On Improving the Results of Statistical and Dynamical Downscaling

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- Motivation – Problem: climate models' climate & variability biases
- Approach to diminishing the effects of model biases, improving downscaling results
- Summary of conclusions
- Details …
- Concluding remarks

Motivation

– Ocean wave variables are not directly available from global climate model outputs

→ need statistical and/or dynamical downscaling

– **Problem 1**: climate models' climate and variability biases

Model climate biases – diff. between simulated & observed long-term mean fields

Model variability biases – departure of simulated-to-observed var. ratio from unity

– **Problem 2**: climate models' output data resolution – monthly typically – not good enough for studying extremes

Can we improve statistical downscaling results using higher resolution data? - yes

– **Problem 3**: Which way is better to project future extremes?

Methodologies

- Downscaling approaches

1. Dynamical downscaling: climate model simulated surface winds → ODGP-2G
2. Statistical downscaling: an observed predictor-predictand relationship:
   - 2.1 Conventional regression model → means, extremes (with high resolution data)
   - 2.2 Non-stationary extreme value model with covariates (predictors) → extremes

- Approaches to diminishing climate model biases:

1. Replace the simulated wind climate with the observed one in dynamical downscaling
2. Use <u>standardized</u> predictor quantities in statistical downscaling

- Results evaluation method:

1. Comparison of the base period climate and variance (simulated *v.s.* observed)
2. Anomaly pattern correlation skill scores

Summary of conclusions

1. Climate model biases

for CGCM2: larger biases in wind than in SLP

    - vary from variable to variable, season to season, & probably model to model
    - can result in large biases in the downscaling results

2. Use of <u>standardized predictor quantities</u> in statistical downscaling can effectively diminish the effects of both model climate and variability biases

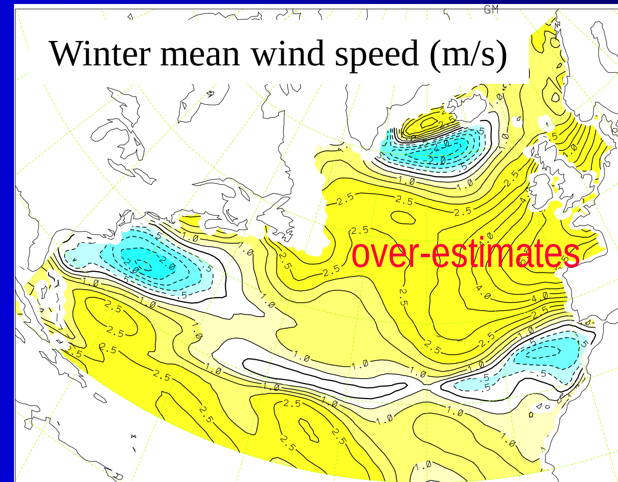
3. In dynamical downscaling, model variability biases remain to be dealt with, whereas the effects of model climate biases can be reduced to some extent by replacing the simulated wind climate with the observed

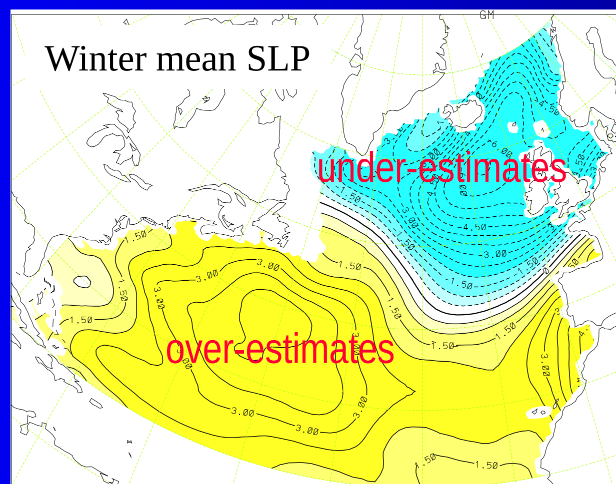
4. The observed anomaly patterns can be better reproduced by using high frequency (e.g. sub-daily) data, rather than seasonal, data in statistical downscaling

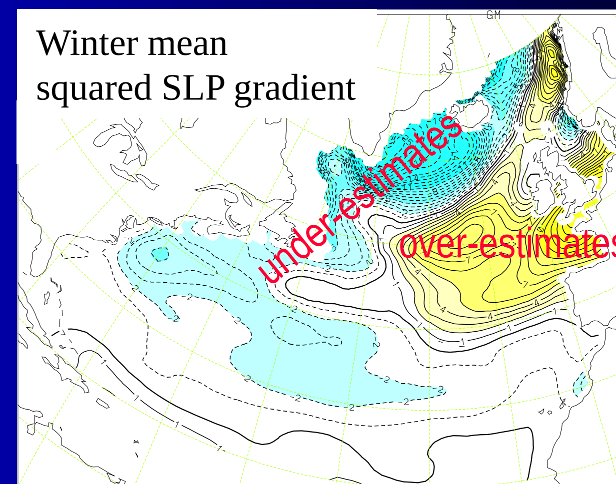
    - stress the importance of higher resolution data availability for downscaling

5. A non-stationary EV model with covariates is the best in reproducing the observed climate of extremes – important for offshore and coastal design and operation

CGCM2 model climate biases:
(simulated minus observed)
climate =1975-1994 means







To diminish the effects of model climate biases, we've used these anomalies as

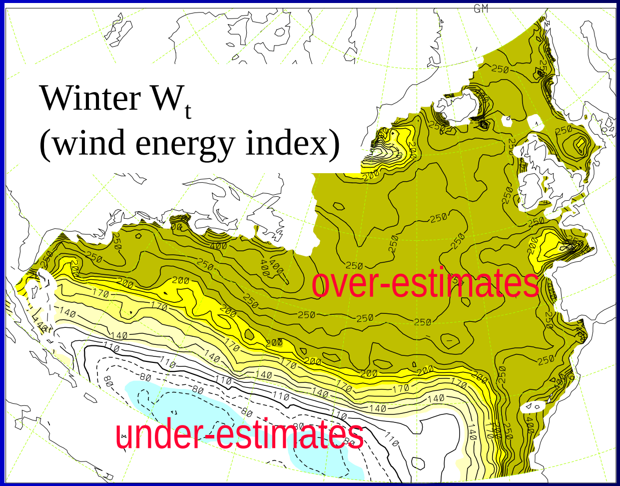
Predictors: W_t – anomalies of seasonal mean squared wind speed (wind energy index)

P_t – anomalies of seasonal mean SLP

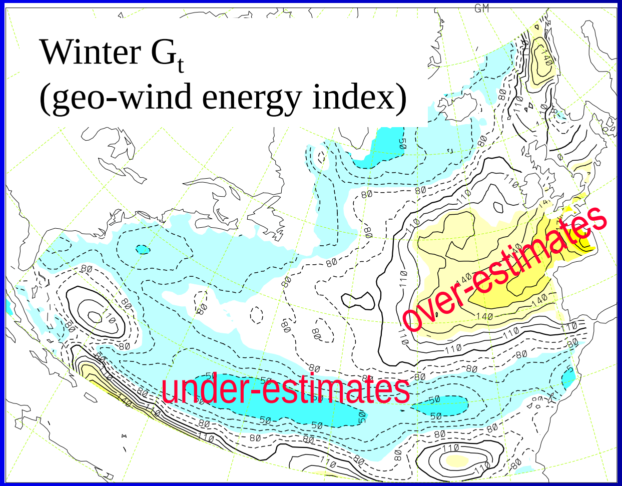
G_t – anomalies of seasonal mean squared SLP gradient (geo-wind energy index)

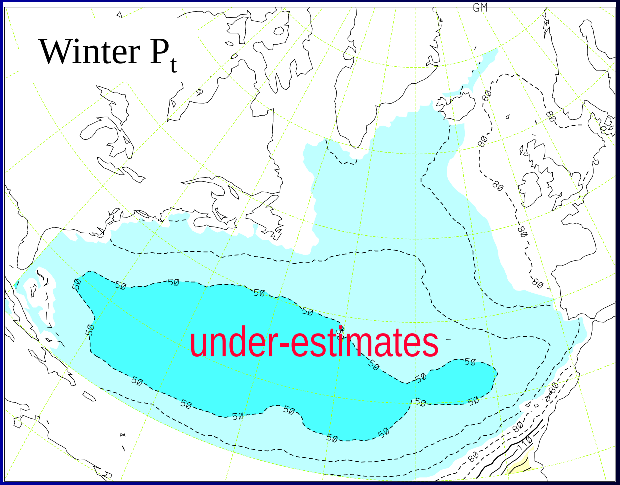
However, this has done nothing to the model variability biases:

CGCM2 model <u>variability biases</u>:
(simulated over observed)
variability =1975-1994 variance



Larger variability biases
→ large effects on estimates of extremes

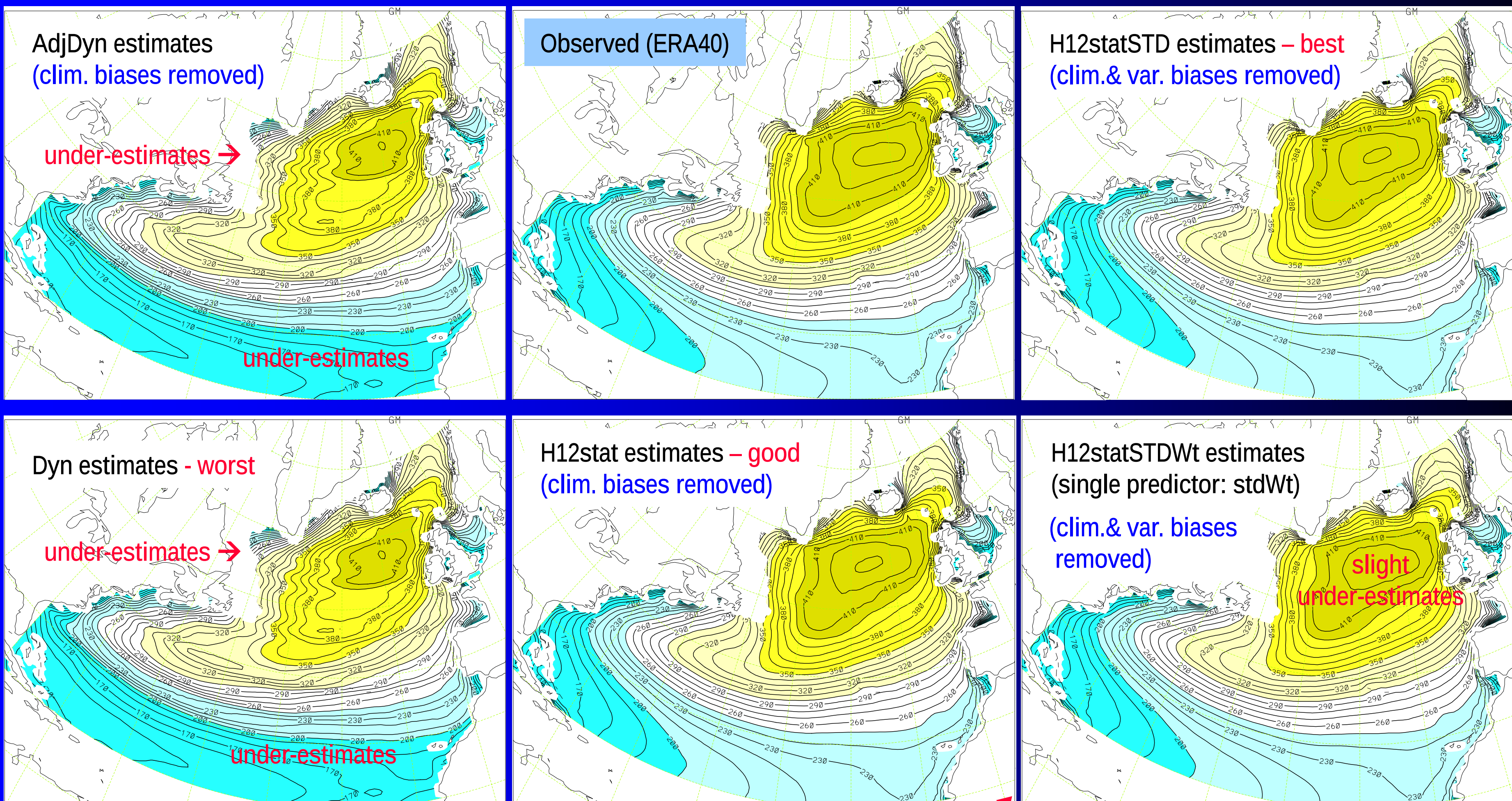




The wind energy index becomes the best predictor for SWH <u>only if</u> it is standardized
(i.e. both the model climate and variability biases are diminished)
- the worst without standardization!
- bad news for wind dependent dynamical downscaling

Evaluation – in terms of reproducing the observed climate of mean SWH

- the climate (1975-1994 mean field) of winter Havg

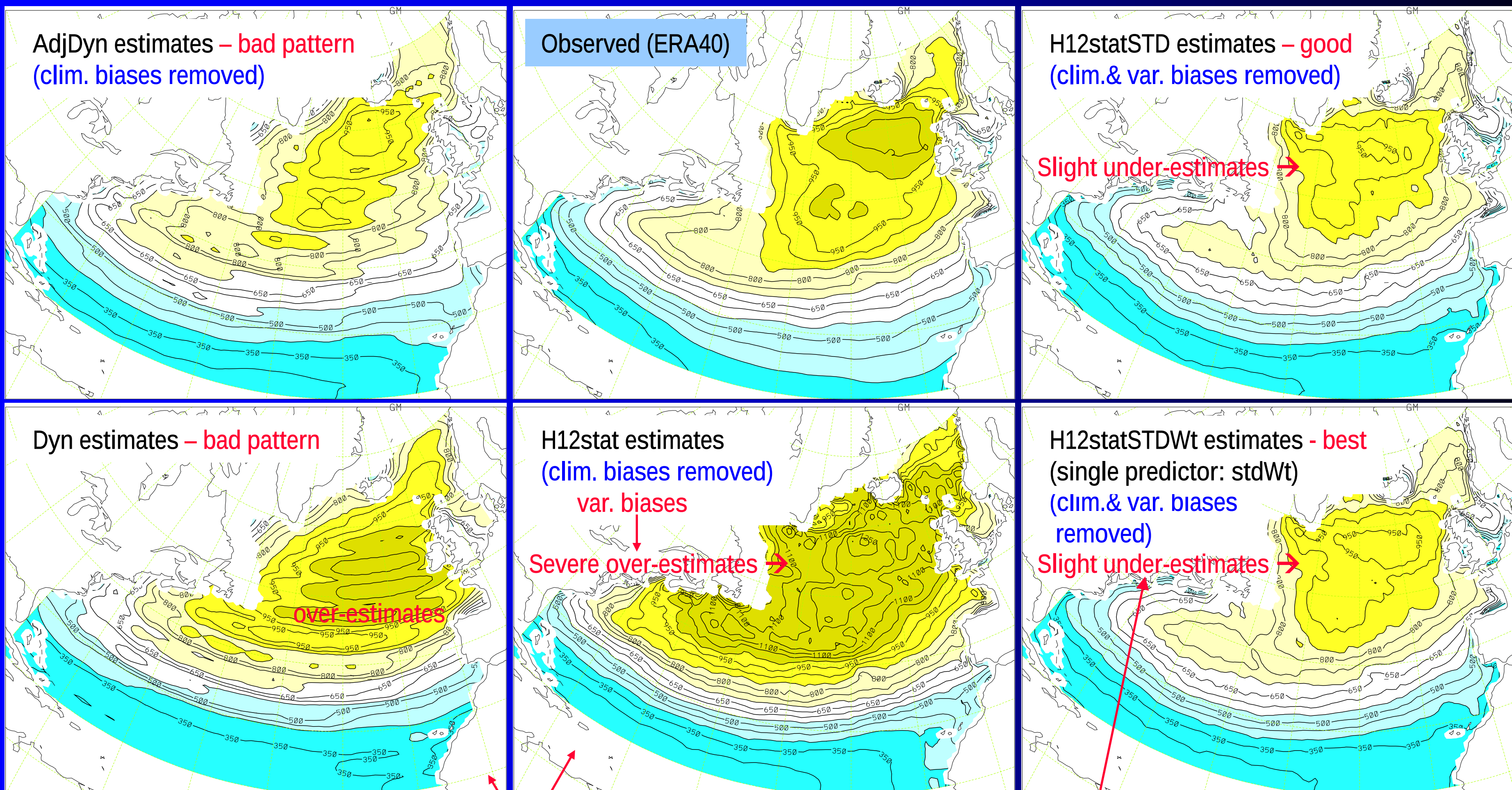


Dynamical

Statistical

Evaluation – in terms of reproducing the observed climate of extremes

- the climate (1975-1994 mean field) of winter Hmax

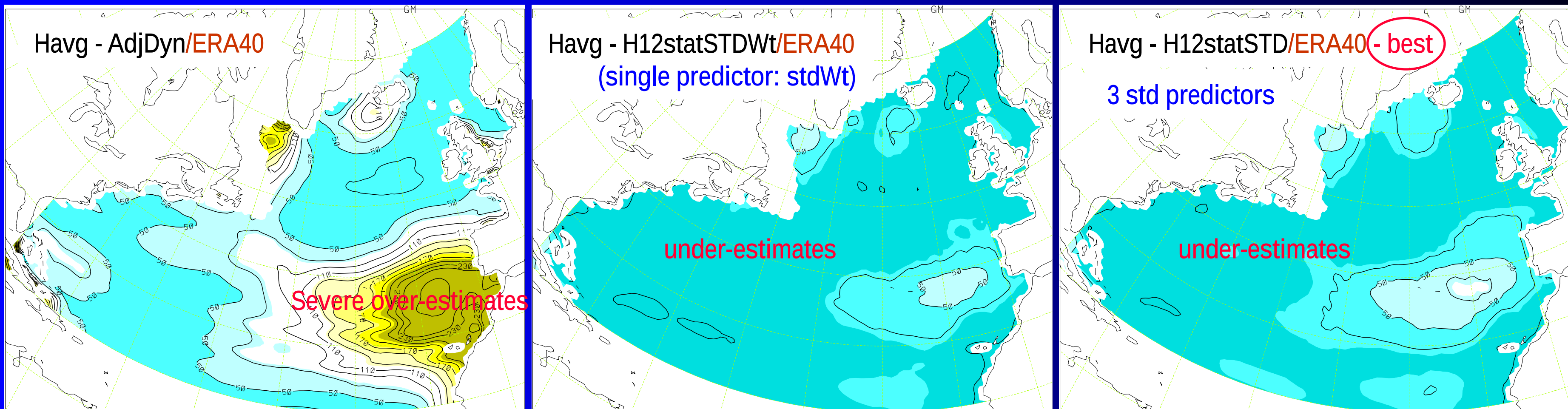


These two won't be discussed further

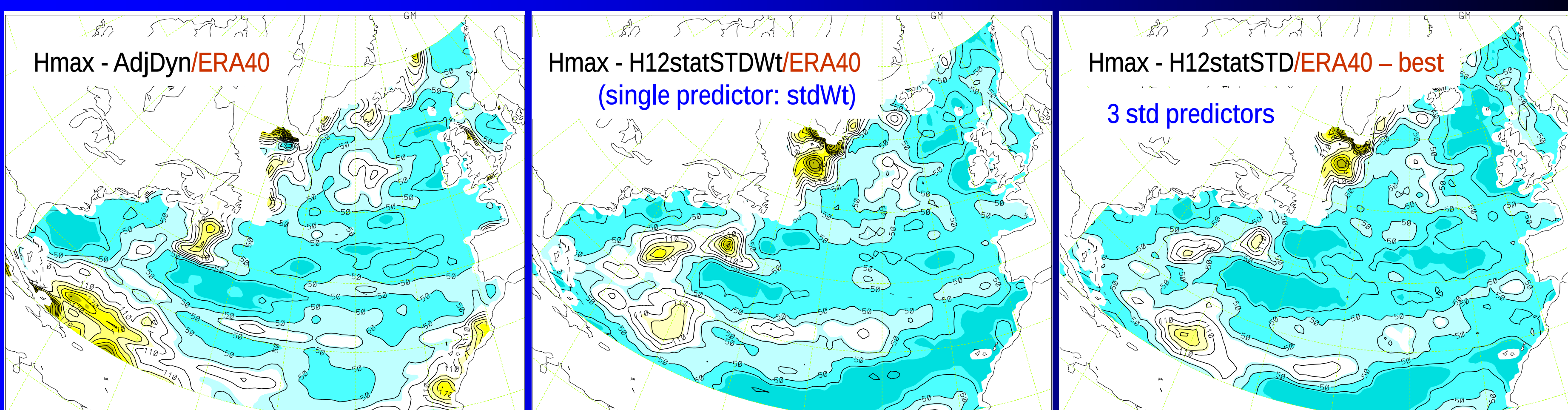
Can be improved by using
higher frequency data
(e.g. 3- or 6-hourly)

Evaluation – in terms of reproducing the observed variance of mean and extremes
(the 1975-1994 variance)

Winter mean SWH:



Winter maximal SWH:



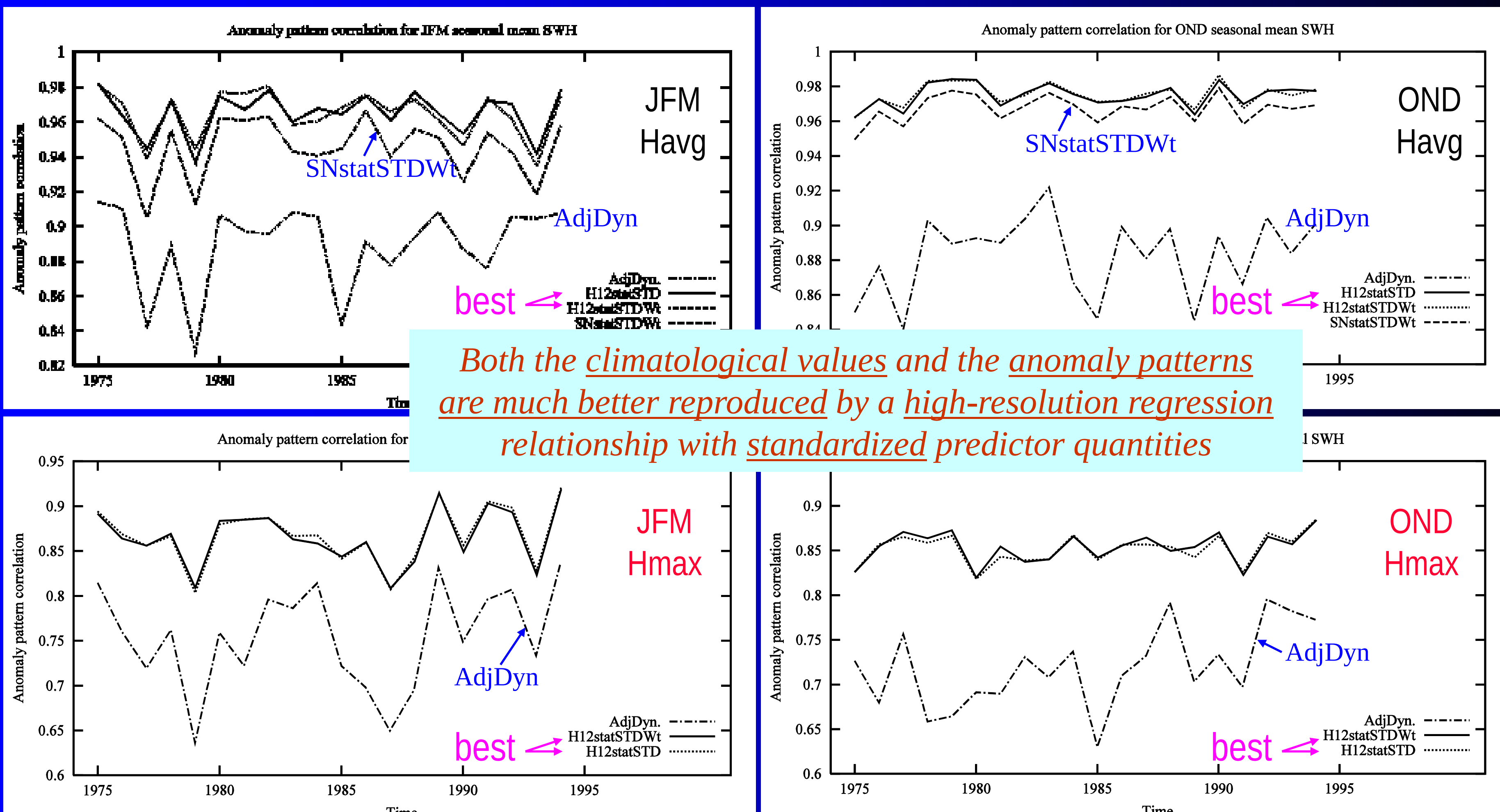
Evaluation – in terms of reproducing the anomaly patterns

Anomaly pattern correlation skill score for year y: (*O* – Observed; *E* – Estimated)

$$\rho_y = \frac{\left\langle \left(O_{ly} - \langle O_l \rangle\right)\left(E_{ly} - \langle E_l \rangle\right) \right\rangle}{\sqrt{\left\langle \left(O_{ly} - \langle O_l \rangle\right)^2 \right\rangle \left\langle \left(E_{ly} - \langle E_l \rangle\right)^2 \right\rangle}}$$

$\langle \cdot \rangle$ -spatial avg over location index l

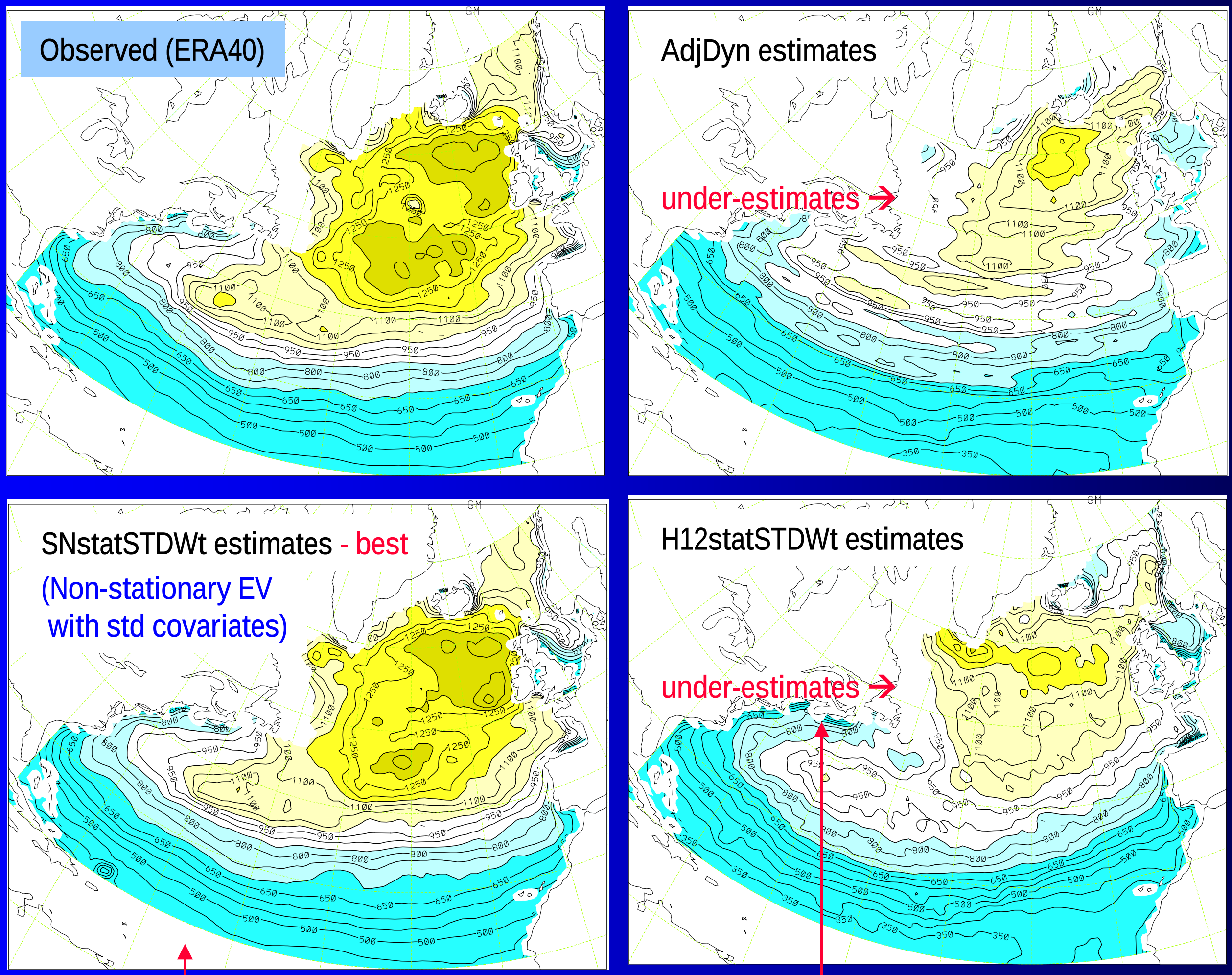
The model climate biases are excluded from this measure of skill



Both the climatological values and the anomaly patterns are much better reproduced by a high-resolution regression relationship with standardized predictor quantities

Evaluation – in terms of reproducing the observed climate of 20-yr return value

- the climate of winter 20-yr return values of SWH: H20yr



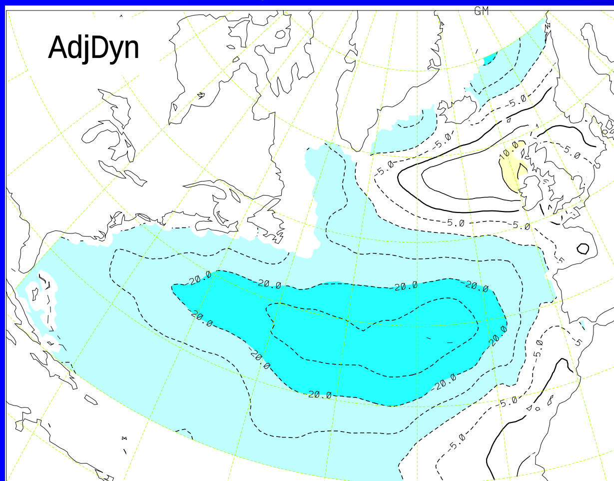
Directly preserves the observed climate of extremes

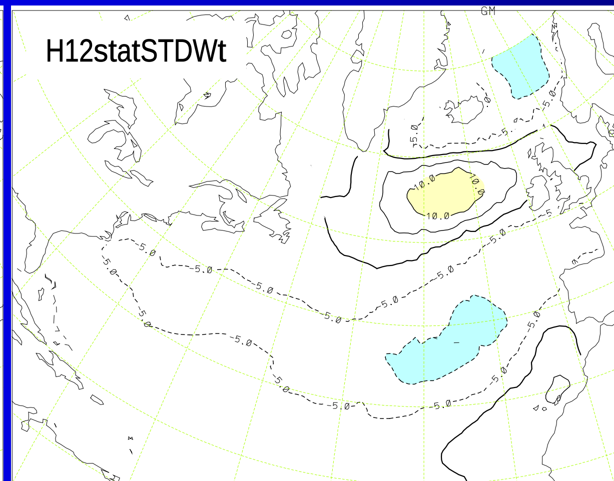
Expected to be improved by using higher resolution data, but…

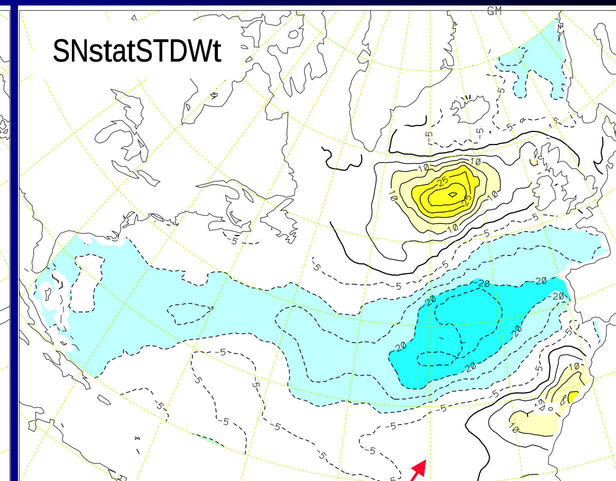
Downscaling results – the projected changes

(2080-2099's minus 1975-1994's climate)

Autumn Havg:

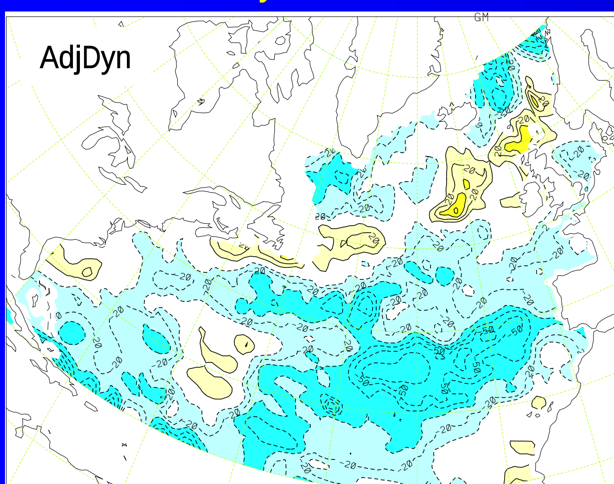


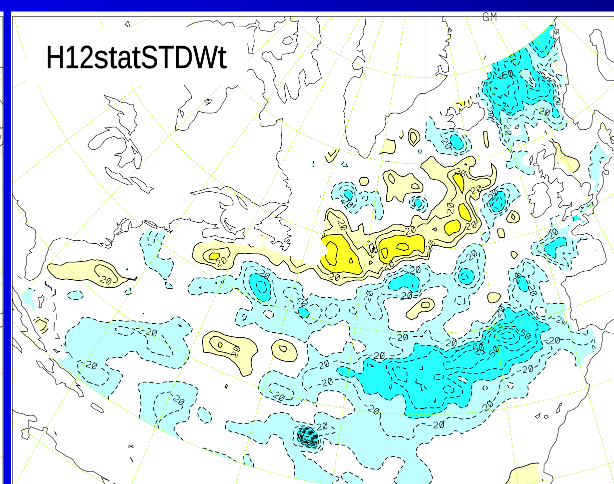


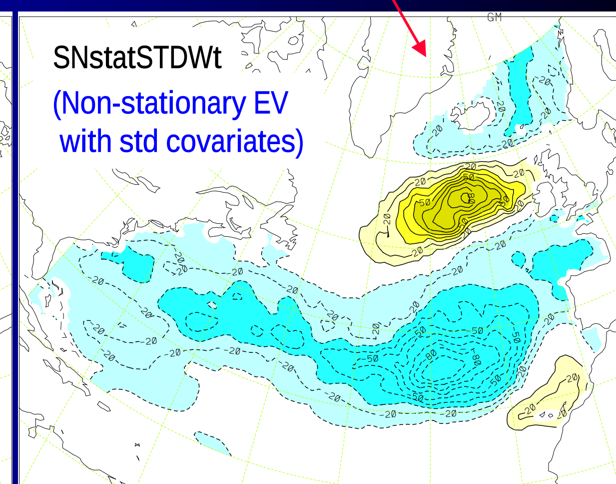


Similar patterns of change, but larger changes projected by the SN models

Autumn H20yr:







For extreme values:

- The observed climate is best preserved by using a non-stationary EV model with std'd covariates
- The anomaly patterns are best re-produced by using a high-resolution regression relationship with standardized predictor quantities (covariates)

Appealing to use a non-stationary EV model with standardized covariates in combination with a high-resolution regression relationship with standardized predictor quantities

For discussion:

Can we adjust climate model simulated surface wind climate and variability to the observed ones for dynamical wave modelling?

$$U_{l,t}^{a} = \left(U_{l,t}^{s} - \overline{U}_{l}^{s} + \overline{U}_{l}^{o}\right)\boxed{\frac{\sigma_{w}^{o}}{\sigma_{w}^{s}}} \text{ and } V_{l,t}^{a} = \left(V_{l,t}^{s} - \overline{V}_{l}^{s} + \overline{V}_{l}^{o}\right)\frac{\sigma_{w}^{o}}{\sigma_{w}^{s}}$$

Simulated climatology Observed climatology

The observed-to-simulated wind speed std ratio

Any better way?

Summary of conclusions

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   for CGCM2: larger biases in wind than in SLP

   - vary from variable to variable, season to season, & probably model to model
   - can result in large biases in the downscaling results

2. Use of <u>standardized predictor quantities</u> in statistical downscaling can effectively diminish the effects of both model climate and variability biases

3. In dynamical downscaling, model variability biases remain to be dealt with, whereas the effects of model climate biases can be reduced to some extent by replacing the simulated wind climate with the observed

4. The observed interannual variability can be better reproduced by using high frequency (e.g. sub-daily) data, rather than seasonal, data in statistical downscaling

   - importance of higher resolution data availability for downscaling

5. A non-stationary EV model with covariates is the best in reproducing the observed climate of extremes – important for offshore and coastal design and operation

Thank you very much!