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Lower-Atmosphere
Upper-Ocean Interactions:
The Influences of Breaking Waves

A Dissertation Submitted in Accordance with the Requirements for the Degree of Doctor of Philosophy in the College of Science by

Brian Scanlon

School of Physics
National University of Ireland, Galway

Supervisor: Dr. Brian Ward

October 2015
Abstract

Wave breaking at the ocean surface is an important process for air-sea exchange. Whitecaps are visual sea surface signatures of breaking waves. By measuring the fractional coverage of whitecaps on the sea surface, it is possible to quantify wave breaking. This thesis comprises of three distinctive pieces of research. I compare model simulations of sea surface temperature to high resolution observations for three unique cases. The model runs over a daily cycle using a 1-dimensional 2nd moment closure turbulence scheme with the inclusion of a wave breaking model. The comparisons reveal poor performance when the wave breaking model is included. Subsequently, attempts to improve on our understanding of wave breaking were made. I developed a technique for estimating whitecap coverage estimates of both actively breaking (stage A) waves, and maturing (stage B) foam. The Spatial Separation of Whitecap Pixels (SSWP) allows for accurate distinguishing of stage A and stage B whitecap regions by manually evaluating the pixel intensity, location (with respect to the crest of the wave), texture and shape of a given whitecap region. Finally, measured $W_A$ and overall whitecap coverage ($W_T = W_A + W_B$) for the North Atlantic dataset were then compared with modeled estimates of whitecap coverage, derived using a semi empirical formula and various wave-field model parameters. High resolution model estimates of the wave-field are provided by the European Center for Medium Range Weather Forecasting (ECMWF) Wave Model (WAM). Results reveal good performance between $W_A$ and modeled generated $W_T$ for specific tuning values, which are provided.
Acknowledgments

I would firstly like to thank my supervisor, Brian Ward, for all his support and guidance over the course of this work. I am immensely grateful for all his patience and dedication to improving my work. He went well beyond the call of duty helping me on my journey to becoming a respected scientific researcher. I would also like to thank my fellow students for their company and support, Sebastian Landwehr, Joao de Almeida, Graigory Sutherland, Niall O Sullivan, Anneke ten Doeschate, Leonie Esters and post docs Adrian Callaghan, Danielle Wain, Ciaran Kennedy, Chiara Uglietti, and Kieran Walesby. I would like to thank my fellow coauthors Brian Ward, Gary Wick, Adrian Callaghan, Øyvind Breivik, Jean Bidlot and Peter Janssen for their patience, support and opportunities. I am very grateful to Peter Minnett who provided the M-AERI data for the study outlined in section 3.1. I would like to thank the captains and crew of the R/V Knorr, during the North Atlantic Ocean cruise in 2011, and the R/V Tangaroa, during the Southern Ocean cruise in 2012.

This research is supported by the Research Council of Norway (Grant 207541: OILWAVE), and the EU FP7 project CARBOCHANGE under grant agreement no. 264879, and by the College of Science (Fellowship). Dissemination of part of the research through international conferences were financially supported by the Marine Institute under the Marine Research Sub-program funded by the Irish Government and the Smartbay Ireland Postgraduate scheme via the PRTLI Partnership, by the College of Science travel fellowship, and by European Cooperation in Science and Technology (COST).
1 Introduction

As 71% of the Earth’s surface is covered in water, it is beneficial to improve on our understandings of air–sea interaction. Physical processes that occur in, and interact between, the upper ocean and lower atmosphere, are currently poorly accounted for. In this study, we concern ourselves with the process of wave breaking which can promote the air–sea transfers of gas, heat and momentum, and the production of marine aerosols and ocean turbulence.

1.1 Importance of wave breaking

Wave breaking acts as a mechanism of energy transfer from the wave-field to the upper ocean (Cardone, 1969). Turbulent kinetic energy (TKE) is dissipated from the waves and injected into the upper few metres of the ocean (Melville, 1996) due to wave breaking (Craig and Banner, 1994; Kantha and Clayson, 2004; Hwang and Sletten, 2008; Breivik et al., 2015). Previous studies that attempted to parameterize upper ocean mixing (Osborn, 1980; Agrawal et al., 1992; Terray et al., 1996; Sutherland et al., 2013) have demonstrated the complexity involved when quantifying TKE injection due to wave breaking. As a result, parameterizations of upper ocean mixing
Introduction
tend to mix weakly or too strong when compared to observations. On a
global scale, this poor representation of upper ocean mixing poses as a
significant weakness to ocean-only models and ocean-atmosphere coupled
forecast systems (Fan and Griffies, 2014; Breivik et al., 2015), whereby the
modeled mixed layer depth (MLD) is commonly underestimated which leads
to the modeled sea surface temperature (SST) being overestimated. Such
SST and MLD biases serve to upset delicate feedbacks in the climate system
(Sheldon and Czaja, 2014).

Wave breaking enhances air–sea transfer of gas (Asher and Wanninkhof, 1998;
Woolf, 1997) and heat (Andreas and Monahan, 2000) both by disrupting the
water surface microlayer and by promoting eddy diffusion through forming
of temporary low impedance vents in the upper water column (Monahan
and Spillane, 1984). Despite 40 years of active research attempting to
parameterize gas transfer (Liss and Slater, 1974; Monahan and Spillane,
1984; Wanninkhof and McGillis, 1999; Asher et al., 2002; Wanninkhof et al.,
2009; Bell et al., 2013), the scientific community still demands globally
representative parameterizations of air-sea gas exchange for more accurate
predictions of our climate.

Figure 1.1: Schematic illustrating the evolution of a typical breaking wave:
a spilling wave crest (I), bubble plume formation (II), evolution
into stage-B whitecap (III), and decay of the whitecap (IV),
(Scanlon and Ward, 2013).

Breaking waves trap and entrain air into the upper ocean (Fig. 1.1). This
process of air entrainment forms plumes of bubbles which are injected to depths below the surface on the order of metres. Once the bubbles reach the maximum depth, they rise to the surface, horizontally diverge from one another and decay via bubble bursting. This mechanism of bubble bursting is responsible for the production of film and jet droplets which are transported into the upper atmosphere where they play an influential role as sea salt aerosols (SSA) (Monahan, 1986; Andreas et al., 1995; Lewis and Schwartz, 2004; O’Dowd and de Leeuw, 2007; de Leeuw et al., 2011). The presence of SSA in the atmosphere contribute significantly to the Earth’s radiation budget (Andreas and Edgar, 1998), cloud formation (O’Dowd et al., 1999) and ocean-atmosphere transport of organics (Blanchard, 1963).

Sea foam coverage on the sea surface generated via wave breaking serves to increase the ocean albedo (Koepke, 1984; Frouin et al., 1996; Gordon, 1997) and thus exerts a strong influence on the global radiation budget (Frouin et al., 2001).

For these reasons, we must acknowledge that wave breaking plays a vital role in upper-ocean lower-atmosphere interactions. Thus it is of importance to achieve suitable quantification of wave breaking.

1.2 Quantification of wave breaking

The spatial and temporal evolutions of air entrainment due to breaking waves can be monitored by appealing to their surface signature whitecap manifestations (Monahan and Lu, 1990). Previous studies have attempted to quantify wave breaking by estimating the sea surface area covered in
whitecaps using imaging techniques (Blanchard, 1963; Monahan, 1971; Toba and Chaen, 1973; Ross and Cardone, 1974; Monahan and O’Muircheartaigh, 1986; Asher and Wanninkhof, 1998; Hanson and Phillips, 1999; Stramska and Petelski, 2003; Lafon et al., 2004, 2007; Sugihara et al., 2007; Callaghan et al., 2008a; Goddjin-Murphy et al., 2011), satellite sensing (Monahan et al., 1981; Pandey and Khar, 1982; Koepke, 1986; Anguelova and Webster, 2006; Salisbury et al., 2013) and acoustics (Thorpe, 1982; Monahan and Lu, 1990; Ding and Farmer, 1994).

While the community agrees that the extent of whitecap coverage $W$ can be represented by a power-law of wind speed, there exists significant differences between various whitecap coverage parameterizations published over the past 45 years (see Figure 1.2 or Anguelova and Webster, 2006; Goddjin-Murphy et al., 2011). A plethora of theories arose which attempted to account for these differences. Such theories hypothesized the differences between
results of previous studies arose due to variations of (1) methodologies used, (2) convergence of whitecap observations, (3) quality control, and (4) natural variation of environmental conditions. These sources of variation are explained below:

1. Variations in methodology: Over 45 years, significant improvement in technology has made available to researchers cost effective high resolution imaging systems, data storage solutions and image processing software. The first extensive dataset of $W$ were achieved from photography (Monahan, 1969), which involved the dissection and weighing of whitecap regions. More recently, the implementation of digital imaging techniques were employed (Monahan, 1993; Sugihara et al., 2007; Callaghan and White, 2009) using both manual and automated image processing techniques. An alternative methodology for obtaining whitecap parameterizations involves satellite sensing of microwave emissivity of the sea surface. Such remote sensing inherits large uncertainties and noise compared to studies involving in-situ observations. This highlights the importance of minimizing systematic and human (subjective) error when conducting future studies. For further information, please see (Anguelova and Webster, 2006).

2. Convergence of whitecap observations: As observations of $W$ are considered to be independent of time, it is vital that a sufficient number of wave breaking events are sampled such that a population-representative estimate of $W$ is obtained. This highlights the importance of adopting appropriate sampling sizes, intervals and rates when conducting future studies. Please refer to Callaghan and White (2009) for further information on the convergence of whitecap observations.
3. **Quality control:** Measurements of whitecaps can contain significant sources of contamination such as imagery containing sun glint, human-induced whitecaps (such as bow breakers and wakes due to ship) and seagulls. Various studies employ manually controlled quality checks during data processing stages which requires large amounts of dedication, effort and time. Studies choosing to approach data processing autonomously without manual quality control checks can incur significant uncertainties for $W$ observations (Scanlon and Ward, 2013).

4. **Natural variation of environmental conditions:** For any given wind speed, whitecap coverage has been observed to correlate for variations of wave-field development (Callaghan et al., 2008b; Goddijn-Murphy et al., 2011), SST (Monahan and O’Muircheartaigh, 1986; Bortkovski, 1987; Bortkovski and Novak, 1993; Callaghan et al., 2014) sea – air temperature (atmospheric stability) (Thorpe, 1982; Monahan and O’Muircheartaigh, 1986; Monahan and Woolf, 1989; Monahan and Lu, 1990), salinity (Monahan and Zietlow, 1969), fetch (Nordberg et al., 1971), latitude (Monahan et al., 2015) and surfactants (Callaghan et al., 2012, 2013).

To address the variable lifetimes of whitecaps (Callaghan et al., 2012), few studies (Bondur and Sharkov, 1982; Monahan and Woolf, 1989; Monahan and Lu, 1990; Asher and Wanninkhof, 1998; Reising et al., 2002; Bobak et al., 2011) have attempted to separate whitecap coverage into two stages of evolution; actively breaking waves (stage A) and maturing foam (stage B), following the definitions in Monahan and Lu (1990). In doing this, quantifications of the coverage of stage A ($W_A$) provide a suitable proxy for
dynamical air–sea processes such as air transfer (Asher and Wanninkhof, 1998) and wave energy dissipation (Scanlon et al., 2015). Quantifications of stage B coverage ($W_B$) provide a suitable proxy for the area of whitecaps undergoing bubble bursting processes and thus the generation of SSA (Monahan, 1986).

1.3 Objectives of this presented study

A number of objectives arise following a review of published literature related to wave breaking, whitecap coverage and air–sea interactions.

1. Evaluate state-of-the-art upper ocean turbulence models which include TKE injection due to wave breaking on reproducing temperature profile measurements over a daily (diurnal) cycle.

2. Evaluate current methods and explore alternative methods of acquiring whitecap coverage observations. Attempt to separate whitecap coverage observations into its actively breaking stage (stage A) and its maturing stage (stage B).

3. Obtain an extensive dataset of $W_A$ and $W_B$ which conform to acceptable standards of quality control and data certainty.

4. Provide an investigation into the variability of $W_A$ and $W_B$ and their correlations with environmental parameters such as wind speed, SST and atmospheric stability.

5. Examine the ratio of $W_A/W_B$ and conclude if it is a constant.
6. Validate a whitecap model using various wave model parameters.
Bibliography


Bibliography


2 Summary of Research Papers

The work presented in this thesis consists of three peer-reviewed articles of which I am lead author. For each of the three articles, I provide major contributions.

First article:

Near-surface diurnal warming simulations: validation with high resolution profile measurements


This article involves the application of various configurations of a 1-dimensional second moment closure turbulence model, solar absorption model, and wave breaking model, in replicating upper ocean measured temperature profiles. Such attempts to replicate the upper ocean temperature profiles prove to be a very important, as accurate estimates of sea surface temperature (SST) are required for estimating accurate heat flux across the air–sea interface. Three unique datasets are provided, showcasing highly stratified upper ocean during daytime high solar irradiance and low wind conditions (near Baja,
California), well mixed upper ocean during a night-time to morning-time transition in moderately low winds and high salinity conditions (Gulf of Lions, Mediterranean Sea), and day-night transition in low wind conditions (Seychelles-Chagos Thermocline Ridge, Indian Ocean). High resolution temperature profiles were measured using the Air–Sea Interaction Profiler (ASIP) and its earlier variant Skin Depth Experimental Profiler (SkinDeEP). Model and observation comparisons reveal that the model configurations, especially those that include a wave breaking model, show difficulties reproducing observed conditions. **G. Wick provided the model simulation runs. B. Ward provided the high resolution measurements. I am credited with the analysis of the data, forming of conclusions and writing of the manuscript.**

**Second article:**

Oceanic wave breaking coverage separation techniques for active and maturing whitecaps


This article provides a new standardised technique of processing sea surface imagery with the goal of extracting estimates of actively breaking (stage A) whitecap coverage \(W_A\) and maturing (stage B) whitecap coverage \(W_B\), following definitions outlined in *Monahan and Lu* (1990). This work was motivated by two main concerns, (i) to exploit whitecap coverage as a proxy for quantifying wave breaking, and (ii), previous techniques demonstrated high variability between various whitecap parameterizations (see *Anguelova*
and Webster, 2006). The published technique is called the Spatial Separation of Whitecap Pixels (SSWP), and relies on two key requirements. Firstly an appropriate pixel value threshold must be selected such that whitecap pixels and those of background sea are distinguished. Secondly, sufficient manual evaluation of whitecap regions (grouped whitecap pixels) are categorized as either representing actively breaking whitecaps or maturing whitecaps. This manual evaluation is performed by appealing to four characteristics of the whitecap region, its location (with respect to the wave crest), its visual intensity, its shape and its texture. Once all whitecap pixels are accounted for, stage A and stage B pixels are each summed to provide estimates of $W_A$ and $W_B$ coverage. A large dataset of images (64,540) of the North Atlantic Ocean, obtained during the summer (June/July) of 2011 onboard the R/V-Knorr were processed, providing 207 10-minute averaged estimates of $W_A$ and $W_B$. A secondary image analysis technique, involving the distinguishing of whitecap regions as either stage A or stage B, is introduced and named the Pixel Intensity Separation Technique (PITS). PITS, as the name suggests, relies only on the pixel intensity information to perform separation. This method is evaluated against the SSWP for the entire dataset, revealing poorer performance and larger errors in $W_A$ and $W_B$ estimates. I am credited with the creation of the SSWP method, the manual processing of 64,540 images, the analysis and writing of the manuscript.
Third article:

Modelling whitecap fraction with a wave model


This article describes the use of a semi-empirical equation to derive whitecap coverage using wave-field and meteorological forcing. The semi-empirical equation is based on the assumption that wave breaking is the dominant source of wave-field dissipation. The study incorporates high resolution European Center for Medium Range Forecasting (ECMWF) wave model (WAM) estimates, providing 1-hourly input estimates for the semi-empirical function. Resulting 1-hourly estimates of modeled whitecap coverage were then compared to 1-hourly $W_A$ and total whitecap coverage ($W_T$) observations from the North Atlantic dataset. The comparison shows good agreement, and reveals that model estimates of whitecap coverage are more closely related to observations of $W_A$ than $W_T$. I am credited with the manual processing of 114,265 images, analysis and writing of the manuscript.
3 Research Papers

3.1 Near-Surface Diurnal Warming Simulations: Validation with High Resolution Profile Measurements
Near-surface diurnal warming simulations: validation with high resolution profile measurements

B. Scanlon¹, G. A. Wick², and B. Ward¹

¹School of Physics and Ryan Institute, National University of Ireland, Galway, Ireland
²NOAA ESRL PSD, 325 Broadway Boulder, CO 80305, USA

Correspondence to: B. Ward (bward@nuigalway.ie)

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Abstract.

Sea surface temperature (SST) is an important property for governing the exchange of energy between the ocean and the atmosphere. Common in situ methods of measuring SST often require a cool-skin and warm-layer adjustment in the presence of diurnal warming effects. A critical requirement for an ocean submodel is that it can simulate the change in SST over diurnal, seasonal and annual cycles. In this paper we use high-resolution near-surface profiles of SST to validate simulated near-surface temperature profiles from a modified version of the Kantha and Clayson 1-D mixed-layer model. Additional model enhancements such as the incorporation of a more recent parameterization of turbulence generated by wave breaking and a recent solar absorption model are also validated. The model simulations show a strong variability in highly stratified conditions, with different models providing the best results depending on the specific criteria and conditions. In general, the models with enhanced wave breaking effects provided underestimated temperature profiles while the more coarse baseline and blended approaches produced the most accurate SST estimates.

1 Introduction

Accurate measurements of sea surface temperature (SST) for the upper ocean are important for air–sea exchange of heat (Fairall et al., 1996b) and gas (Ward et al., 2004a). It has been shown that SST values with an accuracy of ±0.2 K are required to compute the air–sea heat fluxes to an accuracy of 10 W m⁻² (Fairall et al., 1996a). Bulk formula heat flux calculations rely on SST values to compute sensible and latent turbulent heat fluxes as well as emitted longwave radiation from the ocean surface, and these models are most sensitive to SST variability in the lower latitudes. According to Fairall et al. (1996b) the most appropriate value of SST for these formulae is the temperature of the cool-skin layer, known as the skin temperature (SST_{Skin}). The cool-skin layer (or the molecular sublayer) is ∼1 mm thick, and is the upper most layer of the sea surface and is in direct contact with the atmosphere. The skin temperature is cooled by the combined effects of the net longwave radiative flux, the sensible heat flux and the latent heat flux and is typically 0.1–0.5 K lower than the temperature of the subskin layer immediately below (Wick et al., 1996; Donlon et al., 2002). The cool skin is almost always present, although its total effect may be compensated by the presence of a warm layer (Fairall et al., 1996b). Common in situ methods of SST measurement obtain temperature at a depth, often 1–4 m, called T_{depth}, or commonly the bulk temperature measurement. These bulk temperatures are the most commonly available measurements obtained from buoys and ships (Gentemann et al., 2009). It is often required that these bulk measurements be adjusted for diurnal warm-layer and cool-skin effects.

In the upper ocean, diurnal warming cycles occur due to the solar heating and oceanic heat loss fluctuations (Price et al., 1986) and are responsible for high variations of SST. For example, in summer heating conditions with low wind, the depth of the diurnal warm layer can typically be on the order of 1 m (mean depth), and the surface amplitude (skin temperature minus bulk temperature) can be as large as 3 K (Stramma et al., 1986; Soloviev and Lukas, 1996). In such conditions, turbulent mixing near the surface is mainly driven...
by wind-induced shear and convection. This convection is driven by densification due to evaporation and possible net surface cooling. Daytime solar heating effects within a stratified upper ocean are isolated to the surface layers. The heating of these layers creates a positive buoyancy flux which restricts deepening of the warm layer (Soloviev and Lukas, 1996), further enhancing the effects of stratification. In moderate wind conditions, solar heat is mixed vertically to a greater depth than what can be achieved directly by radiation. In such cases, the positive surface buoyancy fluxes are overcome by wind driven shear which deepens the diurnal warm layer typically to 10 m depth. In turn, the surface amplitude is typically reduced to 0.2 K (Price et al., 1986).

Previous studies using models and near-surface temperature profile measurements have demonstrated the potential for significant variability in the near-surface temperature especially during the daytime at low winds and with strong solar heating (Fairall et al., 1996a; Soloviev and Schluesel, 1996; Webster et al., 1996; Donlon, 1999; Gentemann and Minnett, 2009; Gentemann et al., 2009). Clearly, one-dimensional models which only consider transport in the vertical direction have limitations and cannot account for advective effects. Advection can introduce errors in modelled temperature gradients from horizontal currents of a different temperature as noted by Kantha and Clayson (1994). The 1-D models, however, can be very informative in evaluating the mixing processes associated with stratification and diurnal warming. The goal of this paper is to compare model simulations to observed high resolution temperature profile measurements in low to moderate wind and high solar irradiance environments to evaluate the model’s skill to accurately reproduce the temperature profile. It is important to note that this study evaluates the ability of the models to exactly reproduce a specific realization of observations. It does not address a more traditional statistical evaluation of model uncertainty.

Observed temperature profiles of the upper 5 m of the ocean were measured by the Skin Depth Experimental Profiler (SkinDeEP) (Ward et al., 2004b) and also by its successor the Air–Sea Interaction Profiler (ASIP) (Ward et al., 2012). The profiles presented here were obtained during three separate field experiments: Gulf of California in 1999 (hereafter GC99), Gulf of Lions (Mediterranean) in 2003 (hereafter GL03), and the Indian Ocean in 2007 (hereafter IO07). SkinDeEP is an autonomous profiler capable of measuring temperature to a sub-centimetre resolution. At its typical rising velocity of 0.5 m s$^{-1}$, the resolution is 3 mm (see Ward et al., 2004b for a complete description of SkinDeEP). ASIP is similar in concept to SkinDeEP, but has a much larger sensor range, can profile to 100 m, and has a larger battery capacity. Coupling the high resolution profile data from the near-surface along with M-AERI radiometric data of the true skin temperature, provides a complete temperature profile of the upper ocean.

This article attempts to validate the model simulations of a 1-D second moment turbulence closure mixed-layer model based on Kantha and Clayson (1994) for the GC99, GL03, and IO07 time periods, using available meteorological data and bulk measurements while neglecting the effects of advection. Further refinements to the model, including wave breaking effects (Kantha and Clayson, 2004) and a recent solar transmission model (Ohlmann and Siegel, 2000), are incorporated into the model for validation. Section 2 discusses the cruise data, instrumentation and provides a theoretical background for the models used in this study. Section 3 shows the results from the comparisons of the measured SkinDeEP data and the modelled simulations, followed by our conclusions.

2 Material and methods

2.1 Instruments

The surface temperature profiles were obtained from either SkinDeEP (Ward et al., 2004b) or ASIP (Ward et al., 2012). Both of these instruments are autonomous vertical profilers designed to study the upper ocean with high resolution sensors. For this study, we are concerned with temperature profiles in the upper 5 m, which are provided by the FP07 thermometer mounted on both profilers. SkinDeEP has the ability to obtain more than 100 consecutive profiles without intervention and contains a CPU capable of high-frequency sampling and data storage (Ward, 2006). Autonomous profiling is accomplished with a volume adjusted buoyancy variance system. While in operation, it was attached to a spar buoy via 50 m of a synthetic, high breaking strain tether line. Profiling started with the instrument sinking to its programmed depth which was monitored by the onboard external pressure sensor, at which the buoyancy was changed to positive and temperature measurements were acquired as it rose to the surface. The temperature data was provided with the FP07 thermistor, which was calibrated against a slower, accurate thermometer.

ASIP is an autonomous vertically profiling instrument designed to profile from below so as to provide undisturbed measurements all the way to the surface. It is equipped with high resolution sensors for the measurement of temperature, salinity, light, oxygen, and turbulence. There are three thrusters which submerge it to a programmed depth (maximum 100 m), whereupon it ascends through the water column towards the surface under its own buoyancy, recording data at 1000 Hz, generating 192 kbytes s$^{-1}$ which is stored with a single board computer.

The skin temperature for all cruises was continuously measured by the Marine-Atmospheric Emitted Radiance Interferometer (M-AERI, Minnett et al., 2001); a passive infrared radiometric interferometer which makes radiance measurements in the 500–3000 cm$^{-1}$ wave number range with a resolution of 0.5 cm$^{-1}$. The radiometer comprises of a gold rotating mirror that allows for both sea and sky views at complementary angles to nadir and zenith. The accuracy of the
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Table 1. Times, location and number of profiles for the deployments of the three case studies.

<table>
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<th>Region</th>
<th>Date</th>
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<th>Longitude</th>
<th># of profiles</th>
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<td>283</td>
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<td>22°31.48 N</td>
<td>109°35.43 W</td>
<td>161</td>
</tr>
<tr>
<td>GL03</td>
<td>113/114</td>
<td>23:08-11:23</td>
<td>42°18.47 N</td>
<td>5°05.65 W</td>
<td>117</td>
</tr>
<tr>
<td>IO07</td>
<td>39/40</td>
<td>19:02-7:20</td>
<td>7°59.77 S</td>
<td>67°27.70 E</td>
<td>72</td>
</tr>
</tbody>
</table>

Fig. 1: Time series of the downwelling shortwave radiation, wind speed, and skin temperature for the GC99, GL03 and IO07 periods respectively. The grey vertical column marks the time of the deployment period. The data is 60 minute averaged.

The data collected from the IO07 cruise represents a high resolution view of the temperature structure in a highly stratified area of the Indian-Pacific warm pool, the “Seychelles—Chagos Thermocline Ridge”. The 10th deployment of the cruise occurred on 8-9 February and resulted in 72 profiles captured in highly stratified conditions. The period started at 19:02 LT and finished at 07:21 the next morning. The mean wind speed was 4.35 ± 0.38 m s⁻¹. The solar heat flux ramped up from 0 to 102 W m⁻² towards the end of the deployment (Fig. 1). Table 1 displays additional information regarding the GC99, GL03 and IO07 deployments.

For all three field campaigns, meteorological sensors were deployed to provide a time series of the following parameters: wind speed and direction; air temperature; relative humidity; barometric pressure; downwelling long- and short-wave radiation. There was also gyroscopic information available to determine the ship’s speed, heading, and bearing for wind speed correction. Air–sea heat fluxes were calculated using the COARE bulk flux algorithms (Fairall et al., 1996b).

2.3 Models

Five variations of the Kantha and Clayson (1994) (KC94 hereafter) second moment closure, one-dimensional mixed-layer model provide 1 min resolution simulations of the upper ocean for the durations of the GC99, GL03 and IO07 cruises. The first, or, “baseline” configuration most closely corresponds to that described in KC94. The model name is shortened to “Base” for representation in tables and plots.
The basic turbulence scheme is that of KC94, but the vertical resolution is enhanced to simulate the details of the near-surface temperature profile. A nine-wavelength band solar absorption model of Paulson and Simpson (1981) (PS81 hereafter) is used in this configuration to account for solar heating effects within the water column. It is a common assumption in ocean modelling to assume that the Karman–Prandtl law of the wall is valid near the air–sea interface. This assumption works well in shear flows adjacent to a rigid boundary but fails in the presence of breaking waves near the surface (Craig and Banner, 1994). This is due to the turbulent kinetic energy (TKE) equation being based on local shear production and dissipation near the surface. Kantha and Clayson (2004) (hereafter KC04) suggest that the influence of wave breaking strongly elevates the dissipation rate in the upper few metres of the ocean and the effects cannot be ignored (see also Terray et al., 1996; Agrawal et al., 1992). A second version of the model incorporating the TKE equation of KC04 to account for these effects is termed the “enhanced wave breaking model” (shortened to EWB in figures). This addition incorporates TKE injection parameters due to breaking waves and Langmuir circulation. Weller and Price (1988) found that stratified thermal layers in shallow diurnal mixed layers can be rapidly destroyed by Langmuir circulation. Thus the inclusion of a parameter for Langmuir cells is important. The new parameterization for TKE input at the surface is proportional to a power law of the water-side friction velocity \( u^* \). The inclusion of these parameters increases TKE and dissipation rates in the upper ocean, leading to enhanced mixing in the mixed layer. KC04 reported the effects of including Langmuir circulation in the model resulted in lower SST values. The reader is referred to Kantha and Clayson (2004) for more information.

The third model used in this study is named the “blended model” (shortened to “blend” in figures). This model transitions between the use of the baseline model and the enhanced wave breaking model at a wind speed of \( 2 \text{ m s}^{-1} \). The turbulence scheme below \( 2 \text{ m s}^{-1} \) is that of the baseline model while it shifts toward that of the enhanced wave breaking model at higher winds. This blending was introduced in an attempt to reproduce the range of diurnal warming amplitudes observed in previous shipborne observations of the surface temperature (not shown). The turbulence coefficients are also revised within this model to follow Kantha (2003).

Solar insolation is a very important parameter for the effects of diurnal warming. It has been reported that between 60 and 90% of solar irradiance is attenuated within the upper 10 m of the ocean (Ohlmann et al., 1998). Variations in the assumed absorption rate of insolation can have a significant effect on the simulated profiles. The “PS81” nine-band solar transmission model, of Paulson and Simpson (1981) is used for the three models described so far. This is also the scheme currently used in the Profiles of Ocean Surface Heating (POSH) model (Gentemann et al., 2009). This solar transmission model computes solar transmission through the air–sea interface by fixing the sea surface albedo to a constant value of 0.055 which has been recorded to produce instantaneous errors of ± 40 W m\(^{-2}\) (Ohlmann and Siegel, 2000). The reader is referred to Fairall et al. (1996b) and Ohlmann and Siegel (2000) for further information.

The fourth model version tested incorporates a more recent solar absorption profile developed by Ohlmann and Siegel (2000) (hereafter OS00) along with the “enhanced wave breaking model” and is called the “enhanced solar transmission model” (shortened to “EST” in figures). It is a two-equation solar transmission parameterization that depends on the assumed absorption rate of insolation can have a significant effect on the simulated profiles. The reader is referred to Kantha (2003) for more information.

The final version of model tested is an enhancement of the “blended model”. It transitions between the baseline and enhanced wave breaking models in the same fashion as the blended model but also incorporates the OS00 two-equation solar transmission model described for the enhanced solar transmission model in place of the PS81 nine-band model. It is called the “blended solar transmission model” (shortened...
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Figure 2 illustrates the time evolution of the \( T_{\text{skin}} \) estimations from the five models and observed temperatures for the GL03 case study. Both blended models produce identical temperature estimates for this period.

3 Results

In this section, the model simulations of the five model versions discussed in the previous section are compared to high resolution in situ measurements. For comparison, the model-simulated and measured temperature profiles are bin averaged to 2 cm depth intervals, with increased resolution nearer the surface at depths of 0, 0.0025, 0.0075 and 0.015 m.

3.1 Model performance in day-time stratification conditions

Observational measurements from GC99 are used in the case of model validation in highly stratified conditions. The average solar irradiance is 802 W m\(^{-2}\) (peaking at 912 W m\(^{-2}\)) and the mean wind speed is 1.1 m s\(^{-1}\) for the duration of the deployment (Fig. 1). Diurnal warming effects are very evident in this data set with warm-layer depths observed between 0.2 and 1.0 m throughout this deployment period (Fig. 3, top left). Comparing the simulations for each of the five different mixing schemes shows interesting results. Time-series plots for the five models show the temporal evolution of the temperature differences between modelled and measured profiles (Fig. 3). The optimal temperature difference interval (±0.2 K) is coloured white in the plots. This interval represents required \( T_{\text{SST}} \) values to compute heat fluxes to within a ±10 W m\(^{-2}\) accuracy. The baseline model achieves the greatest white area of the three curves, providing good simulation results for this example of highly stratified conditions. This is mainly due to the baseline model predicting the most accurate warm-layer depth, resulting in a minimal mean temperature difference of 0.03 K from 0.5 to 5 m depth (Fig. 4). All five mixing schemes struggle to resolve the upper half metre correctly. It is important to note that it is difficult to conduct point-to-point comparisons given the potential for advective effects not considered in one-dimensional models. It is still interesting, however, to compare the relative performance of the different models. The two blended models achieve the highest temperature differences of the five models with an overestimation of 2.5 K for a brief period that morning. This occurs at the beginning of the deployment when the water column was observed to be well mixed (Fig. 3). All the models predict a diurnal warm layer at 1 m depth during this period, which accounts for the simulated temperature overestimations. The blended and baseline models overpredict temperatures during another period between 11:45 and 12:15 LT, when the solar heat flux drops to 700 W m\(^{-2}\) (Fig. 1). The observed warm-layer depth deepens by half a metre during this period (Fig. 3, top left). The
five models do not simulate this temporary deepening which could be related to their one-dimensional nature. The blended and baseline models strongly overestimate temperature during this period (Fig. 2), which strongly affects the models’ overall performance. The enhanced models perform well in this brief period, which is due to the overestimated warm-layer depths now matching the observations (Fig. 3).

The models are best compared by averaging their performance over multiple events. Mean temperature profiles for the five model versions were computed for the duration of GC99 (Fig. 4). The standard deviations corresponding to these mean temperature profiles are given in Table 3, showing to be in close proximity of each other. On average the baseline mixing model overpredicts the SST\textsubscript{BL} value by 0.28 K. The enhanced wave breaking and solar transmission models underpredict SST\textsubscript{BL} values by 0.85 K and 1.0 K respectively, for the entire deployment while the blended model over predicts SST\textsubscript{BL} by 0.7 K (Fig. 4). The blended solar transmission model gives the best results as it under predicts SST\textsubscript{BL} by 0.11 K and also provides the best results down to a depth of 0.1 m.

The enhanced wave breaking and solar transmission models predict deeper than observed warm-layer depths in Fig. 4. This affects the simulations by underestimating temperature within the observed warm layer and overestimating the temperature approximately 1 m below this layer depth (Fig. 4). This is evident in the EWB and EST plots in Fig. 3, where the yellow coloured areas in the centre of the plots represent the temperature overestimation. This is due to the enhanced models overestimating mixing in the upper few metres. This overestimation of mixing deepens the diurnal thermocline and creates an underestimation in temperature in the layers above, which can be observed as the blue coloured areas.

### 3.2 Model performance in nighttime conditions

Observational measurements from GL03 are used to validate model simulations in conditions corresponding to night-time cooling and the initiation of diurnal warming. The deployment started at 23:08 (CET) and continued throughout the night until 11:23 (CET) the next morning. The mean wind speed is $6.29 \pm 0.52$ m s$^{-1}$ and the solar heat flux steadily rises from 0 to 876 W m$^{-2}$ due to the morning solar heating (Fig. 1). The modelled simulated and observational data were bin averaged to depth intervals of 2 cm for the 117 profiles, with a higher resolution near the surface like that used in the previous section.

The plots (Fig. 5) show the times series of the measured profiles and temperature differences (model minus measured) of the five model versions for this period. Due to the small temperature changes observed, the white temperature difference interval represents 0.1 K for clarity (Fig. 5). The measured time-series plot (Fig. 5) shows a well mixed water column for most of the deployment period. A warm layer is formed at 10:00 LT with the increase of morning solar heating. The plot in Fig. 6 shows the mean temperature difference profile of the modelled minus the measured profiles for the deployment. The enhanced model and blended model simulations become quite singular (Fig. 6). The five models provide a mean temperature overestimation of 0.05 K from 0.0025 to 5 m depth, while the baseline model over predicts by 0.085 K. All the models struggle to simulate the cool skin temperature correctly. The cool skin correction applied in the models was too weak (Fig. 6) and the simulated SST\textsubscript{SK} values were overestimated by nearly 0.3 K. It is clear that the enhanced and blended models simulated the depth of the diurnal warm layer quite well as the temperature difference profile in Fig. 6 is relatively straight. The baseline model simulates a shallow, diurnal mixed layer which can

---

**Table 3. Standard deviations associated with the mean temperature difference profiles for the three case studies.**

<table>
<thead>
<tr>
<th>Region</th>
<th>Base</th>
<th>EWB</th>
<th>Blend</th>
<th>EST</th>
<th>BST</th>
</tr>
</thead>
<tbody>
<tr>
<td>GC99</td>
<td>0.0855</td>
<td>0.0947</td>
<td>0.0826</td>
<td>0.0957</td>
<td>0.0870</td>
</tr>
<tr>
<td>GL03</td>
<td>0.0906</td>
<td>0.0906</td>
<td>0.0939</td>
<td>0.0909</td>
<td>0.0939</td>
</tr>
<tr>
<td>IO07</td>
<td>0.0348</td>
<td>0.0347</td>
<td>0.0348</td>
<td>0.0356</td>
<td>0.0355</td>
</tr>
</tbody>
</table>

---

**Fig. 3. Time-series temperature depth plots for the GC99 case study: observational plot and temperature difference (modelled minus observed) plots for the five model versions. Red curve represents observed solar irradiance (W m$^{-2}$). The white area used represents an ideal $\Delta T$ of $\pm 0.2$ K.**
be observed in Fig. 6, as the temperature difference curve changes slope rapidly below 2 m depth. Due to this, the temperature has been overestimated near the surface and underestimated below the observed mixed layer (Fig. 5). The enhanced and blended models are within the ±0.2 K temperature difference. It is evident that the enhanced and blended models produce the best results for this period for nighttime well mixed conditions.

### 3.3 Model performance for day–night transition

ASIP measured temperature profiles from the IO07 data set are used in this study to validate the models’ performance in the highly stratified Cirene region of the Indian–Pacific warm pool. The downwelling shortwave radiation and wind speed for this modelling period are illustrated in Fig. 1. The deployment takes place over nighttime and continues for a brief period after sunrise. The measuring period begins at 19:02 LT with a diurnal warm-layer depth of 5 m and a surface amplitude reduces to 0.1 K over the period. A time-series plot of the observed temperature structure of the upper surface amplitude reduces to 0.1 K over the period. A time-series plot of the observed temperature structure of the upper

The cool skin correction model applied in the simulations is on average 0.17 K above the required correction (Fig. 8). This incorrectly improves the SSTSubskin directly beneath.

**Fig. 4.** GC99 dataset: differences between the modelled and in situ measurements for the Base (blue), Blend (yellow), EWB (green), EST (red) and BST (cyan) models. The surface points are the differences between modelled and M-AERI skin temperatures.

**Fig. 5.** Time-series temperature–depth plots for the GL03 case study: observational plot and temperature difference (modelled minus observed) plots for the five model versions. Red curve represents observed solar irradiance (W m$^{-2}$). The white area used represents an ideal ΔTT of ±0.1 K.
3.4 Overall model performance

In this section, all the available observed profiles (1165) are collectively used to validate the five model versions. A mean temperature profile for these profiles is shown in Fig. 9. A temperature gradient exists at 0.2 m depth, implying that strong effects of stratification are evident. The mean diurnal warming (SST_{subskin} − T_{Depth}) is about 0.7 K for all observations.

The mean temperature difference profiles for the five models using all of the available profiles are shown in Fig. 10. The conditions are mixed in a low to moderate wind environment and with strong solar heating present (Fig. 1). The majority of deployments show strong characteristics of stratification in the water column (Fig. 9). Overall, the baseline model simulations provide the most accurate SST_{subskin} values with a slight mean underestimation of 0.016 K. The blended model also works well with a mean overestimation of 0.045 K. The enhanced models show strong temperature underestimations throughout the warm layer (Fig. 7) which strongly affects the cool-skin temperature estimations. The enhanced models underestimate SST_{subskin} by 0.30 K. The blended solar transmission model performs the best for depths from the subskin to 0.1 m, and achieves the closest SST_{subskin} of all five models with −0.05 K, with the baseline model achieving 0.06 K. The blended model also works well with a mean overestimation of 0.045 K. The enhanced models show strong temperature underestimations above 0.2 m depth, influenced by the increased mixing parameters associated with the addition of the KC04 enhancement. The little difference between the results from the two enhanced model versions implies that the OS00 solar transmission enhancement has a low impact on the results compared to that of the KC04 enhancement.

Comparing Figs. 9 and 10, it is clear that the baseline model predicts the most accurate mixed-layer depth, within negligible temperature variations up to 0.1 m depth. A minor temperature overestimation occurs above 0.1 m depth for the baseline and blended model versions, caused by the use of the nine-band solar absorption model. The addition of the OS00 solar transmission model corrects this warming overestimation above this depth, which can be observed from the temperature profile simulated by the blended solar transmission model in Fig. 10. The blended solar transmission model performs the best for depths from the subskin to 0.1 m, and achieves the closest SST_{subskin} of all five models with −0.05 K, with the baseline model achieving 0.06 K. The blended model also works well with a mean overestimation of 0.045 K. The enhanced models show strong temperature underestimations above 0.2 m depth, influenced by the increased mixing parameters associated with the addition of the KC04 enhancement. The little difference between the results from the two enhanced model versions implies that the OS00 solar transmission enhancement has a low impact on the results compared to that of the KC04 enhancement.

The cool-skin correction in the plot (Fig. 10) is very strong for all the models. It causes an underestimation of 0.09 K with respect to the warm-layer correction. In particular, this has a strong impact on the overall performance of the blended solar transmission model.

4 Conclusions

A strong variability in the results was shown to exist between the models for highly stratified conditions (Fig. 4). Overall, the baseline model produces the most accurate temperature estimates for the cruise periods used in this study.
The enhanced models showed a strong temperature underestimation in the diurnal mixed layer for simulations in highly stratified conditions. This is caused by the models’ overestimation of the mixed-layer depth, a direct result of the models’ high prediction of mixing near the surface. This is in agreement with previous studies (Kantha and Clayson, 2004; Ohlmann and Siegel, 2000) which have recorded reduced temperatures in the diurnal mixed layer and increased mixed-layer depths. The enhanced models work well when wind induced mixing at the surface is a dominant factor, creating a well-mixed upper ocean. For this study, the Karman–Prandtl law of the wall assumption provides more accurate SST values than the estimates achieved from the K04 enhanced wave breaking model when the upper ocean is maximally stratified. Overall, the OS00 solar transmission model provides more accurate temperature estimates in the diurnal mixed layer compared to the nine-band absorption model. The blended solar transmission model which transitions between the two surface turbulence approaches and includes the OS00 model provides very good results immediately below the surface.

The cool-skin correction applied in the models produced underestimations when compared to the measured SST$_{Skin}$. On average the cool-skin correction underestimated SST$_{Skin}$ by 0.09 K for all the models. A revised cool-skin correction could considerably improve the performance of the blended solar transmission model (Fig. 10).

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3.2 Oceanic wave breaking coverage separation techniques for active and maturing whitecaps
Full length article

Oceanic wave breaking coverage separation techniques for active and maturing whitecaps

Brian Scanlon, Brian Ward *

School of Physics and Ryan Institute, National University of Ireland Galway, Galway, Ireland

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ABSTRACT

Whitecaps on the ocean surface mark localized areas where interactions between the atmosphere and ocean are enhanced. Contemporary methods of quantifying total whitecap coverage rely on converting color sea surface images into their binary equivalent using specific threshold-based automated algorithms. However, there are very few studies that have separated and quantified whitecap coverage into its active (stage-A) and maturing (stage-B) evolutionary stages, which can potentially provide more suitable parameters for use in breaking wave models, air–sea gas transfer, aerosol production, and oceanic albedo studies. Previous active and maturing whitecap studies have used a pixel intensity separation technique, which involves first separating the whitecap and background pixels, and subsequently establishing a second threshold to distinguish between active and maturing whitecaps. In this study, a dataset of more than 64,000 images from the North Atlantic were initially processed to determine the total whitecap coverage using the Automated Whitecap Extraction method. The whitecap pixels of each image were then distinguished as either stage-A or stage-B whitecaps by applying a spatial separation technique which does not rely solely on pixel intensity information but also on the location (relative to the wave crest), visual intensity, texture and shape of each whitecap. The comparison between the spatial separation and pixel intensity separation techniques yielded average relative errors of 34.8% and −44.0% for stage-A and -B coverage, respectively. The pixel intensity method was found to be less suitable when compared to the spatial separation method as it relies on the
assumption that the pixel intensity for stage-A is always greater than that for stage-B.

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1. Introduction

Whitecap coverage on the ocean surface is a direct result of breaking waves and is a visual representation of areas on the ocean surface where enhanced air–sea interactions of gas and aerosols occur (Anguelova and Webster, 2006). Many studies have been carried out to quantify the area of ocean surface covered by whitecaps ($W$) (Monahan and O’Muircheartaigh, 1980; Anguelova and Webster, 2006; Sugihara et al., 2007; Callaghan et al., 2008; Goddijn-Murphy et al., 2010) and there have been many attempts to parameterize whitecap coverage with wind speed (see Figure 1 in Anguelova and Webster, 2006, for a summary of parameterizations over the past 42 years).

According to the nomenclature of Monahan and Lu (1990), there are two stages of evolution in the lifetime of a whitecap. At the initial occurrence of a wave breaking, the wave crest velocity exceeds that of the wave, spills, traps air, and entrains it below the sea surface. A condensed bubble plume is created beneath the surface. This initial phase is known as stage-A or active whitecapping and has a characteristic lifetime $O(1 \text{ s})$. Due to the strong gravitational forces and wave momentum present, a high mixing potential is created at the air–sea interface. Directly after the gravitationally driven stage-A event, bubbles are overcome by turbulence and buoyancy forces, the bubble plume expands, returns to the sea surface forming a large whitecap, and decays through bubble bursting processes. This phase is known as stage-B or maturing whitecap, and it is during this phase that the majority of bubble bursting occurs. Stage-B whitecaps typically have longer lifetime than that of stage-A, often being observed for times up to 10's of seconds (Callaghan et al., 2013). Fig. 1 shows a schematic of the evolution of a typical whitecap, from the stage-A occurrence to the evolution of a stage-B. Both stages of whitecapping can be quantified by measuring the area of the image containing the active and maturing whitecaps.

Active whitecaps play a strong role in the air–sea gas transfer due to their high mixing potential. Monahan and Spillane (1984), Woolf (1997) and Asher and Wanninkhof (1998) have attempted to use whitecap coverage estimates to obtain more accurate models for gas transfer velocities. Andreas and Monahan (2000) reported that stage-A whitecaps cycle roughly 4 orders of magnitude more air through the near surface ocean than do stage-B whitecaps for a given wind speed. Stage-A values have been regarded as the most suitable parameter for quantifying the rate of wave breaking, playing a vital role in modeling turbulence injected into the upper ocean due to wave breaking. Wave modelers such as Hanson and Phillips (1999) have used $W$ estimates to parameterize the dissipation of wave-field energy as a wave breaks.

Decaying whitecaps, due to their bubble bursting nature, have been previously quantified and related to studies involving sea-salt aerosol particle production (Monahan et al., 1986), underlining the importance of the quantification of stage-B whitecaps. Bubble bursting in stage-B whitecaps result in film and jet droplets being produced, creating atmospheric aerosols which have been reported to impact on air–sea sensible and latent heat fluxes (Andreas et al., 1995). Anguelova and Webster (2006) states that sea spray processes must be adequately parameterized and included in climate models. Surfactant concentrations at the air–sea interface can strongly affect the persistence of stage-B whitecaps (Callaghan et al., 2013). Discriminating stage-A from $W$ could potentially remove the dependence of surfactants from whitecap estimates, providing a more relevant parameter for gas-transfer models and rate of wave breaking.

Methods of quantifying $W$ have developed over the past several decades, and it has generally involved the analysis of photographic and videographic images of the sea surface where areas of whitecap were identified and quantified. Initially, this involved labor-intensive methods whereby photographs of sea surface were physically dissected to remove the areas of whitecapping and
Fig. 1. Schematic illustrating the evolution of a typical breaking wave: a spilling wave crest (I), bubble plume formation (II), evolution into stage-B whitecap (III), and decay of the whitecap (IV).

subsequently weighed, in order to determine values of $W$. This method was developed by Monahan (1969) and was widely used up into the late 1980s (Monahan, 1971; Toba and Chaen, 1973; Monahan et al., 1981). More recent methods involve the acquisition of high-resolution digital images of the sea surface at rates of 1 Hz or better using digital camera technology. These raw images lend themselves to image processing techniques, such as the Automated Whitecap Extraction (AWE) algorithm (Callaghan and White, 2008) specifically developed for quantifying whitecap coverage. This advancement in technology allows for more accurate estimates of $W$ as well as the possibility to process thousands of images rapidly. Such algorithms can distinguish image pixels as either whitecap or background using an automatically determined pixel intensity threshold. This threshold can vary from one image to the next due to background ambience illumination fluctuations, wave slope, image capturing angle, and the presence of sunglint.

Previous studies have considered alternative methods of studying whitecap coverage using satellite radiometric data (Anguelova and Webster, 2006), acoustic sensors to measure the rate of bubble formation (Monahan and Lu, 1990), the rate of wave breaking (Ding and Farmer, 1994), and parametric estimates of total energy dissipation rate in wave models (Anguelova and Hwang, 2012).

Although there is a strong motivation to distinguish stage-A and stage-B whitecaps, there has been little success in the development of an automated technique. This is due to the complexity of determining the stages of the evolution of whitecaps based on the visual characteristics, which can be highly variable from one image to the next. A few studies have attempted to distinguish total whitecap coverage into its two stages ($W_A$ and $W_B$) (Ross and Cardone, 1974; Bondur and Sharkov, 1982; Monahan and Woolf, 1989). The technique applied by Monahan and Woolf (1989) involved the determination of a second pixel intensity threshold to distinguish between stages A and B whitecaps for individual images. The underlying assumption for this method is that the pixel intensities of stage-A whitecaps exceed that of stage-B whitecaps.

This article introduces a new technique, called the spatial separation of whitecap pixels (SSWP) which allows a user to manually distinguish pixel groups as either contributions towards $W_A$ or $W_B$ by evaluating their location on the wave-field, brightness, texture and slope through the observation of the original image. The pixel intensity threshold separation technique (PITS) is evaluated by comparing its results to that of our SSWP method. Conclusions are provided as to the most suitable method for distinguishing stages of whitecaps for use in future analysis.

2. Digital image processing of sea surface images

Digital images of the sea surface are comprised of many elements such as ocean background, whitecaps, sunglint, sea gulls, and residual foam formed along wind rows (Langmuir circulation). These digital images comprise of a number of pixels, depending on the image resolution. For 8-bit cameras, the pixels have intensity values ranging from 0 to 255 for their three constituent colors: red, green and blue. Sea surface images are commonly converted to grayscale, which reduces the pixel values from three scales to one.

Once converted to grayscale, the pixel values can be used to distinguish the regions of whitecap pixels from non-breaking background sea by assuming that the pixel intensity of whitecaps is greater
than that of the background sea. This thresholding method is accepted by many authors as being the most suitable for distinguishing whitecap regions in images and has been widely in use since the early 1970s (Nordberg et al., 1971; Monahan, 1993; Asher and Wanninkhof, 1998; Sugihara et al., 2007; Callaghan and White, 2008).

The image pixels can be categorized into 256 bins \( i \) depending on their pixel intensity values \( I \).

The pixel population, \( PP(i) \), represents the number of pixels in the \( i \)th bin for a sea surface image of \( m \times n \) resolution:

\[
PP(i) = \sum_{j=1}^{m} \left( \sum_{k=1}^{n} l(j, k) = i \right),
\]

where \( l(j, k) \) is the pixel intensity value at coordinates \( (j, k) \) of the image. The percentage whitecap coverage \( W \) can be obtained by integrating \( PP(i) \) for values of \( i \) above a threshold \( T \):

\[
W(\%) = \frac{\int_{i=T}^{255} PP(i) \, di}{\int_{i=0}^{255} PP(i) \, di} \times 100 \%
\]

By applying a suitable threshold, the whitecap pixel intensity spectra (WPIS) can be distinguished from the \( PP(i) \). There has been much research into selecting the most appropriate pixel intensity value \( T \) for distinguishing whitecaps in an ocean surface image (Monahan, 1993; Sugihara et al., 2007; Callaghan and White, 2008). The AWE algorithm (Callaghan and White, 2008) was used in this study to find estimates for \( T \). The algorithm can calculate the most suitable threshold as an automated process, allowing for large amounts of images to be processed quickly and efficiently. The AWE algorithm has been previously used in whitecap threshold applications for Callaghan and White (2008), Callaghan et al. (2008) and Goddijn-Murphy et al. (2010) and has proven to be a robust method for automated thresholding.

Other methods such as batch grayscale thresholding (BGT) have been used to extract \( W \) values from time-series of images by applying a singular threshold value. Authors such as Sugihara et al. (2007) have used this method successfully from stable camera platform views of the sea surface and from airborne vehicles (Bobak et al., 2011) to achieve estimates of whitecap coverage from 10 minute time-series of images. The method assumes that the pixel intensity distribution of whitecaps and background sea is uniform for all images captured within a relatively short period allowing for a singular pixel intensity threshold to be applied to the batch of images to distinguish regions of whitecaps. The \( PP(i) \) for each image is computed and added together to create a \( PP(i) \) for the entire batch. \( W(i) \), representing the series of whitecap coverage estimates for every possible threshold, is then calculated using Eq. (2). The most suitable threshold is selected by locating the lowest percentage difference between adjacent values in the \( W(i) \) series (Sugihara et al., 2007).

A modest area of the sea surface is required to be processed in order to achieve converging \( W \) estimates. Callaghan and White (2008) states that a dataset of 100s of images will achieve convergence for \( W \) estimates. Large image footprints can introduce larger deviations for mean pixel intensities for background sea and whitecaps, making it more difficult to distinguish whitecaps using the threshold technique. This is also true for high altitude images taken from airborne vehicles. Bobak et al. (2011) discusses the negative impact of high altitudes for camera systems. Smaller image footprints require larger numbers of images to achieve accurate \( W \) estimations for the particular conditions. However, the processing of larger image sets requires longer capturing time, and as the meteorological conditions at sea can fluctuate on short-timescales, this can introduce larger errors for calculating complementary mean meteorological parameters.

For oceanic studies, it is a rare occurrence to find periods of steady meteorological conditions. Changes in conditions can result in the \( W \) values not converging, making it important to reduce the time of image capture and thus minimizing this effect. According to Callaghan and White (2008), the convergence of 300 images can yield less than approximately 5% difference for mean \( W \) estimates, based on a 20 minute capturing period. Sugihara et al. (2007) achieved mean estimates of \( W \) from 600 images in a 10 minute time frame but no information on the image footprint is given. An image footprint of approximately 5000 m² was used by Callaghan et al. (2008), which would provide an
Fig. 2. Pixel intensity spectrum of background sea, stage-B and stage-A pixels for a typical image assuming normal distributions. The vertical lines represent threshold values $T$ and $T_*$.

average total sea surface area of $2 \times 10^{6}$ m$^2$ per $W$ estimate (assuming an average of 400 images per $W$ datapoint). A high resolution camera capturing larger image footprints in a shorter time frame will help minimize the effects of meteorological fluctuations and obtain an accurate representation of the sea surface.

3. Active and mature whitecap separation

Previous methods (Monahan and Woolf, 1989) of separating stage-A and stage-B whitecaps relied on a manual setting of a second pixel intensity threshold ($T_*$). This method assumed that the pixel intensity spectrum of stage-A pixels ($I_A$) is greater than the pixel intensity spectrum of stage-B pixels ($I_B$). According to Monahan (1993), the visible albedo of stage-A whitecaps ($\sim$0.6) is greater than that observed for stage-B whitecaps (0.2–0.5), and this can be used as a basis for the optical separation. According to this method, pixel intensity spectra for individual images will comprise of three distributions: background, stage-A, and stage-B pixels which can be separated by selecting two appropriate thresholds $T$ and $T_*$ (Fig. 2).

Application of the first threshold $T$ is widely in use for separating background sea and whitecap pixels (both stage-A and -B). The use of the secondary threshold to distinguish whitecaps into their active and maturing stages assumes that the intensity spectra contained in $PP(i)$ of stage-A ($I_A$) and stage-B ($I_B$) can be distinguished solely on their intensity values.

According to Callaghan and White (2008), an individual whitecap region (both active and maturing) consists of pixels of multiple intensities, typically appearing more intense in the middle of the whitecap region and becoming less intense out towards the edges. This occurs due to the nature of a whitecapping event where the visible signature for an underlying bubble plume beneath the surface is typically at its deepest in the middle of the whitecap (Monahan and Lu, 1990). This can cause an overlap in pixel intensity values for stage-A and stage-B whitecaps, with near edge pixels of a stage-A region being similar in intensity to the pixels in the middle of a stage-B region. This makes the separation of stage-A and stage-B pixels difficult, due to the overlap between $I_A$ and $I_B$.

3.1. Spatially observed and separated technique

Accurate discrimination of stage-A and stage-B whitecaps can be achieved by visually inspecting whitecap regions in an image and determining their stage of evolution based on their location relative to the crest of the wave, shape and visual intensity. According to the definition of an active whitecap,
the location must be either in front of or on top of a wave crest. The region where an active whitecap is confined is a small area on the ocean (with respect to the length scale of the wave) and is restricted in expanding due to its relatively short lifetime. Once gravitational forces of the plunging bubble plume are overcome by buoyancy forces, the whitecap enters the second stage of its evolution. This gives rise to a maturing whitecap which is visibly larger in area, appears less bright, and has a less uniform texture than an active whitecap. Stage-B whitecaps have been described as a *hazy foam patch* by Monahan (1993). A new method, called the spatial separation of whitecap pixels (SSWP), allows manual separation of whitecap pixels in order to distinguish them as either stage-A or -B.

The SSWP method allows whitecap pixels to be separated into their stages of evolution without relying solely on pixel intensities. This manual method is based on inspecting the image and grouping whitecap pixels as either contributions to stage-A or stage-B, with spatial freedom, using a graphical input device system. Despite the subjective nature of this analysis, the SSWP method is a valuable tool and can allow a user to accurately determine the stage of evolution of a whitecap through strict adherence to the stage-A and -B definitions outlined previously and by appealing objectively to the whitecaps visual characteristics within the image. Fig. 3 is an example of a sea surface image containing both active and maturing whitecaps along with the SSWP processed image showing the stage-A pixels colored in blue and the stage-B pixels colored green.

The SSWP method relies on the use of one threshold ($T$) to distinguish whitecap pixels from unbroken background water using the AWE algorithm (Callaghan and White, 2008). The $W$ pixels are then discriminated by manually drawing regions of interest (ROI) and specifying them as either A or B whitecaps. The $W$ pixels are then color coded (as in Fig. 3) to help re-evaluate and identify errors (similar to those used in Fig. 3c). The processing algorithm was designed to be maximally efficient, requiring minimal input from the user and maintain high fluidity when processing consecutive images. The user can easily and quickly distinguish the stages of whitecaps and extract high quality results. After the user separates the whitecap pixels of an image, the results are displayed to help
flag any mistakes made. The method requires approximately 10 s per image, allowing for a typical dataset of 900 images to be processed in 3 h. This processing method also allows for errors such as contamination due to seagulls or sun glint to be removed which can often be present after applying the AWE threshold.

4. Results and discussion

A dataset of sea surface images was obtained in the North Atlantic onboard the R/V Knorr in the summer of 2011. The camera was mounted on the O4 deck at a height of 19 m above sea level and at an angle of 75° to the nadir. This provides an image footprint of 7592 m² of the sea surface. The camera had a focal length of 70 mm and obtained images at 0.5 Hz. The image resolution of the captured image is 2560 × 1920 and is cropped to 1231 × 810 during the AWE algorithm process.

A set of 69 30-minute imaging periods were selected, in favorable overcast conditions, and processed using the SSWP method. This amounted to over 64,540 images having their whitecap contents distinguished, with individual $W_A$ and $W_B$ values extracted. Wind speed ranged from 3.0 to 16.8 m s$^{-1}$ (Fig. 4), water temperature ranged from 8.5 to 23.8 °C and atmospheric stability (water–air temperature) ranged from −3.4 to 7.0 °C for these selected image capturing periods.

The BGT (batch grayscale thresholding) method and AWE algorithm were both considered for distinguishing whitecap pixels from each image by calculating specific $T$ values. The AWE-derived $T$ values were applied to each image and manually inspected during the SSWP analysis. The AWE algorithm was found to produce superior threshold values for individual images. The data were then split into 10- and 30-minute datasets (300 and 900 images respectively) and BGT analysis was carried out to obtain the most suitable $T$ value. An average relative error (and standard deviation $\sigma$) for $W$ of 54.78% ($\sigma = 10.940$) and 139.66% ($\sigma = 26.243$) is introduced for 10- and 30-minute periods respectively when applying the BGT derived $T$ values. The large deviations represent the distribution of averaged error of the 69 30-minute and 207 10-minute periods. While the BGT method can achieve modest automated whitecap results when paired with large datasets of images and statistical analysis, it is not implemented in this study for the following reasons: first, the images in this study were obtained onboard the R/V Knorr in open seas, introducing an unstable platform and changing the angle of inclination of image capture. Second, the images in this study were all manually inspected and evaluated leaving the idea of quick batch analysis redundant. Third, the AWE can apply individual thresholds to each image, providing an accurate WPIS for this study. However, it is interesting to note the large error introduced when using BGT methods on images obtained from an unstable platform.

Fig. 4. Histogram of the wind speeds in 1 m s$^{-1}$ bins for the 69 30-minute periods.
Fig. 5. Four sea surface images (a)–(d) in the first row with SSWP distinguished $W_a$ (blue) and $W_b$ (green) regions in the second row. The third row shows the results when using the PITS method of separation by applying a $T^*$ threshold. The fourth row shows the SSWP whitecap pixel distributions. Table 1 provides relevant values for the images. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Complementary data for the images displayed in Fig. 5. Wind represents the nearest 1 minute true wind speed (m s$^{-1}$) averaged over a 30 minute window.

<table>
<thead>
<tr>
<th>Image</th>
<th>Wind</th>
<th>$T$</th>
<th>$T_a^*$ ($\pm \sigma$)</th>
<th>$T_b^*$ ($\pm \sigma$)</th>
<th>SSWP (%)</th>
<th>$E_{sep}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>3.6</td>
<td>177</td>
<td>201 (±22.7)</td>
<td>200.2 (±14.5)</td>
<td>0.15</td>
<td>0.05</td>
</tr>
<tr>
<td>(b)</td>
<td>7.4</td>
<td>195</td>
<td>225 (±7.8)</td>
<td>219.8 (±14.2)</td>
<td>0.32</td>
<td>0.37</td>
</tr>
<tr>
<td>(c)</td>
<td>12.7</td>
<td>178</td>
<td>238 (±20.6)</td>
<td>213.9 (±20.3)</td>
<td>0.94</td>
<td>1.30</td>
</tr>
<tr>
<td>(d)</td>
<td>16.4</td>
<td>174</td>
<td>228 (±25.3)</td>
<td>207.6 (±18.5)</td>
<td>0.48</td>
<td>6.75</td>
</tr>
</tbody>
</table>

Assuming that the SSWP method achieves the best possible estimate of $W_a$ and $W_b$ from sea surface images, the results can be used as a basis to compare and evaluate the PITS method results for the same dataset of images. Extraction of $W_a$ and $W_b$ estimates using the PITS method can be achieved by analyzing the SSWP distinguished pixel intensities spectrums for stage-A and -B whitecap regions ($I_a$ and $I_b$) in each image and attempting to calculate a second pixel intensity threshold $T^*$ to best separate them. Assuming that the PITS is a viable separation technique, then the mean pixel intensity for stage-A pixels must be greater than the mean of stage-B pixels (i.e., $I_a^* > I_b^*$). If we assume a normal distribution for stage-A and -B pixel intensity values, then the deviations of $I_a$ and $I_b$ around their mean values must be less than $I_a^* - I_b^*$ so as to achieve modest separation error (due to overlap of $I_a$ and $I_b$ spectra (Fig. 2)).

A detailed overview of the image processing is introduced using a small number of images as examples. Four images were selected showing different breaking wave events (Fig. 5). Each of these
Fig. 6. $E_{sep}$ values for various $T^*$ thresholds used for Fig. 3.

images was selected for a different wind speed range, i.e., 3.6, 7.4, 12.7, and 16.4 m s$^{-1}$. These images are then analyzed using the SSWP and PITS techniques to determine values of $W_A$ and $W_B$.

The second row of images in Fig. 5 show the SSWP results with marked areas of stage-A (blue) and stage-B (green) whitecaps. The third row in 5 shows the distribution of stage-A and stage-B pixels by separation using an intensity threshold $T^*$ (refer to Table 1 for values). The fourth row of Fig. 5 shows the intensity spectra of stage-A ($I_A$) and of stage-B ($I_B$) whitecaps. Also included in these images are the normal distributions shown to ±3 standard deviations using the mean values $I_A$ and $I_B$ with their respective deviation values shown in Table 1.

The first threshold $T^*$ for each image is set by the AWE algorithm. Pixel intensities below $T^*$ are considered that of unbroken background sea and the pixel intensities exceeding $T^*$ are considered that of whitecaps. These pixels were then grouped, spatially separated and distinguished as either stage-A or stage-B whitecaps using the SSWP method. Extracting the pixel intensity spectra of both stages of whitecaps, the mean values were found providing $I_A$ and $I_B$. If $I_A > I_B$, all intensity values between these two means were tested as a potential $T^*$ threshold. The most appropriate $T^*$ was obtained by comparing the relative change in pixel numbers for stage-A and -B and selecting the value with the lowest relative error. A separation error ($E_{sep}$) is defined to quantify this relative error and calculate the most appropriate $T^*$ value:

$$
E_{sep} = \frac{\int_{T^*}^{255} PP(i)di - \int_{T}^{255} PP(i)di}{\int_{0}^{255} PP(i)di} \times \frac{100}{1} \quad \text{for stage-A}
$$

$$
E_{sep} = \frac{\int_{T}^{T^*} PP(i)di - \int_{0}^{T} PP(i)di}{\int_{0}^{255} PP(i)di} \times \frac{100}{1} \quad \text{for stage-B}.
$$

Fig. 6 shows the $E_{sep}$ range for all $T^*$ values between $I_A$ and $I_B$, for image (c) in Fig. 5. For this individual image, the majority of $I_A$ have intensities above 250 (Fig. 5 column (c), row 4). $I_B$ was calculated to be 242.6, with a standard deviation of 20.6. The $I_B$ spectrum was more evenly spread across the range between $T$ and the maximum pixel value (255), achieving a $T_B$ of 213.9, with a standard deviation of 20.3. The value for a second threshold $T^* \in \frac{I_B}{I_A} < \frac{I_B}{I_A}$ was obtained on the basis of achieving the closest $W_A$ and $W_B$ values to those obtained by the SSWP method. For $T^* = 238$, $W_A$ and $W_B$ values are calculated with the lowest $E_{sep}$ values of 0.3% and −0.2% respectively.

Incorporating the second threshold into the original images displayed on the top row of Fig. 5, illustrations of the spatial distribution of the PITS method are shown on the third row of Fig. 5. For images (c) and (d), it can be clearly observed that the outer edges of the stage-A whitecap regions
Table 2
Definition of specific types of sea surface images, based on the whitecap content.

<table>
<thead>
<tr>
<th>Type</th>
<th>Content</th>
<th>Condition (if any)</th>
<th>$E_{sep}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 2a</td>
<td>$W_A$ &amp; $W_B$</td>
<td>$\bar{I}_A &gt; \bar{I}_B$ (Eq. (3))</td>
<td>$E_{sep}$</td>
</tr>
<tr>
<td>Class 2b</td>
<td>$W_A$ &amp; $W_B$</td>
<td>$\bar{I}_B &gt; \bar{I}_A$</td>
<td>Not defined</td>
</tr>
<tr>
<td>Class 1</td>
<td>$W_A$ or $W_B$</td>
<td></td>
<td>$=0$</td>
</tr>
<tr>
<td>Class 0</td>
<td>Neither $W_A$ or $W_B$</td>
<td></td>
<td>$=0$</td>
</tr>
</tbody>
</table>

have lower pixel intensities than $T_*$ and cannot be distinguished as $W_A$ without capturing more high intensity pixels from the center of stage-B whitecap regions.

4.1. Comparison for a 30 minute dataset

The PITS method is further evaluated by extracting SSWP-derived $I_A$ and $I_B$ spectra for 917 images as part of one 30 minute dataset. This dataset corresponds to a mean wind speed of $11.4 (\pm 0.8) \text{ m s}^{-1}$, providing a suitable high rate of wave breaking. The viability of employing a secondary threshold $T_*$ to the WPIS of each image to separate $W_A$ from $W_B$ is evaluated using $E_{sep}$ values in the same fashion as Eq. (3). Certain criteria are in place to allow for processing of images containing different types of whitecap content.

In summary, images containing both $W_A$ and $W_B$ regions but with averaged stage-B pixel intensities exceeding that of stage-A, ($\bar{T}_B < \bar{T}_P$) are not eligible for the PITS technique. These images are called ‘Class 2b’ images. In the case of images containing only one stage of evolution of a whitecap, it can be distinguished sufficiently using only the first threshold $T$. These images are called ‘Class 1’ images and result in $E_{sep}$ errors equal to zero after applying the PITS technique. Similarly, $E_{sep}$ values are also zero for a third image type which contains no whitecap pixels, called ‘Class 0’ images. The final type of image, called ‘Class 2a’, contains examples of both stages of whitecap evolution and meets the criterion that $\bar{T}_A > \bar{T}_B$. These images are processed in the same fashion as the images in Fig. 5 and $E_{sep}$ values are found using Eq. (3). These image types are summarized in Table 2.

For this particular image dataset, $E_{sep}$ was calculated to be 68.5% and 16.2% for estimating $W_A$ and $W_B$ using the PITS method, respectively. Image classes 2a, 1 and 0, with a breakdown of 37.2% for 2a, 35% for 1 and 9.0% for 0 were used to calculate these final $E_{sep}$ values. The percentage of ‘Class 2b’ images in the dataset was 18.8%, an indication of the number of images which contradict the initial assumption of $\bar{T}_A > \bar{T}_B$, and thus could not be processed using the PITS method.

4.2. Comparison for the entire dataset

The entire dataset of 64,540 images was used to evaluate the PITS method. Considering all the available images (classes 2a, 1 and 0), 68.9% and 74.3% are the average $E_{sep}$ values for $W_A$ and $W_B$ respectively, with 21.6% of the total images being of class 2b.

These high values demonstrate that the PITS method is not suitable for obtaining accurate $W_A$ and $W_B$ estimates. The $W_A$ and $W_B$ values obtained from the PITS method (for images of class 2a, 1 and 0) compared to those of the SSWP (for all image types), provide relative errors of 34.8% and $-44.0\%$ respectively.

Fig. 7 shows the averaged $W_A$ and $W_B$ values for each of the 69 30-minute periods derived from the SSWP method and plotted against that derived from the PITS method. The vertical and horizontal error bars for each datapoint represent the 95% confidence intervals. It is interesting to note that the PITS method overestimates $W_A$ and underestimates $W_B$ when compared to the SSWP-derived values in this study (Fig. 7).

The PITS- and SSWP-derived $W_A$ error bars are observed to be of similar magnitude (change of 15.4% on average), while the PITS-derived $W_B$ error bars are significantly lower ($-48\%$ on average) than the SSWP-derived $W_B$ error bars (Fig. 7). It is important to note that the PITS-derived $W_A$ and $W_B$ values are averaged from a sample population of images which exclude images of class 2b (21.6% of
total images). The absence of this class of image is quantified by appealing to the changes in average and standard deviation estimates for the overall whitecap coverage \( W \) of the entire data, which are \(-22.2\%\) and \(-31.3\%\) respectively. These values show that this reduction in images plays a vital role in explaining the observed changes in variance of averaged \( W_A \) and \( W_B \) estimates when using the PITS method.

However this does not fully account for the observed variance changes induced by the PITS method. Further analysis of the SSWP- and PITS-derived values conducted for images of class 2a, 1, and 0 removes the changes of variance due to this under sampling and reveals variance changes of 2.9% and \(-23.6\%\) for \( W_A \) and \( W_B \) averages respectively. This implies that the PITS method significantly reduces the variability of the periodic averages of \( W_B \). This is caused by a PITS-induced convergence of \( W_B \) estimates of individual images, revealing an underestimation in the quantification of \( W_B \) regions which is scaled to the size of the whitecap, with the largest maturing events being underestimated the most. This underestimation occurs for class 2a images when \( I_A \) and \( I_B \) overlap quite extensively (refer to the bottom row Fig. 5) allowing for large numbers of high intensity stage-B pixels to be interpreted as contributions towards \( W_A \) when the second threshold is applied.

5. Conclusions

A method for whitecap discrimination between stage-A and stage-B whitecapping has been presented. This technique allows images to be processed by determining a region-of-interest for the two types of whitecapping. The separation is achieved manually by observing the sea surface image and evaluating the whitecap pixels with respect to the crest of the wave, its visual intensity, shape and texture, thereby determining if the whitecap is actively breaking or maturing.

A second pixel intensity threshold separation (PITS) method was evaluated by comparing the \( W_A \) and \( W_B \) values, extracted from 64,540 high resolution sea surface images, to those extracted by the SSWP method. The PITS method employs a secondary threshold to separate whitecap pixels dependent on pixel intensity, a method used in the previous studies.

The Batch Grayscale Threshold (BGT) method introduces large errors when distinguishing whitecap coverage estimates from the batches of images captured from an unstable camera platform, compared with those distinguished by the Automated Whitecap Extraction (AWE) algorithm. The application of the AWE algorithm is recommended for future analysis.

The comparison study reveals that the PITS method introduces significant separation errors, an average of over 68.9% \( (\text{relative error}) \), compared with those attained from the SSWP method. This
results in changes to mean whitecap coverage estimates for stage-A and -B of 34.8% and \(-44.0%\) respectively, when compared to SSWP derived coverage values.

Separation of whitecap pixels into their evolutionary stages, defined by (Monahan and Lu, 1990), is best carried out by spatial separation by appealing to all available characteristics such as location (with respect to wave crest), intensity, shape and texture rather than solely relying on a pixel intensity threshold.

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References


3.3 Modelling whitecap fraction with a wave model
Modelling whitecap fraction with a wave model

BRIAN SCANLON
AirSea Lab, School of Physics and Ryan Institute, NUI Galway, Galway, Ireland.

ØYVIND BREIVIK
Norwegian Meteorological Institute, Bergen, Norway

JEAN-RAYMOND BIDLOT AND PETER A.E.M. JANSSEN
European Centre for Medium-Range Weather Forecasts, Reading, UK

ADRIAN H. CALLAGHAN
Scripps Institution of Oceanography, University of California, San Diego, La Jolla, California, USA

BRIAN WARD∗
AirSea Lab, School of Physics and Ryan Institute, NUI Galway, Galway, Ireland.

ABSTRACT
High resolution measurements of actively breaking whitecap fraction ($W_{FA}$) and total whitecap fraction ($W_{FT}$) from the Knorr11 field experiment in the Atlantic Ocean are compared with estimates of whitecap fraction modeled from the dissipation source term of the ECMWF wave model. The results reveal a strong linear relationship between model results and observed measurements. This indicates that the wave model dissipation is an accurate estimate of total whitecap fraction. The study also reveals that the dissipation source term is more closely related to $W_{FA}$ than $W_{FT}$, which includes the additional contribution from maturing (stage B) whitecaps.

1. Introduction
Accurate estimates of the energy dissipated from the oceanic wave field due to wave breaking is a vital requirement for improving wave models, upper-ocean turbulence models, and knowledge of ocean–atmosphere interactions for gas transfer.

Whitecaps appear when the wind exceeds approximately $3 \text{ m s}^{-1}$ under open ocean conditions (Monahan 1971; Stramska and Petelski 2003; Scanlon and Ward 2015). The occurrence of whitecaps increases with the duration, fetch (Nordberg et al. 1971), and intensity of the wind (Komen et al. 1994). With persistent wind forcing, the waves will eventually reach an equilibrium state, where the energy dissipated from wave breaking balances the energy injected by the wind.

Whitecaps from breaking waves mark regions of enhanced air-sea transfer of gases through bubble-mediated processes (Monahan and Spillane 1984; Woolf 1997; Asher and Wanninkhof 1998; Woolf et al. 2007). Whitecaps are also important as they affect the brightness temperature of the sea surface, as seen by passive radiometer instruments (Monahan and O’Muireachtaigh 1986; Anguelova and Webster 2006; Salisbury et al. 2013), as well as affecting the ocean color, as seen by satellite-borne instruments in the visible and near infrared wavelength range (Gordon 1997; Frouin et al. 2001). Whitecaps correlate strongly with the energy dissipated through wave breaking (Cardone 1969; Monahan 1986; Kraan et al. 1996; Cavaleri et al. 2007; Thompson et al. 2009), increasing the turbulence in the upper ocean (Craig and Banner 1994; Terray et al. 1996; Kantha and Clayson 2004; Gemmrich 2010; Gemmrich et al. 2013).

This study is concerned with the comparison of whitecap estimates from the dissipation source term of the ECMWF wave model to in-situ whitecap estimates from the Knorr11 campaign in the North Atlantic. Obtaining a robust relationship during this comparison can provide the basis for the development of global predictions of whitecap coverage. The paper is organized as follows: section 2 provides information on the measurements of total whitecap fraction, section 3 compares the model estimates with measurements, and section 4 discusses the results with implications for the development of global predictions of whitecap coverage.

∗ Corresponding author address: Brian Ward, AirSea Lab, School of Physics and Ryan Institute, NUI Galway, Galway, Ireland.
E-mail: bward@nuigalway.ie
During this process, a threshold value is obtained from the Automated Whitecap Extraction (AWE) algorithm (Callaghan and White 2009). This threshold value was determined using the Automated Whitecap Extraction (AWE) algorithm (Callaghan and White 2009) through the Automated Whitecap Extraction (AWE) algorithm (Callaghan and White 2009) algorithm, after which the overlying pixel values (those deemed part of a whitecap) are set to 1, while pixel values below the threshold are set to 0. This results in binary images consisting of maximum pixel values representing whitecap regions and minimum pixel values representing background sea. Subsequent manual inspections of whitecap regions are carried out using the Spatial Separation of Whitecap Pixels (SSWP) method (Scanlon and Ward 2013), after which the regions are classified as either actively breaking (stage A) or decaying (stage B) whitecaps, as defined in Monahan and Lu (1990).

3. The dissipation source term in spectral wave models

Third generation spectral wave models (Hasselmann et al. 1988; Tolman 1991; Komen et al. 1994; Ris et al. 1999; Tolman et al. 2002; Janssen et al. 2004; Holthuijsen 2007; Cavaleri et al. 2007) solve the action balance equation (Komen et al. 1994; Janssen et al. 2004), which in deep water with no current refraction reduces to the following energy balance equation:

\[
\frac{\partial F}{\partial t} + \nabla \cdot (\mathbf{c}_F F) = S_{\text{in}} + S_{\text{nl}} + S_{\text{diss}},
\]

written here in flux form. Here \( F(k) \) is the spectral energy density at wavenumber \( k \), and \( \mathbf{c}_F \) is the corresponding vector group velocity. The source terms refer to wind input \( S_{\text{in}} \), nonlinear transfer \( S_{\text{nl}} \), and dissipation \( S_{\text{diss}} \), respectively.

The turbulent kinetic energy (TKE) flux from breaking waves into the ocean, \( \Phi_{\text{oc}} \), is related (see e.g. Janssen et al. (2004); Rascle et al. (2006); Janssen (2012); Janssen et al. (2013); Breivik et al. (2015)) to the dissipation source function of a spectral model as:

\[
\Phi_{\text{oc}} = \rho g \int_0^{2\pi} \int_0^\infty S_{\text{diss}} \, d\omega \, d\theta \quad \text{[W m}^{-2}\text{]}.
\]

As has been discussed by Craig and Banner (1994), the energy flux (Eq 2) should approximately relate to the third power of the friction velocity:

\[
\Phi_{\text{oc}} \approx \rho_u u_c^3,
\]

where \( u_c = \sqrt{\frac{T_{\text{oc}}}{\rho_u}} \). This flux is also related to the total whitecap fraction \( W_{FT} \), as first discussed by Ross and Cardone (1974) and later among others (Kraan et al. 1996; Goddijn-Murphy et al. 2011). We follow Kraan et al. (1996) and assume that there is a linear relationship between the energy dissipation and the whitecap fraction:

\[
\Phi_{\text{oc}} = \gamma \rho_0 g W_{FT} u_c E.
\]

Here \( \gamma \) represents the average fraction of total wave energy dissipated per whitecap event, set to 0.01 in our case, following Kraan et al. (1990). In Eq (4) the total wave energy dissipation per whitecap event is given by the product of the average turbulent kinetic energy flux \( \Phi_{\text{oc}} \) and the whitecap fraction \( W_{FT} \).
energy per unit mass is $\rho_wgE$, which is modulated by the wave variance $E = (H_0/4)^2$. The term $\omega_\phi = 2\pi/T_0$ is the radian peak frequency.

Here, we make the implicit assumption that air-entraining whitecaps represent the dominant mechanism of wave energy dissipation, and neglect any contribution from non-entraining microscale breaking, and other dissipative mechanisms. However, we acknowledge recent studies which suggest that energy dissipation by microscale breaking waves may be an important energy sink in certain sea states (Sutherland and Melville 2013).

Although Kraan et al. (1996) suggests to use the peak frequency in Eq (4), we have in the following chosen to instead use the mean frequency of the wind sea part of the wave spectra $\omega = 2\pi/T$ (Fig 1) as it is more important for the whitecap production. Swell-dominated seas exhibit less whitecap coverage than pure wind seas (Sugihara et al. 2007; Callaghan et al. 2008b; Goddijn-Murphy et al. 2011). The swell separation scheme of ECWAM defines wind sea as those wave components of the spectrum that are subject to wind forcing. The remaining part of the spectrum is assumed to be non-local swell. The separation between wind sea and swell is thus a function of the relative direction as well as the speed difference between the wind (or friction velocity) and the wave component:

$$1.2 \times 28(u_*/c) \cos(\theta - \phi) > 1,$$

where $c$ is the phase speed of the waves, $\theta$ is the direction of the waves and $\phi$ is the wind direction (see ECMWF (Sec 6.7 2013)). The mean wind-sea period is used instead of the peak period as it is a more stable parameter:

$$T = m_{-1}/m_0.$$  

The moments are defined as:

$$m_n = \int_0^{2\pi} \int_0^{\infty} f(f, \theta) d\theta df.$$  

(7)

For the computation of the wind sea mean period, the swell components are left out by setting the appropriate wave amplitudes of $F(f, \theta)$ in Eq (7) to zero.

a. The ECWAM model integration

The most recent global uncoupled version of ECWAM [see ECMWF (2013), model cycle 41R1] was run for the period June-July 2011 on 11 km resolution with one-hourly output of integrated wave parameters. Wind fields with six-hourly temporal resolution were taken from the operational analyses at 16 km resolution, interpolated to the ECWAM 11-km grid. Fig 2 shows ECWAM neutral wind speed $U_{10N}^{mod}$ plotted against measured neutral wind speed $U_{10N}^{mod}$. Both time-series are time-averaged estimates of the 128 hourly whitecap measurement periods, and display good agreement.

The 1-hourly ECWAM wave energy dissipation flux $\Phi_{\omega_c}$ is used in Eq (4) to obtain modeled whitecap fraction estimates:

$$W_{FC}^{mod} = \frac{\Phi_{\omega_c}}{\rho_w g \omega E}.$$  

(8)

where $\omega = 2\pi/T$. For default settings [$\gamma=0.01$, following Kraan et al. (1996)], the model whitecap estimates are computed for each of the 128 hourly periods and compared with measured $W_{FT}$ and $W_{FA}$ estimates. For comparison, a scale of 1/3-power coverage is used, aiding in data linearity in terms of $u_*$, identified as the most dominant forcing term (Eq 3). This scaling minimises the effects of model error propagation due to polynomial expansion of uncertainties and errors associated with $u_*$ and also helps to increase the influence of low wind-speed measurements in the fitting process. Linear fitting techniques are employed to investigate and evaluate important properties:

$$W_{FC}^{mod} = MW_{FC} + C.$$  

(9)

where $M$ is the slope, $W_{FC}$ is a generic term for observed whitecap fraction and $C$ is the intercept. The linear relationships are evaluated using the squared correlation coefficient, $R^2$. Once linearity is established, agreement of model estimates with observations is evaluated using both $M$ and $C$. Due to the high population of outliers, the robust bisquare method of reweighing residuals (Huber 1996) is employed during comparison, to extract best fit relationships.

In our model, the wind energy input is included in the $\Phi_{\omega_c}$ term (Eq 3). Fig 3 shows this relation by plotting 1/3-power model estimates of $\Phi_{\omega_c}/\rho_w$ against $u_*$. Linear fitting
Fig. 3. Extraction of the model relation of wave energy dissipation, $\Phi_w$, and wind energy input, $\rho_uu^3$, by means of plotting the 12K 1-hourly model estimates of $(\Phi/\rho_uu^3)^{1/3}$ against $u$. Observed $\Phi_w$ thresholds for whitecap production by Hwang and Sletten (2008) (HS08) and $u_\text{a}$, threshold for actively breaking whitecap production by Scanlon and Ward (2015) (SW15) are provided for illustration.

reveals an expected cubed power $u_\text{a}$ relation with model estimates of $\Phi_w$. We consider the inclusion of a friction velocity threshold $u_\text{a}T$, which introduces an intercept term in Eq (3) such that:

$$\Phi_w \propto \rho_u(u_\text{a} - u_\text{a}T)^3. \tag{10}$$

Such thresholding methods (Eq 10), as introduced by Monahan and O’Muircheartaigh (1986), have been employed by many studies attempting to quantify whitecap coverage with wind speed (Monahan and O’Muircheartaigh 1986; Asher and Wanninkhof 1998; Reising et al. 2002; Callaghan et al. 2008a; Scanlon and Ward 2015) and energy dissipation (Hwang and Sletten 2008). In such mentioned studies, whitecap coverage was observed to occur above specific thresholds of wind energy input. Fig 3 illustrates two such examples of observed coverage: (i) wave energy dissipation threshold (HS08) obtained by Hwang and Sletten (2008) which considers whitecap observations from a multitude of previous studies, and (ii) the adopted friction velocity threshold (SW15) at which actively breaking whitecaps are observed to occur (Scanlon and Ward 2015).

We also consider the influence of wave slope $s$ through the empirical relation

$$\gamma = \gamma_0 \tanh s, \tag{11}$$

where $s = \alpha \tilde{H}_w$, and $\gamma_0$ is a constant (see Fig 1 for a time-series of $s$). Here $\alpha$ is a constant, $\tilde{H}_w$ is the mean wavenumber and $H_w$ is the significant wave height. Assuming the deep water relation $k = \alpha^2/\gamma$, the $W_{\text{mod}}$ values are recalculated using Eq (11) and Eq (8) and compared with $W_{\text{FT}}$ and $W_{\text{FA}}$ observations.

It is important to make the distinction that our estimates of wave slope are acquired from averaged open ocean wave spectra parameters which are subjected to non-local contributions of swell, and may not accurately reflect the locally measured wave slopes upon which breaking occurs, and thus may not be a sufficient proxy for wave crest acceleration prediction and wave stability. Such locally measured wave slopes have been related to the energy dissipated by wave breaking events (Melville and Rapp 1985) and to breaking probabilities (Banner et al. 2010). In our case, the wave slope can be interpreted as a proxy for the presence of swell, such that higher wave slopes are associated with wave-fields comprised of locally generated wind-waves and minimal contributions due to the presence of swell, and lower wave slopes relating to the strong presence of swell. In such cases, wave slope has been observed to adjust the wind-wave energy transfer (Taylor and Yelland 2001). While we already introduce a method of removing swell from the analysis by using the mean period of the wind-wave spectra $\bar{T}$ in Eq (8), it is interesting to analyse if additional wave slope dependencies are observed for the fraction of energy dissipated due to whitecap coverage $\gamma$.

b. Comparison results

Fig 4a shows the 1/3-power plot of $W_{\text{mod}}$ against measured whitecap fraction $W_{\text{FT}}$, for default settings ($\gamma=0.01$), showing good linearity with one another ($R^2=0.78$ and $R^2=0.74$, for $W_{\text{FT}}$ and $W_{\text{FA}}$ respectively) despite poor quantitative agreement ($M \neq 1$). A bias towards model estimates at low coverage (and wind) values can also be observed.

The slope $M$ of the best fits in Fig 4a can be tuned by adjusting the value of $\gamma$, achieving better agreements between model and measured quantities. However such adjustments to $\gamma$ also affect the magnitude of the intercept $C$. This value $C$ can be viewed as quantification of the positive (or negative) bias of the modeled $W_{\text{mod}}$ estimates, and thus values of $C$ should be minimised.

In Fig 4b, supplemental tuning of $W_{\text{mod}}$, using $W_{\text{FT}}$ measurements as comparison, was achieved by setting $\gamma = 0.0074$. This resulted in an improved agreement ($M = 1$), at a cost of introducing a higher intercept ($C=0.045$). For the case when using $W_{\text{FA}}$ as comparison, setting $\gamma = 0.034$ achieved the same improved agreement ($M = 1$), but with a reduced intercept of $C=0.021$ (Tab 1).

Further success at minimising the model bias ($C$) at low coverage (and wind) conditions was achieved by introducing a friction velocity $u_\text{a}$ threshold into the whitecap
model:

\[ W_{\text{mod}} = \begin{cases} \Phi_{\text{mod}} (\frac{\eta_u - \eta_T}{\eta_u})^3 & \eta_u > \eta_T \\ 0 & \eta_u \leq \eta_T \end{cases} \]  

where \( \eta_T = 0.065 \text{ m s}^{-1} \) is the friction velocity threshold, an equivalent (assuming a neutral drag coefficient) adaptation to the observed \( U_{100} \) threshold for the onset of actively breaking whitecaps (Scanlon and Ward 2015). The consequence of Eq (12) is that a minimum value of wind energy is required for whitecaps to occur. Table 1 displays the performance of the different configurations of the whitecap semi empirical model, when compared with observations. The inclusion of the threshold term (Eq 12) provides improved agreement (\( M = 1, C \approx 0 \)) and linearity (\( R^2 \)) with observations, significantly reducing the model bias \( C \). The modeled whitecap fractions \( W_{\text{mod}} \) show best agreement with observed \( W_{\text{FA}} \) (\( M=1, C=7.5 \times 10^{-5} \)).

Concurrently, the influence of wave slope is implemented in Eq (12) by using Eq (11) and setting \( \phi = 0.0360 \) & 0.0078 for \( W_{\text{FA}} \) and \( W_{\text{FT}} \) respectively. The implementation provides no improvement (not shown), even for cases involving various multiples of \( s \) by adjusting \( \phi \) from small to large numbers. This suggests that the semi empirical model sufficiently considers the effects of wave slope (Melville and Rapp 1985; Melville 1994; Taylor and Yelland 2001; Banner et al, 2010).

Fig 5 presents the model estimates \( W_{\text{mod}} \) achieved using the semi empirical equation (8) with the applied fric-
tion velocity threshold modification (12) plotted against $W_f$ observations in logarithmic space. Fig 5 comparison showcases the best agreement obtained in this study between model and observed data.

When we use $W_{fa}$ instead of $W_{ft}$ as a basis for tuning $\gamma$, strongly reduced model bias ($C$) and larger $\gamma$ values (4.5 times greater) are obtained. As $\gamma$ is defined as the average fraction of total wave energy dissipated from whitecaps, it implies that $W_{fa}$ (i.e. the actively breaking whitecap fraction) is more related to dissipation by wave breaking. The reduced $\gamma$ values obtained when using $W_{ft}$ indicate that the contribution of decaying foam coverage (stage B) in $W_{ft}$ measurements are an inferior source for wave-field dissipation.

One plausible explanation for this may be due to the effect of water chemistry on whitecap foam stabilisation, which is not directly linked to wave energy dissipation. Callaghan et al. (2013) explicitly showed that the addition of soluble surfactant at a concentration of 207 micro grams per litre to seawater in laboratory experiments of breaking waves, extended the lifetime of whitecap foam by about a factor of 3. Furthermore, field studies have shown that whitecap decay times are highly variable, indicating the potential importance of natural surfactants may play in oceanic whitecap foam decay (Callaghan et al. 2012).

4. Conclusions

Whitecap fraction values estimated from the dissipation source term using an empirical relation (Kraan et al. 1996) provide robust linear agreement with hourly averages of open ocean whitecap observations.

Tuning the $\gamma$ parameter allows for further agreement with observations ($M=1$), most notably when combined with a $u_{*T}$ threshold modification (Eq 12). Reduced model biases ($C$) and considerably higher values of $\gamma$ are achieved for comparisons involving $W_{fa}$ observations. This indicates that the actively breaking whitecap fraction is more strongly related to the dissipation source term in ECWAM, than for the case with total whitecapping $W_{ft}$, which includes the stage-B contribution.

However due to the remaining scatter in the model-data comparison, we suggest that further study needs to be carried to further refine and characterise the relationship between whitecap foam signatures and wave breaking energy dissipation. In particular, the provisions of bulk estimation of wave energy dissipation due to microscale breaking and additional sampling of wider ranges of environmental conditions and sea states would prove beneficial.

We conclude that our modeled whitecap estimates are suitable proxies for total whitecap fraction and actively breaking whitecap fraction, and thus for applications that incorporate them such as quantifying air-sea exchange of bubble mediated gases. This implies that global estimates of $W_{ft}$ and $W_{fa}$ could be derived from a wave model, and this could be used for further improving calibration of satellite estimates of whitecap coverage. The availability of global whitecap estimates could also benefit a wide range of studies that involve, or are influenced by, whitecaps.

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References


4 Conclusions and Future Work

4.1 Synopsis

This study focuses on wave breaking at the ocean surface, a process which adds heightened complexity when attempting to predict interactions between the upper ocean and lower atmosphere.

In section 3.1, we provided a comparison study between model predictions and in-situ observations of SST. The model predictions were computed using 5 different configurations of turbulence and solar absorption schemes. The turbulence schemes employed consisted of law of the wall scaling of turbulent kinetic energy (TKE), and additional TKE injection due to wave breaking. Most notably, the incorporation of the wave breaking process provided diurnal warm layer depths inconsistent with observations and thus underestimated predictions of SST.

In section 3.2, we provided a method of measuring whitecap coverage in its active stage (actively spilling crests) and in its maturing stage (decaying foam) from digital images of the sea surface, called the Spatial Separation of Whitecap Pixels (SSWP) method. Despite the SSWP method requiring manual operation, accurate results can be achieved from the digital imagery.
An additional method of separation, called the Pixel Intensity Threshold Separation (PITS) was introduced. The PITS method relies on pixel intensity information to distinguish whitecap regions as active or maturing. The performance of the PITS method was evaluated by comparing PITS-derived coverage with SSWP-derived coverage for 64,540 images. The comparison revealed that the PITS method cannot accurately distinguish the two stages of whitecaps. Thus we conclude that the PITS method is unsuitable.

In section 3.3, we acquired observations of actively breaking and total whitecap coverage from 114,265 images using the SSWP method and utilized them to investigate a semi empirical whitecap model of Kraan et al. (1996). The semi empirical model was forced by a timeseries of wave energy dissipation, significant wave height and mean period of the wind-waves from a high resolution rerun of ECWAM wave model. The comparison of observations with model predictions demonstrated linear agreement and allowed for tuning of the implicit \( \gamma \) coefficient, which from definition quantifies the average fraction of wave energy lost per breaking event. Highest values of \( \gamma \) were obtained when the model was tuned with actively breaking whitecap observations, demonstrating the importance of active breakers as a major source of wave energy dissipation. Lower \( \gamma \) values (4.5 times lower) were obtained when the model was tuned with total whitecap coverage observations. As total whitecap coverage consists of actively breaking and maturing stages, we deduce that the lower \( \gamma \) values are a result of the inclusion of maturing whitecap coverage.
4.2 Conclusions

Considerable temperature biases were observed for various model configurations in section 3.1. In particular, the inclusion of TKE injection due to wave breaking following Kantha and Clayson (2004) overestimated upper ocean mixing and thus resulting in deeper MLD and cooler SST predictions. This demonstrates the need for more reliable and condition-representative parameterizations of upper ocean mixing which consider TKE injection due to wave breaking.

A new method of separation of whitecap coverage into its active and maturing stages of evolution was presented. In section 3.2, we provide a Spatial Separation of Whitecap Pixels (SSWP) method and evaluate its performance against alternative methods. Although the method relies on manual operation, it provides a framework to achieve accurate estimates of $W_A$ and $W_B$.

An extensive dataset of $W_A$ and $W_B$ was acquired over the course of this study, totaling 125,860 images or 622 10-minute averages. The data was processed using the SSWP method and high level of quality control. Unfortunately an investigation into the variability of $W_A$ and $W_B$ with primary (wind speed) and additional (SST, atmospheric stability, wave-field development) environmental parameters is not presented in this study. Comments on the ratio of $W_A/W_B$ are also not presented.

A whitecap model based on wave model parameters has been established in section 3.3. The whitecap model allows for predictions of stage A and total whitecap coverage to be calculated from globally-operational state-of-the-art
wave models such as ECWAM. As ECWAM provides global 6-hourly wave-field parameters at a grid resolution of 0.5 degrees, representative whitecap predictions can thus be calculated and provide benefit global studies involving air–sea gas transfer, aerosol production and calibration of satellite-sensed whitecap algorithms.

4.3 Future Work

To acquire and process additional sea surface imagery in future studies using the SSWP method would prove beneficial for two reasons.

1. To analyse the influence of secondary parameters on whitecap coverage requires a large dataset of observations which represent wide ranges of environmental conditions. A large dataset of observations will be required. This will prove to be a difficult task to accomplish, requiring extensive numbers of observations and significant processing time.

2. To further investigate the $\gamma$ coefficient and its dependencies to environmental parameters. It is not currently known if $\gamma$ is a constant nor if it is globally representative.

Thus it is my intention to acquire additional observations to build the dataset of $W_A$ and $W_B$ to sufficiently represent cold, moderate and warm SST conditions and among other ranges of additional environmental parameters.

I hope to explore the use of alternative imaging methods such as stereoscopic and Infrared-capable setups. Stereoscopic imaging can estimate the rate of change of wave-field elevation. This will allow for wave peaks and troughs to
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be distinguished in a sea surface image and thus create an opportunity for the development of an automated version of the SSWP method. Similarly, Infrared imaging can allow for a method of separating stage A and stage B solely based on temperature thresholding (see Jessup et al., 1997; Zappa et al., 2001; Marmorino and Smith, 2005; Sutherland and Melville, 2013). Such imaging systems would require a stable platform and thus establishing a suitable location to conduct monitoring would be of vital importance.

In addition to bulk estimates of the various whitecap coverage stages $W_A$ and $W_B$, breaking crest length framework (Phillips, 1985) could be adopted which would provide crest length spectral information of wave breaking events. Such framework has been adopted to relate breaking events to upper ocean TKE (Thompson et al., 2009; Sutherland and Melville, 2013).