Quantifying the effects of ocean observations and circulation models on oil spill trajectory forecast skill

Submitted April 12, 2012
(revised 6/1/2012)

Alexander Crosby and Eoin Howlett
55 Village Square Drive, South Kingstown, RI 02879, USA
T +1 401 789-6224  F +401 789-1932  www.asascience.com

With contributions from:
Carl Schoch
Coastwise Services, 1199 Bay Ave., Homer, AK 99603, USA

Yi Chao
Remote Sensing Solutions, Inc. 2824 East Foothill Blvd, Pasadena, CA 91107, USA

John Farrara
University of California Los Angeles, JIFRESSE, Los Angeles CA 90095, USA
# Table of Contents

1 Table of Contents ................................................................................................................................. 1

List of Figures ........................................................................................................................................ 3

Executive Summary .................................................................................................................................. 5

2 Introduction ........................................................................................................................................ 6

2.1 Project Goal .................................................................................................................................... 7

2.2 Data Description .............................................................................................................................. 8

2.2.1 ROMS Simulation without Data Assimilation ......................................................................... 8

2.2.2 ROMS with Data Assimilation ................................................................................................. 9

2.2.3 NCOM ....................................................................................................................................... 9

2.2.4 HYDROMAP Tides .................................................................................................................. 9

2.2.5 HFRADAR .......................................................................................................................... 10

2.2.6 PWS FE Drifters .................................................................................................................... 10

2.2.7 PWS WRF .......................................................................................................................... 11

3 Methods ............................................................................................................................................ 11

3.1.1 Drifter Data ............................................................................................................................ 11

3.1.2 Particle Advection Model ....................................................................................................... 11

3.1.3 HFRADAR Concessions ........................................................................................................ 12

3.1.4 Wind Forcing ......................................................................................................................... 13

3.1.5 Skill Assessment ................................................................................................................... 13

4 Results & Discussion ......................................................................................................................... 15

4.1.1 ROMS ..................................................................................................................................... 17

4.1.2 ROMS with Data Assimilation ............................................................................................ 18

4.1.3 NCOM .................................................................................................................................... 19

4.1.4 HFRADAR .......................................................................................................................... 20

4.1.5 HYDROMAP Tides ................................................................................................................ 21

5 Conclusions ....................................................................................................................................... 22

6 Acknowledgements ............................................................................................................................ 24

7 References ......................................................................................................................................... 25
8 Appendix A: Variance in Root Mean Squared Separation Distance ....................... 27
9 Appendix B: Sample Drifter Simulations ................................................................. 31
LIST OF FIGURES

Figure 1. Weighted root mean squared separation distance categorized by hydrodynamic forcing. Statistics on the left were calculated based on an observed drifters time in the forcing dataset’s geographic extent, while those on the right only used data inside the radar footprint. 15

Figure 2. Weighted root mean squared separation distance categorized by hydrodynamic and wind forcing. Statistics on the left were calculated based on an observed drifters time in the forcing dataset’s geographic extent, while those on the right only used data inside the radar footprint. ...................................................................................................................................... 16

Figure 3. Weighted root mean squared separation distance for ROMS hydrodynamic forcing categorized by drifter type.......................................................................................................... 17

Figure 4. Weighted root mean squared separation distance for ROMS with Data Assimilation as hydrodynamic forcing categorized by drifter type. .............................................................. 18

Figure 5. Weighted root mean squared separation distance for Global NCOM surface layer hydrodynamic forcing categorized by drifter type. .............................................................. 19

Figure 6. Weighted root mean squared separation distance for HFRADAR observations of surface currents categorized by drifter type .............................................................................................................................. 20

Figure 7. Weighted root mean squared separation distance for RPS-ASA’s vertically averaged Tidal hydrodynamic forcing including a Seasonal Flow component categorized by drifter type. 21

Figure 8. Unbiased weighted variance in root mean squared separation distance for all forcing datasets. Bars on the left represent statistics based on individual forcing dataset’s geographic extents, and those on the right are limited to the HFRADAR’s geographic extent.............................. 27

Figure 9. Unbiased weighted variance in root mean squared separation distance for the standard ROMS model categorized by drifter type ................................................................. 28

Figure 10. Unbiased weighted variance in root mean squared separation distance for the ROMS model with data assimilation categorized by drifter type ................................................ 28

Figure 11. Unbiased weighted variance in root mean squared separation distance for the Global NCOM model categorized by drifter type ................................................................. 29

Figure 12. Unbiased weighted variance in root mean squared separation distance for the HFRADAR observations dataset categorized by drifter type ................................................................. 29

Figure 13. Unbiased weighted variance in root mean squared separation distance for RPS-ASA Hydromap Tidal dataset that includes mean seasonal flow categorized by drifter type. .... 30

Figure 14. Simulated drifter trajectories and separation distance from the observed drifter (in Red on map) for the Argo 5623 surface deployment ................................................................. 31

Figure 15. Simulated drifter trajectories and separation distance from the observed drifter (in Red on map) for the SVP 85928 10m deployments ............................................................................ 32

Figure 16. Simulated drifter trajectories and separation distance based on the ensemble of trajectory simulations – No wind forcing .............................................................................................. 33
Figure 17. Simulated drifter trajectories and separation distance based on the ensemble of trajectory simulations – with WRF wind forcing
EXECUTIVE SUMMARY

This project evaluated the effect of improved hydrodynamic nowcasts/forecasts and HF radar-derived surface current measurements on the performance of an oil spill trajectory forecasting model. The analysis also looked at the effect of data assimilation in the models. With support from NASA/JPL and UCLA, ASA used model and observation data developed during the Prince William Sound Field Experiment (PWS FE) in 2009 for the analysis.

The following data were used for the skill assessment for the time period overlapping the PWS FE:

- ROMS Model Simulation without Data Assimilation (ROMS)
- ROMS Data Assimilation System (ROMSDAS)
- High Frequency Radar (CODAR) Observations
- Drifter Trajectories from the 2009 PWS FE
- Global U.S Navy NCOM Model Output*
- HYDROMAP PWS Tidal Product w/ Mean Seasonal Flow
- Meteorological Model Forcing (WRF)

The goal of the project is to evaluate the data sets and how they could be used to improve oil spill predictions generated by the Alyeska Tactical Oil Spill Model (ATOM). ATOM is currently operational for Prince William Sound and is operated by the Alyeska Pipeline Service Company.

To support the harmonization and statistical analysis required by this project– Matlab was used in order to have direct control over the reading and manipulation of the various data, enabling meaningful comparison. This framework allows us to generate particle trajectories forced by the numerical model output and radar observations, and to visualize and compare with the PWS FE drifter tracks using standard time series forecasting statistics.

Both ROMS hydrodynamic model simulations with and without data assimilation performed similarly, but ROMSDAS has a lower weighted root mean squared error (RMSE) than the standard ROMS model output. NCOM performs with the highest RMSE when compared to all of the environmental forcing datasets; this is not unexpected as it is a global model with coarse resolution to resolve coastal areas. The Hydromap tidal forcing that is currently included in ATOM performs slightly better than the NCOM forcing. Statistically, the HFRADAR forcing has the lowest RMSE of all the results, which is expected given that they are actually observations of the surface currents.
2 INTRODUCTION

Under the National Contingency Plan the United States Coast Guard serves as the Federal On Scene Coordinator (FOSC) for oil spill response and NOAA is designated to provide the Scientific Support Coordinator (SSC). NOAA’s Office of Response and Restoration staffs the SSCs with oceanographers, modelers, chemists, and biologists available 24 hours a day. During a real oil spill the primary Decision Support Tool (DST) for evaluating potential trajectories is the General NOAA Oil Modeling Environment ( GNOME). GNOME forecasts spill trajectories based upon the best wind and ocean circulation forecasts available at the time of the response. Twice daily overflights of the spill are made to validate the real oil spill trajectory. However, NOAA does not officially respond to oil spills until formally requested by the U.S. Coast Guard. Therefore, the GNOME model as implemented by NOAA is generally not used in oil spill drills or in pre-staging equipment in advance of an oil spill. This was demonstrated recently in Cook Inlet during the Mt. Redoubt volcanic eruption of 2009. The oil terminal at Drift River was in imminent danger of being overwhelmed by the ash flow, but the U.S. Coast Guard had not issued a request for spill trajectory scenarios from NOAA. Spill response organizations such as Alyeska Pipeline Service Company (Alyeska) in Prince William Sound (PWS) need oil spill trajectory forecasts for better planning scenarios and to anticipate the placement of protection and response equipment.

Alyeska has its own oil spill trajectory model for Prince William Sound called the Alyeska Tactical Oil Spill Model (ATOM) developed by Applied Science Associates (ASA). ATOM was developed originally in 1989 and has continually evolved. ATOM incorporates many of the latest developments of its commercial companion models, OILMAP and SIMAP. OILMAP is used widely by oil companies and response agencies in over 100 countries. It integrates GIS and data management tools that allow it to use a wide variety of environmental data in different formats to drive the model – this allows for ensemble forecasting and the ability to compare many oil spill simulations using different forcing conditions. This model is used for contingency planning, drills, spill response, and spill impact evaluations. In the event of a spill in Prince William Sound, Alyeska will use ATOM to generate spill trajectories using a hydrodynamic database in ATOM and connection to real-time weather forecasts.

ATOM provides a framework to run multiple ensemble trajectories using different environmental data for forcing conditions. Currently, ATOM can use currents from a database of tidal constituents and seasonal flows created by a hydrodynamic model as well as wind forcing. The performance of ATOM critically depends upon the quality of the surface winds and currents data, with the spatial coverage sufficiently large enough to cover both offshore and nearshore coastal areas.
A central element of the OSRI research and development effort is the Prince William Sound Observing System (PWSOS), first developed under the Sound Ecosystem Assessment (SEA) research program, funded by the Exxon Valdez Oil Spill Trustee Council (EVOSTC), and more recently as part of the Alaska Ocean Observing System (AOOS). The conceptual design of the PWSOS is that an atmospheric model is operated in real-time to pass wind fields to a hydrodynamic model. The hydrodynamic model will in turn generate a Nowcast/Forecast simulation and pass both the wind and current predictions to an oil spill model. As currently envisioned, the models are planned for use in a predictive mode. For example, planned uses include providing real-time spill trajectories and 48-hour forecasts to guide oil spill response decisions.

Modeling efforts such as ATOM are appropriate in support of scientific purposes, such as contingency planning, training and community outreach, ecological risk assessment, and can provide a better understanding of the Prince William Sound ecosystem. Because of the assumptions inherent in the construction of any model, an oil spill model is not an exact replica of the real world. Rather, the role of model building in the context of oil spill response should be viewed as advancing the state of models and for the prediction of ecological consequences. Therefore, a crucial element of any modeling program is a rigorous validation of model results.

2.1 Project Goal

The goal of this project was to evaluate the skill of different hydrodynamic forcing data for use in the prediction of surface oil spill trajectories. The project also explores whether data assimilation techniques can improve model skill and also evaluates the impact of wind forcing on the trajectory comparisons.

To this end, simulated drifters were forced with a variety of hydrodynamic forcing datasets including numerical model output and gridded observations to assess their relative performance in predicting observed drifter trajectories collected as part of the 2009 Prince William Sound Field Experiment (PWS FE). The PWS FE was a joint effort in the summer of 2009 to measure weather and oceanographic conditions, numerically model atmospheric and oceanic circulation, and release of several types of drifters to simulate current trajectories at different depths, in order to evaluate the skill of weather, wave and ocean circulation models. An overview of the PWS FE is described in Schoch and McCammon (2012).

The particle advection model used to force the simulated drifters was transported from ATOM to MATLAB in order to provide direct access and manipulation of both forcing datasets and drifter
observations, allowing for rapid development to support visualization and statistical quantification of the results. The goal of the project was to evaluate the performance of these data sets and how they could be used in ATOM to improve oil spill predictions.

The particle model initializes a simulated drifter at an observed drifter’s release point and re-initializes every two days or when a drifter was redeployed during the 2009 field experiment. Forcing dataset skill is evaluated using the root mean squared distance of the simulated drifter from the observed drifter.

This report summarizes the datasets used for environmental forcing of simulated drifters as well as the observations used for validation of simulated trajectories in the following Data Description section (2.1). Section 3 gives an overview of the methodology used to develop the particle model, force the simulated drifters and evaluate the results. Section 4 is an in-depth presentation and discussion of the results and Section 5 provides a summary of conclusions and recommendations. The appendix provides details for each drifter simulation and comparison for each of the forcing datasets being considered.

### 2.2 Data Description

A combination of data provided by NASA/JPL, UCLA and ASA were used for input forcing to the particle model and as benchmarks for the validation of the simulations. These included numerical model output from ROMS with and without data assimilation, HYDROMAP, and NCOM, as well as gridded HFRADAR observations and observations of drifter trajectories.

#### 2.2.1 ROMS Simulation without Data Assimilation

ROMS (Regional Ocean Modeling System) is a state of the art numerical model that uses a terrain following sigma-style vertical coordinate system and curvilinear coastline-following horizontal domain discretization (Chao et al. 2009). ROMS is developed by Rutgers University and UCLA. The model is a primitive equation model using hydrostatic and Boussinesq approximations. ROMS contains state-of-the-art parameterizations for surface boundary layers, boundary conditions, and turbulence. In the case of the PWS dataset, the model output data every hour, and only the finest resolution (1-km) ROMS output is used. The 1-km ROMS over the PWS domain takes the boundary conditions from the 3-km ROMS over a larger area, which is further nested in a 9-km ROMS model. The ROMS simulations were forced by winds obtained from daily 4km WRF downscaled forecast runs performed at the University of Alaska in Anchorage. This dataset was provided to ASA by JPL and UCLA.
2.2.2 ROMS with Data Assimilation

The ROMS model with data assimilation of the Prince William Sound current velocity field is of interest in the skill evaluation, since it can be compared directly to the ROMS model that does not benefit from integration of observations. The data assimilation component was developed by NASA’s Jet Propulsion Laboratory (JPL) using multi-scale 3DVAR (3-dimensional variational) assimilation methodology. The 3DVAR assimilation is chosen due to its ability to propagate observational effects through the 3-D model grid and to do so in a computationally efficient manner (Li et al. 2008a, 2008b, 2012). Products are produced at 6 hour intervals, and can forecast 2-3 days into the future. Like the standard ROMS models, the model is nested using 3 grids but unlike the standard ROMS model, the data assimilation is performed on all 3 grids. The model used for this comparison assimilated temperature and salinity measurements from in situ and remote sensors as well as the available HFRADAR observations. This dataset was provided to ASA by JPL and UCLA.

2.2.3 NCOM

The global NCOM (Navy Coastal Ocean Model) is a 1/8 degree resolution model that is run at the Naval Oceanographic Office (NAVOCEANO) using forcing from the Navy Operational Atmospheric Prediction System. NCOM assimilates Navy MODAS and NLOM products (Barron et al. 2004, 2006). In the vicinity of PWS, NCOM has a resolution of 14km by 7km. This dataset was obtained from ASA’s in-house Environmental Data Server (EDS) archive and contains only surface velocity data. It should be noted that the U.S Navy does not recommend use of this global model for coastal areas but it was used as a benchmark.

2.2.4 Hydromap Tides

The Hydromap dataset is a circulation product developed specifically for Prince William Sound oil spill forecasting. The dataset is a vertically averaged tidal dynamic dataset that includes a mean seasonal flow component. The dataset is tuned to tidal models and observations using the top 7 tidal constituents. The dataset employs a variable resolution grid to provide high resolution in the topographically complex near shore regions. A cell size of 1.5km covers most deep waters. Cell sizes are halved progressively as the grid approaches the shore. The finest cell size is 186m. This dataset was obtained from ASA’s in-house archive. It should be noted that this data is designed to be used in an oil spill model with additional wind forcing on the oil as the data set does not include any wind-forced components.
2.2.5 HFRADAR

HFRADAR provides surface current measurements for extended coverages within PWS using high frequency radar waves. The footprint of the available data is an irregular shape for a given product output timestep, and this area changes coverage and shape with each timestep sample due to the reach and quality of the radar signals. This dataset was provided to ASA by JPL.

2.2.6 PWS FE Drifters

Four types of drifting buoys were used during the PWS FE to track water velocities at different depths and three were used to quantify the skill of the environmental forcing datasets. Each drifter type is drogued at a different depth, allowing us to examine skill for different depths where 3d hydrodynamic data was available; simulations driven by NCOM, HF Radar, and Hydromap only included the surface layer currents. Argospheres (Metocean Data Systems) are 28-cm diameter spherical buoys designed to track oil floating on the surface. These drifters use an onboard GPS receiver and the Argos satellite system for location and tracking. Microstar drifters (Pacific Gyre) are designed to track the mean surface current at a depth of about 1 meter. A surface float contains the GPS receiver, telemetry system, antenna, batteries and sensors. The U.S. Coast Guard (USCG) Self Locating Data Marker Buoy (SLDMB) made by Metocean is designed specifically for deployment from a vessel or aircraft and for unattended operation during a 30-day lifetime. The SLDMB is accompanied by an onboard electronics package which includes GPS positioning. These were not used in this analysis due to statistical bias created by the short lengths of the individual deployment trajectories. Surface Velocity Program (SVP) drifters (Pacific Gyre) are 38-cm diameter spherical buoys to which a drogue is attached, and they are expected to drift with the water at the depth of the center of the drogue. The drogue is a 2.5 meter long fabric tube suspended at a depth of 10 meters. SVP drifters also use an onboard GPS receiver and the Argos satellite system for location and tracking. Two versions of the Surface Velocity Program (SVP) drifters were used, one set drogued at 10 meters and another set drogued at 40 meters below the sea surface. The raw drifter data was provided to ASA by JPL.

A total of 44 drifting buoys were repeatedly deployed, retrieved, and redeployed during the 16 day period. Model validation of surface and deeper currents in the central basin were emphasized and the majority of drifter deployments occurred within the field of view of radar surface current measurements. Additional deployments occurred around the perimeter of PWS to validate the velocity of surface currents forced mostly by fresh water runoff from perimeter snow fields and glaciers.
2.2.7 PWS WRF

PWS-WRF is an atmospheric modeling system based on the Advanced Research Weather Research and Forecasting (WRF) model (Skamarock et al. 2008). It is part of the PWS-OS modeling system for use within Prince William Sound. Initial and boundary conditions are sourced from operational model output from the National Centers for Environmental Prediction (NCEP) North American Model (NAM) forecast data. PWS-WRF produced 48 hour forecasts during the Prince William Sound field experiment using a two-way grid nesting (12km and 4km resolution) and was validated against observations for that time period (Olsson et al. 2012). This dataset was provided to ASA by JPL and UCLA.

3 METHODS

3.1.1 DRIFTER DATA

The drifter trajectory data originated as text files. This data was normalized into a simple timeseries format with a common nomenclature and stored in the native MATLAB file type (.mat) for fast and easy integration into the MATLAB based particle model.

At run time, quality control and filtering is performed on each drifter track. The goal of the filtering is to remove spurious position information along the track from temporary GPS inaccuracies, as well as false drifter motion recorded while the drifter was being transported by boat, prior to, after, or between deployments.

For each trajectory, to facilitate simulation and drifter comparison, data is removed that falls outside of the forcing dataset’s geographic extent. Sections of the trajectory in which the speed of the drifter exceeds an unrealistic threshold for PWS are removed. The trajectory is resampled at 6 hour intervals corresponding to the ROMSDAS timesteps, and then subsampled to the forcing dataset’s timesteps if they are smaller than 6 hours. To avoid statistical bias, only unique trajectories were included.

3.1.2 PARTICLE ADVECTION MODEL

The model implemented for this project is a simple 2-d advection model that simulates single particle trajectories using gridded hydrodynamic forcing. The simulated drifter is initiated at the start of the observed drifter deployment in time and space. In order to assess the skill of the forcing datasets in the context of oil spill trajectory forecasting the simulated drifter is re-
initialized every 2 days, which is a typical horizon for oil spill forecasting. A simulated drifter is also re-initialized at times when the same observed drifter was redeployed in the field.

At each timestep of the input forcing, the closest point in the dataset’s grid is found and a 3x3 set of points around the closest grid point is used to subset it’s u and v velocities. In cases where the data is stored in an unstructured arrangement (HYDROMAP Tides), the 9 closest points are used to subset their u and v velocities. Some sensitivity to the number of closest points to subset at each timestep was explored. When using a forcing dataset that contains multiple vertical levels, the closest level to the individual drifter depth is used. For datasets that have only a single level (i.e., surface), it is used for all drifters no matter the actual depth of the observed drifter.

An inverse distance weighting is used to calculate the u and v velocity components to use at the simulated drifter location. The derived u and v current velocities are used to move the simulated drifter to its position at the next timestep. The simulation ends at the timestep where the last valid point in the observed drifter trajectory resides.

3.1.3 HFRADAR CONCESSIONS

The HFRADAR observations in PWS provide a unique challenge to simulating drifter trajectories. Since the shape of the coverage changes with each time in the record, simulated drifters may be drifted into areas within the official geographic extents of the HFRADAR grid, but where there may only be intermittent velocity data in the points nearest to the simulated drifter. To deal with this, the particle model continues to force the particle when it leaves the area of coverage with the single closest available u and v velocities.

In the HFRADAR dataset provided, there are some gaps in which records are missing for many consecutive hourly timesteps. These gaps are interpolated to an hourly timestep using the data that does exist in the dataset.

Out of all of the currents datasets, the HFRADAR dataset has the smallest geographic extent. A separate set of statistics are calculated for all of the simulations using all of the forcing datasets, but limiting the drifter observations for comparison to the HFRADAR extents. While this limits the number of samples for comparison significantly for the other forcing simulations, it allows for a more normalized comparison relative to the HFRADAR dataset.


3.1.4 WIND FORCING

An additional set of drifter-trajectory comparisons were performed with wind forcing applied to the trajectory calculations.

To address the impact of adding wind forcing to the simulated trajectories, WRF model data was incorporated for the time period overlapping the PWSSE. To calculate the additional forcing provided by winds and associated drift an empirical formulation was used that depends on wind velocity ($w$) and drifter depth ($z$). The formulation (Youssef 1993, Youssef and Spaulding 1993, 1994) is the same as the method implemented in ASA’s oil spill models, including ATOM.

$C_w$ is the percentage of wind that contributes to the drifter velocity and $C_a$ is the drift angle.

$$C_{wz} = [0.19692 \log_{10}(w) - 0.19047]C_w(w, 0)$$

$$C_w(w, z) = \begin{cases} 
3.9088 - 0.31885w, & z = 0 \\
C_{wz}, & C_{wz} \geq 0, z > 0 \\
0, & C_{wz} < 0, z > 0 
\end{cases}$$

$$C_a(w, z, C_w) = \begin{cases} 
23.627 - 7.97 \log_{10}(w), & z = 0, C_w = 0 \\
e^{4.999w^{-0.1233}z^{0.344w^{-0.2296}}}, & z > 0, C_w > 0
\end{cases}$$

For each simulated drifter position the closest single WRF data point was taken to get 10 meter $u$ and $v$ wind velocity components, and the above empirical formulation was applied to determine the wind contribution to the simulated drifter’s motion.

3.1.5 SKILL ASSESSMENT

To quantify the skill for each simulation, a timeseries of the distance between the simulated trajectory and the observed trajectory is constructed at 6 hour intervals, corresponding to the largest time step in the set of forcing datasets. A weighted root mean separation distance is calculated for each forcing dataset, incorporating all of drifter simulations. Simulated and observed trajectories may be compared using separation distance (Vastano and Barron, 1994; Thompson et al., 2003; Barron et al., 2007; Liu and Weisberg, 2011) and can be useful for assessing the skill in prediction oil spill trajectories (Price et al., 2006, Abascal et al., 2009).

To quantify the variability in this statistic, an unbiased weighted variance is calculated for the weighted root mean separation distance. The following equation can be used to calculate unbiased weighted variance where $w_i$ is a series of weights, $x_i$ is a series of root mean squared separation distances and $x^*$ is the weighted mean of $x_i$. 

$$\text{var}(w_i x_i) = \sum w_i (x_i - x^*)^2$$
\[ \sigma_{\text{unbiased}}^2 = \frac{1}{1 - \sum_{i=1}^{N} w_i^2} \sum_{i=1}^{N} w_i (x_i - x^*) \]

These statistics are decomposed for drifter type as well as for forcing type to evaluate the relative skill at different depths. Standard deviation can be calculated by simply taking the square root of the variance statistics. A summary of the variance can be found in Appendix A.
4 RESULTS & DISCUSSION

The results of simulated drifter tracks for 5 different kinds of hydrodynamic forcing are evaluated using root mean squared separation distance. The sensitivity to the number of points to include in the inverse distance weighting algorithm was explored, but the overarching trends in the data were found to be insensitive to these tests. A 3x3 (9 closest) grid points inverse distance weighting are used for the final comparison based on experience with past projects and is consistent with oil spill and search and rescue modeling approaches.

Figure 1 summarizes the relative skill for each forcing dataset in simulating drifter tracks that were observed in the 2009 PWS FE. In the sections to follow, each forcing dataset is summarized by its relative skill in simulating the different drifter types from the field experiment.

Two sets of analyses were completed; the first comparing drifters throughout the region, the second analysis method only analyzed drifters that fell in the general region of the HF Radar footprint.

![Figure 1](image.png)

**FIGURE 1.** WEIGHTED ROOT MEAN SQUARED SEPARATION DISTANCE CATEGORIZED BY HYDRODYNAMIC FORCING. STATISTICS ON THE LEFT WERE CALCULATED BASED ON AN OBSERVED DRIFTERS TIME IN THE FORCING DATASET’S GEOGRAPHIC EXTENT, WHILE THOSE ON THE RIGHT ONLY USED DATA INSIDE THE RADAR FOOTPRINT.
Another set of simulations were completed that also incorporated wind forcing from the WRF model. As in the previous set, two sets of analyses were completed; the first comparing drifters throughout the region, the second analysis method only analyzed drifters that fell in the general region of the HF Radar footprint.

Adding the wind forcing demonstrates minimal impact on the separation distances, except for the Hydromap tidal simulations. This is expected as ROMS, NCOM, and HF Radar represent complete surface velocities including the influence of wind, whereas Hydromap is purely tidal with no wind-driven component and we would expect to see improved results when wind forcing is superimposed.

**Figure 2.** Weighted root mean squared separation distance categorized by hydrodynamic and wind forcing. Statistics on the left were calculated based on an observed drifters time in the forcing dataset’s geographic extent, while those on the right only used data inside the radar footprint.
4.1.1 ROMS

The standard ROMS model has similar skill in simulating trajectories for the Argosphere and SVP drifters. This may indicate that the model is consistent in the way it simulates the surface and near surface layer currents. The Microstar type drifters were statistically better simulated by the ROMS model, but that may be due to their typically shorter track length when compared to the other surface/near-surface drifters.

Figure 3. Weighted root mean squared separation distance for ROMS hydrodynamic forcing categorized by drifter type.
4.1.2 ROMS with Data Assimilation

The ROMS model with data assimilation is more consistent across surface/near-surface drifters than the standard ROMS model. The absolute skill of the model may be impacted by the timestep of the output. The 6 hour timestep is the coarsest timestep of all of the hydrodynamic forcing data.

![Weighted Root Mean Squared Separation Distance by Drifter Type for ROMS w/ DAS](image)

**Figure 4.** Weighted root mean squared separation distance for ROMS with Data Assimilation as hydrodynamic forcing categorized by drifter type.
4.1.3 NCOM

The global NCOM dataset shows relatively large errors across drifter types. As stated, this is not unexpected as NCOM is a global circulation model not designed for coastal use; NCOM has a relatively coarse grid in the PWS region when compared to the other datasets being assessed. The large error in simulating the 40m drifter trajectories may be due to NCOM’s single layer surface currents used in this analysis. NCOM does provide 3d data but this was not available for this analysis.

FIGURE 5. WEIGHTED ROOT MEAN SQUARED SEPARATION DISTANCE FOR GLOBAL NCOM SURFACE LAYER HYDRODYNAMIC FORCING CATEGORIZED BY DRIFTER TYPE.
4.1.4 HFRADAR

HFRADAR demonstrates the highest error in simulating the Argosphere drifter trajectories from the PWS FE. This may be due to many of the Argosphere track observations falling outside of the area of HFRADAR coverage. Statistically, HFRADAR’s skill in predicting 10m SVP drifter tracks is similar to its skill in predicting the 40m drifter tracks.

**Figure 6.** Weighted root mean squared separation distance for HFRADAR observations of surface currents categorized by drifter type.
4.1.5 HYDROMAP TIDES

The Hydromap dataset has the lowest error in simulating the 40m drifter trajectories. As described, the HYDROMAP currents do not include wind forcing. These results may indicate that the currents at that depth are largely unaffected by the surface conditions and so seasonal effects combined with tidal flow may represent subsurface flow reasonably well. It may be that the statistical error for the Argosphere (surface) and SVP (10m) reflect this as well.

![Weighted Root Mean Squared Separation Distance for HYDROMAP Tides](image)

**Figure 7.** Weighted root mean squared separation distance for RPS-ASA’s vertically averaged tidal hydrodynamic forcing including a seasonal flow component categorized by drifter type.
5 CONCLUSIONS

The results demonstrate a logical trend in the comparison of relative skill between ROMS, ROMS with data assimilation, NCOM, HFRADAR and Hydromap datasets in predicting observed drifter tracks with simulated drifters in the context of the 2009 PWS FE. The observed trend in relative skill is preserved even when calculating the error metrics over the common geographic extent of the HFRADAR dataset. The HFRADAR dataset shows the lowest error in weighted root mean squared separation distance, and it seems logical that observations such as high frequency radar should outperform the numerical model datasets.

The ROMS model that includes data assimilation has a statistically lower error than the standard ROMS model. This indicates that the ROMS w/ DAS model benefits from observation system integration and assimilation for predicting trajectories in PWS, despite the relatively large timestep in model output. These results are consistent with other evaluations (Li et al. 2012, Farrara et al. 2012, Wang et al., 2012)

NCOM and the Hydromap product statistically have the lowest skill in simulating drifter trajectories in PWS. The Hydromap dataset out performs NCOM global circulation.

When wind forcing is added to the simulations, we see a marked improvement in the Hydromap tidal simulations and in fact, the Hydromap + WRF simulations provide skill results very similar to the ROMS model simulations.

It should be noted that these results looked at a comparative analysis. It shows that observation data (radar) performs better than models, and models that assimilate data perform better than non-assimilating models – this is a result that confirms what one would expect.

Trajectory modeling in Prince William Sounds is challenging, primarily due to the complex nature of the meteorology and oceanography – there are many complex processes including orographic effects and freshwater inflow. Very little real-time ocean observing data is available in the region and trajectory modeling to support oil spills, search and rescue and other marine responses will continue to be challenging. Observation data and high resolution models that use observation data for calibration and assimilation can improve the quality of forecasting to support marine response in Prince William Sound.

How do these results impact the use of the existing operational ATOM oil spill model in Prince William Sound? ATOM uses a software architecture that decouples the particle model from the forcing data. This means that ATOM can use a wide variety of wind and current data in different
formats, including point observation data (e.g. buoys), gridded wind fields in Grib/NetCDF (e.g. WRF), ocean currents stored as tidal constituents (e.g. Hydromap data), and time series surface and 3d current data stored in gridded formats such as NetCDF (Hf radar, ROMS etc).

ATOM presently uses current data from the Hydromap tidal database with wind forcing entered by the user. The study shows that Hydromap provided reasonable results when combined with a high resolution wind model. If ATOM had access to high resolution wind model forecasts, the trajectory predictions will be improved.

ATOM could be configured to use operational observation and modeling data for Prince William Sound quite easily because of the use of common data standards. ATOM could also connect to the Environmental Data Server (EDS - U.S Coast Guard) that manages storage and delivery of operational models and observing system data to SAR controllers and oil spill responders. The EDS currently manages data from the national HF radar server as well as a number of regional ROMS model implementations and meteorological wind forecasts. ATOM can connect to the EDS to access these datasets, or ATOM could be configured to connect to data streams from local data providers such as AOOS assuming common and open data standards are used.

Based on the results of this study, it is evident that the oil spill predictions generated by ATOM could be improved through the availability of operational regional models and real-time observations.
6 ACKNOWLEDGEMENTS

Funding for this project was provided through research grant No. 11-10-07 from the Prince William Sound Oil Spill Recovery Institute to the Alaska Ocean Observing System. Applied Science Associates was contracted for the analysis and report writing. Contributions were provided by Y. Chao at Remote Sensing Solutions, Inc. (formerly at JPL), J. Farrara at UCLA, and C. Schoch at Coastwise Services.
7 REFERENCES


Figure 8. Unbiased weighted variance in root mean squared separation distance for all forcing datasets. Bars on the left represent statistics based on individual forcing dataset’s geographic extents, and those on the right are limited to the HFRADAR’s geographic extent.
Figure 9. Unbiased weighted variance in root mean squared separation distance for the standard ROMS model categorized by drifter type.

Figure 10. Unbiased weighted variance in root mean squared separation distance for the ROMS model with data assimilation categorized by drifter type.
Figure 11. Unbiased weighted variance in root mean squared separation distance for the Global NCOM model categorized by drifter type.

Figure 12. Unbiased weighted variance in root mean squared separation distance for the HFRADAR observations dataset categorized by drifter type.
Figure 13. Unbiased weighted variance in root mean squared separation distance for RPS-ASA Hydromap tidal dataset that includes mean seasonal flow categorized by drifter type.
Figure 14. Simulated drifter trajectories and separation distance from the observed drifter (in red on map) for the Argo 5623 surface deployment.
Figure 15. Simulated drifter trajectories and separation distance from the observed drifter (in red on map) for the SVP 85928 10m deployments.
Figure 16. Simulated drifter trajectories and separation distance based on the ensemble of trajectory simulations—no wind forcing.
Figure 17. Simulated drifter trajectories and separation distance based on the ensemble of trajectory simulations—with WRF wind forcing.