ASSIMILATION OF SATELLITE TOTAL SURFACE CURRENT VELOCITIES IN GLOBAL OCEAN FORECASTING SYSTEMS

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Abstract

Observations of ocean velocities are currently limited and are not routinely assimilated in global operational ocean forecasting systems. This may change with proposed new satellite missions designed to observe ocean surface velocities. The ESA Assimilation of Total Surface Current Velocity (A-TSCV) project will use observing system simulation experiments to investigate the assimilation of total surface current velocities in operational global forecasting systems. Synthetic observations of the standard observing network along with synthetic observations of new satellite total surface current velocities are being generated from a high-resolution nature run. The assimilation of these observations will be tested in the Met Office FOAM and the Mercator Ocean forecasting systems.

Keywords: Assimilation, velocities, OSSE, global ocean

1. Introduction

The ocean total surface current velocity (TSCV) is the Lagrangian mean velocity at the instantaneous sea surface (Marié *et al.*, 2020). Accurate forecasting of the ocean TSCV is important for applications such as search and rescue, tracking marine plastic and for coupled ocean/atmosphere/sea-ice/wave forecasting. Direct measurements of the TSCV are currently not available with global coverage. Various satellite missions are being proposed to measure TSCV globally such as SKIM (Ardhuin *et al.*, 2019)

and WaCM (Rodriguez *et al.,* 2019). These satellite missions could provide new opportunities for assimilation of velocities into global forecasting systems in the future.

The ESA Assimilation of TSCV (A-TSCV) project[1] aims to investigate the design, implementation and impact of assimilating synthetic TSCV data in global ocean forecasting systems. The project will use observing system simulation experiments (OSSEs) to test the assimilation methodology and provide feedback on the observation requirements for future satellite missions. Synthetic observations are being generated for all standard data types as well as the new observations expected from SKIM-like satellite missions. Two operational global ocean forecasting systems are being developed to assimilate these data in a set of coordinated OSSEs: the FOAM system run at the Met Office (Blockley *et al.,* 2014) and the Mercator Ocean system (Lellouche *et al.,* 2018). In section 2 we present a description of the OSSE experiment design, in section 3 we show preliminary results demonstrating the assimilation of TSCV and in section 4 some work exploring the velocity forecast error covariances.

2. Observing System Design

OSSEs are used to test the impact of proposed new observations on forecast systems through the assimilation of synthetic observations. The synthetic observations are generated by sampling from a Nature Run which represents the true ocean state for the experiments. For the A-TSCV project the chosen Nature Run is the 1/12° global ocean simulation with the Mercator Ocean real time system model configuration without assimilation. The model, NEMO, was forced by 3 hourly atmospheric fields from the ECMWF Integrated Forecasting System. The same Nature Run was used for the H2020 AtlantOS project for the *in situ* network design experiments and full details are provided in Gasparin *et al.,* (2019). A detailed comparison of the Nature Run to observation products is provided by Gasparin *et al.,* (2018) and verifies the realism of the simulation.

2.1 Simulated observations

The simulated sea ice concentration (SIC), Sea Surface Temperature (SST) and *in situ* temperature (T) and salinity (S) observations are the same observations used in the H2020 AtlantOS project (Gasparin *et al.,* 2019; Mao *et al.,* 2020). Simulated Sea Level Anomaly (SLA) data will sample a constellation of 4 satellites: Jason-3, Sentinel-3a, Sentinel-3b and Cryostat-2. Observations are generated from daily (for SST, SIC, T and S) and hourly (for SLA) mean fields from the Nature Run. Realistic observations errors are added through unbiased white noise perturbations and for SST and *in situ* profiles representation error is simulated by randomly shifting the data within ± 3days.

The simulated SKIM TSCV data is generated from hourly Nature Run fields using the open source SKIMulator tool (Gaultier *et al.,* 2019). The L2c SKIM product contains

[1] https://oceanpredict.org/science/cross-cutting-projects/a-tscv

Eastward and Northward total surface current components of the SKIM swath and this simulated product type will be used for the data assimilation experiments. Figure 1 shows an example of the L2c SKIM data coverage for one day. We plan to initially use data with simple error characteristics, and then explore the impact of more complicated errors on the performance of the data assimilation.

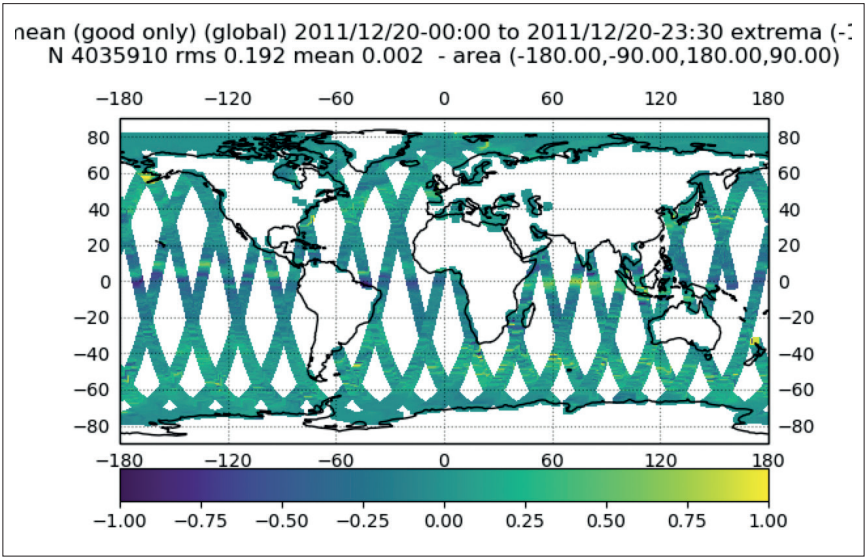

Fig. 1. Example plot of daily SKIM coverage. The speed (m/s) of the simulated TSCV is shown for 20/12/2011.

2.2 Forecasting Systems

The assimilation of TSCV data will be tested in two different operational global ocean forecasting systems, the Met Office FOAM system and Mercator Ocean International (MOI) system, to ensure robustness of the results. It is important to realistically represent the differences between the real ocean and forecast systems in our OSSE experiments. This is achieved by using a lower spatial resolution of ¼ degree in our OSSE experiments, using different initial conditions to the Nature Run and different forcings to represent atmospheric uncertainties. We plan to use the ERA-5 fluxes in both the FOAM and MOI systems, both of which use the NEMO model at version 3.6. While there are some similarities in the two global forecasting systems, they differ significantly in their data assimilation approach, see Table I for a summary.

3. Idealised Observation Experiments

Idealised observation experiments have been performed to demonstrate the assimilation increments produced by a single TSCV observation. In both systems TSCV innovations of 0.5 m/s in the zonal and meridional direction are assimilated at the same locations. The experiments are configured slightly differently for the two forecast systems due to technical differences. In FOAM only the TSCV observations are assimilated. In the MOI system two experiments are performed with all the standard observations and with and without the TSCV observations: the increments due to the TSCV data are calculated from the differences in the assimilation increments between the two experiments. Results for a location in the Mid-Atlantic are presented in Figure 2. The increments for the two systems look very different. The velocity increment is larger for the MOI system and there is a large corresponding sea surface salinity (SSS) increment but very small increments in sea surface height (SSH) and temperature. Conversely, there is no SSS increment in FOAM and larger increments in SSH and temperature. The differences in the increments reflects the differences in the forecast error covariance specification and multivariate balance between the two systems.

Table I. A summary of key differences between the FOAM and MOI systems.

	FOAM	MOI
Assimilation scheme	NEMOVAR 3D-VAR FGAT (Waters *et al.*, 2015)	SEEK filter with a fixed basis (Lellouche *et al.*, 2018)
Assimilation window	1 day	7 days
Forecast error covariances	Spatially and seasonally varying error variances at the surface and flow-dependent parameterisation for the sub-surface error variances. Combination of two length-scales for the horizontal error correlations while vertical error correlations are based on the mixed-layer depth.	Defined through an ensemble of model anomalies from an historic model run. Spatially and weekly varying error covariances following the model 'climatology'.
Multivariate Balance	Multi-variate relationships defined through linearised physical balances (Weaver *et al.*, 2005)	Model covariance matrix based on a reduced basis of multivariate model anomalies.

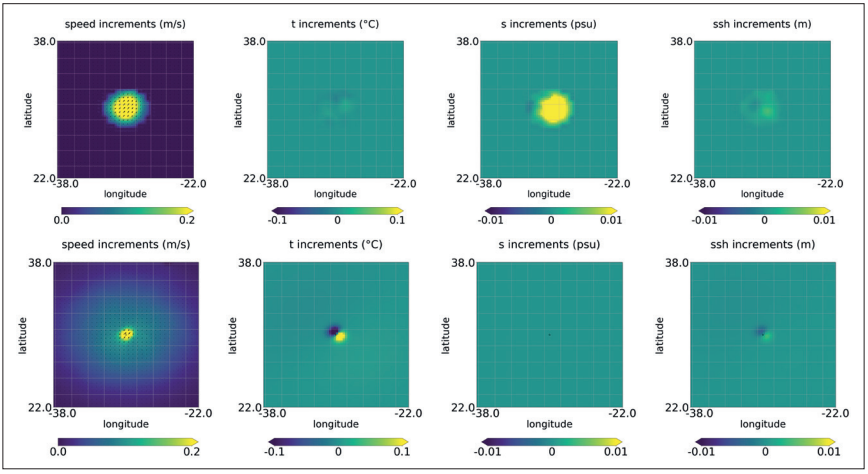

Fig. 2. Surface increments for speed, temperature, salinity and SSH. From MOI (top) and FOAM (bottom).

4. Velocity Error Covariances

FOAM forecast error covariances are prescribed through a set of variances, length-scales and balance relationships, see Table I for more details. For the assimilation of TSCV data, new error variances and length-scales are required for the unbalanced components of zonal (U) and meridional (V) velocities. The velocity balance in NEMOVAR is geostrophic so the unbalanced component represents the ageostrophic velocity component. We have used the NMC method (Parrish and Derber, 1992) to estimate the forecast error covariances from a previous two-year run of the 1/4° FOAM system. The NMC method used 48 hour and 24 hour forecast difference fields, valid at the same time, as a proxy for the forecast error. To produce an estimate of the unbalanced velocity covariances we applied the inverse of the NEMOVAR balance operator to the forecast difference fields to remove the balanced (geostrophic) component. Figure 3 shows the zonally averaged horizontal forecast error correlations for September-October-November for U and V. Two horizontal length-scales are estimated for each variable. The short scales for U and V vary between around 40 km at high latitudes, 70 km at mid latitude and 100 km in the tropics. The short U length scales have longer scales in the x-direction by 10-20 km at most latitudes, while the short V length scales are fairly isotropic except near the equator. The longer scales vary between approximately 200 km in the mid latitudes to 400 km near the equator. Long correlations are seen in the x-direction corresponding to the latitudes of the North and South equatorial currents. Interestingly the correlation scales are higher in the y-direction in the mid-latitudes which could be due to the boundary currents.

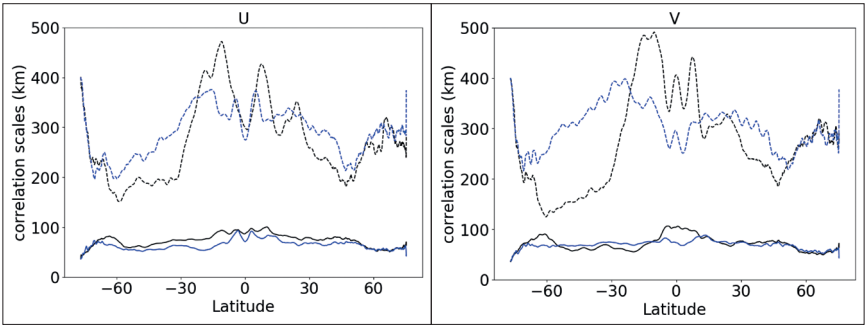

Fig. 3. Zonally averaged horizontal forecast error correlation length scales for unbalanced surface U and V. These are estimated by fitting a Gaussian function with two correlation scales to the NMC error covariance data. Black and blue lines are length scales in the x-direction and y-direction, respectively. Dashed and solid lines are the long and short scale, respectively.

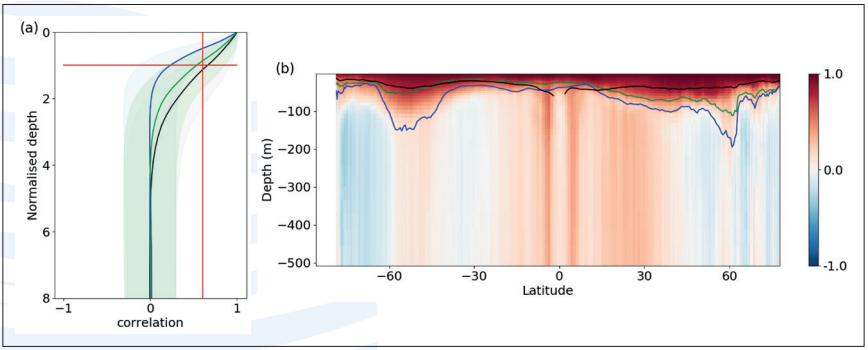

Fig. 4. U vertical forecast error correlations with the surface. Plot (a) shows the global mean correlations plotted against a normalising depth. For the green, blue and black line the normalising quantity is the global mean MldRho, MldZ and Ekman depth respectively. The horizontal red line shows where the normalised depth is 1 and the vertical red line is the value of a Gaussian function when the depth variable equals the correlation length scale. The shaded region shows the standard deviation of the error correlations. Plot (b) shows a latitudinal section of the zonal mean vertical correlations with the surface. The green, blue and black lines are the zonal mean MldRho, MldZ and Ekman depth, respectively.

Vertical forecast error correlations for U are shown in Figure 4 and are compared to an Ekman depth (calculated from the model's vertical eddy viscosity) and two mixed layer depths. The MldZ mixed layer depth is defined as the depth at which the density has increased equivalent to a temperature difference of 0.8 degrees at the surface, the MldRho mixed layer depth is the shallowest depth where density increases by 0.01 kgm^3 relative to 10 m density. The latitude section plot shows how the vertical correlations vary with latitude. In the profile plot, the global mean error correlations are compared to a normalised depth. When the normalising depth (Ekman depth or Mixed layer depth) is a good approximation to the correlation length scale, the correlation profile passes close to the red line intersect. From Figure 4, MldZ (which is the mixed layer depth used to parameterise the Temperature and Salinity vertical forecast error correlations in FOAM) significantly over-estimates the U vertical forecast error correlations with the surface, while MxlRho and the Ekman depth appear to provide a good approximation to the correlation scales. We plan to test both the MxlRho and Ekman depth as a method for parameterising the vertical forecast error correlations in FOAM.

5. Future Work

The preliminary development of the assimilation of TSCV data described above will form the basis of a set of one year OSSEs for both FOAM and MOI systems. Reference runs will be carried out where only the standard observation network is assimilated followed by a second set of experiments where the standard observation network plus TSCV observations are assimilated. The impact of the assimilation of TSCV data will be assessed in terms of its ability to improve the accuracy of the model's surface current forecasts in different regions using standard metrics, and also using simulated Lagrangian drift assessments. The impact on the velocity at depth, and other model variables, will also be assessed. These assessments will form the basis of a new set of requirements from the operational ocean forecasting community for future satellite missions measuring surface ocean currents.

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