Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications

Ben Amon Brushett
B.Eng. (Hons)

Griffith School of Engineering
Griffith Sciences
Griffith University

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Abstract

Effective prediction of objects drifting on the water surface is essential to successful maritime search and rescue (SAR) services, since a more accurate prediction of the object’s likely location results in a greater probability for the success of a SAR operation. SAR drift models, based on Lagrangian stochastic particle trajectory models, are frequently utilised for this task. More recently, metocean (meteorological and oceanographic) forecast data has been used as input to these models to provide the environmental forcing (due to winds and ocean currents) that the object may be subject to. Further, the slip of a drifting object across the water surface due to the ambient wind and waves (irrespective of currents) is described by its leeway drift coefficients, which are also required by the SAR drift model to calculate the potential drift of the object.

This study examined several ways to improve the prediction of an objects drift on the water surface, with the primary focus being the improvement of SAR forecasting. To achieve this, many simulations were undertaken, comparing the trajectories of actual drifters deployed in the ocean, and the corresponding model simulations of drift, using the commercially available SARMAP (Search and Rescue Mapping and Analysis Program) SAR drift model. Each drifter trajectory was simulated independently using a different ocean model to provide ocean current forcing. The ocean models tested included BLUElink, FOAM (Forecasting Ocean Assimilation Model), HYCOM (Hybrid Coordinate Ocean Model) and NCOM (Navy Coastal Ocean Model). The test measures that were used to evaluate the ocean model performance included: 1) the distance error between the actual drifter and the model simulation; 2) the hit rate, where a count was performed to determine how often the drifter was contained within the model defined search area; and 3) a drift length analysis, to determine whether any ocean model had a tendency to over predict or under predict the current speeds experienced by the drifters. The drifter simulations were carried out in several locations around Australia, including the Timor Sea, the Tasman Sea and the Indian Ocean. As each drifter was simulated independently using a different ocean model, consensus forecasting was also able to be investigated. Here, all forecasts for a single drifter were combined into a consensus forecast to determine areas of higher probability within an ensemble of model defined search areas.
The initial results demonstrated that for non-consensus modelling the NCOM and HYCOM models more accurately followed the 5-day trajectory of a drifter in the Timor Sea during 2009, as both ocean models demonstrated similar trajectories.

The results of the Tasman Sea drifter study showed the HYCOM and FOAM models were more accurate than the other models tested when replicating the 5-day drifter trajectories of 63 drifters in the Tasman Sea during 2010. In addition, an analysis of the consensus forecasting results were encouraging, as the areas where two or more ocean models overlapped indicated a greater hit rate than any of the single ocean model forecasts at 120 hours.

The Indian Ocean drifter study, involving an additional 45 drifter trajectories from 2012, demonstrated that a horizontal dispersion coefficient of 1,000 m^2/s was required to produce high hit rates and ensure consensus forecasting could be achieved. Typically the HYCOM and NCOM ocean models performed the best when replicating the 5-day drifter trajectories. The importance of using consensus forecasting was highlighted in this study, as it can be difficult to determine in advance which model was to perform best at any given time. An ensemble of ocean models available for employing a consensus forecasting approach allows the forecaster to account for a greater number of outcomes, consequently encapsulating more of the uncertainties involved in drift forecasting. Additionally, the 4 model consensus search area was found to be more efficient than any single model search area in terms of hit rate per unit of area. Also worth noting, the lower horizontal dispersion coefficients also tested (10 and 100 m^2/s) resulted in low hit rates, and less frequently produced consensus search areas, which indicated that these values may be too low to account for the sum of uncertainties involved in SAR drift forecasting and hence may be less suitable for use with the current suite of ocean models.

An additional study involved determining the leeway drift coefficients of three craft (a 19 foot panga skiff, 20 foot outrigger canoe, and a two-person sit down personal water craft) whose leeway coefficients were previously not known. This was conducted as part of a SAREX (Search and Rescue Exercise) study in conjunction with the US Coast Guard in the western tropical Pacific Ocean during 2012, and it was revealed that the leeway drift coefficients for the panga skiff were significantly higher than those previously determined for similar sized skiffs.
The final component of this study brought together the lessons learnt from the above (including horizontal dispersion parameter settings, using four ocean models for consensus forecasting, and the calculated leeway drift coefficients) and combined them into two case studies, which involved simulating the actual drift of two panga skiffs (one deployed during the SAREX, and the other involving an actual SAR event). The model simulations resulted in the skiffs being located within the four model consensus search areas, which were calculated to be significantly smaller than the individual model search areas, displaying a net benefit in implementing the consensus forecasting approach during SAR incidents.

This overall study provides three significant outcomes, which represent an important step forward for maritime SAR drift forecasting. The first was the implementation of the leeway drift coefficients determined for the panga skiff, outrigger canoe and PWC into the list of leeway targets employed for drift forecasting by SAR organisations worldwide. The second was the research into and the demonstration of the consensus forecasting technique developed herein for several SAR cases, and the subsequent request to incorporate an automated form of the consensus forecasting process into the Australian SAR drift forecasting system. Finally, the study has researched and shown the value of the drifter validation methodologies, which resulted in the request to incorporate an automated version of this drifter comparison methodology into the Australian SAR drift forecasting system.
Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Ben Amon Brushett

January 2015
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<td>3D MvOI</td>
<td>Three Dimensional Multivariate Optimal Interpolation</td>
</tr>
<tr>
<td>3D OI</td>
<td>Three Dimensional Optimal Interpolation</td>
</tr>
<tr>
<td>3DVAR</td>
<td>Three Dimensional Variational</td>
</tr>
<tr>
<td>ACCESS-G</td>
<td>Australian Community Climate and Earth System Simulator - Global</td>
</tr>
<tr>
<td>ADCIRC</td>
<td>Advanced Coastal Circulation and Storm Surge Model</td>
</tr>
<tr>
<td>ADCP</td>
<td>Acoustic Doppler Current Profiler</td>
</tr>
<tr>
<td>AMSA</td>
<td>Australian Maritime Safety Authority</td>
</tr>
<tr>
<td>AOI</td>
<td>Area of Interest</td>
</tr>
<tr>
<td>AOML</td>
<td>Atlantic Oceanographic and Meteorological Laboratory</td>
</tr>
<tr>
<td>AusSAR</td>
<td>Australian Search and Rescue</td>
</tr>
<tr>
<td>BODAS</td>
<td>BLUElink Ocean Data Assimilation System</td>
</tr>
<tr>
<td>BoM</td>
<td>Bureau of Meteorology</td>
</tr>
<tr>
<td>CODE</td>
<td>Coastal Drifter Experiment</td>
</tr>
<tr>
<td>CPSM</td>
<td>Classical Search Planning Method</td>
</tr>
<tr>
<td>CSIRO</td>
<td>Commonwealth Scientific Industry Research Organisation</td>
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<tr>
<td>CWL</td>
<td>Crosswind Leeway</td>
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<td>DWL</td>
<td>Downwind Leeway</td>
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<tr>
<td>EAC</td>
<td>East Australian Current</td>
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<tr>
<td>EDS</td>
<td>Environmental Data Server</td>
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<td>EnOI</td>
<td>Ensemble Optimal Interpolation</td>
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<td>FLDA</td>
<td>Florida Gulf Stream Data</td>
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<td>FNMOC</td>
<td>Fleet Numerical Ocean Model</td>
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<td>FOAM</td>
<td>Forecasting Ocean Assimilation Model</td>
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<td>FSM</td>
<td>Federated States of Micronesia</td>
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<td>GASP</td>
<td>Global Analysis and Prediction</td>
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<td>GDAS</td>
<td>Global Data Assimilation System</td>
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<td>Global Drifter Program</td>
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<td>Geographical Information System</td>
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<tr>
<td>GSI</td>
<td>Gridpoint Statistical Interpolation</td>
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<td>GSLA</td>
<td>Gridded Sea Level Anomaly</td>
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<tr>
<td>HF RADAR</td>
<td>High Frequency Radar</td>
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<tr>
<td>HYCOM</td>
<td>Hybrid Coordinate Ocean Model</td>
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<tr>
<td>IAMSAR</td>
<td>International Aeronautical and Maritime Search and Rescue</td>
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<tr>
<td>IMEI</td>
<td>International Mobile station Equipment Identification</td>
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<tr>
<td>LKP</td>
<td>Last Known Position</td>
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<tr>
<td>MAE</td>
<td>Mean Absolute Error</td>
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<tr>
<td>Metocean</td>
<td>Meteorological and Oceanographic</td>
</tr>
<tr>
<td>MGSVA</td>
<td>Mariano Global Surface Velocity Analysis</td>
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<tr>
<td>MODAS</td>
<td>Modular Ocean Data Assimilation</td>
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<tr>
<td>MOM</td>
<td>Modular Ocean Model</td>
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<td>NATSAR</td>
<td>National Search and Rescue</td>
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<td>NAVO</td>
<td>Naval Oceanographic Office</td>
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<td>NCODA</td>
<td>Navy Coupled Ocean Data Assimilation</td>
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<td>Navy Coastal Ocean Model</td>
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<tr>
<td>NEC</td>
<td>North Equatorial Current</td>
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<tr>
<td>NECC</td>
<td>North Equatorial Counter Current</td>
</tr>
<tr>
<td>NEMO</td>
<td>Nucleus for European Modelling of the Ocean</td>
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<tr>
<td>NLOM</td>
<td>Navy Layered Ocean Model</td>
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<tr>
<td>NMSC</td>
<td>National Maritime Safety Committee</td>
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<td>National Oceanic and Atmospheric Administration</td>
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<td>NOGAPS</td>
<td>Navy Operational Global Atmospheric Prediction System</td>
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<td>Naval Research Laboratory</td>
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<td>Numerical Weather Prediction</td>
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<td>Ocean Forecasting Australia Model</td>
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<td>Ocean General Circulation Model</td>
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<td>Physical Oceanography Division</td>
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<td>PIW</td>
<td>Person In Water</td>
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<td>POB</td>
<td>Person On Board</td>
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<tr>
<td>POC</td>
<td>Probability of Containment</td>
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<td>POD</td>
<td>Probability of Detection</td>
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<tr>
<td>Acronym</td>
<td>Meaning</td>
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<tr>
<td>POM</td>
<td>Princeton Ocean Model</td>
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<td>PWC</td>
<td>Personal Water Craft</td>
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<td>RAN</td>
<td>Royal Australian Navy</td>
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<td>RCC</td>
<td>Rescue Coordination Centre</td>
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<td>RDF</td>
<td>Radio Direction Finding</td>
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<td>RMSE</td>
<td>Root Mean Squared Error</td>
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<td>SAR</td>
<td>Search and Rescue</td>
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<td>SAREX</td>
<td>Search and Rescue Exercise</td>
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<td>SARMAP</td>
<td>Search and Rescue Mapping and Analysis Program</td>
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<td>SAROPS</td>
<td>Search and Rescue Optimal Planning System</td>
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<tr>
<td>SLDMB</td>
<td>Self Locating Datum Marker Buoy</td>
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<td>SRR</td>
<td>Search and Rescue Region</td>
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<td>SRU</td>
<td>Search and Rescue Unit</td>
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<td>SSH</td>
<td>Sea Surface Height</td>
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<td>SST</td>
<td>Sea Surface Temperature</td>
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<td>SVP</td>
<td>Surface Velocity Program</td>
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<td>SVP-L</td>
<td>SVP Drifter once it has lost its drogue</td>
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<tr>
<td>SZM</td>
<td>Sigma Z level model</td>
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<tr>
<td>USCG</td>
<td>United States Coast Guard</td>
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<tr>
<td>USCGC</td>
<td>United States Coast Guard Cutter</td>
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</table>
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To my close friends, thank you all for your support over the years. Many things come and go throughout life, but true friends will always be there, no matter what you are going through. Thanks for sticking by me and for your understanding throughout.

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Finally, I wish to thank Tessa for your constant support and understanding throughout this period. You have been there for me since the beginning of this important chapter in my life, and as it draws to a close, I look forward to starting the next exciting chapter of our lives together.
“A ship in harbor is safe, but that is not what ships are built for.”
— John A. Shedd, *Salt from my Attic*
List of Works Published

Refereed Journal Publications:


**Brushett, BA**, King, BA, & Lemckert, CJ, ‘Evaluation of metocean forecast model data to predict the drift of surface buoys in the Tasman Sea – including consensus forecasting’, *In preparation for submission*.


Other Publications:


Poster Presentations:


Brushett, BA, King, BA, & Lemckert, CJ 2011, ‘Evaluation of met-ocean forecast data effectiveness for tracking drifters deployed during operational oil spill response in Australian waters’ Presented at the 11th International Coastal Symposium (ICS), Szczecin Poland, May 2011.

Oral Presentations:

All Papers Included Are Co-Authored

Acknowledgement of Papers included in this Thesis

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- conception and design of the research project
- analysis and interpretation of research data
- drafting or making significant parts of the creative or scholarly work or critically revising it so as to contribute significantly to the final output.

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- Accept or decline offers of authorship promptly in writing.
- Include in the list of authors only those who have accepted authorship
- Appoint one author to be the executive author to record authorship and manage correspondence about the work with the publisher and other interested parties.
- Acknowledge all those who have contributed to the research, facilities or materials but who do not qualify as authors, such as research assistants, technical staff, and advisors on cultural or community knowledge. Obtain written consent to name individuals.
Included in this thesis are papers in Chapters 2, 3, 4, 5 & 6 which are co-authored with other researchers. My contribution to each co-authored paper is outlined at the front of the relevant chapter. The bibliographic details (if published or accepted for publication)/status (if prepared or submitted for publication) for these papers including all authors, are as follows:

Chapter 2:


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Chapter 3:

**Brushett, BA**, King, BA, & Lemckert, CJ, ‘Evaluation of metocean forecast model data to predict the drift of surface buoys in the Tasman Sea – including consensus forecasting’, *In preparation for submission*

Chapter 4:


Chapter 5:


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Chapter 6:

**Brushett, BA**, King, BA, & Lemckert, CJ, ‘Application of Leeway Drift Data to Predict the Drift of Panga Skiffs: Case study of Maritime Search and Rescue in the Tropical Pacific’, *Unpublished Manuscript*
Appropriate acknowledgements of those who contributed to the research but did not qualify as authors are included in each paper.

(Signed) _________________________________ (Date)______________

Ben Amon Brushett

(Countersigned) __________________________ (Date)______________

Supervisor: Prof. Charles Lemckert
1. Introduction

1.1 Background

When persons or craft go missing at sea, maritime search and rescue (SAR) operations must be undertaken to locate them in a timely manner to ensure their best chance of survival. Maritime SAR operations typically require drift forecasting to be undertaken to predict their movement over time, as typically the person or object will drift with the ambient winds and currents, and hence they will not remain at their last known position. Typically a SAR drift model is employed by the SAR authorities to determine where the missing person(s) or craft may have drifted over the elapsed time, and hence establish the most likely area to conduct a search.

To effectively replicate the drift of an object at sea, metocean (meteorologic and oceanographic) environmental data (winds and currents) are required as input to the SAR drift model to represent the environmental conditions that the search object may be subjected to, whilst adrift. This thesis employed a maritime SAR drift model, SARMAP (Search and Rescue Mapping and Analysis Program), to test various different metocean datasets when used to simulate the drift of objects at sea and provide operational search areas accordingly.

The key focus of this study was to improve SAR response by improving the drift modelling process of a search object. Additionally, as many of the fundamental aspects of maritime SAR drift modelling are shared with marine pollutant drift modelling, the findings herein may also be applied to improving the forecasting of drift for marine pollution incidents and other marine emergency situations.
Australia’s maritime search and rescue region (SRR) (Figure 1-1) covers 52.8 million square kilometres, which is around 1/10th of the earth’s surface (Australian Maritime Safety Authority, 2008). This vast area provides a significant challenge when it comes to locating persons or craft lost at sea. The cost of providing search and rescue capabilities to the Australian region in the 2008-09 year was $61.749 million (Australian Maritime Safety Authority, 2009). If SAR operations can be improved through improved definition of search areas, there is the opportunity to save lives and also the potential to reduce the financial cost in doing so.

In situations where a long term search event occurs, that results in extended drift forecasting durations, search areas may expand over time and become so large that the available resources are not able to adequately search them. In such an event it is vital that a search area prioritisation technique be implemented, where portions of the total search area may be determined as having a higher probability or likelihood of containing the search object and thus search assets can be tasked to those areas accordingly.

Figure 1-1: The Australian maritime Search and Rescue Region (SRR) as indicated by the grey shaded area.
The majority of the latest SAR drift models incorporate the latest ocean and atmospheric forecast models when completing operational SAR drift forecasts (Breivik, et al., 2013). These ocean current forecast models are able to predict the ocean and atmospheric state up to several days ahead at much more frequent time intervals and at higher spatial resolution than previously available (particularly when compared with hindcast ocean current data). With a more accurate forecast of the ocean state, there is the potential ability to generate more precise search areas, which increases the chances of locating the person(s)/craft lost at sea and enables a more resource and cost effective search to be undertaken.

As there are several different ocean models available in the Australian region including BLUElink, FOAM (Forecasting Ocean Assimilation Model), HYCOM (Hybrid Coordinate Ocean Model) and NCOM (Navy Coastal Ocean Model) (refer to 1.6.3 this study investigated which ocean model may be the most reliable for drift forecasting (SAR and/or pollutant response purposes). In addition to this, the concept of consensus forecasting was investigated to determine whether an ensemble of all four ocean models to produce a consensus forecast can demonstrate an improvement in reliability or performance over using a single ocean model, and whether the search areas generated by the consensus forecasts may provide a method for search area prioritisation.

1.2 Significance of the Research

According to the National Maritime Safety Committee (2008) in the years between 1999 and 2004, there were 241 reported/recorded fatalities resulting from marine incidents occurring within Australian waters. The report further quantified that the cost per boating fatality in Australia was approximately $1.5 million, and it was estimated that the total cost of boating fatalities in Australia from 1992 through to the start of 2008 would have exceeded $1.5 billion. The outcomes of this present study have the potential to assist in reducing the number of lives lost at sea and in doing so also reduce the associated cost in providing SAR services.

An increasing number of asylum seeking refugees have been undertaking passage from Southeast Asia to Australia, predominately in unsafe, overcrowded and unseaworthy vessels. As a direct consequence of this, there has been a significant rise in the number
Chapter 1

of SAR incidents, number of persons rescued and also related fatalities from these unsafe voyages. According to AMSA statistics, the number of lives saved in Australia coordinated through AMSA RCC has increased from 286 in 2008-09 (Australian Maritime Safety Authority, 2009) to 8,978 in 2012-13 (Australian Maritime Safety Authority, 2013a). These statistics highlight the need for effective maritime search and rescue systems. Figure 1-3 indicates the SAR operations in the Australian SRR for July 2012 – June 2013, note the high density of SAR incidents between Indonesia and Christmas Island. To respond to the increase in number of these SAR incidents, the best SAR systems available are required to ensure as many lives are saved as possible.

It is imperative to adopt the most advanced search and rescue drift models and techniques to conduct successful and cost effective searches for missing persons or craft and locate them in a timely manner. Figure 1-2 shows the average survival time of a person immersed in water at different temperatures, which highlights how important timeframes are to those lost at sea. As there are many uncertainties present in SAR drift modelling, the forecast search areas need to be large enough to account for the sum of all of these uncertainties. As a result of this, after a person or object has been missing for a significant period of time, there becomes a time when the search area becomes so large that the search object may move out of that search area before the available search and rescue units (SRU) conducting the search of that area are able to complete the search. It is at this stage that the probability of finding a person or object lost at sea greatly diminishes and lives may be lost. This research aims to determine the most appropriate input forecast environmental data for SAR drift models, and to provide a methodology to define more effective search areas and in turn have the potential to save lives.
Figure 1-2: Graph showing the average survival time of a person immersed in water at different temperatures. Image source: Australian Maritime Safety Authority (2013b)

Figure 1-3: Map showing the locations of SAR incidents and SAR operations in Australia for July 2012 to June 2013. The red dots represent both land and maritime SAR incidents. The red solid line shows the bounds of the Australian Search and Rescue Region. Image source: National Search and Rescue Council (2013).
1.3 Purpose of the Study

The purpose of this study was to provide quantification as to the effectiveness of the currently available metocean forecast models in their application to operational response to SAR drift forecasting and marine pollution incidents. Prior to this study commencing, ocean models had not been widely used in Australian waters for operational response to SAR, so their effectiveness in this area was somewhat unproven, however the ocean models had been used in response to several marine pollution incidents, with positive results, which indicated their potential suitability for use in SAR incidents.

The outcomes of the study were to potentially provide the SAR operator or marine pollution responder with guidance as to which of the metocean forecast models (or combination of these) are likely to provide the most reliable or accurate outcome. This may decrease the response time needed for searching, and increase the likelihood of finding the lost person alive, or in the case of a marine spill, mitigating the environmental impacts of that spill.

Research Questions:

A review of current practices has led to the following questions, which if addressed would lead to an improvement SAR drift forecasting.

1. Given four different ocean models, which model may more frequently perform best in an area of interest when used for drift forecasting, in terms of mean absolute error (MAE), hit rate and average search area size over a drift forecast period up to 120 hours (5-days)?

2. Can an ensemble of several individual search areas from different ocean model forecasts be combined into one consensus forecast to improve the search area predictions when compared to using a forecast from any one of the ocean models?

3. Do the consensus overlap areas between several ocean model forecasts contain a higher hit rate per unit of search area than any of the single ocean models?
4. Can the reduction in search area obtained from the consensus forecast overlap regions be effectively used as a method to priorities search areas in cases where search assets are limited or the search area is prohibitively large?

5. When using the Monte Carlo random walk stochastic particle model for SAR drift forecasting, what horizontal dispersion coefficient is the most effective (10, 100 or 1,000 m²/s) to contain the search object for a significant portion of time, without prohibitively enlarging the search area, and whilst still allowing consensus forecasting to be utilised?

6. Given several water craft common to the tropical Pacific island communities whose leeway drift coefficients were not previously known, can these leeway coefficients be determined through field tests, for use in SAR drift models to accurately predict their drift in the event of a SAR case?

Each of the chapters throughout this study build on the previous chapter by progressively incorporating and addressing the points outlined above. The final body chapter culminated in the implementation of all the improvements established within previous chapters and applied to the successful simulation of an actual SAR incident.

1.4 Organisation of the Study and Thesis Structure
This thesis introduces the current state of SAR drift modelling, and outlines the aspects where further research was warranted to improve the current state of knowledge. A review of the current literature is included to provide a background for the studies that follow.

The main body of the thesis is centred on a series of individual research papers, which have been written as standalone chapters. Each chapter builds on the common theme of improving SAR drift modelling, with each subsequent chapter further improving the processes developed. A common theme links each chapter through the thesis as a cohesive body of work; however each chapter may be read independently of one another. A by product of ensuring the chapters may be understood independently is a small amount of similar material which was required to give each chapter context.
Chapter 1

The overall conclusions/recommendations follow the main body chapters, which discuss the findings of the study and provide recommendations for future research.

A brief overview of the content of each of the body chapters is outlined below.

Chapter 2

The application of current and wind forecast datasets for predicting the movement of a single surface drifter at sea was investigated in Chapter 2. The study utilised six ocean current models and two wind models to predict the drift of an SLDMB drifter which had been deployed in the Timor Sea during operational oil spill response. This chapter first reported the merits of using an ensemble of drift forecasts combined from different ocean current and wind forecasts as an operational approach considered to have merit, and hence warranted further exploration.

Chapter 3

The objective of the study undertaken in Chapter 3 was to determine which ocean current model best replicated the drift trajectory of Surface Velocity Program (SVP) drifters, to indicate which ocean model was able to more effectively simulate the ocean currents in the Tasman Sea region. The study examined the use of four different ocean models (BLUElink, FOAM, HYCOM and NCOM) as forcing for the SAR drift model, SARMAP, which was used to forecast 63 individual 5-day trajectories of SVP drifters (both with and without drogues attached) in the Tasman Sea throughout 2010. The drift forecast calculations were initially carried out using the International Aeronautical and Maritime Search and Rescue (IAMSAR) automated manual solution (AMS) and then repeated using the Monte Carlo stochastic solution, both of which are contained within the SARMAP system. This ensured that the results were applicable to users of either of the solution methodologies. Three measures of model performance were employed, which included the mean absolute error (MAE) and the root mean squared error (RMSE) for the minimum and average distance between the 1,000 model simulated drifter positions and the actual drifter position, as well as a non parametric hit rate, which indicated how often the actual drifter was located within the SARMAP model predicted search area. An analysis of the performance of each of the individual ocean current models was carried out, as well as the performance of the consensus forecast, which used all four ocean model forecasts to produce a single ensemble forecast. This
Chapter 1

Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications

further demonstrated the validity of utilising consensus forecasting when modelling the drift of objects on the water surface and demonstrated improvements over using a single ocean model forecast.

Chapter 4

Chapter 4 expanded on the ocean model evaluation methodology described in Chapter 3 using the same four ocean models, however the study focussed only on SVP drifters with their drogue attached, located in the Indian Ocean during 2012. The Monte Carlo stochastic model solution was employed, and three different horizontal dispersion parameters (Low = 10 m²/s, Medium = 100 m²/s, and High = 1,000 m²/s) were tested to evaluate how well they performed in terms of minimum and average distance MAE, hit rate and search area size. To ascertain if there was a benefit in applying consensus forecasting when determining search areas, consensus forecasting was further explored by computing the search area size and corresponding hit rate for 2+ model consensus (two or more model overlap area), 3+ model consensus (three or more model overlap area), and 4 model consensus search area forecasts. This enabled a comparison to be made between each of the single ocean model average search area sizes (and corresponding hit rates), and the average search area sizes (and hit rates) encountered with each of the consensus forecasts. Hence conclusions were able to be drawn as to the potential benefit of focussing search efforts on the smaller search areas that were defined to have model consensus, rather than focussing on the larger single ocean model forecast search areas.

Chapter 5

The focus of Chapter 5 was to determine the drift characteristics (leeway coefficients) of three craft common to Pacific island communities through leeway field studies. The movement of an object adrift at sea is affected by the ocean currents, the winds and the waves, and each object is affected by these forces differently due to the objects shape and area exposed above and below the waterline. An accurate description of the leeway of an object is required as input into SAR drift models (such as SARMAP) to effectively forecast the object’s drift and hence formulate search areas most likely to contain that search object. The more accurate the leeway coefficients are (obtained through extensive field testing) the less uncertainty there is in the way that objects will
drift and hence the more accurate (and smaller) the search area may be. When the search area is smaller, it can be more efficiently covered by the available search resources, hence increasing the likelihood of finding the search object and in turn reducing the financial cost in doing so.

Chapter 6

The study in Chapter 6 brought together various components from each of the preceding chapters to show how the various components may be applied to actual SAR drift scenarios. The chapter describes the application of the SARMAP model to forecast the 5-day drift of a panga skiff deployed during the leeway field study. The leeway coefficients of the panga skiff collected during the leeway field study (described in Chapter 5) were input into SARMAP and consensus forecasting was applied with the use of the four ocean current models (described in Chapter 2, 3 and 4). During the leeway field study an actual SAR case unfolded, whereby a skiff (of the same design to those being studied) was reported missing. The data collected during the leeway tests undertaken the preceding week was sent through to the US Coast Guard to forecast the panga’s drift and plan search areas. The search was successful, with the panga being located on the first search (some 72 hours after starting to drift due to a disabled engine) with the two occupants in good health being subsequently rescued. The SAR incident provided validation that the leeway drift coefficients obtained during the study were effective for the use in SAR drift models. The incident was then recreated by hindcasting the incident using SARMAP and the four ocean models with the application of the consensus forecasting approach.

1.5 Overview of Methodology for Drifter Comparisons

This study focussed on using a Lagrangian approach (moving point source comparison, free in space) to the testing methodology as opposed to the traditional Eulerian approach (stationary point source comparison, fixed in space). The chosen approach can be more computationally intensive when compared with the Eulerian approach, due to the need to take spatially and temporally varying comparisons; however SAR applications are Lagrangian by nature, so this was the logical choice for this study.
A large sample of drift scenarios were simulated by forecasting the trajectories of drifter buoys through the use of the SAR drift model, SARMAP.

The SARMAP model is a Lagrangian particle tracking model which contains two numerical solutions to generate search areas. The first is an automated version of the manual solution (AMS) as defined by IAMSAR (International Aeronautical and Maritime Search and Rescue). This solution uses a minimal number of particles (from one to six depending on the search object’s leeway details). Forecast winds and currents are used to simulate the movement of the model particles. Each model particle then has a radius applied to account for the sum of all anticipated errors, and a given safety factor based on the search number. A rectangle/square is then applied to surround all of the model particles radii which define the final search area. Further details of the IAMSAR solution are given in Section 1.6.2 and in the IAMSAR Manual (International Maritime Organisation, 2008).

The second solution is known as the Monte Carlo stochastic method, which uses a large number of particles (typically >1,000) and a horizontal dispersion parameter to control the spreading of particles.

Horizontal dispersion (also referred to as horizontal diffusion) refers to the process by which horizontal transport or spreading occurs. As many of the ocean models are not able to adequately resolve all levels of the horizontal dispersion process (due to horizontal and temporal resolution restraints) hence parameterisation of the sub grid scale processes must be made. Typically the horizontal dispersion is measured in units of m²/s.

The values of horizontal dispersion vary from region to region and over time, depending on the amount of horizontal current shear present. For example, high horizontal current shear zones correspond to high horizontal dispersion values, and conversely low horizontal current shear zones corresponding to lower horizontal dispersion values.

Additionally, the horizontal dispersion coefficient is often used within SAR drift models to both a) account for drift associated with sub-grid scale turbulent processes that the ocean forecast models do not provide, and b) account for the uncertainties within the environmental forcing data (waves, winds and currents). This has an effect of spreading and diffusing the model particles, thus increasing the search area size, which has the
benefit of increasing the likelihood of containing the search object within the search area, at the expense of search efficiency in potentially having to search a larger area.

It is common practice to use pre-set dispersion parameters within the trajectory models (SARMAP) as the horizontal dispersion coefficient from the ocean models are not often available, and hence not able to be input into SARMAP in regular operational use. The SARMAP model has three defined horizontal dispersion coefficient values which are user selectable. In the model they are referred to as uncertainty values, with low uncertainty corresponding to a horizontal dispersion coefficient of 10 m$^2$/s, medium uncertainty with 100 m$^2$/s and high uncertainty with 1,000 m$^2$/s.

As it is uncommon to know specifically what horizontal dispersion coefficients may be required in every specific scenario, the three user selectable values provide an adequate range of values to cover a range of possible scenarios. For example – in an enclosed estuary, where the current flow direction is bound and relatively predictable, a horizontal dispersion coefficient of 10 m$^2$/s may be selected, whereas in a turbulent open ocean environment, where current eddies, wind gusts and waves may be present, a larger horizontal dispersion coefficient of 1,000 m$^2$/s may be more suitable.

A drifter dispersion study by Mantovanelli, et al., (2012) in the waters off the east coast of Australia indicated that near shore dispersion may average ~85 m$^2$/s whilst offshore diffusivities averaged ~1,133 m$^2$/s. These near shore and offshore dispersion values correspond closely to the SARMAP user selectable medium and high uncertainty values, respectively.

A sense of the magnitude of the horizontal dispersion coefficient present in the surface layers of the model currents can be estimated through the application of Smagorinsky’s method (Smagorinsky, 1963) whereby the horizontal current shear in the surface currents is utilised to determine the approximate horizontal dispersion coefficient required to parameterise the sub-grid scale processes.

The ensemble of 1,000 particles are forced by the forecast winds and currents, and are dispersed according to the dispersion parameter applied. A convex hull or polygon is applied to surround all 1,000 particles which defined the search area. This system is more commonly used by the latest SAR drift models due to its advantages over the
other solutions available. Further details of the Monte Carlo stochastic solution are given in Section 1.6.2).

The Monte Carlo stochastic solution was used throughout each of the studies herein, however one study (Chapter 3 – Tasman Sea Drifter Study) utilised the IAMSAR solution in parallel with the Monte Carlo stochastic solution to enable a comparison between the two solution methodologies to take place.

The ocean models used to provide current forcing to the SAR trajectory model (SARMAP) included BLUElink, FOAM, HYCOM and NCOM, whilst the atmospheric forecast models used to provide wind forcing included GFS (for all studies) and NOGAPS only used for study in Chapter 2). Each drifter forecast was run as if it were an actual SAR case, by specifying the time and location for the beginning of the simulation (coinciding with the drifter position), selecting a single ocean model and wind forecast model and running the simulation for a forecast period of up to five days (120 hours). After the simulation was complete, an error analysis was undertaken at intervals throughout the simulation to determine how effective that combination of forecast winds and currents were at replicating the drifter track (for example BLUElink ocean currents and GFS winds). This process was then repeated with each combination of ocean current and wind forecast data to compare how the metocean forecast data varied, and which combinations provided a more reliable result. If four ocean models and one atmospheric forecast model were available, a total of four single forecast combinations were available to forecast a given drifter track.

The assumption of independence between the ocean models and the wind models is not strictly accurate, as each ocean model also uses a wind model for its atmospheric forcing when generating an ocean forecast. As such, when running drift forecasts with environmental forcing from ocean models paired with different wind models that were not used to force the ocean model, inconstancies or artefacts may be introduced into the drift modelling. These artefacts can be important where there are large differences in the wind models, and where there are strong wind induced surface flows. These artefacts were deemed unlikely to be significant in the present study, due to its design and desired outcomes.
Any artefacts which may result from drift forecasts using non-linked wind models and ocean models would be very small in the present study, and as such it was deemed acceptable to pair up wind models with current models which were not associated. It is quite common practice in numerical drift modelling to pair non-associated wind and ocean models for a number of reasons, the foremost is practicality in terms of data accessibility and availability.

The present study required that non-paired wind and ocean models be used for several reasons to achieve the desired outcomes of the study. The following indicates the rationale as to why the drift modelling was carried out as it was in the present study:

- The GFS wind model (which was used for all of the studies) was not used as atmospheric forcing for any of the ocean models to determine the surface currents – therefore there was no bias between pairing combinations (i.e. if NOGAPS was used, it may skew the results towards better performance results for NCOM and HYCOM - as both used NOGAPS to provide atmospheric forcing). Hence, using the independent wind model – eliminates any potential biasing of ocean current model performance results.
- The majority of the simulations within this present study utilised low to very low leeway search objects (drifters) which are only minimally influenced by the wind fields, thus reducing the impact the winds may have on the model results.
- Finally, the study was primarily focussed on determining the effectiveness of the ocean models when used in SAR and/or oil spill response. Keeping the wind model constant throughout all of the simulations, enables the performance of the ocean models to be identified by isolating an additional variable.

The error analysis undertaken for this study included measuring the distance from each of the 1,000 ensemble member model particles to the actual drifter (for a single drifter forecast) and taking both the average and the minimum distance to the drifter (in km) at intervals throughout the model simulation. From these average and minimum distances, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) were calculated for the all of the drifter tracks modelled in each study area (Refer to Equation 1-1 and Equation 1-2 respectively). These statistics give a good indication of the accuracy of the forecasts when reproducing the drifter tracks over time.
Chapter 1

MAE = \frac{1}{n} \sum_{i=1}^{n} |f_i - m_i|

Equation 1-1

Where:

- \( f_i \) = forecast drifter position
- \( m_i \) = measured drifter position
- \( n \) = number of drifter simulations

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (f_i - m_i)^2}{n}} \]

Equation 1-2

Where:

- \( f_i \) = forecast drifter position
- \( m_i \) = measured drifter position
- \( n \) = number of drifter simulations

Consensus forecasting was able to be implemented as the process outlined above generated a multi model ensemble of forecasts for the same drifter track. Consensus forecasting is a potentially useful technique to give more confidence in the accuracy of a forecast by focussing on the areas where several of the single model forecasts (ensemble members of the consensus forecast) overlap. For example, the four model consensus search area is the area where all four single model forecasts coincide. Consensus forecasting may also be used to prioritise search areas when available resources are limited as the area of overlap for four model consensus is always smaller than the individual search areas that make up that consensus area (refer to Figure 1-4).
Figure 1-4: Map showing an ensemble of predicted search areas at the end of the simulation (120 hours) for a drifter off the coast of NSW using the IAMSAR solution (within the SARMAP system). Ocean currents were obtained from BLUElink (blue outlined area), FOAM (green outlined area), HYCOM (yellow outlined area) and NCOM (red outlined area) to generate the individual search areas. Consensus search areas are shown by the shaded grey regions. These shaded regions increase in intensity when the number of individual search areas which overlap or coincide increases. As shown, the drifter is located within the four model consensus search area, which is considerably smaller than each of the single search areas which form part of the consensus.

Another statistic was utilised to evaluate the effectiveness of the SAR drift model used (SARMAP) and the environmental forcing models tested in their ability to predict search areas that contained the drifter (or search object). This statistic was a non-parametric hit rate, whereby the frequency that the actual drifter was located within the model predicted search area at any given time, was calculated. When the drifter was located within the search area, a “hit” was recorded and when the drifter was not located within the search area, a “miss” was recorded. This measurement gave an overall percentage of how often the drifter was located within the model defined search area at given time intervals throughout the simulation.

There were individual studies undertaken for several different water bodies around Australian and the Pacific region. These included the Timor Sea (Chapter 2), the Tasman Sea (Chapter 3), the Indian Ocean (Chapter 4) and the Western Pacific Ocean (Chapter 6).
The drifters which were used in this study have very low leeway coefficients (they are very minimally affected by the wind) however the appropriate leeway coefficients were applied when modelling the trajectories and subsequent search areas of the drifters, as defined by a review of relevant scientific literature.

An actual SAR case was simulated (Chapter 6), using a similar process to that used for the drifter forecasts outlined above, to quantify how effective the modelling software, the environmental forecast datasets, the consensus forecasting approach, and the calculated leeway coefficients were at forecasting or replicating the drift patterns exhibited from an actual scenario involving a disabled craft. Hit rates and RME values (as outlined above) were calculated for this SAR scenario to give quantification to the overall effectiveness.

1.6 Review of Relevant Literature

1.6.1 Maritime Search and Rescue (SAR)

Background

Maritime SAR incidents have been carried out in Australian waters for centuries. One of the first documented SAR cases in Australian waters occurred in 1656 which involved the shipwreck of a Dutch merchant ship approximately 100 km north of where Perth (Western Australia) is today. The Vergulde Draeck was en route from Texel (Holland) to Batavia (Indonesia). There were approximately 193 crew on board before the ship went down, however only 75 people made it to shore including the Master and Understeersman. Once ashore the Master sent a small boat with the Understeersman and six of the fittest survivors on to Batavia to return with assistance. The seven made it to Batavia where a search party was dispatched back to pick up the remaining survivors; however none were found (Green, 1973).

In the past, search areas for SAR incidents were calculated from basic manual calculations of drift due to approximate wind and current conditions. This has progressed “light years” (White, 2003) in recent times with the implementation of numerical modelling software, real time environmental data measurements, and most recently, environmental forecast data. This all provides the SAR planner with a
potentially more accurate search area, in a greatly reduced timeframe than was historically possible.

There are several government bodies involved in the provision of search and rescue in Australia. Search and rescue is conducted by both state authorities (state police) and federal bodies Australian Search and Rescue (AusSAR). The Australian Maritime Safety Authority set up AusSAR which operates the Rescue Coordination Centre (RCC). The RCC coordinates all major SAR missions within the Australian SRR. Depending on the severity or location of the SAR incident the RCC will either coordinate the search efforts themselves, or pass the coordination down to the relevant state police authorities. The RCC coordinates both maritime and aviation SAR activities (Australian Maritime Safety Authority, n.d.).

The National Search and Rescue Council (NATSAR) is an organisation which was founded initially in 1976 by the various state and federal SAR bodies primarily to ensure there was a consistency and uniformity to the SAR procedures across the SAR bodies throughout Australia. Later the focus of the NATSAR council changed to formulate, discuss and ratify national search and rescue policies (National Search and Rescue Council, 2013).

**Developments**

As previously mentioned, early SAR calculations were carried out using manual calculations and incorporating mean ship drift data and wind estimates to calculate approximate areas of interest (AOI) as to indicate the best location to search for the missing person or object. Mean drift data was provided by ships and calculated by observing how the oceanic currents affected their course whilst en-route from port to port. The ship drift databases were developed over time and gave a crude representation of the seasonal trends in oceanic currents. Ocean currents are however very complex, varying significantly over spatial and temporal scales, so the above method was not able to account for many of the spatial and temporal changes in the ocean currents.

The manual solution method used by early SAR responders involved manually calculating the datum (datum can be defined as the most probable location of the search object subject to its movement over time), search area (area in which the search object is
most likely to be contained) and the effort allocation (the allocation of the search effort in terms of deploying planes and boats etc.). This was done by utilising a range of equipment including worksheets, dividers, triangles and manoeuvring boards. This process could take up to three hours to complete (White, 2003) which is significant when several subsequent searches may have to be planned in one day, and every minute in a response situation is important.

Manual calculations for the planning of SAR response have developed to include sophisticated numerical models which represent the current state of the art for SAR response planning. Current state of the art maritime SAR response includes the use of technically advanced numerical models; two of these models currently available are SARMAP (Search and Rescue model and response system) and SAROPS (Search and Rescue Optimal Planning System). SARMAP is currently being used by the Irish Coast Guard, Maritime New Zealand, Sasemar Spain, Singapore Civil Aviation and Singapore Port Authority, the Argentine Coast Guard and the US Navy (Applied Science Associates, 2014). SAROPS was implemented by the US Coast Guard in 2007 and has subsequently been successfully used for SAR response (Bernstein, 2009). These models utilise environmental forcing from complex oceanic and atmospheric forecast models to forecast the movement of the drift object. From this forecast drift, the SAR models develop a search area, provide search patterns based on the available resources (both sea and airborne), and give the probability of detection and probability of containment of the search object within the search area. A more detailed description of the SARMAP model is provided in Section 1.6.2. Model forcing is provided to the models through the utilisation of an environmental data server (EDS) that feeds high resolution (both temporally and spatially) forecast wind and current data.

**SAR Modelling**

An improved forecast of the likely drift (and hence search area) of the person or object lost at sea is now possible with the development of maritime SAR models. The majority of recently developed SAR models consist of three main components – the trajectory or drift model, the environmental forcing parameters (to drive the trajectory model), and the search area model. Usually the trajectory model and the search area model are incorporated into one numerical modelling system (eg. SARMAP or SAROPS) which
calculates the likely drift trajectory of the search object and then calculates the search area within which the search object would most likely be located. This part of the model can also be used to calculate the best search pattern, given the available search resources (eg. fixed or rotary wing aircraft and vessels).

The environmental forcing (wind and ocean currents) can vary in a number of different ways, depending on the data available, and is usually provided by atmospheric or oceanic measurements (of wind velocity or ocean current velocity), or through forecast/nowcast/hindcast models. The data may be either a point source (single point) or spatially varying (multiple points spread onto a regular grid), and either temporally constant (no time variance throughout the simulation) or time varying (data at regular time intervals; hourly, six hourly or daily). The environmental forcing which has been found to deliver the most reliable results for the forecast of drift objects (and hence probable search area) is generally a high resolution, temporally and spatially varying forecast model that incorporates as many measurements into a regular data assimilation system which is used to auto correct the model forecast.

The advent of advanced SAR modelling systems has greatly impacted the SAR community due to the improved ability of complex calculations to be solved in a much shorter timeframe than previously possible, which in turn allows for more expedient and precise responses to be undertaken.

There are several different numerical approaches to SAR modelling, two of these include the International Aviation and Maritime Search and Rescue (IAMSAR) accepted Automated Manual Solution (AMS) method, and the Monte Carlo stochastic method. The SARMAP system is capable of modelling the drift of an object (and hence search area) using either of these two methods. The AMS method is a computerised version of the Manual Solution Method and gives an expanding square search area in which the object should be contained. The Monte Carlo stochastic method uses a large number of Lagrangian particles with a horizontal dispersion parameter to form an expanding convex hull search area which surrounds all of the model particles (Applied Science Associates, Inc., 2013). Further detail of these two solution methods is provided in Section 1.6.2.
A comprehensive review of the state of search theory until 2001 is provided by Frost & Stone (2001). The review also covers the state of SAR models available at the time, where most of the SAR models were automated versions of the manual solution. It was recommended by Frost & Stone (2001) that stochastic SAR models be further developed and implemented by SAR agencies, which has subsequently occurred with the majority of the latest SAR models being based on a stochastic particle solution. Breivik, et al. (2013) provided a review of the recent developments in the SAR numerical modelling field and the current state of the field.

A paper by Spaulding and Howlett (1996) outlines previous studies involving the use of SARMAP for modelling search and rescue scenarios. This includes the hindcast of two marine incidents. The first scenario involved a couple who had jumped off the Peu Bridge in Naragansett Bay, Rhode Island in November 1993. Several simulations were undertaken to determine a search area for their bodies, assuming different buoyancies of the bodies (positive, neutral and negative). The initial search for the couple proved unsuccessful, however several months later (August 1994) several bones were found within the search area as defined for the neutral and negatively buoyant scenarios as predicted by SARMAP. These bones were positively identified as being from the couple. The second scenario involved a shipping container which was lost off the coast of Valparaiso, Chile in April 1994. This scenario involved using SARMAP to track a partially submerged shipping container over 18 hours which was carried out successfully.

The study undertaken in Chapter 6 documents the use of the SARMAP drift model to predict the drift of a panga skiff which was reported missing near the Chuuk Islands in the Federated States of Micronesia (FSM). The scenario was simulated with SARMAP, using the leeway parameters for the panga skiff as calculated in Chapter 5. Additionally consensus forecasting was applied, where four ocean current models BLUElink, FOAM, HYCOM and NCOM were used to build a consensus forecast. The drifter was located within the four model overlap area, as simulated by the consensus forecast.
Chapter 1

Leeway Drift

Leeway drift is the movement or drift of a floating object across the water surface due to the effects of a wind and wave field (relative to the ocean currents). The definition of leeway has evolved over time, with each definition becoming more definitive with less ambiguity.

The U.S. National Search and Rescue Supplement to the International Aeronautical and Maritime Search and Rescue Manual (National Search and Rescue Committee, 2000) had adopted the following definition of leeway:

“The movement of an object through water caused by winds blowing against exposed surfaces”.

This definition of leeway does not include the reference height for the winds or depth for the ocean currents, and hence there is some room for individual interpretation. To overcome this ambiguity, the most recent definition of leeway listed by Breivik, et al. (2011; 2013) is the most rigorous to date and contains definitions of reference heights for wind speeds and depths for currents. This definition is as follows:

“Leeway is the motion of the object induced by wind (10 m reference height) and waves relative to the ambient current (between 0.3 and 1.0 m depth)”.

This definition allows the SAR responder to use standard 10 m reference height model forecast winds and the surface layer of ocean current forecast models or surface currents measured by HF radar. This most recent definition of leeway has been adopted for the present study.

It has been well documented that drifting objects tend to track downwind due to the wind force on the exposed surfaces of the object adrift, however the direction of this (predominately) downwind drift is not at all times directly downwind, and often a deflection angle (arising from a crosswind component, perpendicular to the downwind direction) is apparent. The crosswind component, when added to the downwind component causes divergence of the object away from downwind (either to the left or right, depending on the physical properties of the object and the circumstances). This drift variance is known as leeway divergence (Allen, 2005). A sound understanding of the leeway divergence characteristics of a search object is vital for accurate calculation of the search area, to increase the probability of locating the search object.
There are two different methods in which leeway can be described, firstly using the leeway speed and divergence angle, and secondly using the respective downwind and crosswind leeway vector components. Leeway speed can be defined as the speed by which an object is pushed through the water due to the wind (and waves), whilst the divergence angle can be defined as the angle at which the object diverges from the downwind direction (Anderson, et al., 1998). The former method (leeway speed and divergence angle) has some limitations as it does not account for the different physical mechanisms which control the downwind and crosswind leeway drift. Analytical models of these mechanisms would be very complex due to the physics involved, however a statistical model can appropriately resolve the differences between the downwind and crosswind drift, and hence by splitting the numerical solution into the two vector components, these two processes can be treated individually. Additionally, the numerical solution for the leeway speed and divergence angle method can become computationally unstable in low wind conditions. The major benefit of using the leeway speed and divergence angle method is that it is more computationally efficient than the downwind leeway (DWL) and crosswind leeway (CWL) method (Allen, 2005).

The two leeway vector components which act upon the drifting object are the DWL and the CWL. The DWL always acts in the direction of the wind; however the CWL acts in a direction perpendicular to the direction of the wind, and consequently can act to either the left or right of the down wind direction. Figure 1-5 (Allen, 2005) shows a visual representation of the DWL and CWL components of leeway drift, and how the vectors combine to give the final resultant leeway velocity vector (L). The DWL is the more dominant of the two leeway components due to the majority of the force acting on the drift object is in the downwind direction. The leeway components (DWL and CWL) may be comparable to hydrodynamic drag and lift respectively (Breivik & Allen, 2008).
The leeway rate is the ratio of the leeway velocity (L) to the 10m wind speed ($W_{10m}$), and is expressed as a percentage of the wind speed (see Equation 1-3). The DWL and CWL can be calculated from the leeway speed (L) and divergence angle (Lα) via Equation 1-4 and Equation 1-5 respectively (Allen, 2005).

$$\frac{|L|}{W_{10m}} = \text{Leeway Rate}$$

Equation 1-3

$$DWL = \text{Downwind Leeway Component} = |L| \cos(L\alpha)$$

Equation 1-4

$$CWL = \text{Crosswind Leeway Component} = |L| \sin(L\alpha)$$

Equation 1-5

The preferred method of modelling leeway utilises the DWL and CWL instead of leeway speed and divergence angle, as the models respond better to directional
fluctuations at low wind speeds, and a different statistical model can be applied to each of the DWL and CWL individually (Breivik & Allen, 2008).

A drift object is subjected to forces from the wind, waves and currents. Previous research has indicated that the drift of an object due to wave action (wave forcing) only becomes significant once the drift objects have a length scale greater than that of the wavelength (Breivik, et al., 2013), and as the majority of common search objects have a length much less than the wavelengths commonly encountered, any effects due to wave forcing would be minimal and therefore may be disregarded.

The three equations below (Equation 1-6, Equation 1-7 and Equation 1-8) summarise the total drift of an object (adapted from Hackett, et al. (2006)). The total drift of an object is defined as the summation of the drift due to currents which are relative to the earth plus the drift due to leeway which is the slip of the object across the water surface relative to the ambient currents (Equation 1-6). The drift due to currents is a product of the surface currents which are derived from Ekman drift, baroclinic motion, tidal currents and inertial currents, as well as the drift due to Stokes drift which is a result of wave induced currents (Equation 1-7). Finally, the leeway drift is defined as the sum of the drift due to the wind forces plus the drift due to the wave forces acting on the object (Equation 1-8).

\[ D_T = D_C + D_L \]  
\[ \text{Equation 1-6} \]

Where: \( D_T \) = Total Object Drift  
\( D_C \) = Drift Due to Current forces (relative to the earth)  
\( D_L \) = Drift Due to Leeway (relative to the currents)  

And  
\[ D_C = D_{Sc} + D_{Sd} \]  
\[ \text{Equation 1-7} \]

Where: \( D_C \) = Drift due to Currents  
\( D_{Sc} \) = Drift due to Surface currents  
\( D_{Sd} \) = Drift due to Stokes drift (wave induced currents)
And

\[ D_L = D_{Wi} + D_{Wa} \]

Equation 1-8

Where: \( D_L \) = Drift Due to Leeway

- \( D_{Wi} \) = Drift due to Wind forces
- \( D_{Wa} \) = Drift due to Wave forces (able to be omitted for objects with a length less than the wavelength)

Two wave effects can contribute to Stokes drift, these include effects due to wind generated waves (which act in the downwind direction), and swell generated effects (which act in the direction of the swell and may not be in the same direction as the wind). Due to the difficulty in ascertaining the contribution due to wind generated waves and that from swell, most leeway studies assume that the Stokes drift is a result of wind generated waves only and act in the downwind direction. This assumption is reasonable for low wave energy zones, where the contribution to Stokes drift by swell may be small; however the swell-induced Stokes drift may become an important factor in higher energetic areas with larger swell sizes.

Further, once the drift due to surface currents has been subtracted from the total drift, the empirically derived leeway drift of the object is not able to be distinguished from the downwind leeway drift effects and the downwind Stokes drift effects (due to both acting in the same direction). Therefore, the effects of Stokes drift on the drift of the object are automatically included in the regression of the downwind leeway of the object. As a result Breivik, et al. (2011) recommend that it is most practical to express leeway of small craft as a function of the wind only.

To summarise, when the lengths of the drift object or craft used are significantly less than the wavelength, the effects of wave forces may be assumed to be negligible. Additionally, as the wind generated wave-induced Stokes drift is accounted for in the leeway coefficients, the total drift of the objects may be calculated as a sum of the drift due to the surface currents and the drift due to the wind.

There are several factors which influence the leeway drift characteristics of an object. These include the ratio of how much of the object is exposed to the wind with respect to...
how much of the object is submerged in the water. The greater the surface area of the 
object that is exposed to the wind, compared to the amount in the water, will increase 
that object’s leeway drift, such as a shallow draft yacht with sail up. The greater the 
surface area of the object that is submerged in the water column, and the less that is 
exposed to the wind, will reduce that object’s leeway drift, such as a deep sea drifter 
with a large underwater drogue and a small surface float. This ratio is referred to as the 
air/underwater drift ratio (Chapline, 1960).

Another matter to complicate leeway drift calculations is that the leeway speed is not 
constant, and it varies with wind speed. The faster the wind speed, the greater the 
object’s leeway parameters are. Each floating object reacts differently to wind fields 
(based on their physical size and air/underwater drift ratio) however most objects show 
a generally linear increase in leeway speed with wind speed (Breivik & Allen, 2008). 
The most effective way to model leeway as a function of wind speed has been found to be 
the use of linear regression techniques. The leeway speed of a floating object is 
referred to as a percentage of the 10 metre height referenced wind speed (refer to 
Equation 1-1).

Every SAR case is different and the search object can range from a person in water 
(PIW) to a small dinghy, a life raft, centre console motorboat, a large yacht etc. As each 
of these objects behave differently in terms of their leeway drift, their search areas need 
to be calculated according to the type of search object in the given SAR case, to ensure 
the highest chance of success in the SAR operation. The search areas vary with the 
leeway characteristics of the search object, and an object with a deep draft will have 
little leeway divergence so it should track predominately with the ocean currents. This 
scenario may produce a smaller search area as the divergence to the left or right of 
downwind could be reduced. Conversely if the search object has a high leeway 
divergence, the search area will be larger as it will need to cover the extended areas to 
both the left and right of downwind, to account for the possibility of the object 
diverging in either direction.

A simplistic table was set up by Chapline (1960) which defined the leeway speeds as a 
percentage of wind speed (V) for five groups of common search objects (refer to Table 
1-1). This was a good start for basic SAR response, however more detail and more 
specific leeway characteristics for a greater variety of vessels and search objects needed
to be developed. Allan and Plourde (1999) built on the work of Chapline (1960) and after many field studies were able to compile a very comprehensive table for a wider variety of search objects. Another point of consideration in regards to the early leeway calculations by the US Navy (in the drift characteristics of life rafts / life boats) is that the designs of commonly used life rafts and life boats have changed significantly since these studies were undertaken and the designs which were studied are not commonly used anymore, thus it is important that leeway studies are constantly updated to account for the latest most common craft likely to be in distress.

Table 1-1: Leeway speeds (as a percentage of 10m wind speed, V) of common search objects (Chapline, 1960)

<table>
<thead>
<tr>
<th>Group</th>
<th>Vessel Type</th>
<th>Leeway Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group I</td>
<td>Surfboards</td>
<td>2% V</td>
</tr>
<tr>
<td>Group II</td>
<td>Heavy displacement, deep draft sailing vessels</td>
<td>3% V</td>
</tr>
<tr>
<td>Group III</td>
<td>Moderate displacement, moderate draft sailing vessels such as trawlers,</td>
<td>4% V</td>
</tr>
<tr>
<td></td>
<td>trollers, sampans, draggers, seiners, tuna boats, halibut boats, etc.</td>
<td></td>
</tr>
<tr>
<td>Group IV</td>
<td>Moderate displacement cruisers</td>
<td>5% V</td>
</tr>
<tr>
<td>Group V</td>
<td>Light displacement cruisers, outboards, planning hull types, etc.</td>
<td>6% V</td>
</tr>
</tbody>
</table>

Chapter 5 provides further details on leeway drift and outlines the study which was undertaken to derive the leeway drift characteristics of three tropical Pacific island craft, identified as common SAR targets, whose leeway coefficients were previously unknown. The full methodology utilised to measure and calculate the leeway components (leeway speed, divergence angle, downwind leeway and crosswind leeway) is described in detail (refer to Allen, et al., (2013) and Brushett, et al., (2014)).

1.6.2 ASA Modelling Software

SARMAP – Search and Rescue Model

The SARMAP software was developed by Applied Science Associates Inc. (ASA) to predict the likely drift trajectory and the probable search areas for people or objects lost at sea. The trajectory/drift model is driven by metocean environmental data which is accessed through the COASTMAP environmental data server (EDS). The COASTMAP EDS allows SARMAP to access the latest time and spatially varying forecast and
hindcast winds and currents around the globe. The trajectory model is coupled with search area algorithms which calculate the probable search areas after the forecast drift trajectory of the object has been calculated. As mentioned in Section 1.5, the SARMAP system has two solution methods available for calculating the probable drift and search areas. These are the Automated Manual Solution (AMS) method as outlined in the IAMSAR manual, and the Monte Carlo stochastic particle method. SARMAP includes both solution methodologies as initially the AMS method was the only accepted solution methodology by SAR agencies, and for SARMAP to become accepted by the various SAR agencies around the world, it needed to contain the method which complied with their existing manual methods (Frost & Stone, 2001).

The AMS method is an automated method of solving the tried and tested manual solution method (Frost & Stone, 2001). The manual solution method is based on the Classical Search Planning Method (CPSM). Automating the solution process vastly increases the speed at which the planning stage of the SAR mission can be undertaken, which enables the expedited deployment of search and rescue units. It also allows for a more complicated calculation process than hand calculations can provide. Dependent on the leeway specifics entered, the solution tracks one, two, three or six datum points for each search object, which in turn define the search area. One datum is computed when the object has only a leeway speed defined (no divergence) and will track directly downwind. Three datum points are computed when leeway speed, and divergence angles are defined; one for downwind, and one each for divergence to the left and right of downwind. When there are two leeway speeds defined and no divergence angle, a minimax solution is calculated, with the two downwind datum points (one for each maximum and minimum leeway speeds). Finally when there are two leeway speeds defined and a divergence angle, the model will use the minimax solution to compute six datum points including the two directly downwind (one fast and one slow), two to the left (one fast and one slow) and two to the right of downwind (one fast and one slow). The search area is calculated to cover all datum points for each scenario run to ensure the search object has the highest likelihood of being contained in the search area.

The Monte Carlo method takes on a stochastic approach by using a large number of particles to simulate possible drift trajectories. The drift trajectories are subject to the defined leeway parameters (DWL and CWL) as well as a small random component.
These particle trajectories are then used to produce a probability density grid based on the number of drifts and their proximity to each other. Depending on the horizontal dispersion coefficient used and the duration of the SAR incident, the Monte Carlo method of SAR modelling can produce a smaller or more efficient search area than the AMS method (Applied Science Associates, Inc., 2013).

1.6.3 Ocean Current Forecast Models
This study utilised several different ocean models, which included BLUElink, FOAM, HYCOM and NCOM. Continuous model development, improvement and additional data availability result in changes being implemented into these ocean models over time, and hence the settings and parameters for each of the models also changed with time as the models evolved. This study took place over several years (from 2009 to 2012) and is comprised of several individual shorter studies. As a result of this, the specifics for each of the ocean models changed slightly from one study to the next. A detailed description of the models and their parameters etc. is provided within each of the chapters which are specifically tailored to address the model version that was used in that particular study. The following model descriptions contain a general outline of the forecast models used throughout this study; however the reader is urged to consult the model descriptions within each relevant chapter for the details of the version of the models used for that particular study.

Table 1-2 shows a brief overview of the various parameters and details of the four ocean models.

**BLUElink**
The BLUElink project became operational in 2007 and is the result of collaboration between a number of Australian government bodies including the Australian Bureau of Meteorology (BoM), Royal Australian Navy (RAN) and the Commonwealth Scientific Industry Research Organisation (CSIRO). The BLUElink project was undertaken to develop an operational global ocean general circulation model with a focus on the waters surrounding Australia (Brassington, et al., 2007). The model has a daily temporal resolution and a horizontal resolution of 1/10° (approx 11.1 km). The BLUElink system
was updated in December 2011 to BLUElink-2, which included a higher vertical resolution in the top layers (layer thickness reduced from 10 m to 5 m), more frequent data assimilation (increased from twice weekly to daily), and atmospheric forcing was changed from the GASP (Global Analysis and Prediction) model to the ACCESS—G (Australian Community Climate and Earth System Simulator - Global) model (Brassington, et al., 2012).

**FOAM**
The Forecasting Ocean Assimilation Model (FOAM) is a global ocean model run by the UK Met Office. The FOAM system utilises the Nucleus for European Modelling of the Ocean (NEMO) model for its ocean circulation model. FOAM v0 was available operationally until October 2010, after which an upgrade was introduced and FOAM v1 became available which was operational until January 2013 (Storkey, 2011; Blockley, et al., 2013). The FOAM model is run on a global grid (orca025) with a horizontal resolution of 1/4° (~27.7 km). The output is then interpolated onto a standard 1/6° (~18.5 km) Mercator grid for dissemination to operational users. The vertical coordinate system consists of 50 z-levels of varying thickness, with the uppermost layer being 1 m thick (Storkey, et al., 2010). Atmospheric forcing for the FOAM model is provided by Met Office Numerical Weather Prediction (NWP) atmospheric forecast model. The mean surface fluxes were provided to the FOAM model at 6-hourly intervals for FOAM v0, which increased to 3-hourly intervals for FOAM v1 (Storkey, 2011).

**HYCOM**
The Hybrid Coordinate Ocean Model (HYCOM) is a three dimensional global ocean circulation model which was initiated through collaboration with a number of academic, federal and industry institutions, and further developed through the Global Ocean Data Assimilation Experiment (GODAE). The global HYCOM model (Chassignet, et al., 2009) uses a hybrid vertical coordinate structure that incorporates three vertical coordinate systems; constant depth or pressure layers (z-layer), isopycnal or constant density following layers (ρ-layers) and terrain following layers (σ-layers). The horizontal resolution of the HYCOM model is 1/12° globally with a single daily
averaged output interval. The Navy Operational Global Atmospheric Prediction System (NOGAPS) atmospheric model provides atmospheric forcing to the HYCOM model at 3-hourly intervals (Dombrowsky, et al., 2009). The Expt. 90.8 version of HYCOM ran from May 2009 through to January 2011, and Expt. 90.9 version ran from January 2011 through to August 2013.

**NCOM**
The Navy Coastal Ocean Model (NCOM) is a 3D global ocean current forecast model which was developed by the Naval Research Laboratory (NRL) and was transitioned to be run operationally by the Naval Oceanographic Office (NAVO). The model has been under constant development since 1998, when it replaced the SZM (Sigma Z-level Model) (Barron, et al., 2007). The NCOM ocean circulation model is based on the Princeton Ocean Model (POM) with some carry over components of the SZM. The model grid has global coverage, with a horizontal resolution of 1/8° (~13.8 km). A \(\sigma\)-z layer system is used for the vertical coordinates with a topmost surface layer thickness of 1m. Atmospheric forcing for the NCOM model is provided by the NOGAPS system, which supplies atmospheric fluxes at 3-hourly intervals (Barron, et al., 2007).
Table 1-2: Model details for the four ocean models used in this study (adapted from [Dombrowsky, et al., 2009; Hernandez, et al., 2009; Cummings, et al., 2009]).

<table>
<thead>
<tr>
<th>Model Name</th>
<th>BLUElink</th>
<th>FOAM</th>
<th>HYCOM</th>
<th>NCOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country</td>
<td>Australia</td>
<td>United Kingdom</td>
<td>United States</td>
<td>United States</td>
</tr>
<tr>
<td>Organisation</td>
<td>BoM</td>
<td>UK Met Office</td>
<td>HYCOM.org</td>
<td>US Navy</td>
</tr>
<tr>
<td>Horizontal Resolution (~km)</td>
<td>1/10° (11.1)</td>
<td>1/4° (27.7) [global]</td>
<td>1/12° (9.3)</td>
<td>1/8° (13.9)</td>
</tr>
<tr>
<td>Vertical Coordinate System</td>
<td>Fixed OFAM: 47 z levels OFAM2: 51 z levels</td>
<td>Fixed 50 z levels</td>
<td>Lagrangian 32 ρ/σ/z levels</td>
<td>Fixed 40 ρ/z levels</td>
</tr>
<tr>
<td>Surface Layer Thickness (m)</td>
<td>OFAM: 10 OFAM2: 5</td>
<td>1</td>
<td>Exp 90.8: 3 Exp 90.9: 1</td>
<td>1</td>
</tr>
<tr>
<td>Temporal Resolution</td>
<td>24 hr</td>
<td>24 hr</td>
<td>24 hr</td>
<td>6 hr</td>
</tr>
<tr>
<td>Grid Limits (Higher Resolution)</td>
<td>Global (Australia: 16°N - 75°S, 90°E - 180°E)</td>
<td>Global (SPA: 0°N - 60°S, 100°E - 77°W)</td>
<td>Global</td>
<td>Global</td>
</tr>
<tr>
<td>Ocean Circulation Model</td>
<td>MOM4.1</td>
<td>v0: NEMO 3.0 v1: NEMO 3.2</td>
<td>HYCOM</td>
<td>POM/SZM</td>
</tr>
<tr>
<td>Data Assimilation Type (System)</td>
<td>EnOI (BODAS)</td>
<td>AC</td>
<td>3D MvOI (NCODA)</td>
<td>3D OI (MODAS/NCODA)</td>
</tr>
<tr>
<td>Data Assimilation Frequency</td>
<td>OFAM: 2 x per week OFAM2: Daily</td>
<td>Daily</td>
<td>Daily</td>
<td>Daily</td>
</tr>
<tr>
<td>Data Assimilated</td>
<td>Satellite SSH &amp; SST, In-situ Temperature &amp; Salinity Profiles</td>
<td>Satellite SSH &amp; SST, In-situ Temperature &amp; Salinity Profiles, Sea Ice Conc.</td>
<td>MODAS SSH &amp; SST, In situ Temperature &amp; Salinity</td>
<td>MODAS SSH &amp; SST, In situ Temperature &amp; Salinity</td>
</tr>
<tr>
<td>Atmospheric forcing Model</td>
<td>BL: GASP BL-2: ACCESS-G</td>
<td>UKMO NWP</td>
<td>NOGAPS</td>
<td>NOGAPS</td>
</tr>
<tr>
<td>Atmospheric Forcing Frequency</td>
<td>3 hr</td>
<td>v0: 6 hr v1: 3 hr</td>
<td>3 hr</td>
<td>3 hr</td>
</tr>
</tbody>
</table>

Where: z represents fixed depth layers, σ represents terrain following depth layers, and ρ represents density following depth layers.

### 1.6.4 Wind Forecast Models

**GFS**

The Global Forecasting System (GFS) is a global spectral model operationally run by the US National Oceanic and Atmospheric Administration (NOAA). The model has a temporal resolution of 6 hours and a forecast length of up to 384 hours (16 days). After one week, the resolution of the model reduces (both spatial and temporal) to allow for...
computational efficiency. The vertical coordinate system of the model is based on a hybrid sigma/pressure layer system which contains 64 unequally spaced layers (Bi, et al., 2010). The 10m reference height wind speed (U and V velocity) used in this study was posted from the spectral model to an equally spaced horizontal latitude-longitude grid with a resolution of 1/2° (approximately 55.5km). The forecast model is updated every 6 hours with assimilated data through the Global Data Assimilation System (GDAS). Within GDAS operates the Gridpoint Statistical Interpolation (GSI) analysis system, which is a three dimensional variation (3DVAR) data assimilation system (Kleist, et al., 2009). Further information in regards to the GFS model including output can be found at (http://www.emc.ncep.noaa.gov/-index.php?branch=GFS).

**NOGAPS**

The Navy Operational Global Atmospheric Prediction System (NOGAPS) is a spectral general circulation model (GCM) which has been under constant development at the NRL over the last 20 years. It is the principal source of atmospheric forcing for the US Navy ocean models (eg. NCOM, HYCOM) and short term numerical weather prediction (NWP). NOGAPS uses a one way coupling system to capture ocean – atmosphere interaction. NOGAPS has global coverage, with horizontal resolution ~ 1/2°. The forecast length of the NOGAPS product is 144 hours with temporal resolution of twelve hours (at 00 and 12 UTC) and updates at 06 and 18UTC to enable background forecasts, which are used in the analysis. Outputs from the model include momentum flux, both latent and sensible heat fluxes, precipitation, solar and long wave radiation and surface pressure, as well as 10 metre U and V wind velocities (Rosmond, 1992; Rosmond, et al., 2002).

**1.6.5 Drifter Buoys**

There are numerous different designs of drifter buoys currently employed to track ocean currents which include Self Locating Datum Marker Buoys (SLDMB) deployed operationally by many of the emergency response organisations worldwide, and the SVP drifter which were developed for the Global Drifter Program (formerly the Surface Velocity Program) run by NOAA.
**Surface Velocity Program (SVP) Drifters**

In the past, many different drifter types have been used, however now there is some standardisation of drifter design. Several different styles of buoys are still produced; however different companies manufacture the same style drifters. The drifters used in this study were SVP drifters. SVP refers to the Surface Velocity Program for which the buoy was developed.

The SVP drifter buoys consist of three main sections: the buoy, the cable and the drogue. The centre of the drogue when deployed is 15 metres deep, and the diameter of the sock is one metre. This large drogue ensures the drifter is effectively steered by the ocean currents, and is minimally affected by wind and wave action. Without the drogue, the drifter would be heavily influenced by ambient wind and wave activities, thus reducing its effectiveness to follow ocean currents accurately. Figure 1-6 shows the layout and various components of the SVP drifters.

Niiler, et al. (1995) found that the wind induced slip of drifters with a drag ratio of greater than 40 (as is the case with the SVP drifter) was found to be less than 1 cm s\(^{-1}\) for wind speeds less than 10 m s\(^{-1}\). This shows that the SVP drifters are very well anchored to the water column and the influence on them by the winds is limited. Later studies by Pazan and Niiler (2001) found that when the drogue was detached (resulting in a much lower drag ratio) the leeway was significantly greater, at ~ 8.6 cm s\(^{-1}\) in up to 10 m s\(^{-1}\) of wind speed.
1.6.6 Drifter Trajectory Modelling

Modelling the movement of drifters can provide a sound method for validating both SAR models and the environmental forcing data used as input into those models.

A pilot study was undertaken by Asia Pacific ASA in 2008 to ascertain the suitability of using ASA trajectory models (SARMAP and OILMAP) forced by BLUElink and NCOM ocean currents and GFS winds to predict the tracks of several SVP drifter buoys in Australian waters. This study showed that the forecast models had some skill in Australian offshore waters, however no drifters were tracked in coastal waters. It was identified that additional studies would be beneficial to further explore their effectiveness, when tracking drifters in tidally dominated coastal waters. This would require the addition of tidal currents to the large scale ocean currents (BLUElink and

Figure 1-6: Diagram of SVP Drifter. Image Source: National Oceanic and Atmospheric Administration (2010).
NCOM) which was unavailable at the time of that study, however this aggregation technology is now available via the COASTMAP EDS. Unfortunately SVP drifters do not frequently come into coastal areas, and hence a targeted deployment of drifters would need to take place to sample those areas.

Previous studies in the United States involving the use of search and rescue models to predict drifter trajectories were undertaken by Bernstein (2009). In that study, five Ocean General Circulation Models (OGCM) and two current databases were used to provide the surface layer currents. The OGCMs used were the Hybrid Coordinate Ocean Model (HYCOM), the Navy Coastal Ocean Model (NCOM), the Advanced Coastal Circulation and Storm Surge Model (ADCIRC), the Fleet Numerical Meteorological and Oceanography Centre’s model (FNMOC) and an aggregated dataset consisting of NCOM and ADCIRC models (AGG). The two current databases were the Florida Gulf Stream Data (FLDA) and Mariano Global Surface Velocity Analysis (MGSVA). The purpose of this study was to quantify which models worked best given a geographic location, establish whether there was a seasonal dependence, and to ascertain whether the models had a tendency to over or under predict the drifts. The drifters used were the SLDMB drifter buoys deployed by the US Coast Guard in normal coastal operations to provide confirmation as to what the ocean currents were doing in the areas of interest.

From the results, a decision making matrix was generated to enable SAR operators to make quick informed decisions as to what current forecasts to use, given the location and season of interest. The results showed that overall the NCOM model maintained the most skill when compared to the other ocean current products used throughout the study.

Chapter 1

1.7 References


Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications


STATEMENT OF CONTRIBUTION TO CO-AUTHORED PUBLISHED PAPER

This chapter includes a co-authored paper. The bibliographic details of the co-authored paper, including all authors, are:


My contribution to the paper involved:

The concept and design of the study, background literature search, compiling and processing of data, undertaking the numerical modelling, processing and analysing the model results, interpreting the results, and drafting the paper.

(Signed) _________________________________ (Date)______________

Ben Amon Brushett

(Countersigned) ____________________________ (Date)______________

Corresponding author of paper: Ben Amon Brushett

(Countersigned) ____________________________ (Date)______________

Supervisor: Prof. Charles Lemckert
2. Evaluation of met-ocean forecast data effectiveness for tracking drifters deployed during operational oil spill response in Australian waters

Abstract
Pollution of the marine environment from hydrocarbon spills is a potential environmental issue with many incidents being reported in recent times. The need for a better understanding of the ocean circulation for spill predictions is essential so that correct response actions can be implemented to minimise environmental damage. There are currently several ocean current models available in the Australian region. This study was aimed at investigating which forecast currents work best when tracking surface drifters deployed during operational oil spill response. The track of a drifter deployed during the Montara well release in the Timor Sea (October 2009) was modelled using six different current models including BLUElink, FOAM, GSLA, HYCOM, NCOM and NLOM. Wind forcing was also required to simulate the track of the drifter and was provided by two wind forecast models, GFS and NOGAPS. Therefore, an ensemble of 12 different model forcing combinations were possible. The NCOM current model with NOGAPS winds produced the best result with an absolute error of 7.19 km after 120 hours (5 days); however NCOM currents with GFS winds tended to more closely predict the track throughout the entire simulation, although the error at the end of the simulation was slightly higher at 11.51 km.
2.1 Introduction
The Montara well release is a recent long-duration hydrocarbon spill incident which occurred between August and November 2009 in the Timor Sea, within Australian waters. The region where this spill took place has a very high ecological significance as it is in close proximity to the Kimberley coast, which is one of the most remote, rugged and untouched stretches of coastline in Australia. There was the potential for great ecological destruction had this incident not been responded to in a timely and effective manner, utilising the most up to date technology available. The use of metocean forecast data and numerical trajectory models are required to adequately forecast the movement of a spill (King, et al., 2011).

If a sound knowledge of the slick movement can be forecast, the most effective spill response can be undertaken. This can lead to a reduction in the potential costs of the cleanup and can help to reduce the impact the spill has on the natural environment.

During the Montara incident several self locating datum marker buoy (SLDMB) drifters were deployed in close proximity to the slicks to “ground truth” the oceanic currents. This is common practice in oil spill events and search and rescue (SAR) scenarios as it gives the response team a better understanding of the nature of the surface currents and how well they are being replicated by current forecast models.

This study investigates the use of a numerical trajectory model SARMAP which is forced by six different ocean general circulation models (OGCM) and two wind forecast models to determine which combination of current and wind models predicted the track of a drifter deployed during the Montara response. These models include; the Australian BLUElink model (Brassington, et al., 2007), the UK Forecasting Ocean Assimilation Model - FOAM (Storkey, et al., 2010), the Australian Gridded Sea Level Anomaly - GSLA geostrophic sea surface currents, the US HYbrid Coordinate Ocean Model - HYCOM (Chassignet, et al., 2009), the US Navy Coastal Ocean Model - NCOM (Barron, et al., 2007), and the US Navy Layered Ocean Model - NLOM (Shriver, et al., 2007).

As each of the six different current models vary significantly in terms of their horizontal and temporal resolutions, vertical coordinate systems, data assimilation methods and
bathymetry; this study investigated how these differences affected the model’s ability to be used for short term drift prediction.

The study also examined how consensus forecasting can be used in oceanography to predict the drift of objects at sea, and increase the confidence of those predictions, by utilising an ensemble of different model predictions. Previous works by King, et al. (2010) investigated the use of consensus forecasting by using a combination of four different model generated datasets (two current models and two wind models) to forecast the track of oil and drifters in incidents which recently occurred in Australian waters.

The work by Bernstein (2009) was similar as it studied the use of several different datasets to track drifters. It differed however as the region of focus was coastal waters off the United States of America, and as such many of the current models it utilised were different to those available in Australian waters.

Table 2-1 outlines the various parameters of the current and wind models which were used in this study. Contained therein are model type, horizontal and temporal resolution, vertical coordinate systems and their extent of coverage. The vertical coordinate systems vary significantly between all of the models used in this study, ranging from z-level (fixed geopotential layers), \( \sigma \)-coordinate (terrain following layers), isopycnal (density following layers), Lagrangian layers, and various combinations of these systems. The number of layers, the type of vertical coordinate system used and the thickness of these vertical layers all have an impact on the model’s ability to replicate the surface currents. The models which have higher resolution in the vertical layers (and a higher temporal resolution) have a significantly increased response to inertial oscillation. This means that the model can produce more accurate surface currents as it is better able to respond to inertial changes, such as those imparted on the model water surface by fluctuations in the wind field.

As shown in the table the horizontal resolution also varies greatly between each of the models, ranging from as coarse as \( 1/4^\circ \) for GSLA right down to \( 1/32^\circ \) for NLOM. This has strong implications when modelling meso-scale eddies. Typically a resolution of \( 1/8^\circ \) or finer is required to permit eddies in the model, with finer resolution much more desirable, but of course finer resolution comes at a computational cost. Also if the
model does not have the resolution to describe certain physical characteristics, parameterisations need to be employed to account for this shortfall. These parameterisations can lead to increased error in the forecast model if not defined correctly (Hernandez, 2011).

Table 2-1: Current and wind model parameters.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Model Type</th>
<th>Horizontal Resolution</th>
<th>Vertical Coordinate</th>
<th>Temporal Resolution</th>
<th>Grid Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUElink</td>
<td>Current</td>
<td>1/10° (11.1 km)</td>
<td>47 z levels</td>
<td>24 hr</td>
<td>Global [16°N - 75°S, 90°E - 180°E]</td>
</tr>
<tr>
<td>FOAM</td>
<td>Current</td>
<td>1/6° (18.5 km)</td>
<td>50 z levels</td>
<td>24 hr</td>
<td>Global [0°N - 60°S, 100°E - 77°W]</td>
</tr>
<tr>
<td>GSLA</td>
<td>Current</td>
<td>1/4° (27.8 km)</td>
<td>Surface Only</td>
<td>24 hr</td>
<td>9.75°N - 59.75°S, 57°E - 175°W</td>
</tr>
<tr>
<td>HYCOM</td>
<td>Current</td>
<td>1/12° (9.3 km)</td>
<td>32 Isopycnal / σ / z</td>
<td>24 hr</td>
<td>Global</td>
</tr>
<tr>
<td>NCOM</td>
<td>Current</td>
<td>1/8° (13.9 km)</td>
<td>40 σ / z level</td>
<td>6 hr</td>
<td>Global</td>
</tr>
<tr>
<td>NLOM</td>
<td>Current</td>
<td>1/32° (3.5 km)</td>
<td>7 Lagrangian layers</td>
<td>24 hr</td>
<td>Global (&gt; than 200m deep)</td>
</tr>
<tr>
<td>GFS</td>
<td>Wind</td>
<td>1/2° (55.6 km)</td>
<td>64 σ levels</td>
<td>6hr</td>
<td>Global</td>
</tr>
<tr>
<td>NOGAPS</td>
<td>Wind</td>
<td>1/2° (55.6 km)</td>
<td>30 σ levels</td>
<td>6hr</td>
<td>Global</td>
</tr>
</tbody>
</table>

Figure 2-1: Location map showing the location of the drifter 23967 off the Western Australian coast.
The drifter began 350 km off the West coast of Australia, just off the continental shelf, in waters approximately 600m deep (refer to Figure 2-1). Throughout the five day track the drifter proceeds initially in a North East direction before swinging towards the North West into deeper waters (~1000m), and finally tracking South West for the remainder of the time into shallower waters (~300m).

**2.2 Modelling Methods**

Several SLDMBs were deployed by responders during the Montara well release to ground truth the prevailing ocean currents at the location. These SLDMBs were deployed with the leeway characteristics of a person in water (PIW). Applied Science Associates’ (ASA) SARMAP trajectory modelling software was used to numerically model a single particle trajectory with the leeway parameters for a PIW, which included a wind factor of 1.1% and a wind divergence angle of 40°, as indicated by Allen and Plourde (1999). This Lagrangian approach was selected as drifters are Lagrangian by nature, so it was the most logical method to adopt.

A 120 hour track of drifter 23967 was chosen for this study. The track was initiated at 00:15 14/10/09 at location 11.313056° S, 124.128889° E and finished five days later at 00:15 19/10/09 some 133 km to the south west of its initial position.

Six different forecast/hindcast current models were used to provide the current forcing, and two different wind forecast models were used to provide the wind forcing on the drifter. As each of the current models did not include any tidal signal, tidal currents were aggregated with the oceanic circulation models to provide a total surface current. Each of the six current models were combined with each of the wind forecast models for the 120 hour period, which resulted in an ensemble of 12 different model combinations. The locations of the drifter and the modelled drifter were output for every hour throughout the model run to analyse the absolute error. The great circle distance formula was used to calculate this difference in position, and is given in Equation 2-1 below. The equation for the bearing of the error from the drifter to the modelled drifter is given by Equation 2-2.
Chapter 2

Distance (km) = \( \cos(\text{lat}_1) \times \sin(\text{lat}_2) + \sin(\text{lat}_1) \times \cos(\text{lat}_2) \times \cos(\text{lon}_2 - \text{lon}_1) \) \times 6371

Equation 2-1

Bearing (rad) = \( \arctan(\cos(\text{lat}_1) \times \sin(\text{lat}_2) - \sin(\text{lat}_1) \times \cos(\text{lat}_2) \times \cos(\text{lon}_2 - \text{lon}_1), \sin(\text{lon}_2 - \text{lon}_1) \times \cos(\text{lat}_2) \) \]

Equation 2-2

Where: \( \text{lat}_1 \) = Actual latitude of drifter (in radians)
\( \text{lat}_2 \) = Modelled latitude of drifter (in radians)
\( \text{lon}_1 \) = Actual longitude of drifter (in radians)
\( \text{lon}_2 \) = Modelled longitude of drifter (in radians)

2.3 Results/Discussion

The results for the simulation of drifter 23967 for a period of 120 hours (5 days) from 14/10/10 until 19/10/10 are shown graphically in Figure 2-2 (GFS) and Figure 2-3 (NOGAPS). The symbols on the track lines represent the locations of the drifter (or modelled drifter) at 6 hourly intervals. As shown in these figures NCOM and HYCOM performed the best throughout the simulation, with BLUElink and NLOM performing the worst.

Tidal oscillations were more evident with the model runs which came into shallower waters (NLOM, GSLA, FOAM) compared with those which tended to stay in deeper waters (BLUElink, NCOM, HYCOM).

Initially the drifter travelled north east for 12 hours before turning north west for 30 hours and then finally followed a south westerly track for the rest of the duration. None of the forecast models were able to replicate the initial north easterly drift which may have been due to the presence of a meso-scale eddy which was either misplaced or absent in the models.

All of the models produced results which tended to follow the south west track of the drifter, however due to their inability to replicate the initial north easterly component of the drift; the final error for some models was quite high.
Chapter 2

Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications

Figure 2-2: Drifter 23967 predicted paths over 120 hours from midnight 14/10/09 to 19/10/09 using various current forecast models and GFS winds.

Figure 2-3: Drifter 23967 predicted paths over 120 hours from midnight 14/10/09 to 19/10/09 using various current forecast models and NOGAPS winds.
An analysis of the error was carried out for each simulated drifter track (using each combination of forecast currents and winds) and is summarised in the tables which follow. Table 2-2 shows the absolute error (in km) for all six current forcing runs when coupled with GFS winds, and Table 2-3 shows the absolute error (in km) for the same six current forcing however utilising NOGAPS for wind forcing. The minimum and maximum final error after the 120 hour simulation is shown in **bold** and *italics* respectively.

### Table 2-2: Error analysis for Drifter 23967 using various forecast current forcing and GFS forecast winds.

<table>
<thead>
<tr>
<th>Time (hrs)</th>
<th>BLUElink (km)</th>
<th>FOAM (km)</th>
<th>GSLA (km)</th>
<th>HYCOM (km)</th>
<th>NCOM (km)</th>
<th>NLOM (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>20.45</td>
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<td>14.07</td>
<td>18.88</td>
<td>12.46</td>
<td>19.54</td>
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<td>19.67</td>
<td>18.19</td>
<td>27.53</td>
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<td>36.83</td>
<td>25.31</td>
<td>28.97</td>
</tr>
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<td>48</td>
<td>47.36</td>
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<td>32.37</td>
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<td>72.12</td>
<td>48.57</td>
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<td>39.10</td>
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<td>59.05</td>
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<td>57.75</td>
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<td><strong>11.51</strong></td>
<td><strong>104.61</strong></td>
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</tbody>
</table>

### Table 2-3: Error analysis for Drifter 23967 using various forecast current forcing and NOGAPS forecast winds.

<table>
<thead>
<tr>
<th>Time (hrs)</th>
<th>BLUElink (km)</th>
<th>FOAM (km)</th>
<th>GSLA (km)</th>
<th>HYCOM (km)</th>
<th>NCOM (km)</th>
<th>NLOM (km)</th>
</tr>
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<tr>
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<td>41.08</td>
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<td>24.89</td>
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</tr>
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<td><strong>27.13</strong></td>
<td><strong>7.19</strong></td>
<td><strong>95.46</strong></td>
</tr>
</tbody>
</table>
Figure 2-4 shows the error analysis for the six current models combined with GFS winds plotted as a time series with time (in hours) across the x axis, and error (in km) along the y axis. As shown there is a general trend for the models to increase in error as time progresses, however both NCOM and HYCOM increase in error up until around the 70 hour mark, where the modelled drifter tends to veer back towards the track of the actual drifter.

Average and maximum winds for the area of interest were 6.43 knots and 11.45 knots respectively for GFS, and 9.02 knots and 14.39 knots respectively for NOGAPS. These figures indicate that on a whole, the NOGAPS winds were significantly stronger than the GFS winds. As the drifter only has a wind factor of 1.1% of the 10m wind speed, the overall effect of this stronger wind on the movement of the drifter is quite small. This effect can be seen in Figure 2-5 which shows a stick plot of the error of the actual drifter track and the modelled drifter track when forced with NCOM currents. The stick plot shows error as distance and direction (as opposed to the conventional speed and direction of standard stick plots) during the 5 days the drifter track was modelled. The length of the “sticks” is representative of the distance the modelled drifter was away from the actual drifter, whilst the angle at which the “sticks” point outwards is representative of the direction towards where the modelled drifter was compared to the actual drifter. The solid line indicates the simulation which utilised GFS winds, where the dashed line indicates the simulation which utilised NOGAPS winds. This figure shows the effects the two different wind models had on the drifter. It indicates there was more of a southerly trend in the error of the NOGAPS runs, compared to the GFS runs.
Figure 2-4: Error analysis for drifter 23967 over 120 hours from 14/10/09 – 19/10/09 using 6 different ocean current models and GFS winds.

Figure 2-5: Stick plot showing 6 hourly distance and direction of error from actual drifter track to NCOM predicted track using GFS (solid line) and NOGAPS (dashed line) winds.
2.4 Conclusion
The NCOM model was the most accurate over the 5 days modelled, for both the GFS and NOGAPS wind fields. This is possibly due to NCOM’s higher temporal resolution and vertical resolution, especially in the surface layers, when compared to the other current models. NCOM employs five 1 m thick layers in the surface, and has a temporal resolution of 6 hours. Both of these attributes enabled a much faster response from the atmospheric forcing to the surface layers (which is where the drifters are acting) resulting in a much more dynamic and responsive surface layer. The results reveal that with such a large range of outcomes from commonly used models the need for further testing and validation is essential and that every endeavour should be made to continue drogue deployment at spill events for model validation purposes.

2.5 Acknowledgements
This research was supported under the Australian Research Council’s Linkage Projects funding scheme LP0991159. The authors would also like to thank the Australian Maritime Safety Authority for providing the drifter data.

2.6 References


STATEMENT OF CONTRIBUTION TO CO-AUTHORED PUBLISHED PAPER

This chapter includes a co-authored paper. The status of the co-authored paper, including all authors, is:

**Brushett, BA, King, BA, & Lemckert, CJ**, ‘Evaluation of metocean forecast model data to predict the drift of surface buoys in the Tasman Sea – including consensus forecasting’, *In preparation for submission.*

My contribution to the paper involved:

The concept and design of the study, background literature search, compiling and processing of data, undertaking the numerical modelling, processing and analysing the model results, interpreting the results, and drafting the paper.

(Signed) _______________________________ (Date)______________

Ben Amon Brushett

(Countersigned) _______________________________ (Date)______________

Corresponding author of paper: Ben Amon Brushett

(Countersigned) _______________________________ (Date)______________

Supervisor: Prof. Charles Lemckert
3. Assessment of metocean forecast model data applied to predict surface drifter trajectories in the Tasman Sea – including consensus forecasting

Abstract
Meteorologic and oceanographic (metocean) forecast models are used for predicting the drift of objects in the ocean, in particular for maritime Search and Rescue (SAR). With the availability of several ocean models for the same region, it can be difficult to foresee which model will perform the best in a given SAR situation. In this study, the Lagrangian particle trajectory model (SARMAP) was used in conjunction with four ocean models to predict the movement of Surface Velocity Program (SVP) drifters in the Tasman Sea. The ocean models used in this study include the Australian BLUElink model, UK Forecasting Ocean Assimilation Model (FOAM), US Hybrid Coordinate Ocean Model (HYCOM) and the US Navy Coastal Ocean Model (NCOM). The drift calculations were carried out independently using the International Aeronautical and Maritime Search and Rescue (IAMSAR) solution and the Monte Carlo random walk solution. Through forecasting 63 5-day SVP drifter tracks throughout 2010, this study quantified the HYCOM ocean model was consistently more reliable (throughout the year modelled) and is therefore potentially better suited to drift modelling for SAR response in the Tasman Sea. Further, the paper details the application of consensus forecasting, whereby all four ocean model forecasts were used to demonstrate improvement over using a single ocean model forecast. Further studies involving the
investigation of intra-annual and inter-annual variability of the performance of each ocean model would have merit; however this was beyond the scope of the current study.

3.1 Introduction

The development and implementation of numerical search and rescue (SAR) models used to predict the drift of objects or people lost at sea has enhanced the maritime SAR field by providing the SAR operator with rapid and accurate search area predictions. Maritime SAR models require accurate forecast wind and current data as input to simulate the likely drift and hence predict the search areas for objects or persons lost at sea. The increasing number of Ocean General Circulation Models (OGCM, hereafter referred to as “ocean models”) with ocean current forecast capability now available to SAR operators poses the question; Which is the most reliable single ocean model for predicting the ocean currents, given a specific region? This study was aimed at determining which of the available ocean models perform best when used in conjunction with a Lagrangian SAR drift model in the waters off the east coast of Australia, and quantifies what magnitudes of error can be expected for predicting a search object’s drift over a 5-day period, when using four different ocean models. The ocean models used in this study include the Australian BLUElink model, UK Forecasting Ocean Assimilation Model (FOAM), US Hybrid Coordinate Ocean Model (HYCOM) and the US Navy Coastal Ocean Model (NCOM). The Global Forecast System (GFS) wind forecast model was also used to provide wind forcing to the Lagrangian SAR drift simulations. Additionally, with the availability of more than one ocean model, the concept of consensus forecasting was investigated, to determine whether the use of all four models to produce a consensus forecast can demonstrate an improvement in reliability over using just one model.

The domain selected for this study is bound by the Australian mainland on the west, extending offshore towards the east into the Tasman Sea, approximately 1100km to 165°E. The north-south extents cover an area from 27° S to 37° S, which coincides approximately with Brisbane (Queensland) in the north, and Eden (New South Wales) to the south (see Figure 3-1). This gives an area of almost 1.5 million square kilometres of deep water, and was chosen as there was a high density of Surface Velocity Program (SVP) drifters located in the area throughout the 2010 year (SVP drifter tracks depicted...
by the grey lines in Figure 3-1). These drifters have been deployed by numerous agencies in the world’s oceans over the past three decades and have formed a very large dataset, which is useful for providing estimates of the sea surface current fields. The study region was also recently identified by the Australian Maritime Safety Authority (AMSA) as being a particularly difficult area to model search and rescue simulations. This difficulty is in part due to the highly active East Australian Current (EAC) which runs down the western side of the study domain (just offshore of the Australian coastline).

![Figure 3-1: Location map showing the study domain as the shaded area off the east coast of Australia in the Tasman Sea. The grey lines represent the drifter trajectories throughout the region during 2010; bold black tracks indicate the 5-day drifter tracks which were modelled in this study.](image)

The flow dynamics in the region are dominated by the EAC, a western boundary current flowing from north to south along the eastern coast of Australia (Ridgeway & Dunn, 2003). This current has been described as being both complex and highly energetic, however it is slightly weaker than other western boundary currents (such as the Gulf Stream) and is dominated by a series of mesoscale eddies which produce highly variable and dynamic flow regimes (Ridgeway & Hill, 2009). The EAC has been reported to
separate from the coast at approximately $32^\circ$ S where it flows eastwards into the Tasman Sea towards New Zealand as a zonal front (Coleman, 1984). This separation point has been observed to occur between $27^\circ$ S to $35^\circ$ S (Thompson & Veronis, 1980; Coleman, 1984; Suthers, et al., 2011).

Once the EAC separates from the coast and turns eastwards, it forms a series of fronts and jets (Ridgeway & Dunn, 2003) in which warm and cold core eddies are formed from the meanders pinching off (Coleman, 1984). A comprehensive review of the EAC is contained within (Suthers, et al., 2011). Figure 3-2 below shows the BLUElink model ocean currents in the study region on March 1st 2010. In Figure 2, the EAC can clearly be seen as the strong southerly current between Brisbane and Sydney, and the separation point forming an anticlockwise eddy can be seen offshore adjacent to Newcastle. A further series of eddies and meanders are evident in further offshore waters.

![Figure 3-2: Ocean currents supplied by BLUElink for March 1st 2010, filtered to show every second vector. Note the presence of the EAC as the strong southward current off the coast of Coffs Harbour and its separation from the coast near Newcastle to form a series of eddies eastwards into the Tasman Sea.](image)

To quantify each ocean model’s predictive ability, the search and rescue modelling software SARMAP (Applied Science Associates, Inc., 2013; Spaulding, et al., 2006)
was utilised to simulate the movement of 63 Surface Velocity Program (SVP) drifters in the Tasman Sea using each of the ocean models. The SARMAP system consists of three main SAR planning tools. The first includes dual particle tracking models with integrated geographic information system (GIS) capability. The particle tracking models within SARMAP are user selectable to either the internationally recognised Automated Manual Solution (AMS) as described by the International Aeronautical and Maritime Search and Rescue (IAMSAR) manual (International Maritime Organisation, 2008) or the Monte Carlo random walk solution (Spaulding, et al., 2006). The second component of SARMAP is the coupling to the COASTMAP environmental data server (Spaulding, et al., 2003) which provides wind and current data for the particle tracking models. The third component of SARMAP is a Search and Rescue Unit (SRU) deployment plan. Once a search area has been established (by either of the particle tracking models) the SRU plan can be implemented automatically (with multiple SRUs of different types) which gives the user the probability of containment (POC) and the probability of detection (POD) depending on the number and type of SRUs which have been implemented in the search.

SARMAP was initially developed in the early 1990s and subsequently has been used by many search and rescue organisations including Australian SAR agencies (Australian Federal Police, the Australian Maritime Safety Authority, and several of the Australian State Water Police agencies). The SARMAP model has been validated by numerous studies including Spaulding and Howlett (1996), Spaulding, et al. (2006) and Chu and Tsai (2010) as well as during the response to many operational incidents.

In this study the SARMAP search and rescue model facilitated the comparison between different ocean model forecasts by utilising a standard platform in which the currents from the different models can be used to simulate the 5-day ocean drifter trajectories.

The numerical solutions to the particle tracking models within SARMAP include the IAMSAR solution and the Monte Carlo random walk solution. Both of these solutions use ocean currents, winds, and leeway parameters to calculate the drift of the search object due to the environmental forcing it is subjected to. SARMAP is able to effectively represent the drift of an object due to the combined wind and wave action through the use of the predefined leeway parameters of that specific object. The leeway parameters define how the object will drift due to the effects of wind and waves on the
emerged/exposed portion of the object. The ocean currents and winds used in this study to simulate the movement of the drifters were obtained from global forecast models.

Typically only one or the other solution methods (either IAMSAR or Monte Carlo) are employed by SAR agencies. Hence, the use of the two solution methods herein is purely for the purposes of making these results applicable to both of the user groups, and is not intended to provide a quantitative comparison between each solution, nor is the study intended to describe which solution method is superior to the other.

Previous work by Brassington, et al. (2007; 2008; 2011) investigated the use of SVP drifters to measure the surface currents in the EAC. Brassington, et al. (2007) describes the first targeted deployment of SVP drifters (deployed offshore from Brisbane), which had limited success with only two (out of the eight deployed) entraining into the EAC. This was due to the drifters being deployed too far offshore (155° E – 155.5° E) to be entrained southwards into the EAC. Brassington, et al. (2008) shows the second targeted deployment, much closer inshore (154.5° E – 154.75° E), improved on the previous deployment with all six drifters deployed being entrained into the EAC.

Brushett, et al. (2011) investigated the use of multiple forcing input data to replicate the 5-day track of a drifter deployed during operational oil spill response in the Timor Sea. Six different ocean models (BLUEnlink, FOAM, GSLA, HYCOM, NCOM and NLOM) and two different wind models (GFS and NOGAPS) were used to provide a combination of 12 model simulations. It was found that NCOM and HYCOM performed the better than the other models, showing consensus in their forecasts. It was also shown that changing the wind model (from GFS to NOGAPS) had very little impact on the final positions over the 5-day model period, due to the minimal leeway coefficient values of the drifter.

Bernstein (2009) completed a study in the North Atlantic Ocean and Caribbean, comparing six different ocean models available in the region of study. These models included Advanced Coastal Circulation and Storm Surge Model (ADCIRC), Fleet Numerical Meteorological and Oceanographic Center’s Model (FNMOC), Hybrid Coordinate Ocean Model (HYCOM), Mariano Global Surface Velocity Analysis (MGSVA), Navy Coastal Ocean Model (NCOM), and an aggregated ADCIRC+NCOM (AGG) model. The drifters used in the study were Coastal Drifter Experiment (CODE)
type Self Locating Datum Marker Buoys (SLDMB) deployed by the US Coast Guard in operational response situations. These drifters have a cruciform shape with four floats (one on the extent of each arm) and are designed to follow the surface currents in the top 1m of the water column. Results from this study concluded that in the region of study, NCOM was the most skilful ocean model year round.

Consensus forecasting in the oceanographic field was successfully demonstrated in an operational capacity for forecasting the fates of marine pollutant spills and operational support, in both coastal and offshore waters (King, et al., 2010; 2011; Brushett, et al., 2011). Utilising several different metocean forecast products as input to trajectory models can facilitate modelling the same scenario multiple times with different environmental forcing. A comparison of the model outcomes can then be undertaken, and when more than one outcome is in agreement with others, this provides the user with a greater confidence that outcome is correct. This is in concurrence with a study of consensus modelling in the atmospheric forecasting field by Fritsch, et al. (2000) that states: “Using ‘consensus’ as the basis for a decision emanates from the notion that the cumulative knowledge of all concerned individuals is greater than that of a single individual.” It is important however not to discard the other outcomes as not being possible outcomes, as in the very dynamic oceanographic field, such outlying results can still prove to be correct. However, consensus forecasting suggests that more weight can potentially be given to those outcomes which are in agreement, and less weight to those which are not.

### 3.2 Methodology

A repeated measures approach was undertaken for this study to quantify the performance of four ocean models (BLUElink, FOAM, HYCOM and NCOM) in their ability to track surface drifters in the Tasman Sea during a single year (2010). This approach was determined to be the most appropriate as it enabled each independent 5-day drift scenario to be tested with each of the four ocean models as input forcing, whilst all other parameters in SARMAP remained unchanged.

The two particle tracking models within SARMAP were used to generate each of the search areas for the drifters used in this study. Each of the 5-day drifter tracks were
simulated using the IAMSAR solution in separate scenarios, using each of the ocean models available and the GFS (Global Forecast System) winds. Once this was complete, each of these scenario simulations were re-run using the Monte Carlo solution. This enabled a comparison to be undertaken between each of the ocean model’s predicted search areas, and ensured that result for both solution methods were available.

The drifter trajectories used in this study were randomly selected from the first 5-days of each month during 2010, and those which were located within the study area for the entire 120 hours. This ensured no biased sampling took place. A total of 63, 5-day drifter tracks were included in the study. The drogue on/off status was recorded and leeway parameters assigned accordingly (either SVP if the drifter still had the drogue attached or SVP-L if the drifter had lost the drogue). The SARMAP model was initially run with the IAMSAR solution repeatedly with each of the four ocean models for each drifter; this gave a total of 252 scenarios. Each of the scenarios was then re-run using the Monte Carlo solution, giving the final total scenario count of 504 for this study.

3.2.1 SVP Drifter Details

Drifters from the SVP, now called the Global Drifter Program (GDP) have been a common tool for measuring the surface currents of the ocean since 1979. At the time of this study, the GDP had 1054 drifters deployed operationally worldwide. Although the present day number of drifters in Australian waters is limited, there were 20 active drifters within the study area throughout 2010.

The drifter data was obtained from the NOAA GDP Drifter Data Assembly Centre website (http://www.aoml.noaa.gov/phod/trinanes/xbt.html) which contains both the raw data for the past several years, as well as quality controlled historic data. The raw data tends to be disparate in time, with many non-regular time intervals, which makes error analysis at regular time intervals more problematic. Therefore, historic data was used for this study, which had been quality controlled and had the drifter positions kriged at six hourly intervals (Hansen & Poulain, 1996). This regular time interval enabled the error analysis to be carried out at six hour intervals with no further manipulation. The common SVP drifter consists of a surface float (which contains GPS and satellite communications), and a long holey sock drogue which is centred at around
15 metres from the water surface. These drifters contain a drogue on/off switch so the user can be made aware of the time when the drifter loses its drogue, which is a common occurrence. In this study, once the SVP drifter has lost its drogue, it was referred to as an SVP-L. It is important to know whether or not the drogue is attached as the drifter exhibits different water following characteristics (leeway parameters) once the drogue is detached.

Leeway is defined here as the movement of the object with respect to the currents, due to the wind and wave forces upon the exposed surfaces of object (Hackett, et al., 2006) and not the wind drift in the surface currents. The leeway characteristics of an object vary depending on the shape of the object and the area of the object which is submerged in the water, as well as the area of the object which is exposed to the wind (emerged area). Leeway can be expressed by either, a wind-factor and a wind-angle, or by the down wind leeway (DWL) and cross wind leeway (CWL) vector components. Both of these measures of leeway are described relative to the downwind direction.

The SARMAP system contains the leeway coefficients for over 60 different classes of drift objects, as defined by Allen and Plourde (1999). The leeway characteristics of an SVP (or SVP-L) type drifter were included into SARMAP by incorporating the observed drift characteristics of these buoys. Previous studies by Niiler, et al. (1995) revealed that SVP drifters essentially follow the surface currents to within ~1 cm/s (0.01 m/s) in up to 10 m/s winds in a downwind direction, which is ~0.1% of the wind speed. Whilst the influence of such a small leeway would be minimal on the movement of the drifter, it was included for comprehensiveness. Once SVP drifters have lost their drogues; they have a greater leeway coefficient (by an order of magnitude). Studies by Poulain, et al. (2009) and Pazan and Niiler (2001) both indicate that the downwind slip or leeway of the SVP-L is around 10 cm/s (0.1 m/s) in 10 m/s winds, which is ~1% of the wind speed. Again due to the symmetrical nature of the SVP-L, they also have a downwind leeway movement with no discernible crosswind leeway parameter. For this study, the downwind leeway coefficients applied to the SVP and SVP-L drifters were 0.1% and 1.0% respectively.
3.2.2 Environmental Forcing Data

The four different ocean circulation models used to provide current forcing in this study were the Australian BLUElink model (Brassington, et al., 2007), UK Forecasting Ocean Assimilation Model (FOAM) (Storkey, et al., 2010), US Hybrid Coordinate Ocean Model (HYCOM) (Chassignet, et al., 2009) and the US Navy Coastal Ocean Model (NCOM) (Barron, et al., 2007). Wind force acting on the drifters was provided by the GFS atmospheric forecast model (National Oceanic and Atmospheric Administration (NOAA), 2014) which is applied to the drifters through their leeway components. Table 3-1 provides an overview of some of the various resolutions and parameters associated with the ocean models.

An important component of ocean models is the inclusion of atmospheric forcing, which is typically attained through the use of atmospheric forecast models. Atmospheric forcing used in ocean models may include wind stress, wind speed/direction, heat flux and precipitation. These components all contribute to the state of the ocean, and hence to the circulation in the upper layers of the ocean. The inclusion of wind induced currents in ocean models is of particular importance when focussing on circulation and transport in the upper ocean (surface layers). Wind induced currents are generated as a result of wind shear on the water surface, and are one of the dominant driving mechanisms of the surface currents (Kim, et al., 2009).

Data assimilation is important to ocean and atmospheric models as numerical models and associated open boundary forcing data for those models are not able to completely represent the physical processes that occur in the ocean and atmosphere, at the time and spatial scales in which they occur (from very small scale turbulence to large scale motions). The use of data assimilation systems, allow model forecasts to be updated or corrected with observed or measured data, which is essential to provide accurate model forecasts of the state of the ocean and atmosphere and counter the models tendency to move away from the true ocean or atmospheric state as time progresses. Each of the four ocean models in this study employs a data assimilation system as part of their operational forecasting systems. There are many different data assimilation systems available which range from relatively simple systems such as Analysis Correction (AC), and Optimal Interpolation (OI) to much more complicated systems such as variational or ensemble (Cummings, et al., 2009). The commonly assimilated variables in ocean
data assimilation systems include satellite observed sea surface height (SSH) and sea surface temperature (SST), as well as in-situ temperature and salinity profiles. Satellite observed sea ice concentration is also assimilated by some ocean models.

A description of each of the ocean current models and the wind model utilised in this study is outlined in the following sections.

**BLUElink**

The BLUElink project is a collaboration between the Australian Bureau of Meteorology (BoM), the Royal Australian Navy (RAN) and the Commonwealth Scientific Industry Research Organisation (CSIRO) and became operational in 2007 (Brassington, et al., 2007). The BLUElink project was undertaken to develop an ocean general circulation model for the oceanic waters surrounding Australia. The Ocean Model Analysis and Prediction System (OceanMAPSv1.0) was developed through BLUElink and incorporates several key components, including an ocean circulation model, a data assimilation system and a numerical weather prediction system (Taylor, et al., 2010). The Ocean Forecasting Australia Model (OFAM) is based on the Modular Ocean Model (Griffies, et al., 2004) version 4p0d (MOM4p0d) which has global coverage at a coarse horizontal resolution of approximately 2° with an increase in horizontal resolution in the Australian region (90°E – 180°E, 75°S – 16°N) to 1/10° (~11.1 km) to permit mesoscale eddy formation/propagation. There are 47 z-level vertical layers in the model with the uppermost layer being 10m thick. Atmospheric forcing for the ocean model is provided by atmospheric heat, mass and momentum fluxes through the BoM operational global prediction system, GASP (Global Analysis and Prediction System) at 3-hourly intervals (Taylor, et al., 2010).

Data assimilation is managed by the BLUElink Ocean Data Assimilation System (BODAS) which uses a multivariate ensemble optimal interpolation (EnOI) scheme that assimilates satellite derived Sea Surface Temperature (SST) and Sea Surface Height (SSH), as well as in situ temperature and salinity profiles. The data assimilation for operational forecasts is updated twice weekly. Further information on BODAS is outlined in Oke, et al. (2008; 2009) and Schiller, et al. (2008).
**FOAM**

The Forecasting Ocean Assimilation Model (FOAM) is a global ocean model run by the UK Met Office. The ocean general circulation model utilised by FOAM is based on the Nucleus for European Modelling of the Ocean (NEMO) model. FOAM v0 was used for the first 10 months of 2010, after which an upgrade was introduced and FOAM v1 became available, which was used for the final 2 months of 2010. A further description of FOAM v0 is provided in Storkey, et al. (2010) and a brief discussion of the minor upgrades which were implemented into v1 is provided in Storkey (2011). The global model is run on a 1/4° (~27.7 km) grid (orca025) however the output data (eg. U and V current fields) is interpolated onto a standard 1/6° (~18.5 km) Mercator grid for dissemination. The vertical coordinate system within the model consists of 50 z-levels of varying thickness, with the uppermost layer being 1m (Blockley, 2009; Storkey, et al., 2010). The FOAM model is forced by the Met Office Numerical Weather Prediction (NWP) atmospheric forecast model, which provides mean surface fluxes to the model at 6-hourly intervals (v0) and at 3-hourly intervals (v1) (Storkey, 2011).

The data assimilation system for the FOAM model utilises an Analysis Correction (AC) scheme whereby satellite SST, SSH and sea ice concentration, as well as in situ temperature and salinity profiles are assimilated into the model at 24 hour intervals. The observations are progressively nudged into the analysis over the Incremental Analysis Update (IAU) period of 24 hours (Storkey, 2011).

**HYCOM**

The Hybrid Coordinate Ocean Model (HYCOM) is a three dimensional global ocean circulation model which was developed as part of the Global Ocean Data Assimilation Experiment (GODAE). The global HYCOM model (Chassignet, et al., 2009) uses a hybrid vertical coordinate structure that incorporates the three vertical coordinate types currently used by ocean models. These coordinates are; constant depth or pressure layers (z-layer), isopycnal or constant density following layers (ρ-layers) and terrain following layers (σ-layers). Each of these vertical coordinate systems cannot function optimally over all areas of the ocean; however the HYCOM model is able to make best use of each of the coordinate systems in the areas that they perform best, thus optimising the results. Isopycnal layers are used in the open stratified ocean, then...
transition smoothly to the terrain following coordinates in shallow coastal regions, and z layer coordinates are used in the mixed layer and/or unstratified waters. The horizontal resolution of the HYCOM model is 1/12° globally with a single daily output interval. The Navy Operational Global Atmospheric Prediction System (NOGAPS) atmospheric model provides atmospheric forcing (wind stress, wind speed, heat flux, and precipitation) to the HYCOM model at 3-hourly intervals (Dombrowsky, et al., 2009).

The HYCOM ocean model assimilates observed data through the Navy Coupled Ocean Data Assimilation (NCODA) system (Cummings, 2005). The NCODA system contains an initial quality control system (NCODA OceanQC) to ensure that the raw observations are not erroneous. The quality controlled observations are then fed into the NCODA three dimensional multivariate optimum interpolation (3D MvOI) system which produces 3D analysis fields or 3D increments that are then provided to ocean models (such as HYCOM) for forward propagation (Lunde & Coelho, 2009). The observations that are assimilated by the NCODA system include remote sensed satellite SST and SSH data, in situ salinity and temperature profiles, and remote sensed sea ice concentration. The data from the NCODA OceanQC system are assimilated into HYCOM through a daily data assimilation update cycle (Hernandez, et al., 2009; Cummings, et al., 2009).

**NCOM**

The Navy Coastal Ocean Model (NCOM) is a 3D global ocean circulation model which was developed by the Naval Research Laboratory (NRL) and has been under development since 1998, as a replacement to the NRL Sigma Z-level Model (SZM). The NCOM model has a horizontal resolution of 1/8° and is based predominately on the Princeton Ocean Model (POM) with some components of the SZM. Vertical resolution is controlled by a 40 layer hybrid σ-z coordinate system with 19 σ-coordinate layers in the upper 137m (topmost surface layer thickness of 1 m) and 21 z-coordinate layers from 137m to 5500m (Barron, et al., 2007). Further details of the NCOM model and vertical coordinate system are covered in Barron, et al. (2006). Atmospheric forcing for the NCOM model is provided by the NOGAPS atmospheric fluxes at 3-hourly intervals (Barron, et al., 2007).
Chapter 3

The NCOM system initially used only the Modular Ocean Data Assimilation System (MODAS) (Fox, et al., 2002) to produce temperature and salinity fields that were then assimilated into NCOM (Barron, et al., 2007), however as data assimilation techniques improved and new systems became viable, the data assimilation process progressed to NCOM utilising several data assimilation systems to achieve its ocean forecasts. The Navy Coupled Ocean Data Assimilation (NCODA) system was developed to provide 3D Multivariate Optimum Interpolation (MvOI) data assimilation system for ocean models (Cummings, 2005). In situ observations of temperature and salinity and satellite SST and SSH are processed into the NCODA 3D MvOI system through different techniques. The in situ data is processed through the NCODA OceanQC (quality control) system which then feeds into the NCODA 3D MvOI system to produce 3D temperature and salinity profiles. The satellite altimetry (SSH) data is processed through the Navy Layered Ocean Model (NLOM) which produces global 2D SSH fields, and global satellite SST data is processed through the 2D OI (optimum interpolation) MODAS system. These 2D fields are then combined in the 3D MODAS system to create synthetic 3D temperature and salinity fields which are then fed into the NCODA 3D MvOI system. The NCODA system combines the two sets of 3D profiles (originally from in situ observations and remote sensed satellite observations) which are then assimilated into the NCOM model over a 3 day hindcast (Lunde & Coelho, 2009).

**GFS**

The Global Forecasting System (GFS) is a global spectral model operationally run by the US National Oceanic and Atmospheric Administration (NOAA). The model has a temporal resolution of 6 hours and a forecast length of up to 384 hours (16 days). After one week, the resolution of the model reduces (both spatial and temporal) to allow for computational efficiency. The vertical coordinate system of the model is based on a hybrid sigma/pressure layer system which contains 64 equally spaced layers (Bi, et al., 2010). The 10m reference height wind speed (as U and V velocity) used in this study was posted from the spectral model to an equally spaced horizontal latitude-longitude grid with a resolution of 1/2° (approximately 55.5km). The forecast model is updated every 6 hours with assimilated data through the Global Data Assimilation System (GDAS). Within GDAS operates the Gridpoint Statistical Interpolation (GSI)
analysis system, which is a three dimensional variational (3DVAR) data assimilation system (Kleist, et al., 2009). Further information in regards to the GFS model, including output can be found at (http://www.emc.ncep.noaa.gov/index.php?branch=GFS).

Table 3-1: Model parameters for the ocean models used in this study (adapted from Dombrowsky, et al., 2009; Hernandez, et al., 2009; Cummings, et al., 2009).

<table>
<thead>
<tr>
<th>Model Name</th>
<th>BLU/Link</th>
<th>FOAM</th>
<th>HYCOM</th>
<th>NCOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizontal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resolution (~km)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1/10° (11.1)</td>
<td>1/4° (27.7)</td>
<td>1/12° (9.3)</td>
<td>1/8° (13.9)</td>
</tr>
<tr>
<td>Vertical</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coordinate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fixed 47 z levels</td>
<td>Fixed 50 z levels</td>
<td>Lagrangian 32 ρ/σ/z levels</td>
<td>Fixed 40 σ/z levels</td>
</tr>
<tr>
<td>Surface Layer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thickness (m)</td>
<td>10</td>
<td>1</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Temporal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resolution</td>
<td>24 hr</td>
<td>24 hr</td>
<td>24 hr</td>
<td>6 hr</td>
</tr>
<tr>
<td>Grid Limits</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Higher Resolution)</td>
<td>Global (Australia: 16°N - 75°S, 90°E - 180°E)</td>
<td>Global (SPA: 0°N - 60°S, 100°E - 77°W)</td>
<td>Global</td>
<td>Global</td>
</tr>
<tr>
<td>Ocean Circulation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td>MOM4</td>
<td>v0 – NEMO 3.0</td>
<td>HYCOM</td>
<td>POM/SZM</td>
</tr>
<tr>
<td>Data Assimilation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type (System)</td>
<td>EnOI (BODAS)</td>
<td>AC</td>
<td>3D MvOI (NCODA)</td>
<td>3D OI (MODAS/NCODA)</td>
</tr>
<tr>
<td>Data Assimilation</td>
<td>Twice weekly</td>
<td>24 hrs</td>
<td>24 hrs</td>
<td>24 hrs</td>
</tr>
<tr>
<td>Frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data Assimilated</td>
<td>Satellite SSH &amp; SST, In-situ Temperature &amp; Salinity Profiles</td>
<td>Satellite SSH &amp; SST, In-situ Temperature &amp; Salinity Profiles, Sea Ice Conc.</td>
<td>Satellite SSH &amp; SST, In-situ Temperature &amp; Salinity Profiles, In-situ float displacement, Sea Ice Conc.</td>
<td>MODAS SSH &amp; SST, In situ Temperature &amp; Salinity</td>
</tr>
<tr>
<td>Atmospheric</td>
<td>GASP</td>
<td>UKMO NWP</td>
<td>NOGAPS</td>
<td>NOGAPS</td>
</tr>
<tr>
<td>forcing Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Atmospheric</td>
<td>3 hr</td>
<td>v0 – 6 hr</td>
<td>v1 – 3 hr</td>
<td>3 hr</td>
</tr>
<tr>
<td>Forcing Frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Where: z indicates fixed depth layers, σ indicates terrain following depth layers, and ρ indicates density following depth layers.
3.2.3 SARMAP Model Solution Methods

**IAMSAR**

The IAMSAR search prediction method within SARMAP tracks particles with a given leeway and creates a search area which encompasses all of the tracked particles. The forcing or movement of the particles is provided by ocean currents and winds (through the leeway parameters). For objects with only a leeway speed factor and no divergence angle, the model will track only one particle (directly downwind, with the leeway speed factor specified). When an object has a leeway speed factor and divergence angle, the model will track three particles, one directly downwind, and one to the left and one to the right of downwind. If the object has two leeway speed coefficients, as well as leeway divergence angles, then the model will track six particles, three with the maximum leeway speed (directly downwind and left and right divergent angles) and three with the minimum leeway speed (directly downwind and left and right divergent angles). Once the particles have been tracked, a radius is applied to each model particle to account for the sum of the errors of position \( (E) \) that may be relevant to the scenario. The sum of the errors is defined by the sum of the initial incident position error \( (E_i) \) plus the drift error \( (E_d) \), refer Equation 3-1. This is then multiplied by a safety factor \( (f_s) \) or search factor to give the search radius \( (R_0) \) refer Equation 3-2. A rectangle circumscribing all of the radii is then calculated, thus describing the search area (International Maritime Organisation, 2008).

\[
E = E_i + E_d
\]

Equation 3-1

Where: \( E \) = Sum of the errors of position  
\( E_i \) = Initial position error  
\( E_d \) = Drift error

\[
R_0 = E \times f_s
\]

Equation 3-2

Where: \( R_0 \) = Optimal search radius  
\( E \) = Sum of the errors of position  
\( f_s \) = Safety factor
Monte Carlo

The Monte Carlo solution within SARMAP uses a stochastic Lagrangian particle trajectory model. Particle forcing is generated in the same way as the IAMSAR solution, by using ocean currents and winds and the objects leeway parameters, however due to the Monte Carlo solution containing a large number of model particles, an additional dispersion parameter is also added to the particle movement. Horizontal dispersion is used in the model to both account for uncertainties or errors in the drift of the search object (due to the uncertainties in the environmental forcing and leeway characteristics) as well as to account for the sub grid scale processes or turbulence which are not able to be resolved in the ocean current models. The Monte Carlo solution is often employed in search and rescue models worldwide (Isaji, et al., 2006; Breivik & Allen, 2008; Ullman, et al., 2006). A large number of particles (up to 30,000) can be used to simulate the likely trajectory and search area of an object adrift. Each of the particle trajectories are simulated through the random-walk solution, as a first order Markovian process. The ensemble of particle trajectories is then used to determine the resultant search area. The location of the particles used in the Monte Carlo simulation may be positioned on a probability grid, which creates a probability density map of the search object’s possible location within the likely search area. As the simulations in this study used 1,000 particles, the minimum value in the probability grid was set to 0.1%, which represents one particle per grid cell. This ensured that only the cells with non zero values were included. As some particles move apart from each other, there may be instances where there are zero values in grid cells which produce gaps in the probability density grid, this usually occurs towards the outer limits of the search area (see Figure 3-3). A polygon which was the minimum size to enclose all of the model particles was used to define the search areas in this study. The size of the Monte Carlo search area is strongly dependent upon the horizontal dispersion parameters used; higher dispersion creates larger search areas due to particles being entrained further afield into nearby current fields.

Figure 3-3 shows an example search area off the east coast of Australia with the Monte Carlo search area solution (shown as the coloured probability grid and the green bound, darker grey filled polygon) and the IAMSAR search area solution (shown as the dark blue bound, light grey filled rectangular polygon with corners labelled A,B, C and D). The IAMSAR solution may produce a search area which overlaps over land; this may
occur when the search object still remains in the water and is close to the coastline, as the model formulations expand the search area over time as a radius from the centre, in all directions.

Figure 3-3: Map showing the search areas for the IAMSAR solution (blue bound, light grey shaded area) and the Monte Carlo solution (green bound, darker grey shaded area) 72 hours into a drifter simulation where the drifter tracked from the north to south, as indicated by the black dots shown at 6 hour intervals. The Monte Carlo solution also provides a probability density grid, as illustrated by the coloured grid, where red indicates higher probability and blue indicates low probability of containing the search object.

3.2.4 SARMAP Model Parameters

Uncertainties in the modelled drift paths are accounted for by each of the two solution methods in different ways. The IAMSAR solution applies a drift error ($E_d$) to the drift calculations to include uncertainties in the objects drift path. These uncertainties may arise from potential errors in the environmental data (e.g., currents and winds) which force the objects drift trajectory, and also the potential error which may arise from uncertainties in the objects drift characteristics (leeway characteristics). For the scenarios included herein, the drift error was set to 0.3 in accordance to the IAMSAR manual (International Maritime Organisation, 2008). The drift error can be manually changed to account for more or less confidence in the environmental products (winds...
and currents) or the leeway drift characteristics, where the IAMSAR manual states that the drift error may range between 1/8 (0.125) and 1/3 (0.33).

A safety factor of 1.1 was applied to the IAMSAR solution, which is the recommendation in the IAMSAR manual for a “first search”. According to the IAMSAR manual, the safety factor can range between 1.1 for the initial search up to 2.3 for the fourth and successive searches. As the safety factor increases, so too does the search area by the factor applied, for example the search radius is increased by 10% for a safety factor of 1.1. This safety factor increases the search area size to increase the likelihood of containing the search object within the search area, thus increasing the probability of containment.

The Monte Carlo solution does not require a drift error or safety factor within its calculations, as errors or uncertainties in time and space are accounted for by the “Uncertainty Level” applied to the calculation, and by the stochastic nature of the Monte Carlo solution itself. The uncertainty level is user selectable in the SARMAP model as Low, Medium or High. These settings control the amount of horizontal dispersion applied to each of the particles tracked by the model. The three user defined horizontal dispersion parameters within SARMAP are Low (10 m$^2$/s), Medium (100 m$^2$/s) and High (1,000 m$^2$/s). The greater the uncertainty level, the faster the particles spread apart from each other, thus increasing the search area. The uncertainty factor was set to ‘High’ for the Monte Carlo scenarios. The ‘High’ setting indicates a horizontal dispersion parameter of 1,000 m$^2$/s and is applicable to the energetic state of the Tasman Sea, which includes the highly variable East Australian Current and its associated meanders, eddies, fronts and jets. Drifter dispersion studies in waters off the east coast of Australia (Mantovanelli, et al., 2012) indicate that near shore diffusivities may average ~85 m$^2$/s (up to 1,010 m$^2$/s) whilst offshore diffusivities averaged ~1,133 m$^2$/s (up to 7,802 m$^2$/s).

The model run duration was set to 120 hours to generate a 5-day forecast of the drifter trajectory. The initial error of 0.5 Nm was used as the SVP/SVP-L drifter data had a position accuracy of two decimal places to the degree. The search object was set at either SVP or SVP-L depending on the drogue on/off status of the drifter; this ensured that the correct leeway of the drifter in its different configurations was properly accounted for. The wind and current input data was interpolated from their native output.
time step (usually 6-hourly or daily) to the time step of the SARMAP model, which was 10 minutes in this study. A 60 minute output interval was used to store the drifter locations throughout the 120 hour scenarios.

The single particle for the IAMSAR solution refers to the model tracking an object with a single leeway component (directly downwind leeway with no cross wind leeway, due to the symmetrical nature of the drifters). Sensitivity testing was carried out to determine the optimum number of particles for each Monte Carlo simulation. Tests showed that 1,000 particles was the optimal particle number which provided efficient model run times and practical output file size, without compromising the ability for particles to be entrained into nearby current fields and thus being able to encapsulate the variability in the current field. Hence, the particle number was set to 1,000 for simulations using the Monte Carlo solution.

A list of the model parameters which were used for all SARMAP simulations are detailed in Table 3-2.

Table 3-2: Input parameters for the SARMAP model runs for both IAMSAR (middle column) and Monte Carlo (right column) scenarios.

<table>
<thead>
<tr>
<th></th>
<th>IAMSAR</th>
<th>Monte Carlo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run Duration:</td>
<td>120 Hours</td>
<td>120 Hours</td>
</tr>
<tr>
<td>Initial Error:</td>
<td>0.5 Nm</td>
<td>0.5 Nm</td>
</tr>
<tr>
<td>Search Objects:</td>
<td>SVP/SVP-L</td>
<td>SVP/SVP-L</td>
</tr>
<tr>
<td>Uncertainty Factor:</td>
<td>Not input in model</td>
<td>High</td>
</tr>
<tr>
<td>Wind Forcing:</td>
<td>GFS</td>
<td>GFS</td>
</tr>
<tr>
<td>Current Forcing:</td>
<td>BLUElink/FOAM/HYCOM/NCOM</td>
<td>BLUElink/FOAM/HYCOM/NCOM</td>
</tr>
<tr>
<td>Model Time step (Δt):</td>
<td>10 Minutes</td>
<td>10 Minutes</td>
</tr>
<tr>
<td>Model Output:</td>
<td>60 Minutes</td>
<td>60 Minutes</td>
</tr>
<tr>
<td>Number of Particles:</td>
<td>1</td>
<td>1,000</td>
</tr>
<tr>
<td>Safety Factor:</td>
<td>1.1</td>
<td>Not input in model</td>
</tr>
<tr>
<td>Drift Error:</td>
<td>0.3</td>
<td>Not input in model</td>
</tr>
</tbody>
</table>

3.2.5 Error Analysis

Three different statistical measures were used in this study to quantify each of the ocean model’s ability to predict the track of the drifters. These measures include two statistical error analysis and one non-parametric hit rate analysis:
1 – Mean Absolute Error (MAE) measured in kilometres;

2 – Root Mean Squared Error (RMSE) measured in kilometres and;

3 – A non-parametric hit rate test.

The statistical error analysis and the hit rate tests were carried out for both the IAMSAR and the Monte Carlo solutions. The hit rate test was undertaken to quantify the number of times the drifter was contained within the IAMSAR solution search area and the Monte Carlo solution search area.

The MAE was utilised in this study as it effectively indicates the average error over the range of the dataset at a given time interval as a function of distance (in kilometres). This is useful in practical applications when defining search areas which rely on the accuracy of the forecast. In this error analysis, the measured drifter positions were compared to the SARMAP model predicted drifter positions using the two model solutions (IAMSAR and Monte Carlo). As this study used two different SARMAP model solutions (IAMSAR and Monte Carlo), there was a difference between the methods in which the distances were calculated. For the IAMSAR solution, the distance error was calculated from the measured position of the drifter at a given time interval to the model particle located in the centre of the square IAMSAR search area at the corresponding time interval (indicating an average forecast distance error). Due to the Monte Carlo solution containing an ensemble of 1,000 particles at each given time interval throughout the simulation, the distance error was calculated for (a) the minimum distance between the measured drifter position and the nearest model particle (of the 1,000 modelled), and (b) the average distance of all of the 1,000 particles at a given time interval compared to the measured drifter location. The error distance was always referred to as an absolute distance that is positive, independent of direction. The formula for MAE is given below in Equation 3-3:

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |f_i - m_i|
\]

Equation 3-3
Where: \( f_i \) = forecast drifter position

\( m_i \) = measured drifter position

\( n \) = number of drifter simulations

The RMSE analysis was also used in this study as it gives a greater weighting to larger errors than the MAE. In critical situations (such as SAR incidents) where large errors are particularly unfavourable, this method is able to more readily identify those large errors. The RMSE is often used for comparing modelled results against measured or observed results, and is also a good indicator of model precision. This error analysis was also completed by comparing the discrepancies in the measured position of the drifter to the forecast position of the model drifter with the same approach as described for the RME above. The formula for RMSE is given below in Equation 3-4:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (f_i - m_i)^2}{n}}
\]

Equation 3-4

Where: \( f_i \) = forecast drifter position

\( m_i \) = measured drifter position

\( n \) = number of drifter simulations

The non-parametric hit rate test was performed to ascertain whether the search object (SVP or SVP-L) was contained within the search area. This was also carried out for both the IAMSAR and the Monte Carlo solutions. The test was undertaken to give statistics as to the frequency in which a search object may be contained within a forecast search area at given time intervals, for the search areas generated by the different ocean models in the study region. The IAMSAR method quantified whether the search object was contained anywhere within the square search area at the corresponding time interval, whilst the Monte Carlo method quantified if the search object was contained within the search area generated by enclosing all of the 1,000 model particles within a convex hull polygon at the corresponding time interval. The Monte Carlo search area
polygon is not constricted to a regular rectangular or square shape and may be any convex enclosed shape providing it includes all of the model particles.

Sensitivity testing was also carried out to quantify how the hit rate analysis responded to the underlying assumptions of calculating the hit rate. Two methods of counting the hit rate were tested. The first method included counting the hit at the corresponding time interval (e.g. at 24 hours only or at 120 hours only, and did not take into consideration any of the previous hits up until that time). The second method involved counting the hits up to (and including) the corresponding time interval. It was found that the data was only moderately sensitive to these two approaches at calculating the hit rate, and thus shown herein are the values from the first method, counting hits at the corresponding time.

The hit rate was calculated for each of the single model forecast search areas as well as the consensus search areas. Search areas where two or more of the single model forecast search areas overlapped or coincided were described as consensus areas. The consensus search areas were defined as either including two or more single model forecast overlaps (2+), three or more single model overlaps (3+) or including all four single model forecasts (4). The size of the 3+ consensus and 4 model consensus search areas would always be smaller than the largest individual search area included in that consensus search area. Figure 3-4 shows an example ensemble search area at 120 hours using the IAMSAR solution, the blue square represents the BLUElink model forecast search area, the green square represents the FOAM model forecast search area, the yellow shows the HYCOM model forecast search area and the red square shows the NCOM model predicted search area. The lightest grey shaded area indicates the search area which has a single model agreement, the next darker grey shows the search area where two models had agreement (two model consensus area), the third darkest grey shows the search area were three models had agreement (three model consensus area) and the darkest grey (in the centre of the search area) shows the area where all four models were in agreement (four model consensus area). The black dots show the location of the drifter at 6 hourly intervals (every second drifter position labelled with corresponding hours into model simulation). As indicated, the drifter (at 120 hours) was located within the four model consensus search area (at 120 hours).
3.3 Results

3.3.1 Mean Absolute Error (MAE)

Both the IAMSAR and the Monte Carlo solutions were used to simulate the 63 different drifter tracks for each of the four ocean models (thus giving a combined sample number of 504 scenarios). From this sample the MAE was calculated for each of the four ocean models, over the year long dataset of 5-day trajectories.

**MAE – IAMSAR Solution**

Figure 3-5 shows the MAE of the drift, as simulated by the IAMSAR solution over the 120 hour simulation. The results indicate that for the IAMSAR solution, FOAM and NCOM had very similar MAE values over the first 24 to 36 hours, after which the MAE for NCOM tended to increase at a greater rate than FOAM. The model with the smallest MAE until approximately 65 hours was HYCOM, after which FOAM returned a marginally smaller MAE than HYCOM until 120 hours. Throughout the 120 hour simulation period BLUElink was shown to consistently record the highest MAE.
Figure 3-5: MAE calculated for each of the four ocean models, over the year long dataset of 5-day trajectories for IAMSAR solution up to 120 hours. Note the results for FOAM and NCOM overlap closely for the initial 36 hours.

**MAE – Monte Carlo Solution**

Figure 3-6 shows the MAE of the model particles over 120 hours as simulated by the Monte Carlo solution. The *minimum* model particle distance MAE is given in Figure 3-6 (a) whilst the *average* model particle distance MAE is given in Figure 3-6 (b). The minimum MAE was shown to be substantially less than the average MAE for all of the ocean models. An increase in MAE over time was shown for all four of the ocean model forecasts. As shown, the minimum MAE for both NCOM and FOAM was similar throughout the 120 hour simulations. The HYCOM model produced the lowest minimum MAE over the 120 hour duration, and BLUElink produced the highest minimum MAE over the 120 hour duration. The rate that the BLUElink minimum MAE increased was shown to slow and plateau after approximately 72 hours. The results for the average MAE were similar for FOAM, HYCOM and NCOM until approximately 48 hours, after which NCOM average MAE tended to increase at a slightly higher rate than FOAM and HYCOM. At the end of the 120 hours, FOAM (closely followed by HYCOM) produced the lowest average MAE of the four models. BLUElink recorded the highest minimum and average MAE (consistent with the IAMSAR solution) throughout the 120 hours modelled.
Figure 3-6: MAE calculated for each of the four ocean models, over the year long dataset of 5-day trajectories for Monte Carlo solution up to 120 hours for minimum distance (a) and average distance (b).
3.3.2 Root Mean Squared Error (RMSE)

The RMSE was calculated for both the IAMSAR and Monte Carlo model solutions, for each of the 63 drifter tracks, and each of the four ocean models over the year long dataset of 5-day drift trajectories.

**RMSE – IAMSAR Solution**

Figure 3-7 shows the RMSE of the IAMSAR solution model simulated drift, up to the end of the 120 hour simulation. From the beginning until approximately 65 hours, HYCOM exhibited the lowest RMSE out of the four models, whilst FOAM indicated the lowest RMSE from 65 to 120 hours. FOAM and NCOM revealed similar RMSE values until approximately 36 hours, after which the rate at which the RMSE increased was shown to become greater for NCOM for the remainder of the 120 hours. BLUElink showed the highest RMSE of the four models throughout the 120 hours modelled.

![Figure 3-7: RMSE calculated for each of the four ocean models, over the year long dataset of 5-day trajectories for the IAMSAR solution from zero to 120 hours.](image-url)

Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications
RMSE – Monte Carlo Solution

Figure 3-8 shows the RMSE of the model particles as simulated by the Monte Carlo model solution, over the full 120 hour simulation.

Figure 3-8: RMSE calculated for each of the four ocean models, over the year long dataset of 5-day trajectories for the Monte Carlo solution up to 120 hours for minimum distance (a) and average distance (b).
The minimum modelled particle distance RMSE is given in Figure 3-8 (a) whilst the average modelled particle distance RMSE is given in Figure 3-8 (b). The RMSE values (minimum and average) for all four models were shown to increase with time over the 120 hour simulation period. The HYCOM model simulation exhibited the lowest minimum RMSE out of the four ocean models throughout the 120 hours. The HYCOM simulation showed the lowest average RMSE until approximately 65 hours, after which the FOAM simulation produced a slightly lower average RMSE until 120 hours. BLUElink returned the highest minimum and average RMSE values throughout the simulation period. Initially the BLUElink RMSE values grew rapidly, however after approximately 72 hours the rate of increase in both minimum and average RMSE was shown to slow.

3.3.3 Hit Rate

The method used for calculating the hit rate included counting whether the drifter was contained within the search area polygon at the given time interval (for both IAMSAR and Monte Carlo solutions). The two time intervals used in this study to calculate the hit rate were at 24 hours (one day into simulation) and at 120 hours (end of the 5 day simulation).

**IAMSAR Solution**

The hit rate for the IAMSAR solution at 24 hours and at 120 hours is shown in Table 3-3. At 24 hours all of the models returned a similar hit rate, with BLUElink, FOAM and NCOM all recording a hit rate of 12.7%, followed by HYCOM at 11.1%. At 120 hours HYCOM performed significantly better than any other single ocean model with a hit rate of 27%. Each of the hit rates were shown to increase from the 24 hour time interval to the 120 hour time interval (except for FOAM – which remained the same at 24 and 120 hours), indicating that the IAMSAR method for determining the search area size increased considerably with time (and hence provided a greater ability to contain the search object within the search area later in the scenario). It may be noted that this does not imply that there is a greater chance of finding the search object (probability of success) at 120 hours compared to 24 hours. It shows that the probability of
containment of the search object within the search area may be greater at 120 hours compared with 24 hours. It is possible that the search area at 120 hours may be too large to comprehensively search with available resources (depending on the given SAR situation), and hence the actual probability of detection may fall later in the search period due to a compromised search ability.

The results show that the 24 hour hit rate for the 2+ model consensus was less than that of each of the single models (at 7.9%), potentially due to the smaller search area generated by 24 hours of drift and hence reduced opportunity for the search areas to coincide. This was also true for the 3+ and 4 model consensus search areas, which both returned low hit rates at 24 hours of 1.6%.

The hit rates at 120 hours for the consensus search areas were shown to increase over the respective 24 hour hit rates. The 2+ model consensus hit rate at 120 hours was 22.2% which was second only to the HYCOM hit rate at 120 hours. The 3+ and 4 model consensus hit rates at 120 hours were 6.3% and 3.2% respectively. The increase in hit rate for the 120 hours compared with the 24 hours may be due to the larger search areas at 120 hours, which thus provided a higher likelihood of search areas overlapping to form consensus search areas.

<table>
<thead>
<tr>
<th>Model</th>
<th>24 Hours</th>
<th>120 Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUElink</td>
<td>12.7%</td>
<td>15.9%</td>
</tr>
<tr>
<td>FOAM</td>
<td>12.7%</td>
<td>12.7%</td>
</tr>
<tr>
<td>HYCOM</td>
<td>11.1%</td>
<td>27.0%</td>
</tr>
<tr>
<td>NCOM</td>
<td>12.7%</td>
<td>20.6%</td>
</tr>
<tr>
<td>2+ Consensus</td>
<td>7.9%</td>
<td>22.2%</td>
</tr>
<tr>
<td>3+ Consensus</td>
<td>1.6%</td>
<td>6.3%</td>
</tr>
<tr>
<td>4 Consensus</td>
<td>1.6%</td>
<td>3.2%</td>
</tr>
</tbody>
</table>

**Table 3-3: IAMSAR solution hit rate calculated for each of the four ocean models plus consensus areas, over the year long dataset of 5-day trajectories at 24 hours and 120 hours.**

**Hit Rate – Monte Carlo Solution**

The hit rate at 24 hours and at 120 hours utilising the Monte Carlo solution are shown in Table 3-4. The results show that HYCOM returned the highest hit rate of any single model, at both the 24 hour and 120 hour times returning values of 88.9% and 82.5%
respectively. At both time intervals NCOM had the second highest single model hit rate. BLUElink recorded the lowest single model hit rate at 24 hours; however FOAM recorded the lowest single model hit rate at 120 hours. The hit rate for each individual model at 120 hours was shown to decrease when compared to their respective 24 hour hit rate. This indicated that when the Monte Carlo solution was utilised, hit rates were shown to reduce with the passage of time.

The 24 hour hit rate for the 2+ model consensus area was slightly less than that of the highest single model (HYCOM) however it was higher than any of the other three single models at, 84.1%. The 3+ model consensus search area hit rate at 24 hours was 76.2%, whilst the 4 model consensus search area was 61.9% at 24 hours.

The 2+ model consensus hit rate at 120 hours was the same as at 24 hours, and was the highest of any hit rates (including single models) at 120 hours, returning a value of 84.1%. The 3+ and 4 model consensus hit rates at 120 hours were 69.8% and 42.9% respectively which shows a reduction compared to their respective 24 hour hit rates.

<table>
<thead>
<tr>
<th>Model</th>
<th>24 Hours</th>
<th>120 Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUElink</td>
<td>73.0%</td>
<td>68.3%</td>
</tr>
<tr>
<td>FOAM</td>
<td>74.6%</td>
<td>63.5%</td>
</tr>
<tr>
<td>HYCOM</td>
<td>88.9%</td>
<td>82.5%</td>
</tr>
<tr>
<td>NCOM</td>
<td>79.4%</td>
<td>77.8%</td>
</tr>
<tr>
<td>2+ Consensus</td>
<td>84.1%</td>
<td>84.1%</td>
</tr>
<tr>
<td>3+ Consensus</td>
<td>76.2%</td>
<td>69.8%</td>
</tr>
<tr>
<td>4 Consensus</td>
<td>61.9%</td>
<td>42.9%</td>
</tr>
</tbody>
</table>

3.4 Discussion
The results obtained from this study quantified the expected spatial uncertainty when used to predict the drift of an SVP or SVP-L drifter over 120 hours in the Tasman Sea, using a search and rescue Lagrangian particle drift model in conjunction with four individual ocean models. The hit rate analysis for the IAMSAR model solution showed that all of the models returned low hit rates, with the “search object” being located within the model predicted search area a maximum of 12.7% of the time at 24 hours,
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and 27.0% of the time at 120 hours. This suggests that the search areas given by the IAMSAR solution may not be large enough to include the search object for a significant portion of time in a complex flow field such as the Tasman Sea.

The results for the simulations using the Monte Carlo solution indicated the “search object” was contained within the predicted search area more frequently, as indicated by the higher hit rate exhibited by the Monte Carlo solution scenarios. This may be in part due to the Monte Carlo solution returning larger model predicted search areas than the IAMSAR solution (for most scenarios) using the model parameters specified. Additionally, the nature of the Monte Carlo solution, allows for some of the modelled particle drift trajectories to become entrained in nearby current fields thus increasing the dispersion of the search area. This may result in other separate higher probability search areas being formulated, which may take on any shape and area not restricted to regular rectangular areas. The IAMSAR solution only shows a single uniform rectangular search area under all circumstances, which may not expand at a high enough rate to successfully contain the search object over time.

Further analysis of the results indicated that the rate at which the search areas increased in size was on average ~25 times from the 24 hour average search area compared to the 120 hour average search area for the IAMSAR solution. This rate of search area growth over time was much greater than that demonstrated by the Monte Carlo solution, which showed a rate of average search area size increase from 24 hours to 120 hours of approximately 8.5 times. This indicates that the search areas for the IAMSAR solution grow at a rate approximately 3 times greater than the rate at which the Monte Carlo search areas grow. This may explain why the hit rates increased over time for the IAMSAR solution, however they were shown to decrease over time for the Monte Carlo solution.

Using the IAMSAR solution for search area prediction, HYCOM demonstrated the smallest distance errors (MAE and RMSE) from the beginning to approximately 65 hours, whilst FOAM had the smallest distance errors (MAE and RMSE) from 65 to 120 hours. Likewise, when the Monte Carlo solution was used, HYCOM demonstrated the smallest average particle distance errors (MAE and RMSE) from the beginning to approximately 65 hours, and FOAM indicated the smallest average particle distance errors from approximately 65 to 120 hours. The results obtained from the use of the
BLUElink model more frequently indicated higher error values and lower hit rates than the three other models used in this study.

The indicated lower performance (in terms of hit rate and RMSE/MAE) that the BLUElink ocean model exhibited when compared to the other ocean models used to produce search areas for drifters in the Tasman sea during the 2010 year, may have been attributable to several of the BLUElink model data assimilation parameters. A review of the data assimilation systems employed by each of the ocean models indicated that some of the data assimilation parameters in the BLUElink system may not have been as effective as those used in the other ocean model data assimilation systems.

The results indicate that the model update frequency or data assimilation frequency is important to constrain the ocean model forecasts. The data assimilation frequency specifies how frequent the ocean model is re-run with the latest observed and/or measured data which has been assimilated into a new forecast. The BLUElink ocean model used a twice weekly data assimilation update cycle, whilst the three other ocean models (FOAM, HYCOM and NCOM) all employed daily data assimilation update schemes. The higher update frequency ensures a minimum time interval between assimilation updates, and therefore greater ability to minimise the potential forecast errors which may accumulate over time. The less frequent assimilation of data may allow the model to deviate from the ocean state over the longer forecast periods before the data assimilation update can correct the model. The next generation of BLUElink contains daily forecast updates (data assimilation frequency), so this may assist in addressing the discrepancy which has been identified herein.

(Cummings, 2005) identified that changes in SSH can be attributed to ocean dynamics such as mesoscale eddy and meander formation, and that the most important observing system for SSH is satellite altimetry data. As the Tasman Sea is a highly energetic body of water which contains many eddies, fronts, jets and meanders (Ridgeway & Dunn, 2003; Coleman, 1984) it can be inferred that accurate satellite altimetry data is crucial for effective data assimilation systems and ocean models operating in the Tasman Sea. Each of the four ocean models described herein utilise satellite altimetry to measure SSH and derive sea level anomaly (SLA) for use in their respective data assimilation systems. The two satellite SSH products common to all of the data assimilation systems used by the ocean models in this study were along-track Jason and Envisat satellite data.
Whilst the satellite measured SSH data may be the same between all four models, the
data assimilation schemes which are used to feed this SSH data into the forecast models
differ, and some data assimilation schemes may be more effective than others.

A consensus forecast approach has been presented, where any of the consensus search
areas are significantly smaller than the individual search areas combined, as the
consensus areas relate only to the area that is common between the individual single
model search areas at a given point in time. In certain cases there is the potential for the
total 2+ model consensus area to be larger than an individual model area (at a given
point in time) if there are two separate 2+ consensus areas formed from the four
individual model areas and these two areas are summed. The 3+ or 4 consensus area
cannot be larger (and are generally considerably smaller) than any of the individual
model areas which form part of that consensus area.

At 24 hours, the search areas generated by the IAMSAR method were substantially
smaller than at 120 hours, and therefore there was less of an opportunity for the search
areas overlap to form consensus, and those areas that did overlap to form consensus
would be much smaller and thus have less of an opportunity to contain the search
object. This may explain the calculated hit rate at 24 hours for all of the consensus areas
for the IAMSAR solution was lower than the hit rate of each of the individual model
areas. At 120 hours, the search areas for IAMSAR had increased considerably compared
to the areas at 24 hours, thus giving a greater opportunity for individual model search
areas to coincide and form consensus areas. The 3+ and 4 model consensus areas
showed a lower hit rate than each of the single model areas at 120 hours due to the
search area size of those consensus areas being much smaller than the individual model
search areas. The hit rate at 120 hours for the 2+ consensus area was greater than the
individual NCOM, BLUElink and FOAM areas, which may be in part due to the case
where the 2+ consensus search area can grow larger than the individual model areas
(through the summation of two separate 2 model consensus areas), thus potentially
having a higher likelihood of containing the drifter.

The hit rate for the 2+ consensus area calculated by the Monte Carlo solution was
higher than all single models except HYCOM at 24 hours, and higher than all single
model areas at 120 hours (potentially due to the summation of two separate 2 model
consensus areas). The hit rate for 3+ consensus areas was greater than the hit rate for the
individual FOAM and BLUElink areas at both 24 and 120 hours, however not quite as high as the individual NCOM or HYCOM at 24 or 120 hours, however the average search area size for the 3+ consensus areas was substantially less than each of the four individual search areas (at 24 and 120 hours) which indicates the potential for a more efficient search area.

The results showed that in terms of hit rate, HYCOM was the most reliable single model for the period modelled and the Monte Carlo solution provided the highest hit rate of 82.5% at 120 hours. When all of the ocean models were used to generate a 2+ model consensus search area using the Monte Carlo solution, the hit rate increased to 84.1%, while the 3+ and 4 model consistencies hit rates at 120 hours were 69.8% and 42.9% respectively.

3.5 Conclusions/Recommendations

This study investigated the use of four different ocean models (BLUElink, FOAM, HYCOM and NCOM) with the focus on quantifying which ocean model was the most reliable when used in conjunction with a search and rescue model (SARMAP) to predict the drift of a search object in the deep offshore waters of the Tasman Sea. The study was undertaken over a one year period for 2010, to ensure that a full range of seasonal conditions were included, and used both SVP and SVP-L drifter buoys as drift targets for the SARMAP drift model.

Two predicted search area solution methodologies were tested, those being the IAMSAR solution and the Monte Carlo solution. It was found that the Monte Carlo (high uncertainty) solution returned a higher hit rate than the IAMSAR solution; which was potentially due to the Monte Carlo solution returning larger search areas, given the complexity in the current field of the Tasman Sea.

When using the IAMSAR solution it was found that HYCOM was the most reliable single ocean model to approximately 65 hours. After 65 hours FOAM returned slightly smaller MAE and RMSE values. When using the Monte Carlo solution, HYCOM returned the smallest minimum MAE and RMSE distance errors throughout the full 120 hour simulation, and the smallest average MAE and RMSE distance errors until approximately 65 hours. After approximately 65 hours FOAM returned a slightly
smarter average MAE and RMSE. The HYCOM model returned a greater hit rate than
the other three individual ocean models tested at 120 hours, for both the IAMSAR and
Monte Carlo solutions. Overall HYCOM was identified as being the most reliable single
model as it predominately displayed higher performance compared with the other ocean
models tested, using three different test measures; MAE, RMSE and Hit Rate for both
IAMSAR and Monte Carlo solutions.

Consensus forecasting was investigated to ascertain if utilising several ocean models in
a consensus forecast could provide benefit over using a single model forecast. The 3+
and 4 model consensus search areas were smaller in size than those of each single
model search areas contained within the corresponding consensus search area
prediction. The hit rate for the consensus search area decreased when compared to the
best performing single model search area for the IAMSAR solution; however the hit
rate for the consensus search areas increased over some of the single model search areas
for the Monte Carlo solution, indicating that there was the potential for benefit from this
consensus approach when using the Monte Carlo solution.

The analysis herein suggests that larger search areas which contain the “search object” a
greater portion of the time may be more valuable than a smaller search area which does
not contain the search object for a significant portion of time. For example, there is
potentially little benefit gained in searching a smaller search area, if the likelihood of
the search object being located within that area is minimal. Given some of the low hit
rates calculated herein, it could be more advantageous to search a larger area, which
potentially has a much greater likelihood of containing the search object. This
judgement is in part balanced by the fact that large search areas can be prohibitively
large and there may be insufficient resources to comprehensively search that area.

Future works investigating the influence of geographic location upon model reliability
may be warranted. The effect of seasonality and inter-annual variability upon forecast
model reliability may also be explored, and could provide an insight into the potential
reliability of forecast models throughout different seasonal influences. As the ocean
models are ever evolving in terms of development, it is recommended that regular
reassessment of model performance is carried out to ensure the most up to date models
are being tested for reliability.
The consensus forecasting approach described herein returned positive results indicating further research is warranted in this field to further develop the consensus forecasting methodology in the oceanographic and maritime search and rescue fields.

3.6 Acknowledgements
This research was supported under the Australian Research Council’s Linkage Projects funding scheme LP0991159. The authors express our appreciation to the reviewers of this paper.

3.7 References


Chapter 3

Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications


Lunde, B. N. & Coelho, E. F., 2009. *Implementations of the Navy Coupled Ocean Data Assimilation system at the Naval Oceanographic Office*. Biloxi, MTS/IEEE.


Chapter 3


STATEMENT OF CONTRIBUTION TO CO-AUTHORED PUBLISHED PAPER

This chapter includes a co-authored paper. The status of the co-authored paper, including all authors, is:


My contribution to the paper involved:

The concept and design of the study, background literature search, compiling and processing of data, undertaking the numerical modelling, processing and analysing the model results, interpreting the results, and drafting the paper.

(Signed) _________________________________ (Date)______________

Ben Amon Brushett

(Countersigned) _________________________________ (Date)______________

Corresponding author of paper: Ben Amon Brushett

(Countersigned) _________________________________ (Date)______________

Supervisor: Prof. Charles Lemckert

Abstract

The following study describes a technique to improve maritime search area prediction by using consensus forecasting to quantify areas of higher probability within a model defined search area. The study included forecasting search areas for 45 five-day drifter tracks, each simulated independently using a different ocean model (BLUElink, FOAM, HYCOM and NCOM) throughout 2012 in the eastern Indian Ocean, off the coast of Western Australia.

It was found that zones where all four model search areas overlapped (defined here as a consensus search area) was significantly smaller than those areas generated by any single model forecasts. This consensus area was quantified to be up to 56.9% smaller at 24 hours and 72.5% smaller at 120 hours, however the hit rate (the frequency that the actual drifter, or target was contained within the forecast search area) was reduced by up to 26.2% at 24 hours and 52.8% at 120 hours compared to any single model forecast hit rates. This indicated that the four model consensus search area had a higher hit rate per unit of search area than any individual model search area. Hence if search resources were a limiting factor for a particular search effort, the available resources may be most effectively deployed by prioritising the effort initially to the smaller, four model consensus search area.
4.1 Introduction

Lagrangian stochastic particle trajectory models are widely used by search and rescue (SAR) agencies worldwide to forecast the potential drift and estimate the most likely search area for persons, craft or other objects adrift at sea. Environmental forcing including sea surface currents and winds are required by particle trajectory models to simulate the metocean conditions that an object adrift at sea may be subject to. Operational forecast, nowcast or hindcast currents (typically obtained from ocean models driven by ocean observing satellite measurements) and winds (from atmospheric forecast models and measurements) are routinely used as input into SAR drift models to provide the required and best available environmental forcing (Spaulding, et al., 2006; Breivik, et al., 2013; Brushett, et al., 2011).

There are currently several different ocean and atmospheric models available for the same given locations and timeframes, and hence it may be difficult for the SAR operator to determine which single ocean model (or atmospheric model) may best perform when being used as input into SAR drift models at a given location and timeframe. One forecast model may perform best in a specific location or at a certain time, but not so well in another location or timeframe and hence it is important to have a number of models available operationally. Studies by King, et al., (2010; 2011) investigated the use of multiple metocean datasets for operational drift prediction purposes. Where possible, self locating datum marker buoys (SLDMBs) are routinely dropped in the vicinity of the LKP (last known position) during SAR incidents to ground truth the surface currents in the area, and hence can be used to continuously validate which ocean model may best replicate the surface currents during the incident (Breivik, et al., 2013).

With the availability of several different ocean models, an ensemble forecast may be constructed by re-running the SAR drift model with each of the available individual ocean model forecasts, and combining the resulting forecast search areas from each of these SAR drift model runs into an ensemble or consensus forecast. This ensemble forecast can be used to provide an indication of the likely search areas based on each individual ocean model forecast, as well as an indication to areas where consensus between the ocean models may have been achieved (where two or more ocean models are in agreement with each other). The consensus areas may provide a higher
confidence in the SAR drift model forecasts due to several independent ocean models predicting a similar outcome, compared to the areas where there was no consensus evident.

To date there has not been any comprehensive research in the application of consensus forecasting to search and rescue drift modelling. Brushett et al., (2011) undertook preliminary investigations into the use of multiple metocean datasets combined into an ensemble or consensus forecast to predict the trajectory of a drifter deployed during operational oil spill response, focussing on six ocean models and two wind models (thus generating an ensemble of 12 combinations). The concept of consensus forecasting to prioritise search areas has not been extensively investigated, and as such one of the aims of the present study is to assess whether there may be potential benefits to be gained from implementing consensus forecasting to SAR drift forecasting on an operational basis.

The present study investigated the use of a search and rescue particle trajectory model (SARMAP) to predict the 5-day trajectories (and resultant search areas) of 45 Surface Velocity Program (SVP) drifters off the coast of Western Australia throughout 2012. The SAR drift model used ocean currents and winds provided by ocean models and an atmospheric model, to provide the required environmental forcing. Each of the 5-day drifter trajectories was independently simulated with SARMAP using GFS model winds and each of the four available ocean current models (BLUElink, FOAM, HYCOM and NCOM). The above process was repeated for four independent experiments. The horizontal dispersion coefficient ($K$) was changed between each experiment, with values of 1,000 m$^2$/s, 100 m$^2$/s and 10 m$^2$/s being used for experiments 1 to 3 respectively, to ascertain the effect the horizontal dispersion coefficient had upon the drifter forecasts. A fourth experiment provided a single deterministic solution, where no horizontal dispersion was included in the model simulations.

There were several key objectives to address in this paper. The first included determining which ocean model was the most reliable, during the study period and within the study domain, from the four ocean models available. The second objective was to test three different horizontal dispersion parameters used within the SAR drift model and quantify their respective average distance errors, hit rates, and the average size of their search areas. The third objective was to utilise all four ocean models in a
single ensemble forecast, to quantify if there was an improvement in defining the forecast search area over using a single ocean model.

4.2 Data and Models

The following sections contain an outline of the study domain (4.2.1), an overview of the SVP drifters (4.2.2), the details of the SAR drift model, known as SARMAP (4.2.3), and a summary of each of the environmental forecast models (forecast currents and winds) that were used as input for SARMAP throughout this study (4.2.4).

4.2.1 Study Domain

The spatial domain for the study extended out from the Western Australian coastline offshore into the Indian Ocean (refer to Figure 4-1). A review of AIS (Automatic Identification System) vessel track data revealed the region of interest contained shipping routes with high vessel traffic (Australian Maritime Safety Authority, 2013). Search and rescue incident data (National Search and Rescue Council, 2012; 2013) indicated a high density of SAR incidents within this area, possibly due to the high density of vessel traffic. A review of the status of the SVP drifters in the Global Drifter Program (GDP) from NOAA (National Oceanic and Atmospheric Administration) during 2012 indicated that there were a sufficient number of drifters throughout the domain to conduct the study. Figure 1 shows the study domain (light grey shaded area), the SVP drifter tracks used for the study (thick black lines represent the 5-day tracks from the 1st to the 5th of each month and dark grey lines represent the 5-day tracks from the 6th to the 10th of each month), and other SVP drifter tracks within the area (thin light grey lines), some with and some without drogues attached. Note that not all of the other SVP drifters within the study domain (indicated by thin grey lines) had their drogues still attached; many of the drifters in the region were missing their drogues and hence were deemed not suitable to be used for the present study.
4.2.2 SVP Drifter Details

Drifters from the Global Drifter Program (GDP), previously known as the Surface Velocity Program, have been measuring the upper ocean circulation since the first deployments of modern holey sock drogues in 1979 (Lumpkin & Pazos, 2007). SVP drifters have been used extensively worldwide as a means to measure the physical properties of the surface layer of the ocean, including temperature, current velocity and later barometric pressure at sea level.

The quality controlled kriged SVP drifter data for January to September 2012 was collected from the online historical and near real time database (National Oceanic and Atmospheric Administration, 2014) run by NOAA’s Atlantic Oceanographic and Meteorological Laboratory (AOML), Physical Oceanography Division (PHOD). The drifter data was available as either near real time raw data (which is temporally disparate and not quality controlled) or historical quality controlled kriged data where...
the drifter positions are temporally and spatially interpolated to regular 6 hour time intervals and associated positions (Lumpkin & Pazos, 2007). The drogue on/off status for each of the drifters within the chosen spatial domain was examined, and only drifters with drogue still attached were used for this study. This ensured that effects of wind (leeway drift) on the drifter were minimised, and ensured that the drifter was moving predominately with the ocean currents, as the study was intended to focus on the ability of the four different ocean current models to replicate the track of the drifters.

Previous work by Niiler, et al., (1995) indicate that SVP drifters with their drogues attached follow the surface currents to within ~1 cm/s (0.01 m/s) in up to 10 m/s winds, in the direction of the wind (downwind). This relates to a leeway speed of approximately 0.1% of the wind speed and a divergence angle of 0° (directly downwind). The low leeway speed indicates the SVP drifters move almost entirely with the ocean currents, and are very minimally influenced by the wind. Studies by Poulain et al. (2009) and Pazan and Niiler (2001) indicate that the leeway of SVP drifters which have lost their drogues (known as SVP-L) is approximately an order of magnitude larger than when the drogues are attached. The increase in leeway is due to the SVP-L drifters having minimal area submerged compared to the area exposed to the wind, resulting in a low drag area ratio (the ratio of the drogue area to the tether and float area), hence why they were excluded in this study which was intended to focus on the movement due to ocean currents.

4.2.3 SARMAP Drift Model

The search and rescue modelling software SARMAP (Applied Science Associates, Inc., 2013; Spaulding, et al., 2006) was utilised in this study as a means to quantify the predictive ability of each of the ocean models through simulating the trajectories of 45 SVP drifter tracks in the Indian Ocean. The SARMAP model has been validated by numerous studies worldwide including Spaulding and Howlett (1996), Spaulding, et al., (2006) Chu and Tsai (2010) and Brushett, et al., (2011) as well as the successful application to numerous operational search and rescue incidents.
SARMAP Model Solution Method

The stochastic particle tracking model within the SARMAP system employs a Monte Carlo solution (Spaulding, et al., 2006; Isaji, et al., 2006) where an ensemble of passive model particles are used to provide a stochastic simulation of the drift and subsequent search area for the search object. The model particle trajectories are simulated through the use of a stochastic particle model, where the position of each of the model particles is a Markov variable. This “zeroth” order Markov model (known as the Markov-0 model) is referred to as the “random walk” model. Higher order Markov models also exist, including the first order (Markov-1) “random flight” model, where the position and velocity are both Markov variables, and second order, Markov-2 model, where the position, velocity and acceleration are all Markov variables. Studies by (Spaulding, et al., 2006) compared the three Markov models, and evaluated the use of the Markov-0 and Markov-1 models to predict the movement of drifters in a coastal environment. It was found that no significant predictive benefit was evident when using Markov-1 compared to Markov-0 hence for computational efficiency the Markov-0 was used.

As is commonplace with many stochastic particle trajectory models (Breivik & Allen, 2008; Spaulding, et al., 2006; Griffa, 1996; Zambianchi & Griffa, 1994), the numerical solution within SARMAP separates the simulated drift of a search object into two key velocity elements. The first velocity element accounts for the drift of the object due to the mean flow field (typically provided by ocean current and wind forecast models). The second velocity element allows for drift due to the turbulent velocity field (sub grid scale turbulent processes which may not be replicated in the ocean current and wind models). Treating these two velocity processes separately enables the model to account for the total displacement of the search object due to the contribution from the large scale circulation, and smaller scale turbulent motion.

Several assumptions were made for the model to remain applicable, and are outlined in relation to the present study as follows:

1) The velocity field is two dimensional – based on the drift of the object at the sea surface, or within the upper surface layer and does not account for any vertical motion.

2) The turbulent velocity field is homogeneous in space and stationary in time – homogeneity and stationarity was assumed for the turbulent velocity field only.
Chapter 4

The mean flow field was indeed allowed to be inhomogeneous and nonstationary. As such, variations in space and time to the mean flow were assumed to be accounted for by the spatially and temporally varying surface currents, provided by the ocean models. This assumption is permissible as the mean flow field is the predominate source of inhomogeneity and nonstationarity in the ocean.

3) The two velocity components (U & V) are independent of each other – there is no spatial correlation between the U and V components of surface current velocity.

Additional assumptions include:

4) The model particles are independent of one another – there is no interaction between the model particles.

5) The model particles are passive – they do not interact with or affect the movement of the currents, they are merely transported by the currents.

6) The scales of the turbulence velocity are infinitesimal compared to the mean flow field.

Due to the velocity components being independent of each other (assumption 3), they may be treated individually, and hence the drift due to each component can be computed separately. The following equation gives the incremental particle displacement ($dx$) in one dimension only ($x$) due to a single velocity component. The second component incremental particle displacement ($dy$) can be solved independently in a similar manner.

\[ dx = U dt + dx' \]

\[ dx' = K^{1/2} dw \]

\[ K = \sigma_u^2 T \]
Where: $dx = \text{Total particle displacement during time increment, } dt$

$dx' = \text{Particle displacement due to turbulent velocity field only}$

$U = \text{The mean flow field } U(x,t) \text{ (with respect to } x \text{ and } t)$

$dw = \text{Random increment from a Gaussian (normal) distribution with zero mean and second order moment (variance) of } 2dt.$

$K = \text{Turbulent dispersion coefficient (m}^2\text{/s)}$

$\sigma_u^2 = \text{Turbulent velocity variance (m}^2\text{/s}^2)$

$T = \text{Turbulent time scale}$

To ensure that the correct turbulent velocity variance is given by: $< (dx'/dt)^2 > = \sigma_u^2$ in Equation 4-2, the turbulent time scale $(T)$ must follow: $T = dt/2$ in Equation 4-3.

Following Equation 4-1, the total displacement $dx$, at the time increment $dt$, for each model particle is given as the sum of the displacement due to the mean flow field $U(dt)$, and the displacement due to the turbulent velocity field $dx'$. The mean flow displacement is given as a deterministic result at time increment $dt$, whilst the displacement due to the random turbulent velocity field is represented as a stochastic process where each of the model particles receive a random impulse from the turbulent velocity field, which is uncorrelated from one time increment to the next. The uncorrelated turbulent velocities between model time increments indicates that each of the model particles do not retain memory of the previous turbulent velocity input at the previous time increment.

In regards to assumption 6) the turbulent time scale $T$, and the time increment $dt$, are much smaller than the temporal variations of the mean flow field $U$, and actual time $t$. Hence the applicability of the model remains true where time is significantly greater than the turbulent time scale $(t >> T)$. 

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The mean squared separation of model particles ($S_x^2$), or dispersion of model particles for the random walk model used herein is given by the following equations:

\[ S_x^2 = \langle (x - \langle x \rangle)^2 \rangle \]

\[ S_x^2 = 2Kt \]

Where:
- $S_x^2$ = the mean squared separation, or dispersion of particles around $\langle x \rangle$
- $x$ = particle displacement (x component)
- $\langle x \rangle$ = the mean particle displacement (x component)
- $t$ = time

From Equation 4-5 it can be seen that the mean squared separation of particles or dispersion of particles $S_x^2$ around $x$ will increase linearly with time, hence the model defined search area (which is based on the spread of model particles) will also increase linearly with time.

Figure 4-2 shows the particle dispersion for an example scenario which was run with no winds or currents ($Udt = 0$), to show the transport of model particles due to the small scale turbulent component only ($dx'$). The scenario was run for 120 hours with 1,000 particles and a horizontal dispersion coefficient of 1,000 m$^2$/s. The analytical solution for particle dispersion ($S^2$), as given by Equation 4-5 (solved for both x and y components) is represented by the hollow red circle. This indicates that the mean (or 50th percentile for circular normal distribution) of all model particles are expected to be contained within the red circle with radius $S = (4Kt)^{1/2}$.

There are several different methods that can be used to solve or approximate the solution to differential equations such as Equation 4-1. The SARMAP model uses the Euler method to solve Eq. 1 for each timestep throughout the model simulation and for each of the model particles individually (1,000 per scenario in the present study) which are then combined into a single ensemble stochastic output.
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Figure 4-2: Schematic showing the SARMAP calculated particle dispersion and resultant search area (light grey convex hull polygon with solid black border). The red circle represents the analytical solution (from Equation 4-5) for the mean squared separation of particles ($S^2$). Note: the results shown were from a trial scenario, where there was no transport due to winds or currents included. Hence dispersion occurred about the release point (red point in the centre) with no net movement away from this location. The scenario was run for 120 hours with 1,000 particles and a horizontal dispersion coefficient of 1,000m$^2$/s.

SARMAP Model Parameters

The SARMAP model includes settings and parameters which may be changed by the user to optimise values to best correspond to a certain study or incident of interest. The key model parameters which were used for the SARMAP drift modelling are described in the following section, and summarised in Table 4-1. To ensure that the most effective model parameters were used for this study, the parameters were selected after a sensitivity testing process (sensitivity testing described in section 4.3.5) which indicated how the model responded to changes in parameters such as model time step, and stochastic ensemble particle numbers.

Maritime SAR cases most commonly extend from less than a day out to several days duration, and in less common cases, sometimes up to several weeks depending on the location and the case. The model simulation time (model duration) of 120 hours (5-
days) was selected as it corresponds within the length of time of most SAR cases. Thus the model simulation time selected ensured that the results and findings of this study were relevant to the majority of SAR incidents (up to 5-days in length).

An initial position error of 0.5 Nm was used to account for uncertainties or errors in the initial location of the drifter for each scenario, where the accuracy of the drifter location was two decimal places of a degree.

The SARMAP model has three user selectable settings to control the horizontal dispersion coefficient employed by the particle trajectory model, and are listed as low (10 m$^2$/s), medium (100 m$^2$/s) and high (1,000 m$^2$/s). Additionally the model may be run with zero horizontal dispersion. When the horizontal dispersion coefficient is set to zero within the model and only a single model particle is used, the result is a deterministic simulation which uses only the ocean currents and the winds (through the object’s leeway) to transport the model particle/s, and does not include the influence of any small scale turbulence (through dispersion or random walk component of drift). The SARMAP drift simulations for each of the 45 SVP drifter tracks were repeated for each of the four ocean models, and each of these simulations was then repeated four times under the different horizontal dispersion coefficient values outlined above (low, medium, high and deterministic), making for 16 replicates for each of the 45 drifter tracks. Hence, the total number of simulations carried out for this study was 720.

The environmental data (ocean currents and winds) used as forcing to the SARMAP model were obtained from global forecast models. Due to the very small influence of the winds on the drogue SVP drifters, all of the model simulations used the same single winds sourced from the Global Forecast System (GFS) model run operationally by NOAA. There were however four different ocean current models which were to be individually compared, and combined into a four model consensus forecast. The four ocean current models used were as follows; BLUElink, Forecasting Ocean Assimilation Model (FOAM), Hybrid Coordinate Ocean Model (HYCOM), and finally the Navy Coastal Ocean Model (NCOM).

A model time step ($\Delta t$) of 10 minutes (600 sec) was used to ensure that accurate forecast trajectories could be produced whilst maintaining computational efficiency. When selecting model time step size, it is important to ensure that the time steps are not too
large that the model particles travel too far and skip grid cells in the environmental data (spatially varying winds and currents) as some of the horizontal variability in the velocity fields will be missed and thus not well replicated in the forecast trajectories. Similar studies involving stochastic particle trajectory models for; predicting the drift of oil slicks on the water surface using an oil spill model (Abascal et al., 2010) and, predicting the drift of SVP drifters using a SAR model (Sayol et al., 2014) both used a model time step of 30 minutes (1,800 sec).

Sensitivity testing was carried out (refer to Section 4.3.5 for details) to determine the optimum particle number in regards to numerical accuracy and computational effort. As a result of this testing, the particle number was set to 1,000 for each model simulation. This is the same particle number as used by (Ullman, et al., 2006) in drifter modelling studies which involved forecasting the trajectories of a number of drifters using stochastic particle trajectory models (both random walk and random flight).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Simulation Time:</td>
<td>120 Hours</td>
</tr>
<tr>
<td>Initial Position Error:</td>
<td>0.5 Nm</td>
</tr>
<tr>
<td>Search Object</td>
<td>SVP</td>
</tr>
<tr>
<td>Leeway Speed</td>
<td>0.1%</td>
</tr>
<tr>
<td>Divergence Angle</td>
<td>0°</td>
</tr>
<tr>
<td>Horizontal Dispersion Coefficient:</td>
<td>1,000, 100, 10 and 0 m²/s</td>
</tr>
<tr>
<td>Wind Forcing:</td>
<td>GFS</td>
</tr>
<tr>
<td>Current Forcing:</td>
<td>BLUElink, FOAM, HYCOM, NCOM</td>
</tr>
<tr>
<td>Model Time Step (dt):</td>
<td>10 Minutes</td>
</tr>
<tr>
<td>Model Output Frequency:</td>
<td>60 Minutes</td>
</tr>
<tr>
<td>Number of Ensemble Particles:</td>
<td>1,000</td>
</tr>
</tbody>
</table>

### 4.2.4 Metocean Models – Environmental Forcing Data
The current velocity (from ocean models) and wind velocity (from an atmospheric model) used as environmental forcing for the SARMAP model was spatially subset from the respective global model output, to cover the domain of the study, and temporally aggregated into a continuous record for the period of the study. BLUElink model currents were obtained from the Australian Bureau of Meteorology (BOM),
FOAM model currents from the UK Met Office, HYCOM model currents from the HYCOM.org consortium, NCOM model currents from the US Navy, and GFS model winds from NOAA.

**BLUElink**

The BLUElink project was a collaboration between several Australian government agencies, including the Bureau of Meteorology (BoM), who currently run the system operationally. As the focus of the BLUElink project was to provide an ocean general circulation model for the waters surrounding Australia, the model has increased resolution (1/10°) in the Australian region (90°E – 180°E, 75°S – 16°N), with coarse resolution (2°) for the rest of the globe. The Ocean Model Analysis and Prediction System (OceanMAPSv2.0) was developed through BLUElink and incorporates several key components, including an ocean circulation model (OFAM), a data assimilation system (BODAS) and a numerical weather prediction system (ACCESS-G). The Ocean Forecasting Australia Model (OFAM) is based on the GFDL Modular Ocean Model version 4. There are 51 z-level vertical layers in the model with the uppermost layer being 5m thick. Atmospheric forcing for the ocean model is provided through the BoM operational global prediction system, ACCESS-G (Australian Community Climate and Earth System Simulator - Global) at 3-hourly intervals (Brassington, et al., 2012).

**FOAM**

The Forecasting Ocean Assimilation Model (FOAM) is a global ocean model based on the NEMO (Nucleus for European Modelling) model and run operationally by the UK Met Office. The ocean currents from FOAMv1 were used throughout this study. An overview of the FOAM model, is given by Storkey (2011) and Blockley, et al., (2013). A validation of the FOAMv1 upgrade is contained within Blockley, et al., (2012) where FOAM model current velocities were compared with in situ current meters, and velocities derived from SVP drifters. The ocean currents are made available on a standard 1/6° (~18.5 km) Mercator grid for dissemination after being interpolated from the 1/4° grid that the system runs on. Fifty z-levels (of varying thickness) are used in the vertical domain, with the uppermost layer being 1m thick. Three hourly atmospheric
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Fluxes are provided to the FOAMv1 model from the Met Office Numerical Weather Prediction (NWP) atmospheric forecast model (Storkey, 2011).

**HYCOM**

The Hybrid Coordinate Ocean Model (HYCOM) is a global ocean circulation model which was developed as part of the Global Ocean Data Assimilation Experiment (GODAE). The horizontal resolution of the HYCOM model is 1/12° globally with a single daily averaged output interval. Three coordinate types are used in the vertical domain: constant depth layers (z-layers) which are used in the mixed layer; isopycnal following layers (ρ-layers) which are used in the open stratified ocean and terrain following layers (σ-layers) used in the shallow coastal waters (Chassignet, et al., 2009). The topmost layer is 1m thick. The Navy Operational Global Atmospheric Prediction System (NOGAPS) atmospheric model provides atmospheric forcing (wind stress, wind speed, heat flux, and precipitation) to the HYCOM model at 3-hourly intervals (Dombrowsky, et al., 2009).

**NCOM**

The US Naval Research Laboratory (NRL) has developed the Navy Coastal Ocean Model (NCOM) since 1998. The global ocean current model has a horizontal resolution of 1/8° and is a combination of the Princeton Ocean Model (POM) and the SZM (sigma Z-level model). A hybrid vertical resolution system is employed, with 19 σ-coordinate layers in the upper 137m (surface layer thickness of 1m) and 21 z-coordinate layers from 137m to 5500m (Barron, et al., 2007). Further details of the NCOM model and vertical coordinate system are covered in (Barron, et al., 2006). Atmospheric forcing for the NCOM model is provided by the NOGAPS atmospheric fluxes at 3-hourly intervals (Barron, et al., 2007).
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Figure 4-3: Surface currents supplied by BLUElink (a), FOAM (b), HYCOM (c) and NCOM for January 5th 2012. The vectors have been filtered to show every fourth vector to improve clarity. The presence of the Leeuwin Current can be seen in all four forecasts flowing southwards along the West Australian Coast. Note the varying density of the current vectors which is indicative of the differing horizontal resolution of the four models.

GFS

The Global Forecasting System (GFS) is a global spectral model operationally run by NOAA (US National Oceanic and Atmospheric Administration). The horizontal resolution of the model output 10 m height winds (U and V components) is 1/2° (approx 55.5 km). The model has a temporal resolution of 6 hours out to 7 days (168 hours). Sixty-four unequally spaced layers (based on a sigma/pressure layer system) are used in the vertical domain (Bi, et al., 2010). Further information in regards to the GFS model including output can be found at (http://www.emc.ncep.noaa.gov/index.php?branch=GFS).

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Table 4-2. Current and wind model parameters (adapted from Brushett et al., 2011).

<table>
<thead>
<tr>
<th>Model</th>
<th>Horizontal Resolution</th>
<th>Vertical Coordinate</th>
<th>Temporal Resolution</th>
<th>Grid Limits [Higher Resolution]</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUElink</td>
<td>1/10° (11.1 km)</td>
<td>47 z levels</td>
<td>24 hr</td>
<td>Global [16°N - 75°S, 90°E - 180°E]</td>
</tr>
<tr>
<td>FOAM</td>
<td>1/6° (18.5 km)</td>
<td>50 z levels</td>
<td>24 hr</td>
<td>Global [0°N - 60°S, 100°E - 77°W]</td>
</tr>
<tr>
<td>HYCOM</td>
<td>1/12° (9.3 km)</td>
<td>32 Isopycnal/σz</td>
<td>24 hr</td>
<td>Global</td>
</tr>
<tr>
<td>NCOM</td>
<td>1/8° (13.9 km)</td>
<td>40 σ/z level</td>
<td>6 hr</td>
<td>Global</td>
</tr>
<tr>
<td>GFS</td>
<td>1/2° (55.6 km)</td>
<td>64 σ levels</td>
<td>6 hr</td>
<td>Global</td>
</tr>
</tbody>
</table>

Where: z represents fixed depth layers, σ represents terrain following depth layers

4.3 Modelling Procedure

The various components of the procedure undertaken to complete the modelling are outlined in the following sections. Included are an overview of the process carried out for the drift forecast modelling (4.3.1) followed by details of the consensus forecasting approach (4.3.2), calculation of the search areas (4.3.3), error analysis (4.3.4) and finally sensitivity testing of the SAR drift model to the model settings (4.3.5).

4.3.1 Overview of Modelling Process

Four separate experiments were undertaken to assess the effects of the horizontal dispersion parameter upon each of the 45 drifter forecasts (for each of the four ocean models) in terms of the modelled search area size, hit rate, and average model particle distance error. The experiments utilised the three fixed horizontal dispersion parameters within SARMAP (identified in the model as high, medium and low uncertainty) in addition to an experiment which provided a deterministic solution with zero dispersion and no random walk component to the modelled drift. The horizontal dispersion values used in each of the four experiments are identified in Table 4-3.
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Table 4-3. SARMAP Experiment number and associated horizontal dispersion coefficient used in the modelling

<table>
<thead>
<tr>
<th>Experiment #</th>
<th>SARMAP uncertainty level</th>
<th>Horizontal Dispersion Coefficient ($K$) [m$^2$/s]</th>
<th>Number of Model Particles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1</td>
<td>High</td>
<td>1,000</td>
<td>1,000</td>
</tr>
<tr>
<td>Experiment 2</td>
<td>Medium</td>
<td>100</td>
<td>1,000</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>Low</td>
<td>10</td>
<td>1,000</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>n/a</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Experiment 4 (one single deterministic model particle with no horizontal diffusion or random walk component) was carried out to test how effective the forecast current models were at replicating the drifter tracks, without the inclusion of transport due to sub grid scale horizontal turbulence. This experiment also provided an opportunity to compare the difference of the minimum distance error for the single deterministic model particle and the mean of the minimum distance from the 1,000 particle ensemble predictions. The minimum distance from the single deterministic model particle to the actual drifter location is also referred to as the ‘off mark distance’ by Spaulding, et al., (2006).

The modelling process involved downloading the environmental forcing data (four ocean current models and one wind model) for the whole study domain and for the period of interest (January 2012 to October 2012 inclusive). Next, the quality controlled kriged drifter data was downloaded for the study domain from the NOAA drifter website, and the location of the drifters for the first 5 days (1$^{st}$ to the 5$^{th}$) and second 5 days (6$^{th}$ to the 10$^{th}$) of each month was extracted. The drifter IDs were cross checked with the drifter status database, to ensure that only drifters with the drogue still attached were used in this study. Any drifter which was identified to have lost its drogue was discarded. This process was undertaken to maintain uniformity between each individual drifter (keep the same leeway) and to ensure that wind effects on the drifter movement were kept to a minimum. Ensuring the wind effects were minimal to non-existent ensured that the performance of the ocean current models could be isolated and assessed without the added complication of assessing wind effects as well. A total of 45 drifter tracks were identified to comply with the prerequisites outlined above. For each of the four experiments, each drifter track simulation was set up to run from the actual drifter’s start location (on either the 1$^{st}$ or 6$^{th}$ of each month at 00:00) for a period of 120 hours,
utilising the GFS winds and each of the ocean current models individually as environmental forcing, and the horizontal dispersion parameter identified in Table 4-3. Thus for each of the four experiments there were a total of 180 drifter simulations, which summed to 720 drifter simulations in total across all four experiments.

4.3.2 Consensus Forecasting

Operational support for oil and maritime pollutant spill forecasting has successfully undertaken preliminary consensus forecasting approaches for predicting the trajectories and fates of maritime spills in both coastal and offshore waters (Brushett, et al., 2011; King, et al., 2011; King, et al., 2010). When several different meteorologic or ocean models are available for a given region of interest, each meteorological/ocean model can be used as input into stochastic particle trajectory models to build an ensemble of trajectory forecasts, each based on different input data from an environmental forecast model. This process allows a comparison between each of the ocean models to be undertaken, to investigate if/when two or more of the ocean model predictions are in agreement. If two or more of the ensemble of forecasts are in concurrence (or consensus), the user may have a greater confidence that the predicted outcome may be more accurate than the other presented alternative outcomes from the trajectory forecasts. The consensus principle is applied in this study to search and rescue forecasting and is analogous to a study of atmospheric consensus modelling whereby Fritsch, et al. (2000) states that “Using ‘consensus’ as the basis for a decision emanates from the notion that the cumulative knowledge of all concerned individuals is greater than that of a single individual”. When utilising consensus forecasting it is important for the user to also consider the other remaining outcomes (those outcomes not forming part of the consensus) as possible outcomes, but potentially of a lower probability or confidence. Consensus forecasting suggests that it may be possible to give more weight to those outcomes which are in agreement and form part of the consensus, and less weight given to those outcomes which do not form part of the consensus.

An example ensemble forecast built by using the inputs from the four ocean models (BLUElink, FOAM, HYCOM and NCOM) is shown in Figure 4-4 at the end of a 120 hour SARMAP simulation using a dispersion coefficient of 1,000 m²/s. The drifter track is shown as the black line, with white indicators every 24 hours. The movement of the
drifter in this case was from the south towards the north. The consensus search areas are indicated by the grey shaded regions, which increase in intensity where more ocean model forecast search areas coincide or overlap. As shown, at 120 hours the drifter is located within the northern extent of the 4 model consensus area, close to the border with the 3+ model consensus area. It can be seen that the 4 model consensus area is considerably smaller in area than the combination of all four search areas, and significantly smaller than any of the individual search areas.

The same scenario is shown in Figure 4-5 for the four experiments as outlined in Table 4-3, which included horizontal dispersion parameters of 1,000 m$^2$/s, 100 m$^2$/s, and 10 m$^2$/s as well as a deterministic forecast with no horizontal dispersion. Each of the figures show forecast search areas for the four experiments using each independent ocean model, (a) BLUElink, (b) FOAM, (c) HYCOM and (d) NCOM. Each concentric search polygon in the figures show the same search solution with a different horizontal dispersion coefficient (10 m$^2$/s being the smallest dark shaded polygon and 1,000 being the largest lighter shaded polygon). The drifter track is indicated by the thick/solid black line with white circle markers for each 24 hour interval. The thin black line indicates the track for the deterministic forecast which does not include horizontal dispersion.

As is indicated in these results, all of the ocean models contained the drifter within the search area at 120 hours when the horizontal dispersion coefficient of 1,000 m$^2$/s was used, however only HYCOM contained the drifter within its search area when a horizontal dispersion of 100 m$^2$/s was used, and none of the ocean model predicted search areas contained the drifter with the lowest horizontal dispersion of 10 m$^2$/s. This highlights the need for adequate horizontal dispersion within the search model to ensure the search object is contained within the search areas. This is of course balanced by the need to adequately search these areas, which may be prohibitive with available search assets should the areas be expanded too far.
Figure 4-4: Map showing the predicted search areas at the end of the simulation for a 5-day drift path during January (drifter ID 10057120) in the Indian Ocean using currents from BLUElink, FOAM, HYCOM and NCOM ocean models as input into SARMAP to generate the individual search areas. This result was generated using a horizontal dispersion coefficient of 1,000 m²/s. The drifter moved from the south towards the north as time progressed as indicated by the time labels. Consensus search areas are shown by the overlapping shaded grey regions. These shaded regions increase in darkness with the increasing number of coinciding individual search areas. As indicated in the figure, the drifter is located within the northern extent of the darkest region being the defined 4 model consensus search area which is significantly smaller than any of the individual search areas.
Figure 4-5: Map showing individual search areas and track lines for forecasts using (a) BLUElink, (b) FOAM, (c) HYCOM and (d) NCOM ocean models. Each concentric search polygon represents a different horizontal dispersion coefficient from 1,000 m$^2$/s, 100 m$^2$/s, and 10 m$^2$/s. (10 m$^2$/s being the smallest dark shaded polygon and 1,000 m$^2$/s being the largest lighter shaded polygon). The actual drifter track is indicated by the thick/solid black line with white circle markers for each 24 hour interval. The thin black line indicates the track for no dispersion (deterministic forecast) which is similar to the mean position of model particles for experiments 1, 2 and 3.
4.3.3 Search Area Calculation

The search area from each of the SARMAP forecasts was determined by the convex hull (polygon) that completely enclosed all of the 1,000 ensemble model particle locations. Several other studies, including Melsom, et al., (2012) and Breivik & Allen (2008) have successfully employed the convex hull approach to define search areas in stochastic particle tracking models for drift applications. Figure 4-2 shows a sample convex hull search area as generated by the SARMAP model. Visible are the 1,000 model particles indicated by the small circles and the predicted search area, represented as the grey shaded convex hull, bound by the solid black line.

A schematic of how the consensus search areas are defined is shown in Figure 4-6. Case 1 (a) indicates an idealised case where all four model forecast areas (represented by the four different coloured circle outlines) overlap. The number of coinciding model forecast areas is indicated by the numbers within the overlap regions and the increasing shading indicates a greater number of coinciding model areas (increasing consensus). Hence the individual model forecast areas are simply defined as the area of their respective coloured circles. The combined search area (b) is the combined area from all four models. The 2+ model consensus search area (c) is defined as the sum of the areas where two, three and four model areas coincide. Likewise the 3+ model consensus search area (d) is defined as the sum of the areas where three or four model areas coincide, and finally the 4 model consensus area (e) is defined as only the area where all four model areas coincide.

The combined search area is always larger than each of the individual model areas, but cannot be larger than the sum of all four model areas combined (due to any overlaps). The 3+ and 4 model consensus areas are always smaller than each of the individual areas that contribute to the model consensus areas. The 2+ model consensus search area can result in a special case, where two separate, 2 model areas form (f) and the total 2+ search area can sum to an area greater than the individual model areas which form part of the consensus.
Figure 4-6: Schematic to describe the consensus search area definitions. Case 1 indicates an idealised case where all four model areas (represented by the four different coloured circle outlines) overlap. Number of coinciding models is indicated by the numbers and increasing intensity shading. Case 2 indicates the special case which may permit the 2+ model consensus search area to become larger than any of the individual search areas contributing to generating that consensus.

4.3.4 Error Analysis

Three statistical measures were trialled in this study to determine the effectiveness of each of the four ocean models when used to predict drifter trajectories. The same error analysis was undertaken also for each of the individual dispersion coefficient experiments. The error analyses included; 1) the mean absolute error (MAE) in distance between model particles and the actual drifter location; 2) a non-parametric hit rate to determine how frequently the drifter was contained within the model defined search area; and 3) a drift length comparison to determine whether the modelled drift lengths tended to over or under predict the length the actual drifter travelled. The following sections outline the various assumptions and processes that were applied when calculating the error analyses.
**MAE**

An error analysis was carried out for each of the 720 drifter simulations to quantify the spatial discrepancies between the model predicted drifter positions and the actual (measured) drifter position. At a given time interval, the distance errors between each of the 1,000 model particles and the actual drifter were computed, and then the minimum and the average of these distances was recorded. The mean absolute error (MAE) was then calculated from the minimum and mean distance errors for each drifter at 12, 24, 48, 72 and 120 hour intervals, for each of the four ocean model simulations, and for each of the four independent experiments. The formula used for calculating the MAE is shown in Equation 4-6 below.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |f_i - m_i|$$

Equation 4-6

Where:  
$f_i$ = ensemble mean (or minimum) model forecast drifter position  
$m_i$ = measured drifter position  
$n$ = number of drifter simulations

The MAE is a valid descriptor for use in modelling drifter track scenarios as it gives the displacement of the predicted versus the observed location as an absolute value, which is a potentially valuable indicator of how effective the model results compare to the actual results. The error distance herein was quantified to always be positive as well as, independent of directionality.

**Hit Rate**

To quantify how often the drifter (search object) was located within the model defined search area, a non parametric hit rate was used. The hit rate method for model verification has been applied successfully to several previous drifter trajectory modelling studies including Bernstein (2009) and Melsom, et al., (2012). The hit rate analysis indicates the frequency that the drifter was located in the search area at predefined intervals (12, 24, 48, 72 and 120 hours), and thus gave an indication of the
effectiveness of the model formulated search areas in containing the drifter. The hit rate was calculated as the number of drifter scenarios which returned a hit, divided by the total number of drifter scenarios (i.e. $38/45 = 0.84$), and may be expressed either as a decimal fraction or a percentage (i.e. 84%) as was applied herein.

**Drift length**
An analysis of the drift length at 120 hours was undertaken to determine whether each of the four ocean models had a tendency to over drift or under drift compared to the actual drifter length. This gave an indication of the current strengths provided by the ocean models compared to those experienced by the drifter. To ensure that the analysis directly compared the transport given by the ocean models, the drift length analysis was carried out for the model results from experiment 4, which contained only a single model particle and no horizontal dispersion (referred to as the deterministic result). By analysing the deterministic result, the transport of the model particle was only influenced by the mean flow velocities (ocean model currents) with no effect from turbulent velocities (from random walk dispersion).

Two measures were selected to analyse the drift lengths. The first was a count to determine the number of scenarios which resulted in an over drift or under drift. This was completed by comparing how many scenarios resulted in a longer drift length and how many resulted in a shorter drift length than that of the actual drifter for each of the 45 drifter scenarios. These results were then divided through by the total number of scenarios to give a percentage of over or under drifts for each ocean model.

The second analysis was undertaken to determine the average length of drift for the model simulated drifts (for each ocean model) and compared to the average length of the actual drifters. This gave an indication of the average magnitude that the ocean models may be over or under representing the current speeds. It should be noted that the drift lengths analysed within this section do not take into consideration the direction of the drift, only the magnitude of the drift at 120 hours.
4.3.5 Model Sensitivity Testing

Sensitivity testing was carried out to determine how the number of particles used in the Monte Carlo solution compared with the analytical solution for horizontal dispersion. Further tests were carried out to examine how changing the dispersion parameter \((K)\) may affect the search area size over time.

**Number of Model Particles**

To determine the sensitivity of the SARMAP model to the number of model particles, a test was undertaken whereby a sample scenario was re-run 10 times, whilst keeping all parameters the same, but varying the number of model particles each time the scenario was re-run. A scenario was set up which contained a horizontal dispersion coefficient of \(10\, \text{m}^2/\text{s}\), was run for a period of 120 hours, with a 10 minute model time step, and did not include winds or currents (to remove the net transport variable). Ten different particle numbers were tested, which included; 10, 50, 100, 500, 1,000, 2,000, 5,000, 10,000, 20,000 and 30,000. To give an indication of the dispersion, or mean squared separation of model particles \((S^2)\), the average particle distance from the origin was calculated for each of the model particles at intervals throughout each scenario. This was then compared to the analytical solution (from Equation 4-5) for dispersion. The results indicated that as the number of model particles increased, the error when comparing \(S^2\) to the analytical solution decreased. It was found that a model particle count of 1,000 returned an \(S^2\) value within 5% of the analytical solution, throughout the 120 hour scenario duration. This was deemed to be an acceptable margin, particularly when considering computational efficiency.

**Dispersion Parameter \((K)\)**

Testing was carried out to determine how varying the dispersion coefficient changed the SARMAP model defined search area size (convex hull containing all 1,000 model particles). The base scenario was set up with the same parameters as outlined above, however the particle number was fixed at 1,000 and the dispersion parameter was varied between each of the model runs. Dispersion values of 1, 10, 50, 100, 250, 500, 750 and 1,000 \(\text{m}^2/\text{s}\) were tested. The results indicated that when no winds or currents were
included (particles moved due to turbulent dispersion only) the search area size increased linearly over time. Additionally, a linear increase in search area size was observed with an increase in the horizontal dispersion coefficient.

4.4 Results and Discussion

The results of the four experiments are presented and discussed in the following three sub sections, including the mean absolute error (4.4.1), the hit rate and search area size (4.4.2) and the drift length analysis (4.4.3).

4.4.1 Mean Absolute Error (MAE)

The MAE was calculated for each of the four ocean model simulations for the minimum distance errors and the average distance errors when compared to the actual drifter location. Figure 4-7 contains the MAE graphs for each of the four experiments. The graphs on the left (a, c and e) show the minimum distance MAE for experiments 1 to 3 respectively, whilst those on the right (b, d and f) indicate the average distance MAE, again for experiments 1 to 3. The lower central graph shows the MAE for the deterministic solution provide by experiment 4, which contained a single model particle, and hence no average or minimum distance error could be calculated, only the absolute error from the single model particle.

A comparison of the minimum and average distance MAE graphs reveals that the MAE (calculated for each ocean model) in experiment 4 was closer to the average distance MAE calculated in experiments 1 to 3, when compared to the minimum distance MAE calculated in experiments 1 to 3. This result was anticipated, as the single particle deterministic solution should theoretically be very close to average or centre of the 1,000 particle ensemble solutions. The MAE graphs indicate that the minimum distance MAE was considerably smaller – for each ocean model, across each experiment, and throughout the 120 hour scenario duration – when compared with the corresponding average distance MAE.
Upon comparison of the minimum distance error for experiments 1 to 3, it was observed that the error values increased as the horizontal dispersion coefficient decreased. This can be explained by the reduced spread of model particles for the lower horizontal dispersion values, which meant that there was potentially less likelihood of an individual model particle being closer to the actual drifter location, when compared to the larger spread of model particles with the higher dispersion values. The reverse was observed for the average distance MAE, where the average distance MAE was shown to slightly increase, with an increase in the horizontal dispersion coefficient, potentially due to particles being able to disperse further away from the mean drifter location.

When the horizontal dispersion was decreased to 10 m$^2$/s (experiment 3), the minimum distance error was shown to be similar in magnitude (only slightly less) compared to the corresponding average distance error. This shows that the smaller, less dispersed cluster of model particles that occurs with a lower horizontal dispersion coefficient behaves more like a single entity. The MAE graphs also revealed that the lower the value used for the horizontal dispersion coefficient, the closer the model results converge on the single particle deterministic solution (experiment 4), where the random walk component of the drift becomes less evident in the model solution.

The three ocean models FOAM, HYCOM and NCOM all displayed a similar average distance MAE (between approximately 27 and 28 km) at the 24 hour interval for experiment 1 (as indicated in Figure 4-7b). The average distance MAE for BLUElink at 24 hours for experiment 1 was substantially higher (37.8km) than the other three models, indicating that the three other models performed better. At 120 hours, the better performing ocean model in terms of the lowest average distance MAE for experiment 1 was NCOM (90.0 km), closely followed by FOAM (90.4 km). The second highest average distance MAE at 120 hours was given by HYCOM (101 km) and the highest was BLUElink at 109 km. The average distance MAE results for the remaining experiments (2, 3, and 4) all followed the same trend as outlined above for experiment 1, with slightly reduced values. A comparison of the average distance MAE (for a single model) was made between experiments 2, 3 and 4 and the differences were minimal (within 2 km of each other).
Experiment 1 – 1,000 m$^2$/s Dispersion

Experiment 2 – 100 m$^2$/s Dispersion

Experiment 3 – 10 m$^2$/s Dispersion

Experiment 4 – No Dispersion – Deterministic Solution

Figure 4-7: MAE calculated for each of the four ocean models, for the 45 5-day trajectories. Shown are results for each of the four experiments. Left panes show the minimum distance MAE, whilst the right panes show the average distance MAE.
4.4.2 Hit Rate and Search Area Size

The hit rate and search area size for experiments 1, 2 and 3, at 24 and 120 hours are shown in Table 4-4. Results include each of the individual ocean model forecasts (BLUElink, FOAM, HYCOM and NCOM) as well as the consensus forecasts (2+, 3+ and 4). Note there was no hit rate or search area size given for experiment 4, as it contained only a single particle and zero dispersion, hence no actual search area was computed, only a single deterministic track line.

The individual model hit rates at 24 hours in experiment 1 showed that HYCOM produced the highest single model hit rate at 93.3%, with a corresponding average search area size of 4,936 km$^2$ which was the smallest of any single model’s average search areas. This indicates that, on average, HYCOM had the most efficient search area (in terms of hit rate per search area size) compared to the other three ocean models at 24 hours. The highest overall hit rate (95.6%) of both single model and consensus forecasts was returned by the 2+ model consensus area (5,880 km$^2$), which was larger than each of the individual model average search areas. This result is indicative of cases where a number of separate 2+ search areas occurred which sum to a greater value than the individual areas (refer to Figure 4-6 (b) for visual explanation). The 3+ model consensus search area returned an overall hit rate at 24 hours for experiment 1 of 86.7%, with a corresponding average search area of 4,188 km$^2$. This search area was smaller than any of the other single model forecast average search areas, whilst maintaining an overall hit rate greater than two of the other individual models, thus demonstrating a potential benefit in using the 3+ consensus area. The 4 model consensus area returned an overall hit rate of 68.9% at 24 hours, with a corresponding search area of 2,400 km$^2$. This result shows a reduction in overall hit rate of approximately 26% compared to the highest hit rate of a single model, however the corresponding search area decreased by approximately 56%. This indicates that the 4 model consensus search area is more efficient than any of the single ocean model forecasts in terms of hits per search area size.

Both NCOM and FOAM demonstrated the highest single model hit rate at 120 hours (80%). Coincidentally both NCOM and FOAM also displayed the smallest average search area size returning areas of 31,541 km$^2$ and 32,491 km$^2$ respectively. The 2+ model consensus search areas demonstrated the highest overall hit rate (88.9%) of all
the single model and consensus determined search areas, likewise it also returned the highest average search area (38,083 km$^2$) which again indicates the formation of multiple 2+ search areas which sum to a greater size than the individual search areas. The 3+ model consensus area returned a hit rate greater than two of the single models (73.3%), however the size of the search area (23,803 km$^2$) was considerably smaller than any of the single model search areas. Finally, the 4 model consensus search area returned a hit rate of 37.8%, which was the lowest of all the single model or consensus forecasts, and represents a decrease in hit rate of approximately 53% compared to the highest single model hit rate. However the search area size was also substantially smaller than all other search areas (10,174 km$^2$), which represents a 70.3% reduction in search area size compared to the average single model search area at 120 hours.

The results in Table 4-4 show that both the hit rates and the average model search areas for experiment 2 were considerably lower than those shown in experiment 1, which was due to the lower horizontal dispersion coefficient reducing the spread of model particles and thus reducing the search area sizes. The average single model hit rate and search area at 24 hours for experiment 2 was 23.9% and 577 km$^2$ respectively, compared to experiment 1 results of 87.8% and 5,335 km$^2$. The same trend was evident at 120 hours, with average single model hit rates and search areas for experiment 2 of 11.7% and 3,812 km$^2$ respectively, compared to 73.9% and 34,236 km$^2$ for experiment 1. All of the model consensus areas at both 24 and 120 hours were shown to be smaller than any of the individual model search areas for experiment 2. The overall hit rate for the 2+ model consensus search area at 24 hours was greater than two of the single model hit rates, and at 120 hours greater than one of the single model hit rates. The 3+ and 4 model consensus areas at both 24 and 120 hours returned lower overall hit rates than the single models, however their corresponding search areas were very small, which provided little opportunity to contain the drifter.

The single model hit rates at both 24 and 120 hours for experiment 3 were very low, with averages of 5.6% and 2.2% respectively. This was attributed to the small search areas, on average 65 km$^2$ at 24 hours and 410 km$^2$ at 120 hours. The hit rate for consensus forecasts was zero for all except the 2+ model consensus at 24 hours showing a low 2.2%. As a result of the small search areas generated for experiment 3, the instances where more than one model forecast overlapped to generate the consensus
areas was very low, and hence consensus was infrequently achieved. The results indicate that under the circumstances outlined in the present study, the horizontal dispersion parameter used in experiment 3 is too low to generate search areas which are able to adequately contain a search object over the timeframes investigated herein.

As consensus may not be achieved in all scenarios, it was determined that a conditional hit rate should be defined to give a true indication of the performance of the consensus forecast areas. Should the overall hit rates be calculated for the consensus areas based on the assumption that consensus occurred for every forecast; the results would underestimate the performance of the consensus forecast areas. This is due to the calculation for overall hit rate being processed for all scenarios (45 in this case) where consensus may only be achieved (for example) in 30 out of those 45 scenarios.

Both methods of calculating hit rate are useful, but provide different information. The overall hit rate allows a direct comparison to be made between the consensus forecasts and the single model forecasts as both are calculated from the same number of scenarios. This gives the forecaster an indication of the expected result from either a consensus forecast or single model forecast, given a scenario where it is unknown if consensus may or not actually occur. This differs to the conditional hit rate, which is useful to the forecaster if they have an actual scenario where consensus is achieved, and then a more accurate expected hit rate can be obtained from the conditional hit rate based on the knowledge of consensus being present.

The results for the two methods (both overall hit rate and conditional hit rate) were calculated and are presented in Table 4-4. The conditional hit rates are indicated by the results within parentheses, with (--) denoting no change compared to the overall hit rate.

The hit rate analyses show there was no difference when comparing the two methods in experiment 1, which indicates that consensus was achieved in all of the 45 scenarios. This may be due in part to the high dispersion parameter, and hence larger resultant search areas generated in experiment 1 allowing a greater opportunity for consensus overlap regions to occur.

Some increases in the conditional hit rate compared to the overall hit rate were shown in experiment 2. These increases occurred for the 3+ and 4 model consensus areas (2+ model consensus remained unchanged) at 24 hours and the 2+ and 3+ model consensus
areas at 120 hours (4 model consensus remained unchanged). The increases were relatively small, except for the 4 model consensus at 24 hours, which increased from an overall hit rate of 6.7% to a conditional hit rate of 25%. This indicates that whilst the 4 model consensus did not occur frequently (12 out of 45 scenarios, or 26.7%), when it does occur there is a 25% probability that the drifter would be found within the four model overlap area.

A comparison of the overall and conditional hit rates for experiment 3 revealed the only difference evident was an increase in the conditional hit rate for the 2+ consensus area at 24 hours. There were no changes to the hit rates for 3+ or 4 model consensus at 24 hours or 2+, 3+ and 4 model consensus at 120 hours as they were all zero. The reason that there were zero hits within the consensus areas for experiment 3 (except 2+ at 24 hrs) was due to the very low dispersion coefficient (10 m²/s) being used in experiment 3, creating small search areas and hence little opportunity for overlap regions to occur. Additionally, the search area statistics show that there were no 4 model consensus areas for experiment 3, and the average 3+ model search area was very low (4 km²).
Table 4-4. Results showing hit rate and average search area for each of the ocean models and the consensus forecasts. Experiment 1 (High dispersion) shown at top, Experiment 2 (Medium dispersion) shown in middle and Experiment 3 (Low dispersion shown at bottom). Note: hit rates in parentheses indicate the conditional hit rate – where the hit rate for consensus was calculated only for the number of times that the consensus condition was met. No change from overall hit rate compared to conditional hit rate is indicated by (--).

<table>
<thead>
<tr>
<th></th>
<th>24 hours</th>
<th>120 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hit Rate</td>
<td>Search Area (km²)</td>
</tr>
<tr>
<td><strong>Experiment 1 – High Dispersion (1,000 m²/s)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BLUElink</td>
<td>84.4%</td>
<td>5,568</td>
</tr>
<tr>
<td>FOAM</td>
<td>88.9%</td>
<td>5,396</td>
</tr>
<tr>
<td>HYCOM</td>
<td>93.3%</td>
<td>4,936</td>
</tr>
<tr>
<td>NCOM</td>
<td>84.4%</td>
<td>5,439</td>
</tr>
<tr>
<td>2+ Cons</td>
<td>95.6%</td>
<td>5,880</td>
</tr>
<tr>
<td>3+ Cons</td>
<td>86.7%</td>
<td>4,188</td>
</tr>
<tr>
<td>4 Cons</td>
<td>68.9%</td>
<td>2,400</td>
</tr>
<tr>
<td><strong>Experiment 2 – Medium Dispersion (100 m²/s)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BLUElink</td>
<td>13.3%</td>
<td>594</td>
</tr>
<tr>
<td>FOAM</td>
<td>33.3%</td>
<td>578</td>
</tr>
<tr>
<td>HYCOM</td>
<td>22.2%</td>
<td>542</td>
</tr>
<tr>
<td>NCOM</td>
<td>26.7%</td>
<td>593</td>
</tr>
<tr>
<td>2+ Cons</td>
<td>20.0%</td>
<td>488</td>
</tr>
<tr>
<td>3+ Cons</td>
<td>8.9% (10.5%)</td>
<td>157</td>
</tr>
<tr>
<td>4 Cons</td>
<td>6.7% (25.0%)</td>
<td>71</td>
</tr>
<tr>
<td><strong>Experiment 3 – Low Dispersion (10 m²/s)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BLUElink</td>
<td>2.2%</td>
<td>68</td>
</tr>
<tr>
<td>FOAM</td>
<td>6.7%</td>
<td>63</td>
</tr>
<tr>
<td>HYCOM</td>
<td>2.2%</td>
<td>65</td>
</tr>
<tr>
<td>NCOM</td>
<td>11.1%</td>
<td>64</td>
</tr>
<tr>
<td>2+ Cons</td>
<td>2.2% (5.9%)</td>
<td>30</td>
</tr>
<tr>
<td>3+ Cons</td>
<td>0.0% (--)</td>
<td>4</td>
</tr>
<tr>
<td>4 Cons</td>
<td>0.0% (--)</td>
<td>0</td>
</tr>
</tbody>
</table>
4.4.3 Drift Length Analysis

The results of the two drift length analyses at 120 hours are outlined in Table 4-5, which includes the number of scenarios which over predicted and under predicted the drift length, compared to the actual drifters, and carried out for the SARMAP simulations using each of the four ocean models. Additionally shown is the average drift length of the SVP drifters over the 45 scenarios, and a comparison to the average drift length as predicted by each of the four ocean models.

In the analysis of the number of scenarios over/under drifted (refer to Table 4-5), it was found that BLUElink had an almost even count of over/under drifts returning a result of 53% over and 47% under drifts. The other three models FOAM, HYCOM and NCOM all returned a higher number of under drifts (76%, 64% and 84% respectively) compared to over drifts.

In terms of drift length over all 45 measured drift tracks, the SVP drifters travelled an average length of 134.7 km at 120 hours (or 26.94 km/day). The BLUElink model was the only one of the four ocean models which returned an average drift length at 120 hours greater than the average of the actual SVP drift length, with an average drift length of 144.3 km. The other three ocean models were shown to under predict the average drift length on average, with HYCOM showing an average drift length of 116 km, FOAM – 91.4 km and finally NCOM with the shortest average drift length of 84.2 km.

The results demonstrate that the BLUElink model overall had a higher tendency to over predict the drift lengths, which indicates that the BLUElink model may have been over representing the current speeds in this region. The reverse is true for the other three models, which were shown to have a higher tendency to under predict the drift lengths. This indicates that the FOAM, HYCOM and NCOM predicted current speeds were weaker than those actually experienced by the drifters in the region.

Histograms that include the frequency distribution of the drift length differences between the predicted drift length and the actual drift lengths for each of the ocean models for the 45 drift scenarios are shown in Figure 4-8, in addition to the cumulative frequency distribution. Bins of 25 km were used to generate the plots. The HYCOM results tend to show the closest to a normal distribution with an almost symmetrical
distribution about zero. FOAM and NCOM both appear to be skewed towards the negative (indicative of under drifting) whilst the BLUElink result is skewed towards the positive (indicative of over drifting).

### Table 4-5. Results of drift length analysis at 120 hours for the SARMAP modelled average length using each of the four ocean models, and comparison to the average length the actual drifter travelled at 120 hours. The forecasts used the deterministic solution, where no horizontal dispersion or random walk contributions to trajectory were included. Also shown are the number and percentage of scenarios which over drifted or under drifted, compared to the actual drifter for the 45 scenarios.

<table>
<thead>
<tr>
<th>120 hours</th>
<th>Number of Scenarios [%]</th>
<th>Length (km) [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Over Drift</td>
<td>Under Drift</td>
</tr>
<tr>
<td>SVP Drifter</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>BLUElink</td>
<td>24 [53%]</td>
<td>21 [47%]</td>
</tr>
<tr>
<td>FOAM</td>
<td>11 [24%]</td>
<td>34 [76%]</td>
</tr>
<tr>
<td>HYCOM</td>
<td>16 [36%]</td>
<td>29 [64%]</td>
</tr>
<tr>
<td>NCOM</td>
<td>7 [16%]</td>
<td>38 [84%]</td>
</tr>
</tbody>
</table>

Figure 4-8: Histograms showing the frequency distribution of drift length (km) differences for each of the ocean models (a) BLUElink, (b) FOAM, (c) HYCOM and (d) NCOM. Negative values indicate the model simulation under predicted the drift length of the actual drifter, whilst positive values indicate the forecast over predicted the drift length. Also shown are the cumulative frequencies of the differences.
4.5 Conclusions and Recommendations

This study examined forecasting search areas for 45 five-day SVP drifter tracks, each simulated independently using a different ocean model (BLUElink, FOAM, HYCOM and NCOM) throughout 2012 in the eastern Indian Ocean, off the coast of Western Australia. Thus a significant sample set was created which also enabled the inclusion of trialling consensus forecasting to quantify areas of higher probability within an ensemble of model defined search areas. Specifically the error analysis for simulations using the high horizontal dispersion coefficient indicated that the HYCOM model was the best performing single model at 24 hours in terms of Average Distance MAE, hit rate, and search area size, but this performance was not maintained over the longer duration of 120 hours. Indeed different ocean models performed better at different times, and using the highest uncertainty parameter, all were suitable for the purpose. However, this result in itself highlighted the importance of using a consensus forecasting approach, as it can be difficult to determine in advance, which is the best performing single ocean model at any given time. Thus, having an ensemble of ocean models available for consensus forecasting allows the forecaster to encompass an array of possible outcomes based on each of the model forecasts. As is routine in many SAR incidents, the deployment of SLDMB drifters at the last known position is vital to ground truth the ocean currents in the region at the incident time, and allows testing to be undertaken to ascertain which single model (or indeed ensemble of models) may perform best on that particular day in that region. This practice must continue to take place to ensure the most reliable model is being used in these situations.

The results for the consensus forecast areas also show potential for application to search area prioritisation, where some areas within a total search area may be given preference over other areas, should there be limited availability of search assets and resources. The results with the use of 1,000 m$^2$/s horizontal dispersion show that a greater reduction in search area is possible (up to 56.9% at 24 hours and 72.5% at 120 hours), whilst maintaining a smaller reduction in hit rate (up to 26.2% reduction at 24 hours and 52.8% reduction at 120 hours) when the 4 model consensus forecasts are used. This indicates a more efficient search area can be provided by the consensus search areas.

The results indicate that the search areas provided by the medium (100 m$^2$/s) and low (10 m$^2$/s) horizontal dispersion coefficients (experiment 2 and 3) are often too small to
contain the drifter or search object for a significant portion of time (demonstrated by the low hit rates returned by these two experiments). This indicates that with the current generation of ocean models, the dispersion of model particles to form search areas and account for the sum of errors of the ocean models and the transport due to sub grid scale turbulence, may not be adequate, and hence a larger dispersion is required to ensure these uncertainties are encapsulated by the SAR drift model, and the search object may be contained more frequently within the model defined search area. Additionally, the results indicated that consensus search areas occurred less frequently for experiment 2 and very infrequently for experiment 3, and hence consensus forecasting may not prove to be useful should the search areas not be large enough to allow consensus to occur for a significant portion of the time.

Three dispersion coefficients were tested in this study, each increasing by an order of magnitude (10, 100 and 1,000 m²/s). The step from 100 m²/s to 1,000 m²/s is a large jump in magnitude, which results in a large increase in search area size. Further testing into other horizontal dispersion coefficients is warranted to determine if there is a value which lies between 100 m²/s and 1,000 m²/s which may maintain a high hit rate, but generate a smaller average search area than those generated by the high dispersion coefficient. This would indicate a more efficient search area.

As this study was focussed on drifters in the Indian Ocean off the coast of Western Australia, it may be warranted to carry out further studies such as this one, in other water bodies around Australia to determine if model performance may be geographic location dependant.

The ocean models are in an ever evolving state, with improvements being implemented on a semi regular basis. These model improvements may result from updated model formulations, increased resolution (spatially and/or temporally), or from newer data assimilation techniques and datasets to be assimilated. It is recommended that regular studies be carried out to test the model performance when considering their ability to predict the drift of objects on the water surface.

The concept of consensus forecasting showed very promising results, whereby the average areas where all four ocean models overlapped was shown to be more efficient than any of the single ocean model average search areas, hence it is recommended that
consensus forecasting be used alongside regular single model drift forecasting on an operational level.

4.6 Acknowledgements
This research was supported under the Australian Research Council’s Linkage Projects funding scheme LP0991159.

4.7 References


Blockley, E. W. et al., 2013. Recent development of the Met Office operational ocean forecasting system: an overview and assessment of the new Global FOAM


Chapter 4


STATEMENT OF CONTRIBUTION TO CO-AUTHORED PUBLISHED PAPER

This chapter includes a co-authored paper. The bibliographic details of the co-authored paper, including all authors, are:


My contribution to the paper involved:

Assisting with design of the study and instrumentation of the craft, field work to deploy and recover craft, data recovery, processing and analysis of data, analysis of results, figure production, background literature search and drafting the paper.

(Signed) _________________________________ (Date)______________

Ben Amon Brushett

(Countersigned) __________________________ (Date)______________

Corresponding author of paper: Ben Amon Brushett

(Countersigned) __________________________ (Date)______________

Supervisor: Prof. Charles Lemckert
5. Determining the Leeway Drift Characteristics of Tropical Pacific Island Craft

Abstract

An accurate understanding of the leeway drift characteristics of drifting objects is required to effectively forecast the drift of persons, vessels or objects lost at sea, and to generate efficient search areas to maximise the probability of successfully locating those missing. Presently, the most effective method for calculating the leeway drift characteristics of an object or vessel is to empirically derive the leeway coefficients of that object through field studies. The main goal of the studies is to measure how the object drifts in relation to the surface currents due to the wind and wave action upon it. This paper outlines the determination of downwind and crosswind leeway coefficients for three small craft common to Pacific island communities for which no accurate leeway coefficients exist. These craft were: a 19 foot (5.8m) fibreglass skiff (known locally as pangas, fibres, or banana boats); a 20 foot (5.97m) fibreglass outrigger canoe; and a 2-person sit down personal water craft (PWC). Due to the vast distances between pacific islands and the remoteness of these locations it can be several days until a search can be mounted to rescue those lost at sea, hence it is paramount that an accurate description of the drift of these tropical pacific craft is available for use in search and rescue (SAR) drift models, to define appropriate search areas. This study successfully derived the leeway coefficients required for each of these three craft. The leeway speed of the outrigger canoe and PWC, both with one person on board (POB) equivalent loading, were calculated to be 2.40% and 4.24% of the wind speed respectively. The
leeway speed of the skiff was found to range between 7.71% and 4.40% of the wind speed for equivalent loading between 1 POB and 13 POB.

The results of these field tests have subsequently been implemented into search and rescue models by several SAR organisations worldwide. These results show that the findings herein have the potential to both increase the likelihood of finding persons adrift at sea alive, as well as reducing search costs through more effective drift prediction and efficient search area formulation.

5.1 Introduction

Several key elements are required to successfully predict the drift of a person or object at sea. These include search and rescue (SAR) drift forecast models, input wind and current forecast data and the drift object’s leeway drift coefficients. Maritime search and rescue (SAR) drift forecast models are used to numerically model the drift of an object at sea; however these models are only as effective as the input data provided. Both accurate external forcing data (winds and currents) and a well-defined representation of how the object may drift due to the external forces upon it are essential model inputs. The forces acting upon a drift object include those from wind, waves and currents. Prior studies have shown that the drift of an object due to wave action (forcing) only becomes significant once the drift objects have a length scale greater than that of the wavelength (Breivik, et al., 2013) and as the drift objects investigated herein have a length less than the wavelength, effects due to wave forcing may be disregarded. Wind and current forcing may be provided through a number of means, including near real time observations and more commonly, numerical forecast models. As the object drifts with the currents, it is exposed to the effects of the wind and waves. The combined effect upon the drift of an object due to wind and waves is described as the “leeway” of the object.

The leeway of an object varies from object to object and therefore a new set of leeway coefficients is required for each drift object to accurately determine their leeway drift characteristics. Without the correct leeway coefficients, it is impossible to accurately forecast how that object may drift. Leeway field tests are currently the most common and most accurate method for determining the leeway coefficients of a drift object. A
standard approach to the leeway field tests is outlined by (Breivik, et al., 2011). The leeway study was carried out at three locations within the tropical North Pacific Ocean during the months of May and June 2012 (refer to Figure 5-1). The initial 5-day drift of the skiffs (and multiple single-day drifts of the PWC and outrigger canoe) commenced approximately 15 km off the western coast of Chuuk Lagoon in the Federated States of Micronesia (FSM). The next study location (one single-day drift of all craft) took place approximately 20 km to the north of Puluwat Atoll (westernmost land features of Chuuk State, FSM). The final study (single-day, all craft) took place approximately 10 km to the west of Apra Harbour, Guam. All drifts were undertaken in deep water where the dominant current forcing was attributable to the westward flowing North Equatorial Current (NEC).

The total drift of an object at sea can be summarized by the three equations below, adapted from Hackett, et al., (2006). Equation 5-1 shows that the total drift is a summation of the drift due to currents (relative to the earth) plus the drift due to leeway (slip relative to the ambient currents). The drift due to currents is a result of the combination of surface currents (derived from Ekman drift, baroclinic motion, tidal currents and inertial currents), as well as drift due to wave induced currents or Stokes drift (Equation 5-2). Leeway drift is the sum of the drift due to the winds acting on the object plus the drift due to the wave forces acting on the object (Equation 5-3).

\[
D_T = D_C + D_L
\]

**Equation 5-1**

Where: 
- \(D_T\) = Total Object Drift
- \(D_C\) = Drift Due to Current forces (relative to the earth)
- \(D_L\) = Drift Due to Leeway (relative to the currents)

And

\[
D_C = D_{Sc} + D_{Sd}
\]

**Equation 5-2**

Where: 
- \(D_C\) = Drift due to Currents
- \(D_{Sc}\) = Drift due to Surface currents
- \(D_{Sd}\) = Drift due to Stokes drift

And
\[ D_L = D_{Wi} + D_{Wa} \]

Equation 5-3

Where: 
- \( D_L \) = Drift Due to Leeway
- \( D_{Wi} \) = Drift due to Wind forces
- \( D_{Wa} \) = Drift due to Wave forces

The effect of Stokes drift may be present for the drift of an object on the water surface, in two forms. The first is Stokes drift due to wind generated waves, and the second is the Stokes drift due to swell. The wind generated wave-induced Stokes drift predominately acts in a downwind direction (the same direction as the wind) however the swell-induced Stokes drift acts in the direction of the swell, which is not necessarily the same direction as the wind generated waves, and hence may not be in the downwind direction. As it was not possible to determine the swell direction in this study and due to the minimal swell encountered, any Stokes drift was assumed to be a result of wind generated waves only, and act in the downwind direction. The swell-induced Stokes drift may become an important factor in higher energetic areas with larger swell sizes. Once the drift due to surface currents has been subtracted from the total drift, the empirically derived leeway drift of the object cannot distinguish between the downwind leeway drift effects and the downwind Stokes drift effects on the drift of the object, and therefore the effects that Stokes drift may have on the drift of the object are included in the regression of the leeway of the object. As a result of this, Breivik, et al. (2011) recommend that for small craft it is most practical to express leeway as a function of the wind only.

Breivik & Allen (2008) suggest that the drift due to wave forces may be ignored for small craft whose length is less than that of the wavelength, as the drift due to wave forcing may only become significant once the object’s length is similar to the wavelength (e.g. large vessels).

In summary, as the lengths of the craft used in this study were significantly less than the wavelength, the effects of wave forces were assumed to be negligible, and as the wind generated wave-induced Stokes drift was accounted for in the leeway coefficients...
derived for the objects, the total drift of the objects was calculated as a sum of the drift due to the surface currents and the drift due to the wind.

The definition of leeway has evolved over time, with each iteration becoming more rigorous and less ambiguous. The most recent definition of leeway is listed by Breivik, et al. (2011; 2013) where it is defined as:

“Leeway is the motion of the object induced by wind (10 m reference height) and waves relative to the ambient current (between 0.3 and 1.0 m depth)”.

This definition allows the SAR responder to use standard 10 m reference height model forecast winds and the surface layer of current forecast models or currents measured by HF radar.

There are two methods of describing the leeway of a drifting object. Both methods refer to the speed of the drift of the object when compared to the 10 m reference height wind speed. The first method refers to the object’s leeway speed and divergence angle referenced to the down wind direction and speed. The second method decomposes the leeway speed and divergence angle into downwind leeway (DWL) and crosswind leeway (CWL) vectors. The former method, utilising leeway speed and divergence angle, has historically been used for manual drift planning, however Allen (2005) noted that when using numerical model solutions for drift planning, the leeway divergence angle can cause the solution to become unstable at low wind speeds when wind direction fluctuates. As a result, the latter method using DWL and CWL is the preferred method for numerical SAR models as it does not suffer the same shortfall and remains numerically stable, even at low wind speeds.

The leeway coefficients can be calculated through either a constrained or non-constrained linear regression with the 10m wind speed. The constrained through zero regression implies that the leeway will be zero when there is no wind, whilst the non-constrained linear regression implies that there may still be some residual leeway drift of the object by forcing other than winds when winds are zero. Utilising the constrained through zero regression provides the most stable numerical solution for modelling search object trajectories, whereas numerical models utilising the unconstrained regression may incur difficulties if zero wind speeds are encountered (due to having no wind direction in which to apply the leeway component). This is generally not a
problem as zero wind speeds rarely occur, however there are several approaches which can be utilised by numerical models to circumvent this potential issue, which include: a) carrying forward the wind direction from the previous model time step to calculate the residual trajectory when there is zero wind speed; b) removing the residual trajectory for cases where there is zero wind speed; or c) no modification to the model code, as conditions with zero wind speeds are infrequent. Each approach has their merits and drawbacks, so it is important to implement the approach which best suits the particular application.

Leeway field tests have been carried out in one form or another since the first recorded results by Pingree (1944) who carried out studies on the drift of Navy life rafts in World War II. A thorough review of the various leeway experiments / field tests conducted up until 1999, as well as a summary of the leeway speed and divergence angle of 63 drift objects is contained within Allen & Plourde (1999). A further review of leeway divergence was published by Allen (2005) who provided the CWL and DWL coefficients for the 63 objects defined in Allen & Plourde (1999). Since then, there have been further leeway field tests undertaken by various organisations and countries worldwide including the United States of America, Canada, Norway and France.

A semi analytical numerical approach to calculating the leeway of shipping containers at various immersion levels was presented by Daniel, et al. (2002). This was a unique approach as thus far, the majority of other leeway studies utilised an empirical approach to determining the leeway coefficients. Daniel, et al. (2002) presented three case studies of previous shipping incidents which occurred in 1993, 1996 and 1997 where shipping containers were adrift at sea, and a case study comparing the results from a previous leeway field test carried out on 20’ shipping containers off Brittany (France) in 1991 – 1992. Leeway field tests were carried out in 2008 as a joint venture between Norway, France and the US. The studies were undertaken in Norway, and investigated the leeway of; a 1:1/3 sized model of a 40’ shipping container, a WWII mine, and a 220 L (550-gallon) oil drum. Another joint venture between Norway, France and the US saw further leeway field tests were carried out in 2009 in Norway (Allen, et al., 2010). This study successfully collected leeway drift data for; a full sized 20’ shipping container, a 4.5m open aluminium skiff, Sunfish sailing dinghy, a Person in Water (PIW) in the deceased position and additional data was collected for the WWII mine. All objects
were appropriately instrumented to follow the direct method of collecting leeway data. Breivik, et al. (2012) combined the shipping container results from the 2008 and 2009 leeway field tests in Norway and compared them to the semi analytical leeway model of shipping containers presented by Daniel, et al. (2002). Further, results were extrapolated to account for different immersion levels of shipping containers (immersion level is one uncertainty faced by SAR responders when modelling drifting objects).

The frequency in which the drift object changes direction from left of downwind (positive cross wind) to right of downwind (negative cross wind) is known as the jibing frequency. Jibing frequency is measured as a percentage per hour over the duration that an object may be adrift. Allen (2005) introduced the jibing frequency concept in terms of defining the search areas for drift objects. A drifting object may jibe suddenly, with an instantaneous change in CWL sign, or it may occur gradually over time which is more difficult to determine. It may be possible to numerically identify a gradual jibe from the drift track and wind data however if there is a limited amount of drift data it may be deemed sufficient to visually interpret a progressive vector diagram of the drift run to identify the jibing events.

The purpose of this study was to undertake a series of leeway field studies to determine the leeway coefficients of three water craft common to tropical Pacific islands, whose leeway coefficients were previously unknown. These three craft included a 5.8m (19’) fibreglass skiff, a 5.97m (19.6’) fibreglass outrigger canoe, and a 2-person sit down personal water craft (PWC). The outcomes of this study allows SAR planners to more accurately forecast the drift of the three objects, and plan search efforts more effectively. Improved definition of search areas increase the likelihood of finding the missing persons or craft quicker, and hence reduced search times increase the probability of finding the missing persons and increase their chances of survival (Australian Maritime Safety Authority, 2011). In addition, search efforts and the related high costs involved with maritime searches may be reduced.
5.2 Methodology

A standard methodology for determining the leeway of floating objects was set out by Breivik, et al. (2011) to ensure subsequent field tests to gather leeway data on other objects of interest could be conducted in a consistent manner. This allows for interchangeable data which is able to be implemented into the various numerical SAR models currently in use by various SAR organisations worldwide. An overview of some maritime SAR models and their use with ocean current forecast data for predicting the drift of objects or craft is included in Davidson, et al., (2009). Further information in regards to these SAR models include; the United States Coast Guard SAROPS (Search and Rescue Optimal Planning System) (Kratzke, et al., 2010); the Leeway model used by the Norwegian Coast Guard (Breivik & Allen, 2008); the SARMAP model used by Maritime New Zealand and the Australian Maritime Safety Authority (Spaulding & Howlett, 1996; Spaulding, et al., 2006); the Canadian Search and Rescue Planning program (CANSARP) utilised by the Canadian Coast Guard (Canadian Coast Guard, 2009); and the French MOTHY (Modèle Océanique de Transport d’Hydrocarbures) system run by Météo-France (Daniel, et al., 2003).

There are two methods for determining the leeway of an object, the direct method and the indirect method (Breivik, et al., 2011). The direct method uses a current meter directly attached or tethered to the object that is being studied, as opposed to the indirect
method which estimates the currents from a nearby vessel or object to infer the leeway slip of the study object. The indirect method is not as accurate as the direct method, however it may be necessary when the study objects are too small to either fit or tether a current meter to (for example, medical waste). The preferred method for determining the leeway of an object is the direct method.

In this standardised methodology, Breivik, et al. (2011) identified four categories of leeway objects which are categorised based on their size and ability to carry various instrumentation, as outlined in Table 5-1 below.

<table>
<thead>
<tr>
<th>Category</th>
<th>Object Size</th>
<th>Leeway Method</th>
<th>Instrumentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Small (e.g. EPIRB, Floating debris)</td>
<td>Indirect</td>
<td>Location device only</td>
</tr>
<tr>
<td>2</td>
<td>Small to Medium (e.g. PIW, PWC)</td>
<td>Direct</td>
<td>Location device plus current meter</td>
</tr>
<tr>
<td>3</td>
<td>Medium (e.g. Life raft, Skiff)</td>
<td>Direct</td>
<td>Location device, current meter and weather station</td>
</tr>
<tr>
<td>4</td>
<td>Large (e.g. Large boat, Shipping container)</td>
<td>Direct</td>
<td>Location device, current meter and weather station</td>
</tr>
</tbody>
</table>

The three objects studied in this field test all fell within categories 2 and 3. The PWC and the Outrigger canoe were both deemed too small to adequately accommodate weather stations, and therefore fell within category 2, whilst the skiffs were outfitted with weather stations, and hence fell within category 3. The direct method was used for calculating the leeway for all three craft in this test as each was able to carry a current meter for direct measurements of the surface currents.

A full description of the background, model setup and results for this study is contained within the technical document Allen, et al. (2013).

5.2.1 Drift Objects

Several craft are common to the tropical Pacific island inhabitants, which include the 19 or 23 foot fibreglass skiff, also commonly known to locals as Pangas, Fibres (due to their fibreglass construction), or Banana boats (due to their curved appearance). Outrigger canoes and PWC are also common.
Skiff
The Search and Rescue Exercise (SAREX) conducted by the USCG during the leeway field tests required a continuous 5-day drift of a 19 foot (5.8 m) fibreglass skiff. Two identical skiffs were used in a leapfrog deployment to safeguard against unforeseen technical issues and a potential loss of data. The two identical 19 foot fibreglass skiffs (Skiff-One and Skiff-Two, refer to Figure 5-2a) were outfitted with the necessary instrumentation including current meters, weather stations, GPS (Global Positioning System) Iridium transmitters and flashing lights. Skiff-One was deployed first, for approximately 24 hours before Skiff-Two was deployed nearby to the location of Skiff-One at 24 hours. Once Skiff-Two was drifting in clear water, Skiff-One was then recovered and once on board the support vessel, the data from the current meter and weather station was downloaded (to ensure the data had recorded correctly and all sensors were working correctly). This deployment system also had the added benefit of being able to check the condition of the skiffs (e.g. if they had filled with rain water from overnight storms) and to ensure all batteries for the instrumentation were fully charged between deployments. This ~24 hour leap frog deployment schedule ensured that any faults with the instrumentation, would only result in a maximum of 24 hours of data lost.

Outrigger Canoe
A variety of different outrigger canoes are common to the tropical Pacific islands, varying from small 1-person craft, up to larger 20 to 30 foot versions, which can be fitted with a sail for longer distance journeys. Some outrigger canoes are constructed in the traditional ways from timber, whilst others are constructed of fibreglass. The outrigger canoe selected for this study was a 5.97 m fibreglass design which was designed to carry 1 to 2 persons (Figure 5-2b).

Personal Water Craft
The PWC used in these leeway drift tests was an older style 2.7m Yamaha 2-person sit down type (Figure 5-2c). PWCs are commonly used for recreational use in coastal and near shore waterways. Other sizes and style PWCs also include one person stand up
style, as well as 3 and 4 person sit down styles. The PWC used in this study had the engine removed and a downward facing ADCP (Acoustic Doppler Current Profiler) mounted through the centre of the hull.

Figure 5-2: Craft tested; (a) 5.8m Skiff, (b) 5.97m Outrigger Canoe, and (c) Personal Water Craft. Line drawings on the right side show the dimensions (in metres) of the corresponding drift objects tested.

5.2.2 Instrumentation

Each of the drift objects were outfitted with various instrumentation; including GPS beacons with Iridium satellite transmitters, ADCP current meters, and weather stations, as well as RDF (Radio Direction Finding) beacons and strobe lights. The following section outlines the instrumentation specifics and data sampling periods utilised on each of the drift objects studied. Table 5-2 gives a brief overview of the instruments fitted to the drift objects.
Table 5-2: Instrumentation installed on drift objects

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>Current Meter</th>
<th>Weather Station</th>
<th>GPS</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outrigger Canoe</td>
<td>Nortek ADCP – Aquadopp 2MHz</td>
<td>--</td>
<td>Clearwater Iridium Beacon</td>
<td>NovaTech RDF Flasher Beacon – RDF-700C1</td>
</tr>
<tr>
<td>PWC</td>
<td>RDI ADCP – Workhorse Monitor 1228.8kHz</td>
<td>--</td>
<td>Clearwater Iridium Beacon</td>
<td>NovaTech RDF Flasher Beacon – RF-700C1</td>
</tr>
</tbody>
</table>

**Location Devices**

Each of the craft was fitted with Clearwater Instrumentation GPS/Iridium transmitter beacons, each with a unique IMEI (International Mobile station Equipment Identification) number, which transmitted the location of each of the drift objects back to the Iridium receiver on board the USCGC Sequoia every 10 minutes (on the 10 minute mark) in near real time (approximately 30 to 45 seconds delay). This enabled the position and speed over ground to be recorded for each of the craft, as well as to facilitate the location and recovery of the craft at the end of each drift run. The skiffs were fitted with Carmanah Marine Lanterns (M704-5) to enable the skiffs to be seen at night or under low light and to aid in their recovery. These lanterns were essentially a solar powered flashing light, with a light sensor that switched them off during the day and on again at night. The outrigger canoe and the PWC were both fitted with NovaTech combination RDF flashing beacons. These devices were fitted with an RDF transmitter that also contained a flashing strobe light which automatically switched on when it was dark.

**Current Meters**

Two different types of current meters were used in this study to measure the sea surface currents relative to the drift objects. The first was the Nortek AquaDopp 2 MHz ADCP, which was fitted to each of the skiffs and the outrigger canoe. The second type of current meter used was an RDI Workhorse Monitor 1228.8 kHz ADCP, fitted to the
PWC in a special gimbal setup to minimise tilt. Skiff-One and Skiff-Two each had their respective ADCP fitted to the transom, where the outboard engine would have been fixed. The outrigger canoe had the ADCP fitted to the side of the hull on the same side as the outrigger, slightly offset from amidships. It was positioned on the outrigger side of the hull to ensure it was not damaged during deployment and recovery.

The sampling frequency, sampling average, blanking distance, bin size, number of bins and head depth for the current meters are all listed for each of the four drift objects in Table 5-3. Data was averaged over the surface 6-8 bins (depending on the current meter), and one minute averages were adjusted to account for magnetic variation, and then rotated a further 180° to account for leeway frame of reference. The one minute samples were then averaged to 10 minute samples as Breivik & Allen (2008) established the maximum correlation of leeway occurred with zero lag at 10 minute samples.

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>Current Meter</th>
<th>Sampling Frequency (Hz)</th>
<th>Sampling Average (min)</th>
<th>Blanking Distance (cm)</th>
<th>Bin Size (cm)</th>
<th>Number of Bins Used</th>
<th>Head Depth (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skiff-One &amp; Skiff-Two</td>
<td>AquaDopp 2 MHz ADCP</td>
<td>1.0</td>
<td>1 &amp; 10</td>
<td>10</td>
<td>10</td>
<td>8</td>
<td>20 – 25</td>
</tr>
<tr>
<td>Outrigger Canoe</td>
<td>AquaDopp 2 MHz ADCP</td>
<td>1.0</td>
<td>1 &amp; 10</td>
<td>10</td>
<td>10</td>
<td>6</td>
<td>5 – 10</td>
</tr>
<tr>
<td>PWC</td>
<td>RDI Workhorse Monitor 1228.8 kHz</td>
<td>1.0</td>
<td>1 &amp; 10</td>
<td>50 &amp; 25(^a)</td>
<td>5 &amp; 10(^a)</td>
<td>6 &amp; 5(^a)</td>
<td>10</td>
</tr>
</tbody>
</table>

\(^a\) Initial PWC run had a blanking distance of 50 cm and 5 cm bin size (x6 bins), subsequent runs had a blanking distance of 25 cm and 10 cm bin size (x5 bins).

**Weather Stations**

A weather station was mounted to each of the skiffs, and was deployed in close proximity to the outrigger canoe and the PWC, as they were too small to directly mount a weather station to. Weather station measurements from the skiffs could then also be made available to the leeway regression calculations for the PWC and outrigger canoe as winds on the ocean are relatively consistent and do not fluctuate considerably over small distances, it is acceptable to use the winds measured on a nearby object (Breivik, et al., 2011). The weather stations fitted to the skiffs were Coastal Environmental
System WeatherPak 2000 units, each fitted with a Gill ultrasonic anemometer, which is an improvement over the older mechanical style anemometer as the ultrasonic versions do not have a dead band. Resolution of wind direction was 1° with an accuracy of ± 3°. The minimum wind speed threshold for the anemometers was 0.01 m/s. The WeatherPaks also measured: wind gust, air temperature, GPS position, internal temperature and battery voltage. The unit fitted to Skiff-Two also contained a humidity sensor and a barometer. The barometer was used to correct the offset of the pressure sensor on the ADCP, which measured the depth of the ADCP in the water. All samples from the WeatherPaks were taken at a frequency of 1 Hz, and then averaged over 10 minutes to align with the 10 minute averages of the current meters. The anemometer height was 1.79 m and 1.83 m above the waterline for Skiff-One and Skiff-Two respectively.

5.2.3 Object Loading

One of the many uncertainties faced with predicting the drift of an object at sea, is the state in which the object or craft is in. Objects will exhibit different drift characteristics depending on the loading to which they are subject. Drift objects/craft which are heavily loaded will sit lower in the water, thus increasing their cross sectional area exposed to currents, as well as decreasing the cross sectional area exposed to wind. This has the combined outcome of increasing the effects of currents whilst decreasing the effects of winds upon the drift of the object, hence reducing the magnitude of the leeway of the object. The reverse is also true, whereby a decrease in the loading of a drift object will increase the object’s leeway, thus allowing it to follow the winds more and the currents less. To understand how the drift objects would drift under these differing loading circumstances it is important to test the object’s leeway drift under varying loadings. Previous studies by Breivik, et al. (2012) and Daniel, et al. (2002) investigated how shipping containers drifted under differing immersion levels (which has the similar effect to differing loadings of the craft).

The skiffs were tested under several different loadings, using sand bags as extra weight. The loadings were tested in terms of persons on board (POB) and included; 1 POB, 2 POB, 4 POB, and 13 POB equivalent loadings. In addition, sand bags were placed at the stern of the skiffs to simulate the weight of the standard 40hp outboard motor. As the
PWC and Outrigger Canoe are smaller objects with limited carrying capacities, they were tested in one configuration – with 1 POB, which would be their most likely loading configuration.

5.2.4 Data Processing

The wind speeds measured on the skiffs were adjusted from their measurement height up to the standard 10 m reference height following Smith (1988). These wind speeds were then corrected by using the GPS positions to allow for the movement of the skiffs. The 10 minute samples of the winds and currents were matched in time, and the measured leeway was decomposed into the DWL and CWL components. The CWL was split into positive and negative depending on whether drift was to the left (negative) or right (positive) of the downwind direction. Additionally, a (-1) times the negative CWL coefficient was also calculated to enable both the positive and negative CWL values to be plotted on the same positive axis. A linear regression using a least squares best fit was carried out for the leeway speed, DWL and CWL, with each regressed against the wind speed (adjusted to 10 m height). This was repeated for both unconstrained and constrained through zero linear regressions. From the linear regression, the slope, y intercept and $r^2$ values were calculated, as well as the standard error term ($S_{yx}$).

The nine leeway coefficients identified by Breivik & Allen (2008) and Breivik, et al. (2011) are shown in Equation 5-4, Equation 5-5 and Equation 5-6 below. Note these can be compressed to six coefficients for the constrained through zero regression, as the y intercept is zero. The subscripts refer to the vector components of leeway; DWL (d), Positive CWL (c+) and Negative CWL (c-).

\[ L_d = a_d W_{10} + b_d + E_d \]  
\[ L_{c+} = a_{c+} W_{10} + b_{c+} + E_{c+} \]  
\[ L_{c-} = a_{c-} W_{10} + b_{c-} + E_{c-} \]

Equation 5-4
Equation 5-5
Equation 5-6
Where: $L =$ Predicted leeway (cm/s) at a given value of $W_{10}$ wind speed.

$a =$ Slope of the regression line through the data, to give leeway as (%) of $W_{10}$ wind speed

$W_{10} =$ Wind speed at 10 m reference height

$b =$ Y intercept or offset term for unconstrained regression

$E =$ additional error term

Progressive vector diagrams (PVD) were generated by plotting the leeway drift with respect to the downwind direction for each drift run. This allowed the jibing analysis to be undertaken, as the PVD allows the switches between positive and negative leeway over prolonged periods (several 10 minute time samples) to be readily identified (thus indicating a jibing event).

### 5.3 Results

The drift tracks from the leeway field tests undertaken in the tropical Pacific ocean during May/June 2012 are shown in Figure 5-3 (Chuuk, FSM), Figure 5-4 (Puluwat atoll, FSM), and Figure 5-5 (Guam). A summary of each of the drift runs is provided in Table 5-4. The results from the analysis and linear regression of the leeway coefficients for each of the individual drift objects (skiff, outrigger canoe, and PWC) are shown in Table 5-5 to Table 5-8. For brevity only the linear regression plots for the leeway speed, DWL and CWL of the 2 POB skiff are shown (refer to Figure 5-6), whilst the full analysis of each of the drift objects (under all loadings tested) including the linear regression plots can be found in the leeway field test technical report (Allen, et al., 2013). The jibing frequency analysis for all drift objects follows and is shown in Table 5-9.

### 5.3.1 Summary of the Drift Runs

Table 5-4 below provides a summary of the drift runs and outlines the deployment times, retrieval times, duration of the run as well as the 10 m reference height wind speed range, and the locations for each of the individual leeway runs. It should be noted
there were three runs that did not return usable data, these included PWC Run-2 (ADCP battery failed), PWC Run-4 (ADCP was tilted beyond tolerances in gimbals during deployment), and Skiff-One Run-5 (skiff was overloaded beyond the 6 POB loading which resulted in unsuccessful recovery).

Table 5-4: Summary of the drift runs

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>Run #</th>
<th>POB #</th>
<th>Deployment Date Time UTC</th>
<th>Retrieval Date Time UTC</th>
<th>Duration hh:mm</th>
<th>10 m Wind Speed Range m/s</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skiff-One</td>
<td>1</td>
<td>2</td>
<td>28/5/2012 0:48</td>
<td>28/5/2012 23:32</td>
<td>22:44</td>
<td>2.0 – 9.1</td>
<td>Chuuk</td>
</tr>
<tr>
<td>PWC</td>
<td>1</td>
<td>0</td>
<td>28/5/2012 1:00</td>
<td>28/5/2012 6:02</td>
<td>05:02</td>
<td>4.8 – 9.1</td>
<td>Chuuk</td>
</tr>
<tr>
<td>Canoe</td>
<td>1</td>
<td>1</td>
<td>28/5/2012 23:06</td>
<td>29/5/2012 6:20</td>
<td>07:14</td>
<td>2.7 – 4.7</td>
<td>Chuuk</td>
</tr>
<tr>
<td>PWC b</td>
<td>2</td>
<td>0</td>
<td>28/5/2012 23:19</td>
<td>29/5/2012 6:00</td>
<td>06:41</td>
<td>n/a</td>
<td>Chuuk</td>
</tr>
<tr>
<td>Skiff-Two</td>
<td>1</td>
<td>2</td>
<td>28/5/2012 22:45</td>
<td>29/5/2012 22:59</td>
<td>24:14</td>
<td>2.7 – 9.3</td>
<td>Chuuk</td>
</tr>
<tr>
<td>Canoe</td>
<td>2</td>
<td>1</td>
<td>29/5/2012 23:30</td>
<td>29/5/2012 22:22</td>
<td>22:52</td>
<td>2.8 – 9.0</td>
<td>Chuuk</td>
</tr>
<tr>
<td>Skiff-Two</td>
<td>2</td>
<td>2</td>
<td>30/5/2012 0:28</td>
<td>30/5/2012 2:05</td>
<td>05:24</td>
<td>2.8 – 6.2</td>
<td>Chuuk</td>
</tr>
<tr>
<td>Canoe</td>
<td>3</td>
<td>1</td>
<td>31/5/2012 22:52</td>
<td>1/6/2012 5:46</td>
<td>06:54</td>
<td>5.3 – 9.0</td>
<td>Chuuk</td>
</tr>
<tr>
<td>Skiff-One</td>
<td>3</td>
<td>2</td>
<td>31/5/2012 22:32</td>
<td>2/5/2012 2:26</td>
<td>27:54</td>
<td>5.3 – 9.1</td>
<td>Chuuk</td>
</tr>
<tr>
<td>PWC</td>
<td>3</td>
<td>1</td>
<td>1/6/2012 22:16</td>
<td>2/6/2012 2:05</td>
<td>03:49</td>
<td>6.9 – 8.4</td>
<td>Chuuk</td>
</tr>
<tr>
<td>Skiff-One</td>
<td>4</td>
<td>1</td>
<td>8/6/2012 21:17</td>
<td>9/6/2012 8:02</td>
<td>10:45</td>
<td>1.4 – 4.7</td>
<td>Puluwat</td>
</tr>
<tr>
<td>Skiff-Two</td>
<td>3</td>
<td>4</td>
<td>8/6/2012 21:11</td>
<td>9/6/2012 8:23</td>
<td>11:12</td>
<td>1.6 – 4.6</td>
<td>Puluwat</td>
</tr>
<tr>
<td>Canoe</td>
<td>4</td>
<td>1</td>
<td>8/6/2012 21:25</td>
<td>9/6/2012 8:55</td>
<td>11:30</td>
<td>1.6 – 4.6</td>
<td>Puluwat</td>
</tr>
<tr>
<td>PWC c</td>
<td>4</td>
<td>4</td>
<td>8/6/2012 21:38</td>
<td>9/6/2012 8:36</td>
<td>11:08</td>
<td>n/a</td>
<td>Puluwat</td>
</tr>
<tr>
<td>Skiff-One d</td>
<td>5</td>
<td>6</td>
<td>12/6/2012 0:24</td>
<td>12/6/2012 0:41</td>
<td>0:17</td>
<td>n/a</td>
<td>Guam</td>
</tr>
<tr>
<td>Skiff-Two</td>
<td>4</td>
<td>4</td>
<td>12/6/2012 0:19</td>
<td>12/6/2012 23:12</td>
<td>21:53</td>
<td>2.2 – 9.6</td>
<td>Guam</td>
</tr>
<tr>
<td>Canoe</td>
<td>5</td>
<td>1</td>
<td>12/6/2012 0:29</td>
<td>12/6/2012 23:21</td>
<td>22:52</td>
<td>2.2 – 9.6</td>
<td>Guam</td>
</tr>
<tr>
<td>PWC</td>
<td>5</td>
<td>1</td>
<td>12/6/2012 0:33</td>
<td>12/6/2012 22:37</td>
<td>22:04</td>
<td>2.2 – 9.6</td>
<td>Guam</td>
</tr>
</tbody>
</table>

b Battery failed.

c ADCP hung up on gimbals during deployment, tilt exceeded tolerances.

d Skiff was overloaded (much greater than 6 POB), unsuccessful recovery.
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Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime
Search and Rescue and Pollutant Response Applications

Figure 5-3: Chuuk drift runs: 28th of May 2012 to 2nd of June 2012

Figure 5-4: Puluwat drift runs: 8th of June 2012 to 9th of June 2012

Figure 5-5: Guam drift runs: 12th of June 2012 to 12th of June 2012
5.3.2 Regression of Leeway Components

A graphical representation of the linear regression for the 2-POB loading of the skiffs is shown in Figure 5-6 (constrained in thick red, unconstrained in thin blue) for the leeway speed (a), CWL (b) and DWL (c). The complete linear regression results for the leeway coefficients (leeway speed, CWL and DWL), and 95% confidence level statistics of the skiff (under the four loadings tested), the outrigger canoe and PWC are summarised in Table 5-5 to Table 5-8.

Figure 5-6: Leeway plots showing the linear regression of leeway components (cm/s) against the wind speed (m/s) adjusted to standard 10m reference height. (a) Leeway Speed, (b) Cross Wind Leeway – including both positive (left of downwind) and -1 times negative (right of downwind) components, and (c) Down Wind Leeway. Thick red solid line shows the constrained through zero linear regression, whilst thin Blue solid line shows the unconstrained linear regression. Dashed lines show the respective 95% confidence limits of the regressions.
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Table 5-5: Unconstrained Linear Regression of Leeway Speed and Downwind Leeway Parameters

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>Leeway Speed</th>
<th>DWL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope (%)</td>
<td>Y (cm/s)</td>
</tr>
<tr>
<td>Panga w/1 POB</td>
<td>3.28</td>
<td>15.72</td>
</tr>
<tr>
<td>Panga w/2 POB</td>
<td>2.87</td>
<td>15.39</td>
</tr>
<tr>
<td>Panga w/4 POB</td>
<td>3.80</td>
<td>6.51</td>
</tr>
<tr>
<td>Panga w/13 POB</td>
<td>3.98</td>
<td>1.61</td>
</tr>
<tr>
<td>Outrigger canoe</td>
<td>1.30</td>
<td>6.13</td>
</tr>
<tr>
<td>PWC</td>
<td>3.46</td>
<td>4.99</td>
</tr>
</tbody>
</table>

Table 5-6: Constrained through zero, Linear Regression of Leeway Speed and Downwind Leeway Parameters

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>Range of 10m Wind Speed (m/s)</th>
<th># of 10-minute samples</th>
<th>Leeway Speed</th>
<th>DWL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope (%)</td>
<td>Y (cm/s)</td>
<td>Syx (cm/s)</td>
<td>r^2</td>
</tr>
<tr>
<td>Panga w/1 POB</td>
<td>1.4 – 4.7</td>
<td>64</td>
<td>7.71</td>
<td>3.73</td>
</tr>
<tr>
<td>Panga w/2 POB</td>
<td>2.6 – 10.6</td>
<td>655</td>
<td>5.32</td>
<td>5.75</td>
</tr>
<tr>
<td>Panga w/4 POB</td>
<td>1.6 – 11.9</td>
<td>227</td>
<td>4.92</td>
<td>2.91</td>
</tr>
<tr>
<td>Panga w/13 POB</td>
<td>2.0 – 5.2</td>
<td>17</td>
<td>4.40</td>
<td>2.15</td>
</tr>
<tr>
<td>Outrigger canoe</td>
<td>1.6 – 9.6</td>
<td>307</td>
<td>2.40</td>
<td>4.44</td>
</tr>
<tr>
<td>PWC</td>
<td>2.2 – 9.6</td>
<td>181</td>
<td>4.24</td>
<td>3.49</td>
</tr>
</tbody>
</table>

Table 5-7: Unconstrained Linear Regression of Crosswind Leeway Parameters

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>+CWL</th>
<th>-CWL</th>
<th>+CWL –(-CWL)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope (%)</td>
<td>Y (cm/s)</td>
<td>Syx (cm/s)</td>
</tr>
<tr>
<td>Panga w/1 POB</td>
<td>-0.66</td>
<td>11.29</td>
<td>2.73</td>
</tr>
<tr>
<td>Panga w/2 POB</td>
<td>-0.20</td>
<td>11.27</td>
<td>5.60</td>
</tr>
<tr>
<td>Panga w/4 POB</td>
<td>2.86</td>
<td>-3.81</td>
<td>3.60</td>
</tr>
<tr>
<td>Panga w/13 POB</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Outrigger canoe</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>PWC</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>
Table 5-8: Constrained through zero, Linear Regression of Crosswind Leeway Parameters

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>+CWL Slope (%)</th>
<th>+CWL Syx (cm/s)</th>
<th>-CWL Slope (%)</th>
<th>-CWL Syx (cm/s)</th>
<th>+CWL -(-CWL) Slope (%)</th>
<th>+CWL -(-CWL) Syx (cm/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panga w/1 POB</td>
<td>2.52</td>
<td>3.63</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Panga w/2 POB</td>
<td>1.47</td>
<td>6.12</td>
<td>-1.64</td>
<td>2.83</td>
<td>1.51</td>
<td>5.21</td>
</tr>
<tr>
<td>Panga w/4 POB</td>
<td>2.21</td>
<td>3.80</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Panga w/13 POB</td>
<td>n/a</td>
<td>n/a</td>
<td>-0.63</td>
<td>1.54</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Outrigger canoe</td>
<td>0.61</td>
<td>2.71</td>
<td>-0.34</td>
<td>1.85</td>
<td>0.54</td>
<td>2.58</td>
</tr>
<tr>
<td>PWC</td>
<td>0.93</td>
<td>3.06</td>
<td>-0.37</td>
<td>1.42</td>
<td>0.86</td>
<td>3.41</td>
</tr>
</tbody>
</table>

5.3.3 Jibing Frequency

The PVD of the five drift runs of the skiff with 2-POB loading is shown in Figure 5-7. Jibing events are more clearly visible in the zoomed figure (b), and are indicated by the four black arrows. A summary of the jibing frequency of all of the drift objects for all of the drift runs is presented in Table 5-9.

![Figure 5-7: Progressive vector diagram (PVD) showing the downwind and crosswind leeway vector components of each drift run for the Fibreglass Skiff with 2-POB loading (a). Zoomed in view (b) shown for the left two tracks. The far left track indicates four of the six jibing events that occurred during that drift run (indicated by four black arrows). Downwind is shown as the black vertical line, with the wind blowing from the bottom of the figure towards the top.](image-url)
### Table 5-9: Jibing Frequency

<table>
<thead>
<tr>
<th>Drift Object</th>
<th>Range of 10m Wind Speed (m/s)</th>
<th>Hours:Minutes of Samples</th>
<th>CWL switches (jibes)</th>
<th>Frequency Per hour (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panga w/1 POB</td>
<td>1.4 – 4.7</td>
<td>10:40</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Panga w/2 POB</td>
<td>2.6 – 10.6</td>
<td>109:10</td>
<td>6</td>
<td>5.5</td>
</tr>
<tr>
<td>Panga w/4 POB</td>
<td>1.6 – 11.9</td>
<td>37:50</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Panga w/13 POB</td>
<td>2.0 – 5.2</td>
<td>02:50</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Panga total</td>
<td>1.4 – 11.9</td>
<td>160:30</td>
<td>6</td>
<td>3.7</td>
</tr>
<tr>
<td>Outrigger canoe</td>
<td>1.6 – 9.6</td>
<td>51:10</td>
<td>4</td>
<td>7.8</td>
</tr>
<tr>
<td>PWC</td>
<td>2.2 – 9.6</td>
<td>30:10</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

### 5.4 Discussion

It was found that depending on the loading of the Panga skiffs, the constrained DWL may be up to 7.23% of the 10m reference height wind speed, which is significantly higher (almost double) than the DWL previously recorded for similar sized / configured craft such as the 4.15m Aluminium Skiff or the Cathedral hull – Boston Whaler, which have DWL coefficients of 3.95% and 3.15% respectively. Should the leeway coefficients of these similar craft be used as a proxy for the leeway coefficients of the Panga skiff, instead of the leeway coefficients calculated herein, the search areas would fall quite short of the actual location of the Panga skiff. The search object would then always be outside of the search area, and continue drifting further outside the search area as time goes on, thus giving a very low probability of a successful search outcome.

The outrigger canoe exhibited much lower leeway speed and DWL coefficients compared to the other craft tested (skiff and PWC), which was not surprising as the outrigger canoe floated deeper in the water compared to the skiff and PWC (approximately double the draft of the skiff and PWC). The combined effect of deeper draft as well as the additional drag of the outrigger would have contributed to retarding the leeway speed.

Whilst the downwind leeway component tends to have a directly linear relationship with the wind speed, the correlation between the crosswind leeway component and wind speed may not necessarily be linearly proportional to wind speed (Allen, 2005; Allen & Plourde, 1999). This is evident in the linear regression (using least squares line of best fit) of CWL to $W_{10}$ wind speed for the results herein, and has often been the case with
other leeway studies (Breivik, et al., 2011; Breivik, et al., 2012; Allen, et al., 2010). The $r^2$ values are not shown in the CWL results tables as they are very low, and have been omitted for brevity. When there is insufficient CWL data to effectively regress against the wind speed, those results may have to be omitted, which was the case with various loadings of the Skiff, the PWC and the Outrigger canoe. The 2 POB loading of the skiff did return adequate data to perform the linear regression of CWL coefficients, due to the extended run times the skiff was loaded in this configuration (over 109 hours in total).

The leeway speed refers to the total leeway speed, or the combined DWL and CWL leeway vectors. This value is greater than the DWL, but not usually significantly greater, as the predominant direction of leeway speed is towards the downwind direction.

The $r^2$ value indicates how well the regression line fits the data. Values close to one indicate a perfect fit, whilst values close to zero indicate a poor fit. As the regression can be either unconstrained, or constrained through zero, an $r^2$ value can be given for both regressions for the same dataset. Typically, unconstrained $r^2$ values will be higher than those constrained, as the constraint through zero can artificially skew the data when it is forced to pass through zero.

The rate of expansion of the search area is related to the uncertainty of the drift characteristics of the object in question. The $S_{yx}$ error term used in many of the stochastic search and rescue models available controls this level of uncertainty in the object’s drift, thus a larger $S_{yx}$ term will result in a more rapidly expanding search area. Whilst a large search area has a higher probability of containment (POC), whereby it is more likely that the search object will remain within the search area; this is balanced by the availability of resources to adequately search that area. The 95% prediction limits (indicated by the dashed lines on Figure 5-6) may vary between the unconstrained and constrained analysis of the leeway coefficients. An unconstrained regression will generally give tighter prediction limits compared to the constrained through zero regression of the same data, as indicated by the data in Table 5-5 to Table 5-8. The 95% prediction limits are directly related to the standard error ($S_{yx}$), and larger $S_{yx}$ values indicate larger or wider 95% prediction limits.
The jibing frequency indicates how often the object changes its CWL sign as a percentage per hour. Jibing is a nautical term which refers to when a yacht changes tack (course) and passes its stern through the eye of the wind. Allen (2005) introduced the use of jibing when defining the search area for objects adrift at sea, and its use in SAR modelling. Modelling the frequency of jibing can be difficult due to the complex dynamics involved with modelling the flow of fluids around a drifting object, especially when that object is at the interface between two fluids of significantly different densities (water/air interface). It is proposed that rapid shifts in environmental forcing, such as a change in wind strength and direction may cause jibing to occur. There are currently no statistical models available to determine the jibing frequency of an object; however it was indicated by Allen (2005) that past observations have yielded a jibing frequency in the range of 3% to 7% per hour, which may be used as a guideline for current and future studies. The skiff only exhibited jibing on the runs when it was under the 2-POB loading, with a jibing frequency of 5.5% which is within the range suggested by Allen (2005). The outrigger canoe jibed on several of its runs, returning a higher jibing frequency of 7.8% which is slightly larger than the aforementioned suggested upper limit of 7%. The PWC did not exhibit any jibing events. Longer run times where the drift object is allowed to drift without being interfered with are required to effectively ascertain the jibing frequency of a drift object, and as the jibing events are relatively rare – a larger number of samples are required to encapsulate these infrequent events.

During the first deployment, to the west of Chuuk (FSM), all of the drift objects tracked in a west to north westerly direction throughout the 5-day deployment duration (Figure 5-3). The skiffs were drifted for approximately 24 hour intervals, alternating between Skiff-1 and Skiff-2 over the 5-days. The other craft (PWC and outrigger canoe) were drifted during daylight hours only over the 5-days. The westerly drift exhibited by all craft during this deployment was attributable to the westerly surface currents which are predominately driven by the easterly trade winds.

The short drift tracks shown in Figure 5-4 depict the shorter duration deployment (~11hrs) nearby to Puluwat, FSM. These tracks all take a south westerly direction, with the skiff tracks being the longest (as they drifted the fastest) whilst the outrigger canoe track was the shortest (due to its slower drift). The winds and weather was calm during this run, with maximum wind speeds of 4.7 m/s (9.1 kts). This was the only run which
took a southerly direction (albeit still with a westerly component) whilst the other deployments near Chuuk and Guam both tracked towards the north west.

Figure 5-5 shows the drift path of the objects when deployed off the western coast of Guam, approximately 9.2 km west of Apra Harbour. The drift objects took a north westward drift trajectory for the first ~ 9 hours of the run, before changing direction to drift towards the north for approximately 5 hours, and then altering course again back towards the north west for the remainder of the drift run. All three drift objects took similar trajectories, which indicate that a wind direction change came through at the times that the objects each changed their courses, and that wind change was the driving force for the objects to change course. This was confirmed in the wind records from the weather station aboard the skiff, which showed the wind changing direction, blowing predominately from the east, before swinging towards the south east, and then back towards the east south east. The skiff and PWC did not record any jibing events during this run, however the outrigger canoe jibed twice, and both times it was observed to jibe there was a change in both wind intensity and direction (recorded by the weather station aboard the skiff), indicating the wind shift caused the outrigger canoe to jibe. Both the skiff and the PWC drifted in a very similar fashion, both finishing within ~2 km of each other, whilst there was a greater separation between these two drift objects and the outrigger canoe, which drifted much slower, and finished the drift run approximately ~7 km behind the other two craft. Whilst it appears that the changes in direction occur earlier for the outrigger canoe (closer to the start of the drift path) compared to the other two drift objects, it is in fact due to the outrigger canoe moving slower, and hence lagging behind the other two drift objects which were able to drift further before the wind change came through, and hence all three objects were subjected to the wind change event at essentially the same time, however their positions slightly varied spatially.

5.5 Conclusions / Recommendations

The methodology undertaken during the leeway field tests to determine the standard leeway coefficients of three common tropical pacific island craft; a 5.8m fibreglass skiff (Panga), a 5.9m outrigger canoe, and a two person sit down PWC, has been described herein. Data was successfully recovered for each of the three drift objects, and their
leeway coefficients were effectively calculated utilising currently recognised methods, in line with other leeway studies undertaken.

It is recommended that the three drift objects (and their associated leeway coefficients) are added to the leeway databases for search and rescue drift objects, and implemented into the various search and rescue models used internationally. Already the leeway data from these three drift objects has been integrated into the USCG SAROPS search and rescue drift forecast system and has been used during several SAR incidents within the Tropical Pacific region with successful results. The leeway coefficients calculated herein are currently being implemented into the Australian and New Zealand maritime SAR systems.

It is imperative that continued research into the leeway of common search objects is undertaken to ensure that the databases of leeway drift objects is as up to date and complete as possible. Revisiting common search objects (e.g. PIW) that have been studied in the past, with new methods and techniques (direct method) and more advanced instrumentation will lead to a better description of their drift characteristics and minimisation of the drift error, and hence reduction in the search area sizes required to adequately contain these objects. It is important that there are regional leeway databases of common craft which are specific to an area, and that these are updated accordingly.

5.6 Acknowledgements

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5.7 References


Chapter 5


Pingree, F., 1944. *Forethoughts on Rubber Rafts*.


STATEMENT OF CONTRIBUTION TO CO-AUTHORED PUBLISHED PAPER

This chapter includes a co-authored paper. The status of the co-authored paper, including all authors, is:

**Brushett, BA, King, BA, & Lemckert, CJ, ‘Application of Leeway Drift Data to Predict the Drift of Panga Skiffs: Case study of Maritime Search and Rescue in the Tropical Pacific, Unpublished Manuscript**

My contribution to the paper involved:

The concept and design of the study, background literature search, compiling and processing of data, undertaking the numerical modelling, processing and analysing the model results, interpreting the results, and drafting the paper.

(Signed) _______________________________ (Date)______________

Ben Amon Brushett

(Countersigned) __________________________ (Date)______________

Corresponding author of paper: Ben Amon Brushett

(Countersigned) __________________________ (Date)______________

Supervisor: Prof. Charles Lemckert
6. Application of Leeway Drift Data to Predict the Drift of Panga Skiffs: Case study of Maritime Search and Rescue in the Tropical Pacific

Abstract

Two case studies were undertaken which demonstrated the use of SAR drift forecasting in an operational capacity to predict the drift of a Pacific Islander panga skiff for a period of 120 hours (5-days) and 72 hours (3-days) respectively. The leeway characteristics of flat bottomed panga skiffs were unknown until recently, when a leeway field study was undertaken in mid 2012 to empirically determine the influence of wind and waves on the drift of panga skiffs (Allen, et al., 2013). The leeway characteristics were then able to be used in SAR drift forecast models to forecast the drift of these craft and determine suitable search areas. As part of the two case studies, four ocean models and one wind model were used as environmental forcing to a stochastic particle trajectory model, which were combined in a four model consensus forecast. Each of the four ocean models were tested to ascertain which individual model was the most accurate (in terms of average distance error of model particles positions compared to actual panga skiff locations). In addition to this, a hit/miss analysis was undertaken to determine whether the panga skiff was located within the forecast search areas for each single model, and for any consensus areas which were defined as; any two or more model consensus (2+), any three or more model consensus (3+), and all four model consensus areas (4). Finally, an assessment of the search area sizes was carried out to assess the single model forecast search area sizes, and how they compared...
with each of the consensus search area sizes. This was completed to establish whether there was potential benefit in focussing search resources upon consensus overlap areas, to more efficiently carry out a search and manage search asset allocation. Asset management and search area prioritisation is especially important with longer duration (several days) search activities that involve much larger search areas, and may not be able to be fully covered with available assets (hence requiring targeting of those available assets upon higher probability areas). The results indicated that the FOAM ocean model forecasts returned the lowest average distance errors across both of the case studies investigated herein. In both of the case studies, all four ocean model forecast search areas contained the panga skiff at the time intervals tested. The four model consensus search area was approximately one third the size of the average single model search area, whilst still containing the search object. This study demonstrated that the consensus search areas provided a more efficient (reduced) search area compared to each of the individual ocean model search area forecasts.

### 6.1 Introduction

Timely response to maritime search and rescue (SAR) cases is vital to the successful location of the missing persons, craft or objects (hereafter referred to collectively as search objects). In maritime SAR cases the position of the missing search object is not fixed, as it may be with many land based/terrestrial SAR cases. Search objects within the maritime environment drift as the result of a combination of the prevailing ocean currents, winds and waves. The drift or movement of the search object causes the search datum to change with time, hence complicating the search efforts further than if the object’s position was fixed. Successfully locating a moving search object requires the object be located within the defined search area at the same time as it is being searched for. However as the search object is drifting, it may pass through the search area at a time before, during or after the search assets (eg. SAR ships and aircraft) are searching it. Hence there is a spatial and a temporal coincidence that must be met for a successful outcome. The added complexity of a moving search datum decreases the chances of locating the search object as time progresses, in part due to the many accumulating uncertainties that are associated with forecasting the drift, over time, of objects at sea.
SAR drift forecast models are routinely used by many SAR agencies to predict the drift of search objects and subsequently generate search areas based on the most likely location of the object as a function of time. It is important that SAR drift models are able to account for the drift of a search object, in addition to accounting for the numerous uncertainties and possible errors that surround SAR cases in general. In addition to the details specific to an incident, such as last known position, time and the type of search object, three main elements are required to ensure the drift of a search object is accurately represented in stochastic particle trajectory SAR drift models. These elements include; 1) leeway characteristics for the search object being modelled; 2) hindcast/nowcast/forecast environmental data (winds and ocean currents); and 3) an estimate of the horizontal dispersion required to account for the smaller sub grid scale turbulence and transport mechanisms that the larger scale ocean models and wind models are not able to reproduce.

There are several different ocean models running (with available output simulation data) for the same geographic locations, which allow the SAR operator to replicate the same scenario forecast with different ocean currents as different model inputs and compare the results. When more than one model forecast coincides or overlaps, there is some degree of consensus between those model forecasts. The greater number of ocean models providing coinciding forecasts may provide the SAR operator with greater confidence in the forecast outcome, and the areas where the model forecasts coincide may potentially be given higher priority for asset allocation over other areas where consensus was not evident. The consensus forecasting approach has been investigated previously (Chapter 2 – Timor Sea Drifter Study (Brushett, et al., 2011), Chapter 3 – Tasman Sea Drifter Study, and Chapter 4 – Indian Ocean Drifter Study) which investigated forecasting the trajectories of multiple ocean drifter buoys in the Timor Sea, Tasman Sea and the Indian Ocean. It was found that a drop in hit rate (the probability that the search object will be located within a forecast search area) was evident with the 3+ and 4 model consensus forecast areas. However, the reduction in search area for those 3+ and 4 model search areas indicated that the consensus areas provided a more efficient search area, where the reduction in hit rate was proportionally smaller than the greater reduction in search area size. Hence, it has been suggested that it may be beneficial to focus search efforts on the consensus overlap areas, especially in
situations where there may not be adequate search assets available to successfully cover any single search area forecast.

This study describes two modelling studies where the Lagrangian stochastic particle model, SARMAP (Search And Rescue Mapping and Analysis Program) (Applied Science Associates, Inc., 2013) was used to forecast the drift (and consequent search areas) of flat bottomed panga skiffs off the Federated States of Micronesia (FSM) in the Pacific Ocean (Figure 6-1). Panga skiffs (19 and 23 foot) are one of the most common craft in the tropical Pacific Islands due to their low construction costs, durability, and seaworthiness. Figure 6-2 shows a photo (a), and dimensioned line drawing (b) of a 5.8m panga skiff. The first case study involved forecasting the 120 hour (5-day) drift of the 19 foot panga skiff, deployed during a United States Coast Guard (USCG) leeway field test, which coincided with a USCG Search and Rescue Exercise (SAREX) in May-June 2012. The panga skiff had been instrumented to collect environmental (winds and currents) and positional data that was then used to calculate the vessel’s leeway characteristics (effect of wind and waves on the drift of the panga skiff, relative to the ocean currents). The instrumentation attached to the panga skiff is visible in Figure 6-2a. The second case study involved an actual SAR incident, which occurred during the leeway field test, and involved forecasting the 72 hour (3-day) drift of a missing 23 foot panga skiff with 2 persons on board (POB). As no leeway data was previously available for panga skiffs (prior to the leeway field test) to enable an accurate forecast of their drift, it was fortunate that the leeway coefficients were able to be determined from the data collected the previous week. The leeway characteristics of the panga skiff were subsequently applied to forecasting the drift of the panga skiff in the SAR case, which resulted in the successful location of the skiff and rescue of the two persons on board, after being adrift at sea for 3 days in the vast expanse of the Pacific Ocean.
The aim of this study was to determine the effectiveness of a SAR drift model and its parameters when being used to forecast the drift of a panga skiff for a period up to 5-days in the Pacific Ocean. As four different ocean models were available for the region (BLUElink, FOAM, HYCOM and NCOM), four separate SAR drift model runs were undertaken to compare the results of each individual current forecast, as well as the result when all four current forecasts were combined into a consensus forecast. The
consensus forecasting technique was evaluated to ascertain its suitability for use in actual SAR incidents to potentially reduce search area sizes, or provide higher confidence search areas based on consensus overlap regions – to more effectively task search assets. This is especially important with large search areas which are common to search events spanning several days (such as those indicated herein). Additionally, the leeway parameters for the panga skiff with a 2 POB loading (Allen, et al., 2013) were tested in the stochastic particle trajectory model to ensure they were able to adequately replicate the leeway component of the drift of the actual objects when used in conjunction with the environmental forecast models.

An outline of the background and methodology adopted is provided in the following section. This includes an overview of the modelling procedure undertaken, as well as a description and background of the stochastic particle trajectory SAR drift model (SARMAP) and the environmental forecast models used (four ocean models and one wind model). A description of the leeway parameters for the panga skiff is included, in addition to an overview of the analysis methods employed to determine ocean model accuracy and success rate throughout the drift simulations. Further, the results of the drift forecast simulations are presented separately for each of the two case studies, followed by a discussion of the results and their implications. Finally conclusions are drawn from the present study and recommendations are suggested for future research.

6.2 Background and Methodology

The stochastic particle trajectory model SARMAP was used in conjunction with four ocean models and one wind forecast model, to forecast the drift of a 19 foot and a 23 foot panga skiff in two separate case studies. The first case study described the 120 hour drift of a 19 foot panga skiff, from the west of Chuuk Islands (FSM) during a US Coast Guard SAREX from 28th May to 2nd June 2012 (Figure 6-1). The second case study involved forecasting an actual SAR incident involving the 72 hour drift of a 23 foot panga skiff which was reported missing with 2 persons on board, north of Chuuk Islands from 3rd to 6th June 2012 (Figure 6-1).
The four ocean models used herein (BLUElink, FOAM, HYCOM and NCOM) have successfully been used previously to provide ocean current forcing for the SAR drift model SARMAP, to predict the trajectories of drifters in the open ocean (Chapter 2 – Timor Sea Drifter Study (Brushett, et al., 2011); Chapter 3 - Tasman Sea Drifter Study; and Chapter 4 – Indian Ocean Drifter Study). Prior investigations into the horizontal dispersion coefficients used within the stochastic particle trajectory model indicated that a value of 1,000 m$^2$/s was effective for containing search objects within the predicted search areas located in open waters for periods up to 5-days (Chapter 3 - Tasman Sea Drifter Study; and Chapter 4 - Indian Ocean Drifter Study). Studies by (Brushett, et al., 2014) and (Allen, et al., 2013) calculated the leeway drift characteristics of a 19 foot Panga skiff under different loadings, from 1 to 12 POB equivalent loading.

The SARMAP model was run four times for each of the two cases, with each replicate using one of the four individual ocean models to provide current forcing. The GFS atmospheric forecast model was used to provide wind forcing and the leeway characteristics for a 19 foot panga skiff with 2 POB were used to account for leeway drift. Once the four model runs per case had completed, they were analysed and combined to produce an additional ensemble to identify any consensus forecast areas.

This current section details various components of the study including; the SARMAP drift model, the current and wind forecast models used as environmental forcing, the leeway coefficients of the panga skiff, the consensus forecasting approach, and finally the analysis methods used to determine the efficiency of each of the individual model and consensus forecasts.

6.2.1 SARMAP Trajectory Model

The SARMAP search and rescue drift model consists of a Lagrangian stochastic particle trajectory model which employs a first order (Markov-0) ‘random walk’ stochastic process to calculate drift trajectories and generate search areas for objects adrift at sea. The first order stochastic models are the lowest level in the series of Markov models, where the particle displacement is treated as a Markov variable, whilst the infinitesimal particle velocity and acceleration are assumed. The two further advanced models in the Markov series, include the random flight model which treats both the particle
displacement and the particle velocity as a Markov variable (and assumes the particle acceleration to be negligible), and the highest order model which treats the particle displacement, velocity and acceleration all as jointly Markovian variables (Spaulding, et al., 2006). Typically the first order (random walk) models are more frequently used in operational search and rescue models (Spaulding, et al., 2006; Breivik & Allen, 2008), whilst the second order random flight model has also been successfully implemented in some search and rescue models. Studies (Spaulding, et al., 2006; Isaji, et al., 2006) have concluded that there may be little benefit utilising the random flight model over the random walk model in cases where accurate dispersion factors are not well known.

Forecast winds and currents from global forecast models were used as external forcing for the stochastic model particles to account for the transport of the search object due to the wind, waves and currents that a drifting object may be subject to. Brushett, et al., (2014) adapted the drift equations by Hackett, et al., (2006) to describe the total drift of an object as the sum of the current drift (relative to earth) and the drift due to the object’s leeway coefficients (relative to the currents) as a result of wind and wave action. As leeway drift is independent of the currents, it can be described as the slip of an object across the water surface due to the wind and wave action upon it. Each model particle is assigned a slightly different leeway value, within the defined standard error bounds (unique to the particular search object) which are calculated when the leeway coefficients were collected during leeway field tests (Allen, et al., 2013; Brushett, et al., 2014). This allows for a spread of leeway values to be used, which assists in accounting for the uncertainties associated with the calculation of the leeway of an object, and the uncertainties in drift of the object in a SAR incident. The small differences in leeway values, in addition to a horizontal dispersion parameter (controlled by the random walk process), are used to generate an ensemble of possible drift trajectories from each of the 1,000 model particles. The grouping of these model particle trajectories enables a search area for the drift object to be formed by encompassing all of the 1,000 model particles within a convex hull shaped polygon.
The SARMAP model was set up so each of the simulations ran with the following parameters:

- 1,000 particles
- 1,000 m\(^2\)/s horizontal dispersion
- 10 min time step
- 60 min output interval
- GFS wind forcing
- BLUEl ink or FOAM or HYCOM or NCOM current forcing
- Panga Skiff – 2POB loading – drift object

### 6.2.2 Environmental Data

The following section gives a brief overview of the measured winds and currents (measured by the skiffs deployed during the SAREX) and the model forecast winds and currents, from global forecast models.

**Measured ocean current data**

The current meter data was analysed, and the surface currents (0-1 m depth averaged) were extracted from the dataset once the current meter data was adjusted to account for the drift of the skiff (by using the onboard GPS to calculate net drift over time). The current meter indicated the measured surface currents speeds were on average 0.26 m/s, with a median current direction towards 309° (approximately northwest) throughout the 120 hour period of deployment.

**Ocean current forecast models**

The four different ocean models used to provide ocean current forcing to the SARMAP model were the Australian BLUEl ink (Brassington, et al., 2012), the UK Met Office Forecasting Ocean Assimilation Model – FOAM (Storkey, 2011), the US Hybrid Coordinate Ocean Model – HYCOM (Chassignet, et al., 2009) and the US Navy Coastal Ocean Model – NCOM (Barron, et al., 2007). An overview showing several of the model parameters including horizontal, vertical and temporal resolutions is provided.
in Table 6-1. Further detail for each of these ocean models is contained within Chapter 3 – Tasman Sea Drifter Study, and Chapter 4 - Indian Ocean Drifter Study. A snapshot of the ocean current vectors in the region from each of the ocean models at the beginning (Figure 6-3) and end (Figure 6-4) of the 120 hour SAREX are shown for comparison.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Horizontal Resolution</th>
<th>Vertical Coordinate</th>
<th>Temporal Resolution</th>
<th>Grid Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUElink</td>
<td>1/10° (11.1 km)</td>
<td>47 z levels</td>
<td>24 hr</td>
<td>Global [16°N - 75°S, 90°E - 180°E]</td>
</tr>
<tr>
<td>FOAM</td>
<td>1/6° (18.5 km)</td>
<td>50 z levels</td>
<td>24 hr</td>
<td>Global [0°N - 60°S, 100°E - 77°W]</td>
</tr>
<tr>
<td>HYCOM</td>
<td>1/12° (9.3 km)</td>
<td>32 Isopycnal/σz</td>
<td>24 hr</td>
<td>Global</td>
</tr>
<tr>
<td>NCOM</td>
<td>1/8° (13.9 km)</td>
<td>40 σ levels</td>
<td>6 hr</td>
<td>Global</td>
</tr>
<tr>
<td>GFS</td>
<td>1/2° (55.6 km)</td>
<td>64 σ levels</td>
<td>6 hr</td>
<td>Global</td>
</tr>
</tbody>
</table>

Where: z represents fixed depth layers, σ represents terrain following depth layers

Figure 6-3: Snapshot of the Surface currents in the area of interest as generated by BLUElink (a), FOAM (b), HYCOM (c) and NCOM (d) at the beginning of the 120 hour SAREX skiff simulation (28th May 2012 0100 GMT).
Wind forecast model

The Global Forecast System (GFS) is an atmospheric forecast model, run operationally by NOAA (National Oceanic and Atmospheric Administration) and provides global atmospheric forecasts at 6 hourly time intervals out to 168 hrs (7 days). The NOAA GFS website contains the most up to date information of the GFS model parameters (http://www.emc.ncep.noaa.gov/index.php?branch=GFS). The forecast winds (U and V components) at the standard 10 m height were used to provide the SARMAP particle trajectory model with atmospheric forcing for the model simulated drift of the panga skiff.

There was not a significant amount of spatial variability evident in the GFS model forecast wind fields in this particular open ocean environment (refer to the wind barbs shown in Figure 6-5). Throughout the duration of the SAREX the GFS winds were shown to be predominately from the East, with some fluctuation from the northeast and southeast throughout. Average wind speed and median wind direction from the GFS
model forecast was shown to be in good agreement with the winds measured by the weather station on board the skiff throughout the 120 hour duration (Table 6-2).

Table 6-2: Comparison of measured and GFS model wind speed and direction throughout the 120 hour SAREX.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measured</th>
<th>GFS Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Speed (m/s)</td>
<td>0.7</td>
<td>3.2</td>
</tr>
<tr>
<td>Maximum Speed (m/s)</td>
<td>11.9</td>
<td>8.7</td>
</tr>
<tr>
<td>Average Speed (m/s)</td>
<td>5.7</td>
<td>6.1</td>
</tr>
<tr>
<td>Median Direction From (degrees)</td>
<td>92.6° (~East)</td>
<td>89.1° (~East)</td>
</tr>
</tbody>
</table>

Figure 6-5: Snapshot of the wind field in the area of interest as generated by the GFS atmospheric model, (a) at the beginning of the 120 hour SAREX skiff simulation (28th May 2012 0100 GMT), and (b) at the end of the simulation (2nd June 2012 0100 GMT).

6.2.3 Drift Object Leeway Coefficients

When objects are adrift a number of forces contribute to its transport. These forces include those resulting from winds, waves, and surface currents (including wind and wave induced currents). The slip of an object across the water respective to the ambient currents is the result of the object’s leeway. The leeway drift of an object is directly due to the wind and wave action on the object, and typically acts in a downwind direction with some degree of divergence in the crosswind direction. Leeway can thus be described as either; speed (in relation to the wind speed) and divergence angle (in relation to the downwind direction); or as vector components including the downwind leeway (DWL) and the crosswind leeway (CWL) component. The current definition of leeway, as defined by Allen and Plourde (1999) is:
“Leeway is the motion of the object induced by wind (10m reference height) and waves relative to the ambient current (between 0.3 m and 1.0 m depth)”

There was no leeway data available for the panga skiff prior to the leeway field study carried out in the waters off Guam and Chuuk in 2012 (Allen, et al., 2013; Brushett, et al., 2014). The initial focus of the leeway field experiment was 2 POB loading, however after further consideration it was determined that it would be beneficial to ascertain how the leeway of the panga skiffs changed with changes to the loading. As a result, several extra drift runs were undertaken at various different loadings. Due to the disparity in sample numbers and run lengths at different loadings, and the variance between runs, the entire leeway dataset (including each of the loading values) was plotted and regressed against the loading values from 1 to 12 POB (equivalent). Leeway values interpolated from 1 to 12 POB were calculated from this regression (refer to section 5.2.5, Allen, et al., (2013)). The interpolated leeway parameters for the 19 foot panga skiff with 2 POB loading are outlined in Table 6-3.

Table 6-3: Constrained Leeway Parameters of 19 foot panga skiff with 2 POB.

<table>
<thead>
<tr>
<th>Leeway Speed</th>
<th>DWL</th>
<th>CWL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope (%)</td>
<td>Divergence Angle</td>
<td>Slope (%)</td>
</tr>
<tr>
<td>5.70</td>
<td>18.8</td>
<td>5.39</td>
</tr>
</tbody>
</table>

6.2.4 Consensus forecasting

The concept of consensus forecasting has been successfully applied to many fields which utilise model forecasts, particularly economic forecasting and numerical weather prediction, whilst its use in oceanographic forecasting has been relatively limited until recent times. Previous studies by King et al., (2010), Brushett, et al., (2011) and King, et al., (2011), have discussed the notion of utilising a number of independent ocean models in operational drift forecasting and comparing or combining the results to assess if consensus between the drift models was achieved. When consensus was achieved between models it was recognised that there was the potential to apply more weight, or a higher probability, to the consensus outcome compared to the results where consensus was not achieved. This agrees with the consensus concept that the cumulative
knowledge of the group is greater than that of the individual (Fritsch, et al., 2000). Having the extra information resulting from several forecast models is beneficial as it provides the forecaster with additional information as to how other scenarios may unfold under different assumptions. The combination of several model forecasts therefore potentially provides a more complete picture of possible outcomes.

With the current availability of several ocean models within the same geographic regions, the application of consensus forecasting within the oceanographic field has been further developed (refer to Chapter 3 – Tasman Sea Drifter Study, and Chapter 4 – Indian Ocean Drifter Study) where four ocean models were used to generate model forecasts in conjunction with the search and rescue model SARMAP, to predict the 5-day movement of surface drifters. Forecasts of the drifter trajectories were undertaken using each of the individual ocean models, as well as using all four ocean models combined into a consensus forecast. It was shown in the two aforementioned studies that the consensus search areas typically returned a higher hit rate per unit of search area than the individual ocean model search areas, thus indicating a potential benefit in focusing search efforts on the higher probability consensus areas.

A bibliographic review of over 200 studies on the topic of combining forecasts, from an array of fields was completed by Clemen (1989). It was found that forecast accuracy could be enhanced through combining several individual forecasts, and that the more simple methods of combining the individual forecasts (for example, a simple average) often performed as well as the more complex combining methods. It was recommended that combining forecasts should be implemented in conventional forecasting practice going forward. A study investigating the use of a consensus forecasting approach for economic forecasts (Agnew, 1985) indicated that the improvement in accuracy of the composite consensus forecast over the individual model forecasts may lie in the fact that often the optimal consensus forecast (the consensus forecast which was closest to reality) can indeed lie outside the range of some of the individual forecasts and their associated errors.

The combination of four single model forecast search areas to form an example of a consensus forecast is shown in Figure 6-6. The individual model forecast search areas are defined by the coloured polygon outlines (Blue – BLUElink, Green – FOAM, Yellow – HYCOM, and Red – NCOM), whilst the shaded overlapping areas indicate
those areas where consensus exists between the single models. The lightest grey indicates the area for any of the single model forecasts, the second lightest grey indicates those regions where 2 models agree, the second darkest area indicates areas where any three of the four single models agree, and finally the darkest grey shaded area indicates the area where all four single models agree, thus defining the 4 model consensus search area. Note that as the number of overlapping model areas increases, the corresponding size of the search areas decrease significantly. This reduction in search area size may therefore be used to refine searches. Whilst the present study has focussed on using a number of ocean current models to generate the consensus forecasts, it should be noted that a similar approach could be undertaken with the use of multiple wind forecast models to build the consensus forecasts, which may be the focus of future research.

Figure 6-6: Schematic showing how the consensus forecasts are combined from the individual ocean model forecast search areas. Higher intensity grey shading indicates the greater number of models forming consensus.
6.2.5  Analysis methods

Three measures were used to evaluate the effectiveness of the model forecasts. They included; minimum distance error; average distance error; and hit/no-hit status. Additionally the search area size was calculated for comparison between individual model forecasts and consensus or combined ensemble model forecasts. The same statistics were carried out at 24 hours and at 120 hours during the two drifter forecast studies contained within Chapter 3 – Tasman Sea Drifter Study, and Chapter 4 – Indian Ocean Drifter Study.

The minimum distance error relates to the smallest distance error that is calculated from each one of the 1,000 model particles when compared to the actual location of the skiff at a given time interval, whilst the average distance error is the average distance from each one of the 1,000 model particles compared to the actual location of the skiff at a given time interval. Typically, the minimum distance error is considerably smaller than the average distance error, due to the possibility for just one of the model particles to coincide closely with the skiff’s position, whilst many of the other model particles may be some distance away. As such, the average distance error provides a more reliable measure of the distance error when comparing forecasts, as all of the 1,000 model particle distance errors contribute to the final averaged value. The hit/no-hit status was used to define whether or not the skiff was located within the single model defined search areas and the consensus model search areas at a given point in time.

The particle distance error (minimum and average), hit/no-hit status and model search area size was determined for the first case at 24 hours, 72 hours and 120 hours, whilst these same statistics were only able to be calculated at 72 hours for the second case. This was due to there being data available in terms of the skiff position throughout the whole 120 hour drift scenario for the first case; however the only skiff position that was known for the second scenario was at 72 hours, when and where the skiff was found by the search aircraft. The 72 hour analysis enabled a comparison of the above statistics to be carried out between the model forecasts for the two case studies.
6.3 Results

The drift forecast modelling for the study was divided into the two separate case studies. The first case study involved the 120 hour drift of a 19 foot Panga skiff, deployed during the SAREX to the west of the Chuuk Islands; and the second scenario involved the 72 hour drift of a 23 foot Panga skiff, after it was reported overdue en route from Nomwin Atoll to the Chuuk Islands. Both case studies present a summary of the drift model runs, the distance error analysis for both minimum and average particle distance error, the hit analysis (whether the panga skiff was located within the forecast search area), and finally, the search area size comparison.

6.3.1 Case 1: SAREX - Leeway Field Test 19 foot Skiff (2 POB) – 120 hour Drift

Summary of the drift run

The drift track of the panga skiff over the 120 hour duration is shown in Figure 6-1. As indicated, the 19 foot panga skiff tracked in a west-north-west direction with a drift speed of approximately 0.59 m/s for the first 12 hours. After 12 hours the skiff changed trajectory, further towards the north, to a more northwest direction where it continued to drift for the remainder of the 120 hour duration. Over the course of the 120 hour drift, the daily averaged drift speeds fluctuated between a maximum of 0.58 m/s (day-1), to a minimum of 0.36 m/s (day-2). The skiff drifted approximately 200 km in a northwest direction from the deployment location to the position at the end of the 120 hour duration. This indicated an average distance of approximately 40 km travelled per day, and an average drift speed over the 120 hours of 0.46 m/s.

Wind speed and direction recorded by the weather station onboard the skiff, and corrected for the drift of the vessel using an onboard GPS, determined that conditions were on average 5.7 m/s (11.2 kts), with a maximum wind speed of 11.9 m/s (23.2 kts), and predominately from the East (93°). Current conditions, measured by an ADCP onboard the skiff indicated that the surface currents the skiff was exposed to were on average 0.26 m/s (0.5 kts), with a maximum of 0.76 m/s (1.5 kts) and predominately flowing towards the northwest (309°).
**Distance Error Analysis**

Figure 6-7 shows the minimum particle distance error analysis (a) and average particle distance error analysis (b) for each of the four SARMAP forecasts (each using an individual ocean model for current forcing) over the 120 hour period that the panga skiff was adrift. As indicated in Figure 6-7 (a) the minimum particle distance error was low over the whole 120 hours for all four models, compared to the average particle distance errors. The average particle distances shown in Figure 6-7 (b) reveals the average distance error grows with time, and the rate of increase in distance error varied with each of the ocean models as time progressed. All four forecasts indicated similar average distance errors up until 24 hours (between 21.5 and 26.9 km), with the lowest being BLUElink, closely followed by FOAM, then NCOM and HYCOM. By 72 hours, FOAM showed the lowest average distance error (42.8 km) followed by BLUElink (51.4 km), NCOM (62.7 km) and HYCOM (66.5 km). At the end of the scenario (120 hours), FOAM still returned the lowest average distance error (52.4 km), again followed by BLUElink (65.4 km), HYCOM (86.8 km) and finally NCOM (106 km).
Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications

Figure 6-7: Minimum distance error (a) and Average distance error (b) between the actual Panga skiff location and each of the 1,000 model particles over the 120 hour forecast duration, for each of the four ocean model forecasts during Case 1.
**Hit Analysis**

A hit or miss analysis was undertaken to investigate whether the panga skiff was located within each of the model defined search areas. This analysis was performed at 24 hour intervals throughout the 120 hour drift for each of the individual model forecasts (BLUElink, FOAM, HYCOM and NCOM), as well as the consensus forecast areas. The consensus forecast areas were defined as being; any two or more model consensus (2+), any three or more model consensus (3+), and all four model consensus (4). It was found that the skiff was located within the predicted search area for each of the four individual model forecasts at each of the 24 hour time intervals over the 120 hour drift. As the skiff was located within all four of the individual search areas, model consensus was therefore achieved for each of those intervals for 2+, 3+ and 4 model consensus. Figure 6-8 shows the individual model defined search areas (bound by coloured outlines) for BLUElink (blue), FOAM (green), HYCOM (orange) and NCOM (red) at 24 hours (a), 72 hours (b) and 120 hours (c). The track of the panga skiff is indicated by the black line, whilst the blue circles indicate 12 hour intervals. The consensus search areas are indicated by the shading of each of the individual model search areas. As the intensity of the shading increases, the number of model forecast areas coinciding increases. Thus light grey indicates single model search areas, whilst the darkest grey indicates the four model consensus search area.
Figure 6-8: Forecast search areas for 19 foot skiff with 2 POB set adrift as part of the SAREX near Chuuk (FSM) May-June 2012. Skiff track is shown by the black line, with blue circles showing 12 hour intervals. Search areas are indicated by the convex hull polygons at 24 hours (upper - a), 72 hours (middle - b) and 120 hours (lower - c). Consensus areas indicated by increasing intensity shaded regions, with single model forecast areas shown as light grey, 2+ model consensus as darker grey, followed by 3+ model consensus and 4 model consensus as the darkest grey.
**Search Area Size**

To enable a comparison to be made between the individual model search area and the consensus search area, the magnitude of the search area was calculated at 24, 72 and 120 hours for each of the individual model areas, as well as for the combined 2+, 3+ and 4 model consensus areas (Figure 6-9). Additionally the size of the search areas contained herein indicate the potential size of search area that may be expected for a 120 hour drift of a panga skiff, using the SARMAP model parameters described, and under the weather conditions experienced during this drift. This may assist SAR agencies with asset management and planning, should a similar event unfold in the future.

As expected, the size of the individual model search areas and the combined consensus search areas all increased with time. The size of the consensus areas was shown to be considerably reduced as the number of overlap areas increased (i.e. the 4 model consensus area was considerably smaller than the 3+ and 2+ model consensus search areas) at all time steps analysed throughout the simulation.

The HYCOM search areas were shown to be larger than each of the other single model search areas and also larger than each of the consensus search areas (2+, 3+ and 4) at each of the time steps investigated (24, 72 and 120 hrs). There was no evident pattern over time with the order of search area size for the other three single model forecast search areas, which all returned similar sized areas. It was observed that the individual search areas (with the exception of HYCOM) were smaller than the 2+ consensus area (summation of the areas where two or more individual model forecast areas overlapped). All individual search areas were larger than the 3+ (summation of areas where 3 or more individual model forecast areas overlapped) and 4 model consensus search areas (area where all four model forecasts overlapped).

At 72 hours the smallest single model search area was NCOM (17,421 km²), followed by FOAM (18,643 km²), and BLUElink (19,015 km²), then finally HYCOM (22,082 km²). The 2+ model consensus search area was 20,910 km², whilst 3+ and 4 model consensus search areas were 13,374 km² and 6,227 km² respectively.
Figure 6-9: Charts showing the size of the individual forecast search areas, and the combined consensus search areas at; 24 hours (upper - A), 72 hours (middle - B) and 120 hours (lower - C) for the 19 foot Panga skiff with 2 POB equivalent loading, adrift during SAREX west of Chuuk Islands.
6.3.2 Case 2: SAR Incident - Missing 23 foot Panga Skiff (2 POB) – 72 hour Drift

Summary of the drift run

The second case study involved an actual SAR incident, being a 23 foot panga skiff with 2 persons on board, which was reported missing whilst en route from Nomwin Atoll to the Chuuk Islands. The skiff had travelled approximately half way along its intended route, when it became disabled due to engine failure. The approximate intended track of the skiff is indicated by the thin black track line in Figure 6-1. The approximate location of the panga skiff when it became disabled is indicated as the thicker black track line in the centre of the intended track line. The panga skiff drifted almost due west from the location where engine failure occurred, and over the 72 hours of drifting it covered approximately 95 km before it was located. This indicates an average drift speed over the 72 hours of 0.37 m/s.

As there was no measured wind data available for the location and time where the 23 foot panga skiff was drifting, an analysis of the GFS model winds was undertaken. It was found that there was little spatial variability in the open ocean environment of the drift region, and hence an analysis of a single wind node in the centre of the drift area was representative of the winds that the skiff may have been subject to during its drift. The analysis of the GFS model wind data indicated that wind speed over the 72 hour drift duration was on average 7.6 m/s (14.7 kts), with a maximum wind speed of 9.7 m/s (18.8 kts), and was predominately blowing from East to east-northeast (82°).

The limited information available for the drift of the 23 foot panga skiff and its location over time was restricted to the approximate start of drifting position, and the location where the skiff was found after approximately 72 hours of drift. Hence the analysis that was able to be undertaken in regards to identifying the accuracy of the individual model search area forecasts was only able to be carried out at 72 hours.

Distance Error Analysis

Figure 6-10 indicates the minimum particle distance error analysis (black bars) and average particle distance error analysis (grey bars) for each of the four SARMAP forecasts (each using an individual ocean model for current forcing) at the time the 23 foot panga skiff was found (72 hours after the simulation started). As shown in Figure
6-10, the minimum particle distance error at 72 hours was low for all four models compared to the average particle distance errors at 72 hours. All four forecasts indicated a similar order of magnitude of the average distance errors at 72 hours. The lowest average distance error at the end of the scenario (72 hours) was derived from FOAM (51.6 km), followed by BLUElink (52.0 km), NCOM (60.4 km) and HYCOM (76.7 km).

![Figure 6-10: Minimum distance error (black) and Average distance error (grey) between the location the Panga skiff was found and the location of each of the 1,000 model particles at 72 hours, for each of the four ocean model forecasts during Case 2.]

**Hit Analysis**

Each of the model forecast search areas were analysed to ascertain whether the location that the 23 foot panga skiff was found coincided with the search areas as generated by each individual ocean model forecast, in addition to the consensus forecast areas (the areas where two or more of the ocean model forecasts overlapped). The modelling indicated that at the time the 23 foot panga skiff was found, it was contained within each of the individual ocean model search areas (refer to Figure 6-11), and hence it was also contained within the 2+, 3+ and 4 model consensus areas (refer to Figure 6-12).
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**Search Area Size**

The size of each of the individual ocean model predicted search areas, as well as the areas of consensus (overlap) was calculated to determine which ocean model produced the smallest search area (whilst maintaining the panga skiff within the search area) and how the individual search area sizes compared in size to the consensus overlap areas.

It was found that all of the individual ocean models returned a similar magnitude search area for the panga skiff at 72 hours (Figure 6-13). The BLUElink model returned the smallest individual ocean model search area (19,878 km$^2$) followed by NCOM (20,474 km$^2$), HYCOM (21,105 km$^2$) and FOAM (21,394 km$^2$). The largest search area corresponded to the 2+ model consensus region (24,855 km$^2$), which included all of the overlap areas where 2, 3 and 4 of the individual ocean model forecast search areas coincided. The 3+ model consensus region (3 and 4 model overlap area) returned a smaller search area than each of the individual search areas (16,303 km$^2$), whilst the 4 model consensus area returned the smallest search area (7,416 km$^2$), which corresponds to the area where all four individual model areas overlap. These results indicate that a more accurate or targeted search area may be established if the 3+ or 4 model consensus areas were used.

![Search Area Size at 72 hours](chart)

**Figure 6-13:** Chart showing the size of the individual forecast search areas, and the combined consensus search areas at 72 hours for the 23 foot Panga skiff with 2 POB, adrift for 3-days after becoming disabled en route from Nomwin Atoll to Chuuk Islands, June 2012.
6.4 Discussion

The latitude of the study region (between approximately 7° N and 9° N) is at the southern extent of the westward flowing Pacific North Equatorial Current (NEC) and in proximity to the interface between the NEC and the eastward flowing Pacific North Equatorial Counter Current (NECC). Studies by Qui & Joyce (1992) indicate that the mean transport (westward) of the NEC exist between the latitude of 7° N to 25° N, whilst the mean transport (eastward) of the NECC exist between the latitudes of 7° N to 2° N. The NEC has an annual mean bifurcation point on the western boundary (near the Philippines) at approximately 13.3 N determined through the analysis of gridded altimetry data (Wang, et al., 2009) and historical temperature and salinity data (Qu & Lukas, 2003). It has been widely identified (Wang, et al., 2009; Qui & Lukas, 1996; Qu & Lukas, 2003; Kim, et al., 2004; Wang & Hu, 2006) that the bifurcation point, and hence mean position of the Pacific NEC varies in latitude depending on the season. The bifurcation point of the NEC is at the northernmost excursion during boreal winter and at the southernmost excursion during boreal summer. As the study took place during the summer, it was anticipated that the NEC may extend further south than at other times of the year and hence would influence the surface currents within the study area, which was observed in the westward drift of the panga skiffs in both cases investigated herein.

The 19 foot panga skiff involved in the SAREX drifted approximately 200 km from its starting location to the location that it was retrieved, 120 hours after initial deployment. This represented an average drift of 40 km per day generally towards 298° (approximately west northwest). The drift direction towards the west was consistent with expectations, due to the predominant easterly trade winds and the resulting westward flowing surface currents in the region.

Through the use of the current meter and GPS attached to the 19 foot panga skiff, it was possible to ascertain the extent to which the two drift components (the drift due to wind and wave induced leeway, and the drift due to surface currents) contributed to the total drift of the panga skiff over the 120 hour deployment. It was found that under the wind and current conditions experienced during the SAREX, the drift of the panga skiff due to leeway was approximately 25% greater than the drift due to the surface currents, with a resulting leeway drift component of 118 km (towards 280°) and current drift component of 94 km (towards 323°). This result may be unexpected, where the
component of drift due to the slip of the panga skiff across the sea surface resulted in a
greater contribution to the drift than the drift due to the currents – however, this resulted
from a combination of the high leeway characteristics of the panga skiff, relatively weak
surface currents, and consistent moderate strength winds during the deployment. The
high leeway of the panga skiff can be attributed to its very shallow draft, and flat
bottom, allowing it to slip across the ocean surface with little hindrance from the limited
submerged sections of the vessel. In other situations, where strong currents dominate
(eg. energetic western boundary currents) and weak winds prevail, it is possible for the
reverse to be true, where the drift due to currents may exceed the drift due to the
vessel’s leeway. An accurate representation of the ocean surface currents is always
essential to accurate drift forecasts, so the transport or drift due to the surface currents
can be effectively represented in the SAR trajectory model. The high leeway component
of the panga skiff’s drift places additional emphasis on the importance of wind forecast
model’s ability to provide an accurate representation of the local wind fields, which are
used to best reproduce the object’s leeway drift component. For objects with low
leeway characteristics, the drift due to leeway and hence wind forecast component is
much smaller, and hence may not be as important as the ocean model forecast currents.

The GFS model forecast winds provided a good comparison in terms of average wind
speed and directionality to the measured winds as collected by the weather stations on
board the panga skiff during deployment. Some of the local small scale variability was
not able to be captured by the GFS model, due to the horizontal resolution (~55 km) and
6 hourly output interval of the model. That aside, there was a good general agreement
between the two datasets with the general trends (easterly winds on average
approximately 6 m/s) being well replicated by the GFS model.

When the measured leeway drift speed and the measured winds were plotted as a time
series, it was noted that the drift of the skiff responded almost immediately to changes
in wind speed. This is in agreement with Fitzgerald, et al., (1993) who indicated that
when 10 minute intervals were used, the correlation between an object’s leeway and the
wind speed with zero time lag was greatest. The rapid response of the skiff to changes
in the wind speed and direction may be due to several factors including; a) the light
weight of the panga skiff, allowing direction or speed changes to occur more readily due
to its lower inertia and momentum, and b) a high leeway rate, thus increasing the effect
the wind has on the panga compared to that of the currents.

The average distance errors calculated for each of the ocean models at 24 hours into the
Case 1 simulation represented a range of 43% to 54% of the total drift distance of the
skiff after the first 24 hours. For reference, this error is much lower than that indicated
in a study by Spaulding, et al., (2006) who reported distance errors in the range of ~80%
of the average distance the drifters travelled over a 24 hour time period, when using a
coastal radar system to provide nowcast currents for simulating the 24 hour trajectories
of drifters in coastal waters off the US. The distance errors for the panga skiff forecasts
at 120 hours ranged from 26% to 53% of the total 120 hour drift length. The resulting
distance error as a percentage of drift length at 120 hours was lower than the error at 24
hours (as a percentage of 24 hour drift length), even though the absolute distance error
values (in km) were larger at 120 hours.

The rate of increase for the average distance error (in km) between the ocean model
predictions and the actual location of the panga skiff throughout the 120 hour drift was
generally linear for the NCOM model, with the same rate of average distance error
increase apparent over the whole 120 hour period. This differed to the results from the
other three models (BLUEl ink, FOAM and HYCOM) whose rate of distance error
increase was similar to that of NCOM for the first 48 hours, after which the rate of
increase in distance error tended to flatten off and show a gradual increase in average
distance error from 48 hours through to the end of the 120 hour drift.

The search areas for each of the individual models (and each of the consensus search
areas) were shown to grow with time throughout the duration of the 120 hour drift. The
growth in search area over time was due to three processes. The first was the horizontal
dispersion coefficient, which is used by the SAR drift model to account for model
particle transport due to small scale ocean turbulence (sub grid scale processes which
are not able to be accounted for within the larger scale ocean models). The horizontal
dispersion coefficient influences the spreading of the 1,000 model particles, with each
model particle trajectory representing a possible drift track of the panga skiff. Each
particle is specified a small random component of drift (due to turbulence) in addition to
the transport due to the ocean currents (provided by ocean current models), and
transport due to wind and waves through the object’s leeway (provided by atmospheric model and leeway coefficients).

The second process that influences the model search area size is the standard error component used to define the search object’s leeway characteristics. The standard error terms for leeway are calculated when the drift object’s leeway is empirically determined, as there may be errors associated with the collection of data, and hence there are possible errors or uncertainties associated with the calculated leeway characteristics. A larger standard error term gives a wider range of possible leeway values and hence provides a larger, more spread out search area, whilst lower standard error gives a narrow range of possible leeway values and hence provides a tighter, smaller search area. Each of the 1,000 model particles are assigned a different leeway value (for DWL and CWL) within the standard error bounds defined for that object, which has the effect of providing some particles with higher leeway coefficients and some particles with lower leeway coefficients, thus influencing how much each particle may be transported due to the influence of the wind. The process where some particles move with higher leeway than others tends to make the model particles spread out from each other, due to slightly differing drift speeds for each of the model particles.

In addition to the search area increasing from the spreading of the model particles due to the influence of the horizontal dispersion coefficient, and the variance in leeway due to the leeway standard error terms, further dispersion or particle spreading is generated through horizontal current shear. Horizontal current shear occurs when surface currents are not uniform across a domain, and hence there are differing current speed and directions within relatively close proximity. Once model particles become entrained into variable (inhomogeneous) neighbouring current fields, they are no longer all subject to the same uniform (homogenous) current speed and direction, and the distribution of particles will spread as they move independently from each other within their own differing current regimes. As model simulation times increase, the effect of the current shear upon the search area increases.

During the 120 hour SAREX drift run, the 2+ consensus search areas were larger than each of the individual search areas at the time intervals investigated (24, 72 and 120 hours), except for HYCOM at 72 and 120 hours, which was slightly larger than the 2+ consensus area, due to some model particles being entrained in a HYCOM predicted
current field towards the west to southwest, which was away from the direction of the other three model forecasts. Additionally, the HYCOM model currents appeared to be stronger than the other three model forecast currents, which would explain the larger search area exhibited by the HYCOM solution due to model particles being transported further afield. The 3+ and 4 model consensus search areas were shown to be considerably less than the single model search areas and the 2+ consensus search areas at all time intervals examined.

The skiff was located within each of the individual model search areas, and therefore also within each of the consensus model search areas, at the time intervals examined throughout the 120 hour drift scenario. This 100% hit rate result indicates that the surface currents provided by each of the ocean models, the winds provided by the atmospheric model, the panga skiff leeway parameters calculated by Allen, et al., (2013), and the horizontal dispersion parameter and the other various SARMAP model parameters selected for the scenario runs were all suitable to successfully forecast the drift of a panga skiff over a 120 hour period.

The results indicate that a more efficient search area may be defined by the 3+ and 4 model consensus or overlap areas, as the search object was still contained within these search areas, whilst the size of the search areas were dramatically reduced compared to the single model forecast search areas. The average over the four single model search areas at 120 hours was ~31,730 km², compared to the size of the 3+ model consensus search area at 120 hours of 18,256 km² (~43% reduction in search area) and the 4 model consensus search area at 120 hours of 5,259 km² (~83% reduction in search area).

Notably from the results of the simulations of drift, there was a large difference apparent between the average distance errors, and the minimum distance errors. This was because the minimum distance error was taken from the single model particle (from a total of 1,000 per simulation) that was closest to the panga skiff location at that given point in time, whereas the average distance error showed the average distance, from all 1,000 of the model particles per simulation, compared to the location of the panga skiff at that time interval. The average distance error gives a more robust indication of the model accuracy as it relies on all 1,000 of the model particles to be as close as possible to the actual panga skiff to return a low error result, whereas the minimum distance error only requires one single model particle to be close to the actual panga skiff.
location to return a low error value, which may occur by chance, should a model particle be advected close to the actual panga skiff location, due to the particle diffusion in the SARMAP model’s random walk process, whilst the majority of the other model particles may be a long distance away.

The 23 foot panga skiff involved in the SAR case drifted approximately 95 km from the probable location where the drifting began and the location where the skiff was found by US Marine C130 search plane, approximately 72 hours later. This indicates an average drift speed over the 72 hours of 0.37 m/s, which is ~17% slower than the drift speed of the 19 foot skiff deployed during the SAREX, which drifted approximately 114 km over the first 72 hours and returned an average drift speed over that time of 0.44 m/s. The lower drift speed of the 23 foot panga skiff may be due to the slightly larger size, deeper draft and hence potentially slightly lower leeway component to its drift. Additionally, the two cases occurred at different times and at different locations, so the prevailing wind and surface current conditions between the two cases would also contribute to the discrepancy in drift speed identified between the 19 foot panga skiff and the 23 foot panga skiff. The 23 foot skiff was found due west of the approximate location where it was suspected to have begun drifting, indicating that the vessel was drifting within the westward flowing NEC, and exposed to the predominantly easterly winds that were typical for the location and the time of year.

The average distance errors calculated for each of the four ocean models at 72 hours demonstrate a range of 54% to 80% of the total drift distance of the 23 foot panga skiff. This error is higher than that indicated by the 19 foot panga skiff drift simulations during the SAREX, which returned average distance errors (as a percentage of the total drift length) at 72 hours between 38% and 58%. The higher average distance errors observed for the 23 foot panga skiff drift may in part be due to two factors. The first originates from the release of model particles in each simulation. The 19 foot panga skiff simulations used a single point source for the release of model particles, as the exact location that the panga skiff began drifting was known. This release type ensures all 1,000 model particles are initially released close together. The 23 foot panga drift simulations however, used a track line source for the release of model particles, as the exact location and time that the drifting began was not known, only an approximate time and track along which the panga skiff had intended on travelling. This type of
model particle release has a greater initial spread of model particles (along the track line) which ensures some of the spatial and temporal uncertainties in drift initiation are encompassed. A greater initial spread of particles can lead to higher average distance errors. The second contributing factor to the larger average distance errors of the 23 foot panga skiff drift simulations was the use of the leeway characteristics of the 19 foot panga skiff as a proxy for the 23 foot skiff, as no leeway values have been determined for a 23 foot panga skiff.

The similar magnitude of drift error statistics between the 19 foot and 23 foot panga skiff drift simulations at 72 hours, and the location of the 23 foot skiff within all four model search areas indicates the validity of using the 19 foot skiff leeway values as a proxy for the 23 foot panga skiff for drift forecasting in the absence of further measurements. It was noted that at 72 hours the order of each of the individual model simulations, in terms of average distance error, from lowest average error (most accurate forecast) to highest average error (least accurate forecast), was the same between the two cases, with FOAM returning the lowest average error, followed by BLUElink, NCOM and finally HYCOM.

The search area sizes for each of the four individual ocean models for the 23 foot panga skiff simulations at 72 hours ranged between 19,878 km$^2$ and 21,394 km$^2$ (average of all four models ~20,713 km$^2$). These search areas are similar in magnitude to those recorded during the 19 foot skiff drift simulation at 72 hours, which returned results between 17,421 km$^2$ and 22,802 km$^2$ (average of all four models ~19,470 km$^2$). It was noted that when comparing the two cases, the search areas for each of the individual ocean models was slightly larger for the second case (23 foot panga skiff) compared to the first case (19 foot panga skiff), except for the HYCOM simulation, which returned a slightly larger area for the first case compared to the second. One of the potential reasons that larger search areas were typically seen for each of the individual model simulations during the second case may be due to the larger initial spread of model particles for the 23 foot panga skiff simulations, resulting from a track line release. The larger result for HYCOM in the first case compared to the second case appears to be due to some of the model particles in the first case being entrained into a stronger current field further towards the west to southwest, thus extending the drift of some particles further towards that direction and consequently enlarging the predicted search area.
Each of the consensus search areas (2+, 3+ and 4 model consensus) at 72 hours were larger for the 23 foot panga skiff simulations compared to the 19 foot panga skiff simulations, which is in line with what was observed for the individual model search areas when comparing the two cases. The 2+ model consensus search area for the 23 foot panga skiff simulations at 72 hours was larger than each of the individual search areas at 72 hours, due to the potential for multiple 2+ model areas to exist, which in this case sum to an area larger than any of the individual model areas. The 3+ and 4 model consensus areas for the 23 foot panga skiff simulations were shown to be smaller than each of the individual model search areas. There was a ~21% reduction in search area size for the 3+ model consensus search area (16,303 km$^2$), and a ~64% reduction in search area size for the 4 model consensus search area (7,416 km$^2$) when compared to the average individual model search area at 72 hours. A similar result was also shown for the consensus analysis for the 19 foot panga skiff case at 72 hours, which returned a reduction in search area compared to average individual model search areas for 3+ and 4 model consensus search areas of ~31% (13,374 km$^2$) and ~68% (6,227 km$^2$) respectively.

The 23 foot skiff was contained within all of the individual model search areas, and thus also within the 2+, 3+ and 4 model consensus search areas at the end of the 72 hour simulation, which was the approximate time that the missing panga skiff was located.

The results from both case studies demonstrate the potential benefit of focusing search efforts on the consensus forecast areas (in particular the 3+ and 4 model consensus areas) which have been shown to be substantially smaller than each of the individual model search areas and in the two cases examined herein, also contain the search object, thus potentially providing more efficient search area definitions.

### 6.5 Conclusions/Recommendations

This study investigated the use of a Lagrangian stochastic particle trajectory model (SARMAP) to forecast the drift of panga skiffs in the western equatorial North Pacific Ocean. Two separate cases were simulated, the first involved forecasting the 120 hour drift of a 19 foot panga skiff during a USCG SAREX, and the second case involved forecasting the 72 hour drift of a 23 foot panga skiff during a real SAR case. Four
independent forecasts were undertaken for each case where each individual forecast utilised one of the four different ocean current models and a single common wind forecast model to provide environmental forcing. Once the simulations were complete, the four forecasts were combined into an ensemble forecast (for each case) and the effectiveness of each individual ocean model, and the combination of ocean models was determined. Any overlap or consensus between the predicted search areas were also identified as well as the minimum and average model forecast particle distance error, search area size, and hit analysis (whether the panga skiff was located within the model predicted search area) were calculated for each individual ocean model forecast and the combined consensus forecasts to determine which model (or combination of models) were most effective when predicting the drift of the panga skiffs.

It was found that the FOAM ocean model produced the smallest average distance errors for both of the case studies at 72 hours, followed by BLUElink and then NCOM. The highest average distance error for both case studies was shown to be HYCOM. The distance errors as a percentage of the drift length at 72 hours for each individual ocean model ranged from 38% to 58% for the first case (19 foot panga skiff) and between 54% and 80% for the second case (23 foot panga skiff).

The search areas at 72 hours were calculated for each of the individual model forecasts, in addition to the consensus forecast areas. An average of the four individual model forecast search areas (at 72 hours) was taken for each of the two cases to determine what the expected average search area size may be. The results showed that the average single model search area (20,713 km$^2$) for the second case was of similar magnitude to (although slightly higher than) the first case (19,470 km$^2$). The search area results indicate the potential search area sizes that may be expected for SAR incidents which involve a similar search object (i.e. similar high leeway coefficients), under comparable environmental conditions and time frames, and when the same SAR model parameters are used.

The search areas calculated for the 2+ model consensus areas were larger than each of the individual model search areas (with the exception of the HYCOM model search areas in the first case). The larger 2+ consensus areas were due to the potential for multiple 2+ model overlap areas to occur, and the sum of these areas are often larger than the individual search areas. The 3+ model consensus search area was shown to
always be less than any of the individual search areas (across both cases); whilst the 4 model consensus search areas were shown to be substantially less than any of the other search areas (approximately 32% to 36% the size of the average single model search area at 72 hours).

A hit analysis was undertaken to assess whether the panga skiff was located within the search area at 24, 72 and 120 hours for the first case, and at 72 hours for the second case. It was found that the skiff was located within each of the individual model forecast search areas, and each of the consensus forecast areas (2+, 3+ and 4 model consensus) at the times specified for each case, thus resulting in a 100% hit rate for both cases.

The results indicate that the area where all four model forecasts coincided - the four model consensus search area - was the most efficient area to search, as it was approximately one third the size of the average individual model search area, whilst still containing the panga skiff.

The leeway coefficients for the panga skiff (with 2 POB) calculated by Allen, et al., (2013) were effective when used to replicate the possible drift paths and hence determine appropriate search areas for 19 foot and 23 foot panga skiffs with 2 POB. From the successful use of the panga skiff leeway coefficients herein, it is recommended that they be used for future SAR incidents, should a similar incident occur involving the need to simulate the drift of a panga skiff for a timeframe up to several days.

The consensus forecasting results show that there is the potential to benefit from the use of consensus forecasting as a tool to aid in the allocation of search efforts/assets within a search area, to either reduce the search area to a more manageable size (given available search assets) or to place more focus upon certain areas if there are adequate search assets available.

Whilst the present study was aimed at comparing the four ocean models and combining all four into a consensus forecast containing four ensemble members (whilst utilising a single wind model for all forecasts) it may prove worthwhile to investigate the incorporation of several wind forecast models in the consensus forecasting procedure, to augment the number of ensemble members available for the combined consensus forecast. Additionally it may prove beneficial to test several of the available global wind
forecast models to ascertain which may perform best when used in operational SAR response. The effect of winds (and hence the relative importance of wind models for drift forecasting) depends upon whether the object of interest contains a high or a low leeway component to its drift. Objects with high leeway rely upon the accuracy of the wind models more so than objects with a low leeway, as the winds may contribute to a higher portion of the object’s movement if it has higher leeway. Conversely if the object has low leeway, the winds have less of an effect on the movement of the object, and it may be the currents that are more important when considering the object’s total drift.

As the ocean models are ever evolving and improving, it is necessary that drift simulation studies continue to be carried out to assess the ability of the ocean models to replicate the drift of objects on the sea surface, and to evaluate which ocean model (or indeed ensemble of ocean models) may perform best.

It is imperative that leeway drift studies continue to be undertaken to increase the database of leeway coefficients for as many different drift objects/craft as possible. Whilst proxy leeway objects can and indeed, are used for SAR drift forecasting (as it would be impossible to catalogue the leeway coefficients for all possible drift objects and craft), the more objects that are contained within the leeway database, the higher the likelihood of being able to get a closer match to the leeway characteristics of the object or craft during an operational incident with an object from the leeway database. If the correct leeway coefficients of an object are able to be defined for a SAR drift simulation, more accurate search areas may be determined, thus reducing the size of and time required to search the areas, and increasing the probability of finding the missing persons or craft sooner, and more efficiently.

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6.7 References


7. Conclusions and Recommendations

7.1 Conclusions

This chapter provides a summary of the main findings and outcomes of the collection of studies provided in this thesis of works. These studies were collectively aimed at improving success with maritime SAR outcomes through improved drift modelling techniques. A summary of each of the main findings from each of the individual studies (Chapters 2 to 6) is contained below.

The study within Chapter 2 focussed on predicting the five-day drift of a single drifter which had been deployed to verify the ocean currents during an operational response to an actual oil spill event in the Timor Sea during 2009. For this study, six different ocean models (BLUElink, FOAM, GSLA, HYCOM, NCOM and NLOM) and two different wind forecast models (GFS and NOGAPS) were used to simulate a prediction of the drifter path to provide a total of 12 replicates of the potential trajectory of the drifter. Conclusions from the study were as follows:

- Over the course of the five-day track, the NCOM ocean model with GFS and NOGAPS winds more accurately followed the path of the drifter.
- The improved performance of NCOM was suggested to be due to the higher resolution of the surface layers of the NCOM model compared to the other ocean models used, and potentially due to the higher temporal resolution (6 hourly as opposed to daily for the other ocean models).
The effect of the choice of the wind forecast model was not significant for drifter studies due to the low leeway coefficient of drifters (by design) to ensure they drift predominately with the currents and are minimally affected by the winds.

In Chapter 3, four different ocean models (BLUElink, FOAM, HYCOM and NCOM) and one wind forecast model (GFS) were utilised to provide an ensemble of the environmental forcing to predict 63 five-day SVP drifter trajectories in the Tasman Sea off the coast of New South Wales, during 2010. Two different SAR drift numerical solution methodologies were tested (IAMSAR and Monte Carlo) to determine their relative performance, and ensure that the results were applicable to users of either method. The distance error (in terms of MAE and RMSE), and a hit rate was used as measures to establish the relative performance of each of the ocean models when predicting the track of the drifter. The consensus forecasting technique was implemented for all of the drifter tracks, for each of the two methods to determine if it had merit for SAR drift forecasting. A summary of the main findings are as follows:

- The Monte Carlo solution (with 1,000 m$^2$'s horizontal dispersion coefficient) produced larger search areas than the IAMSAR solution.
- The Monte Carlo solution overall produced much higher hit rates than those calculated with the IAMSAR method. This was due to the Monte Carlo solution generating larger search areas than the IAMSAR solution.
- The HYCOM model was identified to be the most effective at replicating the drifter tracks over five days within the Tasman Sea, using either solution methods (IAMSAR or Monte Carlo) as it predominately displayed superior performance across the three test measures (MAE, RMSE and hit rate).
- Consensus forecasting showed that at 120 hours for the Monte Carlo solution, the 2+ model consensus area returned the highest hit rate of all. The 3+ model consensus area returned a hit rate higher than 2 of the single models. The 4 model consensus area returned a hit rate lower than all of the individual models – which was due to the much smaller search area defined by the 4 model consensus area providing less opportunity to coincide with the drifter as frequently.
Further development of the consensus forecasting technique was applied to the study within Chapter 4, which investigated predicting 45 five-day SVP drifter tracks in the Indian Ocean, off the coast of Western Australia, during 2012. The same four ocean models and one wind model were used for this study, as used in the Tasman Sea study in Chapter 3. The Monte Carlo model solution was employed, however the horizontal dispersion coefficient was varied, and all of the simulations in the study were completed independently, each with 3 different values (10 m²/s, 100 m²/s, and 1,000 m²/s) to determine how this parameter affected search area sizes, hit rates, and the application of consensus forecasting. To test model performance, three measures were employed which included; the MAE, the hit rate analysis, and an additional test which was a comparison based on the individual track length of each drifter (which compared to the length of each drifter to that of the model forecasts). Additionally a quantification of the search area size was also undertaken to compare the search area sizes. The key findings of this study were as follows:

- The lower horizontal dispersion values (10 and 100 m²/s) returned low hit rates (the drifter was not frequently located within the model predicted search area) as they did not expand large enough to account for the sum of uncertainties involved in forecasting the drift of objects at sea. Additionally the lower dispersion values did not allow for consensus to occur between the models as frequently.
- The HYCOM model was deemed to be the best performing single model up to 24 hours when using the high dispersion coefficient; however this was not maintained over the full 120 hour drift.
- Different models performed better than others throughout the course of the five-day drifts, however all of the individual models produced acceptable hit rates whilst using the high dispersion coefficient.
- When using the high dispersion coefficient, the 4 model consensus area produced an average search area size up to 72.5% smaller than the average single model search area at 120 hours, however the hit rate dropped by 52.8%, thus resulting in a more efficient search area provided by the consensus search areas.
Chapter 5 describes the study where a leeway field test was carried out to determine the leeway coefficients of three common tropical Pacific island craft (5.8 m Panga Skiff, 5.9 m outrigger canoe, and 2 person sit down PWC), whose leeway properties were previously unknown. The leeway coefficients were calculated using currently recognised best practice for determining leeway coefficients. Instrumentation including ADCP current meters, weather stations, and iridium beacons were fitted to the craft to measure the amount of slip across the water surface each craft displayed, due to the action of wind and waves, independent of the ocean currents. Leeway tests were carried out for different loadings of the skiff, to be representative of a different number of persons on board or different amount of cargo on board, thus making the results more applicable to a wider variety of SAR situations where the loading may change. The key findings of this study were as follows:

- The data was successfully recovered from each of the craft, allowing the successful calculation of leeway coefficients to take place for all three craft tested.
- It was found that the leeway drift increased linearly with loading for the panga skiff, thus allowing a linear interpolation to take place to extract the leeway values for any loadings in between those tested.
- The leeway coefficients for the panga skiff were significantly higher than those previously recorded for similar sized craft. This was due to their light weight, shallow draft and flat bottom hull.

A study is described in Chapter 6 where the leeway drift coefficients of the panga skiff were applied to simulate the actual drift of panga skiffs on the water’s surface. This provided the opportunity for: validating the leeway coefficients calculated previously, the applicability of the four ocean models (BLUElink, FOAM, HYCOM and NCOM) for drift forecasting, the consensus forecasting approach, and the SARMAP model and its horizontal dispersion parameters, when used in actual drift scenarios. There were two case studies undertaken; 1) a test SAR scenario which involved forecasting the five-day drift of one of the 5.8 m (19 foot) panga skiffs deployed during the leeway field tests; and 2) a real life SAR scenario involving 2 persons drifting at sea for 72 hours in a 7 m (23 foot) panga skiff. Both cases were simulated with the Monte Carlo solution and a
horizontal dispersion coefficient of 1,000 m$^2$/s, as it was determined to be the most effective in the previous two studies. The key findings of the study are as follows:

- The FOAM ocean model produced the smallest average distance errors of both models over 72 hours.
- The average distance errors for each of the ocean models ranged between 38% and 58% for the first case, and 54% and 80% for the second case compared to the actual drift length of the panga skiffs.
- The increase in distance error for the SAR case was attributed to the model start location, where starting location for the model particles were spread along an assumed track line (as the exact start location was unknown), and the slightly different drift characteristics of the panga skiff that was involved in the SAR case (it was slightly larger than the one tested in the leeway field tests).
- The test panga skiff was located in each of the four model search areas at 24, 72 and 120 hours for the first case, and the panga skiff involved in the SAR case was located in each of the four model search areas where it was found at 72 hours. Thus resulting in a 100% hit rate for all four models over both cases.
- Additionally both skiffs were located within the 4 model consensus search area which was approximately one third the size of the average single model search area, thus indicating the effectiveness of the consensus forecasting technique in two actual drift cases.
- The leeway coefficients for the 5.8 m panga skiff were successfully applied to the 7 m panga skiff, thus verifying the validity of using the 5.8 m panga skiff coefficients as a proxy for the 7 m panga skiff.
- The consensus forecasting technique could be an effective method of prioritising search areas should search assets be limited, or should the search areas be prohibitively too large to search. It was shown that areas with higher consensus (three or four model overlap areas) were smaller than the individual search areas, whilst still maintaining the panga skiff within their bounds at the time intervals tested.

Since the leeway drift coefficients have been calculated for the panga skiff, and subsequently incorporated into the US SAR systems, they have been successfully applied operationally to several different SAR cases in the Western Pacific region, each
involving forecasting the drift of panga skiffs over multiple days in open waters. In each SAR case, the panga skiffs were located and all of the occupants rescued, thus resulting in multiple lives being saved. This positive outcome highlights the importance of the research into the leeway drift of common water craft.

One of the key findings of this thesis, through the investigation of the effectiveness of four different ocean models to track drifters and skiffs in various water bodies around Australia and the Pacific, was that there was no single model which performed the best overall, in all locations, for all performance tests, and all years. Indeed depending on the metric to test the value of each ocean model (distance error, hit rate, or drift length) some models may perform well in one or two, and not so well in another. Hence it is difficult to know in advance which model is going to perform the best on a given day, in a given SAR situation. As a result of this, it is important that the consensus forecasting technique, as tested herein, be considered as an additional decision support technique. The studies showed that a higher probability of locating the drift object within the search area existed if the consensus overlap regions were utilised as a priority to any single model forecast area. It is surmised that the reason for this increase is the use of multiple ocean models ability to account for more of the uncertainties which exist when forecasting the state of the ocean and consequently the drift of an object at sea.

The study resulted in the following outcomes which may presently be implemented on an operational basis to aid in SAR drift forecasting and decision support, both in Australia and internationally.

1) It is recommended that the leeway coefficients of the panga skiff, outrigger canoe and PWC, which were calculated during the leeway field study, be implemented into the database of leeway coefficients within operational SAR drift forecasting systems. Currently the leeway coefficients have been included in the United States, Australian and New Zealand SAR systems. The results from Chapter 6 indicate the validity of the leeway coefficients, as calculated during the leeway field test, through their use in the successful simulation of two independent skiff drift tracks, one over three days and one five days in duration.
2) The study indentified that the consensus forecasting approach may provide additional value to SAR drift forecasting, especially as a decision support tool to potentially be used to prioritise smaller regions within larger search areas that may occur over extended drift periods. It is recommended that the consensus forecasting approach be considered as an extra practice, alongside traditional single model drift forecasting, and be included in operational SAR systems. Presently, the Australian maritime SAR agency has requested that consensus forecasting be included in future versions of the SAR drift system, indicating their willingness to take this new method on board.

3) Finally, this study has highlighted the importance of using SLDMB drifters as a surface current verification tool during operational response to SAR or marine pollution incidents. It is recommended that the practice of deploying SLDMBs during operational response continues to be carried out as their contribution is vital to assist in accurate drift forecasting given the uncertainties still inherent in those databases. The methodology for ocean model forecast verification through comparisons against actual drifters, as outlined herein, has been recognised as a very important procedure to take place during operational SAR events. Hence a further request has been made to automate a drifter and ocean model forecast comparison and verification tool to future versions of the SAR drift system to enable these comparisons to take place during a SAR event with minimal additional effort required by the operational SAR drift forecasters.

7.2 Recommendations
This study investigated several key components in regards to the improvement of SAR drift forecasting and the use of a number of metocean datasets for search area prediction. The research has uncovered several research opportunities which would complement and build on the current research achievements described herein. Further investigation into the following topics would enhance the current understanding of SAR drift modelling, and may lead to further improvements to drift forecasting. The following contains a list of recommendations for future research into this field:
• Ocean models are continuously evolving with latest technology, driven by the ever increasing computational power, data storage technology, data availability from satellites and in situ instrumentation platforms, and data assimilation advancements. This results in improving the temporal and spatial resolution to allow better resolving of smaller scale processes. The continual improvement of the ocean models requires regular reassessment of ocean model performance, through such activities as drifter validation studies.

• Additional research into the affect of inter-annual variability on ocean model performance is warranted, to ascertain whether ocean model performance may be affected by different processes which occur over larger timescales. This would require comprehensive drifter validation studies to be carried out over multiple years to determine if there were any differences between the years. However, as outlined above, ocean models are continually being upgraded, so it may be difficult to determine a multi year timeframe (ie. hard to find a period where ocean models remained unchanged over that period). That is, should the ocean model formulations be upgraded throughout the multi year study period, it may be difficult to isolate whether an increase (or decrease) in ocean model performance may be due to an inter-annual process, or due to the model upgrades.

• A further variable which would warrant further testing is the effect of geographic location upon model performance. A series of studies in multiple water bodies, with similar numbers of drifters, at the same time, and with the same ocean model version throughout the study would need to be undertaken to determine this. Particularly, it would be of benefit to carry out several studies in shallower, tidally dominated water bodies to determine if the processes which occur in that environment were more readily replicated by the ocean and tidal models, and hence whether there may be an improvement in model forecast ability in those areas compared to deeper oceanic waters.
Further investigation is warranted into determining whether there is a horizontal dispersion coefficient value which lies between 100 m$^2$/s and 1,000 m$^2$/s tested herein, which may result in smaller and more efficient search areas, whilst not significantly compromising hit rate and the ability for model consensus to occur.

It was noted that a number of points could warrant further research into the consensus forecasting approach. These are listed as follows:

- Addition of more ensemble members to the consensus forecast. The present study used four members.
- Investigation as to whether the use of several wind forecast models may assist in the consensus forecasting approach. Adding one extra wind model to the forecast ensemble would result in double the number of ensemble members that add to the consensus forecast.
- Assessment of the potential benefit to drift forecasting of pairing the ocean models with the wind forecast models that drive them (i.e. BLUElink - GASP/ACCESS-G, FOAM - NWP, HYCOM - NOGAPS and NCOM – NOGAPS exclusively. This could prove to be beneficial by keeping the same winds for the drift forecast as those that were used to generate the wind induced surface currents in the ocean model and thus keeping coherence between them. This may be important under the following circumstances:
  - Use of a high leeway object, where wind influence on the object movement is significant;
  - Where there may be large discrepancies between the wind forecast models, especially between the wind model potentially used for the drift forecast (i.e. GFS), and the wind model used to drive the ocean model (i.e NOGAPS); and
  - Where there are strong wind driven surface currents evident in the ocean model, typical of higher latitude locations.
- The way in which the consensus forecast is aggregated could have an effect on the prediction. Suggested methods, worth evaluating in the future, could include weighting an ocean/wind model which was predetermined to be more reliable in a specific region higher than other
models with an unknown reliability which form part of the ensemble forecast. This may be done using a consensus density grid for example.

It is recommended that leeway field tests continue to be carried out to increase the database of craft with predetermined leeway drift coefficients to cover as many common craft as possible. Further, it is recommended that common search objects, like persons in water, which have had their leeway drift coefficients determined in the past, be revisited and have their leeway coefficients calculated again when possible, using the latest equipment and techniques. This will result in more accurately defined leeway drift, and hence will improve the accuracy of the total drift of these objects/craft and indeed result in better defined search areas.
Assessment of Metocean Forecast Data and Consensus Forecasting for Maritime Search and Rescue and Pollutant Response Applications
Applications for metocean forecast data - maritime transport, safety and pollution

Abstract
This lecture outlines the recent advances in the incorporation of oceanic and atmospheric forecast datasets into specialized trajectory models. These models are used for maritime safety purposes and to aid in combating oil and chemical marine pollution events. In particular, the lecture examines in detail the system assembled by the authors for improving oil spill trajectory models (OSTM) and chemical spill trajectory models (CSTM) as part of the Australian Maritime Safety Authority’s (AMSA) role in Australia’s national plan to combat pollution of the sea by oil and other noxious and hazardous substances. The main topics of this lecture will include:

- A summary of metocean forecast datasets currently being used operationally in the Australian region
- The incorporation of tidal current dynamics into ocean forecasting models.
- Three case studies of utilising metocean forecast datasets in maritime trajectory models, a study of the Australian Maritime Safety Authority’s OSTM and CSTM systems (OILMAP, CHEMMAP and the Environmental Data Servers).
  1. The Pacific Adventurer oil and chemical Spill, offshore Brisbane (QLD)
  2. The Montara Well Head Platform Blowout, Timor Sea (WA)
  3. The towing of MSC Lugano off Esperence (WA)
A Case Study of Consensus Modelling for Tracking Oil Spills

Abstract

Metocean forecast datasets are essential for the timely response to marine incidents and pollutant spill mitigation at sea. To effectively model the likely drift pattern and the area of impact for a marine spill, both wind and ocean current forecast datasets are required. There are two ocean current forecast models and two wind forecast models currently used operationally in the Australia and Asia Pacific region. The availability of several different forecast models provides a unique opportunity to compare the outcome of a particular modelling exercise with the outcome of another using a different model and determining whether there is consensus in the results. Two recent modelling exercises, the oil spill resulting from the damaged Pacific Adventurer (in Queensland) and the oil spill from the Montara well blowout (in Western Australia) are presented as case studies to examine consensus modelling.