





...a project, with research members from around the globe, that provides infrastructure to support a systematic, communitybased framework for validation and inter-comparison of wave hindcasts and projections

### **MOTIVATION**

- Ocean scale waves are relevant and important for, among other things:
  - harnessing of wave energy, safety, commerce, and economics (e.g., transport of goods), and in coastal areas drive important processes that determine flooding and erosion.
- Buoy, model, and remotely sensed data are used to understand and describe historical spatial and temporal variations but most global scale or ocean basin studies
  - focus on or are limited to wave heights and periods
  - use single datasets and disparate methods that have led to sometimes contrasting results







### **OBJECTIVE**

#### To that end, there is a need to asses how well variability and trends described by current generation datasets compare

Here we aim to

- assess the variance in wave climatology and rates of change across the current generation of hindcast & reanalysis products, and
- evaluate if robust signals of change can be quantified





### APPROACH

Being accomplished via the joint efforts of the COWCliP group, an international collaborative research community of researchers with interests in wind-wave climate variability and change.

10 individual groups contributed and post-processed hindcast or reanalysis global scale datasets in a consistent manner using the same code (provided by Wang and others)

- monthly, seasonal, and annual statistics
- common overlapping time-period 1980-2015 (35 years) (for the most part)



COWCliP meeting in Liverpool, 2017



### **CONTRIBUTED DATASETS**





### **CONTRIBUTED DATASETS**

### Limit the analysis to

- Southern and Northern hemisphere summers and winters
  - DJF and JJA
- Median and 90<sup>th</sup> percentile statistics (p50 and p90)
- Variables: H<sub>s</sub>, T<sub>m01</sub>, D<sub>m</sub>, H<sub>s</sub>Ro (number of rough days)



## DJF p50 climatology (1985-2015)















IORAS global



JRA55 ST2



**Ocean Wave Climate** 



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## DJF p99 climatology (1985-2015)



CSIRO glob24m

GOW1 -

JRA55 ST2





CSIRO 1deg

ERAI

IORAS global





JRA55 ST4





10 Ensemble 8 6 4 2

JRC ERAI







## JJA p50 climatology (1985-2015)



CSIRO glob24m

GOW1

JRA55 ST2







ERA5





CSIRO 1deg

GOW2















## JJA p99 climatology (1985-2015)





CSIRO glob24m



ERA5



JRA55 ST4



IORAS global

JRC CFSR



NOC

10

8

6

2



JRC ERAI

Ensemble









CSIRO 1deg

JRA55 ST2

GOW1





## JJA p99 climatology (1985-2015)



CSIRO glob24m





IRA55 ST2









ERA5





JRA55 ST4









Leaving us with 9 members 6



ERAI





#### **Ensemble DJF**

IORAS

JRA55-ST4

NOC

#### $H_{\rm s}\,{\rm p50}$

S.F

50

S.B

SE

15

### *H*<sub>s</sub> p90

S.F

15

0.05-0.05

### *T<sub>m</sub>* p50



























0.5

1

-0.05	
0.00	

m/yr

0

0 s/yr

0.05-1

-0.5 0 °/yr D<sub>m</sub> p50

#### Ensemble DJF (CFSR driven)

### H<sub>s</sub> p50

### *H*<sub>s</sub> p90

### *T<sub>m</sub>* p50



-0.05 0 0.05 m/yr



#### Ensemble DJF (CFSR driven)

### H<sub>s</sub> p50

#### $H_{\rm s}$ p90

### *T<sub>m</sub>* p50





Altimeter Hs p90 DJF (Young & Ribal, 2019)





#### Ensemble JJA

50

ERAS

#### $H_{\rm s}$ p50

### H<sub>s</sub> p90

50

### *T<sub>m</sub>* p50



D<sub>m</sub> p50

1

































0

m/vr







-0.05

0.050.05

0 s/vr 0.05 -1 -0.5 0 0.5

#### **Ensemble JJA** (CFSR driven)

### *H*<sub>s</sub> p90

15

### $T_m p50$



H, p50







Altimeter Hs p50 JJA (Ribaldi & Young, 2019)



-0.04 -0.02 -0.01 0 0.01 0.02 0.03 0.04 0.05 -0.03

**Ocean Wave Climate** 

Altimeter Hs p90 JJA (Ribaldi & Young, 2019)



Trends







### Trends compared to reference altimeter data<sup>[1]</sup>



### Ensemble mean trend minus altimeter



















### wave height trends: ensemble mean and robustness

#### Method A: (ref: 11,12,13)

Large change with high model agreement: multi-model mean trend > exceeds two standard deviations of internal variability AND at least 90% of the models agree on the sign of change

Small signal or low agreement of models: multi-model mean trend > exceeds standard deviation of internal variability

#### Method B1: (variant of method A)

80% of the models show a trend < two standard deviations of variability (calculated from interannual variations within each model; ie use all model data) (no distinction between large and small model agreement)

Method B2: (ref: Hemer et al 2013; Wang et al, 2014; and others) Multi-model ensemble mean > inter-model standard deviation

#### Method C: (ref: Knutti and Sedláček, 2013)

Dimensionless robustness measure considers natural variability and agreement on magnitude and sign of change. Uses a signal to noise ratio and ranked probability skill score.

#### Small signa

nble average

Regions where at least 80% of the models individually show no significant change are hatched and interpreted as 'changes unlikely'

#### Method D: (ref: Tebaldi et al., 2011; Neelin et al., 2006)

Robust large change: more than 50% of the models show significant trends and at least 80% of those agree on the sign of change

Unreliable large change: more than 50% of the models show significant trends but less than 80% of those agree on the sign of change

Method E: (ref: Mentaschi et al 2017; Alferi et al 2015; Vousdoukas et al 2016) Robust change with high model agreement: Dimensionless coefficient of variation <1, where the CV is the intermodel standard deviation divided by the





### wave height trends: ensemble mean and robustness

Percent area of robust change signal

.. and (avg. rate of change [cm/yr or s/yr])

Region	p50		p90	
	Hs	1	Hs	<b>—</b> ——
NP	45 (0.40)		38 (1.02)	
	22 (-0.44)		29 (-0.70)	
NA	39 (0.56)		37 (0.67)	
	16 (-0.39)		18 (-0.36)	
SP	95 (0.54)		92 (0.70)	
	<0.1 (-0.08)		3 (-0.15)	
SA	83 (0.63)		89 (0.98)	
	6 (-0.13)		1 (-0.08)	
ТА	52 (0.26)		48 (0.28)	
	11 (-0.10)		15 (-0.12)	
ТР	67 (0.30		66 (0.39)	
	19 (-0.15)		21 (-0.34)	
ТІ	51 (0.30)		52 (0.49)	
	12 (-0.15)		11 (-0.22)	
SI	82 (0.38)		69 (0.62)	
	15 (-0.17)		27 (-0.26)	

DJF

	Aff			
Region	p50		p90	
	Hs	ŀ	Hs	
	13 (0.17)		11 (0.52)	
NP	56 (-0.44)		59 (-0.90)	
	33 (0.18)		13 (0.25)	
NA	24 (-0.36)		44 (-0.60)	
	95 (0.85)		95 (1.24)	
SP	1 (-0.20)		1 (-0.11)	
	86 (0.66)		84 (0.85)	
SA	1 (-0.18)		3 (-0.24)	
	56 (0.44)		54 (0.67)	
TA	6 (-0.14)		8 (-0.17)	
	72 (0.39)		66 (0.55)	
TP	15 (-0.19)		21 (-0.33)	
	54 (0.24)		48 (0.42)	
TI	9 (-0.20)		15 (-0.28)	
	81 (0.43)		73 (0.60)	
SI	13 (-0.19)		21 (-0.21)	









ensemble mean trend in annual frequency of rough days



## Method of computing the ensemble



How to compute the ensemble mean... does it matter?



### Method of computing the ensemble





method 1 – method 2



### Summary

- Difficult to robustly quantify inter-model variability introduced by different model settings from the contributed datasets
  - But the winds clearly have the strongest influence [ITWS ("it's the winds stupid!", Vince Cardone)]
  - CFSR winds have a step change in ~1994, which strongly influences trends
- Method of computing the ensemble can make a difference of ~10%
- Robust signals of change are identifiable across dynamically downscaled models (excepting models influenced by step-changes in atmospheric forcing)
  - Robust signals of upward trending Hs are noted across much of the globe
  - Strong agreement among models that Hs is increasing in both summer and winter and for medians and extremes across >90% of the Southern Ocean at a rate of ~1cm/yr
  - Strong confidence that >60% of the Indian and Central Pacific Oceans are experiencing increasing Hs
  - There is high confidence that the North Sea and Eastern North Pacific have experienced decreasing Hs and direction changes
- It is noted however that rates of change are biased positive compared to altimeter Hs trends



# Thank you

# Special thanks to all the COWCliP collaborators





O Norwegian Meteorological



