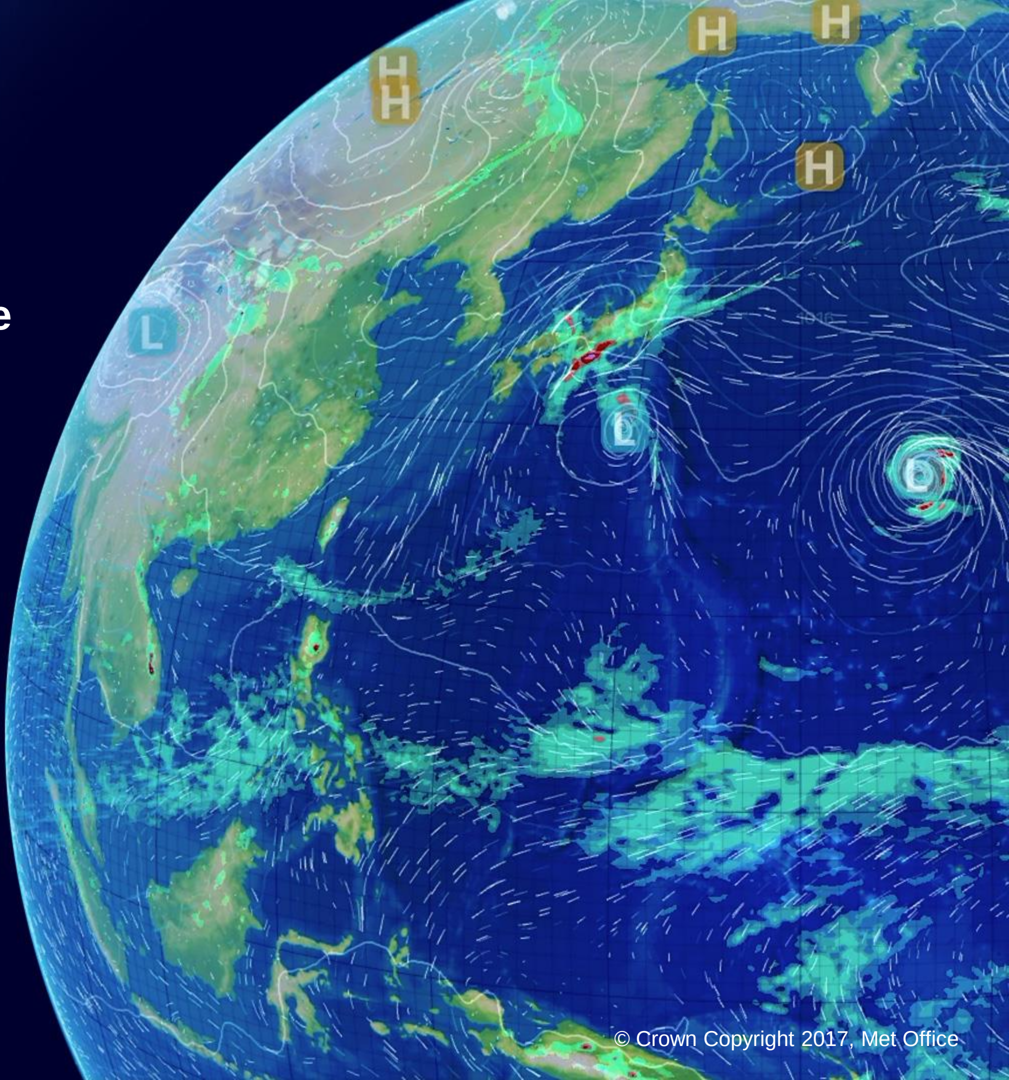
Development of a global ocean and sea-ice ensemble system at the Met Office

Matt Martin, James While, Dan Lea

20th January 2020



Talk outline

1. Introduction
2. Overview of ensemble system
3. Ongoing developments to the system
4. Summary

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Introduction

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Motivation

- Uncertainty information in the ocean and sea-ice can be useful for:
    - users of ocean/sea-ice forecasts
    - propagating uncertainty to other components of coupled ensemble systems (e.g. atmosphere)
    - improving the data assimilation
- We are developing an ocean/sea-ice ensemble system to allow us to provide uncertainty information in the ocean and sea-ice with each forecast.
- Operational implementation of these developments will be within a coupled (atmosphere/ocean/sea-ice/land) ensemble system, but we are developing/testing them within an ocean/sea-ice only framework.
- Initial implementation of coupled NWP at the Met Office will be in 2021 with a deterministic (10km atmosphere, $\frac{1}{4}°$ ocean) system, including weakly coupled DA (based on Lea et al., 2015).
- A coupled ensemble (MOGREPS-G) will also be implemented then, but the ocean ensemble will not be well developed. Initially, SST perturbations will be added to the fields provided to the atmosphere.
- The work here will be implemented operationally after 2021, within the coupled MOGREPS-G system.

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Aim and planned approach

Aim is to develop a coupled ensemble system with the ocean/sea-ice at ¼°, and make use of the ensemble covariances in a hybrid 3DVar/ensemble scheme. Deterministic system will eventually be 1/12°.

Overall approach to get there:

- Develop an ocean/sea-ice ensemble at ¼ degree:
  - Ensemble of data assimilations (3DVar-FGAT at this stage).
  - Each of the members will include an ocean/sea-ice data assimilation with perturbed observations.
  - Each member forced at the surface by an atmospheric ensemble member.
  - Each member will include stochastic model perturbations in the ocean.
  - An inflation scheme will be implemented.
- Test the hybrid ensemble/3DVar DA => see Dan Lea's talk.
- Implement the above within the coupled ocean/atmosphere/sea-ice ensemble system.
- Investigate issues associated with transferring information from low res ensemble to high res deterministic for the hybrid DA, and recentring of the ensemble.

Work in progress!

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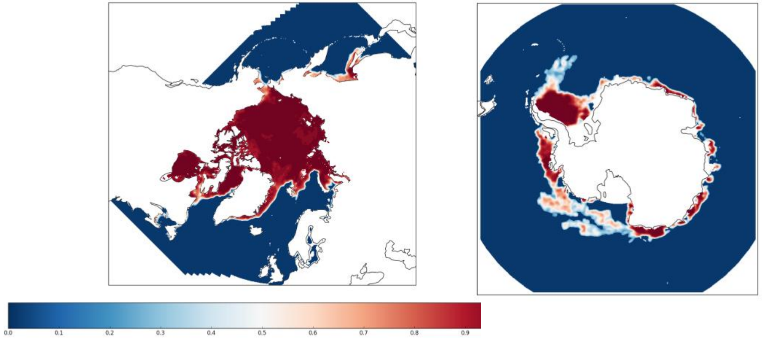
The ocean/sea-ice model and observations

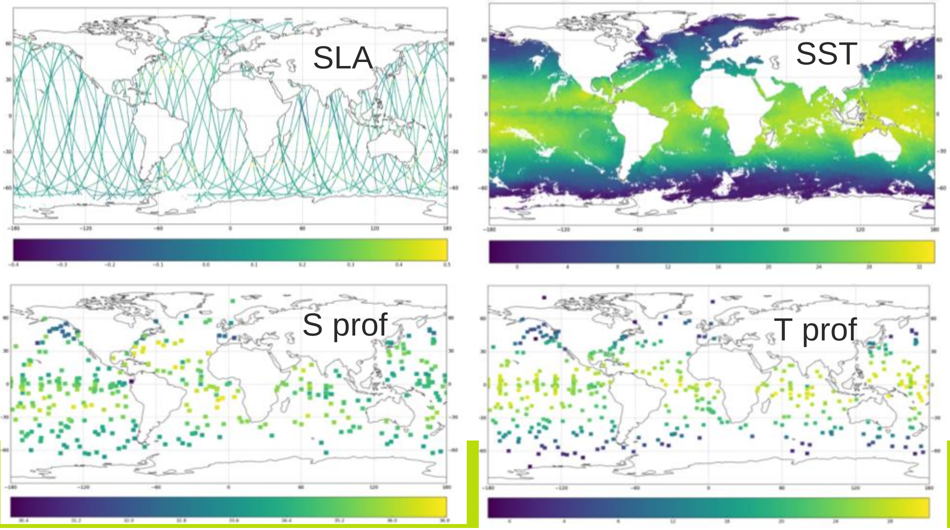
Based on the latest version of the Forecasting Ocean Assimilation Model (FOAM) system:

Ocean Model: NEMO vn3.6, non-linear free surface, TKE vertical mixing.
Sea ice model: CICE vn5.1, multiple thickness categories and multi-layer thermodynamics
Resolution: ORCA025 extended tri-polar grid (~1/4 degree resolution); 75 vertical levels
Described in Storkey et al., 2018.

Observations: Swath satellite and in situ SST, altimeter SLA, T/S profiles, sea-ice concentration.

Sea-ice concentration





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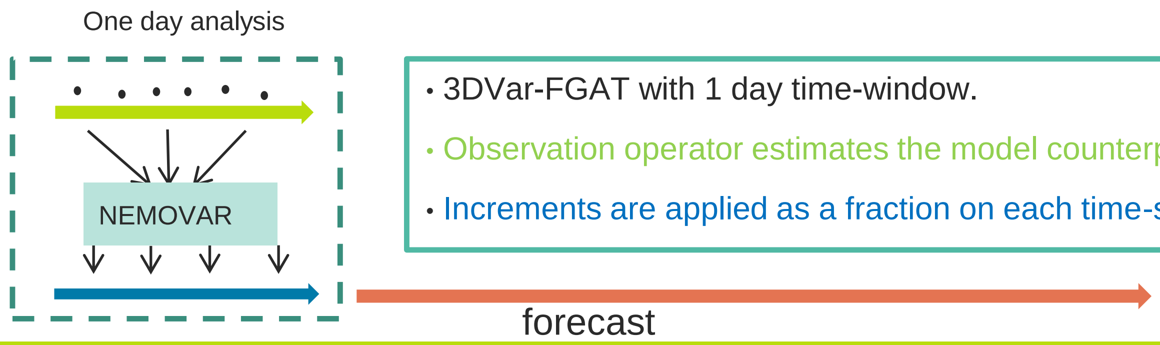
Assimilation scheme: overview

- Data assimilation using the **NEMOVAR** scheme, developed jointly by CERFACS, ECMWF, INRIA and the Met Office.
- Horizontal length-scales: combination of Rossby radius (short scale) and 4 degree scale (long scale).
- Vertical length-scales: Based on the background mixed layer depth (time and space varying).
- Background and observation error standard deviations based on combination of seasonally varying statistical estimates with parameterisation for sub-surface based on dT/dz.
- Multi-variate relationships specified using linearised physically-based balance relationships [Weaver et al. 2005].
- Observation bias correction: SST bias correction to calibrate the L2p SST data from each satellite [While and Martin 2019]. SSH bias correction to account for errors in the mean dynamic topography [Lea et al. 2008].
- Model bias correction: In the tropics, a pressure correction is applied to reduce the impact of model bias on vertical motions. [Bell et al. 2004]



- 3DVar-FGAT with 1 day time-window.
- Observation operator estimates the model counterpart at the nearest time-step to the obs.
- Increments are applied as a fraction on each time-step during 24 hours (IAU).

Overview of ensemble system

Ensemble system overview

- We run 36 members of the FOAM system:
  - Each is forced by a different atmospheric ensemble member.
  - Each has perturbed observations within the 3DVar.

- We also run an unperturbed member (the same as the standard FOAM system). No obs perturbations and forced by deterministic NWP forcing.

- Each member is independent at the moment (until hybrid DA is implemented).

- Each ensemble member is started from the same initial conditions on 1st March 2018. Taken from a previous reanalysis using FOAM.

Atmospheric forcing.

All ensemble members use the CORE bulk formulation to apply atmospheric forcing with forcing updates every:
Wind: 1 hour
Other forcing: 3 hours

The forcing applied to the model can be split into 3 types:

1.

Forcing from the Met Offices full resolution NWP system (the UM).

Used to force the single member Ocean 'control'.

Resolution: N1280 (~10km)

Atm assimilation: Hybrid 4DVar

2.

Forcing from the Met Offices atmospheric ensemble system the Met Office Global Regional Ensemble Prediction System–Global (MOGREPS-G)

Up to 18 members can be forced with this data

Resolution: N640 (~20km)

Atm assimilation: ETKF (until late 2019 => En4DEnVar)

MOGREPS-G uses a combination of the ETKF and inflation techniques to ensure a good spread of members

Every assimilation cycle MOGREPS-G is re-centred on the high resolution NWP system (until late 2019).

3.

Forcing from lagged MOGREPS-G data.

We use 6 hour lagged data

Up to 18 members can be forced with this data

Resolution: N640 (~20km)

Atm assimilation: ETKF

Total members: 1+18+18=37

Observation perturbations.

In each ensemble member perturbations are added to observations of SST, SLA, sea ice concentration, and T&S profiles.

We use two methods, which are combined, to perturb the observations:

$$y'(lon, lat) = y(\underline{lon + \varepsilon_{lon}}, \underline{lat + \varepsilon_{lat}}) + \underline{\varepsilon_{value}}$$

Position perturbation

- Based on ideas developed at ECMWF (Zuo et al. [2018])
- Designed to simulate representation error
- The statistics of Ɛ are not well known but are currently set at 0.1º, both in latitude and longitude.
- Particularly useful for perturbing profiles.

Value perturbation

- Good at simulating measurement error
- The statistics of Ɛ are based on our (imperfect) estimates of the obs errors. Ɛ varies between observation platform.
- Presently we do not specify any vertical or horizontal correlations.

y: Observation y': Perturbed observation ε: Random number of specified distribution

SST & SLA RMS Vs Ensemble Spread (over 1st month)

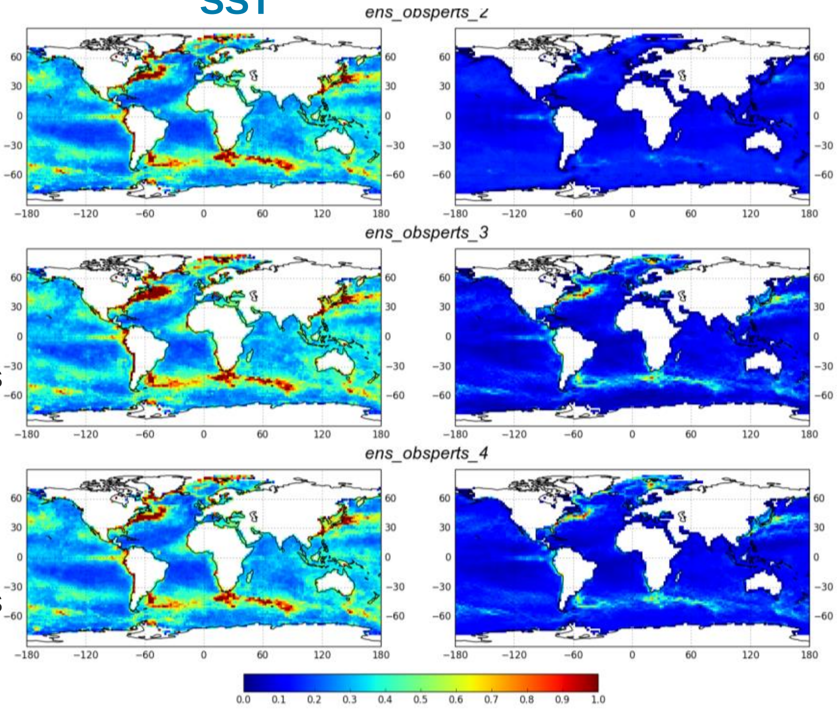
RMS (obs – ens mean) | Spread of ens

SST

Perturb obs values

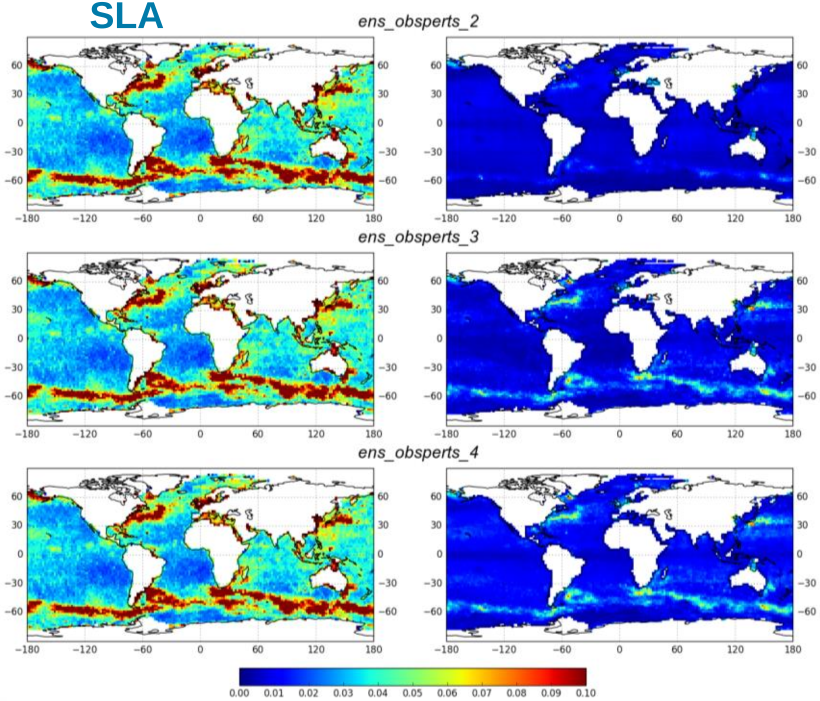
Perturb obs locations

Perturb obs values + locations



RMS (obs – ens mean) | Spread of ens

SLA

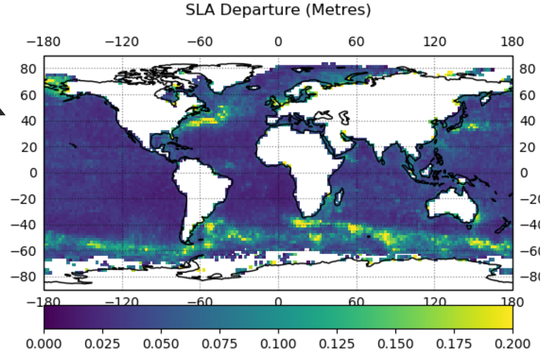


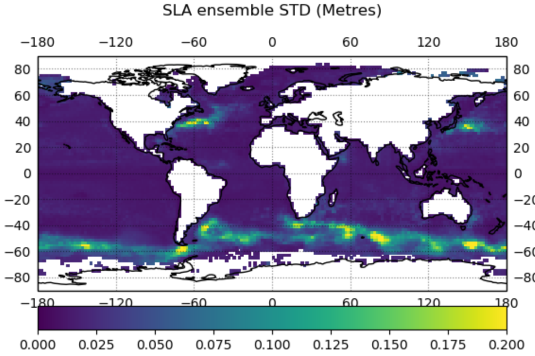
Position perturbations have a bigger impact on spread than the value perturbations.

Results of longer experiments - SLA

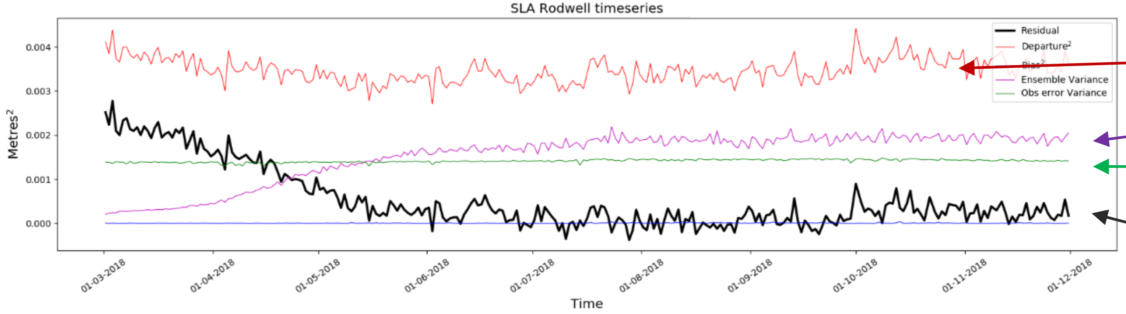
- The ensemble system has run for 10 months (March -> Dec 2018) to look at the ensemble spin-up.
- We have calculated the reliability statistics of Rodwell et al., 2015.

- Spatial plots of the (obs-mean) and ensemble spread for Nov 2018.
- The spread generally follows a similar pattern to the error in the mean.





- For SLA, the ensemble variance (in purple) has spun-up fully after 5 months.
- After that stage the ensemble is reliable: the spread in the ensemble is representative of the uncertainty.



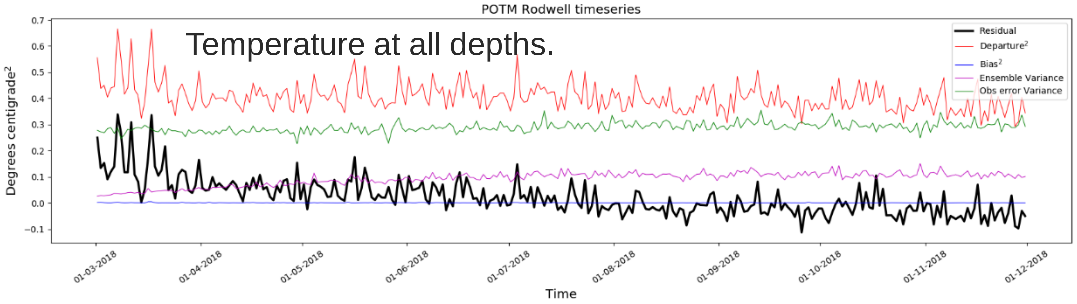
departure ^{2} = (obs –minus- ensemble mean)^{2}

ensemble variance

obs error variance

residual = departure^{2} - ens_var - obserr_var

Results of longer experiments - Temperature



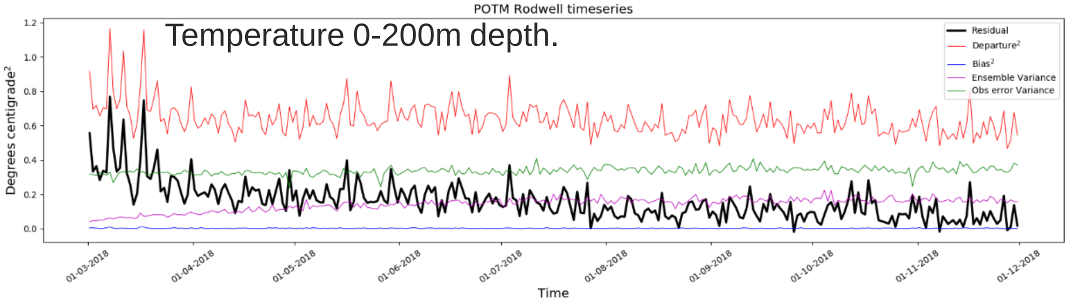
departure ^{2} = (obs –minus- ensemble mean)^{2}

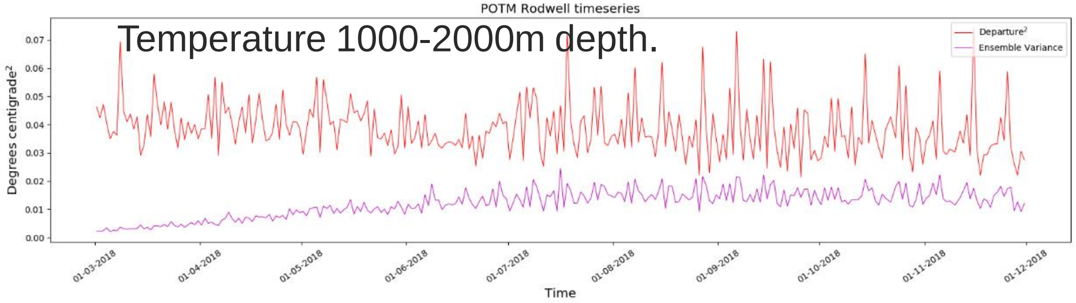
Obs error variance

Ensemble variance

Residual = departure^{2} - ens_var - obserr_var

- Globally seems to produce reasonable spread.
- Upper ocean spins-up within ~ 3 months.
- The deeper ocean 1000 – 2000 m seems to spin-up within about 6 months.





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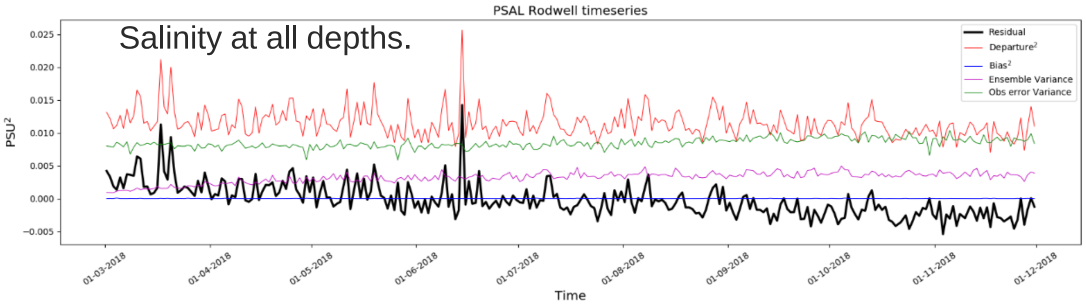
Results of longer experiments - Salinity



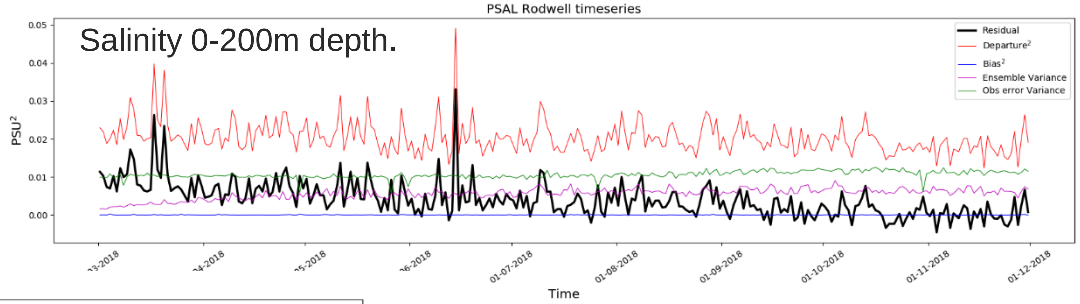
departure ^{2} = (obs –minus- ensemble mean)^{2}

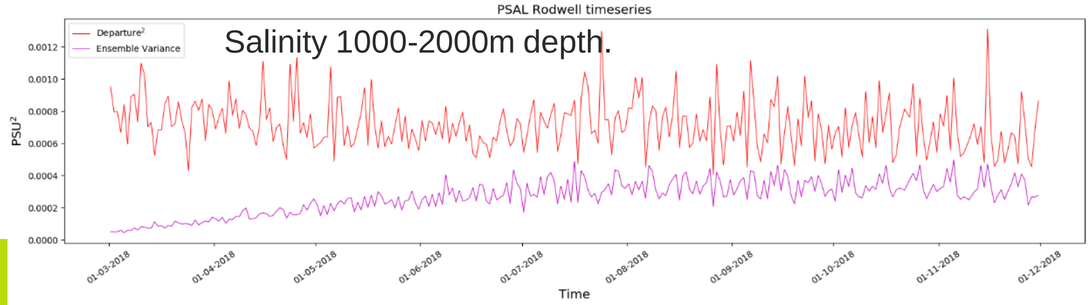
Obs error variance

Ensemble variance

Residual = departure^{2} - ens_var - obserr_var

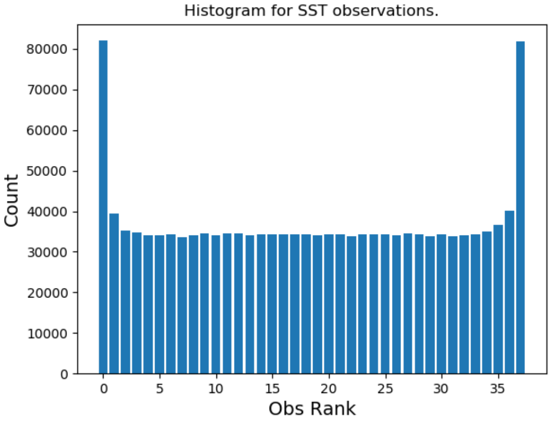
- Overall salinity spread seems reasonable.
- Similar spin-up times to temperature.

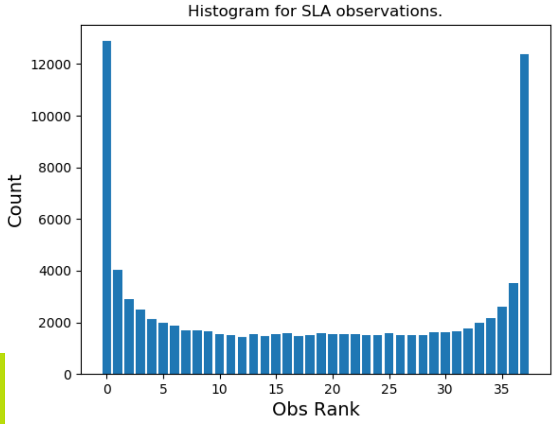


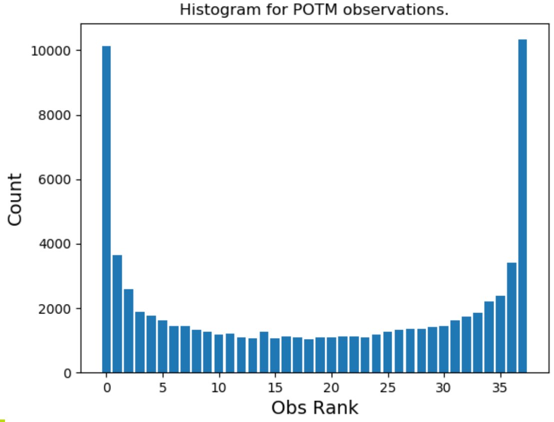


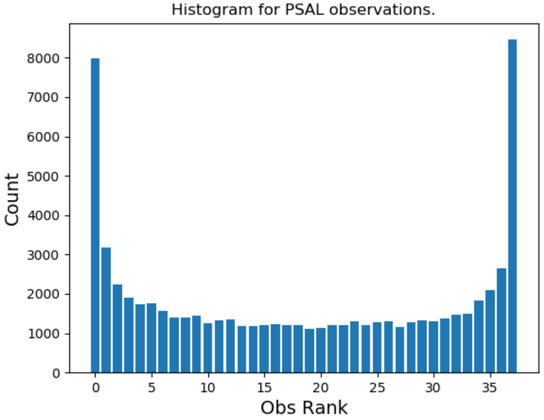
Rank histograms

- Global rank histograms from one day towards the end of the run (22nd Dec 2018) show the ensemble is under-spread overall.
- Perhaps the previous promising reliability stats are misleading when looking globally.
- Perhaps there are regional/regime differences (biases) in the ensemble, or observation errors used in the reliability statistics are affecting our understanding of whether the ensemble is reliable or not.









On-going work: stochastic model perturbations and inflation

Stochastic model perturbations

Andrea Storto wrote some code for NEMO (v3.6) in which three types of stochastic perturbations have been included:

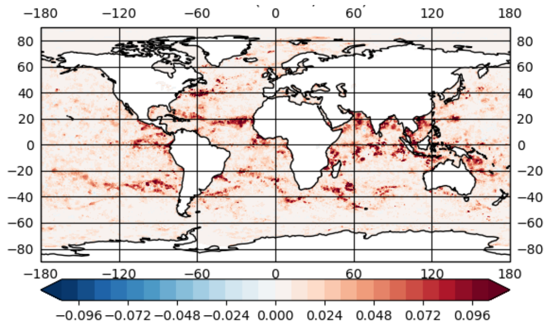
1. stochastically perturbed parameterization tendencies (***SPPT***), which adds perturbations collinear to the unresolved process tendencies.
2. stochastically perturbed parameters (***SPP***), which adds perturbation to supposedly uncertain parameters within parameterized processes;
3. stochastic energy backscatter (***SEB***), which add perturbations to the barotropic streamfunction proportionally to some sources of small-scale dissipated energy, backscattered to the model resolved scales.

Perturbation fields for each type of scheme are correlated in time and space, according to user-specified de-correlation time- and length-scales.

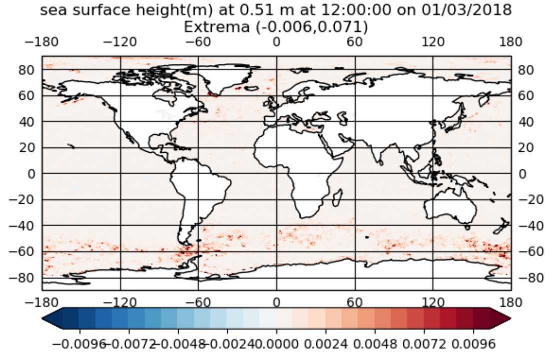
Results on the right after one day show changes in the spread.

The SPPT scheme caused a model crash in the Labrador Sea, which is under investigation.

SST ensemble spread (sto_phys – control)



Impact on the ensemble spread after 1 day



SSH ensemble spread (sto_phys – control)

Ensemble inflation

- If left to itself, our ocean ensemble system tends to underestimate the spread expected due to observation and modelling uncertainty.
- To correct for this, many ensemble systems artificially inflate the ensemble using a variety of methods.
- Two of the main methods in use are additive and multiplicative inflation:

Additive

Addition matrix

$$\mathbf{X}' \leftarrow \mathbf{X}' + \mathbf{\Psi}$$

Ensemble perturbation column matrix

- Approximately simulates the effects of model error.
- Not applied in our system as we are trying to simulate model error with perturbed physics.

Multiplicative

$$\mathbf{X}' \leftarrow \mathbf{\Lambda}\mathbf{X}'$$

Multiplication matrix

- Acts to account for spread over-deflation by the data assimilation.
- Applied in our system.

Ensemble inflation: RTPS scheme

- We are implementing a Relaxation To Prior Spread Scheme (RTPS)[1] inflation scheme.
- This is a multiplicative inflation scheme – it increases the analysis variance, but does not change the subspace spanned by the ensemble.
- It is designed to ‘relax’ the analysis spread towards the forecast spread.

Forecast ensemble error variances

Analysis ensemble error variances

$$\Lambda_{ij} = \begin{cases} \alpha \left(\dfrac{(\mathbf{P}^{\mathrm{f}}_{ij})^{\frac{1}{2}} - (\mathbf{P}^{\mathrm{a}}_{ij})^{\frac{1}{2}}}{(\mathbf{P}^{\mathrm{a}}_{ij})^{\frac{1}{2}}} \right) + 1 & i = j \\ 0 & i \neq j \end{cases}$$

Inflation factor

Relaxation weight

α = 0: Spread unchanged
α = 1: Inflated spread = forecast spread

[1]Described in:
Evaluating methods to account for system errors in ensemble data assimilation; DOI:10.1175/MWR-D-11-00276.1

Ensemble inflation: practical details

- At present we inflate temperature, salinity, SSH, and velocity. We plan to inflate sea ice concentration, but not implemented yet.
- Inflation is applied to the 'unbalanced' (i.e. uncorrelated) increments used in the data assimilation, rather than the real variables. A linear inverse balancing operator is applied to convert the inflated unbalanced increments back into real space before applying them to the model.
  Unbalanced variables are: temperature, unbalanced salinity, and unbalanced SSH.
  => Total increments are: temperature, salinity, SSH, and velocity.
- Inflation is applied after the analysis increments have been calculated; i.e. after the DA inner loop, but before the increments are applied to the model during the IAU step.
- Rather than inflating the ensemble perturbations, we update the analysis increments to give the same effect. It can be shown that inflation is equivalent to updating the increments such that:

$$\mathbf{\Gamma} = (\mathbf{\Lambda} - \mathbf{I})\mathbf{X}'^{\mathrm{f}} + \mathbf{\Lambda}\mathbf{\Gamma}' + \bar{\mathbf{\Gamma}}$$

Column matrix of inflated ensemble increments

Column matrix of ensemble increment perturbations (differences to the mean)

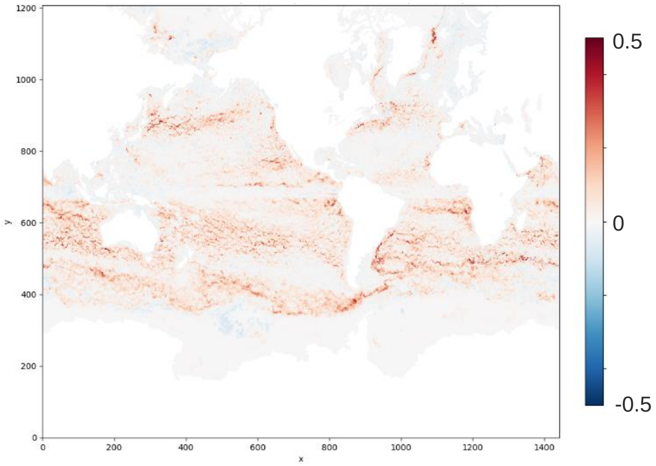
Column matrix of ensemble mean increment (all columns identical)

Ensemble inflation: (very) preliminary results

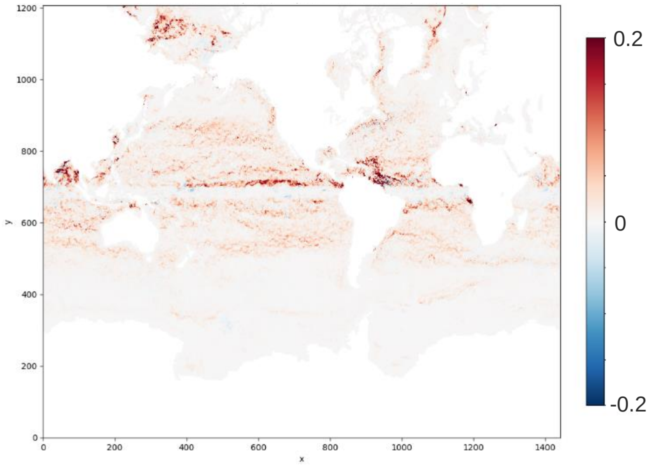
- Code to apply RTPS inflation has been written and (as of last week!) implemented.
- We are doing provisional testing using a run from 1st September 2018, using $\alpha=0.8$. This is the same value as used in the Met Office's atmospheric system.
- Tuning experiments are planned to better estimate α for the ocean system.

Plots of increase in ensemble standard deviation after 4 days due to inflation
i.e. difference in the ensemble spread compared to the control (without inflation)

Surface Temperature (K)



Surface Salinity (PSU)



Summary

Summary

- We are developing an ocean/sea-ice ensemble system and have implemented an ***ensemble of 3DVars*** with ***perturbed observations*** forced by an ***atmospheric ensemble***.
- Work in progress and some of the results are very preliminary.

- The ensemble spins up within ~6 months.
- The global reliability plots based on Rodwell et al. (2015) show SLA, T and S to have a reasonable spread.
- However, rank histograms indicate that it is under-spread.

  => Further work to better understand these results.

- On-going work is to improve the ensemble through the use of stochastic model perturbations, and multiplicative inflation using the RTPS method.

- Developments to make use of the ensemble in the DA will be described by Dan Lea.

Thank you. Questions?

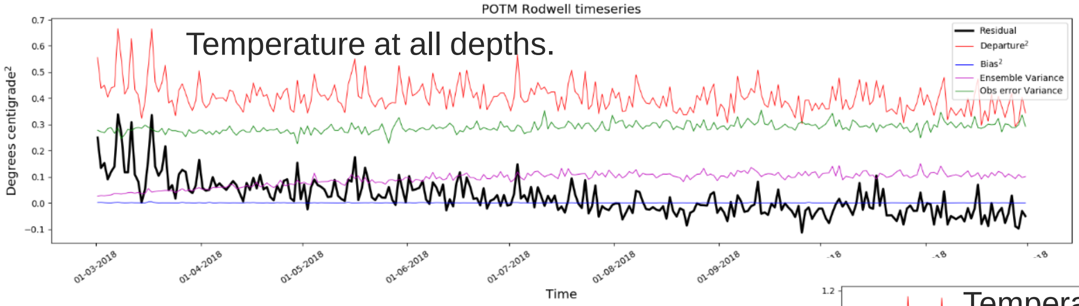
Extra slides

Observation perturbations.

We have tested our setup in a set of 4 experiments:

Experiment	Run length	Observation perturbations
mogreps_cntl	March to May 2018	Value perturbation only. Globally constant statistics based on global mean of measurement error + representativity error.
ens_obsperts_2	March 2018	Value perturbations only. Spatially and seasonally varying statistics of measurement error + representativity error.
ens_obsperts_3	March 2018	Position perturbations only. 0.1º Standard deviation.
ens_obsperts_4	March to May 2018	Position and value perturbations. Value pertubations based on measurement error only. 0.1º Standard deviation for position pertubations.

Results of longer experiments - Temperature



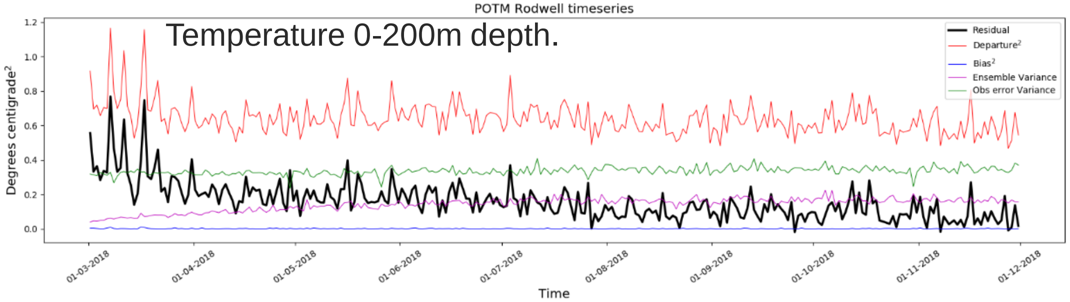
departure ^{2} = (obs –minus- ensemble mean)^{2}

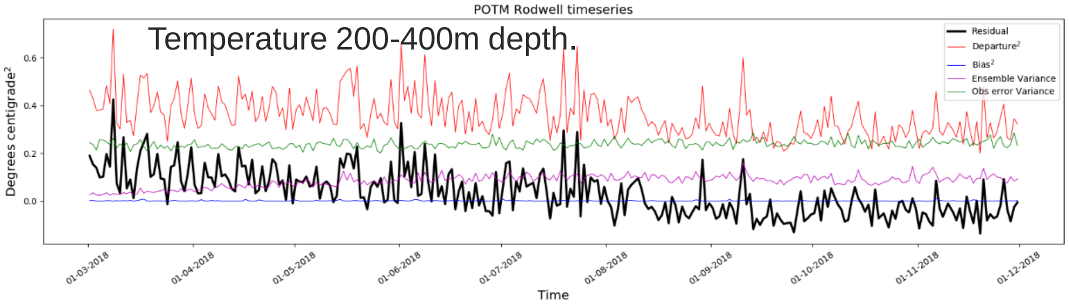
Obs error variance

Ensemble variance

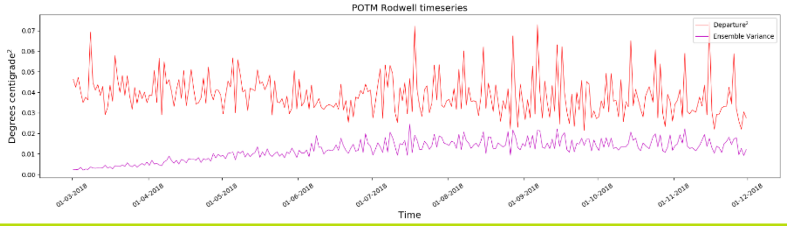
Residual = departure^{2} - ens_var - obserr_var

- Upper ocean spins-up within ~ 3 months.
- The deeper ocean 1000 – 2000 m seems to spin-up within about 6 months.
- Globally seems to produce reasonable spread.

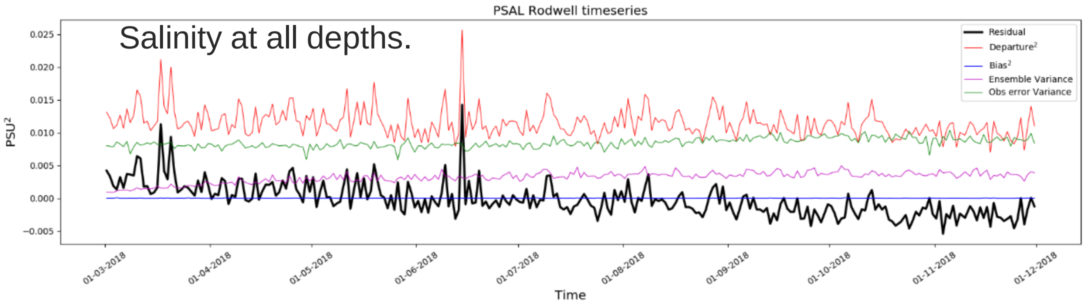




Temperature 1000-2000m depth.



Results of longer experiments - Salinity



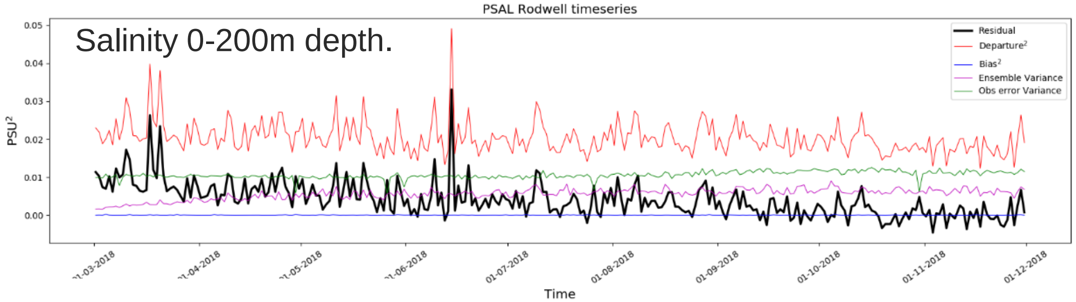
departure ^{2} = (obs –minus- ensemble mean)^{2}

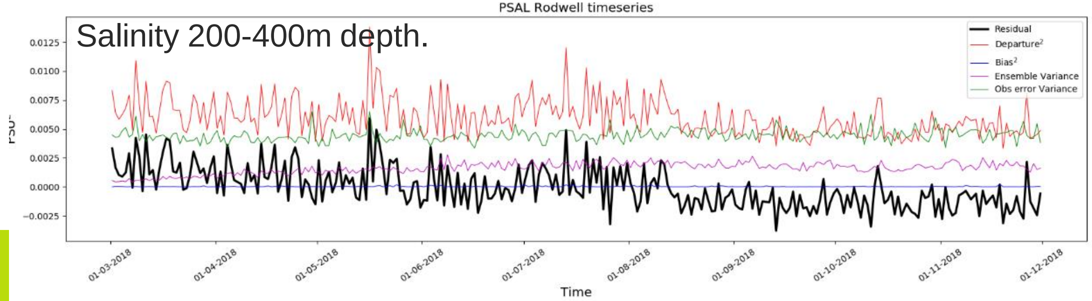
Obs error variance

Ensemble variance

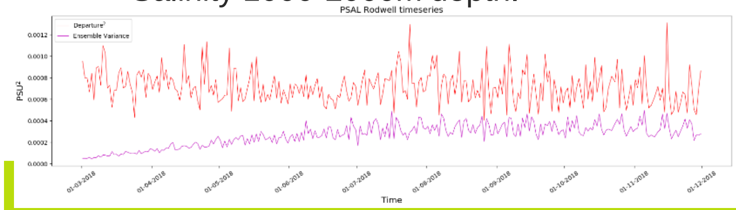
Residual = departure^{2} - ens_var - obserr_var

- Similar spin-up times to T and SLA.





Salinity 1000-2000m depth.

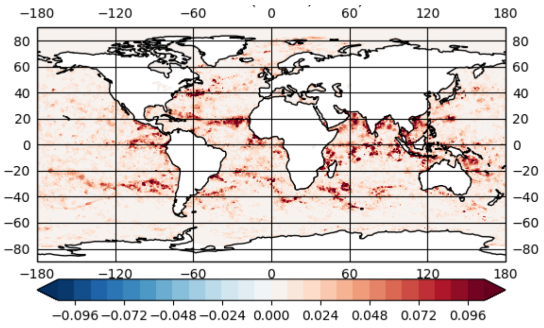


Stochastic model perturbations

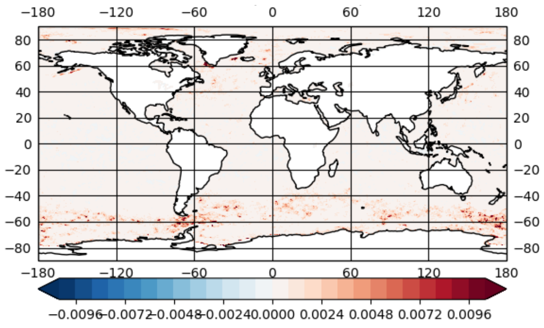
- SPPT. The model tendencies are perturbed for:
  - Lateral viscosity
  - Lateral and vertical diffusion
  - Tracer damping.
  - Solar radiation.
- SPP. Various parameters are perturbed including
  - Vertical diffusion
  - Horizontal viscosity and diffusivity
  - Bottom boundary layer diffusivity
  - Mixing close to river mouths
  - Various TKE mixing parameters, e.g. vertical mixing coefficients for tracers and dynamics
  - Relative wind factor.
  - The perturbations are all specified with a log-normal distribution.
- Results on the right after one day show changes in the spread.
- The SPPT scheme caused a model crash in the Labrador Sea, which is under investigation.

Impact on the ensemble spread after 1 day

SST ensemble spread (sto_phys – control)



SSH ensemble spread (sto_phys – control)

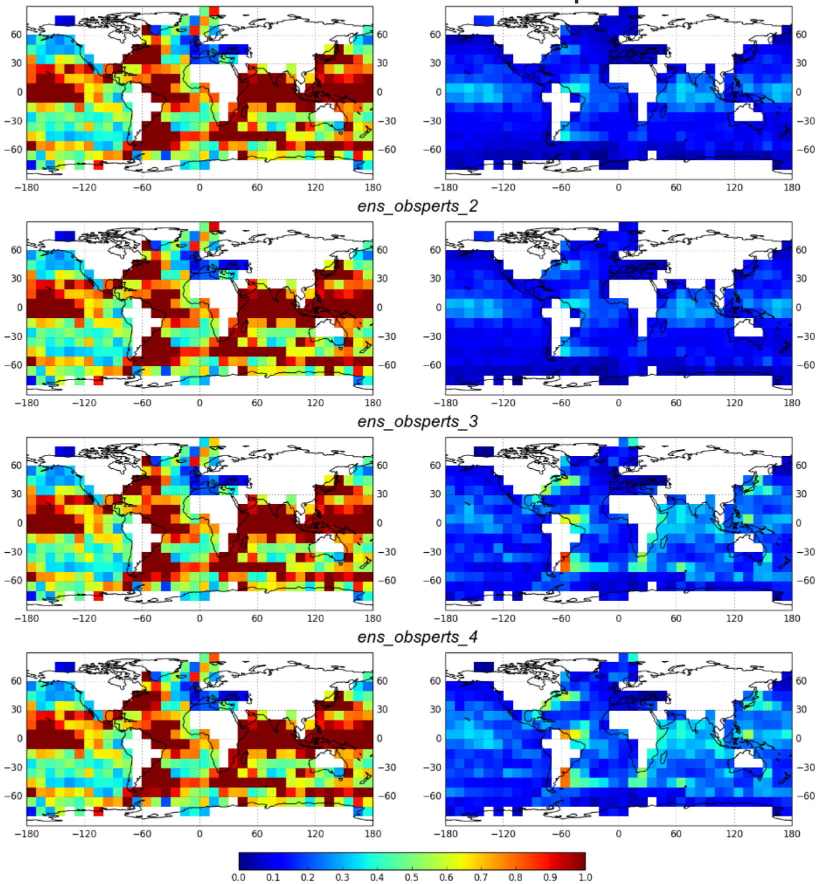


RMS Vs Ensemble Spread (March)

Met Office

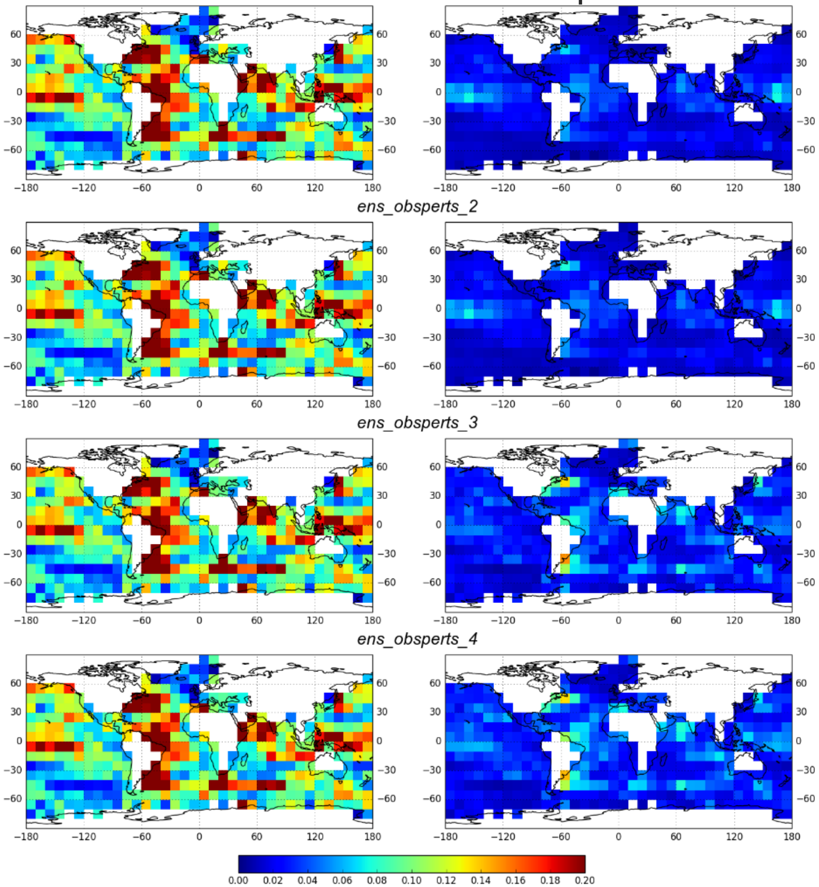
T (0 to 100m)

RMS	*mogreps_cntl*	Spread



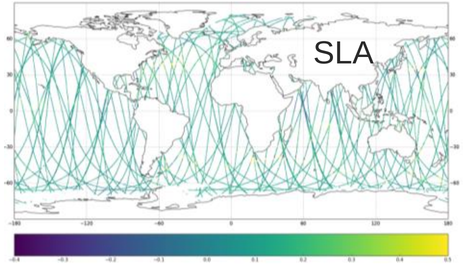
S (0 to 100m)

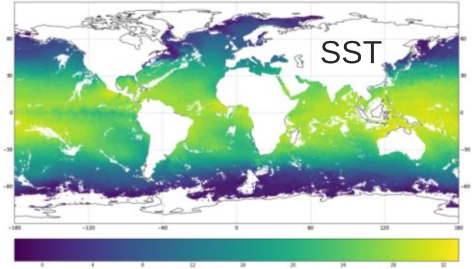
RMS	*mogreps_cntl*	Spread

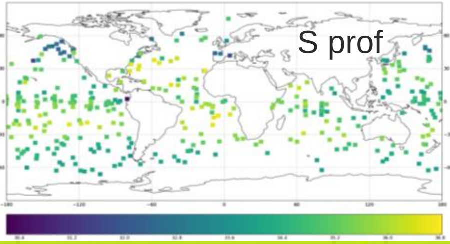


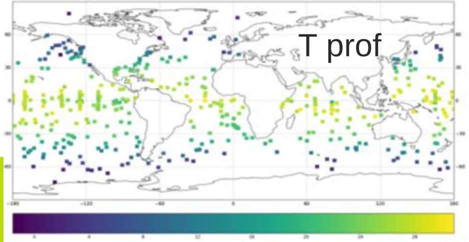
Observations assimilated operationally

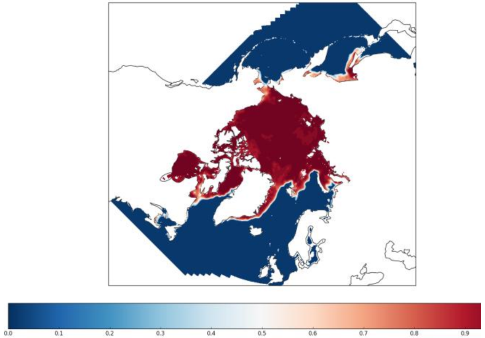
Observed variable	Platforms/sensors	Numbers /day
SST	L2 satellite data: NOAA/AVHRR, MetOp/AVHRR, AMSR2, VIIRS.	~2,000,000
	In situ: ships, drifting buoys	~50,000
SLA	Along-track altimeter data from CMEMS: Jason-3, Cryosat-2, Sentinel-3, Altika	~100,000
SIC	SSMI/S from OSI-SAF	~800,000
Temperature profiles	Argo, moored buoys, gliders, research ships, XBTs, marine mammals.	~700 profiles
Salinity profiles	Argo, moored buoys, gliders, research ships	~500 profiles



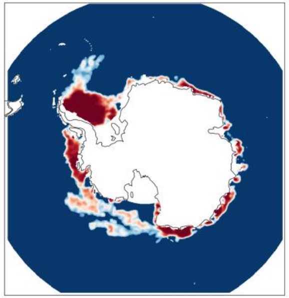








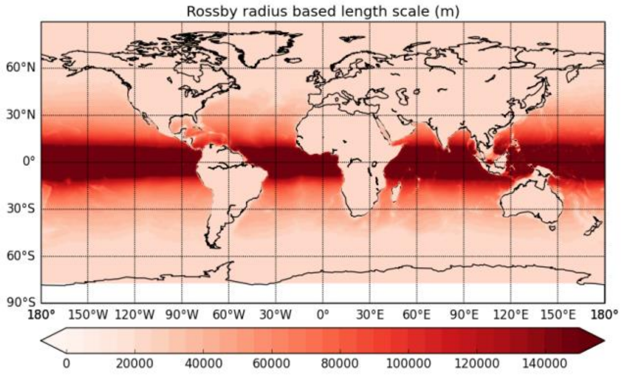
Sea-ice concentration



Horizontal background error covariances

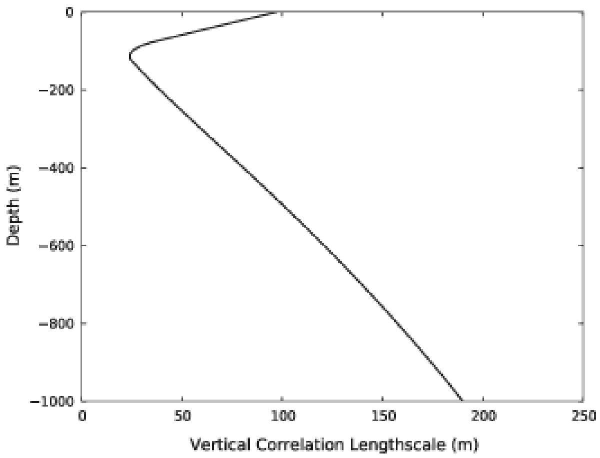
- Horizontal covariances represented as **combination of two Gaussian functions, each with their own variance and length-scale** [Mirouze et al. 2016].
  - Modelled using **2D implicit diffusion** equation which is efficient to run, but need to estimate the re-normalisation factors which is expensive – they depend on the length-scales.
  - If length-scales vary in time then normalisation factors need to be recalculated every cycle which is very expensive.

- Horizontal length-scales specified as: (i) Rossby radius (with min/max as 25km/150km) and (ii) ~400km.
- **Variances associated with each length-scale are spatially and seasonally varying**, so the effective length-scale of the combined function also varies due to the ratio of the two variances, without the need to recalculate the normalisation factors.
- Length-scales reduced towards the coast.



Vertical background error correlations

- Vertical correlations represented as a Gaussian function with specified length-scales, and modelled using the diffusion equation.
- **Flow-dependent vertical length-scales** (L) specified based on the **background mixed layer depth** (MLD) for the current assimilation cycle.
    - At the surface, L=MLD
    - At the base of the mixed-layer and below, L=2 x dz
    - L varies smoothly between the surface and base of the mixed-layer.



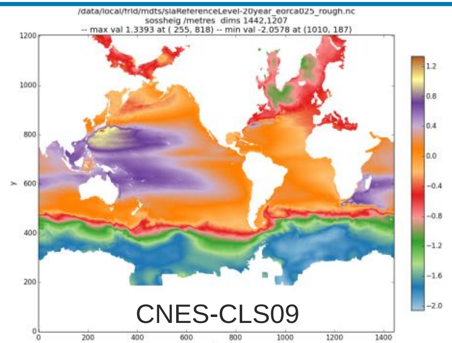
To avoid recalculating the (3D) normalisation factors every cycle, we generate a **look-up table (LUT) of normalisation factors**:

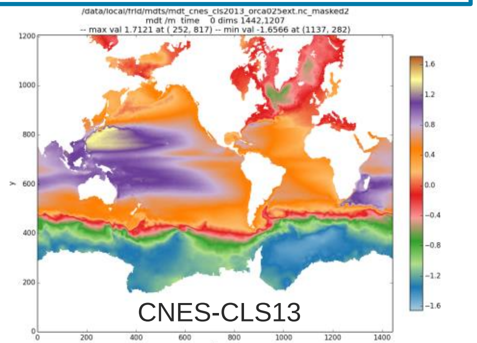
- one 3D field of normalisation factors for a set of discrete MLDs based on the top 42 model levels (<600m depth) in orca025.
- when running, the current background MLD at a particular location is calculated and a vertical profile of the normalisation factors associated with that value are read from the LUT for that horizontal location.

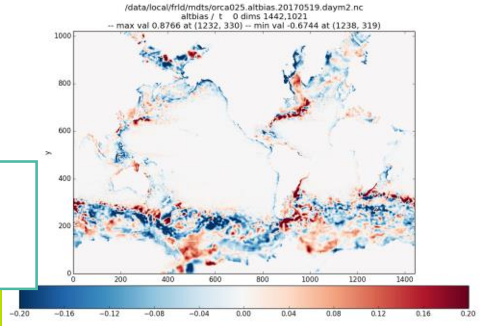
Observation bias correction schemes

- **Variational observation bias correction**:
  - Correct biases in **L2/L3 satellite SST data** using a variational bias correction scheme which also makes good use of reference data, as described in [While and Martin 2019].
  - Deal with **biases in the MDT** during altimeter SLA assimilation using the on-line variational bias correction scheme of [Lea et al. 2008].

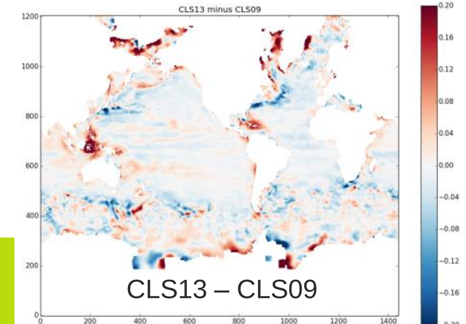
- Altimeter bias correction is calculated online using the SSH innovations and acts on small spatial scales (and is assumed constant in time).
- We tested the MDT bias correction during the update to CNES-CLS13 MDT.
- The **bias correction field associated with the older MDT was making corrections which agree** with the **difference between the new and old MDTs**
- New MDT + bias correction still brings significant improvements to SSH and sub-surface T/S innovations.







Bias field associated with CLS09



Use of ocean ensemble information in data assimilation

In data assimilation, the forecast (background) error covariance is crucial in determining how observational information is spread into the model, and the weight given to it.

In our ***existing data assimilation*** set-up, the background error covariances are *not* static. They are specified as a combination of:

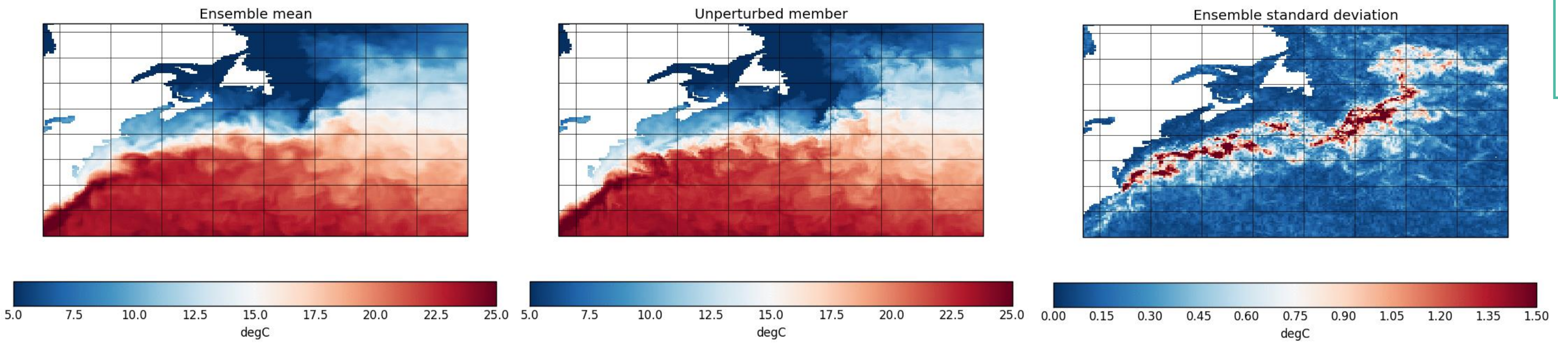
a) Spatially and seasonally varying ***statistical estimates*** from previous reanalyses.

b) Time-varying ***parameterisations*** based on the model background fields.

c) ***Multi-variate relationships*** based on dynamical balances, linearised about the model background state.

The current system works well, but ***doesn't capture the day-to-day variations in the uncertainty*** associated with e.g. the location of fronts/eddies, or deep convection events, or when El Nino events are beginning (timing/magnitude of westerly wind bursts), …So we are not currently making the best use of observations for these aspects.

NEMOVAR has the capability to make use of the ensemble information in a hybrid ensemble/variational scheme.



SST
Dec 2011

temperature

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