Environment and Climate Change Canada
Environnement et Changement climatique Canada

CHALLENGES IN ASSESSING WAVE CLIMATE & TRENDS THEREIN

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Canada

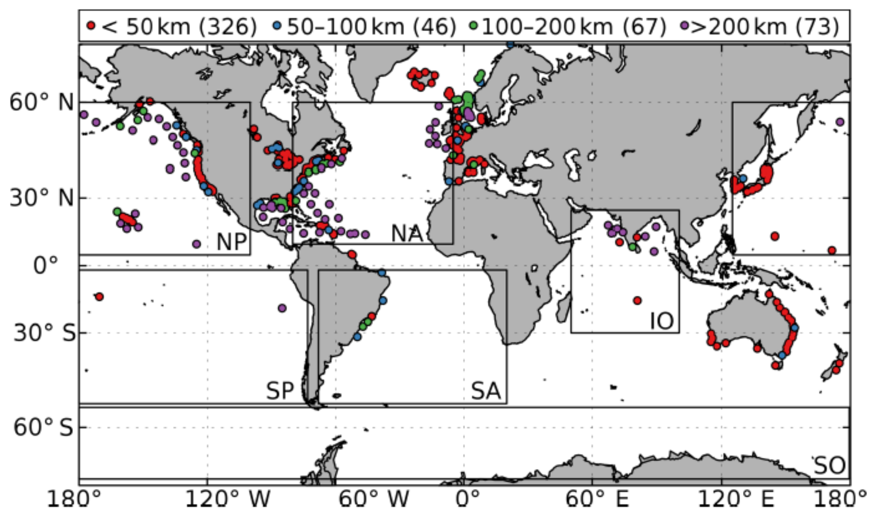
OUTLINE

- Challenges & sources of uncertainty
  - Global wave climate
  - Regional wave climate
    - Arctic region
- Thoughts and tools for addressing data inhomogeneity

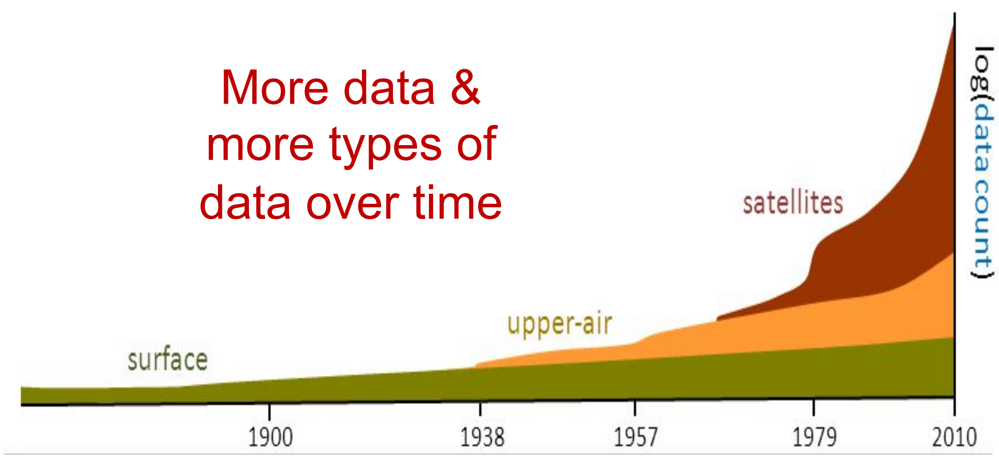
CHALLENGES & SOURCES OF UNCERTAINTY

OBSERVATIONS

- **Temporal inhomogeneity are inevitable** in both in-situ and satellite observations.
- **Poor spatial and/or temporal coverage** of wave observations make homogenization of wave data particularly challenging, which needs more attention than it has received so far.



(Dodet et al, 2020)



CHALLENGES & SOURCES OF UNCERTAINTY

MODEL SIMULATIONS

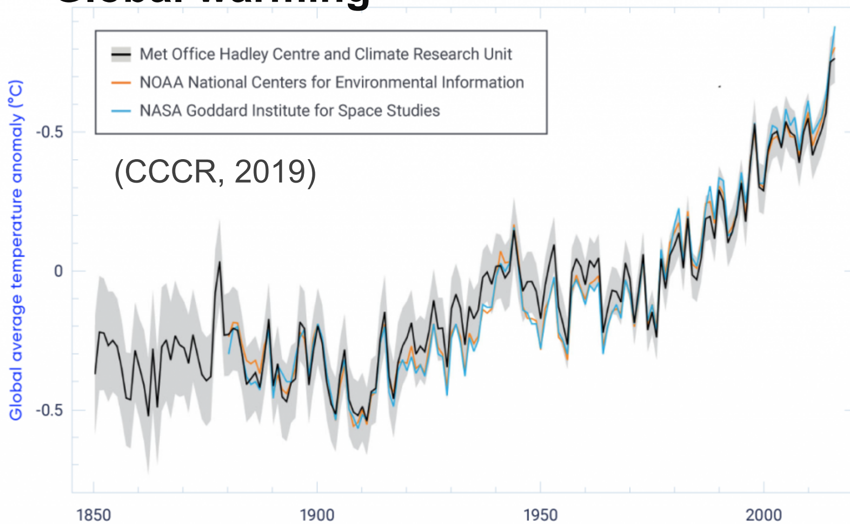
- These challenges have led to the use of **model simulations** (reanalysis/hindcast) as **observation proxy**. However, such proxy data are affected by:
  - Model **resolution/parameterization**
  - **Downscaling** methods (statistical, dynamical, hybrid models)
  - Dynamical model's **reliance on typically less robust data** - surface winds
  - **Data assimilation**

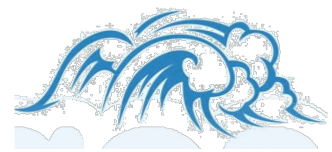
- Also, the assessment of extreme wave climate and trend is confounded with **internal climate variability**

CHALLENGES & SOURCES OF UNCERTAINTY

FUTURE

Global warming





?

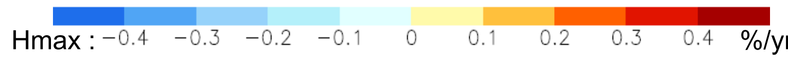
Additional challenges in assessing <u>future</u> wave climate:

- **Forcing uncertainty**
- Limited climate model output:
  - Most climate models do not include ocean waves
  - High resolution wind data are not available from all climate models

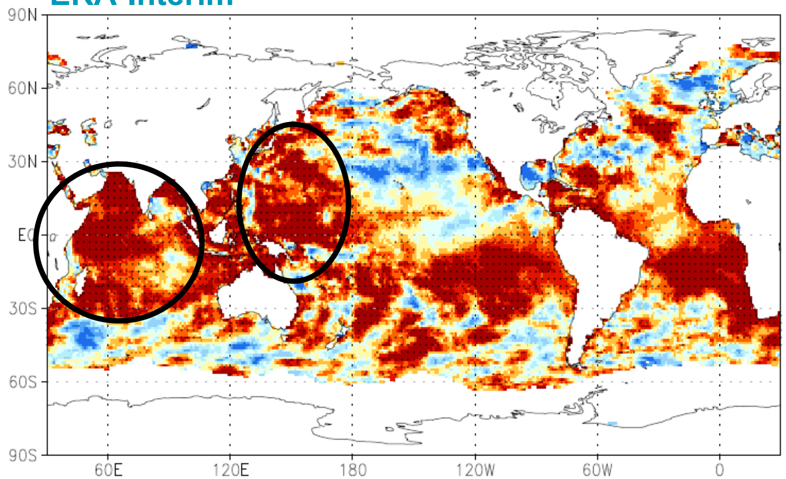
HISTORICAL WAVE CLIMATE

DISCREPANCIES IN WAVE REANALYSIS

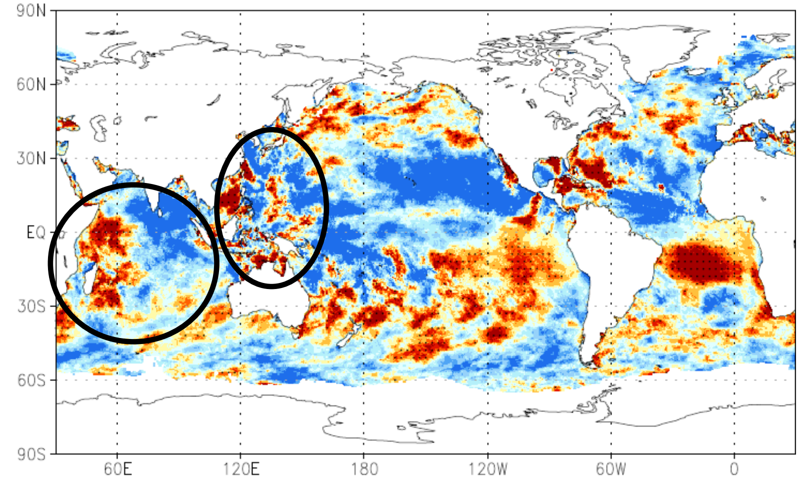
Trend in **annual maximum SWH** (1979-2009)



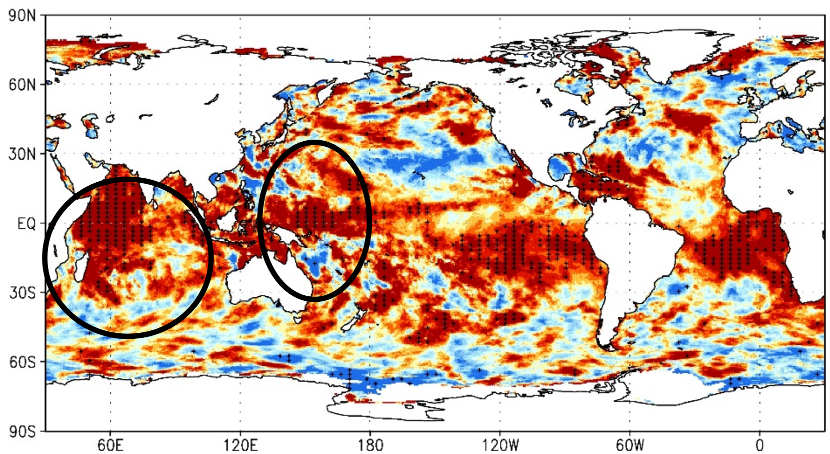
ERA-Interim



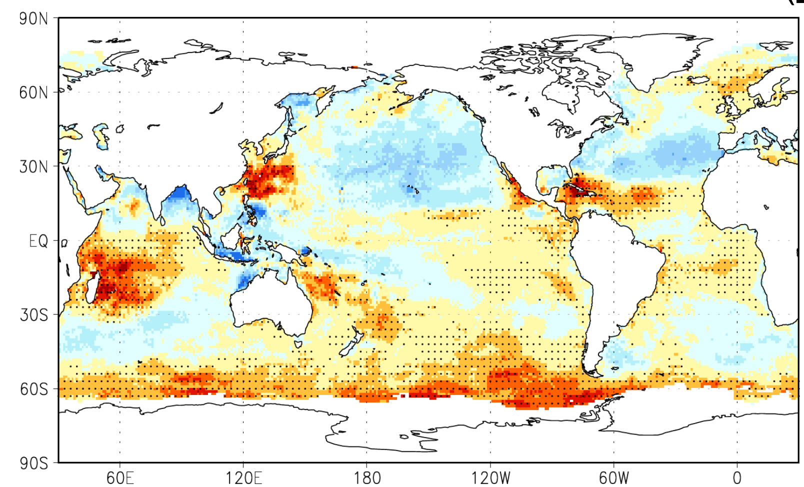
CFSR



ERA5



SOUSEI-derived historical wave ensemble (99 runs)



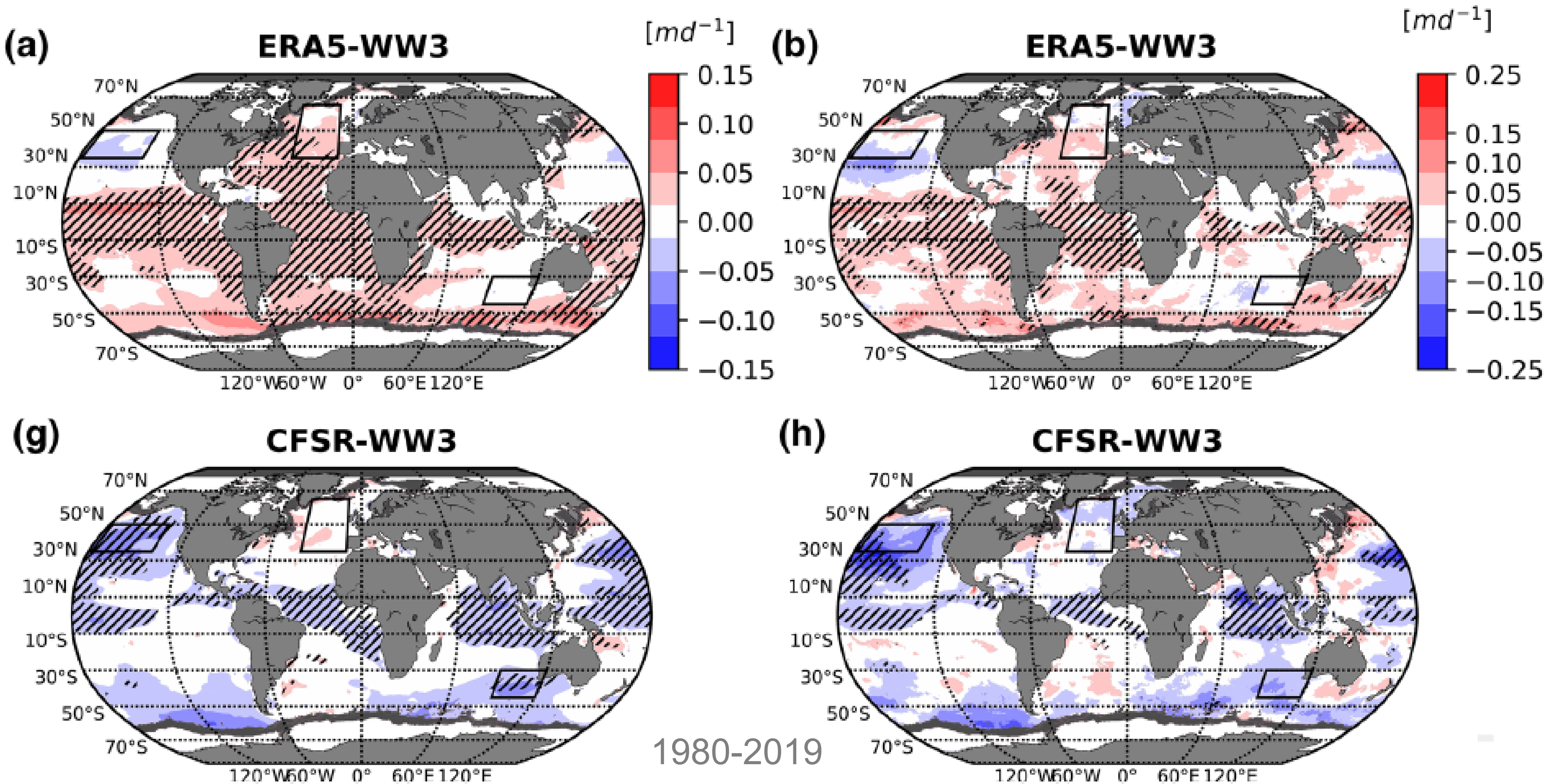
CFSR has very different trends compared to ERA-I and ERA5!

Reanalysis are often used to validate datasets: this is can lead to different evaluations depending on the wave reanalysis used for validation.

DISCREPANCIES IN WAVE HINDCASTS INHERITED FROM WIND REANALYSIS

Similar trend discrepancies (CFSR vs ERA5, ERA-I, MERRA2) are also seen in wave hindcasts (no wave data assimilation) with same wave model configuration and forced by **different wind reanalysis**.

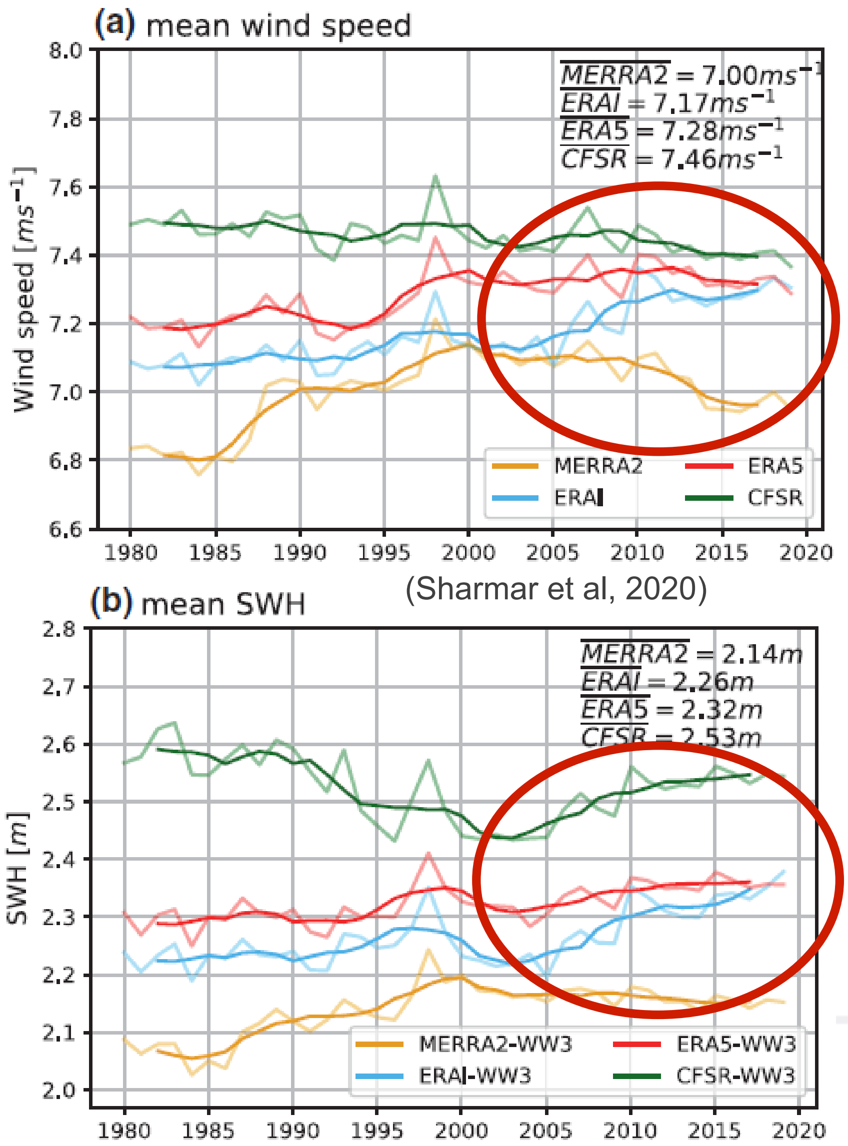
Annual mean SWH **Annual p95 SWH**

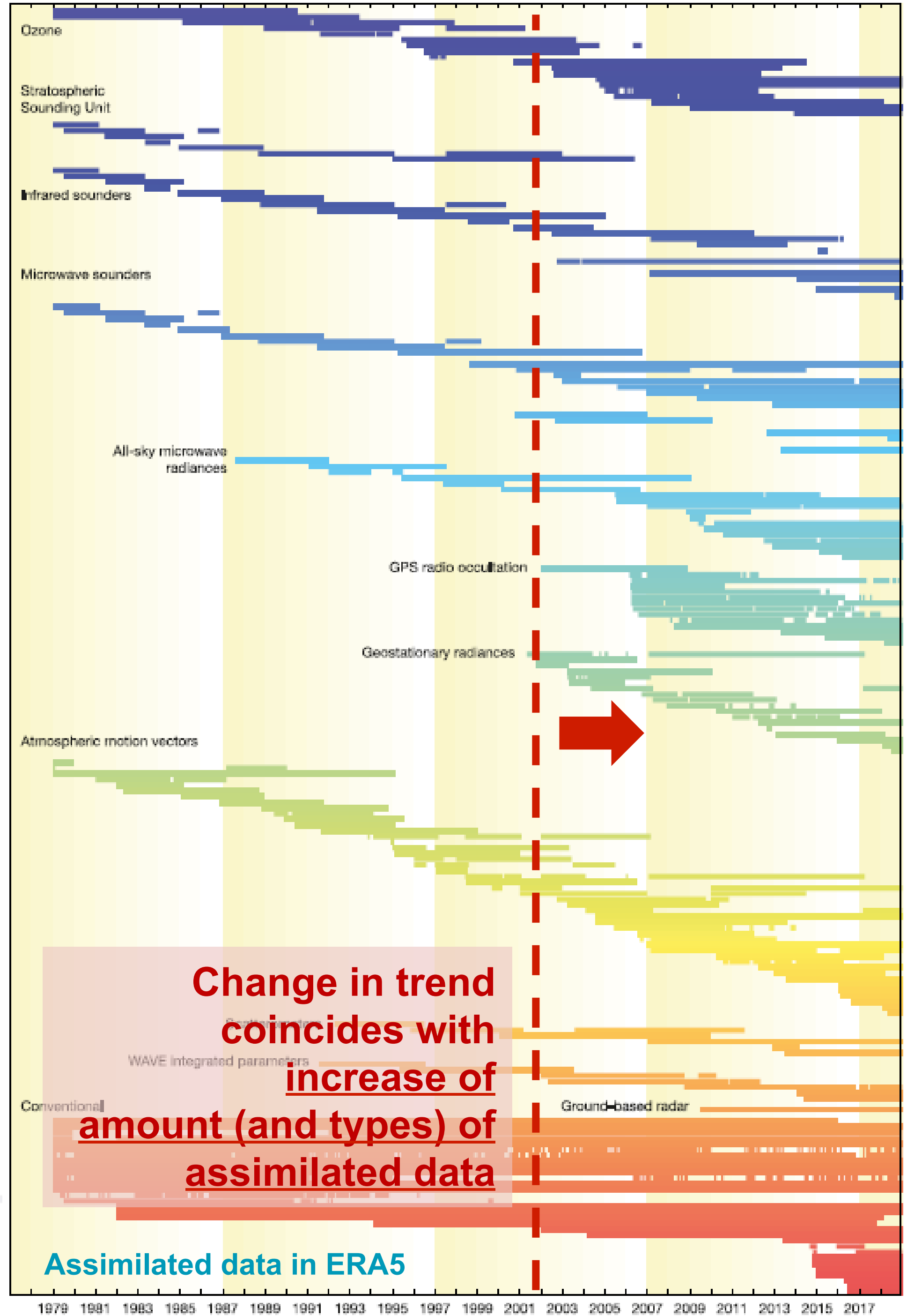


(Sharmar et al, 2020)

GLOBAL MEAN EVOLUTION VS. ASSIMILATED DATA

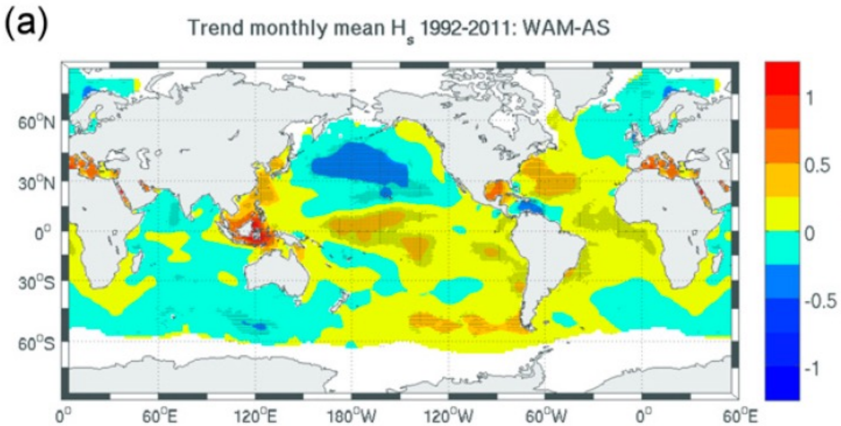
Global annual mean (+ 5-yr running mean)



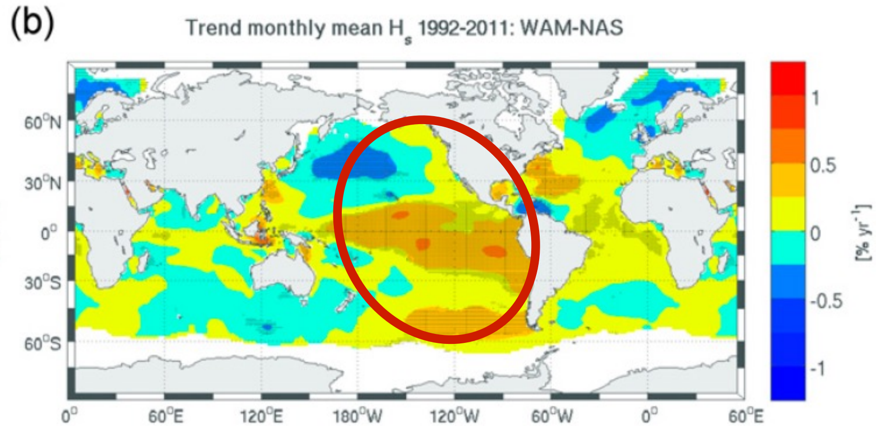


WAVE ALTIMETER ASSIMILATION ALSO AFFECTS TRENDS

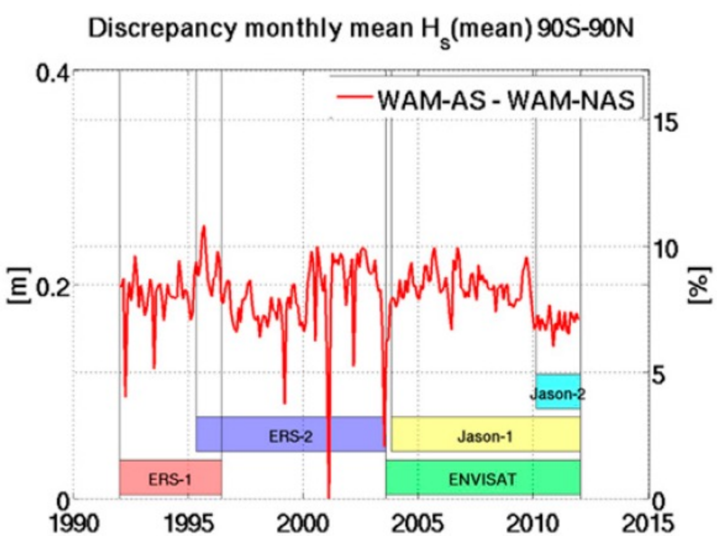
Two stand alone runs forced by **ERA-I** winds with and without **<u>wave altimeter assimilation</u>**

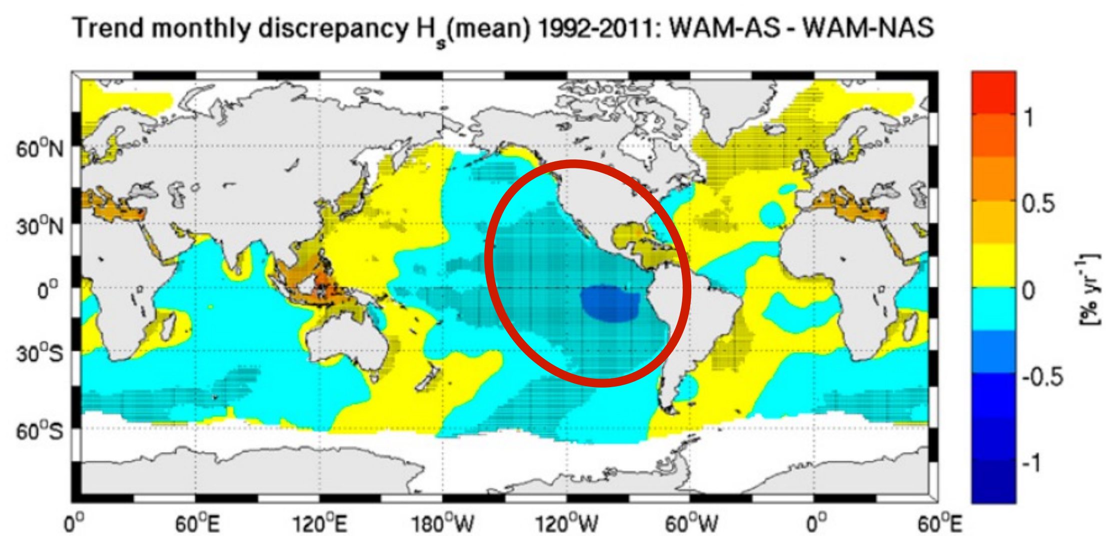


ERA-I wave altimeter assimilation



(Aarnes et al, 2015) ERA-I <u>no</u> wave altimeter assimilation

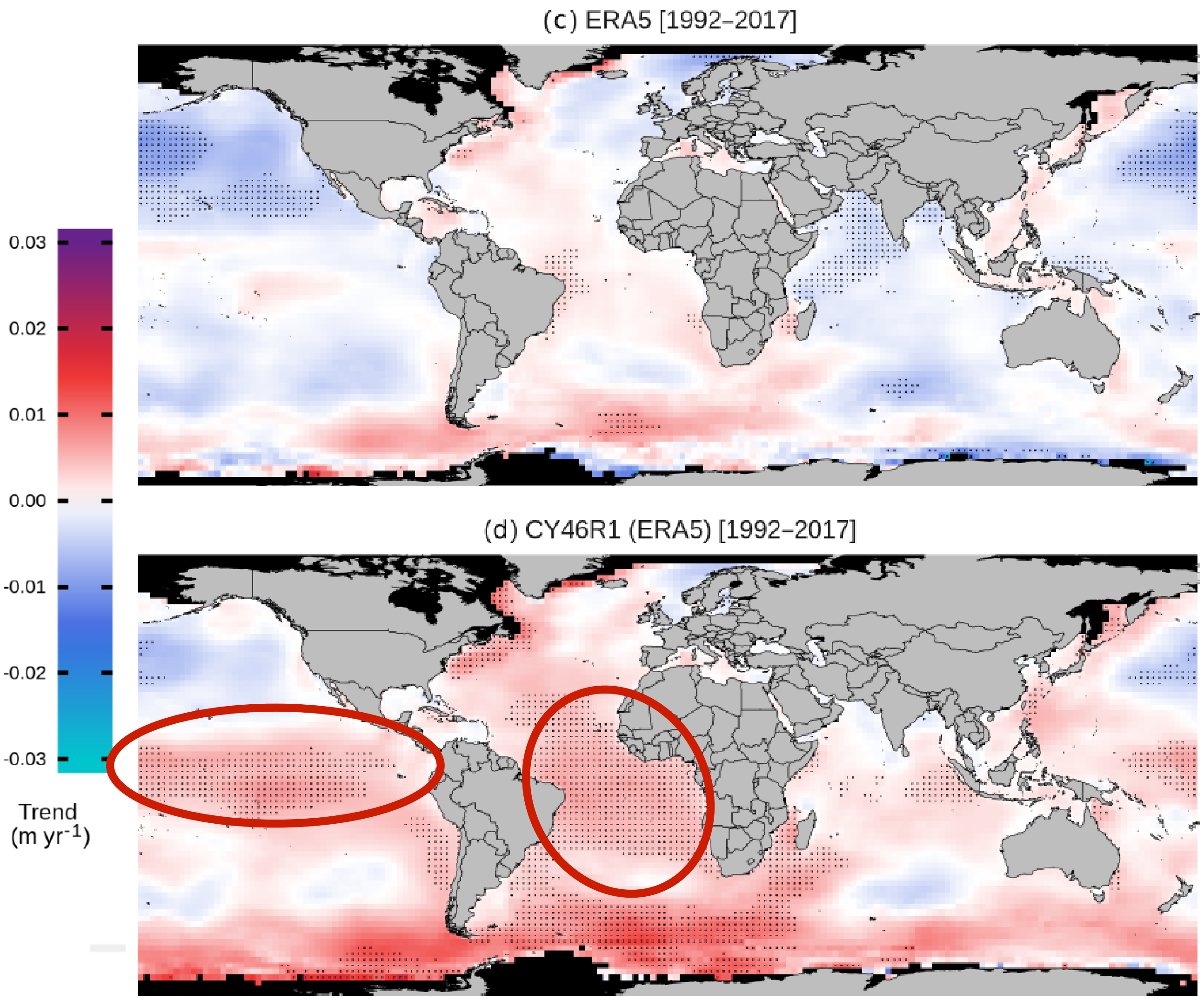




<u>Wave altimeter assimilation</u> <u>leads to a</u> **<u>decrease of the trend</u>** <u>in the</u> **<u>Eastern Pacific</u>**

WAVE ALTIMETER ASSIMILATION ALSO AFFECTS TRENDS

More recent results: **ERA5** wave reanalysis vs stand alone run forced by ERA5 winds without wave altimeter assimilation (also with improved physics, resolution and bathymetry)



ERA5 wave altimeter assimilation

Annual mean SWH

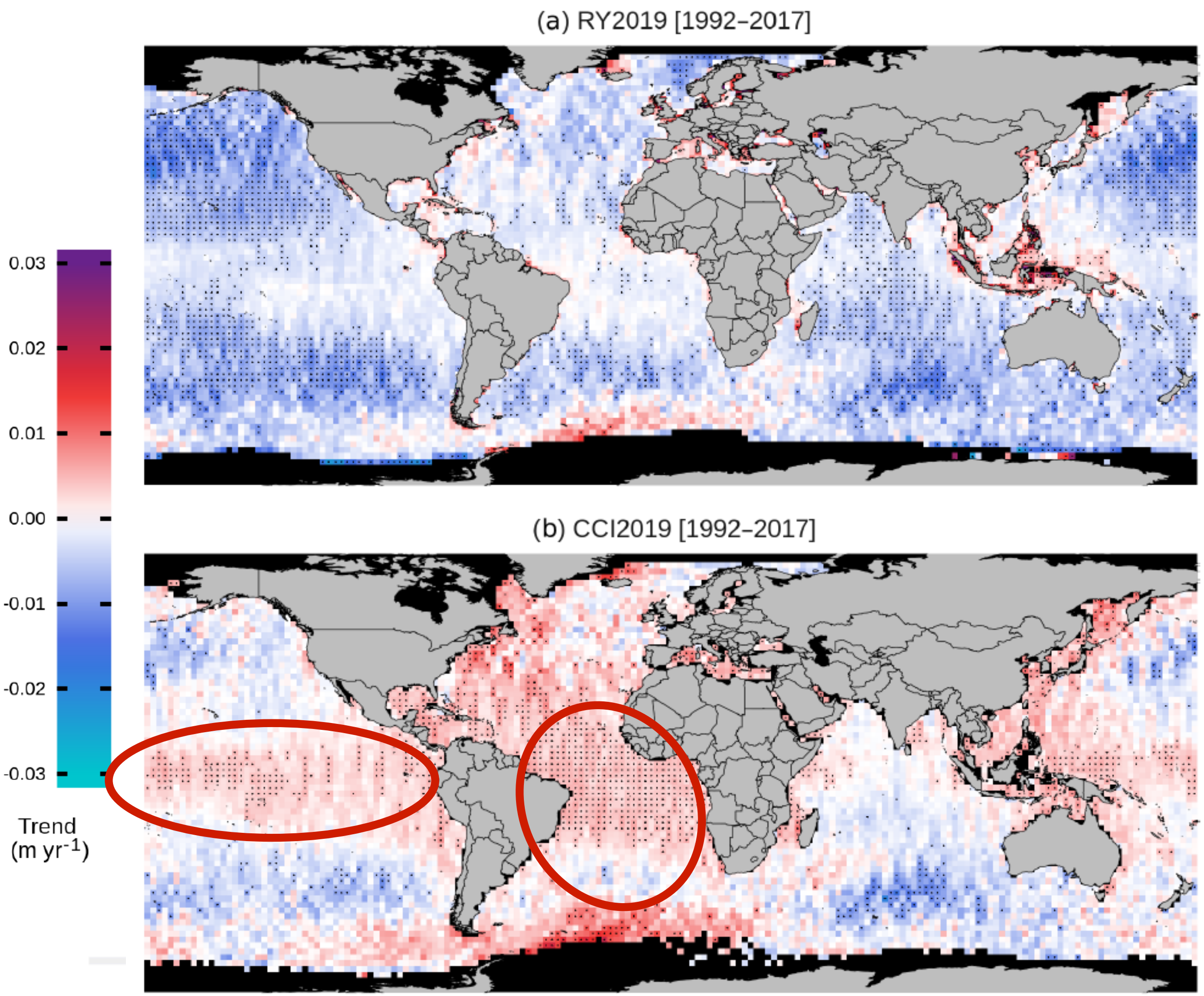
Similarly to what is seen with ERA-I, ERA5-driven simulations also show <u>larger trends when wave altimeter assimilation is **not** considered</u>

Annual mean SWH

ERA5 <u>no</u> wave altimeter assimilation

(Dodet et al, 2020; Timmermans et al, 2020)

DISCREPANCIES IN WAVE ALTIMETER TRENDS

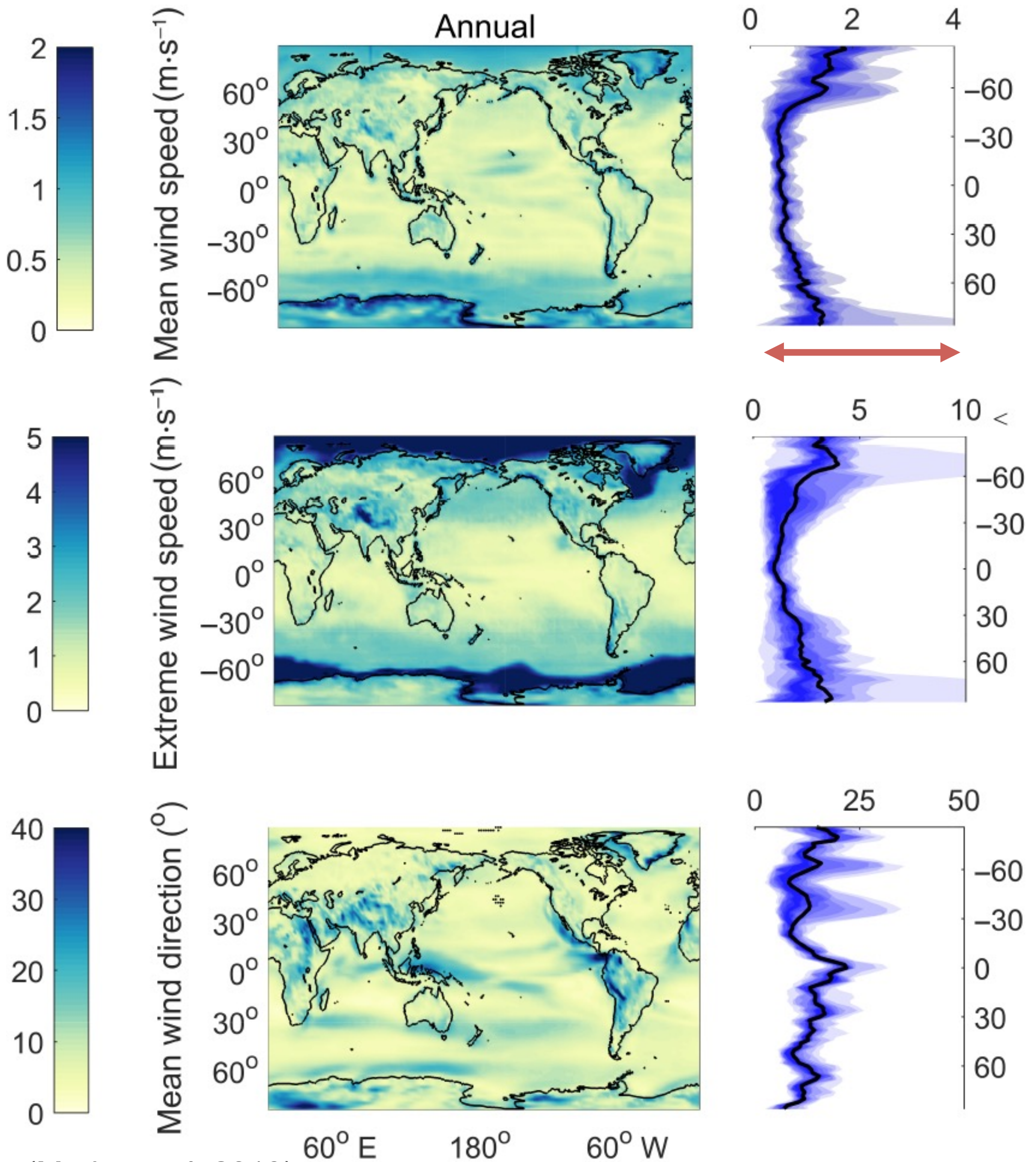


(Dodet et al, 2020)

Annual mean SWH

Differences in altimeter data **post-processing** can lead **to differences in the trends**

UNCERTAINTY IN WIND DATA WITHOUT ASSIMILATION: CMIP5 WIND



(Morim et al, 2019)

Inter-model uncertainty (sd of bias, ref: ERA-I)

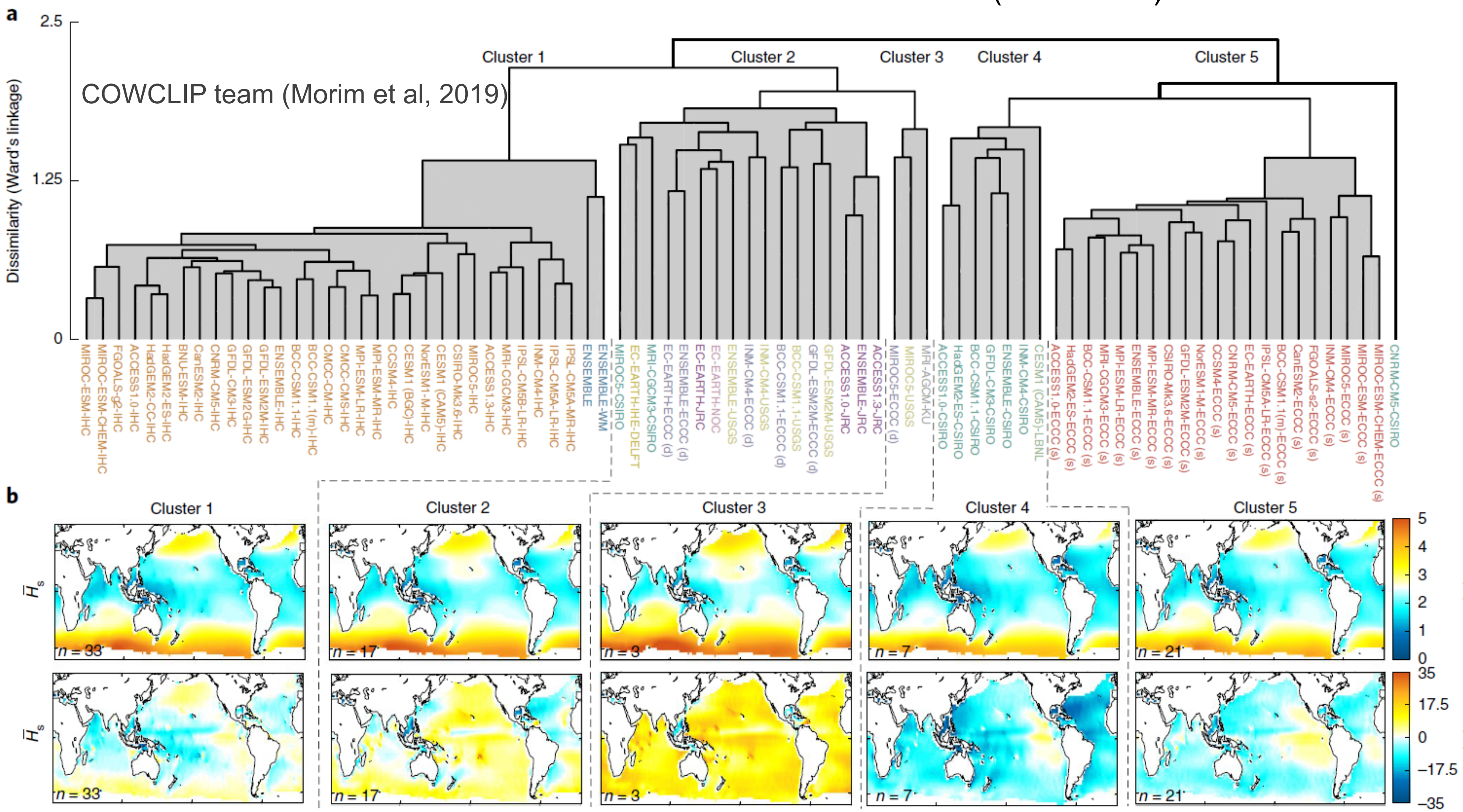
Historical period 1981-2000

Large uncertainty in extreme winds at high latitudes

Uncertainty in wind direction in the tropics

WAVE “DOWNSCALING”/MODELLING UNCERTAINTY

CMIP5-driven historical simulations of annual mean SWH (1979-2004)



Historical CMIP5 simulations **roughly cluster by wave downscaling method (which might or might not include bias calibration).**

However, when look at **projected changes, model variability plays a larger role.**

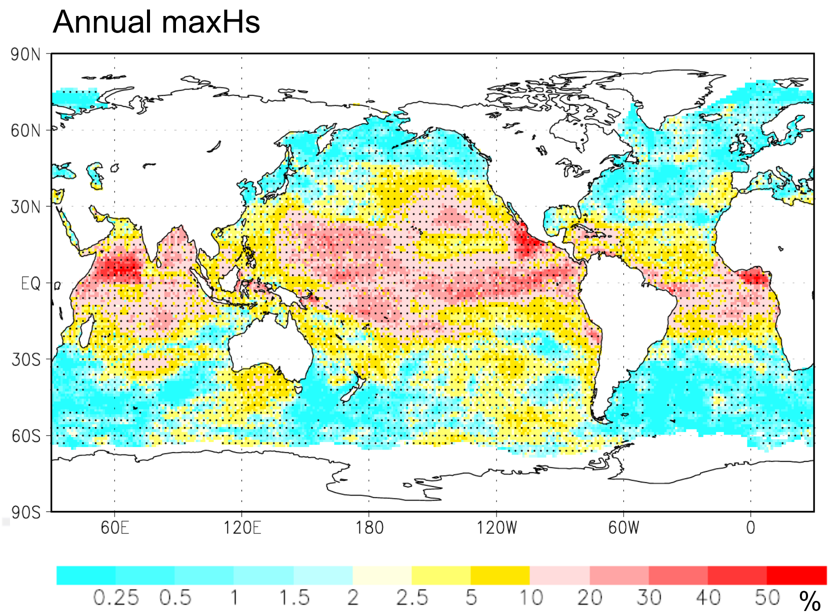
TREND ASSESSMENT IS ALSO CONFOUNDED WITH INTERNAL CLIMATE VARIABILITY

SOUSEI: first large wave ensemble 1951-2010 (99 runs)

Statistical modelling calibrated with ERA-I (relationship between SLP and SWH)

- ✓ Better investigate the role of internal climate variability:
  - ✓ Is the forcing signal in trend significant?
  - ✓ What is the minimum ensemble size to account for most of the variability?

- ✓ Larger sample of extremes: no need to use parameterized distributions for EVA

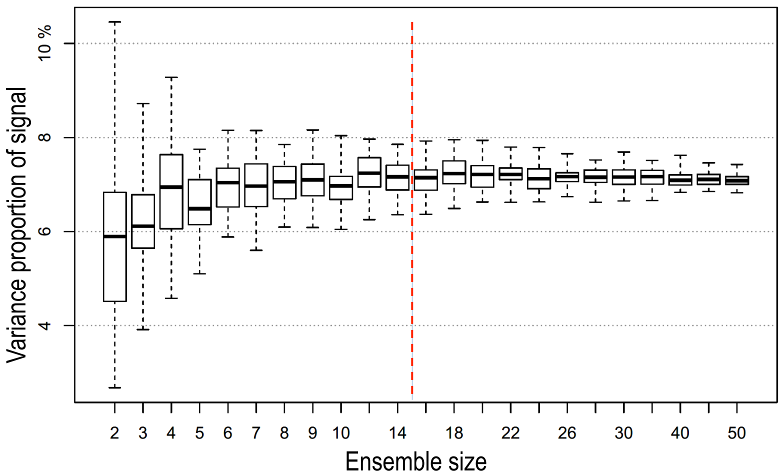


Forcing signal in moving 20-year trends

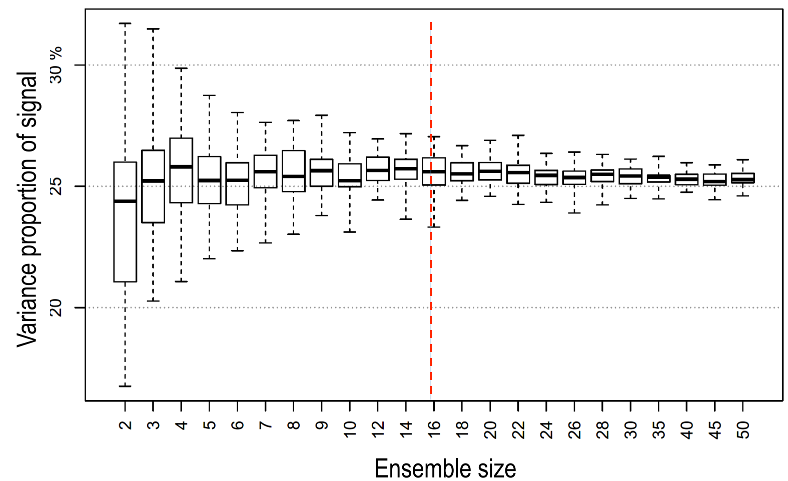
The forcing signal in trend is significant almost globally and is much stronger in the lower latitudes than in the high latitudes.

MINIMUM ENSEMBLE SIZE

Global mean for Ann. maxHs

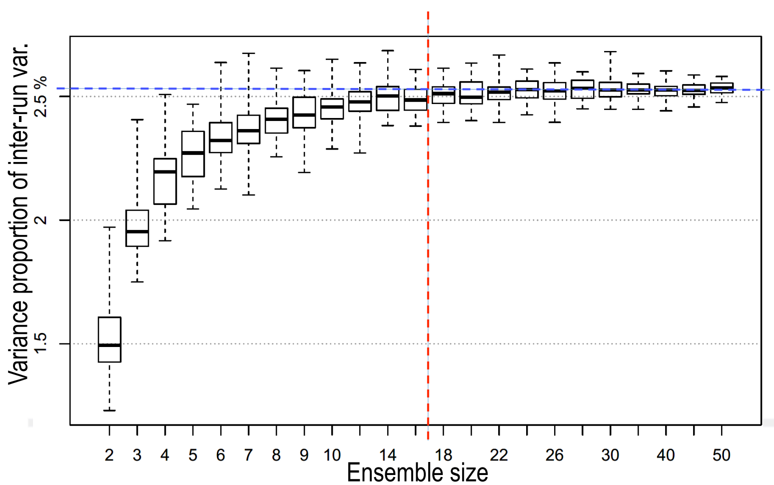


Global mean for Ann avgHs

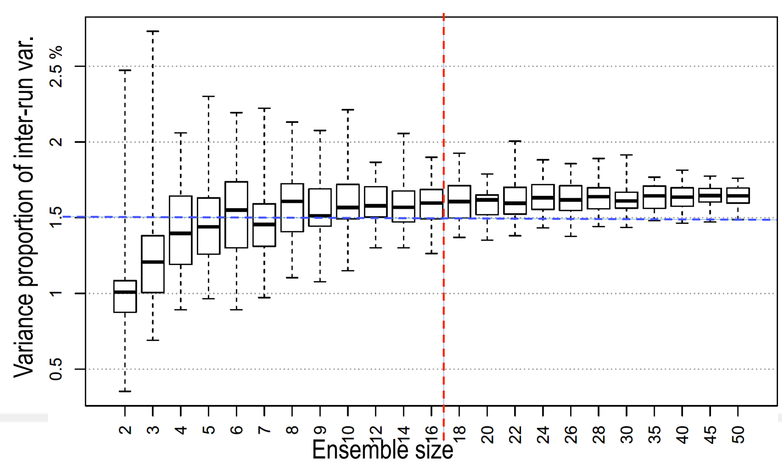


<u>Climate signal:</u> the uncertainty range is much narrower and more stable for ensembles of size bigger than 16

Global mean for Ann. maxHs



Global mean for Ann avgHs

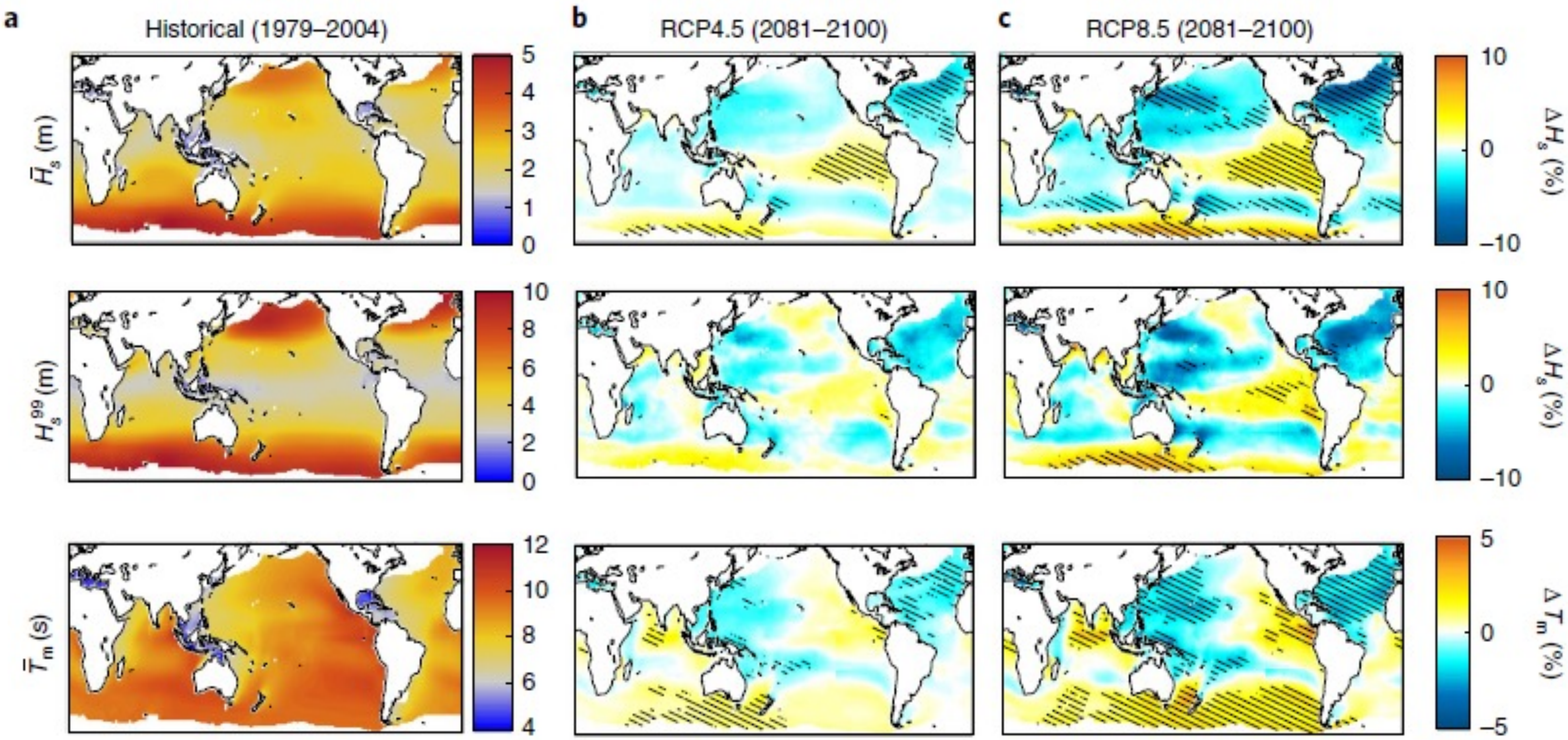


<u>Similar results for inter-run variability:</u> it converges for ensembles of size bigger than 16

FUTURE PROJECTIONS

FUTURE PROJECTIONS

Projected changes in integrated wave parameters



COWCLIP team (Morim et al, 2019) Changes in % as they are less affected by model resolution

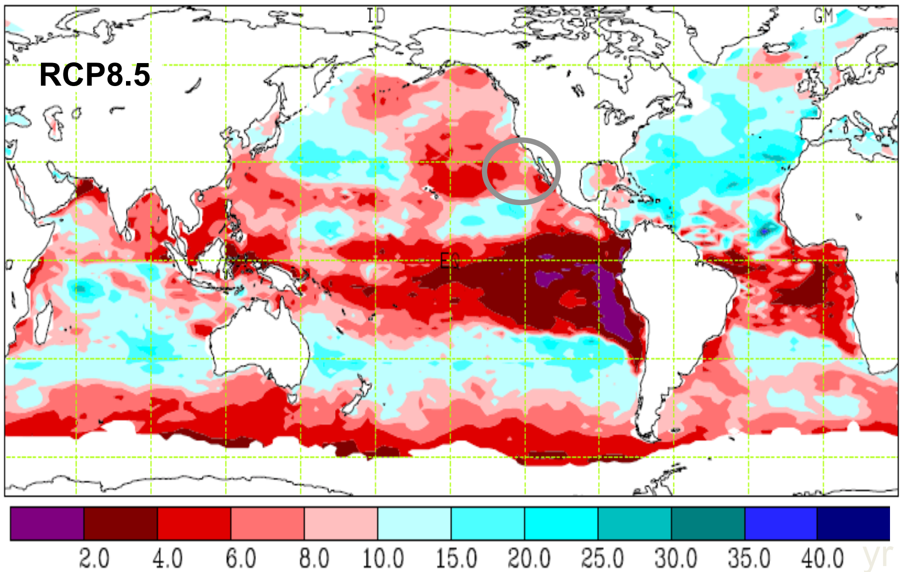
<u>Mean SWH:</u> Increase in SP and Southern Ocean, decrease in NA and NWP

<u>Extreme SWH</u>: Similar pattern but showing non-statistical increase in NP

<u>Mean period</u>: similar as mean SWH but extended areas of increase: swell contribution

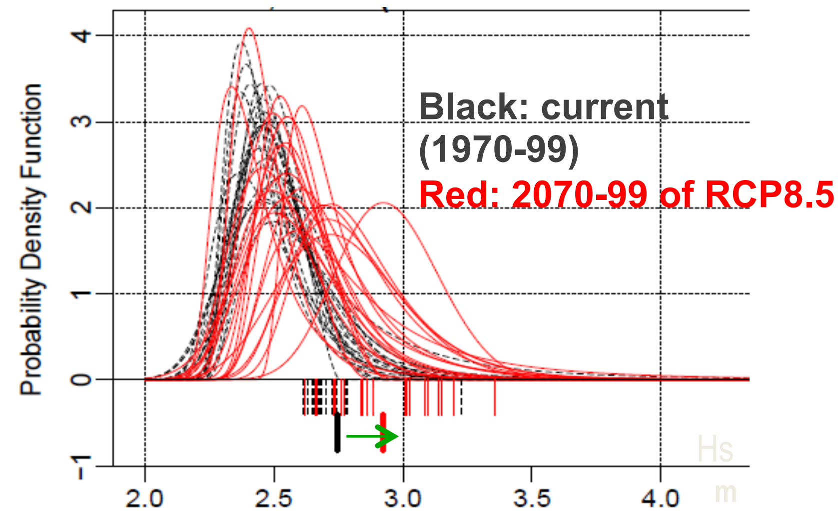
FUTURE: INCREASE IN VARIABILITY

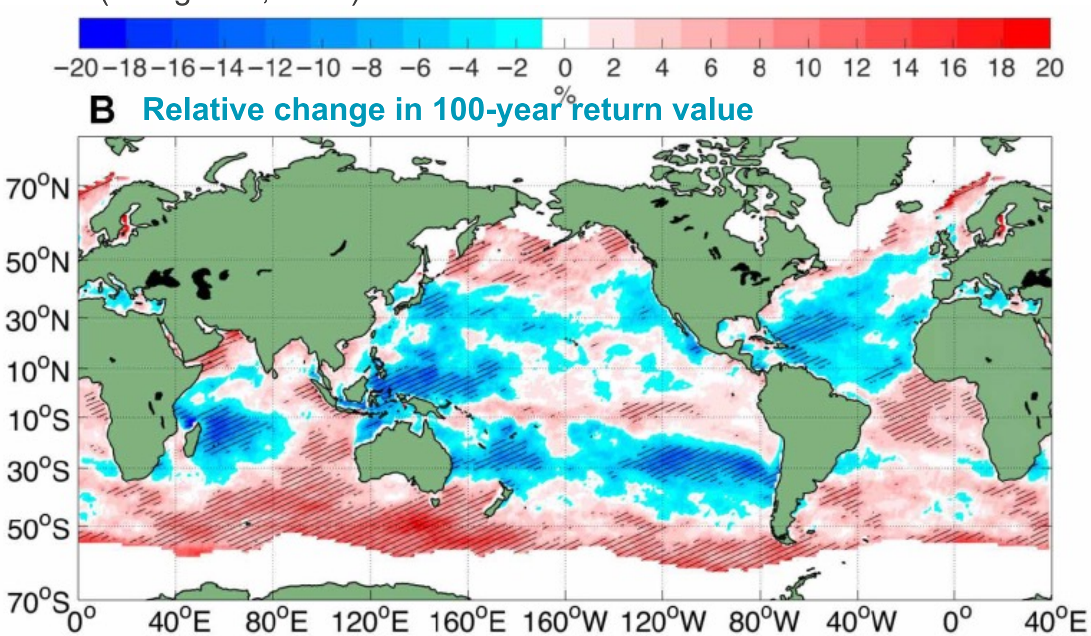
Future return period of historical 10-year return value



(Wang et al, 2015)

GEV distributions for Point (23N, 112E) – west of Cabo San Lucas





(Meucci et al, 2020)

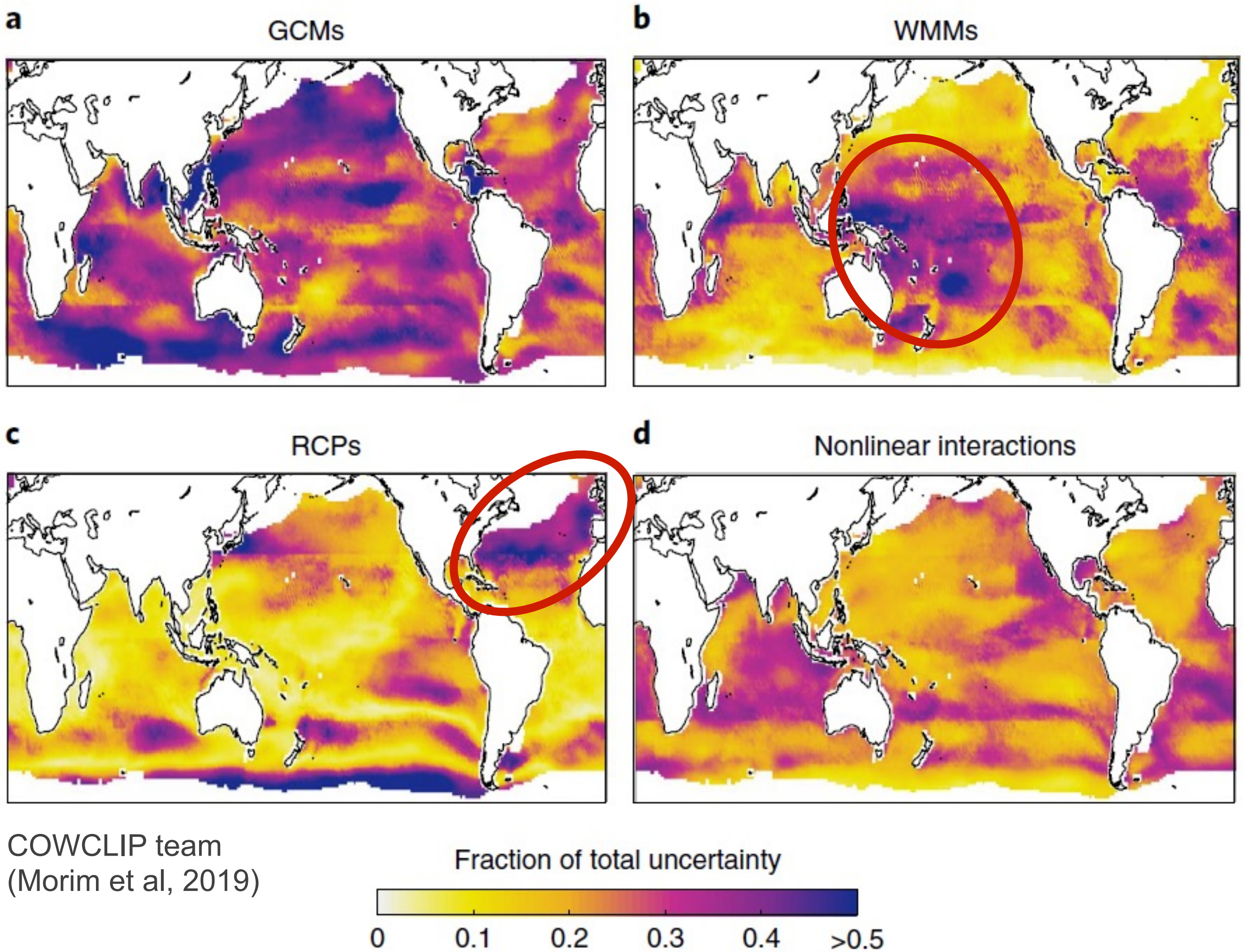
NP: Increase of most extreme SWH while the mean shows (statistically insignificant) decrease

Such **increase in extremes** seems to be caused by an **increase in variability** (wider pdf).

Increase in variability is seen in many areas.

FUTURE PROJECTIONS: FORCING UNCERTAINTY

Uncertainty in projected changes in the annual mean SWH (2081-2100)



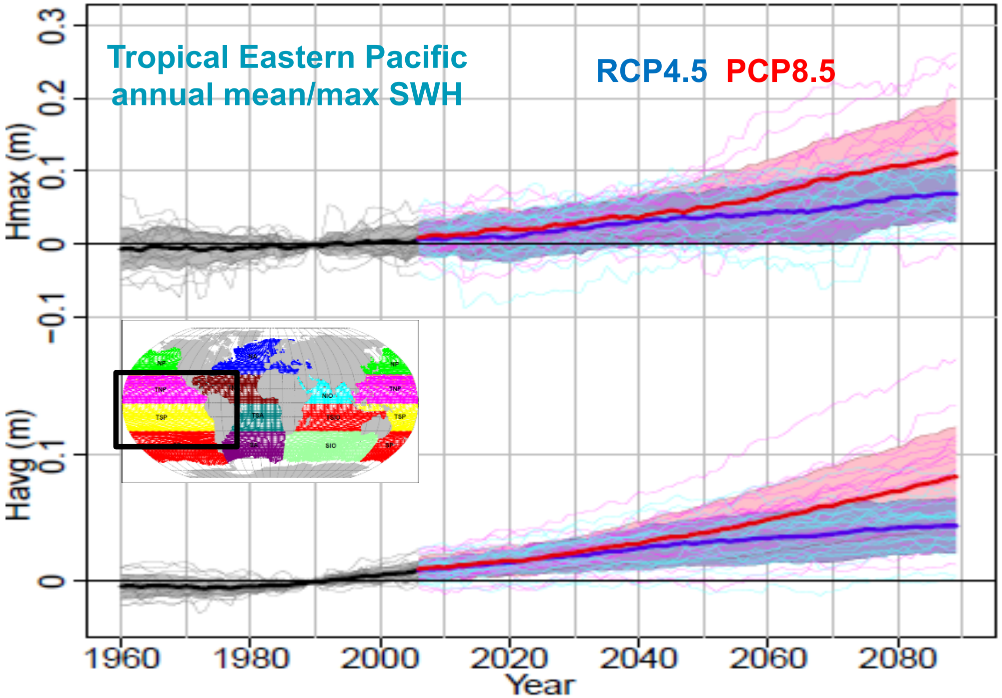
COWCLIP team
(Morim et al, 2019)

<u>Model variability has the largest contribution</u> in general but there are **<u>regional differences</u>**.
In the North Atlantic, RCPs contributes the most to uncertainty; in the tropics the wave downscaling method is more relevant factor that contributes to uncertainty in the projected changes in the annual mean SWH.

FORCING UNCERTAINTY OVER TIME

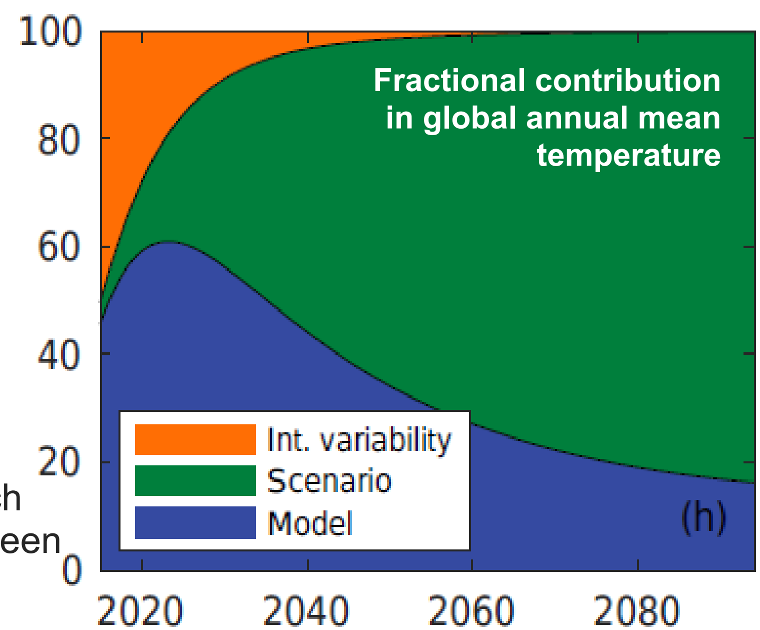
The fractional contribution of individual sources to total uncertainty is not constant over time

For example, as represented by RCP4.5 and RCP8.5, forcing uncertainty increases over time



(Wang et al, 2015)

This has been quantified in more detail for other climate variables such as temperature or precipitation



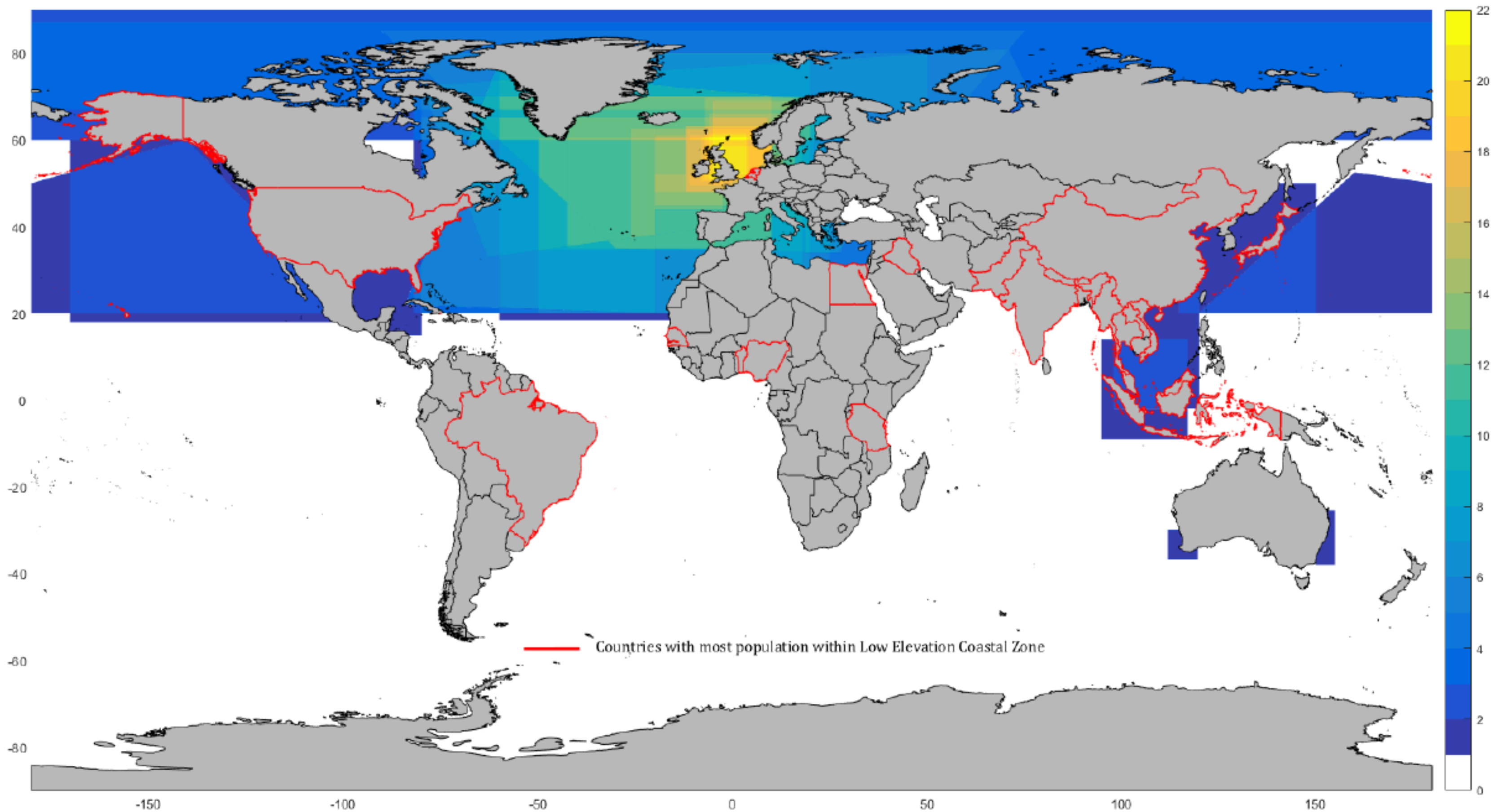
(Lenher et al 2020)

Here the wave downscaling method is the same. Therefore, each red/blue band illustrates model uncertainty, while deviation between bold lines illustrate scenario uncertainty

REGIONAL SCALE

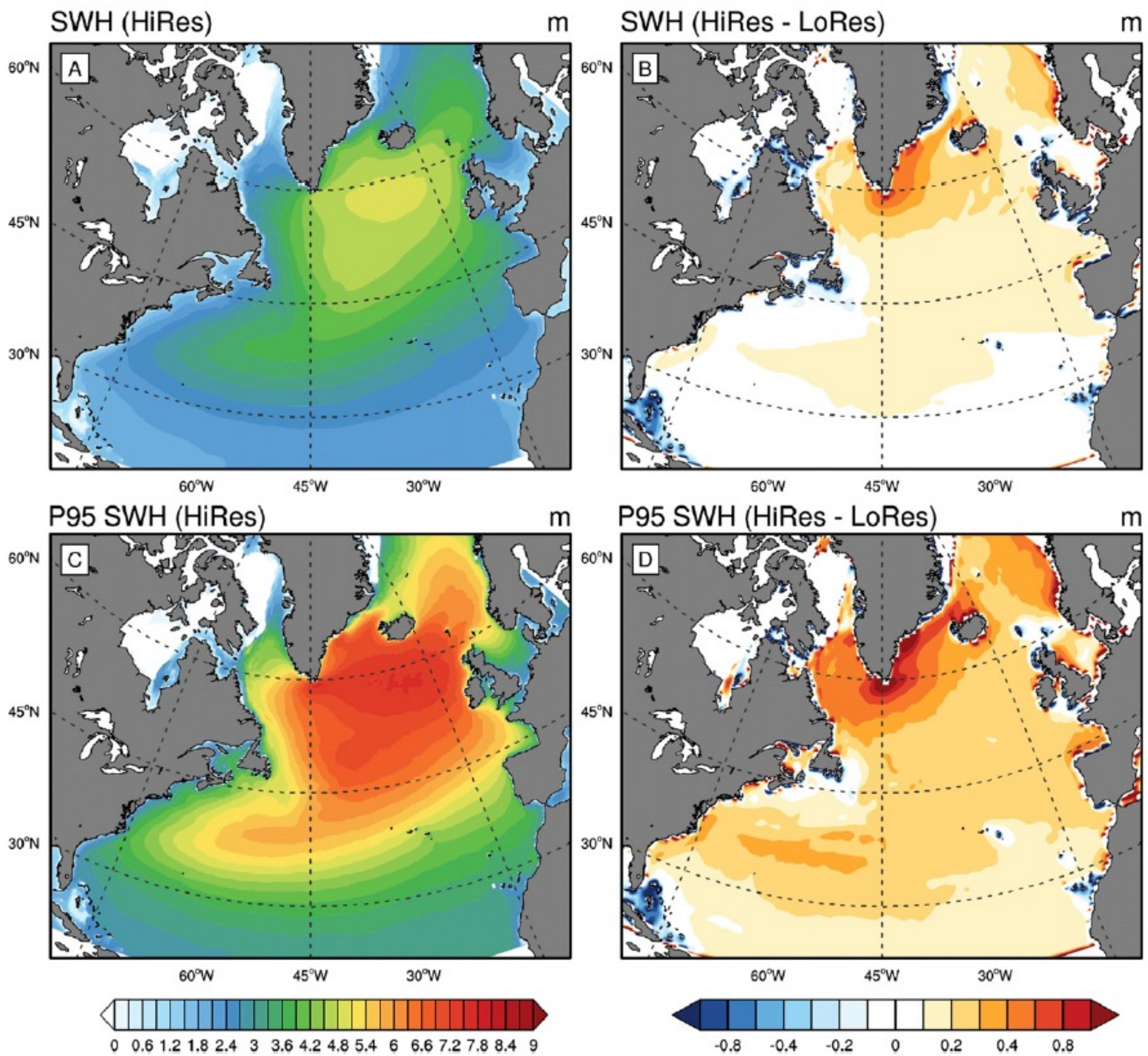
HETEROGENEOUS COVERAGE OF REGIONAL STUDIES OF WAVE PROJECTIONS

Projected changes at regional scale mostly cover the North Hemisphere.



(Morim et al, 2018)

NORTH ATLANTIC: WIND RESOLUTION



(Gavrikov et al 2020)

2 **wave hindcasts** forced by:

70 km vs **14 km winds**

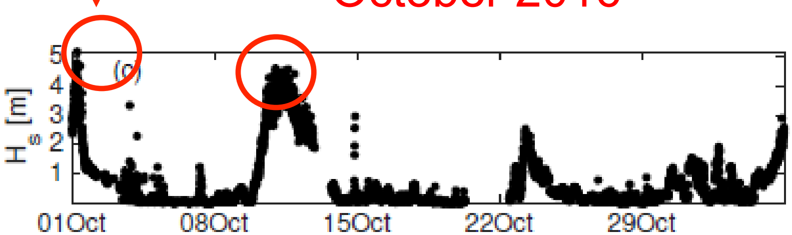
Up to 20% differences in wind speeds along Greenland coast

Higher resolution leads to **better representation of # cyclones,** which affects the assessment of wave extremes

The assessment of trends are less affected by model resolution

ARCTIC REGION: SEA ICE RETREAT

October 2016



(Thomson et al 2018)

How does sea ice retreat might affect waves?

New water areas: **new areas for waves**

Widening of existing water areas:

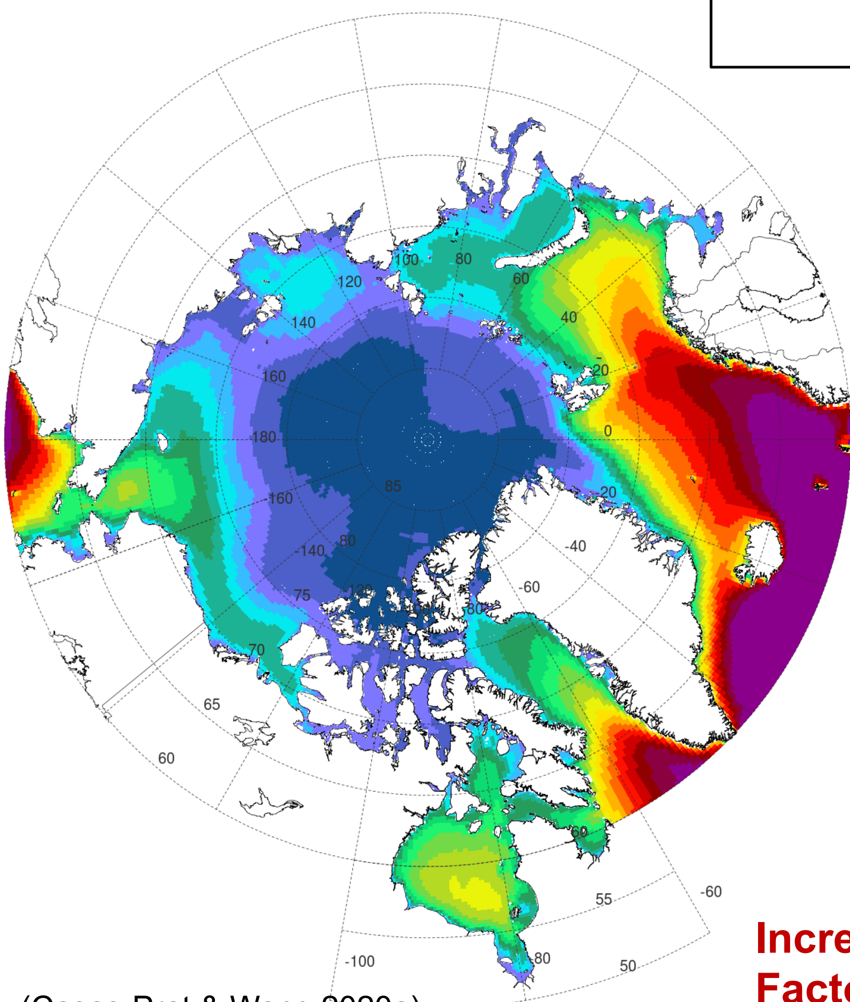
- Larger "fetch" contributes to **wave growth**
- Larger water surface: **increases chance of strong winds** to occur over water areas
- Longer ice-free season: waves become more exposed to fall with **more extreme winds**.
- Development of **swells** (remote waves)

Wind-ice feedback processes: possible **wind intensification** due to sea ice retreat

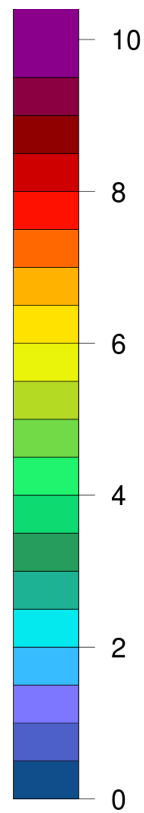
Wave-ice feedback processes: **positive feedback**

ROBUST INCREASE IN WAVE EXTREMES

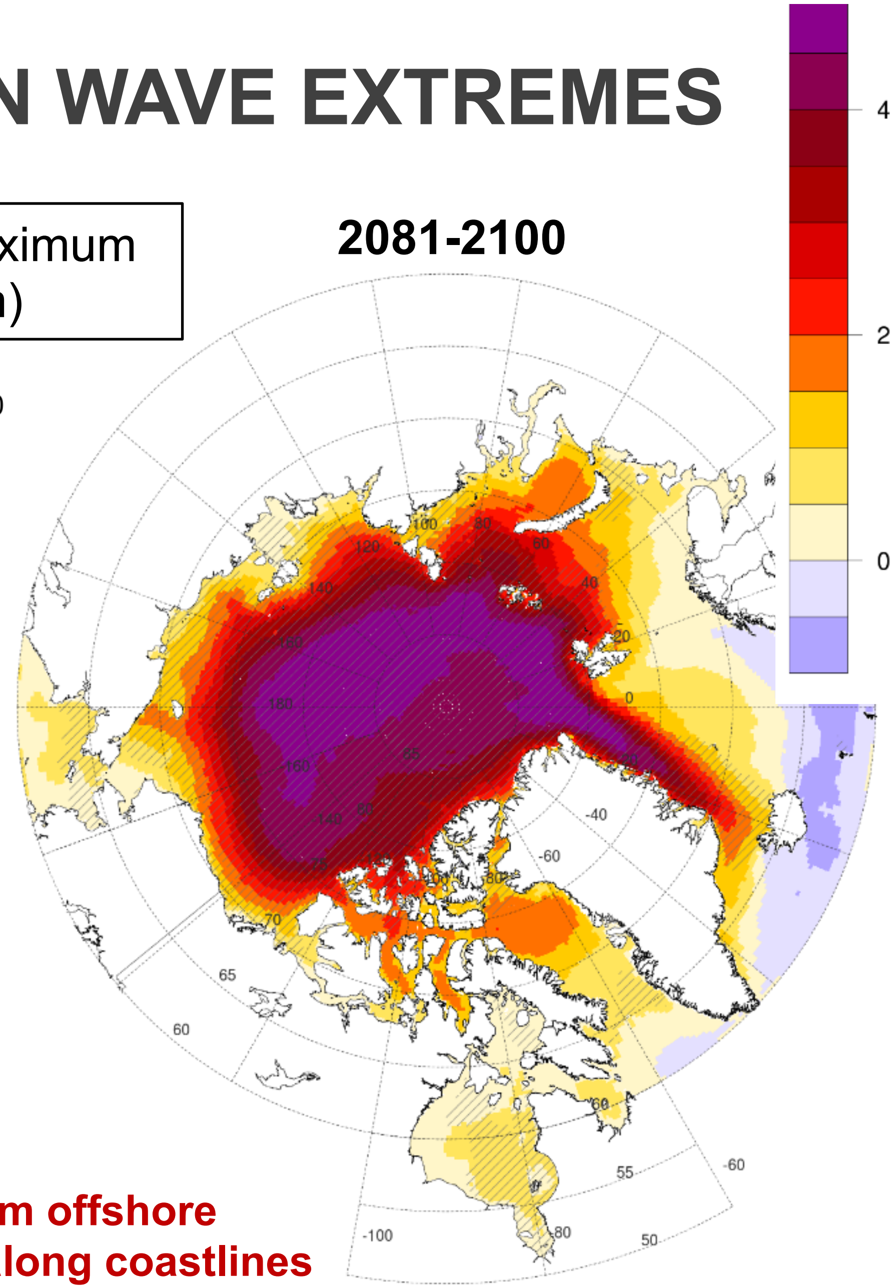
1979-2005



Annual maximum Hs (m)



2081-2100

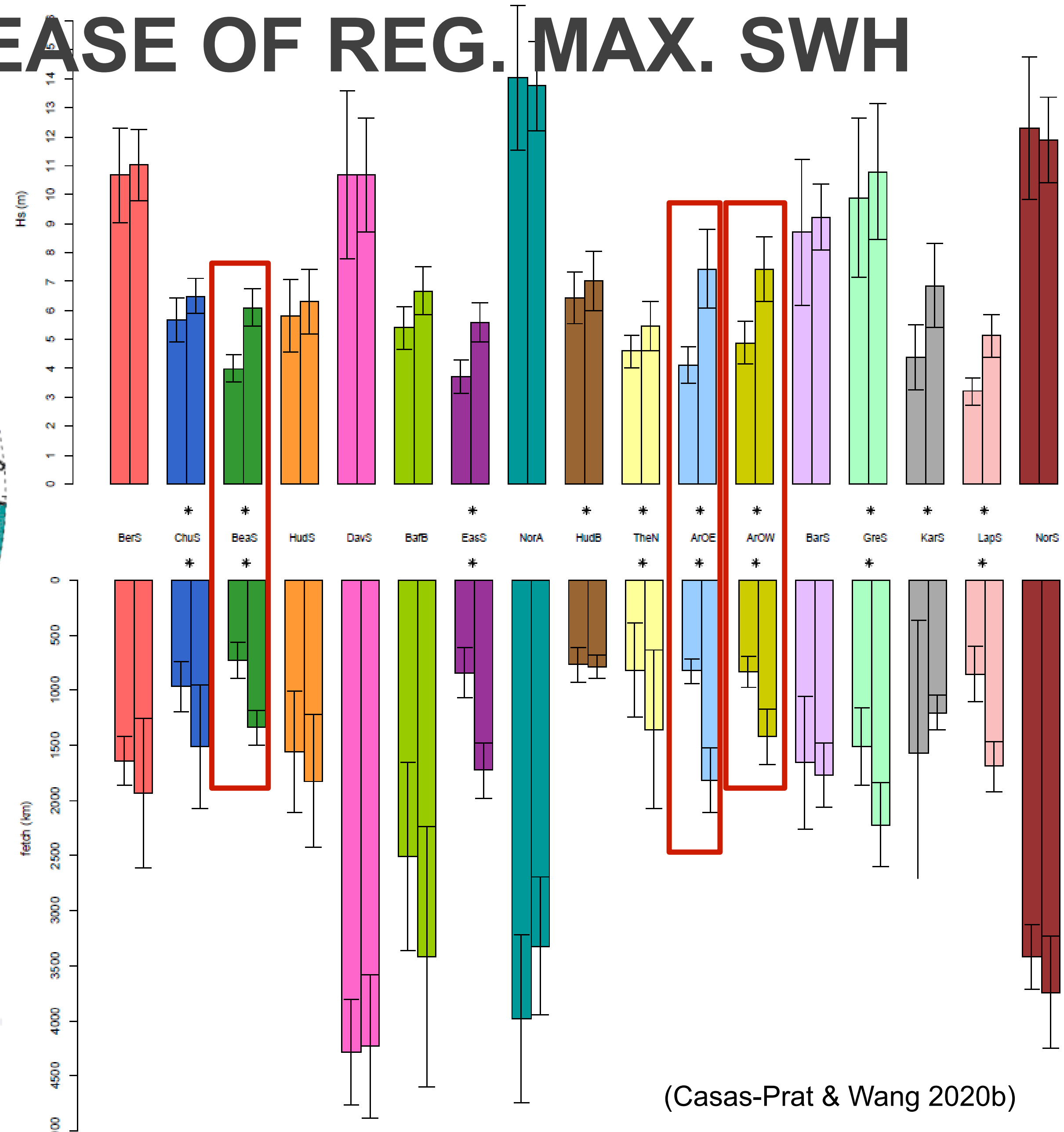


Increase <6m offshore
Factor 2-3 along coastlines

(Casas-Prat & Wang 2020a)

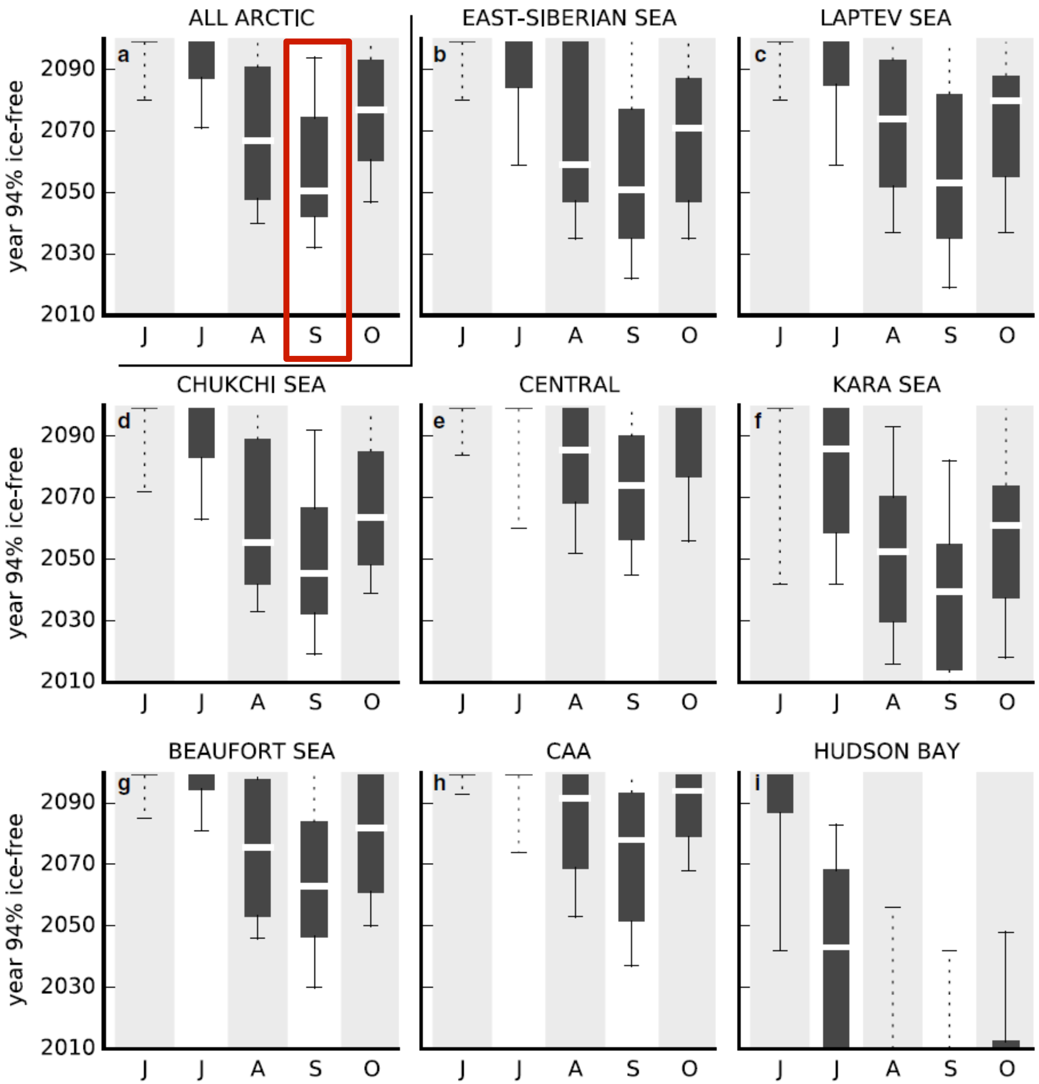
5-member ensemble shows **robust signal in projected changes** in the annual max. SWH

SEA ICE RETREAT PLAYS A LARGE ROLE IN THE INCREASE OF REG. MAX. SWH



(Casas-Prat & Wang 2020b)

FUTURE SEA ICE: LARGE UNCERTAINTY

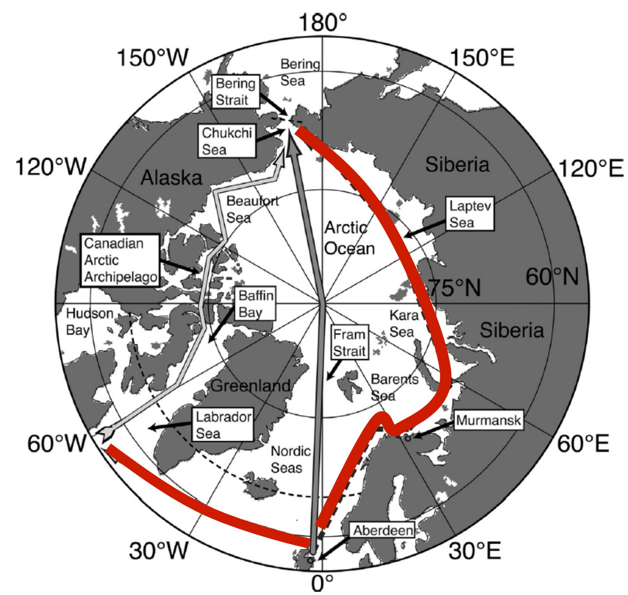


CMIP5 sea ice simulations (Laliberte et al, 2016)

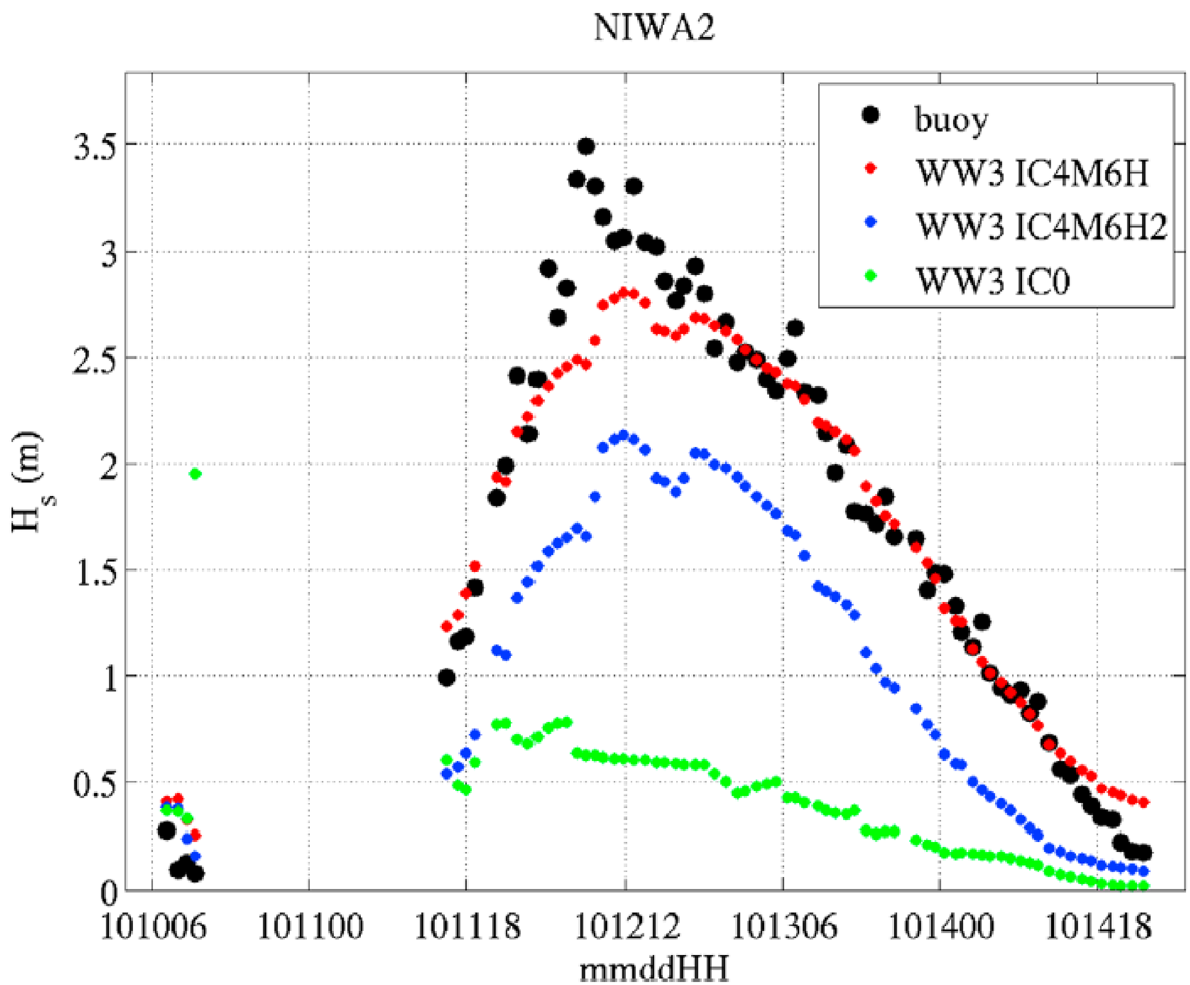
At high latitudes, sea ice coverage is an additional significant factor of uncertainty of wave climate

Arctic Ocean projected to become ice-free by 2045-2070 (in September).

Recent study (Guarino et al 2020) with improved physics:
Arctic could become ice free by 2035.



ICE – WAVE PARAMETERIZATION UNCERTAINTY



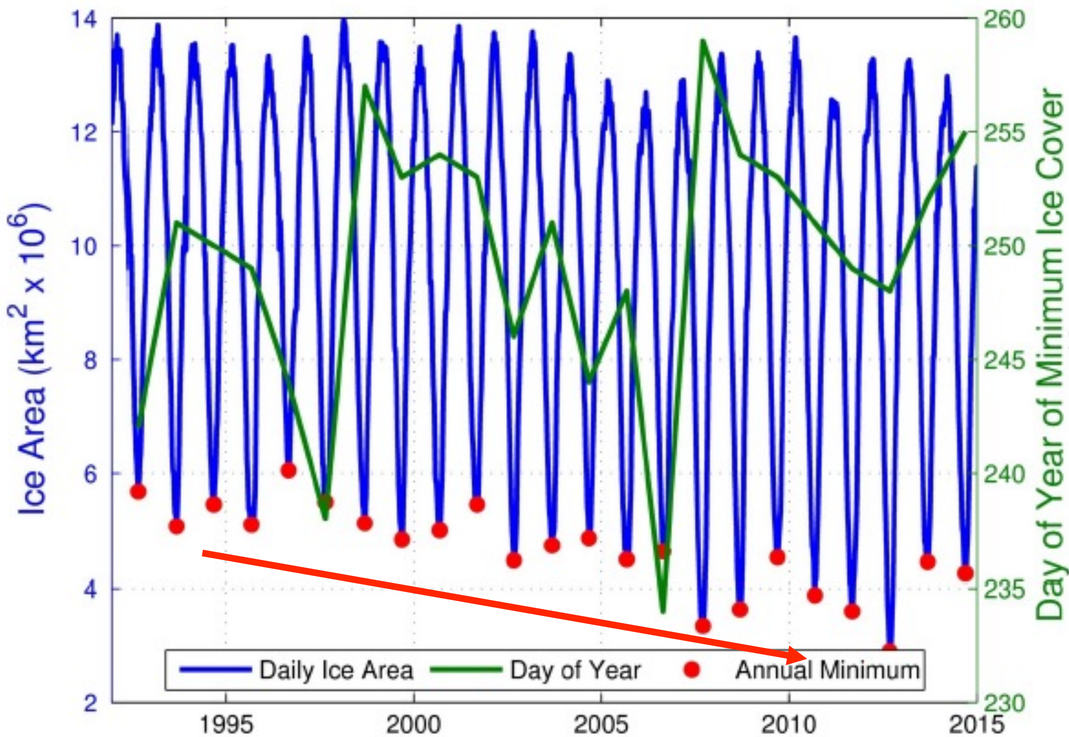
Model parameterization of ice-wave interactions can lead to 80% **discrepancies during storms**

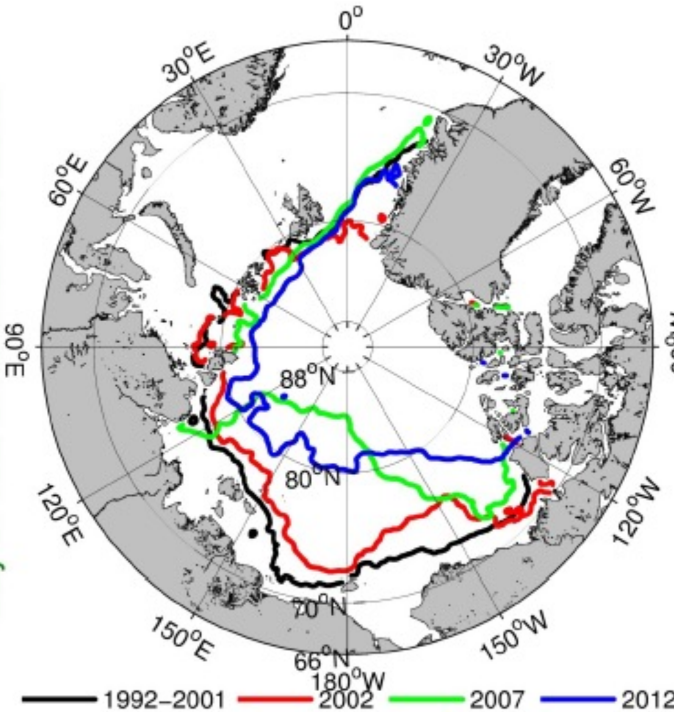
Also, wave-induced ice **breaking/melting is not included** in current climate projections

Current sea ice projections might underestimate sea ice retreat

(Thomson et al, 2018)

SEA ICE: LARGE INTER-ANNUAL VAR





(Stopa, 2016)

Moreover, despite the **steady sea ice** retreat trend, sea ice cover presents **large inter-annual variability**

Large inter-annual variability: more challenging to discern long trend trends from inter-annual/decadal variability in “short” samples.

MORE REGIONAL ANALYSIS ALSO SHOW STEADY SEA ICE RETREAT AND INCREASE IN SWH

Beaufort–Chukchi Seas

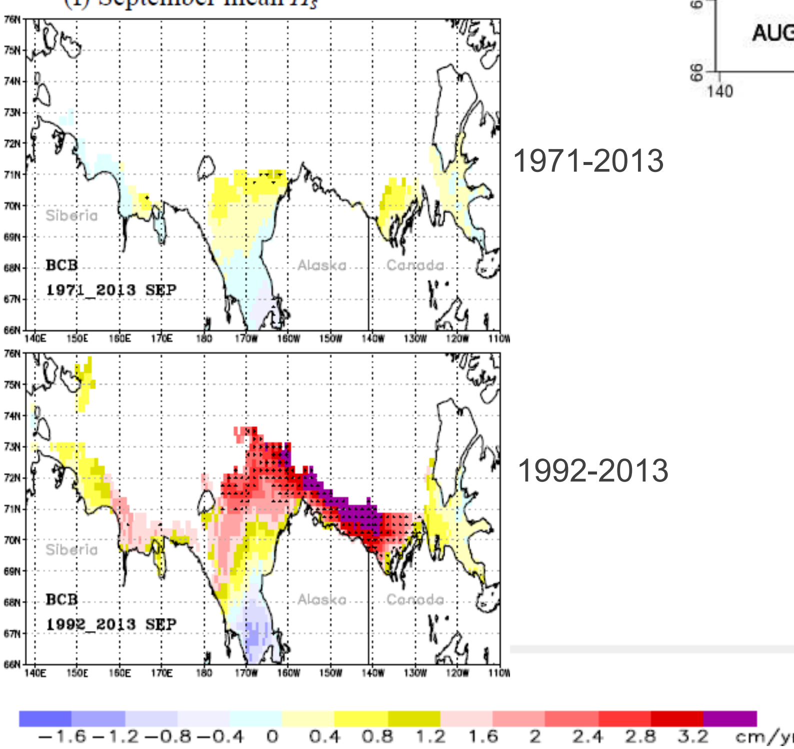
(Wang et al, 2015b)

Davis Straight-Baffin Bay

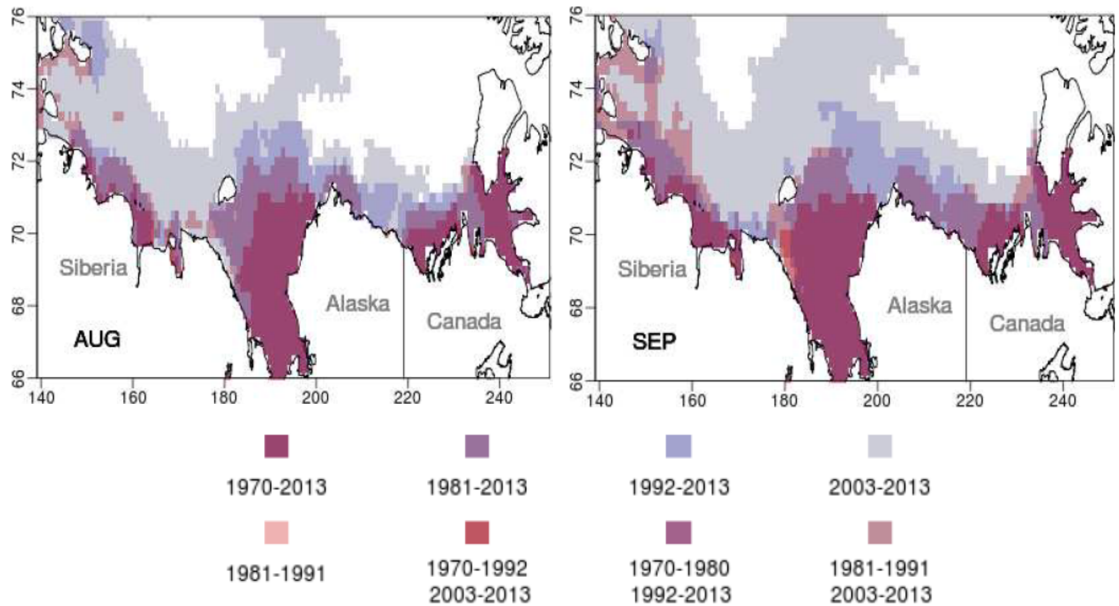
(Wang et al, in revision)

September mean SWH trend

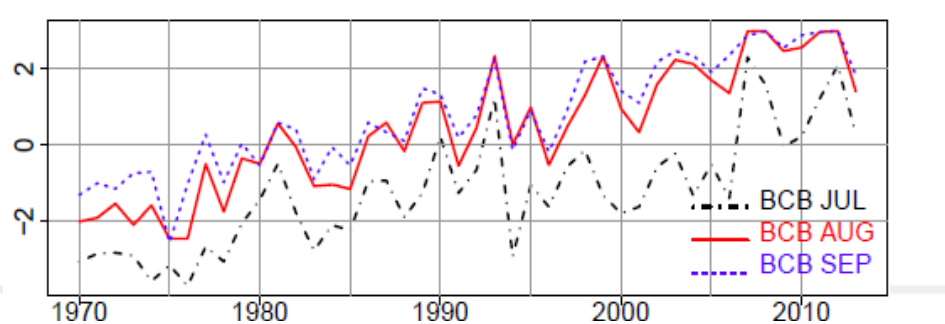
(f) September mean H_s



Mean area of open water:



Normalized time series of the area of open water:



HOMOGENEITY ISSUES: WAY FORWARD

Thoughts/tools for addressing data homogeneity issues

- Wave observations are of short record length and have poor spatial coverage, which make data homogenization particularly challenging.
- Homogenization methods that rely heavily on high observing network density will not work for wave data homogenization. We need a bit innovation here.
- Our data homogenization software RHtests package is freely available at https://github.com/ECCC-CDAS, which includes a method that **doesn't need to use reference series**, can also **<u>test for both documented and undocumented changepoints</u>**.
- **Metadata is critical** for data homogenization, e.g. metadata for reanalysis:

The NCEP1 reanalysis:

The basic radiances are available for the following periods:

- SIRS[a] IR sounders — Apr 1969–Apr 1971
- SIRS on early NMC tapes (not radiances) — Nov 1969–Sept 1992
- VTPR[a] IR sounders — Nov 1972–Feb 1979
- TOVS sounders (HIRS, MSU, SSU)[a] — Nov 1978–present
- HIRS data test system — Aug 1975–Mar 1976

The ERA40 reanalysis

2965

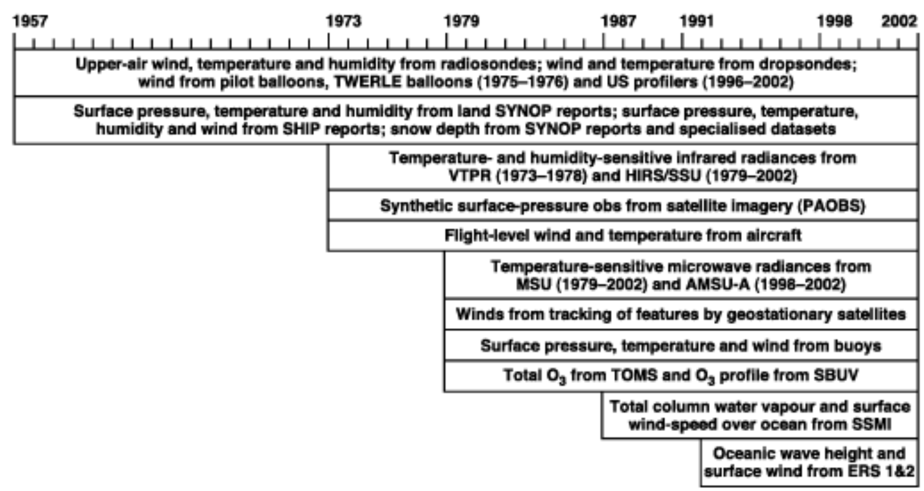


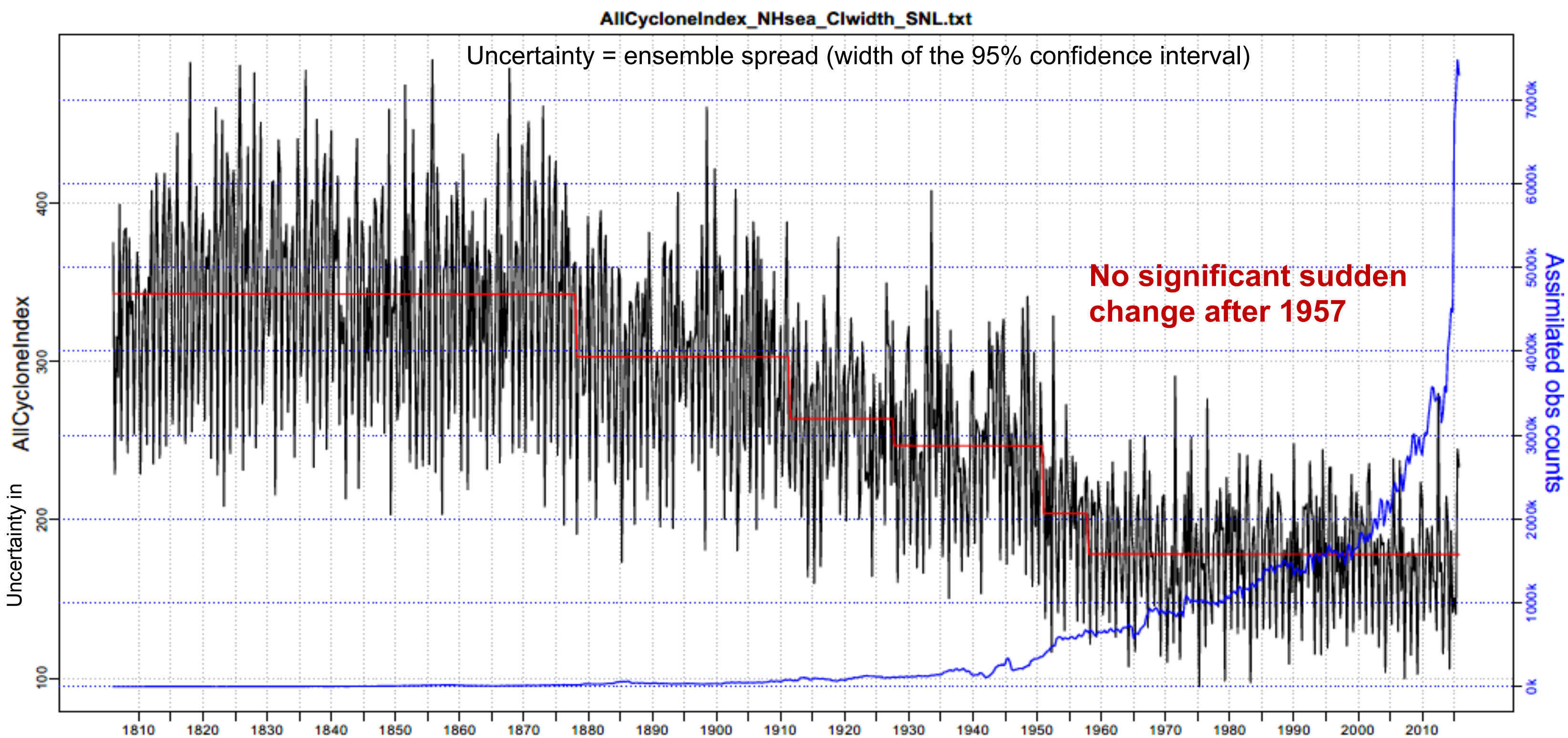
Figure 1. Chronology of types of observations assimilated in ERA-40 from 1957 to 2002. (See appendix A for acronyms.)

- **Time series of seasonal counts of assimilated observations in each area (see next slide)**

- Our next step:

use Twentieth **Century Reanalysis (20CR)-based historical wave simulations** as reference to detect changepoints in modern wave reanalysis, since 20CRv3 does not have data homogeneity issues in the NH sea after 1957:

NH Cyclone Index vs # assimilated observations



1 Yes 18780100 (1−1) 0.950 10.1987 (2.971−3.3796)
1 Yes 19110200 (1−1) 0.950 7.3957 (2.9286−3.3266)
1 ? 19270300 (0.9974−0.9979) 0.950 3.0780 (2.9192−3.3106)
1 Yes 19500400 (1−1) 0.950 5.7210 (2.9044−3.286)
1 Yes 19570400 (1−1) 0.950 4.3143 (2.9413−3.3494)

Thank you! Ques

❖What tests can be done with the RHtests package?

The different versions of RHtests (currently RHtestsV5) is a software package for homogenization of climate data that can be made to approximate a normal/Gaussian distribution, such as annual surface air temperature (SAT), de-seasonalized SAT, atmospheric pressure, etc..

This software allows users to perform four statistical tests:

(1) the Penalized Maximum t (PMT) test for detection of unknown changepoints (Wang et al. 2007) using a reference series (FindU.wRef);

(2) the Student t test for determining the statistical significance of known changepoints using a reference series (FindUD.wRef or StepSize.wRef);

(3) the Penalized Maximum F (PMF) test for detection of unknown changepoints (Wang 2008b) without using a reference series (FindU);

(4) the regular F test for determining the statistical significance of known changepoints without using a reference series (FindUD or StepSize).

It also allows users to convert the daily data series in the RClimDex standard format to the monthly mean series in the RHtests format.

❖ The unique features of the RHtests packages include:

(1) This and the RHtests_dlyPrcp package (presented earlier this afternoon) are the only existing data homogenization software that allows users to test both known and unknown changepoints.

(2) The RHtestsV5 allows users to make Quantile-Matching (QM) adjustments (Wang et al. 2010, Vincent et al. 2012) to daily or subdaily (up to hourly) data series for the changepoints already identified in the corresponding annual or monthly data series.

(3) The lag-1 autocorrelation in the data series being tested is accounted for, which greatly minimizes the false alarm rate (Wang 2008a);

(4) The annual cycle and lag-1 autocorrelation (and linear trend of the base series when no reference is used) are modelled in tandem while accounting for all identified shifts (Wang 2008a);

(5) Both the mean-adjusted and QM-adjusted data series, along with plots of the series and the resulting regression fit are provided in the output.

(6) users can also

   (i) choose the segment to which the base series is to be adjusted;

   (ii) choose to use the whole or part of the segments before and after a shift to estimate the QM-adjustments;

   (iii) choose the level of significance at which to conduct the tests