A Global Multi-Resolution Probabilistic Ocean Current Forecasting System Based on Scale Recursive Estimation

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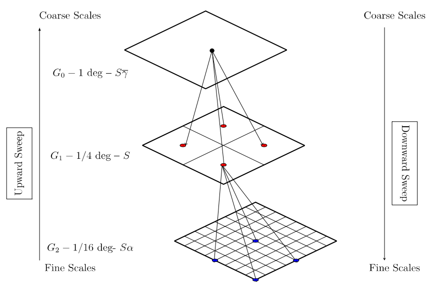
INTRODUCTION

- We present a multi-resolution probabilistic ocean forecasting system developed to support offshore energy operations worldwide.
- The center piece of the system is a multi-resolution data assimilation framework that enables efficient ocean state estimation and prediction at a hierarchy of scales - from global to local.
- The system is composed of an integrated suite of ocean circulation models including a global model of 25 km resolution, Atlantic and Indian Ocean models of 6 km resolution, and 8 fine scale models (< 3 km resolution) for high-priority regions such as the Gulf of Mexico, offshore Brazil, West Africa, and the Caribbean.
- All component models incorporate information from satellite and in-situ observations and additionally incorporate proprietary measurements if and where available.
- The regional scale models are also used in an ensemble mode to provide probabilistic forecasts for specific regions of interest.
- The system was developed jointly by Wood Hole Group Inc. and Tendral LLC. and is referred to as the WHG-TOPS system.

OPERATIONAL IMPLEMENTATION OF A MULTI-RESOLUTION OCEAN PREDICTION SYSTEM

- A global multi-resolution ocean prediction system based on the above methodology has been operational since 2017 and provides daily 7-day forecasts of ocean currents and other quantities in support of the offshore industry (Srinivasan et al., 2018).
- The system is based on the HYbrid Coordinate Ocean Model (HYCOM, http://hycom.org) code, a circulation model that is widely used by the oceanographic community (Bleck 2002, Chassignet et al., 2006).
- Remotely sensed sea level anomalies (SLA) and SST as well as in-situ temperature/salinity (T/S) profiles from the ARGO program are the backbone of the system and thus are systematically assimilated in all nested levels. Other observations – drifters, acoustic Doppler current profilers (ADCPs) and high frequency radar are assimilated only in the finest nest.
- The operational system assimilates about 500,000 along track SLA points, 200,000 SST points and around 1000 profiles daily.
- At each level, the correlation scales and observation selection criteria are based on the underlying Mercator computational mesh. This has the advantage that no additional scale control mechanism is necessary since the same number of grid points account for different scales at different levels in the tree structure.

Multi-level tree structure and a scale recursive data assimilation framework



Models are arranged on the nodes of a multi-level tree. Each level represents a certain scale resolution) and are linked to levels above and below in the tree, essentially providing a connection between processes represented at different scales.

The algorithm consists of a fine-to-coarse filtering step followed by a coarse-to-fine smoothing step corresponding to a generalization of the Rauch-Tung-Stiebel smoothing (Chou et al., 1993, Fieguth et al., 1995, Menemenelis et al., 1998, Rauch et al., 1965, Wilsky 2002).

FEATURES OF MULTI-RESOLUTION ALGORITHM

- The algorithm allows us to combine filtering and smoothing very efficiently while exploiting hierarchical measurements at different scales.
- At each level, the error covariance matrix is built to capture correlations at different scales.
- By performing the upward sweep first information is carried from fine-to-coarse scales, which during the subsequent downward pass can then be transmitted to nodes that are not on the same subtree.
- The processing at each individual model or node is entirely independent of the others at a given level in the tree estimation errors can be obtained at different scales to assess accuracy versus resolution tradeoffs.
- Heterogeneities are easily handled by specifying parameters that vary from one node to another.
- The model considers the random fields to be static in time and only considers variability along scales.
- The analysis at each node can range from a simple OI to more complex formulations such as Ensemble Kalman Filter or 4d Var for more dynamic regions or a mixture of different analysis schemes.
- Independent processing also enables the analysis step to be implemented on emerging computing architectures since all that is needed is a simple Matrix-Vector product.

DETAILS OF THE SCALE RECURSIVE DATA ASSIMILLATION FRAMEWORK

The tree process from parent to sibling and the observation equation is represented as:

$$x(s) = A(s)x(s\bar{\gamma}) + B(s)\omega(s) \tag{1}$$
$$y(s) = C(s)x(s) + \nu(s) \tag{2}$$

Here x(s) is the state vector, y(s) are observations. A(s) and B(s) are appropriate sized matrices that describe the coarse-to-fine scale transition and the driving noise, respectively. C(s) is a selection matrix or observation operator.

For the above downward model, the corresponding upward model (Verghese and Kailath, 1979) is represented as:

$$x(s\bar{\gamma}) = F(s)x(s) + \bar{\omega(s)} \tag{3}$$
$$F(s) = P_{s\bar{\gamma}}A^T(s)P_s^{-1} \tag{4}$$
$$E[\bar{\omega}(s)\bar{\omega}(s)^T] = Q(s) \tag{5}$$

Since *ω(s)* is assumed independent from scale to scale, the above multi scale tree model is Markovian, for any node s, and therefore the processing of data in the sub trees beneath it can be accomplished independently in each of the dependent sub trees.

The scheme for optimal estimation of the state vector, x(s) then proceeds in two steps:

STEP 1: ***Upward Sweep***

A Kalman analysis is first performed going from fine to coarse scales starting at the finest scale. Therefore, for a given level – s – above the finest grid, there will be one analysis from each of the child nodes. The child node analyses are merged to obtain a single predicted value at the next coarse scale. Using this merged value, a filtered estimate is obtained for the coarse scale node using the observation equation and a standard Kalman analysis step.

$$\hat{x}(s|s) = \hat{x}(s|s+) + K(s)[y(s) - C(s)\hat{x}(s|s+)] \tag{6}$$
$$k(s) = P(s)C^T(s)v(s)^{-1} \tag{7}$$
$$v(s) = C(s)P(s|s+)C^T(s) + R(s) \tag{8}$$

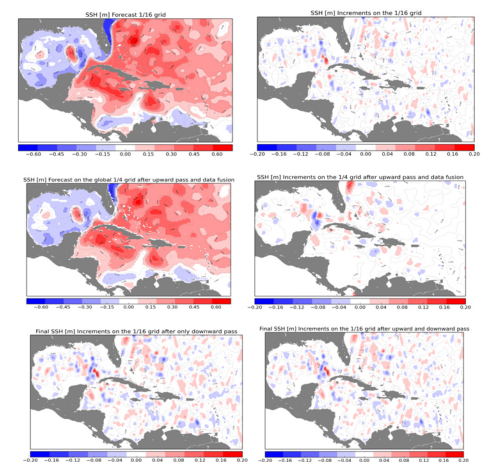
STEP 2: ***Downward Sweep***

After the above procedure is carried out from the finest to coarsest scale, a downward sweep generalizes the Rauch-Tung-Stribel algorithm (Rauch et al., 1965).

$$\hat{x}(s) = \hat{x}(s|s) + J(s)[\hat{x}^s(s\hat{\gamma}) - \hat{x}(s\hat{\gamma}|s)] \tag{9}$$

The smoothed estimate at each node is equal to the sum of the estimate in the upward sweep and the difference in the estimates of the parent node in the upward and downward sweeps weighted by a coefficient, J(s).

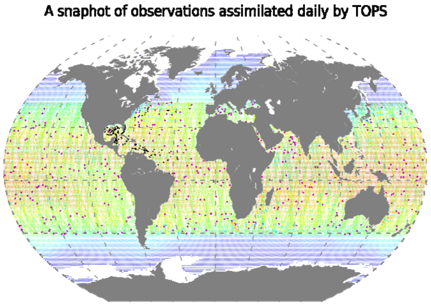
Example of corrections using the scale recursive algorithm for estimating surface height field in a multi-resolution system



Corrections with downward pass

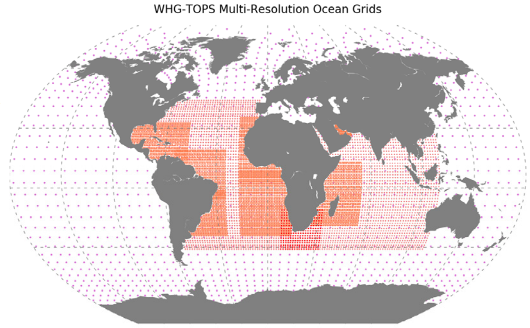
Corrections after upward & downward passes

A snaphot of observations assimilated daily by TOPS



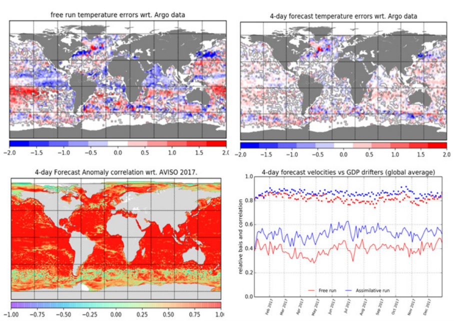
The Multi-Resolution Model Components

WHG-TOPS Multi-Resolution Ocean Grids



The multi-resolution modeling system along with the locations of various component models. The fine scale models (dark coral) are nested within the two basin scale Atlantic and Indian Ocean domains (light coral). The basin scale domains are in-turn nested within the 1/4° global model (magenta).

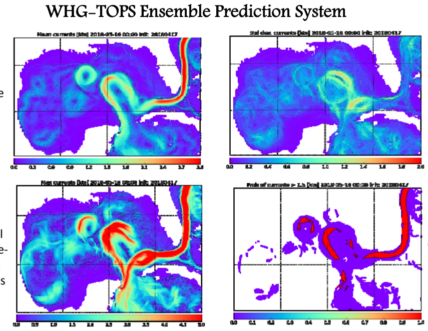
Sample Results from the Operational Multi-Resolution System (2017 Hindcast)



WHG-TOPS Ensemble Prediction System

Ensemble Mean

Ensemble Spread



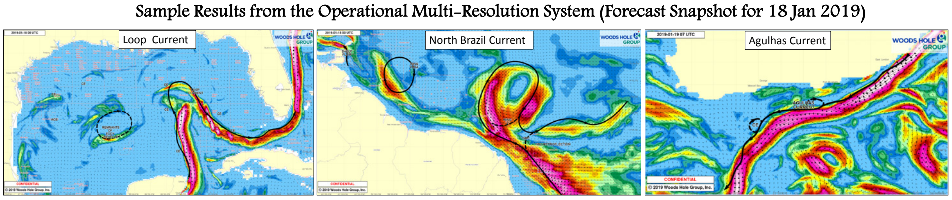
Maximal Ensemble-Derived Velocities

Probability of Currents Exceeding 1.5 knots

SUMMARY

- We have recently implemented a global multi-resolution ocean prediction system using the scale recursive methodology to fuse available information at different scales. This system is currently used to provide ocean current forecast for the offshore industry worldwide.
- In routine comparisons with observations and other ocean prediction systems the multi-resolution system suggests significant potential for prediction across several scales.
- The operational multi-resolution system is run daily and produces a 3-day hindcast followed by a 7-day forecast. The system outputs are distributed through a secure web mapping application. However, daily nowcast currents from the global 1/4° model can be visualized at: http://tendral.com/tops/.
- Work is ongoing to further explore the methodology, assess the accuracy versus resolution tradeoffs, and to extend the system by introducing new streams of data.

Sample Results from the Operational Multi-Resolution System (Forecast Snapshot for 18 Jan 2019)



WHG-TOPS forecast model outputs from 19 January 2019 overlaid with the frontal analyses (black lines) generated by WHG. Visualization on WHG's online Metocean Mapper – an interactive user interface. These fronts are analyzed based on several data sources, including proprietary data, on a daily basis.

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