Projections of ocean wave heights - climate change signal and uncertainty

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- Datasets and Methodologies
- Multi-model projections of changes in SWH
- CGCM2 simulated climate change signal
- Model & forcing uncertainties
- Summary

Datasets:

Previous studies → good SWH-SLP relationship Seasonal <u>mean SLP and squared SLP gradients</u> - predictors (96x48 Gaussian grid)

-"Observations": ERA40 reanalysis for 1958-2001 (44 yr)

3 climate, models

- Projections:

3 f

SC

131		CGCM2	ECHAM4	HadCM3
	IPCC IS92a	3	1	1
	SRES A2	3	1	1
	SRES B2	3	1	1

>15 simulations

- IS92a scenario: 1961-2099 (1961-2049 for ECHAM4)

- A2 & B2 scenarios: 1990-2099

Seasonal <u>mean & max SWH</u> (1.5x1.5 lat/long grid) - predictand -"Observations": ERA40 wave data for 1958-2001 (44 yr)

1. Projections of seasonal mean SWH (quasi-Gaussian)

- Fit the Regression Models:

 $RM_G: h_t = \mathbf{m}_0 + \mathbf{r}_2 G_t$ or $RM_P: h_t = \mathbf{m}_0 + \mathbf{r}_1 P_t$ \triangleleft ----SSE_G or SSE_P $RM: h_t = \mathbf{m}_0 + \mathbf{r}_1 P_t + \mathbf{r}_2 G_t$ SSE compared with

Predictors $\begin{cases} P_t : \text{Seasonal mean SLP anomalies} \\ G_t : \text{Seasonal anomalies of squared SLP gradient} \end{cases}$

- Significance of regression par's ← Likelihood ratio tests **Results:** h_t - correlated with P_t and G_t in all seasons; Model of best fit \rightarrow projections: $\hat{h}_t = \hat{m}_0 + \hat{r}_1 P_t + \hat{r}_2 G_t$

2. Trend analysis on \hat{h}_t : $RM_1: \hat{h}_t = \mathbf{a}_0 + \mathbf{a}_1 t + \mathbf{e}_t$; (3 models combined) $RM_2: \hat{h}_t = \boldsymbol{a}_0 + \boldsymbol{a}_1 t + \boldsymbol{a}_2 t^2 + \boldsymbol{e}_t.$

 $RM_0: \hat{h}_t = \boldsymbol{a}_0 + \boldsymbol{e}_t;$

ANOVA

$$\hat{h}_{trend}(t) = \hat{a}_0 + \hat{a}_1 t + \hat{a}_2 t^2$$

(mostly nonlinear!)

3. Projections of seasonal extreme SWH (non-Gaussian)

- Generalized Extreme Value (GEV) models with covariates:

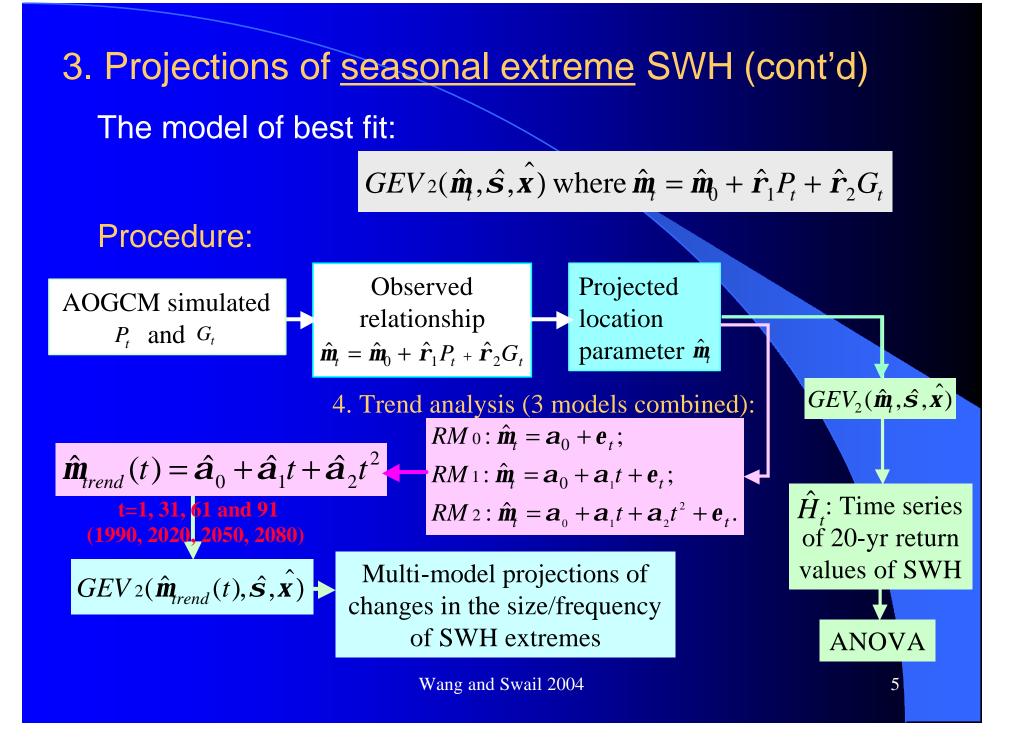
*GEV*₀($\mathbf{m}, \mathbf{s}, \mathbf{x}$) where $\mathbf{m}, \mathbf{s}, \mathbf{x}$ are constants (stationary GEV); *GEV*₁($\mathbf{m}, \mathbf{s}, \mathbf{x}$) where $\mathbf{m}_{t} = \mathbf{m}_{0} + \mathbf{r}_{1}P_{t}$; *GEV*₂($\mathbf{m}_{t}, \mathbf{s}, \mathbf{x}$) where $\mathbf{m}_{t} = \mathbf{m}_{0} + \mathbf{r}_{1}P_{t} + \mathbf{r}_{2}G_{t}$; *GEV*₃($\mathbf{m}_{t}, \mathbf{s}_{t}, \mathbf{x}$) where $\mathbf{m}_{t} = \mathbf{m}_{0} + \mathbf{r}_{1}P_{t} + \mathbf{r}_{2}G_{t}$ and $\log(\mathbf{s}_{t}) = \mathbf{l}_{0} + \mathbf{l}_{1}P_{t}$; *GEV*₄($\mathbf{m}, \mathbf{s}_{t}, \mathbf{x}$) where $\mathbf{m}_{t} = \mathbf{m}_{0} + \mathbf{r}_{1}P_{t} + \mathbf{r}_{2}G_{t}$ and $\log(\mathbf{s}_{t}) = \mathbf{l}_{0} + \mathbf{l}_{1}P_{t} + \mathbf{l}_{2}G_{t}$

P_t: Seasonal mean SLP anomaly

- G_t: Seasonal anomaly of squared SLP gradient
- Likelihood ratio tests → Significance of the regressions & goodness of fit of the GEVs

Results: S_t - independent of both P_t and G_t

 m_t - correlated with P_t and G_t in all seasons.



4. Analysis of Variance (ANOVA) One-way ANOVA: CGCM2 ensemble projections (S = 3; n = 110) for the A2/B2 scenario

$$Y_{ts} = \mathbf{m} + \mathbf{b}_t + \mathbf{e}_{ts}$$
 for $s = 1, 2, ..., S$; $t = 1, 2, ..., n$
 $TSS_Y = SSB_Y + SSE_Y$
 SSB_Y : Forcing signal (var. due to the prescribed forcing)

 SSE_{v} : Var. due to climate noise (internal var.)

CGCM2 simulated climate change signal

F test:
$$F_B = \frac{(SSB_Y / (n-1))}{SSE_Y / [n(S-1)]} \sim F_p[(n-1), n(S-1)]$$

Var. proportion:
$$P_B = \left[SSB_Y - \frac{(n-1)}{n(S-1)}SSE_Y\right] / TSS_Y$$

Small ensemble size (S = 3) → underestimate signal's significance But ANOVA - still better than "ensemble vs. control"

4. Analysis of Variance (cont'd) Two-way ANOVA → model and forcing uncertainties:

 X_{ijt} : mean/extreme SWH projected by model *i* with forcing *j* for time *t*.

 $X_{ijt} = \mathbf{m} + \mathbf{g}_i + \mathbf{q}_j + \mathbf{d}_{ij} + \mathbf{e}_{ijt} \quad \text{for } i = 1, 2, ..., m; \quad j = 1, 2, ..., q; \quad t = 1, 2, ..., n$ $TSS = SSM + SSF + SSI + SSE \qquad 3 \qquad 60$

Total model and forcing uncertainties

SSM: Var. due to diff. among climate models (inter-model variability)

SSF: Var. due to diff. among forcing scenarios (inter-scenario variability)

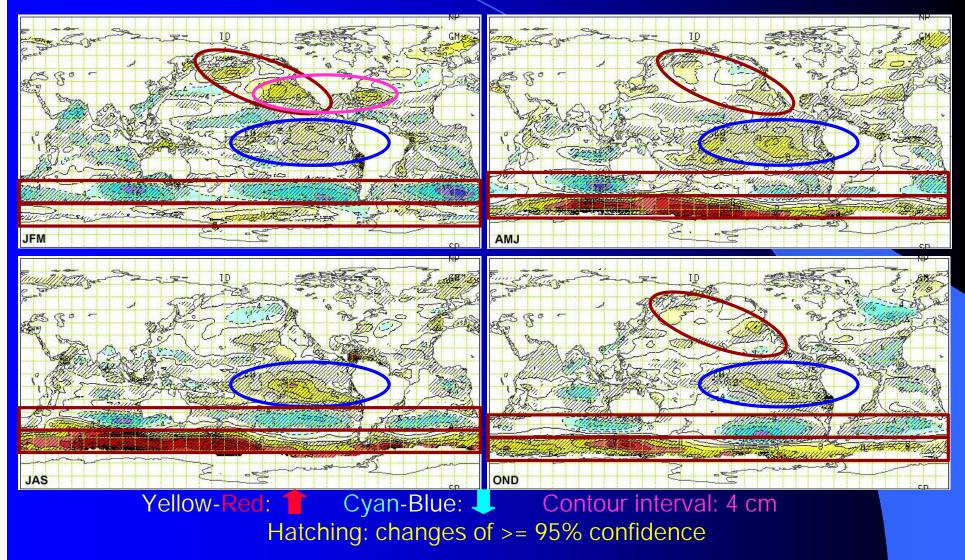
SSI: Var. due to different model sensitivities to forcing differences (interaction)

SSE: Var. due to climate noise (internal var.) and the "common forcing"

F tests → Significance of the 3 var. components & the sum of them

Changes projected by the 3 climate models combined

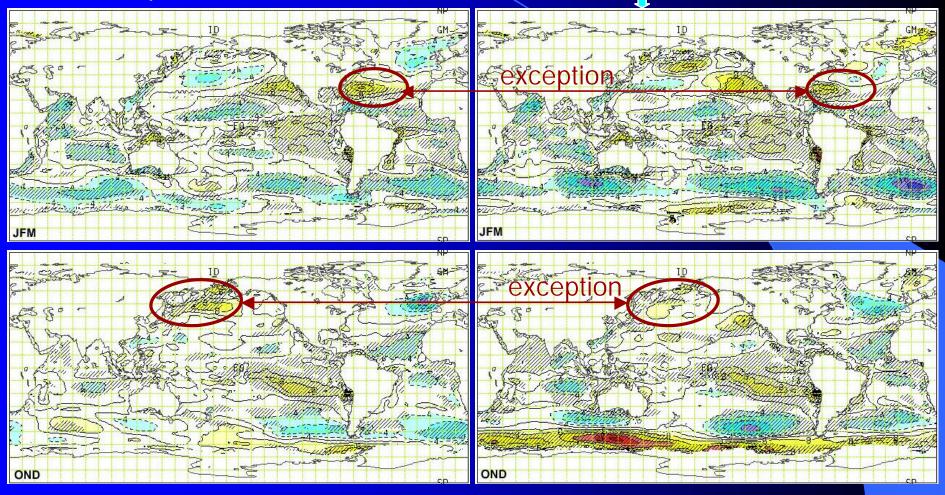
Projected changes in seasonal mean SWH – A2 scenario (2080's minus 1990's)



A2 vs. B2 scenario projections: Similar patterns of change

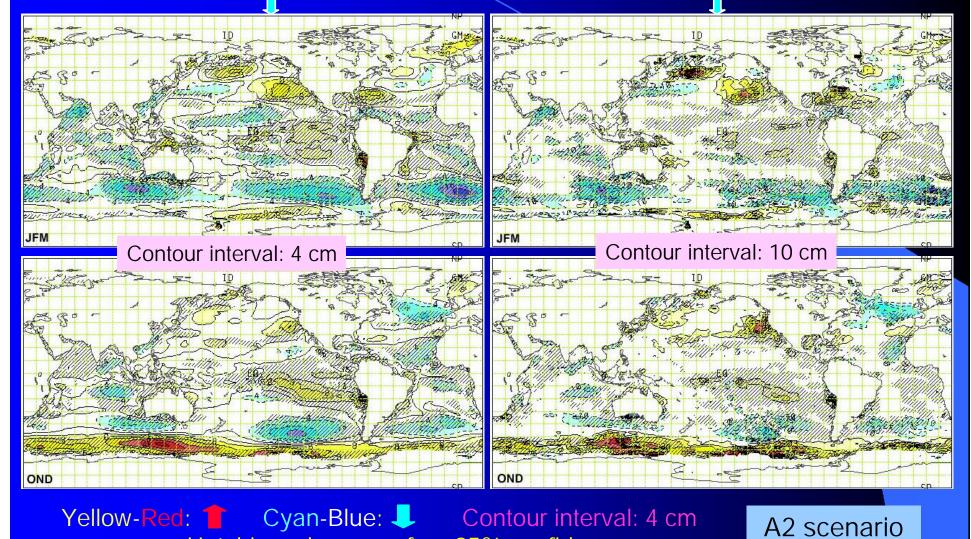
Weaker B2 scenario: generally smaller changes

A2 scenario



Yellow-Red: Cyan-Blue: Contour interval: 4 cm Hatching: changes of >= 95% confidence

Similar patterns of projected changeSeasonal mean SWHSeasonal extreme SWH



Hatching: changes of >= 95% confidence

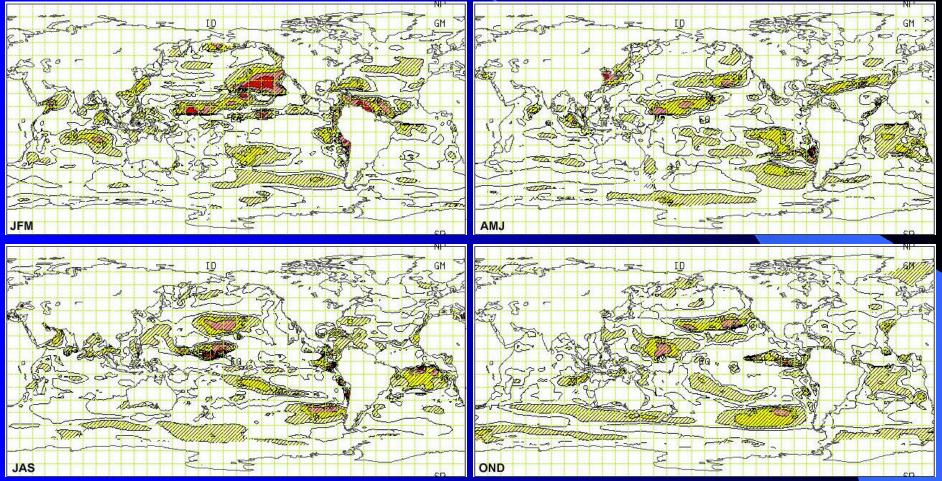
Projected changes = Forced climate change + Internal natural var.

Climate change signal in the CGCM2 ensemble simulations

Forcing-induced var. proportion in seasonal mean SWH - A2 scenario

Hatching: >= 95% confidence

Contour interval: 10%

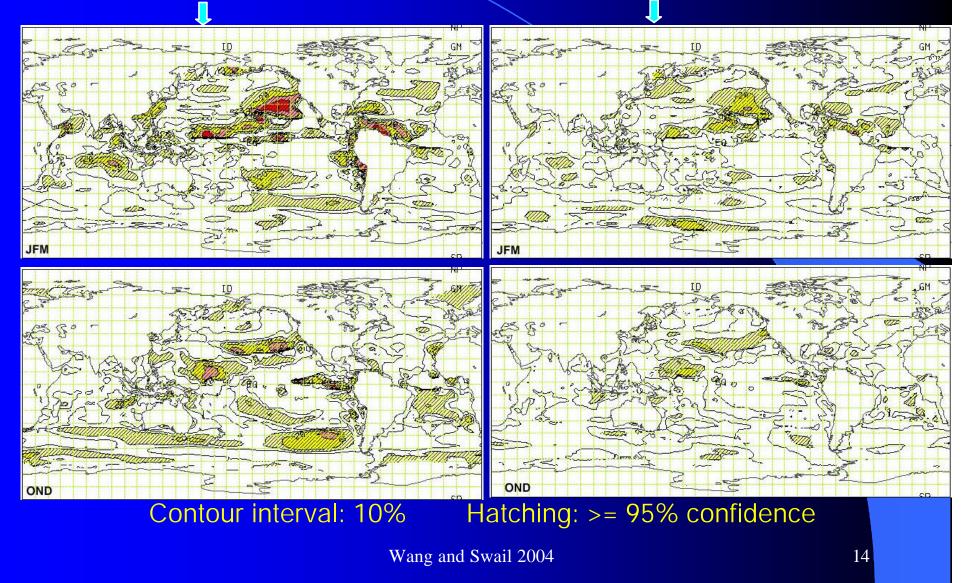


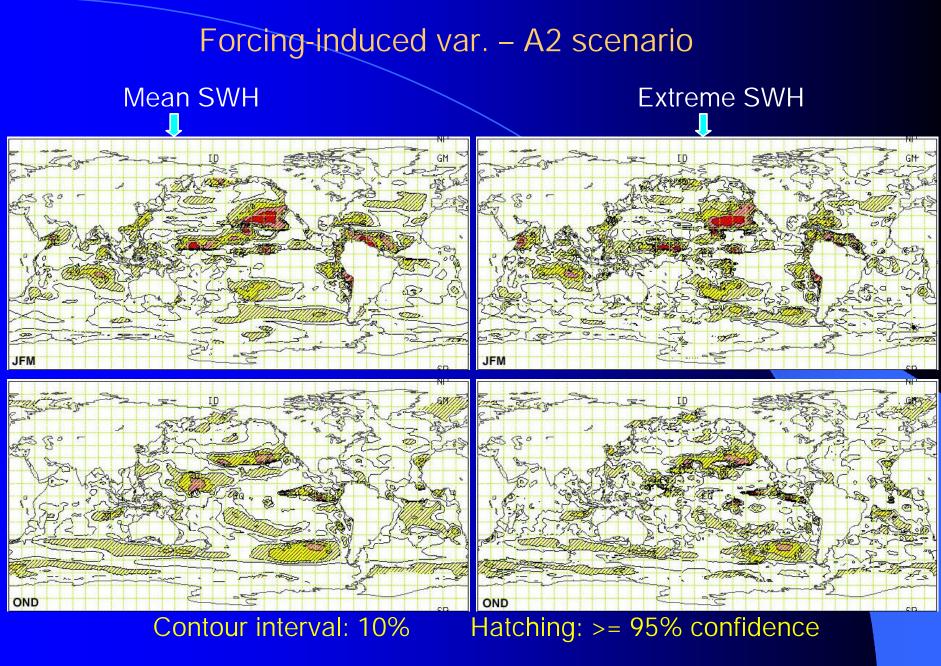
Ensemble size = $3 \rightarrow$ Signal likely more significant than shown here!

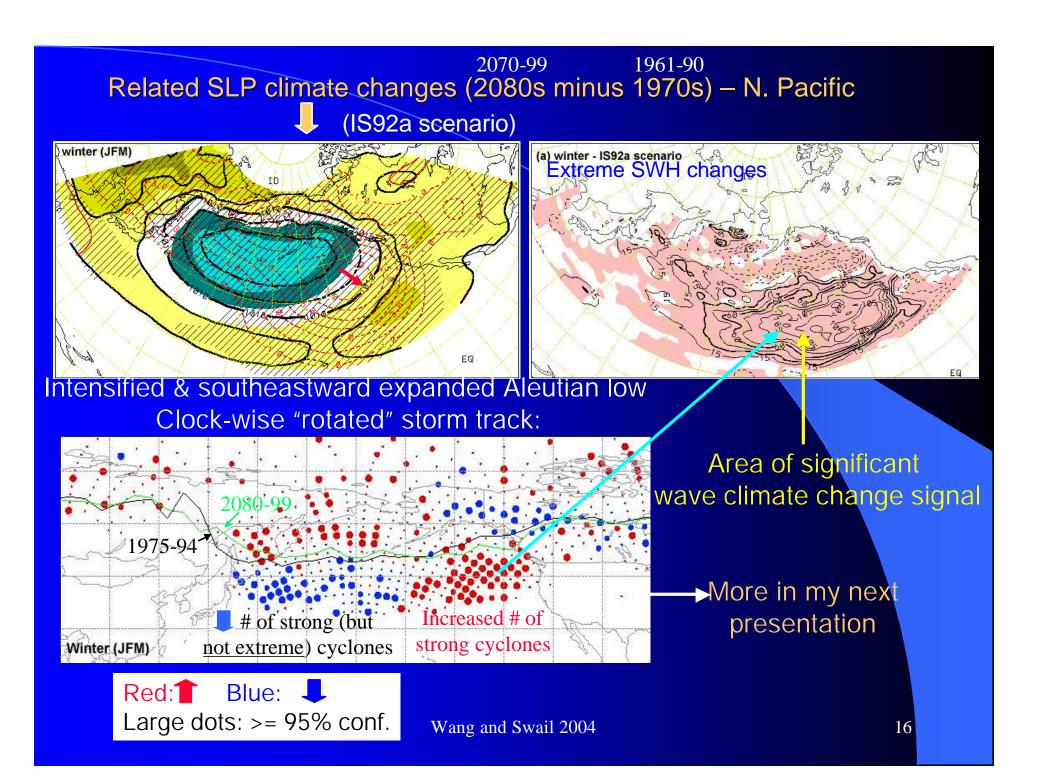
Forcing-induced var. in seasonal mean SWH – A2 vs. B2

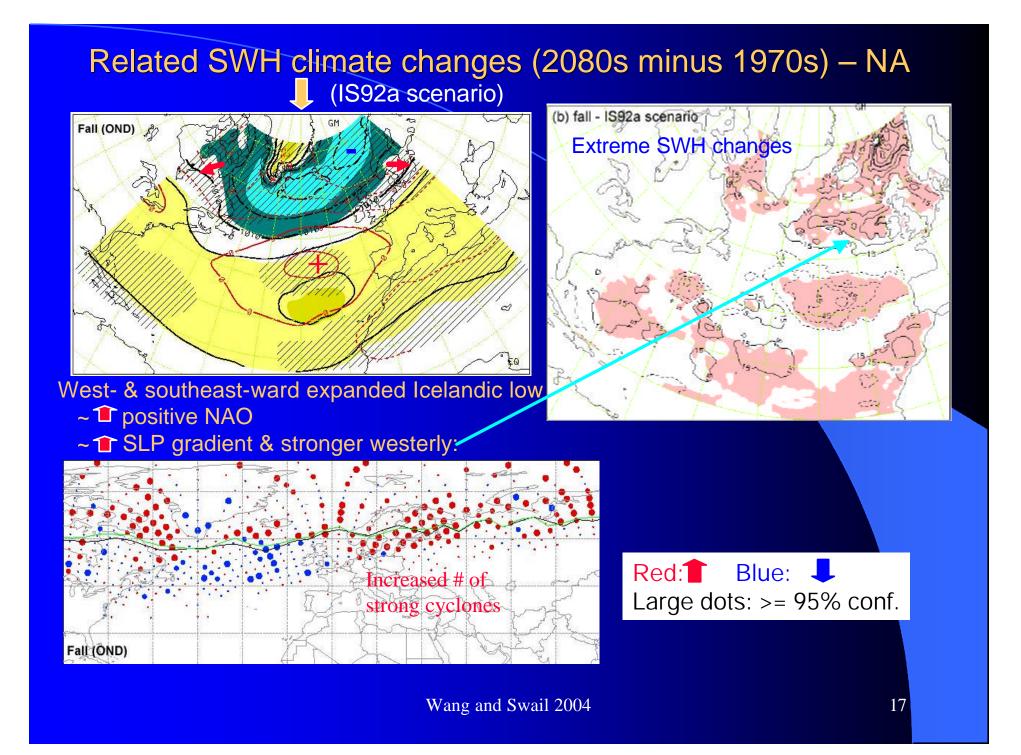
A2 scenario

B2 scenario: weaker signal

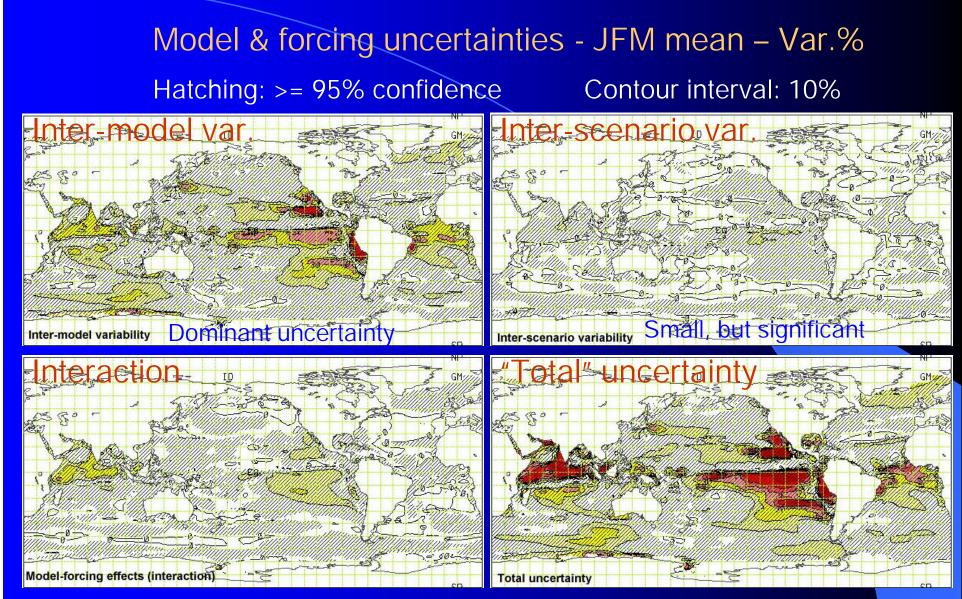






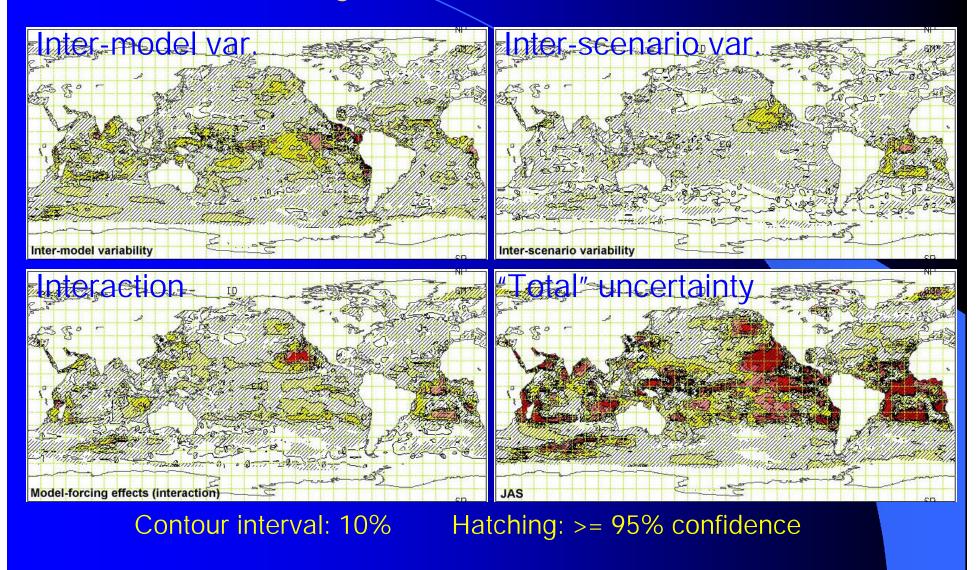


Characteristics of uncertainties



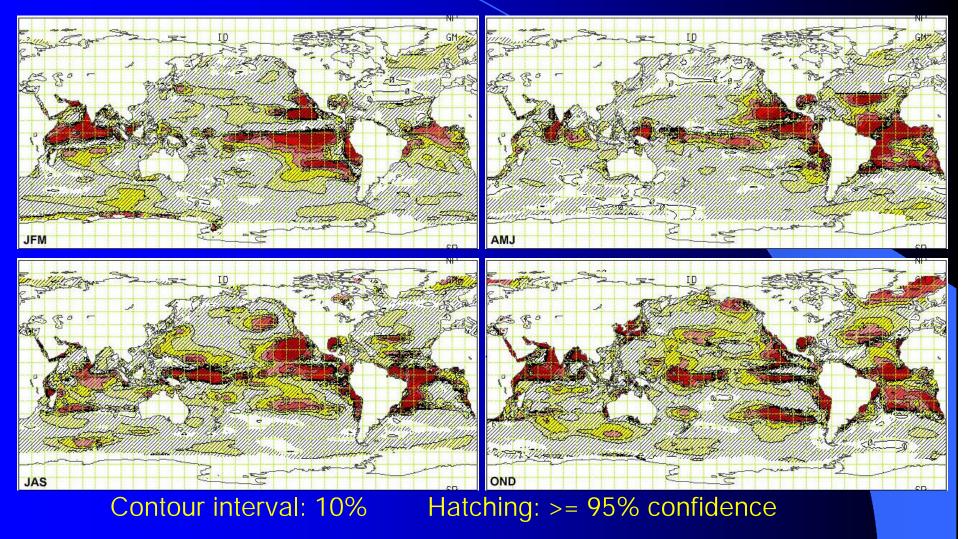
Similar in the other seasons

Model & forcing uncertainties - JAS extreme – Var.%



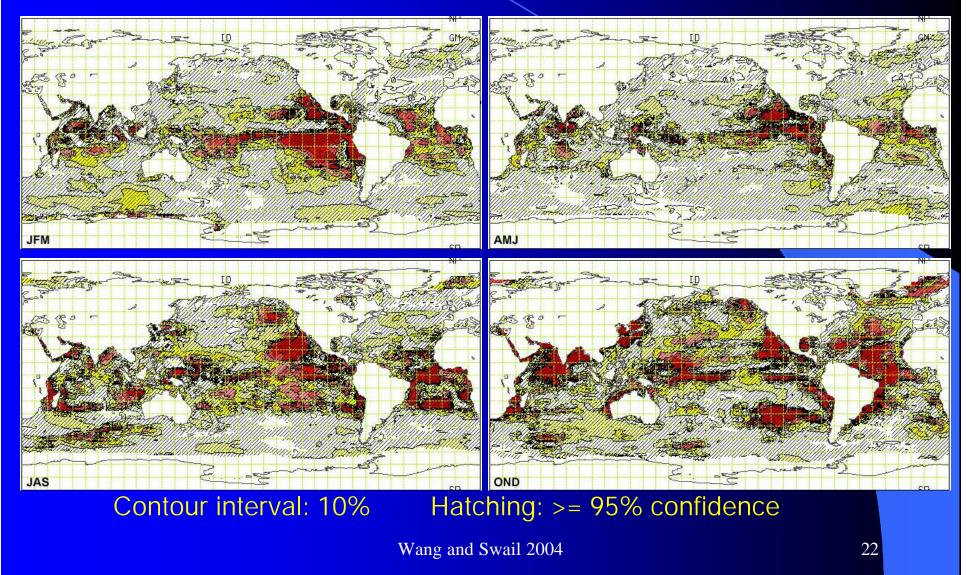
"Total" uncertainty – mean SWH – Var.%

Small in mid-high lat., large in the tropics; less extensive in AMJ & JFM



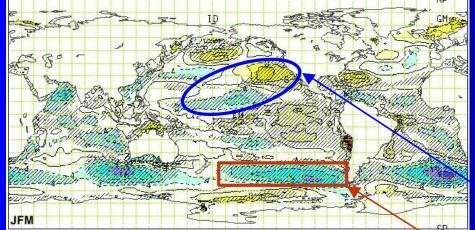
"Total" uncertainty – extreme SWH – Var.%

Similar: small in mid-high lat., large in the tropics; less extensive in AMJ & JFM



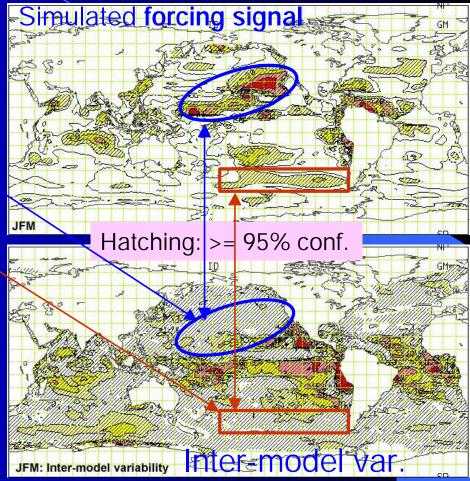
JFM seasonal mean SWH

Projected changes (3 models combined)



Yellow-Red: 📋 Cyan-Blue: 👢

Large projected changes – small model uncertainty → Higher confidence?



Summary

- 1. Multi-model projected changes of SWH:
 - Patterns similar to those projected by the CGCM2 alone
 Smaller magnitude of change

2. Forcing-induced variability in CGCM2 simulations:
 > Statistically significant in some areas, in all seasons
 > Largest in the mid-latitudes of NP (JFM, A2/IS92a)

Summary (cont'd)

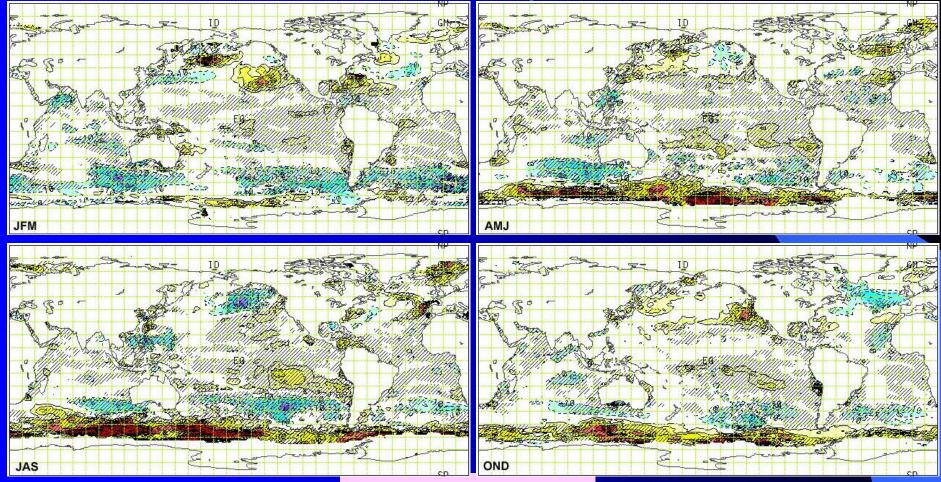
- 3. Uncertainty:
 - > Large in the tropics, but small in the mid-high latitudes (more confident about the projected large changes in mid-high lat.)
 - > Forcing uncertainty is statistically significant, although relatively small → forcing condition matters
 > Development of models → reduced model uncertainty
- 4. The model uncertainty limited to the 3 climate models Other sources of uncertainty not discussed here e.g.: different RCMs, or Dynamical vs. Statistical, or <u>GEV vs. GPD – a separate study</u>

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Thank you very much!

Projected changes in <u>extreme</u> SWH – 3 models combined – A2 scenario (2080's minus 1990's)



Contour interval: 10 cm

Forcing-induced var. proportion in extreme SWH – CGCM2 - A2 scenario

