Ensemble Kalman Filter Based Data Assimilation in Wave Models

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Summary

Motivation, Expected Outcomes

Improved *wind* and wave mean parameters during and after development can provide some long-lasting effects to the forecast, shown by Lefèvre (2012)

- on wind waves through cross-covariances (dramatic increase in the amount of data and coverage)
- improvement of the wind fields in the hindcast (similar to the smoother in Voorrips et al. (1999))
- direct wind analysis to include in the spectra retrieval (by adapting Lionello et al. (1996))

Improved forecast uncertainties from the ensemble

In the ensemble: to improve the initial ensemble spread and uncertainty representation in short ranges.

The forecast-analysis step

- the actual "errors-of-the-day" lye within a lower dimension space than the full system without previous knowledge *if* the ensemble system provides a reasonably good knowledge of these errors, then dimension of the problem can be reduced *locally*
- multivariate vector wind - wave analysis
- a local transformation allows to assimilate observations simultaneously and to distribute processing

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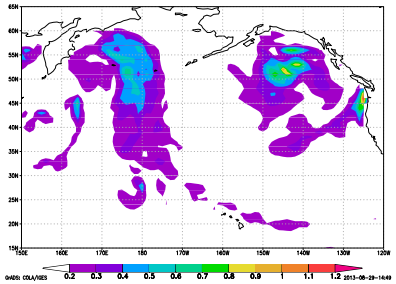
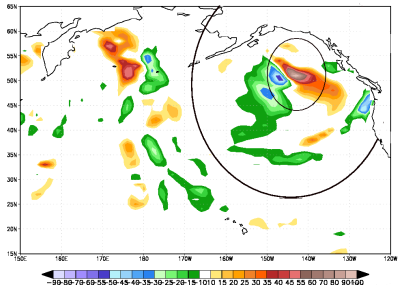
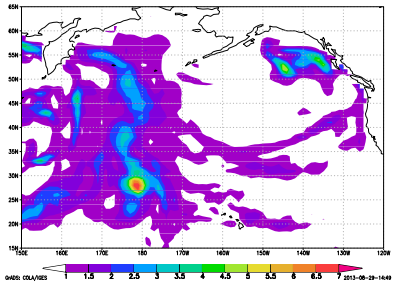
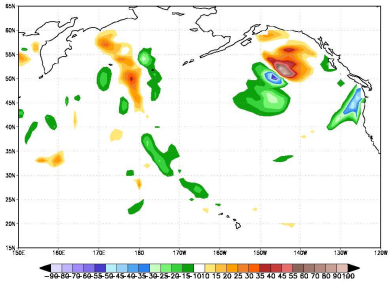
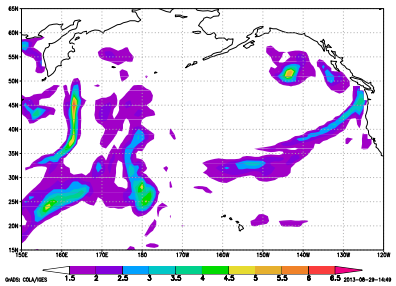
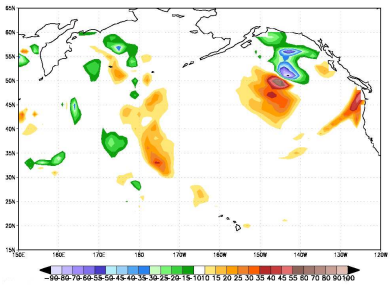
The "Assimilation" or spectra update step into the wave model As in Lionello et al. (1996) and Breivik and Reistad (1994), updated as in ECMWF (2013), except that we introduce the wind explicitly

Summary of conclusions

- Advanced DA method: 4D, multivariate wind-wave
- Model-independent, ensemble and deterministic initialization
- Realistic increments, flow dependent
- ensures cycle-to-cycle member continuity
- potentially multiscale
- TBD: a one-step spectra update (in the analysis)
- Validated in 6-hr forecasts, benefit extended by swells
- Joint wind-wave analysis was the main source of improvement

The Assimilation

Flow-dependent background errors and localization

	Ensemble spread	Column of P^f at A	
H_s			$\overline{\delta H_s \delta H_s}$
W_u			$\overline{\delta H_s \delta U_w}$
W_v			$\overline{\delta H_s \delta V_w}$

The EnKF general approach

m ensemble members (n dimension)

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background perturbations δX^f

forecast error covariance matrix

$$P^k \approx \frac{\delta X^f (\delta X^f)^T}{(m-1)}$$

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observation operator H (model to observation space)

$$\delta Y = H(\delta X^f)$$

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$m \times p \times n$

analysis core

Analysis ensemble X^a

-> the problem is solved *locally and simultaneously* (independent from point to point) Ott et al. (2004) and improved by Hunt et al. (2007)
Solves the problem in the space spanned by the ensemble by expressing the analysis ensemble a linear combination of the background perturbations.

$$X^a = \bar{x}^f + \mathbf{w^a}\delta\mathbf{X^f}$$

w^a base of the space spanned by δX^f, particular conditions hold for w^f ensemble mean and covariance:
$P^f \approx \frac{\delta x^f (\delta x^f)^T}{(m-1)} = \delta x^f \tilde{P}^f (\delta x^f)^T$ where $\tilde{P}^f = \mathbf{I}/(\mathbf{m}-\mathbf{1})$
$[m \times m]$ and $\bar{w}^f = 0$
-> *the problem is solved locally to get the* m *weights* w^a

4D: asynchronous observations and "model observation" disposed in intermediate time slots within a cycle
$\delta y_t = H(\delta {x_t}^f)$ => evolving background error and covariance

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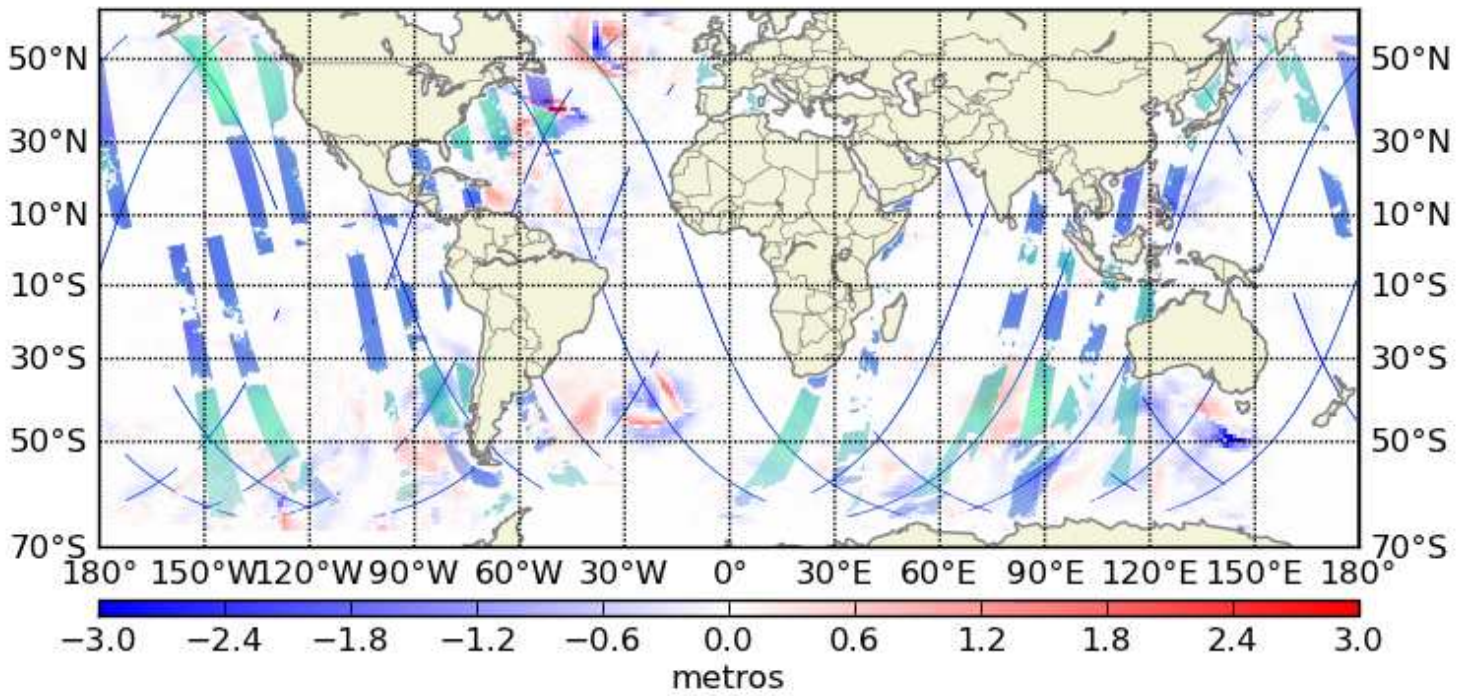
continuity of the ensemble perturbations δx^a close to δx^f

Multivariate analysis and SWH increments

Realistic SWH analysis increments in the full scale of the perturbations

19 December 2012 06:00



Set up: global $1° \times 1°$ WAVEWATCH III®model ensemble in a 6-hour forecast/DA cycle

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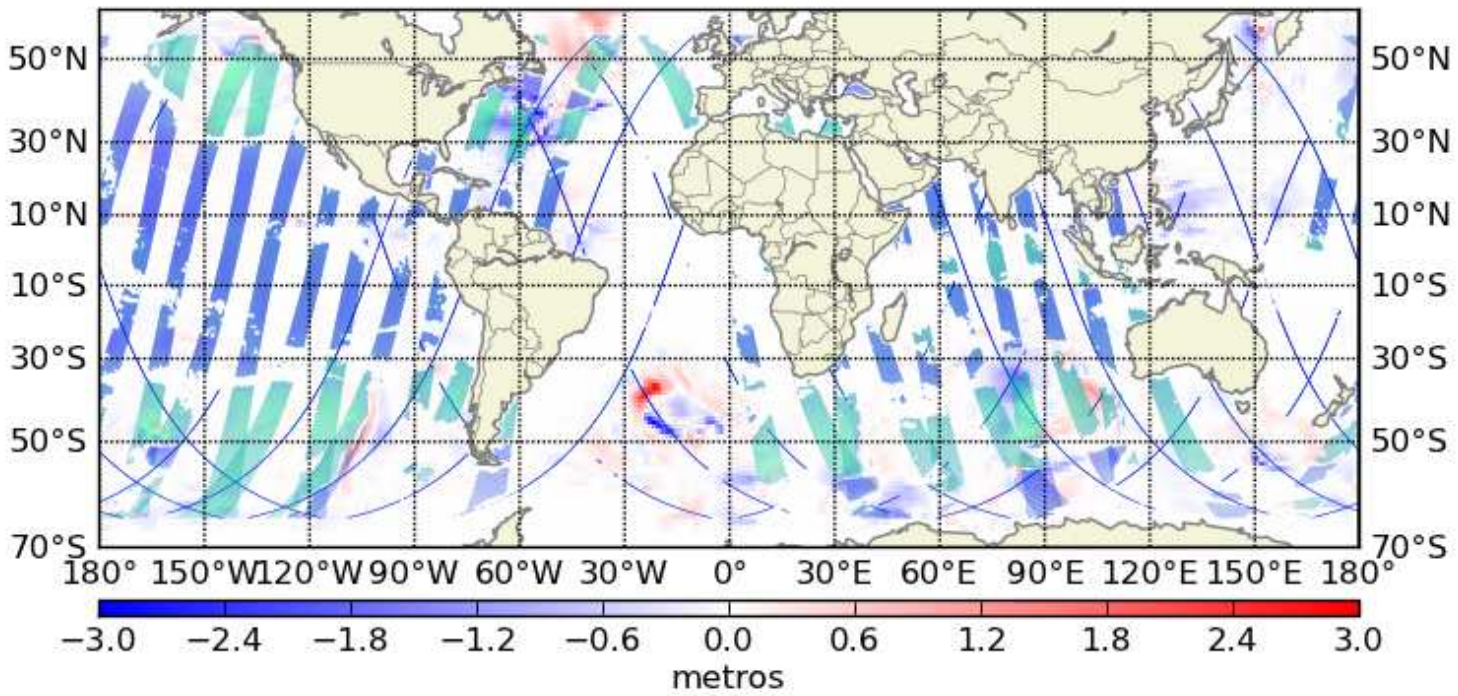
19 December 2012 18:00



Vector winds correct wind fields + directly influence wind waves

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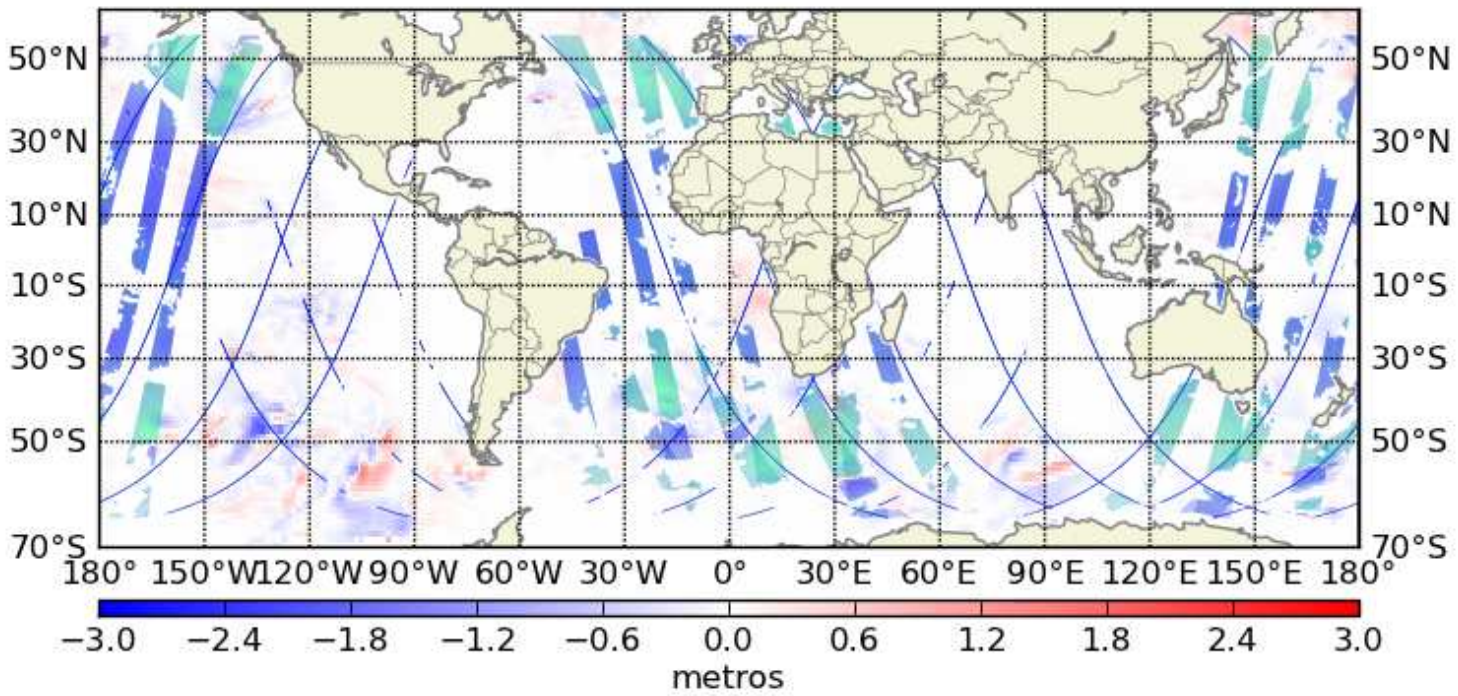

altimeters assess corrections in N Pacific

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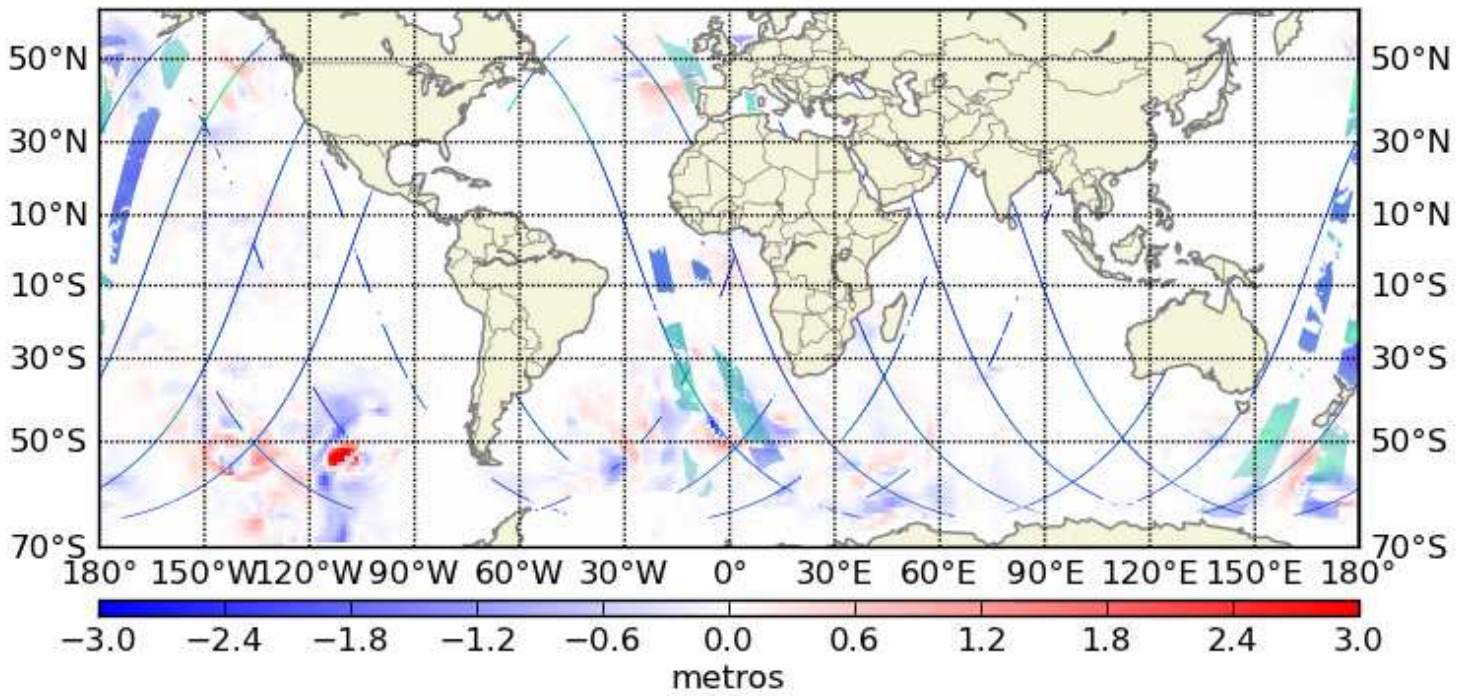
21 December 2012 00:00



consistently correct waves cycle after cycle

Updating the Wave Model Spectra

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Lionello et al. (1996)

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$\varepsilon_* = 5.054 * 10^{-4} \bar{f}_*^{-2.959}$ ECMWF (2013) with $\bar{f}_* = \frac{u_* \bar{f}}{g}$ (no drag change) introduces the wind explicitly

windsea
$$\begin{cases} B = \frac{\bar{f}^f}{\bar{f}^a} = \left(\frac{U^f}{U^a}\right)^{0.3518} \left(\frac{H^a_{ws}}{H^f_{ws}}\right)^{0.6759} \\ A = B \left(\frac{H^a_{ws}}{H^f_{ws}}\right)^2 \end{cases}$$

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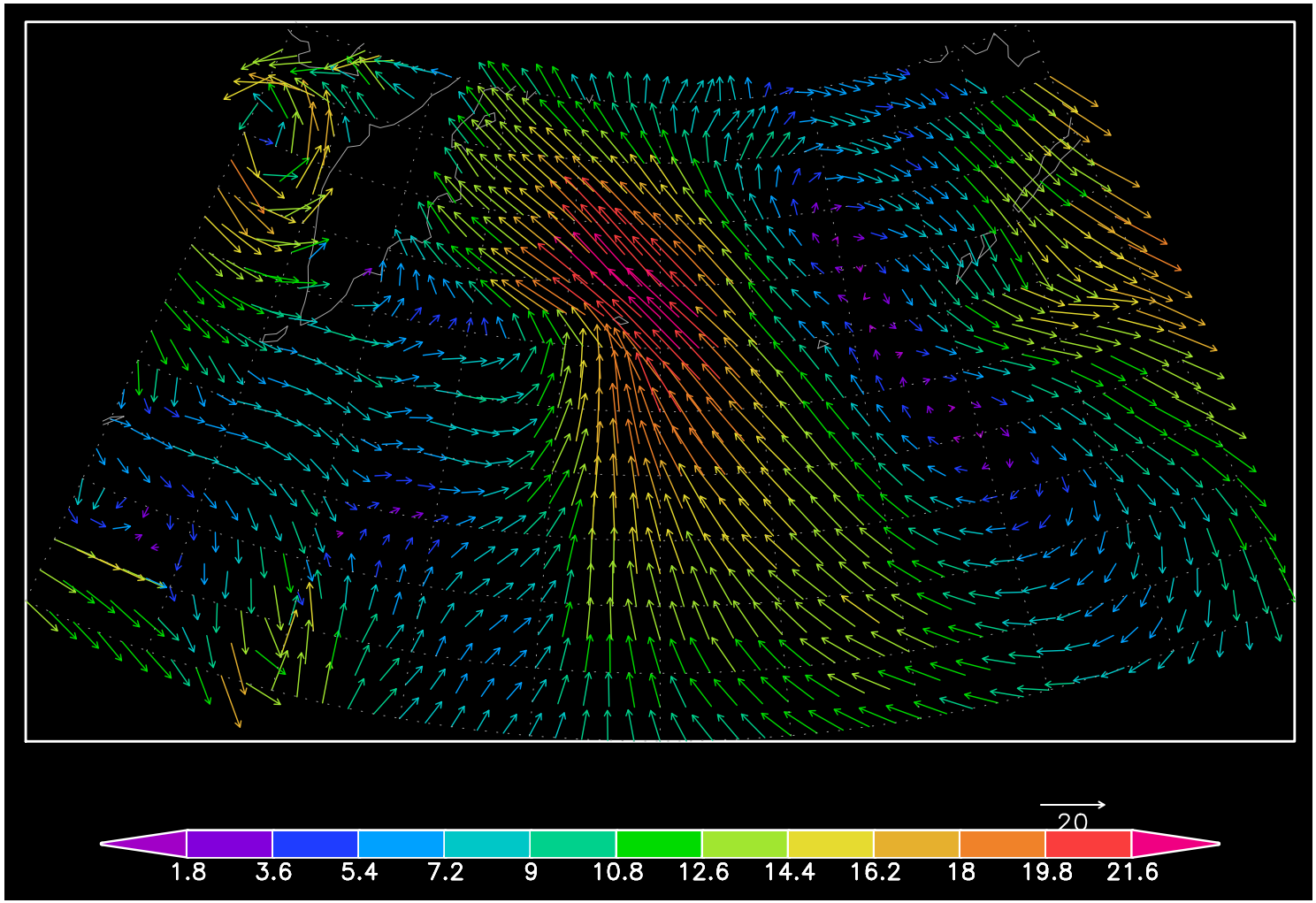
swell

$$\begin{cases} B = \left(\frac{H^a_{sw}}{H^f_{sw}}\right)^{\frac{1}{2}} \\ A = B \left(\frac{H^a_{sw}}{H^f_{sw}}\right)^2 \end{cases}$$

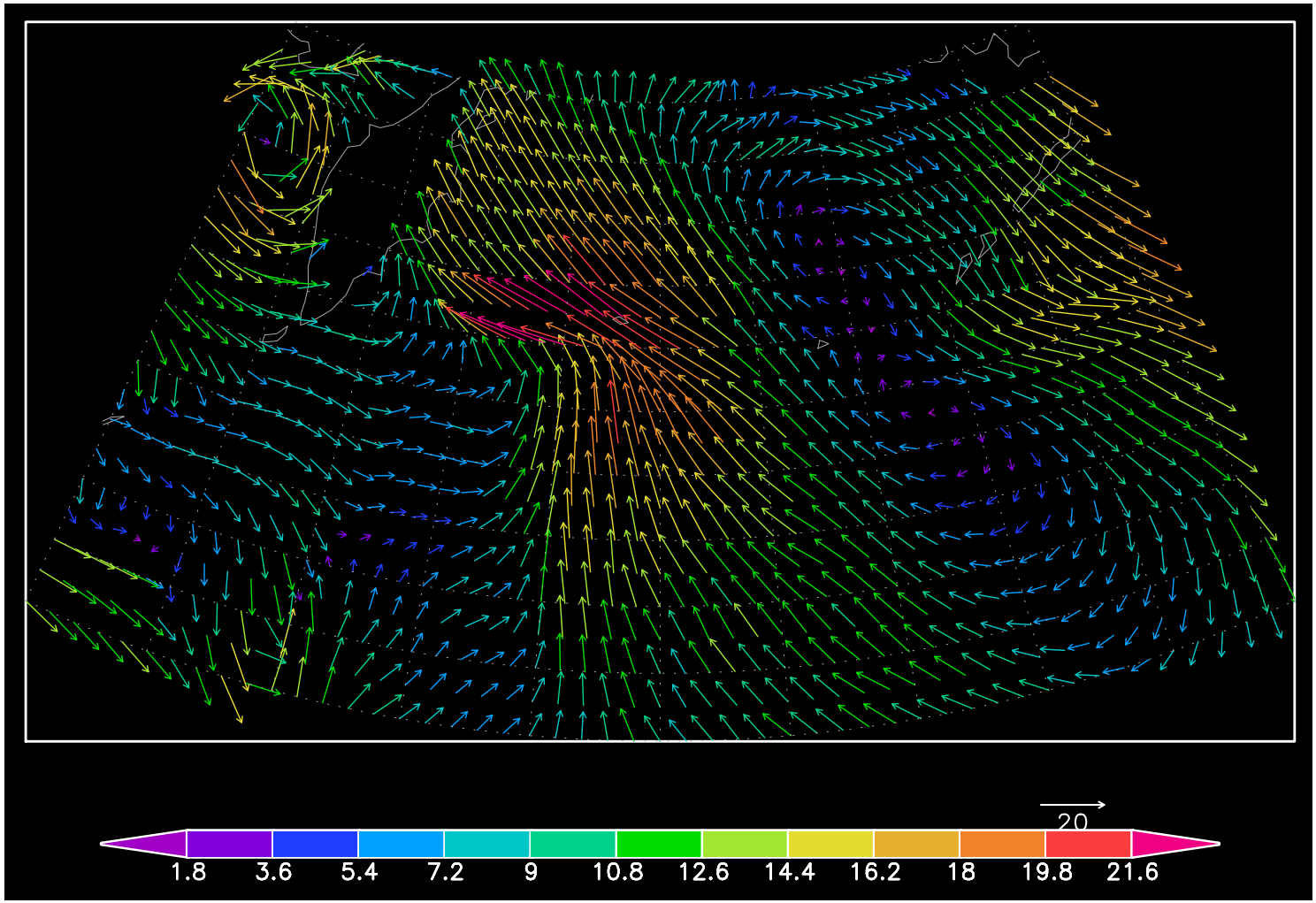
The ensemble mean in the full process

Background wind 19 December 12:00



The ensemble mean in the full process

Wind analysis 19 December 12:00



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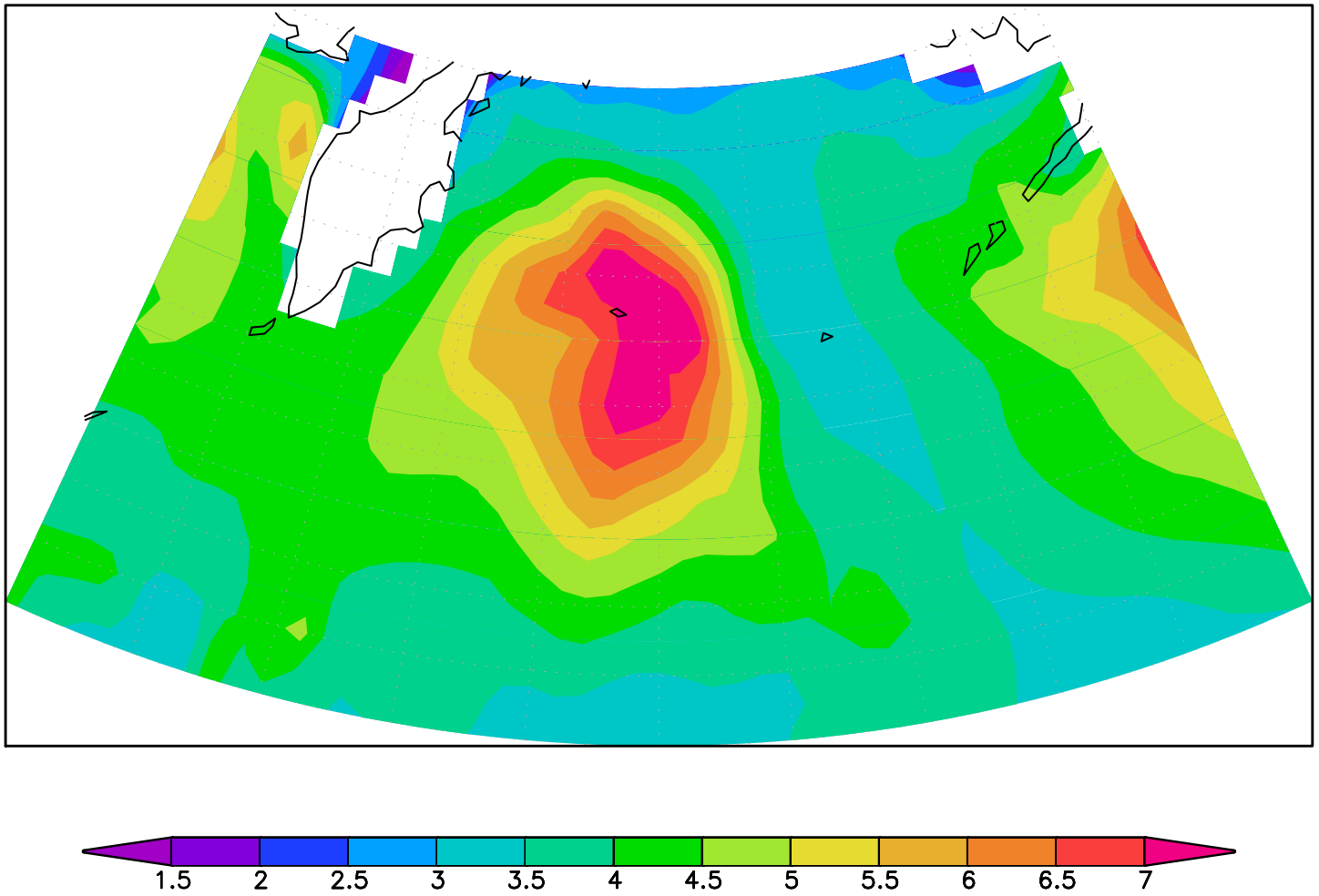
Background SWH 19 December 12:00



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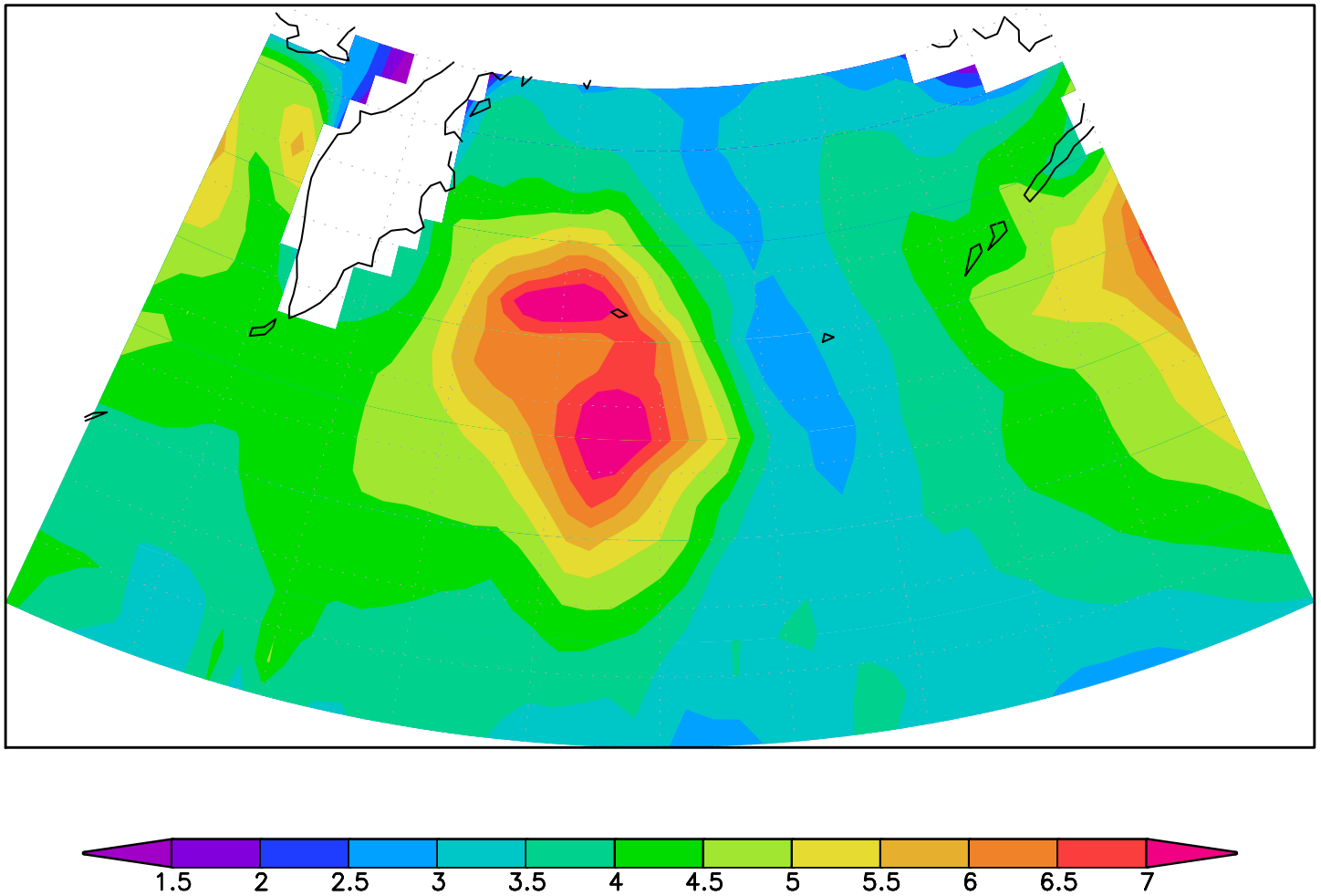
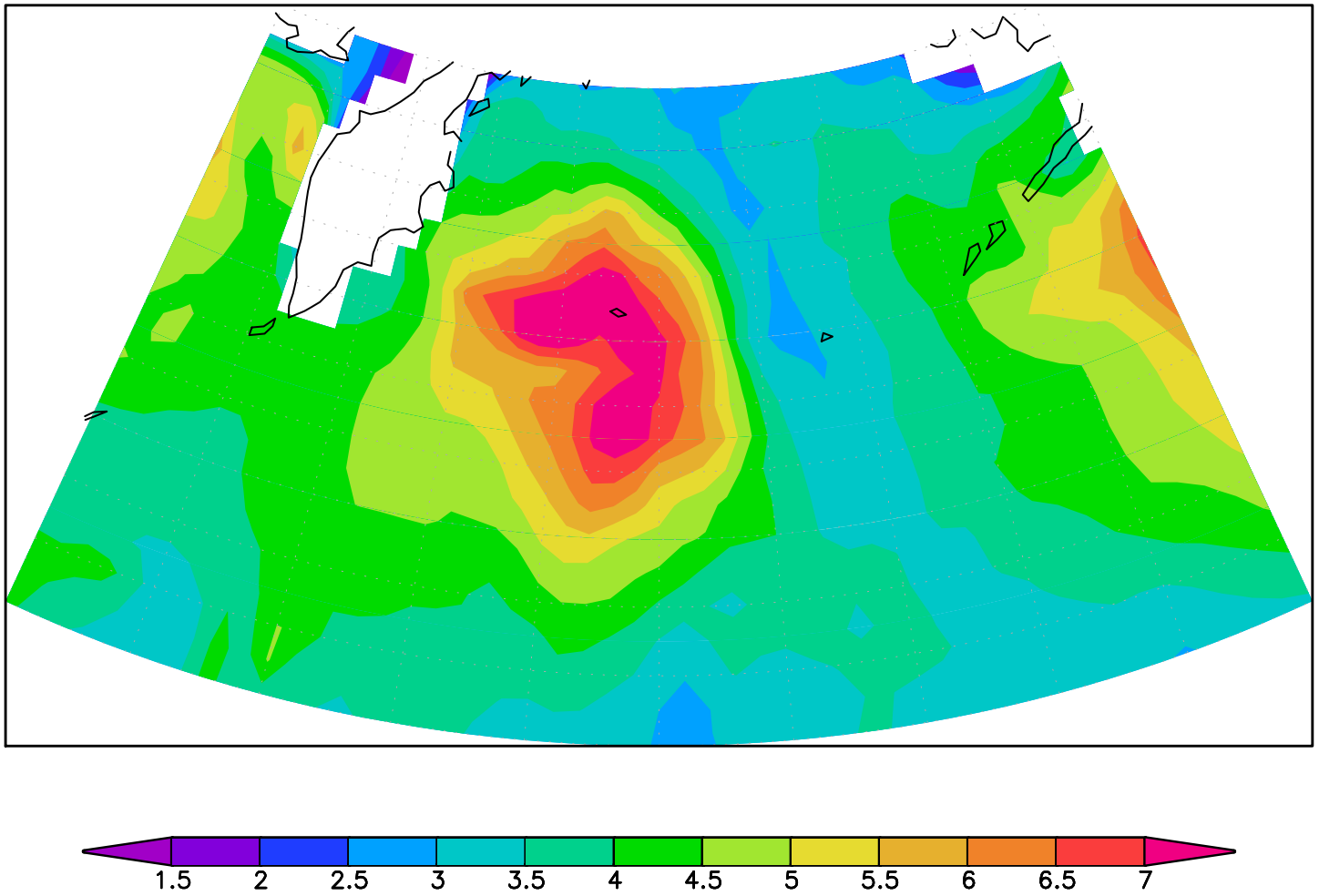


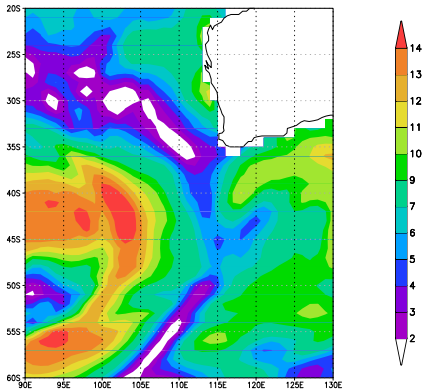
The ensemble mean in the full process

SWH after spectral update 19 December 12:00

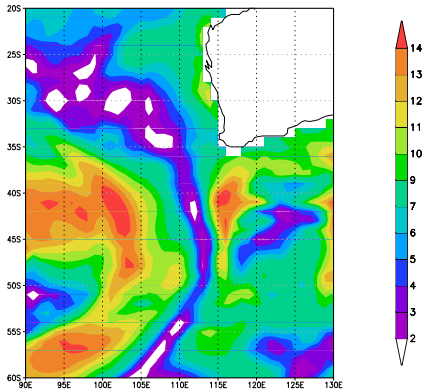


SWH update in mixed seas

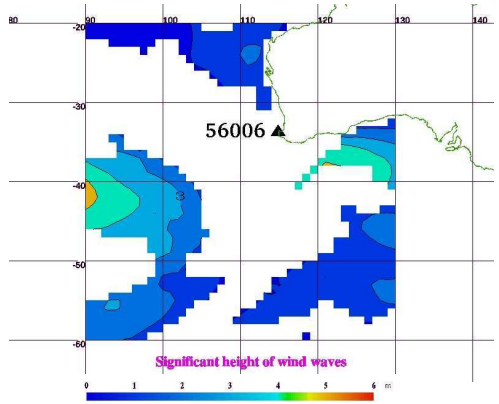
WS background

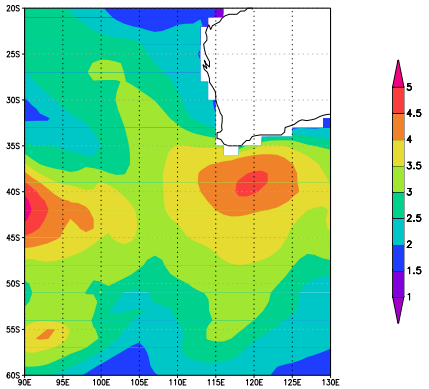


WS analysis



Wind waves (det.)





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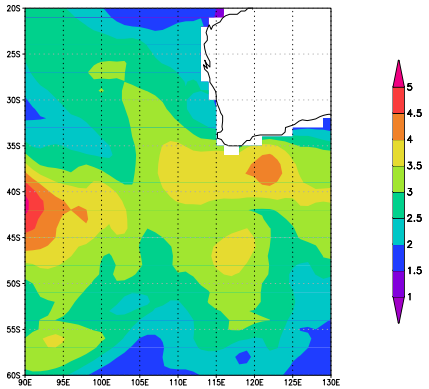

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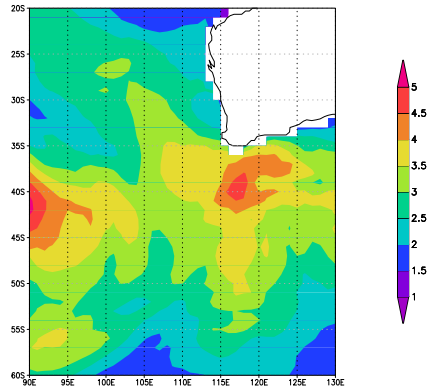


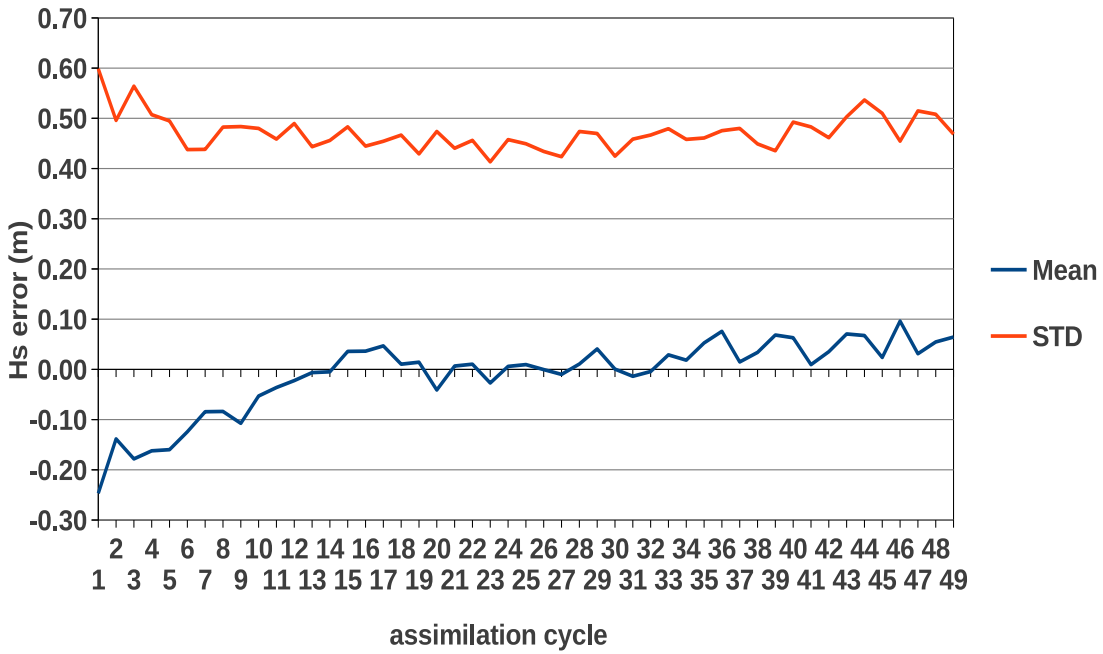
SWH assim.

19 December 06:00

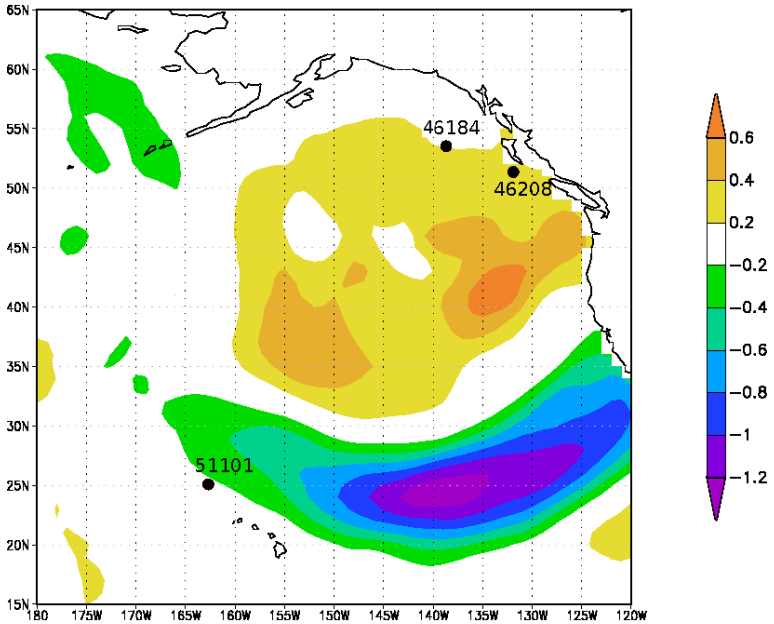
Verification in the 4D-LETKF/WWIII assimilation cycle

Global background validation in the cycle

Globally, the forecasted **SWH error** vs. observations *before* the assimilation reduces during the spin-up and remains lower in the full time period



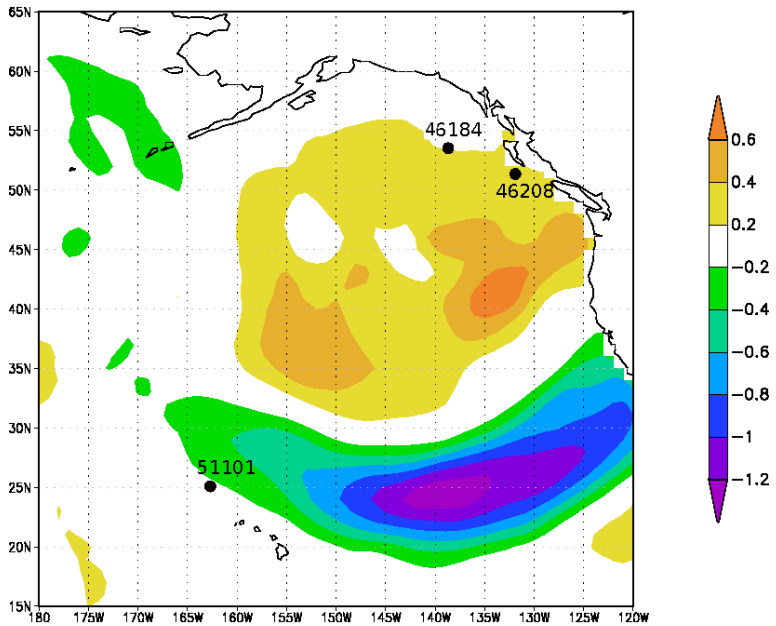
Case performance in the DA cycle



21 December 18:00

Difference in the 6-hr predicted SWH(m), DA vs. no DA cycles

Case performance in the DA cycle



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The forecast is steadily corrected along the cycles, including swells

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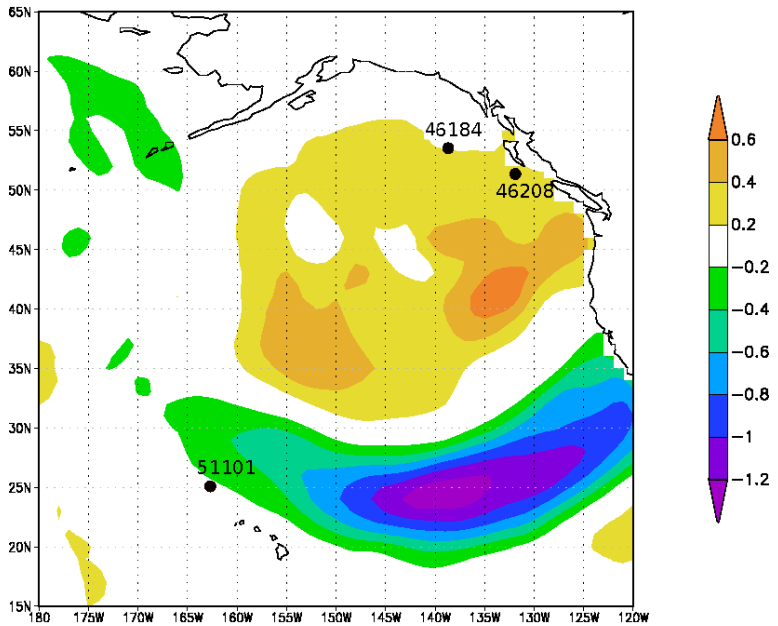

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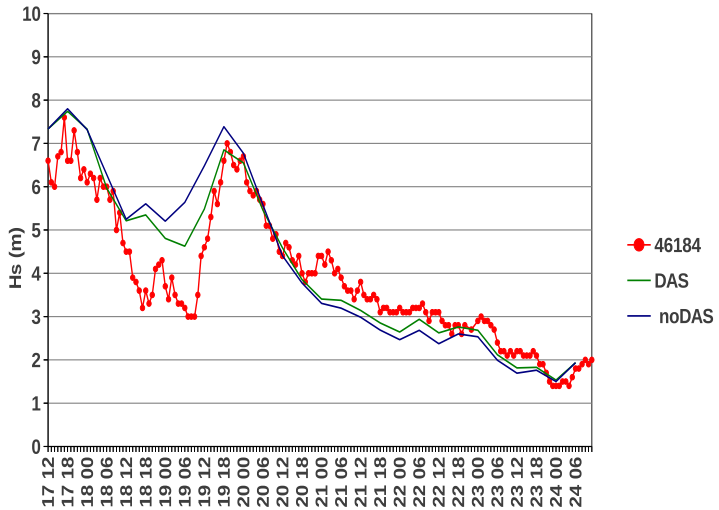
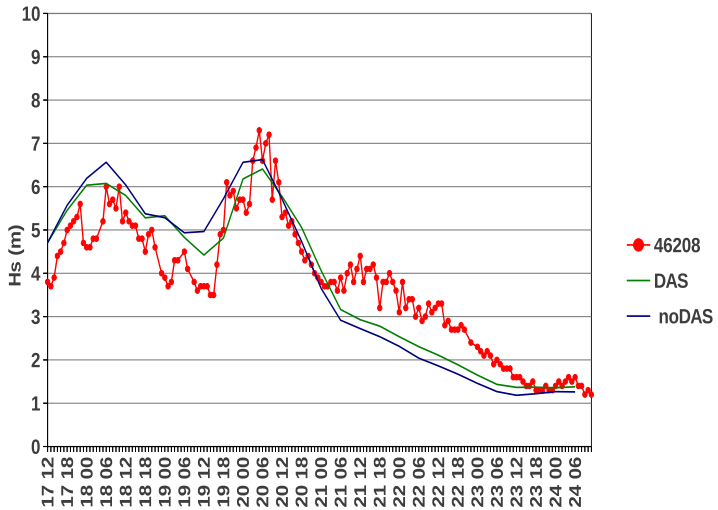
Swell delay was detected in Hawaii on 22 Dec.

Case performance in the DA cycle

Waves *within* the storm (6-hr forecast DA vs. no DA cycles)



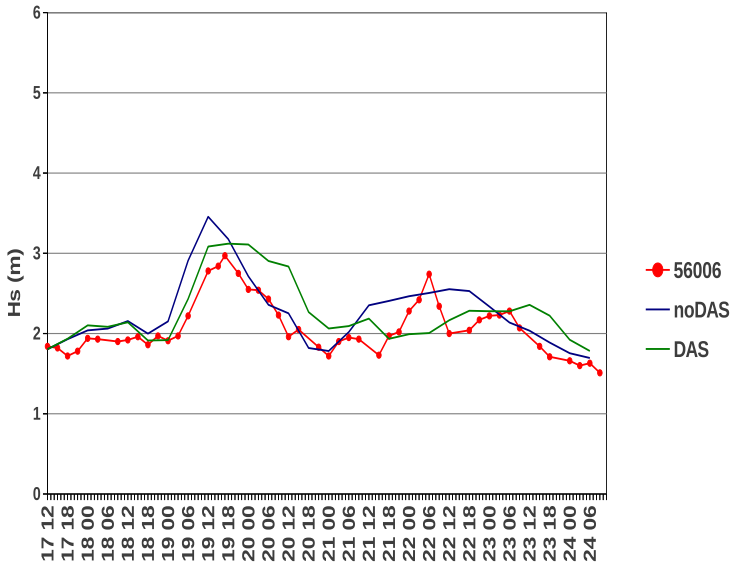


This is the ensemble mean of a prototype: not to be compared to ordinary deterministic model performance

Swells in the 6-hr forecast DA vs. no DA cycles

N Hawaii

SW Australia



Time of arrival is improved in the analysis cycle, *but decay tends to be unrealistic* ···

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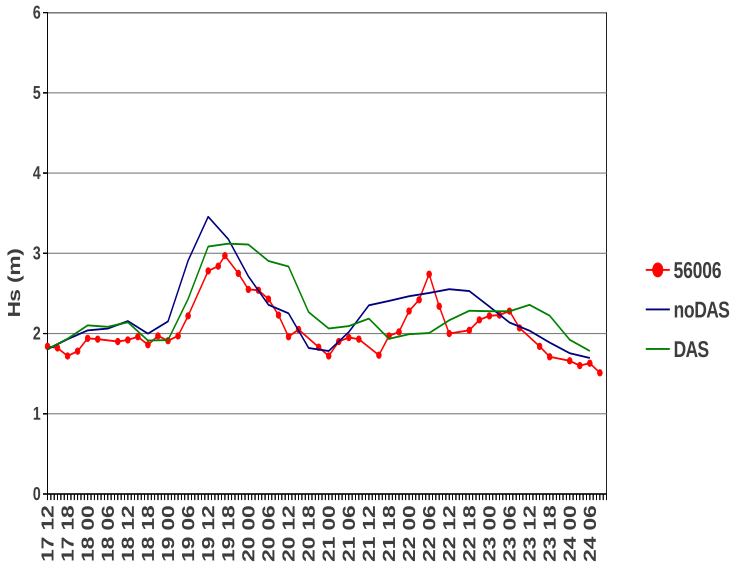
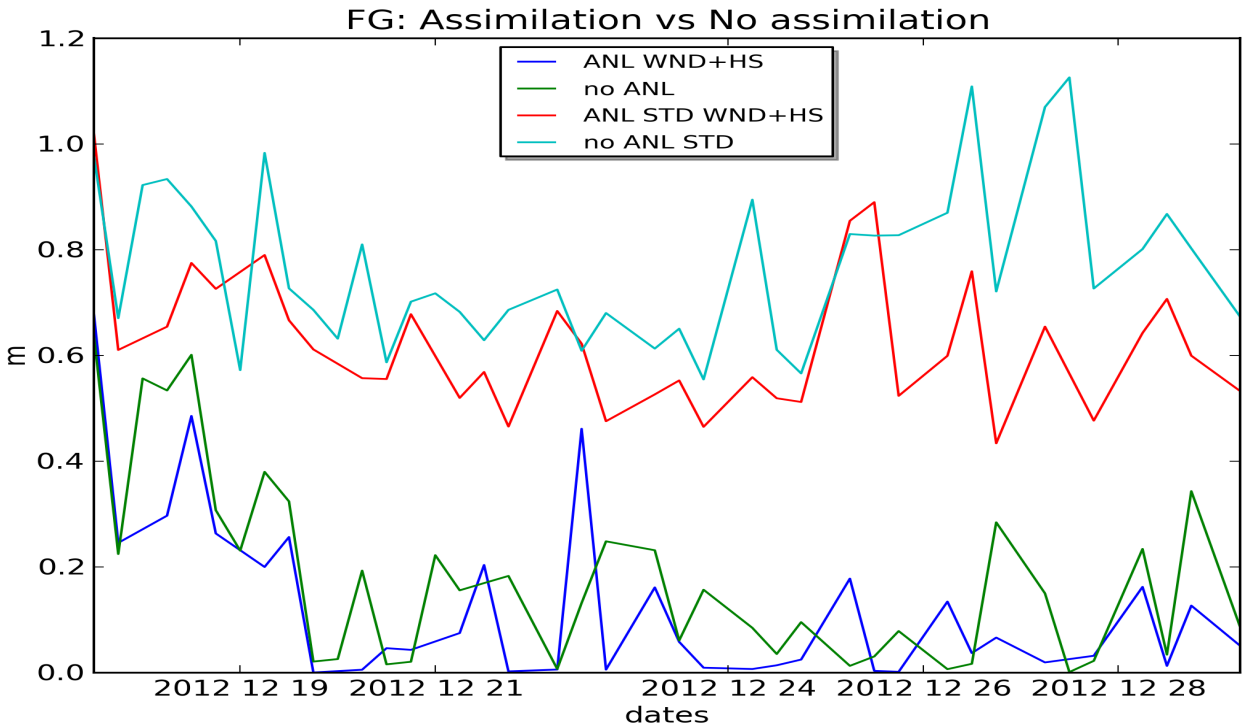


Time of arrival is improved in the analysis cycle, *but decay tends to be unrealistic* $\cdots$ the assumption on swell steepness in the spectral update is not necessarily consistent with a repositioning of the storm

Global validation DA vs no DA 6-hr forecast



LOWER blue and red: with assimilation (mean error and STD)

green and light blue: id. no assimilation

Standard deviation of the errors is clearly reduced by the DA

Bias is less clear due to ocassional spikes in this rough prototype

Conclusions

Final Remarks

- So far we focused the discussion on the ensemble mean, i.e., the *deterministic* approach.
- Validation plots at buoys were based on the 6 hr-forecast (possible impact at longer ranges is out of the scope of this work)
- Evidence of improvement was found on global and case-by-case basis
- Joint definition of storm winds and waves (positioning, intensity and timing) seems to be the main source of improvement
- Benefit is extended in space and time by swells

Pending issues

- unclear differences in the final H_s vs analysis
- considerations on steepness for swell updating may be inadequate

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- considerations on steepness for swell updating may be inadequate
- => spectral update: method to be replaced
- Deterministic model update
- Multiscale approach