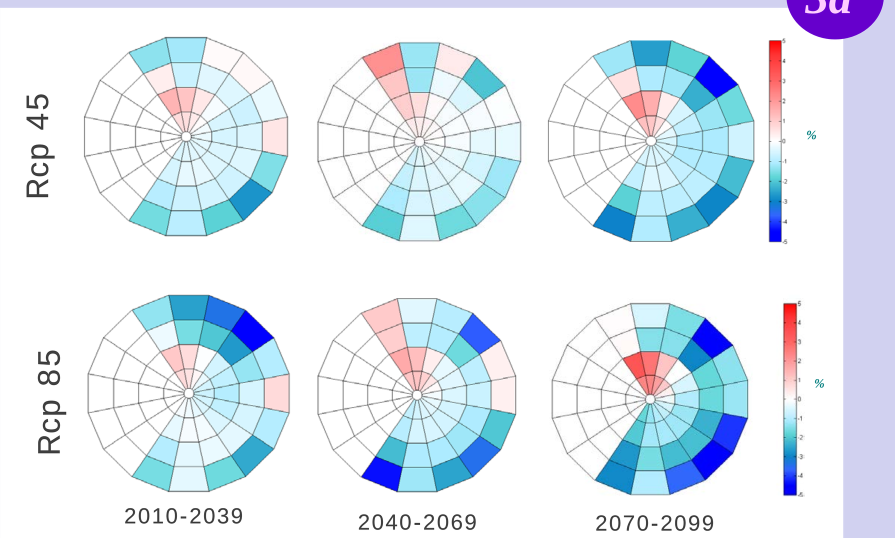


Fig. 21. Percentage of change on the mean spectra for each period of time.

NEARSHORE

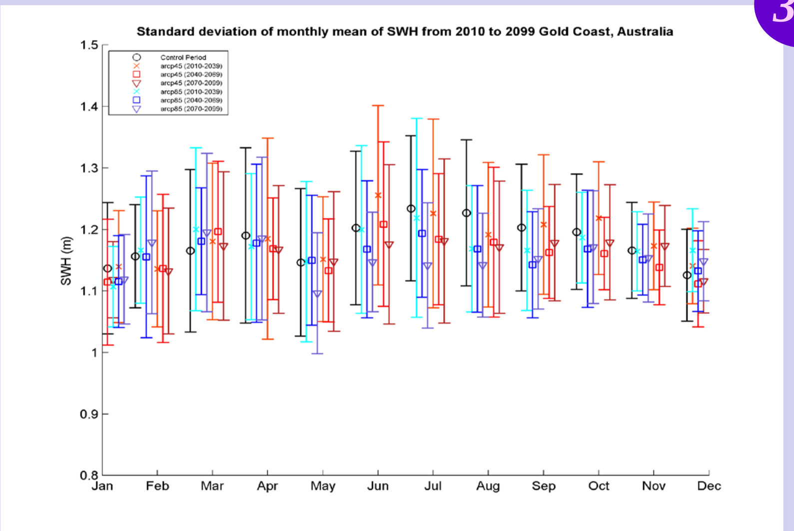


Fig. 22. Standard deviation of monthly mean SWH for each time period and scenario.

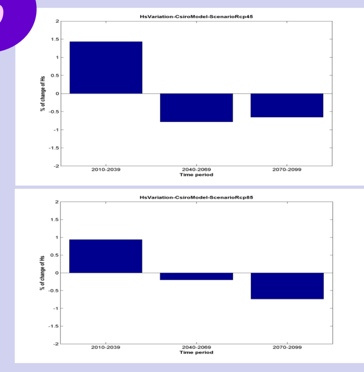


Fig. 23. Percentage of change in SWH for each time period. Upper panel:rcp45.Lower panel:rcp85.

CONCLUSIONS

•The predictor must be defined in two areas, a local area which take into consideration the waves generated in the last day, and a larger area to account the swell waves that are formed by larger storms and travel to the coast defined by the n-days average pressure fields.
•The simplicity and the minimum computational time required are the main advantages of this kind of statistical methods, allowing an easy multimodel ensemble of CIMP5 models..
•The use of spectral data for the wave climate characterization has helped on the development of the statistical model.
•Wave climate projections at the Gold Coast region indicate a relatively small decrease in mean SWH (less than 5%) for both scenarios tested.
•Future works would be based on the comparison of projection results from statistical and dynamical downscaling in Gold Coast region.

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