Closure Between Apparent and Inherent Optical Properties of the Ocean
with Applications to the Determination of Spectral Bottom Reflectance

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
College of Marine Science
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Date of Approval:
April 6, 2009

Keywords: absorption, irradiance, oceanography, backscattering, albedo

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Dedication

This work is dedicated to my sons Heath and Wyatt. Their curiosity and enthusiasm as they learn more about this world is a virtue that everyone should keep throughout their life. Their excitement at seeing a new bug for the first time or their fascination with the shape of a leaf is an inspiration to me. If I can exhibit even half their enthusiasm for discovery I will be a better scientist.
Acknowledgements

The most important acknowledgement is reserved for my wife and partner, Angie. She has supported me in this endeavor through the month long cruises, late nights getting equipment prepped, and years of working nights and weekends on my dissertation. Without her help, I would not have made it this far.

The support from Dr. Carder and the ocean optics lab at USF made this study possible. Ken Carder is my major professor and mentor. David English and Jen Cannizzaro worked collecting and processing data and provided input on ideas for this study. Tom Peacock taught me instrumentation. Bob Chen, Dave Costello, Zhongping Lee, Flip Reinersman, Chris Cattrall, Andy Farmer, Steve Butcher, and Dan Otis all contributed to this work with either ideas and/or data collection.

The members of my committee helped me in several ways. I participated in cruises with and learned a great deal from Pamela Hallock-Muller, Gabe Vargo, and Paula Coble. Margaret Hall deserves thanks for plunging into middle of this dissertation after a committee member dropped out at the last moment. Cindy Heil is both my chair and my supervisor at FWRI.

The Office of Naval Research, Environmental Optics Program, provided the majority of funding for my research under grants N00014-96-1-5013, N00014-97-1-0006, and N00014-02-1-0211. Chuanmin Hu funded my salary for several months.

Kent Fanning invited us on the FSLE cruises and HOBI Labs invited us on two cruises. NRL funded the Friday Harbor optics cruise. The two Jims in the shop helped me get equipment built and designed. Charlie Mazel collected the W FL shelf albedo data used in this study. I worked with so many people here at the College of Marine Sciences that there is not room to acknowledge them all. I'll end with a thank you to everyone.
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Closure Between Apparent and Inherent Optical Properties of the Ocean
with Applications to the Determination of Spectral Bottom Reflectance

James Edward Ivey

ABSTRACT

This study focuses on comparing six different marine optical models, field measurements, and laboratory measurements. Inherent Optical Properties (IOPs) of the water column depend only on the constituents within the water, not on the ambient light field. Apparent Optical Properties (AOPs) depend both on IOPs and the geometric underwater light field resulting from solar irradiance. Absorption (a) and scattering (b) are IOPs. Scattering can be partitioned into backscattering (b_b). Remote Sensing Reflectance (R_{rs}), the ratio of radiant light leaving the water to the light entering the water surface plane (E_d), is an AOP. R_{rs} is proportional to b_b/(a + b_b). Using this relationship, R_{rs} is inverted to determine both absorption and backscattering. The constituents contributing to both absorption and backscattering can then be further deconvolved using modeling techniques.

The \textit{in situ} instruments usually have a fixed path length while AOP measurement path length depends on the penetration and/or return of downwelling solar irradiance. As a consequence, AOP measurements use a longer path length than \textit{in situ} instruments. If the path length of a direct IOP measurement instrument is too short, there may not be sufficient signal to determine a change in value. While the AOP inversions require more empirical assumptions to determine IOP values than \textit{in situ} instruments, they provide a higher signal to noise ratio in clearer waters.

This study defines closure as the statistical agreement between instruments and methods in order to determine the same optical property. No method is considered absolute truth. An R_{rs} inversion algorithm was best under most of the test stations for measuring IOP values. One exception was when bottom reflectance was significant, an inversion of diffuse attenuation (the change in the natural log of E_d over depth) was better for determining absorption and a field instrument was better for determining backscattering. The relationships between AOPs and IOPs provide estimates of unmeasured optical properties. A method was developed to determine the spectral reflectance of the bottom using IOP estimates and R_{rs}. 
1. Introduction

1.1. Light, Water, and Life

Light and liquid water are the basic requirements for life on a planet. Exobiologists recently discovered water on Mars (NASA 2008). The discovery was highly reported because it presents the potential for extraterrestrial life. Light and liquid water on Earth were part of the necessary conditions for the evolution of single-celled photosynthetic organisms that led to an increase in atmospheric oxygen and to higher life forms. These single celled organisms evolved into the phytoplankton that are the basis of the food web in oceanic environments. The absorption of solar radiation by the ocean provides a moderating force on global climate by acting as a reservoir and transport mechanism for heat. Light reaching the benthos supports algae, sea grasses and coral reefs that are nursery grounds for sea life. Ocean optics can be used to study light, heat, and photosynthesis in the ocean, all of which are necessary for life on this planet.

1.1.1. Global Scales of Ocean Optics

The absorption of down-welling solar irradiance by the oceans is critical to global climate. Ninety-seven percent of the world's water supply is in the oceans. The oceans supply the majority of the water for rain on land (Libes 1992). Water has the second highest heat capacity of any liquid (4 J °C⁻¹ g⁻¹ at 17.5 °C) and the highest thermal conductivity. The thermal properties of the ocean result in heat being diffused over a large area through vertical and horizontal convection. Ocean currents transport heat from the equator to the poles warming temperate regions along its path. The thermal gradients within the ocean are more pronounced than on land. If the atmosphere were static and there were no oceans the mean temperature of the earth would be 67°C (Philander 2004). Without the interaction between solar irradiance and the ocean, life might not exist on Earth.

While the physics of the ocean affects its biology, the biology can also affect the physics through feedback mechanisms that determine the depth and quantity of solar irradiance absorbed by the ocean. Seasonal phytoplankton blooms can affect the depth of penetration of solar irradiance. The changes in depth of penetration of solar irradiance can affect the depth of the mixed layer, heat storage, ocean currents, and meteorology of a region. A 0.1 mg m⁻³ change in chlorophyll concentration results in a 10 W m⁻² change in solar flux through the upper 20 m of the equatorial Pacific (Lewis et al. 1990). Upwelling can produce a phytoplankton bloom closer to the surface that results in greater heat absorption and increased stratification, reducing the depth of the mixed layer (Sathyendranath et al. 1991). A westerly wind burst in the western equatorial pacific can
lead to upwelling which results in a phytoplankton bloom that eventually increases sea
surface temperatures. The increase in sea surface temperature increases the atmospheric
vertical convection resulting in a decline in the winds producing the upwelling (Siegel et
al. 1995). If the phytoplankton biomass is lower in the mixed layer, then some of the
light can penetrate below it resulting in heat storage that may not interact with the
atmosphere for up to 9 months (Ohlmann et al. 1996). If transported by slow moving
current like the North Atlantic Drift Current (0.03 m s\(^{-1}\)), this trapped thermal energy
could travel 700 km before winter overturn brings it into contact with the atmosphere. A
10 to 18% increase in 1% downwelling irradiance depths can result in a mixed layer
depth increase of 3 to 20 m (Sweeney et al. 2005). Studies based on coupled ocean and
atmospheric general circulation models indicate that an increased mixed layer depth at
higher latitudes results in lower heat transport back to the equatorial regions (Sweeney et
al. 2005). In the ocean, a biological response to the physical events that bring nutrients
into the euphotic zone can result in a change in wind, ocean currents, and heat transport.

The ocean is an integral part of the global carbon cycle. It contains an estimated
50 times the amount of carbon found on land. Oceanic primary production represents
about 50% of the total global primary production (Field et al. 1998). Photosynthetic
organisms take up dissolved inorganic carbon and are in turn consumed by higher trophic
oceanic organisms. The progression of carbon through the oceanic food web results in
losses to the system as organic carbon sinks out of the euphotic zone to depth. Some of
the small fraction of the carbon reaches the benthic regions, is incorporated into the
sediments, and is sequestered geologically. The benthic oceanic sequestration of carbon
is a significant mechanism controlling atmospheric carbon dioxide concentration over
geological time.

The carbon cycle of the ocean can be affected by anthropogenic increases in
carbon dioxide in the atmosphere affecting the global climate. With changes in global
climate, feedbacks occur that can affect oceanic primary production. The increases in
global ocean surface temperatures may result in changes in ocean circulation, reducing
the upwelling of nutrients resulting in lower primary production (Wood et al. 1992). A
study based on Satellite observations concluded that global productivity has declined by
6% since 1980 (Gregg et al. 2003). Long-term satellite observations exhibit an inverse
relationship between global ocean primary productivity and sea surface temperature
(Behrenfeld et al. 2006). The effects of climate change on ocean productivity are not
settled in the scientific community.

To predict the effects of climate change such as sea level height, environmental
parameters are input into coupled general circulation models. The absorption of solar
irradiance by the ocean is an important parameter in determining the input of heat to the
global ocean. The upper 700 m of the ocean have increased in heat content by 16 ± 3 x
10\(^{22}\) J from 1961 to 2003 (Catia et al. 2008). The increase in heat content results in the
thermal expansion of oceanic waters contributing to an estimated rise of 1.5 +/- 0.4 mm
yr\(^{-1}\) sea level rise (Catia et al. 2008). To better determine the effects of sea level rise,
knowledge of the global optical properties of the ocean are required. According to the
National Snow and Ice Data Center, the sea ice in the Arctic reached its lowest level of coverage in 2007 and second lowest in 2008. With the decline of the Arctic ice sheet, the albedo of the Arctic ocean decreases allowing more solar irradiance to be absorbed. The decline in Arctic sea ice permits additional input of solar irradiance to the ocean and will increase the heat content of the ocean.

Observations on both global and basin scales indicate that anthropogenic climate change is affecting the circulation of the oceans. Infrared satellite reflectance data can be used to track the paths of the currents and regions of upwelling providing information on the changes in ocean circulation (Vastano and Borders 1984). The increase in oceanic temperatures affecting wind patterns combined with fresh water runoff may have resulted in decreases in oceanic circulation. Global circulations models have predicted that freshwater inputs as the result of increased precipitation and ice melt due to climate change could affect North Atlantic Deep Water formation (Rahmstorf 1994). Measurements of equatorial upwelling in the Pacific indicate that it may have slowed by 25% (McPhaden and Zhang 2002). Measurements in the North Atlantic indicate meridional overturning slowed 30% between 1957 & 2004 (Bryden et al. 2005). There are indications of slowing in meridional overturn in the Pacific (McPhaden and Zhang 2002). Satellite measurements and estimates of in situ optical properties aid in the determination of climate change effects on the global ocean circulation.

1.1.2. Local Scales of Optical Oceanography

The interaction between solar irradiance and the oceans can affect the environment on local scales. The sea breezes from the ocean in coastal regions act to moderate climate in those areas as air is advected across temperature gradients. The land has a higher temperature during the day resulting in the wind moving onshore to replace the vertical convection over land. Since the heat capacity of the land is much less than of water, the air cools more rapidly at night resulting in sinking air masses with winds moving offshore. In addition to moderating the atmospheric climate, the winds in conjunction with the tides can affect water transport into bays and estuaries. Winds moving along shore can produce upwelling increasing productivity in a near shore region. The optical properties of the coastal waters can affect the coastal climate even on local scales.

Coastal regions make up only 7% of the US territory but contain half of the human population. About 40% of the world's population lives within 100 km of the ocean. Coastal regions are important both economically and environmentally but can be difficult to study due to higher variability and larger gradients in environmental properties as compared to the open ocean. With increasing populations along the global coastal regions, anthropogenic pollution contributes to eutrophication.

The natural process of riverine input brings fresh water, sediment, and nutrients into the coastal oceans. The euphotic zone can extend to the benthic region providing enough irradiance for primary production on the ocean floor. Upwelling along many
coastal regions provides nutrients for primary production resulting in productive fisheries. Estuarine regions provide nurseries for oceanic organisms. Coral reefs provide a productive benthic region in areas of low nutrient input. The environmental diversity along the coastal region contributes to the variability in the optical properties of the water column making its general characterization more difficult than for open ocean waters.

Optical properties in oceanic regions are less complex to quantify since they often covary with chlorophyll concentrations due to the phytoplankton populations. Most coastal regions do not exhibit that covariance due to the dynamic nature of their environments, containing suspended sediments and humic and fulvic acids. Waters where optical properties covary with chlorophyll are referred to as Case I waters while other types are labeled Case II (Morel 1974). Case I waters often have low attenuation, are far from the coast, and have no bottom contributions. Numeric models of optical properties for Case I waters are simpler in formulation since the main factor that has to be considered is absorption of light by phytoplankton, which is correlated with chlorophyll concentrations. In Case II waters, the light leaving the water can be modified by several factors other than phytoplankton absorption. Dissolved organic compounds from riverine sources can absorb short-wavelength light. Light can be scattered and absorbed by suspended minerals. The bottom can absorb and reflect light that would otherwise propagate deeper. Despite the challenges, characterization of the optical properties of the coastal Case II regions is necessary to produce accurate numerical simulations of the effects of water column constituents on heat budgets (Warrior and Carder 2007) and primary production.

Coastal regions exhibit greater primary production relative to their area due to higher nutrient input and recycling. If the coastal region is characterized as out to the 200 m isobath then they represent about 10% of the primary production with 8% of the surface area of the ocean (Smith and Hollibaugh 1993). If the entire continental shelf is defined as the coastal region, then the primary production is 24.9% of the global ocean with only 16.1% of the area (Walsh 1991). About 30 to 40% of the benthic regions of the coastal zone have a net positive community production (Gattuso et al. 2006). The coastal regions, while constituting a small portion of the global ocean, are important to the global carbon cycle.

1.1.3. Application of Optical Oceanography to Coastal Problems

Seagrass meadows are some of the most productive of coastal environments. One acre of seagrass can produce ten tons of leaves supporting forty thousand fish and fifty million invertebrates (Dawes 2004). Seagrass acreage in Florida has declined by about 60% from 1950 as Florida's population has increased six fold (Dawes 2004). Dredging and eutrophication led to increased water turbidity reducing the available light for sea grasses (Zieman and Zieman 1989). The area covered by seagrass around Florida has been semi-quantitatively estimated by aerial photography in the past. Recent advances in airborne spectral imaging systems have resulted in a more quantitative measurement of
seagrass coverage (Dierson et al. 2003). The importance of seagrass to the coastal ecosystem requires accurate assessments of their health and coverage.

Changes in the optical properties of the ocean waters over coral reefs are one of the many factors contributing to their decline. The existence of coral reefs depends on solar energy reaching the benthic substrate. Scleractinian corals generally require a suitable substrate in warm, clear, shallow waters. Several of the causes for the decline in coral reefs are ocean warming, ozone depletion, nutrification, over fishing, invasive species, light limitation, disease, recreational divers, and commercial harvesting (Hallock et al. 1993, Yentsch et al. 2002, Bellwood et al. 2004, Hallock 2005, Bartow et al. 2005). The optical effects are too much heat, too much ultraviolet to blue light, or not enough irradiance. Optical monitoring of reef regions, either in situ or remotely, can aid in determination of changes in the environment that might lead to a decline in coral reef health.

The ultimate goal for the remote sensing of a coral reef is to go beyond identifying bottom types and identify the major species on the reef. The first order of the problem is to remove the effects of absorption and scattering of the water column (Holden and LeDrew 2001). While correction for absorption is possible if the optical properties are known or can be identified, the scattering of light poses a larger problem. Scattering can mix the upwelling irradiance from adjacent bottoms with different signatures. This is further complicated by a bottom where the reflectance is not uniform from all angles and the depth is variable over scales of less than a meter (Mobley et al. 2003, Mobley and Sundman 2003). Most current methods have focused on coral cover and algal species. The change in total coral cover can be identified through remote sensing through the use of instruments like the Landsat thematic mapper that have a smaller pixel size (Andréfouët et al. 2001, Palandro et al. 2008). Identification of certain reef algal species is possible with hyperspectral imagery. A lookup table of combinations of bottom types, depths, and optical properties can estimate bathymetry and bottom classification on coral reefs (Lesser and Mobely 2007). The goal of identifying major coral species via satellite will possibly have to wait until a satellite with appropriate wavelengths and spatial resolution is launched. The current satellites with narrow band filters over estimate coral coverage while the satellites with broad bandwidth filters underestimate algal coverage while also overestimating coral coverage (Hochberg and Atkinson 2003). The launch of a hyperspectral imagery satellite that is capable of small pixel sizes could possibly lead to at least identification of the major types of coral species on a reef.

Remote sensing techniques have shown some promise especially when combined with other in situ techniques for identifying and tracking harmful algal blooms. Harmful algal blooms were observed to have a low chlorophyll specific backscattering value (Carder and Steward 1985). Further research with in situ optical instruments revealed that there was a relationship between the chlorophyll specific backscattering and the presence of Karenia brevis (Cannizzaro et al. 2008). The low backscattering of the bloom relative to chlorophyll is due to the bloom's origins in optically clear offshore
waters (Walsh et al. 2006, Cannizzaro et al. 2008). The lower backscattering allows the blooms to be better identified in using satellite reflectance measurements (Cannizzaro et al. 2008). The precursor to the red tide is *Trichodesmium* (Walsh and Stiedinger 2001) and it can be identified from satellite due to its high backscattering (Subramanian et al. 1999). The iron rich dust that contributes to a *Trichodesmium* bloom can be detected using satellite imagery (Carder et al. 1991, Lenes et al. 2001). Using satellite imagery, it is now possible to estimate the conditions that might lead to a *K. brevis* bloom and track the bloom once it occurs.

1.2. The Path of Light Through Water

Optical oceanography is simple in basic theory but complex in practice. In its simplest case, light passing through pure water is either absorbed (a) or scattered (b) by the water molecules. The sum of the absorption and scattering equals the total attenuation of light along a perfectly straight path from the source (c). This sounds simple enough but two different cases of light passing through water illustrate how complex it really is. The travel of light through a beam transmissometer can serve to illustrate the path of light under controlled conditions. The travel of sunlight from above the surface of a water column to the bottom and returning can serve to illustrate the path of light in a natural environment. These two cases demonstrate some of the difficulties of measuring the optical properties of a water column and how the path length of light affects these measurements.

1.2.1. Light Through a Beam Transmissometer

A beam transmissometer measures the attenuation (c) by projecting a collimated beam of light over a known distance through the seawater to a detector that only accepts light at a narrow angle (Pettersson 1934, Jerlov 1957, Austin and Petzold 1977). The basic design for this instrument (Figure 1.1) involves a light source (a) that passes through an aperture and lens system (b) that collimates the beam. The light source is either an LED that covers a specific wavelength or it has an optical filter that limits it to a specific wavelength. A beam splitter (c) directs part of the light into a detector (d) to determine the power of the source light. The light exits into the water column (e) where two things can happen, it is either scattered out of the direct path (f) or absorbed (g). The reduced light (h) enters through a window (e) on the other side of the instrument. The light passes through another aperture (i) and enters a detector (j). This second aperture limits the angle of light to only the light traveling straight along the path from the source. Most transmissometers accept light that is approximately 1° from the straight path because the construction of an instrument that can detect light at the low level of a photon traveling directly from the source and the alignment of the optics to accept such a narrow beam would be extremely difficult.
The attenuation value from a beam transmissometer is calculated (Equation 1.1) by taking the natural log of the fractional change from the reference detector ($\Phi_0$) to the measurement detector ($\Phi$) and dividing it by the distance between the two windows ($z-z_0$). The light level declines logarithmically with increases in path length according to Beer's law (Kirk 1994, Mobley 1994). Using this coefficient the change in light over a known distance of seawater for a collimated beam of light can be calculated.

$$c = \frac{\ln\left(\frac{\Phi_0}{\Phi}\right)}{(z-z_0)}$$  

Equation 1.1

Beam transmission is one of the simplest measurements made by optical oceanographers, but it is not a simple task to construct beam transmissometers. They require very precise alignment of the optical path. They require precise regulation of the light source, and precise measurement of the light. The path length of the instrument limits the sensitivity of the measurement. For very turbid waters, a longer path might attenuate light below the level of the detector. For a shorter path, there might not be sufficient change in signal to register in the detector. The compromise path length for most oceanographic measurements is usually 25 cm.

1.2.2. Sunlight Entering the Ocean

The more complex consideration is looking at light entering the water column itself and the different directions and paths it travels (Figure 1.2). Assuming no clouds in the sky, direct sunlight enters the water (thick solid lines) along with skylight (dotted lines). The direct sunlight enters the water at an angle relative to the solar zenith and azimuth angles. Skylight is sunlight scattered by the atmosphere and can enter the water at many different angles. As the light enters the water the path of its angle is changed.
following Snell's law due to the difference in index of refraction between the air and water (Kirk 1994, Mobley 1994). As in the beam transmissometer, two things can happen to the light below the water's surface. Light is either absorbed (a, arrow ends) or scattered (c, dashed arrow). The path actual sunlight takes in the ocean is infinitely complicated.

Figure 1.2. The complex path of sunlight through ocean waters. The thicker solid lines above the water represent direct sunlight and the dotted lines represent diffuse sunlight. The thin solid line represents the path of light below the water before scattering and the dashed lines represent the path after scattering. Arrows that end represent absorption in water column. The letters a through d represent possible paths of the light and are detailed in the text. The letter e labels a downwelling irradiance meter. This case is simplified and several optical paths including surface interactions are not listed but will be discussed in chapter 2.

Downwelling irradiance from above the surface (a) can take several paths before reaching a detector below the surface. The light can either be absorbed (b) or scattered (c). Light that is scattered back towards the surface can either leave the water column or be reflected back down towards the bottom (d). The irradiance detector (e) has a cylindrical collector on the top that will collect light from different scattering angles in the downward direction. The scattered light does not take a straight path to the detector so it travels further than the simple geometric change in depth. A photon can scatter multiple times resulting in a further lengthening of its path. Like the calculation of the attenuation coefficient (see section 1.2.1), the calculation of the diffuse attenuation
coefficient of downwelling irradiance ($K_d$) is the natural log of the fractional change in light between two depths divided by the distance between the two depths. The $K_d$ value is proportional to the absorption and backscattering ($b_b$) of light over the depth measured.

This indirect measurement of absorption and scattering is an apparent property of the water instead of an inherent property such as attenuation measured by a beam transmissometer. The disadvantage of these apparent optical properties (AOP) is that they depend on the sun for a light source and all the natural variability associated with the transfer of solar radiation across the air water interface. The main advantages are that the path taken by the solar radiation is much greater than the path of an artificial light source used by the devices that measure inherent optical properties (IOP). This longer path length means these measurements have a much greater sensitivity to changes in the absorption values than the instruments that measure those properties directly. The other advantage is that the direct measuring instruments, like the attenuation meter, have to use separate detectors for measurement and reference while the AOP values are the result of ratios that divide out multiplicative errors. While inverting inherent values from apparent optical properties requires more assumptions to compensate for changes in the geometric light field, it has some advantages in longer path length and lower instrument related errors.

1.2.3. Effective Optical Path Length

A beam of light only takes a perfectly straight path in a vacuum. When passing through air, light is scattered in different directions. Atmospheric scattering is why the sky has a color instead of appearing black. The result is that it gives light more chances to be modified by the medium it is traveling through. If the medium absorbs light then there is greater chance of a photon of light striking a molecule being absorbed over a longer path between two points. Path length is also crucial to the sensitivity of the measurement method. For an absorption determination, the path length can vary from a 1 cm cuvette in a spectrophotometer to 10's of meters using an irradiance meter to measure $K_d$. If the signal loss from the measurement is low, then a longer path length can increase the loss to a determinable level. The path length the light travels in seawater, whether based on a controlled light source or the sun, affects all optical oceanographic measurements.

The effect of path length will depend on the sensitivity and resolution of the instrumentation making the measurement. The resolution is affected by the range of analog output and the number of bits used in analog-to-digital conversion. Older instruments had outputs in eight-bit resolution (0 to 255) values, while newer instruments have analog to digital conversions (ADC) of twelve bits (0 to 4095) or higher. This means that for an instrument with an output of 0 to 5 volts will have 16 times the resolution at 12 bit as compared to 8 bit. An 8 bit ADC is comparable to a yard stick with only inch marking. A 12 bit ADC adds the sixteenths of an inch markings. Because of the lower sensitivity of older instruments sufficient, path length for the signal was more important.
Figure 1.3. Response of instruments to different optical path lengths. Graph A is for a 12-bit instrument and graph B is for an 8-bit instrument. It is assumed in the example that the instruments are accurate to these resolutions and do not adjust gain settings. The value is the change in counts over the path length of the measurement, not the output of the photocell.

Using both the 8-bit and 12-bit ADC scales, the effect of path length for an absorption measurement can be demonstrated. The absorption coefficient is calculated the same as the attenuation coefficient in Equation 1.1. Figure 1.3 shows the change in
value for 12-bit and 8-bit analog to digital converters. The lower the resolution of the sensors due to its ADC, detector, or other electronics, the more critical the path length of the sensor becomes. A 1-cm cell is useless at a low absorption of 0.01 m\(^{-1}\) even for a 12-bit ADC. A 10-cm cell doesn't function much better, having only a 4-count difference over that path length for a 0.01 m\(^{-1}\) absorption value. The 25 cm cell is better, with 10 counts of difference out of 4095, when using a 12-bit converter. This is the reason that modern instruments like the ac-9 (a reflective tube absorption meter detailed in Chapter 3) use a 24-bit ADC along with very stable electronics and sensitive detectors to compensate for their shorter path length.

At the other end of the scale, a 50 m path length can result in a maximum signal loss for waters with absorption coefficients greater than 0.01 m\(^{-1}\) but has no measurable signal at 0.22 m\(^{-1}\). There is a trade off for instruments with longer path lengths. A shorter path length has a greater range of measurement while a longer path length has greater sensitivity. In Figure 1.3A, the one-meter path length can measure within an absorption coefficient range of 0.002 to 1 m\(^{-1}\) but the 10-meter path has no measurable signal at 1 m\(^{-1}\). Beer's law predicts this relationship.

Path lengths longer than a meter typically use the sun as a light source and the light is measured using irradiance meters or radiometers. Measurements such as diffuse attenuation have a variable path length that decreases as the water column attenuation increases. Looking back at Figure 1.2, the maximum sensor-separation depth for the irradiance meter will be less for higher-attenuation waters. Most irradiance meters and radiometers also have the capability to adjust their integration time based on the light intensity, resulting in low incidences of saturation and higher sensitivity at depth. Therefore, an irradiance meter or radiometer with comparable electronics to a reflective tube absorption meter (Chapter 3) will have a greater sensitivity to changes in absorption in very clear waters like those of the Bahamas but still be able to detect changes in absorption values in turbid coastal waters such as those of the Puget Sound.

1.3. Main Focus of Study

The main regions in this study are highly variable in optical properties. They range from the very turbid Puget Sound to the crystal clear waters over the Bahamas coral reefs. The type of instrument that is suited to measure the optical properties of the seawater over a sea grass bed on the West Florida shelf may not be best for an absorption profile in a harmful algal bloom. The selection of the instrument will depend on the expected range and types of optical values that will give the best information about the study location. A primary goal of this study will involve assessing the best method or model to determine an optical property under the highly variable environments of these study sites.

With advancements in sensor technology and algorithm development, can an apparent optical property measurement substitute for a more direct measurement of a particular optical property? While AOP measurements like \(K_d\) have a greater sensitivity
in response to changes in the inherent optical properties, they also require a greater number of assumptions to determine the optical path length and to separate the effects of the different inherent optical properties. Early modeling efforts were limited by lack of knowledge about the factors affecting the underwater light field, limited computational capabilities, and instruments that only measured at a few wavelengths of light. Advances in the past three decades have minimized these sources of error resulting in greater accuracy in apparent optical property model inversions. Under the right conditions, an inversion of an apparent property may be an even better measurement than some of the more direct techniques (e.g., path limitations).

Closure in optical oceanography usually means statistical agreement between a new model or measurement and a more trusted measurement (Truper and Yentsch 1967, Ivey 1997, Maffione and Dana 1997, Kirk 1981, and IOCCG 2006). Usually studies are trying to prove some model or method by comparing it to another approach that gives a similar result. The confusion with this is that the researcher often makes an assumption that one particular method is more accurate than another for a particular environment. For different environments, that is not always the case. In low attenuation waters, an inversion of an apparent optical property may be more accurate than a profile by an instrument that measures inherent optical properties due to the longer optical path of the AOP measurement. The best way to address this is to have as a first assumption that all methods can potentially be accurate under the right conditions. First, the methods are compared to determine what condition has the greatest effect on the results. By limiting each group of data based on environmental conditions, each method can then be compared to determine where they exhibit the best agreement with the other methods with no bias towards one particular method. This approach aids in determining which method performs best under which environmental condition.

By studying relationships between apparent and inherent optical properties under conditions where the two methods agree, additional optical properties can be determined. The color of the bottom is one of these properties that would have many environmental uses like determining sea grass coverage or coral reef health. The color of the bottom is based on the amount of light at the visible wavelengths reflected from the bottom towards the direction of the observer. The overall diffuse reflectance from an object, such as the benthic substrate, is referred to as albedo. A goal of this research is utilize the mathematical relationships between the different optical properties to estimate the albedo of the bottom in shallow marine environments.

1.4. Hypotheses

Closure among all methods is expected when conditions are favorable to all methods. The ideal conditions expected for the AOP measurements are clear skies with low solar zenith angle and no significant bottom reflectance. The main criteria for the in situ IOP instruments are significant signal noise in the IOP measured and proper function of the instrument. The laboratory measurements based on water samples require that the
depth of the sample be representative of most of the water column. Closure is expected under the conditions where the best conditions for each method intersect.

In comparison of the different AOP inversion algorithms, the more analytical models based on the AOP measurement with the longest path length are expected to be the best in determining the IOP values. The trade off between analytical and empirical approaches is that the more analytical methods typically have greater computer requirements and need more a priori knowledge of the study area. The more analytical models are expected to be best but do require some tradeoffs in computer power and a priori knowledge of the study site.

The combination of longer path length and more analytical approach gives AOP inversions models sufficient accuracy to be used in place of more direct in situ IOP measurements. Previous closure studies have started with the assumption that the direct measurement is the more accurate. This study will compare all AOP algorithms and IOP direct measurements with equal weighting to determine under what environmental conditions each method is most accurate. For oceanic waters with low attenuation, low solar zenith angle, low cloudiness, and no significant bottom influence, the AOP inversions are expected to provide more accurate results for absorption and backscattering when compared to direct IOP measurements.

Preisendorfer (1961) presented an equation that details relationships between absorption and backscattered light to $K_d$. This approach can be used in an iterative type model to invert $K_d$ at multiple wavelengths of light to give IOP values. Applying corrections for the angle of the sun and skylight (Gordon 1989) will lower the error in the inversion. This model should provide the better results over the other tested $K_d$ inversions models in this study since it uses a semi-analytical approach.

Most inversion algorithms of ocean color do not take into account the solar induced fluorescence due to chromophoric dissolved organic material (CDOM). This fluorescence can result in errors by estimating the amount of light leaving the water larger than it should be in the blue to green wavelengths of light. This error can lead to over estimates and under estimates of different optical properties. By assuming a function that initially underestimates the absorption of light by CDOM in the blue to green light region, the error in retrieving optical properties from ocean color measurements can be reduced.

The bottom albedo can be determined through the mathematical relationships between the apparent optical properties and the inherent optical properties. By determining how these properties are related through closure, the spectral reflected light from the bottom can be determined. This method would use common measurements from standard ocean optics instruments instead of complex specialized instruments. This method will not require an initial estimate of the bottom type or a best guess as to how its magnitude varies spectrally.
2. Background

2.1. Introduction

The first section is primarily for the reader with little background in ocean optics. It will present a brief discussion of common optical oceanography terms and theory. A more detailed discussion of ocean optics can be found in the texts Ocean Optics (Spinrad, Carder, and Perry (Ed.) 1994), Light and Photosynthesis in Aquatic Ecosystems (Kirk, 1994), and Light and Water: Radiative Transfer in Natural Waters (Mobley, 1994). A short summary of the evolution of optical oceanography methods and instrumentation is presented to demonstrate the advances that have made the research in this paper possible. A discussion on closure of optical properties provides an overview of past efforts and why the approach of this research is unique. One of the important results of optical closure is the ability to indirectly determine optical properties by combining different types of optical measurements. The measurements taken in the shallow sites of this study are used to determine the spectral bottom reflectance, using an evaluation of the closure levels achieved among different measurement approaches. The study sites and optical variability among them are presented.

2.2 Definitions of Optical Terms

Closure in the field of optical oceanography has typically involved comparing a direct measurement of an inherent optical property to results from a model that inverts an apparent optical property to provide an inherent optical property. An inherent optical property (IOP) is one that is based solely on the constituents within the water column so it is independent of the solar irradiance (Preisendorfer 1961). An apparent optical property (AOP) is dependent on all the inherent optical properties and the characteristics of the geometric light field due to solar irradiance. Closure between more directly measured IOP values from in situ instruments or water samples and the results of an AOP inversion algorithm is usually done with the directly measured IOP values considered the measurement closest to the actual value. This assumption will be tested.

The IOPs used in this study are scattering (b(λ)), absorption (a(λ)), and attenuation (c(λ)) coefficients. Absorption is light at a given wavelength (λ) taken in by matter, raising it to a higher energy state. Scattering is light at a given wavelength where its path is altered by particles or molecules. The sum of absorption and scattering is attenuation (c(λ)). Each of these coefficients is a function of the logarithmic loss in light over a linear path from the source, giving them the units of per meter (m⁻¹). All three of these IOPs represent the light lost along a single straight path. These properties can be separated into categories depending on the type of material interacting with the light:
absorption by particulate matter $a_p(\lambda)$; by dissolved organic matter $a_g(\lambda)$; and by water itself $a_w(\lambda)$. The particulate absorption is further split into absorption due to pigmented particles like phytoplankton ($a_{ph}(\lambda)$) and absorption due to non living matter referred to as detritus ($a_d(\lambda)$). Table 2.1 provides a list of the symbols used in discussions of light in the ocean that are defined in this chapter.

Table 2.1. Common symbols used in optical oceanography and this study. Symbols that are used in only one section are defined in that section.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Quantity</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$</td>
<td>Absorption</td>
<td>m$^{-1}$</td>
</tr>
<tr>
<td>$b$</td>
<td>Scattering</td>
<td>m$^{-1}$</td>
</tr>
<tr>
<td>$c$</td>
<td>Attenuation</td>
<td>m$^{-1}$</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Wavelength</td>
<td>nm</td>
</tr>
<tr>
<td>$K$</td>
<td>Diffuse attenuation coefficient</td>
<td>m$^{-1}$</td>
</tr>
<tr>
<td>$R_{rs}$</td>
<td>Remote sensing reflectance</td>
<td>sr$^{-1}$</td>
</tr>
<tr>
<td>$R$</td>
<td>Radiance reflectance</td>
<td>Unit-less</td>
</tr>
<tr>
<td>$L$</td>
<td>Radiance</td>
<td>W m$^{-2}$ sr$^{-1}$</td>
</tr>
<tr>
<td>$E$</td>
<td>Plane irradiance</td>
<td>W m$^{-2}$</td>
</tr>
<tr>
<td>$\bar{\mu}$</td>
<td>Average cosine of irradiance</td>
<td>Unit-less</td>
</tr>
</tbody>
</table>

Table 2.2. Common subscripts for symbols used in optical oceanography and this study. These symbols can be used in different combinations. For example, $E_{d0+}$ is the planar downwelling irradiance just below the surface.

<table>
<thead>
<tr>
<th>Subscript</th>
<th>Meaning</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d$</td>
<td>Downwelling</td>
<td>$E_d$, $\bar{\mu}(\lambda)_d$</td>
</tr>
<tr>
<td>$u$</td>
<td>Upwelling</td>
<td>$E_u$, $\bar{\mu}(\lambda)_u$</td>
</tr>
<tr>
<td>$b$</td>
<td>Backwards direction</td>
<td>$b_b$</td>
</tr>
<tr>
<td>$f$</td>
<td>Forwards direction</td>
<td>$b_f$</td>
</tr>
<tr>
<td>$p$</td>
<td>Particulate</td>
<td>$a_p$, $b_{bp}$</td>
</tr>
<tr>
<td>$ph$</td>
<td>Pigmented</td>
<td>$a_{ph}$</td>
</tr>
<tr>
<td>$g$</td>
<td>Chromophoric dissolved organic matter (gelbstoff)</td>
<td>$a_g$</td>
</tr>
<tr>
<td>$w$</td>
<td>Water</td>
<td>$L_w$</td>
</tr>
<tr>
<td>$nw$</td>
<td>No water values included</td>
<td>$a_{nw}$, $c_{nw}$</td>
</tr>
<tr>
<td>$o$</td>
<td>Scalar values</td>
<td>$E_o$</td>
</tr>
<tr>
<td>$0+$</td>
<td>Just above the surface</td>
<td>$E_{d0+}$</td>
</tr>
<tr>
<td>$0-$</td>
<td>Just below the surface</td>
<td>$E_{d0-}$</td>
</tr>
</tbody>
</table>
The use of symbols to represent terms in science serves as a short-hand among researchers to avoid overly verbose exchanges. For example, $E_{\lambda}(\lambda)$ represents the downwelling irradiance just below the surface at all wavelengths of light. If the author of a research paper had to repeat the text description of that symbol every time they referred to it, it would substantially increase the length of their paper. Early pioneers in optical oceanography often used symbols that were first used by astronomers and theoretical physicists (Austin 1974, Jerlov 1976, Preisendorfer 1976). However, there was significant ambiguity in the symbols for the different values. Mobley (1994) published a text that suggested a series of common symbols for optical oceanography. Morel and Smith first developed most of these (Morel and Smith 1982). These symbols have become the most common in optical oceanography and are used in databases for these values. Table 2.1 lists the commonly used symbols used throughout this study and Table 2.2 lists the commonly used subscripts. Readers unfamiliar with these terms should bookmark the preceding page as a reference to aid in later discussions in the text.

Scattering is a more complex measurement than absorption because the flux of light scattered by the particle is not the same in all directions. The direction is measured as a solid angle that is based on a unit sphere just as a radian is based on a unit circle. Instead of a circumference of $2\pi$ radians times the circle radius, the unit sphere has a surface area of $4\pi$ steradians (sr) times the spherical radius. Similar to latitude and longitude for coordinates on the Earth, the solid angle has two angles: theta ($\theta$) represents the zenith angle and phi ($\Phi$) represents the azimuth angle. The change in solid angle ($\Omega$) about a direction ($\theta$, $\Phi$) is given as

$$d\Omega(\theta, \Phi) = \sin\theta \ d\theta \ d\Phi$$

Equation 2.1

This represents the incremental area element $\sin\theta \ d\theta \ d\Phi$ on a sphere of radius = 1.0.

Scattering through a given solid angle ($\psi$) is referred to as the volume scattering coefficient ($\beta(\psi, \lambda)$) and has the units per meter per steradian. The volume scattering function is very difficult to measure, especially in situ, so most research focuses on measurements of either total scattering integrated over the entire unit sphere or scattering integrated over the hemisphere of the unit circle with the source at $2\pi$ (backscattering, $b_b(\lambda)$). Integrating $\beta$ over the hemisphere centered at the direction of the light path (0 sr) is forward scattering ($b_f(\lambda)$). An additional subscript is also added to the scattering terms to denote the scattering due to particulates ($b_p(\lambda)$, $b_{bp}(\lambda)$) and water ($b_w(\lambda)$, $b_{bw}(\lambda)$). The scattering by dissolved substances is considered not significantly different from the scattering to water so it is not referenced separately. The absorption (Pope and Fry 1997) and scattering (Morel 1974) coefficients due to water are well known, and removing them from the attenuation ($c_{nw}(\lambda)$) and absorption ($a_{nw}(\lambda)$) values, provides a better comparison to the other methods. The partitioning of these values represents the IOPs that are directly measured or inverted from AOP algorithms (Mobley 1994).

The light energy measured at a particular point over a specific time at a given solid angle, wavelength, and area is the radiance (L). Radiance can be used to derive all
radiometric measurements. A single radiance measurement below the surface is not an optical property of the water column. By itself, it tells us nothing about the underwater light field but only provides us information about light at a particular point from a given direction. When multiple measurements of radiance are integrated over a sphere (scalar irradiance, $E_o$, Eq. 2.2) or downward over a flat planar surface (planar irradiance, $E_d$, Eq. 3), then we can learn more about the underwater light field. It still only represents a point measurement and not the entire water column. A single radiometric measurement still doesn't qualify as an optical property of the water column (Mobley 1994) though some opinions differ regarding irradiance in a particular direction (Zaneveld 1994).

The scalar irradiance at a particular position ($\vec{x}$), a particular time (t) and wavelength of light ($\lambda$) is defined by the integration of radiance at $\vec{x}$, t, $\lambda$, and direction ($\xi$) over the unit sphere ($\Xi$) for the change in solid angle ($\Omega$). The units are watts (W) per square meter ($m^{-2}$).

$$E_o(\vec{x};t;\lambda) = \int_{\xi \in \Xi} L(\vec{x};t;\xi;\lambda) d\Omega(\xi)$$  
Equation 2.2

Downwelling irradiance is calculated by integrating radiance at a given $\vec{x}$, t, and $\lambda$ for direction $\xi$ over the complete azimuth angle and cosine of the upper hemisphere from the zenith angle. The units are watts (W) per square meter ($m^{-2}$).

$$E_d(\vec{x};t;\lambda) = \int_{\phi=0}^{2\pi} \int_{\theta=\pi/2}^{\pi} L(\vec{x};t;\xi;\lambda) \cos \theta |d\theta| d\phi$$  
Equation 2.3

Determining scalar or planar irradiance by integrating individual radiance measurements would be a difficult task. Fortunately, the design of the instrument collector can result in an integration of the radiance for scalar or planar irradiance. A spherical collector with a shield blocking light from other directions can measure downwelling scalar irradiance ($E_{od}$). A disk shaped cosine collector can measure planar downwelling irradiance ($E_d$). To get the upwelling light returning from depth the instrument can be flipped over or a second instrument used ($E_{ou}$ and $E_u$). With multiple measurements at different depths and wavelengths of radiance and irradiance now it is possible begin to learn something about the water column.

Combining measurements, such as change in $E_d$ over depth or the ratio of water leaving radiance ($L_w$) to the solar irradiance entering the water ($E_{do+}$), results in measurements that are related to the inherent optical properties of the water column, since the light units have been normalized. These measurements are then referred to as apparent optical properties or AOPs. The logarithmic change of downwelling planar irradiance over depth is the diffuse attenuation coefficient ($K_d$). The ratio of $L_w$ to $E_{do+}$ is referred to as remote sensing reflectance ($R_{rs}$). These two measurements are commonly made by optical oceanographers, and algorithms relating them to inherent optical properties are explored in this research study.
Rrs measured just above the ocean surface is particularly useful because it is similar to the ocean color measurement made by orbiting satellites without having to correct for the attenuation and backscattering of the light passing through the atmosphere. In addition, using the same radiometer for measuring both Lw and Edo+ ratios out most calibration errors. This measurement is proportional to a ratio of the backscattering divided by the sum of backscattering and absorption for the water column (Gordon et al. 1975, Morel and Prieur 1977). Radiometers that measure at several wavelengths (hyperspectral) combined with advances in the understanding of ocean optics have resulted in model inversion algorithms that are much more analytical and accurate for inversion of Rrs(λ).

The diffuse attenuation coefficient of downwelling irradiance (Kd(λ)) is proportional to the inherent optical properties. The value of Kd(λ) can be expressed in terms of the inherent optical properties (Eq. 4, Preisendorfer 1961).

\[
K_d(\lambda) = \frac{a(\lambda)}{\mu_d(\lambda)} + \frac{b(\lambda)}{\mu_d(\lambda)} - \frac{b(\lambda)}{\mu_a(\lambda)} R(\lambda)
\]

Equation 2.4

The terms \(\mu_d(\lambda)\) and \(\mu_a(\lambda)\) both represent the average cosine of the angles of the light in the downward and upward directions. The average cosine is the average of the cosine of the zenith angle at a particular point in the water column. The arccosine of the average cosine is the average angle of the path of the different beams of radiance along the up and down directions in the water column. For example, a solar beam penetrating the ocean surface with a zero zenith angle has an average cosine of 1.0. After being absorbed and scattered down to 100 meters in the Sargasso Sea, it has a downwelling average cosine of less than 0.75. In other words, the slant path through the water of the average downwelling photon now is ~40 degrees rather than 0 degrees. Finally, R(λ) is below-water irradiance reflectance which is a ratio of E_d(λ) to E_d(λ). Using this relationship, it is possible to retrieve IOPs from K_d(λ) values (Preisendorfer 1961).

2.3. Progress in Ocean Optics

The theoretical relationships behind optical oceanography were discovered first but had to wait for progress in instrumentation to verify them. Early optical measurements of attenuation were Secchi Depths (Hou et al. 2007). They were very crude methods of getting the vertical attenuation coefficient with simple equipment by visually observing the disappearance of a white disk as it was lowered to depth. This data could then be related to the depth of light penetration below the surface of the ocean and the diffuse attenuation coefficient. As technology advanced, submersible single wavelength radiometers became available (Poole and Atkins 1926). By adding filters to these radiometers to balance the response, it was possible to measure the quanta of light available for photosynthesis (PAR) at depth by balancing out the spectral response of the detector. Specific narrow band pass filters on individual photocells made it possible to determine the down-welling irradiance at several wavelengths. Submersible grating...
spectrometers were developed that allowed measurement of the irradiance at hundreds of wavelengths (Tyler and Smith 1966, Morel and Prieler 1977, Carder and Steward 1985). The inversion from theory applied to AOP measurements leads to estimates of the inherent optical properties affecting the underwater light field.

Ocean color detection advanced from a qualitative measurement to the quantitative approach used today. Originally color was determined by visually comparing a series of vials of mixtures of different colored chemicals to determine the color of the ocean. This method was called the Forel-Ule scale and was introduced around 1892 (Wernand 2008). The observation was best when compared to the color observed during the decent of a white Secchi disk. Later methods included photographing the water to estimate the color. Like the spectral irradiance meters, radiance both below and above water was later measured by spectral techniques. The first sensors like the underwater irradiance sensors, were limited to specific wavelengths. Later radiance sensors incorporated small grating spectrometers that allowed a hand-held device to measure the radiance leaving the water at hundreds of wavelengths of light. To minimize the instrument error, down-welling irradiance was measured by aiming the same radiance meter at an isotropic reflecting target illuminated by sunlight (Carder et al. 1985). Ocean color detection evolved from simple visual estimates to hyperspectral sensors capable of quantitative measurement.

Some of the greatest interest in ocean optics occurred when satellites capable of measuring upwelling radiance were launched. The first instrument on a satellite specifically dedicated to detection of ocean color was the Coastal Zone Color Scanner (CZCS). The CZCS for the first time allowed synoptic data about the ocean to be collected over a large region (Gordon et al. 1983). Oceanography went from discrete shipboard measurements that only covered a point in the ocean to airborne sensors that were able measure 10’s of square miles to satellites that could cover 1000s of square miles. The success of the CZCS led to the development of the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) in 1997 (O’Reilly et al. 1998). The CZCS was a proof of concept instrument that had only six wavelength bands (channels). SeaWiFS added three additional channels providing more spectral information. SeaWiFS was the default operational satellite until the 36-channel Moderate Resolution Imaging Spectroradiometer (MODIS) was launched in 1999 (Esaias et al. 1998). The measurement of ocean color by spectral satellite measurements revolutionized the study of oceanography by providing large-area coverage of the ocean at single points in time.

The early algorithms relied on empirical band ratios to estimate chlorophyll in open ocean waters (Gordon et al. 1980). A benefit from this approach is that it allowed rapid processing using the slower computers of the time. This led to some of the first closure experiments between in situ chlorophyll concentrations and Rrs(\(\lambda\)) inversions to retrieve chlorophyll values (Gordon et al. 1983). The SeaWiFS satellite had three more spectral channels than the CZCS, and the algorithms were further improved to provide a larger number of water optical properties and were more analytical (Gordon et al. 1988). This led to more analytical models that moved away from simply estimating chlorophyll
concentration and instead focused on determining the IOPs that could be related to constituents in the water column. With the MODIS sensor and its 36 total channels, the algorithm development turned to the more complex models that are in use today (Carder et al. 1999). The progression naturally followed the progression of the satellite capabilities and computational power that is currently available.

The relationship between the AOP reflectance and the IOP values of ocean water was established well before satellites were considered (Duntley 1942), leading to algorithms that rapidly progressed to their present semi-analytical incarnations. Before CZCS went up, a simplification was determined so that irradiance reflectance was directly proportional to the backscattering divided by the absorption (Gordon et al. 1975; Morel and Prieur 1977) and it used a constant based on the geometric underwater light field. This constant is a function of the volume-scattering coefficient and the radiance distribution as well as the wavelength of light. For the blue-green portion of the spectrum, however, the spectral variation of the proportionality coefficient is low. The constant can be separated into a value that represents the angle of the light entering the water and the angle of the light due to the direction of scattering by the water and constituents within it over depth (f). To further carry the upwelling irradiance through the surface, and convert it to radiance, terms for the transmittance across the air water interface (t), index of refraction of water (nw), and ratio of irradiance to radiance (Q) were introduced (Austin 1974). Finally it was realized that the loss due to backscattering in turbid coastal waters needed to be included. The result is equation 2.5 (Carder et al. 1999).

\[
R_n(\lambda) \approx \frac{r^2 f}{n^2 Q} \left( \frac{b_b}{a + b_b} \right)
\]

Equation 2.5

The backscattering and absorption terms could be broken up into their contributing components resulting in a semi-analytical approach to the inversion of \( R_n(\lambda) \) to IOP values that could be related to constituents within the water column.

Most of the terms that are not IOPs in equation 2.5 are related to factors that affect the path length of light as it travels to depth. If the light has to take an angular path to depth versus a nadir path, it will have a greater chance of being attenuated before it reaches a given depth. Backscattered light will also have a greater chance of attenuation coming up from depth with a longer path length. The path length is a concern for all types of optical measurements in oceanography since a longer path can increase the signal to noise ratio of the measurement. The average-cosine is a parameter that can provide some compensation for path length elongation.

The progress in AOP measurement and modeling ran parallel to the progress in IOP measurement. The goal of a true IOP measurement based on principles of optical physics is difficult to achieve since most IOP measurements require some sort of empirical correction for errors. One of the first methods for separating the absorption due to particulates from the other absorbing constituents was the quantitative filter pad method (Yentsch 1962, Truper and Yentsch 1967, Kishino 1985). This method involves filtering a sample on to a glass fiber filter, where smaller particles become embedded in
the pores of the filter. Previously, particulates were filtered onto a small-pore filter to
cconcentrate them and then carefully scraped off into a solution to be measured in a
spectrophotometer cuvette to determine $a_p(\lambda)$. The quantitative filter pad technique
resulted in an increased path length for the absorption measurement by taking the volume
for a section of the water column and concentrating the particulate matter in a thin layer
over a small area. However, the path through the filter resulted in scattering of the light
requiring an empirical correction to determine the increased path length. Even the more
direct measurements required a correction based on empirical means (e.g., see Keifer and
Mitchell 1988).

The problem with measuring absorption in situ was a need for a long path length
without interference from ambient light or loss of signal due to scattering. The
development of a reflective-tube absorption meter allowed for increasing the path length
while capturing the light lost to scattering (Zaneveld 1990). This instrument became
commercially available using a nine channel rotating optical filter wheel and is capable of
measuring both absorption and attenuation (ac-9, WET Labs Inc). There were still losses
due to backscattering towards the light source, forward scattering near the gap between
the reflective tube and the detector window, and path length elongation due to reflections
off the tube (Kirk 1992). To correct for these it was assumed that at 715 nm the only
absorption was due to water and by calibrating the media to pure water any measurement
beyond 715 nm is due to internal scattering losses. By taking the ratio of the apparent
scattering at a given wavelength to that at 715 and multiplying it by the absorption at 715
nm, the scattering loss can be extrapolated to other wavelengths (Zaneveld 1994). This
correction makes the assumption that the scattering loss is proportional over the
wavelengths measured and is very small relative to overall scattering. This presents an
analytical approach to measuring absorption but it still relies on an assumption that may
introduce some errors. While the ac-9 made the measurement of in situ absorption values
possible it still is not a completely direct measurement.

The backscattering coefficient is one of the more difficult measurements to make
in situ due to the complexity of measuring all of the different angles of scattering and the
low signal over short path lengths. Early measurements were performed in a laboratory
with a complex instrument called the Brice-Pheonix that measured the scattering at
several different angles from a sample in a cuvette (Carder 1970). Petzold (1972)
performed an experiment where through an elaborate submersible device operated by
divers, they were able to measure the volume scattering function at several angles.
Maffione and Dana (1997) discovered that the backscattering coefficient could be related
empirically to a measurement of the volume scattering function at a single angle. The
Hydroscat-6 (HOBI Labs) was developed to measure the volume scattering at six
wavelengths of light at 140° and to then convert that measurement to total backscattering
by multiplying it by a factor of $2*\pi*1.08$. While a profile of the backscattering
coefficient is possible, it depends on an empirical calculation.

While the IOP measurements are a more direct method of determining an optical
property due to a particular constituent in the water column, they still are not a perfect
measurement. All methods require some assumptions, corrections, and empiricism.
Clearly a 10-cm path length is inadequate for measuring absorption and scattering by extremely clear waters such as in the Sargasso Sea, while it is certainly too long for turbid Mississippi River water. While the AOP inversions require more assumptions and empiricism, they can benefit from a greater signal to noise ratio due to the increased path length of the light that is possible. $R_{rs}(\lambda)$ measurements made just above the sea surface do not have to be corrected for the effects of passing through the atmosphere resulting in greater signal to noise than a satellite $R_{rs}(\lambda)$ value. The atmosphere can account for over 80% of the radiance received by a satellite (Kirk 1994). With modern algorithms and instruments, it is possible that AOP inversions can be more accurate under certain conditions than more direct IOP measurement techniques.

2.4. Optical Closure

There are several different definitions of closure but few fit the closure attempted in this research. Curt Mobley discusses three types of closure in his treatise, Light and Water (Mobley 1994). The three types of closure, according to him, are measurement, scale, and model closure. The first type is to get accurate measurements by comparing them against a measurement commonly accepted existing practice. The scale closure is to make the transition from the properties of single particles to a bulk property of the water column. Model closure is to determine if AOP inversion algorithms can accurately produce the values of the IOPs in the water column. Zaneveld (1994) defines optical closure as matching theoretical relationships to independent measurements and is the closest to what is attempted in this study. None of these definitions fit exactly what needs to be done to determine which is the best current method, but parts of each are necessary.

A particular oceanographic measurement can vary from an individual particle to 100s of square miles. A measurement based on a discreet sample from a particular depth can only give information about that particular point. For example, if a researcher is interested in primary production based on chlorophyll, a specific sample measured by extracted pigments in a laboratory grade, calibrated fluorometer will be most accurate. The second most accurate approach would be to profile the water column with a calibrated fluorometer. Less accurate would be to invert satellite $R_{rs}(\lambda)$ to get chlorophyll concentrations. Each technique represents a different size scale. The water sample approach will give a point in the water column, the profile will give one dimension, and the satellite measurement will give a water-column-integrated value for 2 dimensions in the horizontal direction. Because of the differences in scales, comparisons become difficult. To achieve closure the three methods need to be set to a similar scale so they can be fairly compared to each other.

The best way to set a similar scale to compare methods is to have a water column profile for each method. By using an above-water hand-held radiance sensor, the $R_{rs}(\lambda)$ measurement is limited in horizontal scale to that particular point. An inversion of the $R_{rs}(\lambda)$ to get $a(\lambda)$ then represents a vertically integrated value. The IOPs of water just below the surface have the greatest influence on $R_{rs}(\lambda)$, decreasing logarithmically as the depth approaches one attenuation depth ($1/K_d(\lambda)$) (Smith 1981, Barnard et al. 1999).
Since 90% of the affect on the $R_{rs}(\lambda)$ values is from the first attenuation depth, comparison win an IOP profile measurement requires integration over depth by weighting it to $K_d(\lambda)$. For water sample measurements of absorption such as the filter-pad method, the extrapolation of several samples at depth weighted to $K_d(\lambda)$ would be best. Since it is time-consuming to collect and process that many samples, the best alternative would be to use the sample closest to the surface since it has the highest weighting in the $R_{rs}(\lambda)$ measurement. An inversion of $K_d(\lambda)$ from one attenuation depth would be similar to the $R_{rs}(\lambda)$ in weighting of IOPs so no additional weighting is needed for those two to be compared. By integrating IOP profiles and using a near-surface sample for the laboratory-based techniques, the methods are now set to similar scales and can be statistically compared.

The three definitions of optical oceanographic closure by Mobley need to be updated for a comparison to determine which method is best for a particular oceanographic environment. The developers of a particular method generally do scale closure to determine the accuracy of the method. Measurement closure has been achieved for individual measurement techniques by previous studies (Truper and Yentsch 1967, Ivey 1997, Maffione and Dana 1997). The developers of the AOP inversion algorithms have conducted several studies tested for model closure (Kirk 1981, IOCCG 2006).

The difficulty in Zaneveld's (1994) proposal is that to achieve closure between measurement and theory requires some difficult radiometric measurements. To test the relationship between theory and measurement it would require a data set that includes profiles of such difficult measurements as scalar irradiance. Scalar irradiance requires a very sensitive photocell with a spherical collector that has view angles both towards the surface and downwards. Some modern instruments approach the accuracy necessary for this type of measurement but have not been sufficiently widely used to test for closure. The approximate methods mentioned in Zaneveld (1994) are much easier to obtain and use for closure. That is closer to the approach used in this study.

The remaining test for closure is closer to the mathematical definition of closure. According to the Merriam-Webster 2009 dictionary, that definition is a set that consists of a given set together with all the limit points of that set. The best test will compare all the methods for a particular IOP under different conditions and environments to determine when they agree with the other methods and where they diverge from the other methods. The type of closure here is to determine which are the best techniques and under what conditions they are best. This type of closure could be considered set closure where there are groupings of overlapping sets based on environmental conditions.

The closure between the models and the more direct IOP measurements indicates a closure between the AOP measurements and the IOP values. This indicates that the relationship between the AOP model results and the in situ IOP values are significant enough that they can be substituted for one another. In oceanic environments where attenuation is very low, the ac-9 (25-cm path absorption and attenuation meter) may have low signal to noise for $a_{nuv}(\lambda)$ values. In these cases, an inversion algorithm of $R_{rs}(\lambda)$ can
be used to determine $a_{nw}(\lambda)$. In cases where the $R_{ns}(\lambda)$ measurements is suspect, the ac-9 value may be used instead. In areas where methods are expected to give the same result, they can be compared to determine if there is an error in a particular measurement. If there are three independent methods that measure or can be inverted to measure an IOP and two agree, then the other measurement or method may be retroactively corrected based on the differences. If correction is not possible, then the value from the other more reliable methods can be used. The collection of both AOP and IOP data that have been determined to agree, allows for a more robust, accurate, data set of optical properties.

Determining the conditions where the methods agree has the additional benefit of extrapolation to other optical properties based on the mathematical relationships between the AOPs and IOPs. Using the radiative transfer equation (e.g., see Mobley 1994 for a summary) the relationships between measurements such as $R_{ns}(\lambda)$, $K_d(\lambda)$, $a_{nw}(\lambda)$, and $b_{bg}(\lambda)$ permit calculation of other parameters such as scalar irradiance, scattering phase functions, and bottom reflectance. Scalar irradiance can indicate the amount of light available to a phytoplankton cell at a given depth. Scattering phase functions are indicative of the types, sizes, and population distributions for particulate matter in the water column. The percent of sea grass coverage can be indicated by a spectral bottom reflectance. Difficult to measure optical properties can be estimated using AOPs and IOPs under conditions of agreement to give more parameters that are of interest for oceanographic studies.

Closure by treating all methods as equally weighted, points out potential sources for improvement in these methods. If one method has traditionally been accepted as best, then it may be ignored when it obviously produces errors. Errors may not occur under all environmental conditions, so filters have to be applied to separate out the different conditions. The $R_{ns}(\lambda)$ are expected to have more errors for determining $a_{nw}(\lambda)$ under high solar zenith angles while the instruments that have their own light source, such as the ac-9, will not be affected by zenith angle. Once errors are quantified, then correlations with other parameters can be investigated. Cloudiness might affect the AOP inversions while scattering might affect the ac-9-derived absorption coefficients. Analysis of these errors will be used to derive correction factors or modifications in the measurement procedures. By treating all methods as equally likely of error, instead of initially assuming one method is best can yield information useful about all the method, in this study.

2.5. Spectral Bottom Albedo Through Optical Closure

The bottom albedo would be a useful parameter to obtain from mathematical relationships between the different measurements. Bottom albedo is the fraction of light leaving the bottom relative to the light reaching it. It is a difficult parameter to measure due to the types of instruments required for its measure and the methods involved (Hochberg et al. 2003). The bottom albedo could be useful for applications ranging from environmental to defense. Several published algorithms have attempted to deconvolve bottom albedo from $R_{ns}(\lambda)$ measurements (Maritorena et al. 1994, Lee et al. 1999, 2001,
Werdell and Roesler 2003, and Dierson et al. 2003). If a deconvolution of the bottom albedo signal can be achieved from common measurements, determination of bottom albedo would be more common.

The way that albedo could be determined from \( R_{rs}(\lambda) \) measurements is illustrated in the \( R_{rs}(\lambda) \) optimization inversion algorithm (Lee et al. 1999). They point out that \( r_{rs}(\lambda) \) below the surface can be separated into two parts. One portion is due solely to the downwelling light passing through the water column and the return of that light due to backscattering. The second part is due to the light reaching the bottom, being reflected and returning up to the surface. His equation is basically the irradiance reflectance from the water column plus the irradiance due to light reflected off the bottom. The second term includes the albedo as a factor. The \( r_{rs}(\lambda) \) values can be calculated within the Hydrolight model (Mobley 1994) using the best IOP values as input. The water column value can be removed by subtracting from measured \( r_{rs}(\lambda) \) value, a Hydrolight result using a black bottom. The resulting value is the \( r_{rs}(\lambda) \) due to bottom reflectance. A second Hydrolight run using an albedo value of one could be corrected for the water column \( r_{rs}(\lambda) \) and divided into the measured value to get the albedo. The approach is simple in practice but requires very good measurements for the input values and reflectance.

A spectral bottom albedo could aid in environmental studies of sea grasses. Sea grass has made a come back in the in Tampa Bay since a large decline in the 1970s (Dawes et al. 2004). Anthropogenic pollution resulted in large algal blooms that limited light availability to sea grasses and led to the decline in coverage. Careful monitoring is still necessary to determine areas that might be at risk. High resolution spectral \( R_{rs}(\lambda) \) measurements from air craft could determine the bottom albedo of sea grass areas at different times of the growing season. This would allow accurate estimations of coverage with little ship time required for monitoring.

Spectral bottom albedo over coral reef areas could be used to indicate coral health. The rapid decline in reefs over the world has puzzled coral reef ecologists as to the various reasons for the decline (Bellwood et al. 2004). With spectral albedo images of the reef area, zones of algal coverage, coral bleaching, and coral growth could possibly be identified. This knowledge could lead to a better determination of the timing and perhaps the causes of decline. The changes in the images over time could be used to identify regions that are in distress and focus mitigation efforts on those areas. With spectral \( R_{rs}(\lambda) \) images from a low flying air craft combined with side scan sonar measurements of depth, 3-dimension spectral maps could be made to aid coral reef ecological management.

The Navy and port security could benefit from hyperspectral images of bottom albedo. It is very difficult to spectrally match the albedo of a changing bottom. Painted camouflage may be difficult to determine using a video camera that only uses red, green, and blue wavelengths. The human eye is most sensitive to green light so it can be fooled by camouflage. A spectral image of the bottom would be very difficult to fool since the
target would have to match several wavelengths of the spectrum exactly. Using the spectral image, a threat to security or planted mines could be identified using a passive reflectance sensor instead of a sonar system that could be detected. An image of spectral bottom albedo would make even active camouflage difficult to achieve. At certain wavelengths the object would contrast prominently against the bottom.

### 2.6. Locations and Descriptive Optics

Data from 126 stations are utilized in this study covering a wide range of optical values with several different types of synchronous measurements (Table 2.3). $R_{rs}(\lambda)$ measurements were collected at 115 stations. The ac-9 was deployed at all 126 stations. Subsurface downwelling irradiance measurements were collected at 119 stations. Filtered ac-9 $a_{g}(\lambda)$ was collected at 114 stations for water color. Hydrosat-6 $b_{bp}(\lambda)$ values were collected at 119 stations. Filter pad $a_{p}(\lambda)$ values were collected at 82 stations. Spectrophotometric $a_{g}(\lambda)$ data were collected at 84 stations. Filter pad $a_{d}(\lambda)$ were collected at 84 stations. The difference between $a_{p}(\lambda)$ and $a_{d}(\lambda)$ resulted in $a_{ph}(\lambda)$ for 79 stations. All the $R_{rs}(\lambda)$ and $K_{d}(\lambda)$ measurements produced acceptable inversion results within normal ranges so none were considered erroneous measurements. The majority of stations have a variety of AOP and IOP measurements that are used in comparing the different methods in this study.

#### Table 2.3. Study sites: dates, locations, and chlorophyll concentrations.

<table>
<thead>
<tr>
<th>Cruise Name</th>
<th>Date Range for Used</th>
<th>Data Number</th>
<th>Median Chl $\mu g$ L$^{-1}$</th>
<th>SW Corner Latitude by Longitude</th>
<th>NE Corner Latitude by Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoBOP 98</td>
<td>05/20/1998 to 05/29/1998</td>
<td>13</td>
<td>0.15</td>
<td>23.78N by 83.06W</td>
<td>23.84N by 80.88W</td>
</tr>
<tr>
<td>Friday Harbor</td>
<td>08/04/1998 to 08/05/1998</td>
<td>7</td>
<td>8.60</td>
<td>48.50N by 123.00W</td>
<td>48.65N by 122.86W</td>
</tr>
<tr>
<td>CoBOP 99</td>
<td>05/22/1999 to 06/03/1999</td>
<td>15</td>
<td>0.07</td>
<td>23.77N by 76.10W</td>
<td>23.87N by 75.92W</td>
</tr>
<tr>
<td>ECOHAB NOV 99</td>
<td>11/06/1999 to 11/07/1999</td>
<td>4</td>
<td>1.53</td>
<td>26.31N by 83.05W</td>
<td>27.50N by 82.27W</td>
</tr>
<tr>
<td>ECOHAB Mar 00</td>
<td>03/01/2000 to 03/03/2000</td>
<td>9</td>
<td>0.19</td>
<td>26.10N by 83.80W</td>
<td>27.50N by 82.87W</td>
</tr>
<tr>
<td>CoBOP 00</td>
<td>05/20/2000 to 05/29/2000</td>
<td>10</td>
<td>0.12</td>
<td>23.79N by 76.14W</td>
<td>24.21N by 76.03W</td>
</tr>
<tr>
<td>FSLE 3</td>
<td>07/02/2000 to 07/10/2000</td>
<td>9</td>
<td>0.47</td>
<td>27.15N by 83.12W</td>
<td>27.26N by 82.93W</td>
</tr>
<tr>
<td>FSLE 4</td>
<td>11/05/2000 to 11/13/2000</td>
<td>13</td>
<td>0.36</td>
<td>26.85N by 83.50W</td>
<td>27.28N by 82.87W</td>
</tr>
<tr>
<td>HOBI 1</td>
<td>02/07/2001 to 02/07/2001</td>
<td>5</td>
<td>0.30</td>
<td>27.13N by 83.01W</td>
<td>27.21N by 82.82W</td>
</tr>
<tr>
<td>HOBI 2</td>
<td>04/17/2001 to 04/17/2001</td>
<td>5</td>
<td>0.22</td>
<td>27.12N by 83.00W</td>
<td>27.21N by 82.82W</td>
</tr>
<tr>
<td>Link (aka FSLE 5)</td>
<td>04/19/2001 to 04/25/2001</td>
<td>36</td>
<td>0.19</td>
<td>26.09N by 83.72W</td>
<td>27.30N by 82.09W</td>
</tr>
</tbody>
</table>

Data were collected in the Puget Sound of Washington state during a three-day cruise in the summer of 1998. The area provides attenuations much larger than most of the other regions. This area is included as a test to the upper attenuation limit of the models and techniques used in this paper. The $R_{rs}(\lambda)$ from this area has a lower signal than the clearer regions and has a higher proportion of the signal from the longer wavelengths of the visible spectrum. The signal to noise in the ac-9 and other direct IOP measurements is highest in this region.
The stations from Puget Sound had the highest absorption values at 440 nm ranging from 0.227 to 0.568 m⁻¹. The attenuation values at 440 nm were higher than most other areas overall with a median of 0.98 m⁻¹. The maximum chlorophyll levels were highest reaching 10.07 mg m⁻³ at one station. The $a_g(412)$ values were higher than most areas ranging from 0.168 to 0.232 m⁻¹. The $b_{bp}(442)$ values ranged from 0.005 to 0.01 m⁻¹, but, unlike the absorption values, they were not the highest. The stations in the Puget Sound represented the upper range in values except for backscattering.

![Station locations in Puget Sound, Washington, USA. Black dots represent the stations sampled.](image)

Figure 2.1. The area around Lee Stocking Island, Bahamas (LSI), was part of an oceanographic study that emphasized the optical properties of the waters. The study was titled Coastal Benthic Optical Properties (CoBOP) and was sponsored by the Office of Naval Research. The area was surveyed during May for the years 1998 to 2000. The main constituent contributing to the optical properties of these clear waters is the water itself. The water near the island was different from Sargasso Sea water in that it had high ratios of $a_g(\lambda)/a_{ph}(\lambda)$ and $b_{bp}(\lambda)/b_p(\lambda)$. The remote sensing reflectance ($R_p(\lambda)$) in this region has a higher signal and receives a greater portion of its signal from the shorter wavelengths of the visible spectrum. The signal to noise in the ac-9 and spectrophotometric measurements is low in this region.
The stations near Lee Stocking Island of available data had the lowest attenuation. These measurements challenged the lower range of the methods. The attenuation had a median value of $c_{nw}(440)$ of 0.11 m$^{-1}$ with a range from 0.04 to 0.24 m$^{-1}$. These waters also had the lowest chlorophyll with a median of 0.11 mg m$^{-3}$. The median $a_{nw}(440)$ value was low at 0.034 m$^{-1}$ with a range of 0.009 to 0.071 m$^{-1}$. The median $a_g(412)$ value was 0.035 m$^{-1}$ and is equal to the median value for the West Florida Shelf data set. The $a_g(412)$ range was 0.007 to 0.101 m$^{-1}$. The median $b_{bp}(442)$ value was also the lowest at 0.0017 m$^{-1}$, but the area had a wide range of 0.0008 to 0.0478 m$^{-1}$. The stations from the Bahamas provided the lowest attenuation range for testing the methods.

![Figure 2.2. Stations locations near Lee Stocking Island, Bahamas. Black plus signs represent the stations sampled.](image)

The most diverse area studied is the West Florida Shelf, covering from the mouth of Tampa Bay and offshore, to areas off Charlotte Harbor. Most stations were along a track leading out from Sarasota, FL. The cruises cover a period from March of 1999 to April of 2001. The bottom depths ranged from 10 m to 76 m. The optical properties in this area were widely varying depending on the bottom depth and season of collection. Chlorophyll concentration ranged from 0.09 to 2.36 µg l$^{-1}$. Typically the attenuation and $R_{rs}(\lambda)$ values from this area represent a midpoint in optical values between the waters investigated in the CoBOP and Friday Harbor cruises.

The West Florida Shelf data had values in between the Puget Sound and CoBOP data, and also had the largest range of values. In some cases the offshore water had
attenuation values as low as the waters off Lee Stocking Island and sometimes the near shore waters had higher attenuation values than found in the Puget Sound Waters. The attenuations range from 0.07 to 2.19 m⁻¹ with a median value of 0.24 m⁻¹. The $a_{nw}(440)$ values have a median of 0.04 m⁻¹. While the median $a_{nw}(440)$ value is not much higher than the CoBOP waters, the range (0.02 to 0.24 m⁻¹) is much larger. The low absorptions and high attenuations probably reflect a lot more scattering particles from local rivers and resuspension of bottom sediments. The West Florida Shelf data set provided an intermediate range to test the methods.

![Figure 2.3](image)

Figure 2.3. Station locations on the West Florida Shelf. Different cruises are indicated by different symbols.

### 2.7. Morel Case of Study Sites

Andre Morel (1974) published a definition for open ocean waters by defining them as having all optical properties derived from phytoplankton and their degradation products. Examining the *in situ* ac-9 and Hydrosat-6 data for the stations in this study indicates that most of the waters do not fit Morel’s definition. Recent studies have questioned whether these definitions are valid (Lee and Hu 2006, Mobley et al. 2004). Improved $R_{rs}(\lambda)$ inversion techniques have indicated that the ratio between CDOM absorption and phytoplankton concentrations may not be as well established as originally theorized (Siegel et al. 2005). The categories of the data in this study are examined to determine where they fall in the Morel classification method.
The Morel definitions for Case II water are broken down into three groups for this test; CDOM Case II, scattering Case II, and CDOM-scattering Case II. His Case I definition is essentially consistent with all the optical parameters correlating with chlorophyll concentrations. CDOM Case II is defined as CDOM absorption greater than pigmented particulate absorption at 440 nm. Scattering case II is defined as scattering not correlating with pigmented particulate absorption. Morel has an equation that empirically determines b(550) from chlorophyll concentrations for Case I waters (Equation 2.6). The waters that have b(550) values above this equation would be Case II scattering waters. CDOM and scattering Case II waters would have a combination of the two criteria deviating from the Case I definition.

\[ b(550) = 0.45c^{0.62} \]  

Equation 2.6

The waters in Puget Sound were high chlorophyll and were case II CDOM waters. The chlorophyll values did correlate with particulate absorption but did not correlate at a high level with scattering or CDOM (Figure 2.4 A and B). The ratios for \( a_g(440) \) to \( a_p(440) \) or \( a_{ph}(400) \) were mostly above one (Figure 2.4 C). The b(550) values were below the Morel equation (Figure 2.4 D.). The only exceptions were the stations closer to the mouth of Puget Sound, which may have mixed with some open ocean water. None of the Puget Sound data correspond to Morel Case I waters.

The waters in the Bahamas Sound, while optically clear, were dominated by CDOM. The CoBOP IOP data from both the ac-9 and the spectrophotometric methods do not exhibit a correlation with chlorophyll (Figures 2.5 A & B). The \( a_g(440) \) to \( a_p(400) \) or \( a_{ph}(400) \) ratios indicate that even the clear offshore stations are CDOM rich (Figure 2.5 C). Two stations fall above the Morel line for scattering (Figure 2.5 D). These stations scattering Case II stations were either at or near N. Perry or S. Perry reef in the Bahamas. It appears that some process in the reefs is producing both higher CDOM and scattering. Probably the local reef organisms are producing the CDOM while resuspension or carbonate precipitation is increasing the scattering. The CoBOP waters are CDOM Case II except for the reefs on the sound side, which are CDOM and scattering Case II.
Figure 2.4. Analysis of all Puget Sound data to determine Morel Case. A. chlorophyll correlations with in situ measurements, B. spectrophotometric absorption data versus chlorophyll, C. ratios of $a_g$ to $a_p$ and $a_{ph}$, D. Measured in situ scattering (points) as compared to Morel value modeled from chlorophyll concentrations (line).
Figure 2.5. Analysis of all Bahamas data to determine Morel Case. A. Chlorophyll correlations with in situ measurements, B. spectrophotometric absorption data versus chlorophyll, C. ratios of \(a_g\) to \(a_p\) and \(a_{ph}\), D. Measured in situ scattering (points) as compared to Morel value modeled from chlorophyll concentrations (line).
Figure 2.6. Analysis of West Florida Shelf (Link, Table 2.3) data to determine Morel Case. A. Chlorophyll correlations with *in situ* measurements, B. spectrophotometric absorption data versus chlorophyll, C. ratios of $a_g$ to $a_p$ and $a_{ph}$, D. Measured *in situ* scattering (points) as compared to Morel value modeled from chlorophyll concentrations (line).
The West Florida shelf varies from Case I to Case II according to April 2001 cruise data. The IOPs correlate very well with chlorophyll concentration. Based on the correlation with chlorophyll concentrations along the West Florida Shelf, waters would qualify as Case I (Figures 2.6 A and B). The \( a_g(440) \) to \( a_{ph}(400) \) ratios are above the 1:1 ratios but not much higher, and 4 stations had \( a_g(440) \) to \( a_{ph}(440) \) ratios that were below 1 (Figure 2.6 C). Some stations border on Case I water based on CDOM absorption. The stations along the 10 m isobath along with one 20 m station border on a Case I CDOM classification (two black squares closest to shore in Figure 2.3). The scattering-to-chlorophyll curve shows a different story (Figure 2.6 D). All the 10 m isobath stations are above the Morel line. About half the 20 m isobath stations are also above the Morel line. Many of the offshore stations are also above the Morel line for scattering for Day 1 and 2 of a April 2001 cruise when the winds were about 7 to 9 m s\(^{-1}\). After Day 3 the winds died down and the seas were almost flat calm for the last couple of days of the cruise. The scattering appears to be related to resuspension of particulates into the water column as the stations deeper than 20 m fell close to or below the Morel scattering line when the winds subsided. Based on correlations with chlorophyll concentration and the \( a_g(440) \) to \( a_{ph}(400) \) ratios of nearly one, the stations at the 50 and 60 m isobaths border on Case I. The near-shore stations are scattering and CDOM Case II but not strongly CDOM Case II. The scattering at the other stations appears to depend on the wind resuspension of sediments. If the cruise had continued another few days, the waters might have turned Case I as suspended sediment dropped out of the water column. The West Florida Shelf stations ranged from Case II at less than 20 m depth to Case I at greater than 50 m depth.

The regions in this study are not ideally suited for older empirical band-ratio AOP inversion models. Most inversion models are parameterized with data for open ocean conditions. The older band ratio algorithms do not perform as well in Case II waters. The statistical comparisons in this study are expected to show significantly better results for models that used parameters more suited to the region. In CDOM Case II waters, the models not tuned to these regions were postulated to underestimate the amount of CDOM. The CDOM near shore is expected to have a more humic component than the offshore waters due to terrigenous input from rivers. The CDOM fluorescence at 440 nm may result in an underestimate of the magnitude of \( a_{ph}(440) \). If the model separates out \( a_{ph}(\lambda) \), it may not have parameters appropriate for the packaging or pigments found in these particular case II waters. The \( b_{bp}(\lambda) \) values and spectral \( b_{bp}(\lambda) \) shape may be different in case II waters due to larger particle size and an increased mineralgenic component in the detritus absorption. Since most of the areas are not the typical open-ocean Morel Case I waters, they should provide a good test of the AOP inversion algorithms under varying but realistic conditions.
3. Instruments and Methods

3.1. Introduction

The techniques for measurement and analytical quality of the various methods in this research are a very important part of this study. A technician can read a manual, and then go deploy an instrument, but it takes years of collective experience for the measurement to be properly made by a scientific group. Simply put, an instruction manual is no substitute for hands-on training and field experience. Likewise, most technicians can perform a regression on data in Excel and call it an inversion algorithm. However, it will likely only apply to that particular data set unless the two sets in the regression are known to have a linear relationship. The way the data are collected and the analytical methods are of primary importance for optical closure, especially in the diverse environments of coastal regions.

3.2. Slow-Drop Package

The instrument package used in this study had a suite of 13 core oceanographic instruments and up to 4 additional instruments. The data from most of the instruments were merged together based on elapsed time. The data used for this paper from this package come from the ac-9 (a 9-channel absorption and attenuation meter), an ac-9 with a filter attached, a 512-wavelength downwelling irradiance spectrometer, a Hydrosat-6 (a 6-channel backscattering meter) and a CTD (a conductivity, temperature, and depth sensor). The instrument was deployed with floatation devices that put the package near neutral buoyancy. The near neutral buoyancy allowed the package to drop at a slow steady rate independent of the motion of the boat and the seas. This also allowed the package to drift out from the shadow of the ship to prevent shading of the irradiance sensor.

3.2.1 ac-9

A WET Labs, Inc., ac-9 measures attenuation and absorption of all constituents in the water at wavelengths of 412, 440, 488, 510, 532, 555, 650, 676, and 715 nm (Zaneveld 1990). The ac-9 uses a reflective tube to measure absorption in the water column. It accomplishes this by having most of the light that is scattered reflected forwards off a quartz flow tube and into a detector (Figure 3.1.). This is simple in concept but complex in practice. Figure 3.1 shows the basic layout of one of these meters. The light leaves the lamp (a), passes through a pair of apertures (b), a focusing lens (c), a narrow-band-pass filter on a rotating wheel (d), and another aperture producing a collimated beam. This light then goes through a beam splitter (e) with some going to a
detector (f) to take a measurement of how much light is entering the water in the reflective tube. The light beam then passes through a window (g) and travels through 25 cm of water to illuminate a diffuser (k) and is measured by a photocell (l). According to Beer's law, the change in light over a path short enough that only single scattering can take place, is a natural log function using the log of the loss of light over the path to the distance traveled. The measurement would be exact if all the light entering the reflective tube was either absorbed or detected by the photocell but the actual path of the light complicates this measurement.

Figure 3.1. The "simple" path of light through reflective tube absorption meter. a. light source, b. aperture, c. collimating lens, d. filter wheel, e. beam splitter, f. reference detector, g. window, h. initial light path, i. light scatter at 41° or less, j. light scattered at > 41°, k. diffuser, and l. photocell.

The light entering the reflective tube in Figure 3.1 can either be absorbed or scattered (h). The majority of light that is scattered at an angle 41° or less from the straight path (i) will make it to the detector with a minimal change in the length of the path it travels. However light that is scattered at higher angles is usually lost (j). The difficulty is estimating how much light is lost to prevent overestimating absorption by including these losses due to scattering. The losses due to scattering not collected by the detector can vary greatly depending on the optical properties of the constituents within the water sampled. The scattering efficiency and direction of scattering of an individual constituent can vary greatly with size of the constituent and it's index of refraction. The efficiency of scattering can be low for a Karina brevis cell with an index of refraction near water but high for suspended aragonitic particles. The proportion of scattering in a given direction can vary from evenly in the forward (b_f) and backwards (b_b) direction for a water molecule to a majority in the forward direction for a large diatom cell. This means that the losses due to scattered light not recovered in a reflective tube absorption meter are impossible to exactly determine without absolute knowledge of the scattering constituents within the water sample. However, if absolute knowledge of the scattering constituents was already available then there would be no need for using a reflective tube absorption meter. The only way to compensate for this loss is through an empirical estimate that will introduce some error in the measurement. This simple case of a reflective tube absorption meter is more complex than it first appears.
The optical arrangement of the attenuation tube is the same as that of the absorption tube for the light entering the flow tube. However after the light enters, the attenuation tube has a black wall that absorbs the scattered light and the detector has a narrow aperture before it that rejects almost all of the light except that traveling almost the same path as the source light. The result is the change in power in the collimated source beam along a path straight from the source due to both absorption and scattering or attenuation. Subtracting the absorption tube result from the attenuation tube result gives the scattering coefficient.

The data from the ac-9 were calibrated using highly purified water from a deionized water system. The water blank is subtracted from the in situ measurement of \( a(\lambda) \) and \( c(\lambda) \) to determine the constituent values and correct for shifts in instrument calibration. The optical properties of water vary with changes in temperature and salinity and the values from the ac-9 were corrected for this shift (Pegau et al. 1997). The absorption values in the ac-9 have to be corrected for losses due to light scattered at angles greater than 41° (Figure 3.1). Absorption at 715 nm is assumed to be zero and the value is scaled spectrally by using the ratio of apparent scattering at a given wavelength to the scattering at 715 nm (Zaneveld et al. 1992). With all these corrections and careful deployment technique, the ac-9 can measure absorption at an accuracy of 0.01 m\(^{-1}\).

This calibration using pure water is very important with this instrument because the filters in the rotating wheel degrade over time, as does the output from the lamp. While the 25 cm path length makes this instrument more sensitive than similar instruments, it also makes it vulnerable to slight shifts in the path due to a slight flexing of the instrument. The ac-9 is so sensitive that vibrations from stamping on the floor will cause shifts in its readings. This sensitivity to vibration is one of the reasons why it is best to deploy it on a slow-drop package that is free from surges due to the roll of the ship. The surges can also result in changes in water density within the flow tube of the ac-9 resulting in increased scattering. Bubbles can increase scattering within the flow tubes so the instrument must be properly cleared of them before a profile can be started. All this adds up to an instrument with a sensitive direct measurement of \( a(\lambda) \) and \( c(\lambda) \) but with several sources of error due to deployment techniques (Ivey 1997).

A 0.2 µm canister filter was attached to an ac-9 to collect in situ measurements of the absorption due to CDOM. The filter was a high-flow Gelman Suporcap with a 0.8 µm outer filter. This filter was selected because of a very high flow rate and the large outer filter to keep the pores of the 0.2 µm filter from rapidly clogging. To prevent problems with bubbles in the lines, the plastic cannister of the filter was sawed off, exposing the filter membranes directly to the water. The filter was soaked in deionized water until deployment. The deionized water served two purposes. It saturated the filter so that few bubbles were caught within it and it helped rinse the filter if it was to be reused at a later deployment. The filter was only placed on the inlet of the absorption tube for the ac-9. The calibration and corrections for temperature and absorption are the same as for the unfiltered ac-9. Scattering by dissolved substances is similar to that of water so losses should be zero due to the water calibration. However, like in a laboratory
spectrophotometer, there are some losses. This is mostly corrected by subtracting the 715
nm value where absorption is usually zero. When values are below the accuracy of the
instrument, they are extrapolated using the equation below.

\[ a_g(\lambda) = a_g(440)e^{-s(\lambda-440)} \]

Equation 3.1

The shorter wavelengths (generally 412 to 510 nm) were fit to this equation using a
regression model to solve for the coefficient "s" (Bricaud et al. 1981). The values at the
longer wavelengths were then extrapolated. A filtered ac-9 can usually only be deployed
effectively on a slow drop package because the slower rate of pumping through the filter
results in a lag time for the measurement relative to the depth of measurement so the
values can smeared over several depths if the descent is too rapid.

3.2.2. Spectrix Hyperspectral Downwelling Irradiance Meter

A 512-channel radiometer with a cosine collector in a water-resistant housing
(Spectrix) was used to measure the subsurface downwelling solar irradiance (English and
Carder 2006). This meter measures irradiance at wavelengths from about 340 to 890 nm.
It is radiometrically and spectrally calibrated by comparison to a standard lamp, a Licor
1800 irradiance meter, and the RADTRAN modeling program (Cattrall et al. 2002). The
 calibration of the Spectrix includes a coefficient for an immersion factor determined by
carefully submerging it in deionized water in a laboratory tank (Mueller and Austin
1992). The instrument was then mounted clear of all other instruments on a slow drop
package. The slow-drop package could drift away from the shadow of the ship limiting
the possibility of shading the instrument. The slow descent allowed it to record a greater
number of measurements at each depth than a much faster descending package connected
to the ship's wire. The downwelling irradiance data and diffuse attenuation coefficients
\((K_d(\lambda))\) were processed according to the protocols outlined by Costello et al. (2002).
While this instrument predates some of the commercial hyperspectral instruments, it still
has extremely high accuracy because of the attention to calibration and deployment.

The processing of the downwelling irradiance data required a substantial Matlab
routine to correct for wave focusing. Wave focusing is exactly what it sounds like; the
light near the surface is focused and defocused as waves pass over the sensor (Zaneveld
et al. 2001). The resulting light field can vary greatly in irradiance and spectrum. The
alternating bright and dark lines seen on the bottom of a swimming pool on a sunny day
are a perfect illustration of this effect. Ideally the instrument would simply be held at
several depths below the surface to average many measurements. This is only possible if
it is mounted on an expensive platform such as an ROV or AUV (e.g., English et al.
2005) or if the slow drop package had some method of buoyancy control. The wave
focusing even from a slowly descending package can be enough that the near-surface
values can be skewed either too high or too low.

The correction for wave focusing involved first taking an above-water
measurement of \(E_d(\lambda)\). This surface value can be converted to a below-surface value
using algorithms for the loss across the air-water interface (Austin 1974, Carder et al.
1999). The Hydrolight model using the Radtran model (Gregg and Carder 1990) for its
solar input value was used to calculate the factors for transmittance below the surface for
each cast. If a surface value was not available, a near-surface value was modeled using
the Hydrolight program. When the above-water measurement was taken with a different
instrument or calculated by the Hydrolight model, the spectral Fraunhoffer lines were
different for two high-resolution $E_d(\lambda)$ sensors. To compensate for this difference the
routine did a fifth-order fit of $E_d(\lambda)$ versus wavelength for the calculated subsurface
value. This polynomial was then statistically compared to a 5th-order polynomial fit for
the $E_d(\lambda)$ scans in the upper 5 meters. The measured below-water scan with the closest
statistical match was then scaled using the polynomial fit so that it matched the
magnitude of the calculated value but had the spectral shape and resolution of the in-
water measurements. Without these calculated values, the $K_d(\lambda)$ value could have severe
errors.

Spectral scans with more than 75 channels saturated (values at maximum raw
counts of 4095) due to wave focusing were determined to be irrecoverable since there
was not enough spectral information and were deleted by the routine. Because of the lack
of good data near the surface, every possible scan was needed so scans with fewer than
75 values saturated were corrected with interpolated data from near by depths. This
interpolation routine used the data from a scan at a close depth by taking a ratio of
unsaturated values at 550 nm as a factor. If the individual values at a given wavelength
were below the accuracy of the instrument (where the dark current is 95% or more of the
reading), they were set to a value of $1 \times 10^{-6}$ W m$^{-2}$ nm$^{-1}$ (Chris Cattrall personal
communication). These values were not simply set to zero so that mathematic errors
would not occur when the natural logarithm was calculated. Despite all this automatic
filtering and smoothing of the data, there were still some spectral scans that were affected
by wave focusing and would bias the $K_d(\lambda)$ value. To remove these, the Matlab routine
plotted the data and an observer was able to remove the erroneous values by clicking on
the plot at that point. The resulting depth profile of $E_d$ for each wavelength was ready for
the final smoothing.

To smooth the data, the routine fit a 3rd-order polynomial over depth for each
wavelength. For each value deleted during the filtering one of the just below surface
$E_d(\lambda)$ values were added to the data array. These values forced the polynomial fit near
the surface to go through a value unaffected by wave focusing. The fit only went to the
depth where the values were above the noise level value. A third-order polynomial was
selected because sometimes the $E_d(\lambda)$ value would slightly increase at depth. This
increase in $E_d(\lambda)$ at depth was due to Raman scattering, fluorescence, or (in shallow
regions) bottom reflectance (Costello et al. 2002). The $K_d(\lambda)$ values were finally
calculated by taking the natural log of the change in $E_d(\lambda)$ over depth using the smoothed
curve from the 3rd-order polynomial fit.
3.2.3 Hydroscat-6

The Hydroscat-6 is one of the first commercial spectral backscattering instruments that can be used for water column profiles (Maffione and Dana 1997). The instrument deployed on the slow drop package measured at wavelengths of 442, 488, 532, 589, 620, and 671 nm. The volume of water measured by the instrument is calibrated by slowly moving a Spectralon reflective plate through its field of view while immersed in a water bath. The instrument only measures $b_b(\lambda)$ at 140° instead of through the entire hemisphere. This angle of backscattering was selected because modeling studies indicated that the value at this angle was most proportional to the overall backscatter value (Maffione and Dana 1997). The $b_b(140°,\lambda)$ is converted to $b_b(\lambda)$ by multiplying it by $2*\pi*1.08$. This empirical relationship is within 10% of the total measured backscattering. Additional empirical corrections are applied to compensate for losses due to attenuation along the optical path of the instrument.

3.3. $R_{rs}(\lambda)$ Measurement with Spectrix

A 512-channel Spectrix radiometer was used to determine the above-water remote sensing reflectance. The spectrometers are calibrated spectrally using an integrating sphere at quarterly intervals and annually calibrated against the solar constant. The downwelling radiance was measured by aiming the spectrometer at a gray Spectralon calibrated Lambertian panel as close to the vertical as possible without shadowing the card (Carder et al. 1985). The gray card measurement was multiplied by $\pi$ and divided by the percent gray card reflectance to convert it to downwelling irradiance. The angular reflectance of the gray card has been calibrated and is updated annually (Cattrall 2002). The instrument was then directed at the water at a 60° angle to vertical and 90° to the solar plane and the water leaving radiance recorded. The instrument was then directed 30° from the vertical and 90° from the solar plane and the sky radiance was recorded. Both the water and sky radiance are divided by the gray card irradiance measurement. The sky reflectance is then multiplied by the Fresnel reflectance of the water and subtracted from the above water remote sensing radiance of the water (Lee et al. 1998) to correct for reflectance off the sea surface.

3.4. Spectrophotometer Measurements

Surface samples of water were collected and particulate absorption ($a_p(\lambda)$) determined using the Quantitative Filter Pad Method (Yentsch 1962, Kiefer and Soohoo 1982). To determine the absorbance of the filter, a special box was used that incorporated a Spectrix radiometer (Carder et al. 1995). After taking a spectral absorbance reading of the filter, a wetted blank filter was scanned. A few milliliters of hot methanol were passed through the particulate filter to dissolve the pigments within the cells. The bleached filter was measured for absorbance a second time to determine the light absorbed by nonliving particles or detritus ($a_d(\lambda)$)(Kishino et al. 1985) again followed by blank filter. The difference between the $a_p(\lambda)$ and $a_d(\lambda)$ values represented the absorption due to pigmented particles ($a_{ph}(\lambda)$). The filter pad absorption values were
corrected for optical path length elongation due to internal scattering within the filter (Carder et al. 1999). To convert the measured absorbance into per meter absorption, the absorbance value was multiplied by 2.303 to convert from a log base of ten to a natural log, multiplied by the area of the filter pad covered with particles, and divided by the volume of water filtered.

The dissolved organic absorption ($a_d(\lambda)$) was determined by filtering some of the collected seawater through a 0.2 µm filter. The filtrate was then measured for absorption in a 10 cm quartz cell with a Perkins-Elmer Lambda 18 Spectrophotometer. Due to the low signal to noise in wavelengths above 500 nm, the values at longer wavelengths had to be extrapolated using equation 3.1 for some of the lower attenuation samples. The $a_d$ data were added to the $a_p$ data to determine the $a_{ow}$ from spectrophotometric measurements.

3.5. Rrs Inversion Models

Most reflectance inversion models start with the relationship that irradiance reflectance is proportional to the ratio of the backscattering to absorption for a particular medium (Duntley 1942). This relationship simply means that the light observed leaving the water relative to that entering the water is a function of what sends the light back up to what removes the light. For turbid waters, a second term of backscattering is usually added to the denominator to account for the returned light that is scattered back down again (Morel and Prieur 1977, Gordon et al. 1988).

$$R_{rs}(\lambda) = C \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}$$  \hspace{1cm} \text{Equation 3.2}

Like most concepts in optical oceanography the theory is simple but application to the real world is more complex. The models in this study are much more complex than the original models and have many more terms. The models have techniques for separation of $a(\lambda)$ and $b_{bp}(\lambda)$ into the various components that contribute to them. Some of the models attempt to take into account all the possible analytical equations to provide the highest accuracy. Others use some empirical terms so that large satellite images with millions of pixels, each representing a spectral reflectance, can be rapidly processed. A brief overview of these models follows in order from the most empirical to the most analytical.

3.5.1 QAA

The QAA (quasi-analytical algorithm) rapidly inverts $R_{rs}(\lambda)$ for only few wavelengths (Lee et al. 2002). By a series of empirical models and analytical steps, the QAA model calculates $a(440)$, $a(555)$, and $b_{bp}(\lambda)$. Using an equation to estimate the transmittance across the air water interface, internal reflectance and the ratio of upwelling irradiance to radiance, the above water remote sensing reflectance is converted to a below
water irradiance reflectance ($r_{rs}(\lambda)$). The $r_{rs}(\lambda)$ is related to the ratio of backscattering to the sum of backscattering and absorption ($u$) through an empirical equation (Gordon et al. 1988). This equation is solved for $u$ as a function of $r_{rs}(\lambda)$. The empirical algorithms are used to initialize the model by estimating $a(555)$ and the spectral coefficient of backscattering. The $a(555)$ value is then used to semi-analytically calculate $bbp(555)$ using the $u(555)$ value. With the $bbp(555)$ value determined, the $u(555)$ can be used to solve for $a(555)$. This approach can be repeated for as many wavelengths as needed. The model includes a technique for separating the $a(\lambda)$ value into its components.

The QAA model was in the process of being published during this study. Since this model was added last to the analyses, only the values of 440 nm, 555 nm, and $bbp(\lambda)$ were included in the study. The techniques for de-convolving the $a(\lambda)$ into $a_{ph}(\lambda)$ and $a_{g}(\lambda)$ were not yet settled, as noted in personal communication from the author of the model. In addition, adding a third $R_{rs}(\lambda)$ inversion model for $a_{ph}(\lambda)$ may have weighted the statistical comparison towards the $R_{rs}(\lambda)$ inversions. Therefore, this model was used solely as originally communicated and recent changes in it were not included in this study.

3.5.2 MODIS

The MODIS algorithm (Carder et al. 2004) is a combination of empirical and analytical equations. The $a_{ph}(\lambda)$ factors for the equations are determined from a lookup table set for the specific conditions. The sea surface temperature is used to determine whether the pigment absorption portion of the algorithm uses parameters for packaged self-shading or unpackaged phytoplankton pigments. The term $bbp(\lambda)/Q$ is empirically determined as a function of $R_{rs}(\lambda)$ values. The $a_{ph}(\lambda)$ is determined through a hyperbolic tangent function using $a_{ph}(675)$ with empirical factors for each wavelength and packaging case. Equation 3.1 with an estimated $a_{g}(\lambda)$ coefficient is used as a function of $a_{g}(400)$. The IOP values are now defined with $a_{ph}(675)$ and $a_{g}(400)$ as the two unknowns.

Ratios of $R_{rs}(\lambda)$ are used to solve for the two unknown values. The model makes the assumption that $bbp(\lambda)$ is small for most conditions and can be ignored in the denominator of equation 3.2 since it would have little effect on that ratio. The "C" in equation 3.2 is assumed to be constant across each wavelength and divides out. The resulting ratios can then be used to determine $a_{ph}(675)$ and $a_{g}(400)$ algebraically. When the modeled chlorophyll absorption value is too high to use this method, the model switches to an empirical algorithm. This results in a simple, computationally rapid model.

3.5.3. Optimization Model

The $R_{rs}(\lambda)$ inversion algorithm by Lee et al. 1999 is the most detailed and analytical. It is the only model that compensates for the bottom albedo in shallow water. The basic formulation of the model is the sum of the reflectance due to the water column
and the reflectance due to light reflected from the bottom. If the bottom contribution is not significant, a deep-water model is used instead.

This model uses a single parameter model for phytoplankton absorption at each wavelength (Equation 3.3).

\[
a_{\phi}(\lambda) = [a_0(\lambda) + a_1(\lambda) \times \ln(P)] \times P
\]

Equation 3.3

The parameters \(a_0(\lambda)\) and \(a_1(\lambda)\) are determined for each area by a curve fit to the natural log of the ratio of \(a_{\phi}(440)\) to \(a_{\phi}(\lambda)\) at each wavelength versus the \(a_{\phi}(\lambda)\) at each wavelength. The filter pad absorption data from the CoBOP 00, West Florida Shelf, and the Friday Harbor cruises were used to determine the parameters for each of these regions. Equation 3.1 models the absorption due to dissolved organic matter. Back scattering is modeled by the equation from the MODIS algorithm (Equation 3.4).

\[
b_{bp}(\lambda) = X \left(\frac{400}{\lambda}\right)^Y
\]

Equation 3.4

The \(Y\) coefficient for Equation 3.4 is estimated by an empirical relationship with the ratio of \(R_{rs}(440)\) to \(R_{rs}(490)\). Equation 3.1 was used to model the \(a_{d}(\lambda)\) by iterating the \(a_{d}(440)\) value with a slope coefficient (s) of 0.018. The known values for the absorption due to water (\(a_w(\lambda)\)) from Pope and Fry (1997) and back scattering due to water (b_{bw}(\lambda)) from Morel (1974) are used for those terms. The total absorption coefficient for the model was calculated by summing all the modeled constituents (Equation 3.5):

\[
a(\lambda) = a_w(\lambda) + a_\phi(\lambda) + a_{d}(\lambda)
\]

Equation 3.5

The total back scattering coefficient (b_{bp}(\lambda)) was calculated by summing b_{bp}(\lambda) and b_{bw}(\lambda). The resulting a(\lambda) and b_{bp}(\lambda) are inserted into equations that take into account the transfer across the air-water interface, path length elongation, bottom reflectance, and conversion from \(r_{\phi}(\lambda)\) to \(R_{rs}(\lambda)\) (Q factor). The bottom reflectance equation introduces parameters of bottom depth (H) and a factor (X) for the bottom reflectance. The bottom reflectance shape curve is selected based on a white sand curve. The measured \(R_{rs}(\lambda)\) curve is corrected with an offset (\(\Delta\)) to take into account errors due to environmental conditions such as sun glint and cloud reflectance in the measurement. Combining all the terms gives a very complex equation that is computationally intensive and requires more \textit{a priori} knowledge but usually gives the most accurate inversions.

The six unknown parameters (\(a_{\phi}(440)\), \(a_{d}(440)\), X, H, b_{bp}(550), and \(\Delta\)) are iterated to minimize the difference in the RMS error between the measured and modeled \(R_{rs}(\lambda)\). If the model results in a bottom reflectance that is greater than 20% of the total irradiance reflectance, then the model is iterated a second time. If after the first iteration,
the irradiance reflectance from the bottom is not above 20% of the total irradiance reflectance, the model is reset and iterated using an equation that doesn't include the terms for the bottom reflectance.

Unlike the QAA model this model was changed several times throughout this research and the changes were adopted so as to present the most complete analytical model for \( R_{rs} \) inversions. One of these changes to the deep water \( r_{rs}(\lambda) \) "g" factor involved the partitioning of it into effects due to molecular backscattering and particulate backscattering (Lee and Carder 2002, Lee et al. 2004).

3.6. \( K_d(\lambda) \) inversions

The \( K_d \) optimization algorithm is the most complex of the three models and originated from this research. The development of this algorithm was based on a similar approach as that used for the \( R_{rs} \) optimization algorithm. While a \( K_d(\lambda) \) measurement does not have as long of a path length as a \( R_{rs}(\lambda) \), it is very sensitive to absorption and has little influence from bottom reflectance. The order of the three models presented will proceed from most empirical to most analytical.

3.6.1. Kirk

The factors used to invert \( K_d(\lambda) \) to get \( a(\lambda) \) from the Kirk empirical model were formulated from a series of Monte-Carlo runs (Kirk 1991).

$$ a(\lambda) = \frac{K_d(\lambda) \mu_w}{\left[ 1 + (g_1 \mu_w - g_2) \frac{b(440)}{a(440)} \right]^{0.5}} $$

Equation 3.6

The \( \mu_w \) is calculated using Snell's law. The "g" factors correspond to path-length-elongation factors from model runs based on phase functions from San Diego Harbor (Petzold 1972). Their values are \( g_1 = 0.425 \) and \( g_2 = 0.19 \). The \( b/a \) ratio is assumed to be 2.8 based on the mean ratios of ac-9 measurements used in this study.

3.6.2. Loisel

The Loisel Model is an empirical model that uses the below water irradiance reflectance and diffuse attenuation to calculate absorption (Loisel et al. 2001). Since \( R(\lambda) \) was not collected in this study, it was calculated by the method of Carder et al. (1999) using the above water \( R_{rs}(\lambda) \) and a Q factor of 3.9 sr (Morel and Gentili 1993).

$$ a(\lambda) = \frac{(K_d(\lambda)\mu_w)}{\left[ 1 + \left[ 2.54 - 6.54 \mu_w + 19.89 \mu_w^2 \right] \left( \frac{R(\lambda)}{(1 - R(\lambda))} \right) \right]^{0.5}} $$

Equation 3.7
\[ R(\lambda) = \frac{3.9 \cdot R_{\nu}(\lambda)}{(0.52 + 1.7 \cdot R_{\nu}(\lambda))} \]  

Equation 3.8

\( K_d(\lambda) \) is the value calculated from the Spectrix below-water irradiance sensor without normalization. The \( \mu_w \) is the subsurface average cosine calculated using Snell’s law. This model can also determine \( b(\lambda) \) and \( b_0(\lambda) \) but since it relies on the below water reflectance and was not designed to work in the shallow waters with high bottom reflectance, it was only used to determine \( a_{nw}(\lambda) \) in this study.

### 3.6.3. \( K_d \) Optimization

The \( K_d(\lambda) \) optimization model is a combination of several other models and is solved with an iterative process using the solver function in an Excel spreadsheet. The goal of this model is to use a common oceanographic measurement and known relationships between AOPs and IOPs to determine hyperspectral depth profiles of IOP values.

The diffuse attenuation coefficients are normalized to a black sky and sun at zenith by using the correction factors of Gordon (1989).

\[ F \approx \frac{E_d(sun)}{E_d(sun) + E_d(sky)} \]  

Equation 3.9

The symbol "F" is the fraction of direct sunlight in the incident radiation. \( E_d(sun) \) and \( E_d(sky) \) are both obtained from the output of the Radtran solar irradiance model (Gregg and Carder 1990). The angle of the incident radiation below the sea surface is calculated using Snell’s law.

\[ \theta_{sw} = \sin^{-1}\left(\frac{\sin \theta_s}{1.34}\right) \]  

Equation 3.10

The symbol \( \theta_{sw} \) is the angle below the surface and \( \theta_s \) is the above surface angle. A normalization factor (\( D_0 \)) can then be calculated for \( K_d \) at each wavelength converting it to an approximate value for the sun at zenith and black sky.

\[ D_0 = \frac{F}{\cos \theta_{sw}} + 1.197(1 - F) \]  

Equation 3.11

The \( K_d(\text{normalized}) \) is calculated by dividing the \( K_d(\text{measured}) \) by \( D_0 \).

A modeled \( K_d(\lambda) \) for comparison to the \( K_d(\lambda) \) normalized is calculated by Preisendorfer’s equation (Preisendorfer 1961).
\[ K_d(\lambda) = \frac{a(\lambda)}{\mu_d(\lambda)} + \frac{b_h(\lambda)}{\mu_d(\lambda)} - \frac{b_b(\lambda)}{\mu_u(\lambda)} R(\lambda) \]  

Equation 3.12

The \( a_{bg}(\lambda) \), \( a_{ph}(\lambda) \), and \( b_{pp}(\lambda) \) are modeled by the same method used in the \( R_{ss}(\lambda) \) optimization model (Equations 3.1, 3.3, and 3.4 respectively). The \( a_w(\lambda) \) is adjusted for \textit{in situ} temperature differences from the values measured by Pope and Fry (1997) using the correction coefficients determined by Pegau et al. (1997). The average cosine due to scattering (\( \mu_{ws}(\lambda) \)) of upwelling irradiance and is allowed to vary in the iterative process, is limited to values between 0.35 and 0.5 in value (Kirk 1994), and assumed to be constant across all wavelengths.

The average cosine of downwelling irradiance due to scattering (\( \mu_{ds}(\lambda) \)) is determined by iteration and varied spectrally by an empirical equation. Gordon's normalization theoretically removes the effects of the sun angle, diffuse sky light, and refraction on the \( K_d(\lambda) \) value. The \( \mu_{ds}(\lambda) \) values in Preisendorfer's (1961) equation should equal a column-integrated average cosine of scattering in the forward direction (\( \mu_{ds}(\lambda) \)) after the light field effects are removed by Gordon's (1969) normalization. Ratios of \( b_{bp}(\lambda) \) to \( b_p(\lambda) \) were calculated using integrated \textit{in situ} values from the study sites at wavelengths from 400 to 700 nm at 50 nm increments. The ratios were used in an inversion of the Heneyy-Greenstein (1941) phase function to determine the average cosine of scattering in the forward direction. The resulting \( \mu_{ds}(\lambda) \) values were close to linear versus wavelength over the 400 to 700 nm range allowing a linear regression model to estimate its value. The regressions have a correlation of -0.95 between \( \mu_{ds}(\lambda) \) and wavelength. Values of -0.000025 for the slope and 0.95 for the intercept were used to initialize the iterative model.

Absorption values were initialized at 440 nm by using Kirk's (1981) empirical model (Kirk 1981). Kruskal-Wallis (Zar 1994) statistical comparisons between Kirk's model and other methods and models for determining \( a_{nw}(440) \) showed that it was statistically the same. Under certain environmental conditions, Kirk's model was found to produce overestimates. A test of the Kirk \( a(\lambda) \) result was determined by subtracting the quotient of the normalized \( K_d(440) \) value as divided by an assumed \( \mu_{ds}(\lambda) \) of 0.95. If the result was greater than zero, the initial value of \( a_{ph}(440) \) was estimated at 50% of the \( a_{nw}(440) \) value from Kirk's model. If the value was less than \( 0 \), 40% of the value from Kirk's model was used. If this was not done, the model would occasionally iterate to a local minimum. The initial value of \( a_{bg}(440) \) was estimated as being equal to the \( a_{ph}(440) \) initial value.

The influence of the final set of terms in Equation 3.12 (-\( R(\lambda) b_b(\lambda)/\mu_u(\lambda) \)) is very small on the overall model and could possibly be ignored. Including it does improve accuracy of the model especially in highly scattering waters. The \( R(\lambda) \) is estimated by using the values of \( b_b(\lambda) \) and \( a(\lambda) \) from the inversion and entering them into the equation
for deep $r_s(\lambda)$ from Lee et al. (1999) and converting the $r_s(\lambda)$ to irradiance reflectance using a Q factor (Morel and Gentili 1993, Equation 3.12).

$$R(\lambda) = \left(0.336 + 0.68 \left(\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}\right)\right) \left(\frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}\right)$$

Equation 3.13

The backscattering coefficient can be determined by solving for it analytically. To smooth out measurement noise, $K_d(500)$ and $a(500)$ are binned over a 10 nm range. An estimate of $b_b(500)$ is determined by assuming that the last term in Preseindorfer’s (1961) equation (Equation 2.9) is small in value relative to $b_b(500)$, and by subtracting the $a(500)$ from $K_d(500)/\bar{\mu}_d(500)$. The estimated $b_b(500)$ is then inserted into Equation 3.13 to estimate $R(500)$. Since all other terms are now known, $b_b(500)$ can be determined using Preisendorfer’s equation as a function of the three iterated values. The $b_{bp}(500)$ value is calculated by removing $b_{bw}(500)$. This eliminates the need for iterating $b_b(500)$ and adding another source of error in the model.

By solving for $b_{bp}(\lambda)$ at another wavelength and applying the power function equation for $b_{bp}(\lambda)$ (Equation 2.4), it would theoretically determine the coefficient for $b_{bp}(\lambda)$. However, the spectral $K_d(\lambda)$ values would have to be much more accurate than those in this study. Attempts to do an analytical solution resulted in unrealistic values for some stations. The $b_{bp}(\lambda)$ $Y$ coefficient is instead iterated over an expected range of 0 to 2.

The optimization involved minimizing the sum of the absolute value of the measured minus modeled values divided by the modeled values for 400 nm to the lowest error longer wavelength. The lowest error upper wavelength was determined by taking the percent difference between the normalized $K_d(\lambda)$ and $a_\infty(\lambda)/\bar{\mu}_{ds}(\lambda)$ for wavelengths greater than 600 nm. Above 600 nm, $K_d(\lambda)$ is dominated by the absorption due to water. This also results in low signal-to-noise ratios if there are not a significant number of measurements in the upper 5 meters of the water column. If the percent difference was greater than 10%, the wavelength is set as maximum wavelength for the curve fit. This allowed the model to use the largest number of wavelengths to get the best fit.

The iterations were calculated using the solver routine in Microsoft Excel but this model could be used with other iterative code such as in Matlab. Using the macro feature of the spreadsheet the entire data set could be processed automatically. The values iterated were $a_{ph}(\lambda)$, $a_g(440)$, $Y$, $\bar{\mu}_{us}(\lambda)$, the $\bar{\mu}_{ds}(\lambda)$ slope, and the $\bar{\mu}_{ds}(\lambda)$ intercept. The coefficient for $a_\infty(\lambda)$ was iterated through a Visual Basic macro that tested the fit of the modeled $K_d(\lambda)$ using 3 different coefficients. If the percent error was lowest for the median coefficient, it was selected. If the percent error was lowest for the higher or lower coefficient, it was set as the median and the testing repeated. Testing continued until the median value had lowest percent error or a limit was reached. Improvements to this model along with better measurement techniques could eventually eliminate several more of the iterated variables.
3.7. Note on recent progresses in instruments and algorithms

Most of the instruments and models represented the state of the art for optical oceanography at the beginning of this study but because of the rapid change in technology and advancements in understanding of ocean optics, they will likely not be state of the art at the time of this study's publication. The best approach is to use these references as a starting point and go forward from there. However, the latest method or model has yet to go through the rigorous testing that these have been through and may have some faults not yet revealed. It is hoped that the testing performed in this study can act as an approach for testing of the next advancement in optical oceanography measurement or modeling.
4.0 Statistical Methods

4.1. The Unbiased Approach

The approach to optical closure as discussed in the background chapter can vary depending on the objective of the oceanographer. Some are testing their models. Others are comparing instruments. Most are comparing an instrument or algorithm against some commonly accepted optical measurement method. The objective of closure in this study is to determine which method gives the best result under different conditions. No method or model is assumed to be the absolute truth but all are assumed to be close to the truth. By using this method, the results should be more objective than the common approach.

Bias towards a particular instrument or algorithm can potentially influence a researcher's interpretation of the results. This bias sometimes results in the cliché, "You can make anything true with statistics". Actually nothing can be further from the truth. Statistics are simply a mathematic formula and if applied correctly according to mathematically proven methods, they can provide a wealth of information about a data set. The "lies" occur when the statistics are incorrectly applied or the input data set is manipulated to bias it towards one particular outcome. This "lie" is a failure of the researcher and not the statistics. It is like blaming a hammer because the nail was bent.

The statistics are fairly complex so the methods in this section will cover the approach in some detail. Unless otherwise noted, all statistical methods were taken from Zar (1994). All the processing of the statistics was through the Matlab programming language. If Matlab did not have a required statistical method, the method was coded into Mat Lab and debugged using the example data given for the particular method in Zar (1994).

The results following the statistics are presented primarily in graph form. After the initial testing to determine the proper numerical filters based on environmental conditions, the results will be presented by IOP and filter type. The first filter under absorption and the first filter under backscattering will have a detailed analysis of the results. The rest of the sections will have a page summary only mentioning the major observations for each IOP and filter type. The tables of results and statistics are given in the appendix.
4.2. Interpolation and Integration

The IOP values derived from the hyperspectral instruments and methods were spectrally binned to match the wavelengths of the instrument with the lowest spectral resolution. For the absorption values the ac-9 wavelengths of 412, 440, 488, 510, 532, 555, 650, and 676 were used. These wavelengths correspond to those measured by ocean color satellites and the important chlorophyll a absorption peaks.

The center bandwidths for MODIS $a_{\text{ph}}(\lambda)$ values required some interpolation to match the ac-9 wavelengths. The MODIS algorithm derives the $a_g(400)$ value and uses a constant coefficient so Equation 3.1 could be used to calculate a value at any wavelength. However, output for the MODIS algorithm for $a_{\text{ph}}$ is at 412, 443, 490, 510, 555, and 675 nm so it involved only a slight linear interpolation from 443 to 440 nm, 490 to 488 nm, and 675 to 676 nm. This interpolation resulted in slightly better agreement for the MODIS $a_{\text{nw}}(\lambda)$ with the other methods. MODIS $a_{\text{ph}}(\lambda)$ were interpolated to 532 and 650 nm and that interpolation may lead to some error for $a_{\text{ph}}(\lambda)$ and $a_{\text{nw}}(\lambda)$ at those wavelengths since these interpolations were more than a just a few nanometers. An $a_{\text{ph}}(750)$ of zero was added to the data set to aid in the interpolation fit. A Matlab routine using a 4th-order polynomial fit interpolated the $a_{\text{ph}}(532)$ and $a_{\text{ph}}(650)$ values for each MODIS output. This interpolation of MODIS values improves the statistical comparison between it and the other methods by putting all the values at consistent wavelengths.

The $b_{\text{bp}}(\lambda)$ values are compared at the Hydroscat-6 wavelengths. The Hydroscat-6 provides the only in situ measurement of $b_b(\lambda)$ and has measurements at 442, 488, 532, 555, 620, and 675 nm. The models use a power function to spectrally model $b_{\text{bp}}(\lambda)$ so extrapolation to the Hydroscat-6 wavelengths will not require any interpolation. The three $R_{rs}(\lambda)$ inversions all use a similar approach to modeling $b_{\text{bp}}(\lambda)$ so the $R_{rs}$ inversions $b_{\text{bp}}(\lambda)$ values may be similar in results. $K_d(\lambda)$ optimization is expected to have the most error since $b_{\text{bp}}(\lambda)$ is a small contribution to the signal compared to $a_{\text{nw}}(\lambda)$.

The $a_{\text{nw}}(\lambda)$, $a_g(\lambda)$, and $b_{\text{bp}}(\lambda)$ from the depth profiles by the in situ instruments had to be integrated over depth weighted to $K_d(\lambda)$ to compare the values from the $R_{rs}(\lambda)$ and $K_d(\lambda)$ inversions. According to the Beer-Lambert law, light intensity will decline logarithmically as it passes through a material. A simple mean of the IOPs values will not work because the contribution by IOP values near the surface should have a higher weight for their absorption and scattering values. Light is absorbed near the surface so there is less light at depth than at the surface. Less light at depth means less to be scattered back towards the surface. Once the light is scattered back towards the surface, it takes a longer path, increasing its chances of being absorbed as it passes back through the surface layer.

The equation assumes that the downwelling diffuse attenuation is close to the value of upwelling diffuse attenuation (Equation 4.1). The path is assumed to be double the change in depth (dz) since the light travels down to that depth then returns upward.
The IOP value \((a)\) is integrated to one attenuation depth \((1/K_d(\lambda))\) because about 90\% of the contribution to the \(R_{rs}(\lambda)\) signal comes from this depth (Gordon and McLuney 1975). Unless the IOP properties are constant over depth, integration with weighting to the diffuse attenuation coefficient better represents the value returned from an \(R_{rs}(\lambda)\) or water column \(K_d(\lambda)\) inversion algorithm (Smith 1981, Banard et al. 1999, Ivey et al. 2002).

### 4.3. Statistical Tools

Since statistics is a box of tools that can be easily misapplied, it is important to first access what is required. This study is comparing separate populations of data and not trying to determine something about a larger population based on a sample. The first task is to see whether the results of the different instruments and algorithms are statistically similar and when they are not similar, to determine what environmental conditions cause these differences. The next goal is to determine what is closest to the actual value for each IOP. Finally the algorithms and models will be compared to this "ideal" value and analyzed for the conditions where they agree and disagree. The method or model that gets closest to the "ideal" value for given environmental parameters at a given wavelength is judged to be the best method under those conditions.

One objective of this analysis is to avoid preconceptions about the methods and where they may be affected by different environmental parameters. However, data collected that were less than 0 in value were obviously not real data. Negative absorption or backscattering values are not possible. Any values less than or equal to zero were assumed to be due to an error in the measurement or model. To include these data could also cause errors in the statistical calculations. A filter was first used before each statistical test to remove these values. Since these values represent an error for that particular method, they had to be accounted for. Failure to account for outliers would make a method that produced erroneous value under certain conditions appear more accurate than it should. Each value removed was added to a calculation of the percent outliers for each method under the tested filter and wavelength.

Parametric statistics are more powerful than nonparametric statistics but cannot be applied if a set of data is not normally distributed or transformable to a normal distribution. To select the right statistical tool, a test for normality was required. The D’Augustino and Pearson \(K^2\) statistic combines tests for kurtosis and symmetry resulting in a Chi square value that can indicate normality (Zar 1994). Most of the histograms of
IOP values tended to be extremely peaked at one area and skewed towards the lower range values. The testing of the IOP output values from the different methods at the study wavelengths determined that they did not have a normal distribution. Therefore, the Kruskal-Wallis rank sum test with pair wise comparison was determined to be the best nonparametric test to inter-compare the different values (Zar 1994).

4.4. Determining the Filters

Solar zenith angle, cloud coverage, and significant bottom reflectance are external factors that can affect an AOP measurement. Sea surface conditions and sun glint can also contribute to errors in AOP measurements but are difficult to quantify. For this reason, this study will focus on the affects of the prior three conditions to filter the results so that the model inversions are compared in fair manner. Absolutely perfect conditions for AOP measurements are cloudless skies, solar zenith angles less than 45° (but not high enough to result in sun glint), low attenuation waters, and no bottom reflectance. If the stations in this study were filtered to perfect conditions there would not be enough measurements to have a valid statistical comparison. To determine the maximum acceptable solar zenith angle, cloud cover, and bottom contributions, a series of comparisons were performed for $a_{aw}(\lambda)$ and $b_{bbp}(\lambda)$ using the Kruskal-Wallis nonparametric test. The steps for determining the proper filters are listed in Figure 4.1.

Significant bottom contribution is well known as a problem in algorithms inverting $R_{rs}(\lambda)$ to determine IOPs (Lee et al. 1999). Of the $R_{rs}(\lambda)$ inversion methods, only the $R_{rs}(\lambda)$ optimization model includes bottom albedo as one of the inputs so bottom reflectance is expected to be a factor for the MODIS, QAA, and Kd Loisel algorithms. The bottom contribution is usually greatest in shallow clear waters such as those in the Bahamas. While the reflectance should not be a significant effect on the other methods, shallow clear waters could cause errors in $K_d(\lambda)$ inversions, as well as the ac-9 and the Hydroscat-6 measurements. Shallow waters mean that the irradiance measurements used to determine $K_d(\lambda)$ could experience more wave focusing throughout the profile. The irradiance sensor might never get to a depth where light scattering had minimized the effects of wave focusing. In very shallow water the ac-9 may have troubles clearing bubbles that can be compressed and expelled when the instrument is sent to a depth of around 30 m. Even though the source light on the Hydroscat-6 is modulated so that ambient light interference is minimized, a bright white sand bottom in the Bahamas may reflect enough light to cause some errors in its measurement. While the algorithms that include $R_{rs}(\lambda)$ as an input are expected to have the greatest problems with a significant bottom contribution, all methods and instruments will be tested for agreement under the different conditions.
Figure 4.1. Method to determine filters for bottom reflectance, cloudiness, and solar zenith angle.

Before cloudiness or solar zenith angle could be tested, it was first necessary to determine the maximum contribution from the bottom that could be tolerated and still achieve agreement among the methods. The output from the $R_{N}(\lambda)$ optimization model gives an estimated $r_{n}(\lambda)$ due to bottom reflectance. A ratio of this output to the total below-water radiance reflectance was used to filter the stations. The data were filtered to where there were 0%, <= 1% bottom, <= 5%, <= 10%, <= 20%, <= 30%, <= 50%, and > 0%.
>0% bottom contributions. The unfiltered data were also included in the test. A Kruskal-Wallis pair wise comparison ($\alpha = 0.05$) was performed to determine the best agreement among the methods. The maximum acceptable bottom percentage was based on where there was decline in agreement between the IOP results from each method.

After removing the stations where bottom contribution was significant, the next two conditions were expected to have influence on both $K_d(\lambda)$ and $R_{rs}(\lambda)$ measurements. The stations were filtered by cloudiness using less than 3%, 5%, 10%, 20%, 40%, 50%, 80%, and 100% cloudiness. Cloudiness was a subjective estimate based on a visual observation of the sky while collecting an $R_{rs}(\lambda)$ measurement. The reason that 0% was not selected is that there were only 2 stations where there were completely clear skies. The data were filtered according to solar zenith angle. Angles less than 35° were not considered since shallower angles are usually not considered to be a major problem for $R_{rs}(\lambda)$ (if sun glint is not severe) and were not expected to be a problem for $K_d(\lambda)$. However, in hindsight, filters for lower solar zenith angles probably should have been included as some errors were revealed at lower angles for some of the AOP measurements. Solar zenith angles were calculated using a formula based on the location, date, and time (Gregg and Carder 1990). The stations were filtered by less than 35°, 43°, 46°, 48°, 55°, 60°, 68°, and 90° zenith angles. Using a Kruskal-Wallis pair wise comparison with ranks ($\alpha = 0.05$), the groups of different levels of solar zenith angle and cloudiness were tested to determine agreement with each other. Based on the levels of agreement a filter was determined to remove stations that did not meet the criteria.

The IOP output data were categorized into $a_{nw}(\lambda)$, $a_g(\lambda)$, $b_{bp}(\lambda)$, and $a_{ph}$. Each IOP group was filtered for comparisons. The filters were all the data (NF); all the data with minimum bottom influence (NB); minimum bottom, low clouds, and low zenith angle (NBLCLZ); MODIS semi-analytical only with minimum bottom (MODNB); all stations with greater than 0% (BT); and greater than 0% bottom with low clouds and low zenith (BTLCLZ). The MODNB stations were selected because the MODIS algorithm in high chlorophyll waters defaults to a simple empirical algorithm instead of the iterative model. The MODIS algorithm was designed to work on large pixel per kilometer satellite images and not for high-chlorophyll near shore waters. Including the empirical values would have not been a fair test for the most effective part of the algorithm. One filter that probably should have been included was for stations where attenuation was significantly higher. The ac-9, Hydroscat-6, and laboratory spectrophotometer methods may have performed better under this filter than under the other filters. A group is defined as all the stations from a method for an IOP value (either $a_{nw}(\lambda)$, $b_{bp}(\lambda)$, $a_g(\lambda)$, or $a_{ph}(\lambda)$), at a one of the tested wavelengths, filtered to remove values less than or equal to zero, and with a filter applied to remove stations that do not meet certain environmental criteria. With the filters in place, the methods can now be compared under different environmental conditions.
4.5. Test for Normality After Applying a Log Transform

A log transform may result in normal distribution for data that has multiplicative increases in value (Zar 1994). Previous studies have presented evidence that a log normal distribution may apply to biooptical properties (Campbell 1995) for a given location and time. The primary reason for knowing a distribution for measurement values is to interpolate values with high variability over small scales to compare to data collected over larger scales. A log transform was attempted on the $a_{nw}(\lambda)$ data to determine if it would be normally distributed and allow the use of parametric statistics. Statistical testing using the D'Augustino and Pearson $K^2$ test for normality ($\alpha = 0.05$) demonstrated that much of the log-transformed data was not normally distributed. Out of 58 combinations of methods and wavelengths for $a_{nw}(\lambda)$, 29% under the NF filter, 59% under NB filter, and 72% under NBLCLZ data are normally distributed. A parametric statistic will not be valid even with a log transform for this data set. It appears that as the data set moves to more ideal conditions, the data become closer to a normal distribution with a log transform. However, even under the best conditions 28% of the data is not normally distributed so using this transform would result in comparing data with a normal distribution to those not normally distributed. The lack of normal distribution was not unexpected since the data used for this study were collected from three different areas during different seasons and years. If the data were from one area at a single time and included not just near shore data but several deep offshore transects, then a log normal distribution might be valid.

4.6. Statistical Comparisons to the Ideal Values

The Kruskal-Wallis pair-wise comparison with ranks was computed between the methods for each IOP type, filter set, and test wavelength ($\alpha = 0.05$). The results were used to determine which data at which wavelength could be used to calculate an idealized data set for each IOP type and filter. The assumption was made that no technique was better than the other. The exception was the $K_d(\lambda)$ Loisel, $K_d(\lambda)$ Kirk, $R_{ns}(\lambda)$ MODIS and $R_{ns}(\lambda)$ QAA inversion algorithms were not included for the two filters with significant bottom contribution. The Loisel, MODIS, and QAA models do not take into account significant bottom reflectance. The Kirk $K_d(\lambda)$ inversion is an empirical model that did not perform well at longer wavelengths and was left out of the $a_{nw}(\lambda)$ with bottom data because it might bias the result towards the $K_d(\lambda)$ inversions for the ideal data set. The assumption was made that, if for each group there was agreement with over 50% of the other methods in the group, then that technique was close to the actual value. If for a given wavelength there were no methods that reached the level of 50% agreement under the filter, then the methods with the highest level were selected for determining the ideal value. For each sample station in the groups that met the agreement criteria, a median value was calculated and labeled as the ideal value for that group. Because of occasional outliers due to a bad measurement or fault in an algorithm, a median is a better statistic than a mean because it does not factor in large outliers like a mean. Figure 4.2 summarizes the steps to determine the ideal value.
The idealized data for each IOP type were compared to all techniques for each wavelength and filtered subset. While some models were left out of the ideal data set calculation when bottom contribution was significant, all models were tested against the ideal data set. Regression analysis versus the ideal value was performed to determine how close each group matched the ideal line with a slope of one and an intercept near zero. The correlation coefficient was calculated for each group based on the correlation between the group and ideal data, not with the regression line.

The mean percent error and the mean absolute percent error from the ideal value were calculated. Mathematics and physics texts sometimes refer to both absolute and the non-absolute error statistics as percent error. Since both are used in this study, they will be referred to as percent error and absolute percent error. In equation (4.2) for the mean absolute percent error, \( IOP_{nj} \) is the method value, \( IOP_{ij} \) is the ideal value, and \( n \) is the
number of samples after filtering. The mean percent difference is calculated the same way except the absolute value is not taken for the difference between the method and ideal values. The use of several different statistics allowed for better determination of how each method performs under different conditions.

\[
\text{Mean Absolute Percent Error} = \left( \sum_{j=1}^{n} \left| \frac{I_{op,mj} - I_{OP,j}}{I_{OP,j}} \right| \times 100 \right) \frac{1}{n}
\]

Equation 4.2.

The percent error calculated two different ways reveals both the magnitude and direction of the difference from the ideal value. If the absolute value were not used, errors due to accuracy that are even in magnitude about the ideal value would result in an artificially low value for the percent difference. However, because there is no sign to the absolute percent difference, it is not clear whether the error is under, over, or around the actual value. In figure 4.3 a series of numbers increase linearly from 0.025 to 1 by 0.025 steps as an example of ideal data. If 10% error occurs in evenly in both positive and negative directions (Figure 4.3A), then the mean percent error is 0 but the mean absolute percent error is 10%. If the values vary evenly between a 5% overestimate and a 15% underestimate (Figure 4.3B) then the mean percent error is -5% and the absolute percent error is still 10%. This lets us know that on average this method will slightly underestimate the values and has an error of 10%. The linear regression by itself doesn't give a good idea of the overall error. The regression in Figure 4.3A results in a slope of 1 and an intercept of 0.0037 with a correlation of 0.96. This regression looks pretty good but the mean absolute percent difference gives us an error of 10%. Combining the mean percent error and mean absolute percent error gives a lot more information about agreement to the ideal value than regression analysis alone.
Figure 4.3. Examples of how combinations of mean percent error and absolute percent are used to give more information about differences from ideal values.
Determination of outliers for normally distributed data is fairly straightforward, but tests for outliers under other distributions for data can be more difficult. A test was devised to determine what stations needed to be removed from each group to achieve a match to the ideal data that was within 10% of the ideal values. The maximum and minimum slopes of the idealized IOP data for each group were calculated for variations of plus or minus 10% in the data (Figure 4.4). The stations used in the ideal group were first filtered to match the same stations in the group tested. The maximum slope was calculated assuming the maximum value of the idealized data was 10% greater and the minimum value was 10% less. Decreasing the maximum value by 10% and raising the minimum value by 10% calculated the minimum slope. The slope of each group was compared to determine if it fell within the range of slopes. If it did not, then the station with the highest absolute percent error was excluded and marked as an outlier. The slope was then recalculated and compared to the minimum and maximum slopes. This was repeated until the slope fell within range of minimum and maximum slopes. This technique allowed identification of outliers at individual stations for each group. The percentage of outliers was calculated by adding the number of rejected values to the number of negative and zero values and dividing the total by the total number of values for that group. The flow chart for this method is summarized in figure 4.5.

Figure 4.4. Example of slopes for +/- 10% of the ideal data. A) Minimum and maximum slopes are covered by +/- 10% lines. B) Enlarged section that shows the minimum and maximum slope lines (dotted) at low values.
Figure 4.5. Steps used in determination of outlier by comparison against slope values.

The absolute percent errors for each station within a group were tested for correlation with environmental factors and IOP values to determine the possible sources of error for each method under those conditions. An initial test for $a_{\text{nw}}(\lambda)$ and $b_{\text{bp}}(\lambda)$ values found that possible contributions to uncertainty were highest for chlorophyll concentration, percent cloud cover, solar zenith angle, maximum percentage bottom reflectance, $c_{\text{nw}}(440)$, and $a_{\text{nw}}(440)$. Ratios of $b_{\text{bp}}(440)/c_{\text{nw}}(440)$, $b_{\text{bp}}(440)/b_{\text{p}}(440)$, and $b_{\text{bp}}(440)/a_{\text{nw}}(440)$ were also used to help diagnose factors contributing to signals. The correlations were tested for significance using the Fisher $z$ transformation for correlation ($\alpha = 0.05$, Zar, 1994). Only the significant correlations were published in this study. Figure 4.6 provides an overview summary of the statistical method used this study to compare the different methods to the ideal values.
Data from a single method at a given wavelength

Filtered to test different conditions

Filtered to remove missing and values less than or equal to zero

Ideal values filtered to match same number stations as filtered data

Linear regression vs ideal values
- Slope
- Intercept

Correlation

Percent error
- Mean of Percent error

Absolute percent error
- Mean of absolute percent error

Correlation vs parameters for each data group

Correlation tested for significance
- Value not significant
- Value Significant

Outlier Analysis

Figure 4.6. Statistical method for analyzing study data to determine closure.
5.0 Optical Closure Results

5.1. How to Interpret Results

To aid in the presentation of the results, labels are used to represent each method. The Rrs(\(\lambda\)) optimization model (Lee et al. 1999) is referred to as Rrsopt, the Kd(\(\lambda\)) optimization model is referred to as Kdopt, the Kirk Kd(\(\lambda\)) inversion model is referred to as KdKirk (Kirk 1991), and the Loisel Kd(\(\lambda\)) inversion model is referred to as KdLoisel (Loisel et al. 2001). MODIS and QAA Rrs(\(\lambda\)) inversion results will be called MODIS and QAA. The quantitative filter pad method is referred to as Specaph, the spectrophotometric chromophoric dissolved organic absorption or CDOM measurements are referred to as Specag, and the non-water absorption value from the sum of Specaph and Specag is referred to as Spec. The 9-channel attenuation and absorption meter is referred to as ac9 and the 6 channel backscattering meter is referred to as HS6. These abbreviations should make presentation of the results less verbose and help graphics labels fit within limited space.

In examining the results of these statistical tests, there are a couple of considerations. The Kruskal-Wallis Pair-wise comparison with tied ranks (K-W) determines statistical agreement between groups. Agreement under this statistic does not always mean that it is the closest to the actual value but means that it is statistically similar to some of the other methods. For example, it is known that Rrs(\(\lambda\)) inversions are affected by bottom reflectance (Lee et al. 1998). All the Rrs(\(\lambda\)) inversions in this group use a similar approach to determine bbp(\(\lambda\)). Bottom reflectance has a similar effect on the Rrs(\(\lambda\)) curve as bbp(\(\lambda\)) since both can contribute to in Rrs(\(\lambda\)) in the 500 to 600 nm region. If all the Rrs(\(\lambda\)) inversions are overestimating bbp(\(\lambda\)) in a similar manner then they may agree with each other and have good results under the K-W test but they may not be close to the actual value. The methods that return a bbp(\(\lambda\)) value are three Rrs(\(\lambda\)) inversions, a Kd(\(\lambda\)) inversion, and the HS6. The potential for a bias by errors in Rrs(\(\lambda\)) inversions is why only Rrsopt, Kdopt, and HS6 were used to determine the ideal value for bbp(\(\lambda\)) when bottom was present. Because of potential agreement between methods with errors in the same direction, this study does not rely on only one statistic to test these methods.

The percent error term results can cause a little confusion because of the method for determining the ideal value. Only the stations with 50% or greater agreement for the combination of filter, wavelength, and IOP value are included. A median of those values was used instead of a mean. A median was necessary to minimize the influence of large outliers in a particular method for a particular station that could introduce error in the ideal value. Comparing this ideal to the actual data can result in percent difference values that would look much different than if all data were included in the ideal value and a
mean of those data were used. An even distribution about zero would be expected if the mean of all the methods was used for each station but is not expected under this statistical approach. Further complicating interpretation of these data is that a mean of the percent error values is used instead of another median. The reason a mean value of the percent error is necessary is because taking the median would result in values of zero percent error for some of the methods since their value represented the median value for over half the stations. Testing the percent error statistics shows that they are normally distributed for most groups so using a mean is not too far outside limits of statistics. The values are going to be different from the percent difference from the mean but will give more information about errors in the methods.

The outlier analysis is based solely on whether the slope is close to a slope of one. This statistical method was devised to attempt to test for outliers under a case where a normal distribution does not apply. There can still be some outliers based on the intercept. The outlier analysis should be taken with the caveat that it removes data that would cause a multiplicative error but not data that might cause a bias. The best way to look at this statistic is if the method has a low number of outliers and intercept near zero under the initial regression but a high absolute percent error, then there are probably a few really large outliers that are causing the error. If the intercept is high, outliers are low, and the absolute percent error is high then the method probably has a constant bias. The case where outliers are high but the other regression, correlation, and error statistics are good may indicate a consistent factor that causes a small error in these values. None of these statistics are definitive by themselves and all should be examined to get the complete picture.

The absolute percent error values were examined as to their correlation with certain parameters. The correlation only indicates a possible relationship between that parameter and the error. Two things must be considered when examining these results. First, a high positive correlation with a parameter does not mean a high percent error when that parameter is larger. It simply means that the source of error may be that parameter but has no indication on the magnitude of the percent error. Rssopt may have a large correlation with bottom contribution to reflectance but it may only cause a 5% change in percent error. Secondly, correlation does not mean causality. A correlation between absolute percent error and \( b_p/c_{nw}(440) \) occurred along with correlations with significant bottom contribution to reflectance. This correlation is more a factor of the shallow stations during the CoBOP cruise having a significant bottom reflectance while coincidentally having high \( a_g(\lambda) \) to \( a_{ph}(\lambda) \) ratios. The bottom reflectance is correlated with \( b_p/c_{nw}(440) \) for these regions. The correlation with causality is the increased proportion of light from these shallow bright bottoms not the \( b_p/c_{nw}(440) \) value.

While it can be stated that the magnitude of the correlation can explain that proportion of the error, the sum magnitudes of all the correlations for a given group can sometimes be above one. A correlation above 1 is because some of the parameters have interdependencies. The backscattering ratios of \( b_{bp}/a_{nw}(440) \) and \( b_{bp}/b_p(440) \) both depend on the magnitude of the backscattering so they may have similar correlations values.
Chlorophyll concentration can be a surrogate for $a_{nw}(440)$ since, generally, higher chlorophyll concentrations lead to higher $a_{ph}(440)$ values. Sometimes there are parameters that will affect all of the other methods biasing the ideal value. A large correlation between the ac9 and cloudiness or zenith angle indicates that the AOP methods are affected in the same way resulting in a possible error in the ideal value not the ac9 value at that wavelength. By examining these results there can be valuable information for improving the methods but relying just on the correlation value without examining causation and the magnitude of the percent error would not be a valid approach.

The results from each test and the discussion about those specific results are presented in this chapter. Each statistical test is followed by a discussion of the results. The first section will cover the determination of filters. The next section will cover the nonparametric tests to determine the ideal data. The comparisons to the ideal data are sectioned accord to the IOP value tested. The filters are grouped together according to similarities. The unfiltered data and bottom-filtered data are grouped together (NF and NB). The ideal AOP conditions are grouped together (NBLCLZ and MODNB) and the two filters that include only stations with significant bottom contribution are grouped (BT and BTLCLZ). The percent error correlations are presented by IOP type with a focus on major spectral correlations.

5.2. Determination of Filters Based on Bottom, Clouds, and Zenith Angle

In Figure (5.1), the ac-9, Rrsopt, KdKirk, and KdLoisel all demonstrate less agreement for $a_{nw}$ when the percent bottom reflectance is greater than 10%. The agreement in the other models does not necessarily mean that they perform better when bottom is present. It may mean that they have errors in the same direction. An indication of this is the error in the ac9 and KdKirk $a_{nw}(\lambda)$. The ac9 is not affected by bottom reflectance and only bright shallow bottoms should affect the KdKirk model. However the ac9, $a_{nw}(\lambda)$, and $K_d(\lambda)$ values may be affected by shallow clear waters. The ac9 may not be able to get deep enough to clear the small bubbles within the instrument. The downwelling irradiance sensor may not be able to get deep enough to avoid wave focusing. Since all three methods have less agreement when the bottom contribution is above 10%, the filter is set to this value. This filter was applied to the data before testing for affects of cloud cover or zenith angle.
Figure 5.1. Nonparametric statistical analysis of $a_{nw}(\lambda)$ values of each method under different levels of bottom reflectance ($\alpha = 0.05$). The left axis is the mean percent agreement of each method with the other methods averaged over all the wavelengths. The $=>0\%$ bottom contribution value represents the entire data set.

Figure 5.2. Nonparametric statistical analysis of $a_{nw}(676)$ of each method under different levels of cloudiness ($\alpha = 0.05$). The left axis is the percent agreement of each method with the other methods at 676 nm. All other wavelengths exhibited good agreement among the methods.

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The percent cloudiness has a minimum effect on \( a_{nw}(\lambda) \) at levels below 80%. This consistency resulted from an effort to only take measurements when the solar path was cloud-free. It doesn't appear to have much affect except for \( K_d(\lambda) \) inversions at longer wavelengths (Figure 5.2). At 676 nm, the KdKirk and KdLoisel exhibit a drop in agreement for cloud coverage greater than 40%. The Kdopt model also exhibited similar problems in earlier tests but changes to the model appear to have minimized those problems. The difference between 80% and 40% clouds is 10 stations so a significant number of data would be removed to benefit those two models at longer wavelengths. The filter was set for removal of stations where cloud cover was greater than 80% to retain the maximum number of reasonable data points.

Zenith angle did not exhibit any clear affect on \( a_{nw}(\lambda) \) (Fig 5.3). The biggest difference for a single angle was at 55°. However, the overall agreement exhibited improvement when all zenith angles were included. All the \( K_d(\lambda) \) inversions and the Rrsopt models included factors that took into account solar zenith angle. There is no clear reason to filter the data based on zenith angle and agreement for \( a_{nw}(\lambda) \).

![Figure 5.3](image)

Figure 5.3. Nonparametric analysis of \( a_{nw}(\lambda) \) data from each method under different solar zenith angles \((\alpha = 0.05)\). The left axis is the mean percent agreement of each method with the other methods averaged over all the wavelengths.

The percentage of bottom reflectance did have a significant effect on derived values of \( b_{bp}(\lambda) \) (Fig 5.4). A bottom contribution of 0% is best for \( b_{bp}(\lambda) \) but would result in a very small number of stations when combined with filters for both zenith angle and clouds. The smaller number of stations would lower the significance of statistical comparisons. The HS6 possibly exhibited lower agreement because it is the only method measuring \( b_{bp}(\lambda) \) that is independent of the light field. All the \( R_{rs}(\lambda) \) inversions use a
similar method to determine $b_{bp}(\lambda)$ and may have errors caused by bottom contribution that are similar in magnitude in the same direction. The low agreement by the HS6 could also be that the instrument was near its accuracy limit in very clear water while the Rrs($\lambda$) inversions still have sufficient signal due to a longer effective path length. The filter was kept at 10% maximum bottom contribution since it provided an acceptable agreement while retaining the largest number of stations.

Figure 5.4. Nonparametric statistical analysis of $b_{bp}(\lambda)$ values of each method under different levels of bottom reflectance ($\alpha = 0.05$). The left axis is the mean percent agreement of each method with the other methods for all the wavelengths.

There was no noticeable effects below 80% on $b_{bp}(\lambda)$ for cloud coverage (Figure 5.5). Kdopt and MODIS have some improvement by limiting the cloud cover to less than 5% but the number of stations when combined with the other filters was too low (18 stations) for the small gain in agreement. AOP measurements were generally collected only when the sun was not behind clouds and this technique aided in the agreement between methods. Based on this result, the filter was kept for cloud coverage less than 80%.
Figure 5.5. Nonparametric analysis of $b_{bp}(\lambda)$ data from each method under different levels of cloudiness ($\alpha = 0.05$). The left axis is the mean percent agreement of each method with the other methods averaged over all the wavelengths.

With the exception of MODIS, there is a definite drop in $b_{bp}(\lambda)$ agreement for solar zenith angles greater than $46^\circ$ (Figure 5.6). Except for the HS6 and QAA, there is no further change in $b_{bp}(\lambda)$ agreement for zeniths greater than $46^\circ$. The HS6 and QAA show a drop in agreement for zenith angles greater than $68^\circ$. However, the HS6 is the only method independent of ambient light field conditions so the agreement may be a bias in the other methods. Most $R_{rs}(\lambda)$ measurement protocols require that measurements take place when zeniths are less than $45^\circ$. Filtering for Zeniths less than $35^\circ$ leaves too few stations (21 stations) when combined with the other filters. The optimum filter was set at zeniths below $46^\circ$. 
Figure 5.6. Nonparametric analysis of $b_{bb}(\lambda)$ data from each method under different solar zenith angles ($\alpha = 0.05$). The left axis is the mean percent agreement of each method with the other methods averaged over all the wavelengths.

The data were filtered in 6 different ways to fairly test each method (Table 5.1). The total unfiltered data set is 126 stations (No Filter, NF). The no bottom-reflectance filter (No Bottom, NB) was set for bottom contributions less than 10% which resulted in 90 stations. The ideal conditions filter (No Bottom Low Clouds, Low Zenith, NBLCLZ) was set with bottom contribution less than 10%, percent cloud cover less than 80%, and solar zenith angles less than 46° resulting in 46 stations. The MODNB filter removed all the stations where MODIS switched to the empirical default algorithm and bottom contribution was less than 10% resulting in 59 stations. The next filters were set for only stations where bottom is detected based on the Rrs optimization algorithm (Bottom, BT) resulting in 49 stations. This includes even bottom contributions below 10%. The BTLCLZ (Bottom Low Clouds Low Zenith) filter used stations where bottom was present but clouds were less than 80% and solar zenith angle was less than 46° resulting in 30 stations.
Table 5.1. Acronyms for different filter groups. Book mark this page for reference regarding discussions of different filter groups.

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF</td>
<td>Unfiltered represents the entire data set</td>
</tr>
<tr>
<td>NB</td>
<td>No Bottom contribution to reflectance &gt;10%</td>
</tr>
<tr>
<td>NBLCLZ</td>
<td>NB filter + cloudiness &lt; 80% + Solar zenith &lt; 46°</td>
</tr>
<tr>
<td>MODNB</td>
<td>NB filter + MODIS uses the semi-analytical model only</td>
</tr>
<tr>
<td>BT</td>
<td>Bottom contribution to reflectance &gt; 0%</td>
</tr>
<tr>
<td>BTLCLZ</td>
<td>BT filter + cloudiness &lt; 80% + Solar zenith &lt; 46°</td>
</tr>
<tr>
<td>K-W</td>
<td>Kruskal-Wallis pair-wise comparison with tied ranks statistical test</td>
</tr>
</tbody>
</table>

5.3. Nonparametric Analysis to Determine the Ideal Data Set

Agreement between most methods was highest at the shortest wavelength for $a_n(\lambda)$ (Fig. 5.7). At 412 nm, all methods agree (only Rsopt, Kdopt, Spec and ac-9 compared under BT and BTLCLZ filters). At 440 nm, only the ac9 has agreement problems using the BT filter. At 488 nm and higher, the ac9 shows disagreement for filters NF, BT, and BTLCLZ. At 532 and 555 nm, KdKirk shows disagreement using filters NF, NB, NBLCLZ, and MODNB. At 555 nm, KdLoisel shows disagreement under filters NF and MODNB. At 650 and 676 nm, KdKirk and KdLoisel do not show agreement under filters NF, NB, NBLCLZ, and MODNB. At 650 nm, Kdopt did not show agreement under filters NF and BT. For the BT filter at 650 nm only Spec and Rsopt exhibited any agreement with each other but were below the 50% mark. Except for 650 nm under the NF and BT filters, Rsopt, MODIS, QAA, Kdopt, and the Spec have agreement above 50%. These 5 methods are best for $a_n(\lambda)$ according to the nonparametric test.

For $b_{99}(\lambda)$ Kdopt has the lowest agreement (Figure 5.8). It exhibits no agreement for NF, NB, and NBLCLZ at any wavelength. For the MODNB filter Kdopt only has agreement at 671 nm. The HS6 has the next lowest agreement. It exhibits less than 50% agreement for NF at 488 and 589 nm. The HS6 has no agreement for NB filter at 488, 532, 589, and 620 nm. For NBLCLZ the HS6 only shows no agreement at 488 nm. MODIS demonstrates no agreement for the NF filter at 589, 620, and 671 nm. Rsopt has disagreement at 589 nm under the NF filter. The QAA model does not have a problem with agreement under any of the filters. For the BT and BTLCLZ filters only the HS6, Kdopt, and Rsopt are considered since the QAA and MODIS algorithms do not take into account bottom albedo. Under the BT and BTLCLZ filters, the HS6 performs the best with the highest agreement, and no method has less than 50% agreement. The QAA is best for determining $b_{99}(\lambda)$ in deep water while the HS6 is best when there is significant bottom influence according to agreement with a majority of the other methods under the nonparametric K-W test.
Figure 5.7. Percent agreement for $a_{\text{av}}(\lambda)$ to determine ideal data. A. NF Filter, B. NB Filter, C. NBLCLZ Filter, D. MODNB Filter, E. BT Filter; and F. BTLCLZ Filter.
Figure 5.8. Percent agreement for $b_{\text{bp}}(\lambda)$ to determine ideal data. A. NF Filter, B. NB Filter, C. NBLCLZ Filter, D. MODNB Filter, E. BT Filter, and F. BTLCLZ Filter.
MODIS data agree with the majority of the other methods for $a_g(\lambda)$ under the K-W nonparametric analysis (Figure 5.9). At 412 nm, all methods agree with at least 50% of the other methods for all conditions. At 440 nm, $R_{s,opt}$ does not agree under filters NF and MODNB. At 488 nm, only the $a_{c9}$ shows disagreement under filters NBLCLZ, MODNB, and BTLCLZ. For Wavelengths 510 and greater, the $a_{c9}$ did not show agreement under any filter. At 650 nm, $R_{s,opt}$ shows disagreement for NF, MODNB, BT, and BTLCLZ. The Specag shows disagreement at 650 nm for both BT and BTLCLZ for 650 nm. At 676 nm, only $K_{d,opt}$ shows agreement with 50% of the methods for filter NF. $R_{s,opt}$ shows disagreement at 676 nm for filters NF, NB, MODNB, and BT. The Specag also shows disagreement for BT at 676 nm. MODIS is the best method under this nonparametric analysis, only failing to agree with 50% or more of the methods at 676 nm under filter NF. MODIS was only method not tested using the BT and BTLCLZ filters where $K_{d,opt}$ did the best.

$K_{d,opt}$ has the worst agreement for $a_{ph}(\lambda)$ (Figure 5.10). Under filter NF, $K_{d,opt}$ shows disagreement for 440, 488, and 510 nm. However, under filter NB, $K_{d,opt}$ only shows disagreement at 676 nm. Under MODNB, $K_{d,opt}$ shows disagreement at 440, 488, 510, 532, and 676 nm. Under BT and BTLCLZ filters, $K_{d,opt}$ shows disagreement at 412, 440, 488, and 510 nm. $R_{s,opt}$ has the second most disagreements. It exhibits disagreements at 440 and 555 under the MODNB filter. $R_{s,opt}$ also has disagreements at 650 nm for filters NF, NB, NBLCLZ, and MODNB. MODIS only has disagreements at 555 nm for MODNB and 676 nm for NF. At 412 nm under the NF and MODNB filters for NF none of the methods reached 50% all four methods tied at agreement with one other method. Specaph shows no disagreement except for 412 nm under the NF and MODNB filters, making it the best method under the K-W statistic.

Based on the results from the K-W test, an ideal data set was created by taking the median value of the methods that have agreement of 50% or more at a given wavelength and filter. There were 3 cases out of 180 where no method reached the 50% or greater mark where those with the highest value of agreement were used. This data set was compared to the different methods using statistical techniques of linear regression, correlation, and percent error, and outlier analysis. Before comparing the methods to the ideal, the results from the K-W nonparametric test bear further examination. This test can provide some evidence about which method is best under the different filters. However, the K-W test should not be considered conclusive about which method is best because it only tests agreement based on ranks not the actual values.
Figure 5.9. Percent agreement for $a_0(\lambda)$ to determine ideal data. A. NF Filter, B. NB Filter, C. NBLCLZ Filter, D. MODNB Filter, E. BT Filter, and F. BTLCLZ Filter.
Figure 5.10. Percent agreement for $a_{ph}(\lambda)$ to determine ideal data. A. NF Filter, B. NB Filter, C. NBLCLZ Filter, D. MODNB Filter, E. BT Filter, and F. BTLCLZ Filter.
5.3.1. K-W Nonparametric Analysis of $a_{nw}(\lambda)$

Path length of the measurement was key for best performance for determining $a_{nw}(\lambda)$. The K-W nonparametric statistical analysis showed that the ac-9 did poorly for $a_{nw}(\lambda)$ for wavelengths greater than 488 nm. With the exception of the Puget Sound data and some near shore West Florida shelf data, most of the areas in this study had low absorption values. The ac-9 had problems where the signal to noise was lower in the longer wavelengths because of its shorter path length.

The $K_d(\lambda)$ optimization method performed best where bottom reflectance was not significant (NB, NBLCLZ, and MODNB). The processing of the $E_d(\lambda)$ values to get $K_d(\lambda)$ involved using a third order polynomial curve fit to aid in reducing the effects of wave focusing. As depth increased, wave focusing became less of a problem due to scattering by the constituents in the water column. In a shallow water column it was not easy to get to depths where wave focusing was low and mixing of rays from more wave facets in view. This led to spectral inaccuracies in the $K_d(\lambda)$ curve.

MODIS performed best for the unfiltered (NF) data set. MODIS uses fewer optimizations to determine $a_{nw}(\lambda)$ than the $R_{rs}(\lambda)$ Optimization method. The lower number of iterations and fewer variables iterated by the MODIS algorithm keep it from getting stuck in local minima as can occur under the $K_d(\lambda)$ and $R_{rs}(\lambda)$ optimization algorithms (Chen et al. 2004). Cloudiness and zenith angle can affect the other methods by giving spectral errors that emulate CDOM absorption, backscattering, or bottom albedo. MODIS locks $b_{bbp}(\lambda)$ at a fixed ratio to $R_{rs}(550)$ and uses fewer iterations, preventing it from getting stuck at an erroneous value. The addition of the new method of using a higher CDOM spectral coefficient to determine the initial values followed by a lower coefficient to calculate $a_{g}(\lambda)$ was hypothesized to compensate for CDOM fluorescence. The change may have aided the agreement of MODIS under the less than ideal conditions.

With significant bottom reflectance the results for $a_{nw}(\lambda)$ were mixed under the K-W nonparametric analysis. The spectrophotometric methods did best under non-ideal conditions, besting $R_{rs opt}$ at 440 nm. The $R_{rs}(\lambda)$ optimization algorithm fared best when under ideal conditions with significant bottom contribution, besting the spectrophotometric method only at 412 nm. However, when inverting to achieve spectral bottom albedos (details in chapter 7), the $K_d(\lambda)$ optimization method $a_{nw}(\lambda)$ produced the best result. With the exception of 650 nm under the BT filter, $K_{d opt}$ had agreement with at least 50% of the other methods.

Almost all of the ideal conditions were from the COBOP cruises where there was low absorption and the bottom was white sand. This clear water and white sand possibly improved the inversion for $a_{nw}(\lambda)$ using $R_{rs}(\lambda)$ optimization. The bottom reflectance would be very dominant in these $R_{rs}(\lambda)$ scans from the Bahamas and the input bottom
albedo would most resemble that of the white sand albedo used in the $R_{rs}(\lambda)$ optimization models. The spectrophotometric method does better under conditions of high bottom reflectance since there is usually a higher signal to noise ratio closer to shore and the water column is usually well mixed. The spectrophotometric methods were affected more using the other filters since Spec represents a sample from only a near surface depth. The other methods represent an integrated value of the water column optical properties. If there are changes in optical properties near the surface then the other methods may reflect these while the spectrophotometric methods will not. With significant bottom reflectance, $R_{rs}(\lambda)$ optimization and the spectrophotometric methods were best according to the K-W nonparametric statistics but the $K_d(\lambda)$ optimization provided the best results when using Hydrolight runs to determine bottom albedo.

5.3.2. K-W Nonparametric Analysis of $bbp(\lambda)$

There are only 5 methods for determining $bbp(\lambda)$ in this study. All of the $R_{rs}(\lambda)$ inversions have $bbp(\lambda)$ as an output, the $K_d(\lambda)$ optimization algorithm outputs $bbp(\lambda)$, and the Hydroscat-6 gives a more direct measurement of $bbp(\lambda)$. All the $R_{rs}(\lambda)$ inversion algorithms use similar empirical approaches for determining the spectral shape of the $bbp(\lambda)$ curve. The intercept value for $bbp(\lambda)$ is determined iteratively by the Rrs-opt and QAA but empirically by MODIS. The proportion of the contribution by $bbp(\lambda)$ to the $K_d(\lambda)$ value (about 5%) is much smaller than to the $R_{rs}(\lambda)$ value. If the $K_d(\lambda)$ measurements were perfect, then it should produce a good inversion of $bbp(\lambda)$. However, with such a small contribution by $bbp(\lambda)$ along with sources of error in the $K_d(\lambda)$, it means the $K_d(\lambda)$ inversion is the least reliable of the group. The HS6 measures $\beta(\lambda)$ at 140° and then empirically determines the total value by assuming that $bbp(\lambda)$ is 8% greater than a hemispheric integration of the $\beta(\lambda,140^\circ)$. While this method is close to the actual value, the instrument also has an accuracy that can limit it in very clear waters. Of the 5 methods, the $R_{rs}(\lambda)$ inversions should have the best signal-to-noise ratio in deep low attenuation waters due to the long path length of light in an $R_{rs}(\lambda)$ value, but the Hydroscat-6 should be better in more turbid waters and those with bottom influence.

The nonparametric tests show that $R_{rs}(\lambda)$ optimization and QAA produce similar results under conditions with low bottom influence. Both methods use similar approaches to determine $bbp(\lambda)$. This agreement may indicate that they will bias the median $bbp(\lambda)$ ideal value favoring an $R_{rs}(\lambda)$ inversion. This potential bias may make the statistical comparisons with the idealized $bbp(\lambda)$ value not as valid. However, the $R_{rs}(\lambda)$ measurements do have the longest path length so they are probably the most accurate under conditions without significant bottom reflectance.

Under the filters that included only bottom contribution to reflectance, only the $R_{rs}(\lambda)$ optimization, $K_d(\lambda)$ optimization, and Hydroscat-6 were compared using the Kruskal-Wallis analysis for $bbp(\lambda)$ values. All three methods agreed when all conditions were included. Under the ideal conditions including bottom reflectance (BTLCLZ), only the Hydroscat-6 agreed with all the others. This agreement may mean that the HS6 value
was centered between the $K_{dopt}$ and $R_{s\text{sopt}}$ values. Under the BTLCLZ filter, more bottom reflectance is present in the $R_{s\text{n}}(\lambda)$ measurement since more direct sunlight has a greater penetration to depth. The bottom albedo would be more likely to influence the $R_{s\text{n}}(\lambda)$ optimization routine affecting $b_{\text{bbp}}(\lambda)$ during the inversion. While the $R_{s\text{n}}(\lambda)$ optimization generally does better due to a longer path in deep water, the Hydrosocat-6 is best for shallow water according to this test.

### 5.3.3. K-W Nonparametric Analysis $a_g(\lambda)$

MODIS performed best for determining $a_g(\lambda)$ under most filters in the K-W nonparametric tests when there was not a bottom present. MODIS, for this test, uses a higher CDOM slope coefficient for the initial iterations to invert $a_{\text{sw}}(\lambda)$ in presence of CDOM fluorescence (Carder et al. 2006). When the final $a_{\text{sw}}(\lambda)$ and $a_g(\lambda)$ were calculated, MODIS used a lower coefficient that is closer to the slope coefficient for a coastal $a_g(\lambda)$ spectra. Bottom reflectance appeared to affect the $R_{s\text{n}}(\lambda)$ inversion for $a_g(\lambda)$ similar to the affect on $b_{\text{bbp}}(\lambda)$. $K_{d}(\lambda)$ optimization is the only inversion that did not use a set $a_g(\lambda)$ coefficient and iterated the value to determine it. While it did not perform as well as MODIS under conditions without bottom contribution, $K_{dopt}$ did give the best result under the BT filter. The spectrophotometer $a_g(\lambda)$ was best under the BTLCLZ filter. The ac9 performed the worst of the methods for determining $a_g(\lambda)$ spectrally. The ac9 $a_g(\lambda)$ was good for shorter wavelengths but rapidly dropped in agreement at longer wavelengths. The ac9 was probably limited by a shorter path length than the AOP inversion methods and problems with the clearance of bubbles from the filters.

The spectrophotometric method had the best $a_g(\lambda)$ value for the MODNB filter using the K-W nonparametric statistics. This result was surprising since the spectrophotometric method has a fairly high error compared to other methods due to having the shortest path length. A near surface single sample taken from a Niskin bottle or surface sample from a bucket was used for the spectrophotometric $a_g(\lambda)$ so it only represents a point near the surface and not deeper. The MODNB filtered data set has the lowest chlorophylls and is closer to Morel Case I waters so the $R_{s\text{n}}(\lambda)$ inversions were expected to do best. It appears that the accuracy of the spectrophotometric method was underestimated. This good performance may be due to determination of $a_g(\lambda)$ in visible where it has low accuracy by extrapolation from the near UV wavelengths where signal to noise is much higher using Equation 3.1. An $a_g(400)$ value of 0.01 m$^{-1}$ with a slope coefficient of 0.017 nm$^{-1}$ would have a value of 0.055 at 300 nm giving it sufficient signal. The Specag has the benefit of not having to estimate the coefficient for the slope like the AOP inversions. The spectrophotometric method for $a_g(\lambda)$ has the smallest correction for errors due to scattering of any of the methods. The method is more direct and not influenced by other parameters such as solar zenith angle or cloudiness. While these environmental parameters did not greatly affect the $R_{s\text{n}}(\lambda)$ and $K_{d}(\lambda)$ inversions in the determining $a_{\text{sw}}(\lambda)$ under the MODNB filter, they may affect the inversion for $a_g(\lambda)$ by introducing spectral changes. Both parameters would influence the spectral shape of the average cosine and might influence the magnitude of the $a_g(\lambda)$ values from an AOP.
inversion. The performance of the spectrophotometric \( a_g(\lambda) \) under the lowest attenuation conditions was surprising due to the short path length of the technique. However, the Specag may not perform as well under the other statistics.

Kdopt provided the best \( a_g(\lambda) \) measurement for the BT filter and Specag was best for BTLCLZ. Significant bottom reflectance from a bright sand bottom could affect the magnitude of the \( a_g(\lambda) \) value from Rrsopt, resulting in lower agreement. A sand bottom has a linear slope for its albedo that increases with increasing wavelength. This spectral albedo may act against the decreasing values of \( a_g(\lambda) \) with wavelength in a way that underestimates either the magnitude of the bottom albedo or \( a_g(\lambda) \). Kdopt is the only AOP inversion algorithm that did not lock the \( a_g(\lambda) \) spectral coefficient but allowed to iterate over a limited range to achieve the best fit. The \( K_d(\lambda) \) values are more susceptible to spectral changes due to wave focusing and did not perform as well under the BTLCLZ filter. Wave focusing is more likely to occur under ideal conditions like the BTLCLZ filter as opposed to conditions where solar zenith angle or cloudiness is high. Under those cloudy and low zenith conditions the subsurface downwelling irradiance is likely to be more diffuse and would not be as easily focused as direct sunlight. Wave focusing may have caused Kdopt to have greater error under ideal conditions but was not a factor under the less than ideal conditions for \( a_g(\lambda) \) inversions.

The ac-9 only had reasonable values for the first 2 to 3 wavelengths. The ac-9 has a 25 cm path length versus the spectrometer, which has a 10 cm path length. It appears that the ac-9 would be more accurate than the Specag, but the signal was usually below the accuracy of the ac-9 at longer wavelengths. The spectrophotometer was able to make measurements in UV where the absorption by CDOM is higher. This allowed the spectrophotometer data to be interpolated for the longer wavelengths by fitting to a logarithmic slope. The same technique can be applied to the ac-9 to improve the values of longer wavelengths but it does not have the channels in the UV range so only the 412 to 488 wavelengths can be fit.

The ac9 also performed poorer than expected under conditions where bottom was present under the K-W nonparametric analysis for \( a_g(\lambda) \). One of the difficulties with the deployment of the ac9 for \( a_g(\lambda) \) was clearing the flow tube with a 0.2 \( \mu \)m filter attached. For deeper casts lowering the ac-9 to depth to compress the bubbles can clear bubbles. The stations where bottom reflectance was significant were often too shallow to compress the bubbles resulting in some errors for the ac9 \( a_g(\lambda) \) values. The data from the ac9 improved for \( a_g(\lambda) \) measurements in later cruises due to a change in technique. The filter was presoaked in deionized water and left in a container of deionized water until just before the ac9 went over the side. This aided in bubble clearance by saturating the filter pores with water instead of air resulting in improvement in \( a_g(\lambda) \) measurements.

The filters are expensive and to conserve resources, they were often used for multiple casts. When reusing the filters, there is a greater chance of the filter pores becoming filled resulting in a lower flow rate. The lower flow rate results in changes in scattering within the flow tube due to differences in turbulence from the standard
calibration flow rate. The best method would be to replace the filters and leave the ac9 and filter filled with deionized water until the instrument is submerged, but the high cost of the filters (> $100 each) make this a costly approach. The problems with the ac-9 a₉(λ) were the result of deployment techniques that improved over the studies but were limited due to the cost of the filters used for sampling.

5.3.4. K-W Nonparametric Analysis aₚ₉(λ)

This is the only analysis where there was not a profile of the IOP to compare to the other methods. The filter-pad method only represents a single point in the water column while the other methods represent an integrated value. This use of a single point may present some differences for certain site locations where there is a significant variation in IOP properties for the upper water column. The integrated value from the IOP inversion would provide a more accurate determination of the aₚ₉(λ) values for the water column under these conditions.

For the nonparametric analysis, the Specaph performed the best under the NF filter while Kdopt had the most problems under this filter. This problem with Kdopt is possibly due to shallow depths being included along with cloudiness and low solar zenith angle in clear water. Kdopt also had problems under the bottom only filters. While it did well for the NB filter, it had problems at shorter wavelengths under the MODNB filter. It appears that clear water with cloudiness, high zenith angle, and bottom contributed to problems in inverting aₚ₉(λ) from K₉(λ) measurements. However, the other statistics need to be examined before any definitive conclusion can be drawn from this one test.

Kdopt performed well under the NB filter with the exception being the wavelengths of 650 and 676 nm. The Kdopt does not usually fit the modeled curve to these wavelengths because absorption from water is so high that the light is rapidly attenuated near the surface. The rapid attenuation results in few readings collected near the surface with the signal dropping to noise level at a shallower depth. The lower numbers of readings do not provide enough data to smooth out the effects of wave focusing. The R Rs(λ) inversions would have more signal at the longer wavelengths and not a problem with wave-focusing.

Under the K-W nonparametric analysis, MODIS has more agreement with consensus values for aₚ₉(λ) values under ideal conditions without bottom influence when only the semi-analytical model is used. MODIS used a higher a₉(λ) coefficient value for the initial inversion to compensate for CDOM fluorescence. Correction for CDOM fluorescence was expected to improve aₚ₉(λ) inversions due to the potential for CDOM fluorescence to produce error at the 440 nm peaks. This statistic supports that hypothesis.

Rrsopt is best for the BT and BTLCLZ filters under the K-W nonparametric analysis for aₚ₉(λ). Kdopt seems to have problems with shorter wavelengths due to wave focusing in shallower water columns but improves at longer wavelengths. Kdopt method
was not statistically similar to the other methods for wavelengths less than 532 nm, which may have been caused by wave focusing sending longer-wavelength light to depth. Since Kdopt relies on fitting a modeled $K_d(\lambda)$ value to the entire spectrum so the greater $E_0(\lambda)$ in the longer wavelengths due to wave focusing could result in a model slightly overestimating $a_g(\lambda)$ while underestimating $a_{ph}(\lambda)$. Rssopt has a longer path length and uses a shape factor derived from regional $a_{ph}(\lambda)$ measurements using the quantitative filter pad technique. The Rssopt $a_{ph}(\lambda)$ value is close to that of the filter-pad method but isn't limited to just one point in the water column. A caveat to this analysis is that the Rssopt method provides values between the Kdopt and Specaph values therefore, it agrees with two of them while they are too far apart to agree with each other. However, since the spectral shape of phytoplankton absorption is very different from the albedo of sand bottom, it is very likely that Rssopt is the better method for determining $a_{ph}(\lambda)$ for shallow waters.

5.4. Comparisons of Idealized Values

There are 960 different individual sets based on method, IOP type, wavelength tested, and filter type in this study. In comparison to the ideal data set, each set generated a regression slope, intercept, correlation coefficient, mean percent error, mean absolute percent error, and percent outliers for a total of 5760 different values. Because of the large amount of statistical information, only a general summary of the graphs is presented in this section. The tables of the results are presented in the appendix for reference. Only the NB and NF filters will be analyzed in detail as a guide for interpretation of the statistics for each IOP. The rest of the graphics will have generalized observations regarding each set. Each section devoted to an IOP type is followed by discussion of the general results. This section is very long and with a large amount of statistical analysis. If the reader wishes to know directly which methods are best under each filter, a table is given in the last chapter summarizing the overall performance of each method. There is also a general analysis of each IOP type at the end of their sections.

5.4.1. Unfiltered and No Bottom Filters $a_{uw}(\lambda)$

The unfiltered data (Figure 5.11) exhibits good regression results for all methods except MODIS at wavelengths less than 555 nm. At 650 and 676 nm, Kdopt and KdKirk have the highest and lowest regression slopes, respectively. The slopes at 650 nm have the largest difference from unity. KdKirk and KdLoisel have intercepts furthest from zero at the longer wavelengths. MODIS exhibits intercepts furthest from 0 at the shortest wavelengths with intercepts closer to zero at the longer wavelengths. Correlations are good for all methods at wavelengths below 650 nm. MODIS has the lowest correlation at the shorter wavelengths but it is still above 80%. KdKirk and KdLoisel have poor correlations at 650 and 676 nm where water dominates the absorption and little light reaches depth. Overall there is good agreement at the wavelengths where non-water absorption is highest.
The mean percent errors (Figure 5.12) are closer to 0 at the shorter wavelengths for all methods except for KdKirk, KdLoisel, and the ac9. At the longer wavelengths, Kdopt and Spec have larger errors. MODIS, QAA, and Rrsopt continue with low errors at longer wavelengths. The absolute percent difference generally follows the same spectral patterns as the percent difference.

The Spec is the only method with an overall low number of outliers (Figure 5.12C). At 412 nm, the outliers are low (0-1%) for KdLoisel, Spec, and Rrsopt. At 440 nm the outliers are low for ac9, KdKirk, KdLoisel, and Rrsopt. At 440 the rest of the methods all have outliers between 22% and 26%. At 488 nm, ac9, KdKirk, Spec, and Rrsopt are the lowest. At 510 and 532 nm only the ac9, Spec, and Rrsopt are low. At 555 nm only the ac9 and Spec have low outliers. At 650 nm only MODIS is low and at 676 only Rrs opt is low.

The regression slopes, intercepts, and correlation coefficients for the NB filter follow similar patterns as under the NF filter (Figure 5.13). The three Rn(λ) inversions have the lowest error terms (Figure 5.14) under both mean and mean absolute value of the percent difference. The Kd(λ) inversions generally have low error for the shorter wavelengths with increasing error at longer wavelengths. KdKirk has higher error above 488 nm. KdLoisel and Kdopt both start to have higher error above 532 nm. Kdopt has the lowest error overall of the Kd(λ) inversions models. The Spec only has low absolute percent error below 40% at 650 nm and the ac9 only has low error at 412 and 440 nm. Overall the regression results, and percent error are similar to the NF filter.

The percent of outliers (Figure 5.14C) has a different pattern from the error terms under the NB filter for anw(λ). The Spec, which is has one of the highest percent errors, has the lowest percent outliers. The regression terms do not indicate a bias for because its intercept is not much higher than the other methods. The only relatively high outliers are found at 440, 650, and 676 nm for the Spec. Rrsopt has low outliers from 412 to 532 nm and at 676 nm. The ac9 is next best with low outliers from 440 to 532 nm. KdKirk has low outliers from 440 to 510 nm. KdLoisel has low outliers at 412 and 440 nm. MODIS is the only method that had no outliers at 650 nm. The low outliers combined with a high mean percent error indicate that a few stations may be responsible for much of the error in the Spec method.

There are some general trends noted under these filters that continue under several of the anw(λ) filters. The Rrsopt does the best under most conditions at most wavelengths. Outliers seem to cause significant increases in percent error for Spec and ac9. The Rn(λ) models improve their results as the conditions approach ideal. The more empirical Kd(λ) inversions, KdKirk and KdLoisel, have problems with longer wavelengths of light. The interpolated MODIS value at anw(650) nm is better than the models that try to determine that wavelength. MODIS has an intercept much different form 0 at the shorter wavelengths but moves closer to zero at the longer wavelengths.
Figure 5.11. Regression and correlation analysis of $a_{nw}(\lambda)$ versus ideal values using the NF filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.12. Percent error and outlier analysis of $a_{\text{abs}}(\lambda)$ under the NF filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.13. Regression and correlation analysis of $a_{\text{true}}(\lambda)$ versus ideal values using the NB filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.14. Percent error and outlier analysis of $a_{\text{mod}}(\lambda)$ under the NB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.4.2. Ideal Conditions $a_{nw}(\lambda)$

The methods exhibit better agreement under the ideal conditions. Except for MODIS all the slopes are close to one for 412 to 555 nm under the NBLCLZ filter (Figure 5.15A). When the methods get to the longer wavelengths, signal to noise for non-water constituent absorption decreases. The $K_d(\lambda)$ inversions would especially have trouble in for this filter because their path lengths are less than for the $R_{rs}(\lambda)$ measurements. $K_{dopt}$ and MODIS have intercepts at the shorter wavelengths that are different from the other methods (Figure 5.15B). It may be due to their approach for determining CDOM absorption. MODIS uses a higher slope initially then a lower one to calculate the $a_{nw}(\lambda)$ value and $K_{dopt}$ allows the slope to iterate. The correlations except for $K_{dKirk}$ and $K_{dLoisel}$ are good at most wavelengths (Figure 5.15C). These two $K_d(\lambda)$ inversions have trouble at the longer wavelengths through out this study because of their empirical approach to modeling combined with shorter path lengths at the longer wavelengths.

The percent error generally reflects the path length and empiricism of the measurements under the NBLCLZ filter (Figure 5.16). Spec has the highest errors at short wavelengths and is followed by the ac9, the empirical $K_d$ inversions, and then $K_{dopt}$. The errors then get worse as wavelengths increase. All the $R_{rs}(\lambda)$ inversions seem to have low error terms with $R_{rsopt}$ doing the best again for this filter. While the outliers generally reflect the other statistics, $K_{dopt}$ is the exception with very few outliers. This would mean that there are a few stations where $K_{dopt}$ had problems likely due to low solar zenith angles and wave focusing. In one of the West Florida Shelf stations included under this filter, there was even a problem with amberjack schooling around the slow-drop instrument package shading the irradiance sensor. Removing a few stations seems to bring $K_{dopt}$ closer in agreement to the $R_{rs}(\lambda)$ inversions.

Under the MODNB filter the higher chlorophyll waters were removed resulting in lower signal to noise and more divergence from a one to one line for all the methods. MODIS now is using the semi-analytical model only and has a better regression result (Figure 5.17). Getting rid of the empirical portion of MODIS results in statistics that are similar to the more complex $R_{rsopt}$. MODIS and $R_{rsopt}$ are two very different models but the spectral pattern and magnitude of their statistics are close to the same. MODIS no longer has the largest intercept error and instead provides one of the closest to zero.

The $K_{dLoisel}$ model exhibited improvement under the MODNB filter and was close to $K_{dopt}$ in slope for regression and correlation at shorter wavelengths (Figure 5.17). This indicates that the empirical approach of the $K_{dLoisel}$ model is probably better suited for the clearer waters without bottom. With the removal of the band ratio default algorithm for MODIS, the QAA is now the most empirical of the three $R_{rs}(\lambda)$ inversions.

Path length was the reason for the poor results of the Spec under the MODNB filter. It had the intercept most different from zero (Figure 5.17B). The MODIS algorithm
defaults to its empirical band ratio algorithm when the estimated chlorophyll concentration is high. Generally the higher the chlorophyll, the more attenuation there is in the water and the shorter the path length for the AOP inversion. The $R_{rs}(\lambda)$ inversions with the longest path lengths performed the best while the $K_d$ inversions were next, followed by the ac9 and Spec.

The percent error statistics demonstrate a significant improvement for MODIS in determining $a_{mv}(\lambda)$ under the MODNB filter (Figure 5.18). While the QAA and $R_{rs}$opt have some improvements, MODIS using only the semi-analytical algorithm has much lower percent error and absolute percent error, especially in the longer wavelengths. MODIS is better at 650 and 676 nm than any of the other methods. However, MODIS does have an increase in outliers at 488 nm. The Spec and the ac9 have the highest error statistics with numbers similar to those under the NBLCLZ filter. The ac9 does have a low number of outlier at 412 to 488 indicating that removing those should improve its error and correlation statistics at those wavelengths.
Figure 5.15. Regression and correlation analysis of $a_{\text{inv}}(\lambda)$ versus ideal values using the NBLCLZ filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.16. Percent error and outlier analysis of $a_{nw}(\lambda)$ under the NBLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.17. Regression and correlation analysis of $a_{\text{inw}}(\lambda)$ versus ideal values using the MODNB filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.18. Percent error and outlier analysis of $a_m(\lambda)$ under the MODNB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.4.3. **Bottom Reflectance Only** $a_{nw}(\lambda)$

The $K_d(\lambda)$ inversions and QAA are the only methods with slopes close to 1 at shorter wavelengths under regression slope comparisons for the $a_{nw}(\lambda)$ BT filter. $K_{dopt}$ does the best under the regression analysis (Figure 5.19). The bottom influence along with some less than ideal conditions results in the $R_r(\lambda)$ inversions no longer being the best. $Rrsopt$ and the Spec have similar results for slope and intercept but it may be coincidental. $Rrsopt$ and Spec also had the lowest error terms and low outliers (Figure 20). These conditions were the most challenging for all the methods as the correlations were generally below 0.8. The $K_d(\lambda)$ inversions did best with the ac9 doing the worst in what should have been the best conditions for the ac9.

Under the ideal conditions with bottom (BTLCLZ) $Rrsopt$ fairs much better in determining $a_{nw}(\lambda)$ (Figure 5.21). Generally, $Rrsopt$ and $K_{dopt}$ proved the best of the inversions. The Spec did better than the ac9 for this filter and better than most of the AOP inversions. Many of these stations were collected during the CoBOP cruises where the water had low absorption and the bottom was white sand and the bright bottom degraded the MODIS and QAA $R_r(\lambda)$ performances. This means that path length is still a factor for these regions. $K_{dopt}$ and $Rrsopt$ also used pigment absorption shape factors that were from this region. The phytoplankton population is much different in the Bahamas from the population on the West Florida Shelf. The more oligotrophic waters of the Bahamas Sound are dominated by small dinoflagellates instead of some of larger phytoplankton species found on the West Florida shelf (Agard et al, 1995). The use of a specific $a_{ph}(\lambda)$ shape factor tailored to this region may have given these methods an advantage.

The $K_d(\lambda)$ inversions did not fare as well for longer wavelengths under the BTLCLZ filter for $a_{nw}(\lambda)$ (Figure 5.22). Wave focusing and signal to noise problems probably cause problems in these shallow waters. The irradiance sensor probably could not get deep enough to be out of the influence of wave focusing for many of these casts. The bright bottom sand in the Bahamas sometimes resulted in an increase in irradiance near the bottom due to bottom reflectance. This increase resulted in an odd shape to the depth profile of $E_d(\lambda)$ and made the curve fit to smooth wave focusing more difficult and probably resulted in some errors.

The Spec method provided accuracies almost as good as from $Rrsopt$. Recalling that this is a combination of $a_g(\lambda)$ measured in a spectrophotometer and $a_p(\lambda)$ measured using the filter pad method, the short-path (10 cm) of the $a_g(\lambda)$ method appears to be compensated by the longer effective path of the $a_{ph}(\lambda)$ method. Unlike the deeper waters the near shore waters appear to have the right combination of $a_p(\lambda)$ and $a_g(\lambda)$ where the $a_g(\lambda)$ value is not too low and the $a_p(\lambda)$ value is more dominant resulting in better values for the Spec method.
Figure 5.19. Regression and correlation analysis of $a_{nw}(\lambda)$ versus ideal values using the BT filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.20. Percent error and outlier analysis of $a_{\text{mv}}(\lambda)$ under the BT filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.21. Regression and correlation analysis of $a_{\text{olv}}(\lambda)$ versus ideal values using the BTLCLZ filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.22. Percent error and outlier analysis of $a_{nw}(\lambda)$ under the BTLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.4.4. Discussion of $a_{nv}(\lambda)$ Comparisons with Ideal

Rrs\text{opt} was generally the best for most $a_{nv}(\lambda)$ inversions and Kd\text{opt} performed well. MODIS did not fare as well until the completely empirical portion of the model and the bottom were filtered out. However, MODIS performed better than Rrs optimization at 676 nm under many filters. QAA, MODIS, and KdLoisel are further from the ideal under conditions of high bottom reflectance. The ac9 was not the best or the worst of the methods for determining $a_{nv}(\lambda)$ but did not perform as well as expected under conditions that should have favored it.

The algorithm used by MODIS may increase its accuracy at 676 nm over the other models. MODIS uses an algorithm that tunes the packaging effect to the temperature of the water. This algorithm may blend different packaging effects depending on the nitrate depletion temperature (Carder et al. 1999). $R_{rs}(\lambda)$ optimization attempts to fit the shape of the $R_{rs}(\lambda)$ curve by iterating variables and uses a set shape factor for the $a_{ph}(\lambda)$ curve that is applicable to this region. Matching the $R_{rs}(\lambda)$ spectra in the longer wavelengths is difficult due to water absorption lowering the signal from $a_{ph}(\lambda)$ at longer wavelengths. The $R_{rs}(\lambda)$ optimization algorithm does not attempt to fit in the region around 676 nm since this overlaps the region of chlorophyll fluorescence. The set shape factor for $R_{rs}(\lambda)$ optimization may give MODIS an advantage at 676 nm since it adjusts the shape factor for pigmented particulates based on the water temperature. One of the goals of the MODIS algorithm is to determine chlorophyll concentrations through using absorption at 676 nm and this study indicates that it may do that better than the other algorithms.

MODIS does not fare as well as the other algorithms when bottom is present for $a_{nv}(\lambda)$ under regression analysis. MODIS does not include a bottom albedo model like $R_{rs}(\lambda)$ optimization nor does it iterate $b_{bp}(\lambda)$ like the QAA algorithm. These differences mean that the MODIS algorithm will sometimes decrease the $a_{g}(\lambda)$ value or increase $b_{bp}(\lambda)$ to compensate for bottom reflectance. In about 41% of the cases where there is any bottom present, MODIS uses the default band ratio algorithm instead of the semi-analytical algorithm. The band ratio algorithm is not as accurate as the semi-analytical and bottom albedo could easily affect its results. The MODIS algorithm was not parameterized for areas with large bottom reflectance contributions so it was expected that it wouldn't perform as well under these conditions.

MODIS, however, does best for $a_{nv}(650)$ when bottom is present. Since MODIS does not output absorption values at this wavelength, it was interpolated using a 4th order polynomial curve fit in a Matlab routine. This region of the spectrum is very difficult to invert to $a_{nv}(\lambda)$ from $R_{rs}(\lambda)$ due to the low signal to noise ratio because of high water absorption and low constituent absorption. From this result it appears that the previously mentioned good $a_{nv}(676)$ results from the MODIS algorithm allowed a better fit to interpolate $a_{nv}(650)$ and was better than attempting to optimize a curve to this region. MODIS may present a method for other $R_{rs}(\lambda)$ inversion models to get better results in
the longer wavelengths by using the MODIS algorithm nitrate depletion temperature approach for determining $a_{ph}(676)$ and interpolating from $a_{nw}(555)$ to $a_{nw}(676)$.

Overall, $R_{rs}(\lambda)$ optimization did the best for $a_{nw}(\lambda)$ under the regression and error statistical analysis. Its slopes were closest to 1, intercepts closest to 0, and error the lowest. The $R_{rs}(\lambda)$ optimization algorithm generally had the lowest number of outliers under most conditions. One reason for this is that this method required the most a priori knowledge of the area and had a long effective path length. The spectrophotometric method only had a 10 cm path length for $a_g(\lambda)$, the ac-9 has a 25 cm path length, and the $K_d(\lambda)$ measurements had effective path lengths that were less than that of the $R_{rs}(\lambda)$ measurements. If the input parameters for the inversion model are representative of the local conditions then it is expected that $R_{rs}$ Optimization might be the best for determining IOPs especially in clear waters without bottom influence.

$K_{dopt}$ was best or second best depending on conditions, however the $KdKirk$ and $KdLoisel$ models had some of the worst results especially at longer wavelengths. These models are more empirical and are not parameterized for a particular region like $K_{dopt}$. Optimization doesn't rely on a single wavelength and can smooth out the errors through a hyperspectral curve fit. For $KdKirk$ and $KdLoisel$, the $a_{nw}(\lambda)$ values at longer wavelengths where signal to noise is low sometimes had errors over 100%. The optimization model benefited from being able to fit where there was sufficient signal and used extrapolations to the longer wavelengths. The algorithm would not attempt a fit if the $K_d(\lambda)$ values above 600 nm were greater than 10% different from that expected using pure seawater. The $K_d(\lambda)$ optimization algorithm effectively used an extrapolation to estimate $a_{nw}(\lambda)$ at the longer wavelengths and it proved more effective than the other $K_d(\lambda)$ inversions.

The ac9 did fare well for $a_{nw}(\lambda)$ but was limited due to its shorter path length. Unlike the nonparametric analysis, the ac9 was not the worst in regression analysis but usually fell among the other methods and below the optimization type of inversions. Under several conditions the ac9 had a few outliers that seemed to skew the error higher and improved the results when removed. The ac9 has its own light source instead of relying on the solar irradiance. Changes in downwelling light field due to solar zenith angle, clouds, or waves will not affect the ac9 but may affect the $R_{rs}(\lambda)$ and $K_d(\lambda)$ measurements. The ac9 provides a profile of the water column and will not be affected by significant changes in the optical properties over depth. The ac9, unlike the optimization inversions, does not require a priori knowledge of the environment to determine absorption. Under certain conditions the ac9 did much better than the non-optimization models so while it was not the overall best method it is useful when any knowledge of the optical properties of the study area is lacking.

The ac9 did not fare as well as expected under shallow conditions. The ac9 should do better than the AOP methods when there was a significant amount of bottom reflectance but in those cases there is usually also a shallow depth. The ac9 is sensitive to bubbles in its flow tubes. If these bubbles are not removed, they can produce highly
erroneous readings. Failure to properly clear air bubbles has resulted in absorption values over 25 times the actual value in casts during this study. Usually the instrument is sent to depth and the pressure compresses the bubbles so the pump is able to pull them out. In a shallow 10 m site, the depth might not be great enough to clear the instrument and bubbles can cause problems for the ac9. If there is significant sediment resuspension from the bottom it may cause problems for the ac9. Sediment suctioned into the instrument can get trapped increasing scattering. In high-attenuation shallow regions with little resuspension, the ac9 should be better than AOP inversions for determining IOPs and did better for the Friday Harbor sites.

The spectrophotometric method for $a_{nw}(\lambda)$ had diverging results under the regression and percent error statistics. Under the NB, NF, and NBLCLZ filters, it has a slope close to one, an intercept near 0, and good correlation but high percent errors. Under the BT and BTLCLZ filters, the regression results were poor but the percent error was low. For the clear MODNB waters, the Spec did not perform well under all statistical tests. The results under MODNB filter are from the low signal to noise in the low chlorophyll waters but the others may be the fault of a few large outliers. The spectrophotometric method is the sum of the filter pad $a_p(\lambda)$ measurement and the spectrophotometer $a_g(\lambda)$ measurement and combines the errors from both techniques. The $a_g(\lambda)$ measurement in the spectrometer has a low accuracy due to a short path length and probably is responsible for some outliers in the lower attenuation waters. If these outliers are in the same direction it can affect the regression statistics but still result in low percent errors. The spectrophotometric $a_{nw}(\lambda)$ is usually from a surface or just below surface water sample so it does not capture any changes in the $a_{nw}(\lambda)$ value at depth. The AOP methods produce an integrated $a_{nw}(\lambda)$ based on the amount of light reaching each depth. By integrating the ac9 values over depth and weighting them to the $K_d(\lambda)$ values, the integrated ac9 value is similar in measurement to the AOP model inversion values. The other methods may produce similar results while the spectrophotometric method will not agree as well under conditions of changing optical properties over depth even if it is most accurate. If this results in a few high outliers evenly above and below the ideal value line, the Spec method could have good regression statistics but high percent error values.

5.5. Comparisons of $b_{bp}(\lambda)$ to Idealized Values

5.5.1. Unfiltered and No Bottom Filters $b_{bp}(\lambda)$

RrsOpt has the overall slope closest to one and intercept closest to zero under the NF filter for $b_{bp}(\lambda)$ (Figure 5.23). The HS6 has the best result at 442 nm with a 1.01 slope but is further from unity than the Rrs($\lambda$) inversions at the rest of the wavelengths. Of the Rrs($\lambda$) inversions, QAA has the best slope followed by RrsOpt, and MODIS. KdOpt has a slope furthest from one for most wavelengths. RrsOpt has the closest intercepts to 0 followed by QAA, HS6, MODIS, and KdOpt. QAA has an intercept of 0 at 589 nm and RrsOpt had an intercept of 0 at 671 nm. While the HS6 has good results at 442 nm, the RrsOpt has the best regression for $b_{bp}(\lambda)$ under the NF filter.
The \( R_{\text{rs}}(\lambda) \) inversions have the best correlation coefficients with the ideal \( b_{\text{bp}}(\lambda) \) values under the NF filter (Figure 5.23C). The HS6 and Kdopt do not have high correlation coefficients. The highest correlation for the HS6 is 0.57 and for Kdopt is 0.26 both at 532 nm. The QAA, which has a correlation of 1 at 589 nm did the best with a mean correlation of 0.94. Rrsopt is second highest with a mean of 0.93 while MODIS has a mean correlation of 0.81. Rrsopt has the best correlations at 442 and 488. At 532, 620, and 671, QAA and Rrsopt are with 0.01 of each other with correlations above 0.9. MODIS has its highest correlation at 442 nm but trends lower to 0.69 at 589 then improves to 0.77 for 620 and 671 nm. The \( R_{\text{rs}}(\lambda) \) inversions have the best correlations with Rrsopt and QAA exhibiting similar spectral trends under the NF filter.

Rrsopt has the lowest error terms while Kdopt has low mean percent difference but high absolute percent difference for \( b_{\text{bp}}(\lambda) \) using the NF filter (Figure 5.24). In mean percent difference, Rrsopt does best but has a large spike in value at 589 nm. Overall, Kdopt has the second lowest percent error and smoothest curve for mean percent error. The HS6 is third in percent error with negative error terms across the entire spectrum. With the exception of 589 nm where it had a percent error of 0, the QAA had the highest percent error values. The QAA value for \( b_{\text{bp}}(589) \) was usually the median value so it became the ideal value resulting in no percent error for this wavelength. In mean absolute percent difference, Kdopt is the highest overall. QAA is second highest until 589 nm where it is 0 but it quickly rises up in value to slightly below MODIS for 620 and 671 nm. Despite the similarities under the regression analysis, the QAA model has a higher mean absolute percent error for \( b_{\text{bp}}(\lambda) \) than the Rrsopt model. MODIS starts off with a low mean absolute percent error but increases in value at the longer wavelengths. Rrsopt is the lowest for absolute percent error but has a large spike in value at 589 nm. The errors for QAA and Rrsopt may be a result of the iterative method of these models compensating for some of the stations with significant bottom reflectance.

Kdopt has the overall largest number of outliers for \( b_{\text{bp}}(\lambda) \) under the NF filter (Figure 5.24 C). Kdopt is only exceeded in number of outliers at one wavelength. MODIS for 671 nm at is higher than Kdopt in outliers. The QAA, MODIS, and Rrsopt have 0 outliers at 442 nm and the QAA model has zero outliers throughout the whole spectrum. Rrsopt was second best with zero outliers at 488, 620 and 671 nm and low outliers at other wavelengths. MODIS does well with 0 outliers at 442 and 532 nm but rapidly increases in outliers at 620 and 671 nm. Overall the HS6 has outliers of approximately 40% and the Kdopt has outliers near 80% indicating a lot of deviation from the ideal value.

Rrsopt has the best regression results using the NB filter for values of \( b_{\text{bp}}(\lambda) \) with QAA closely following it (Figure 5.25). The regression results using the NB filter are very similar to those under the NF filter. Rrsopt and QAA have the best results followed by MODIS doing pretty good, HS6 having poor numbers, and the Kdopt being the worst. The correlation values follow a similar trend as under the NF filter.
The percent error under the $b_{bp}(\lambda)$ NB filter has three groupings (5.26). $K_{dopt}$ has the highest mean absolute percent error, MODIS and HS6 are next and close in value, and Rrsopt and QAA are lowest. The percent error and absolute percent error for MODIS $b_{bp}(\lambda)$ are similar in magnitude under both the NF and NB filters indicating that MODIS is about 40 to 50% greater than the ideal $b_{bp}(\lambda)$ value across the spectrum. The more empirical approach of the MODIS algorithm for inverting $b_{bp}(\lambda)$ appears to result in an overestimate of $b_{bp}(\lambda)$ under less than ideal conditions and higher chlorophyll waters.

Most methods have the best agreement with the ideal at the shortest and longest wavelengths but tend to have less agreement in the middle of the visible spectrum under the NF and NB filters. The AOP inversions are most influenced by $b_{bp}(\lambda)$ at the middle wavelengths where absorption is the lowest. The magnitude of $b_{bp}(\lambda)$ has the greatest influence on the shape and magnitude of the modeled $R_{rs}(\lambda)$ curve at wavelengths approximately from 500 to 600 nm. Environmental parameters that influence $R_{rs}(\lambda)$ can be masked by the larger absorption values at the longer and shorter wavelengths but can be significant over the middle part of the spectrum. The average cosine of downwelling irradiance, $a_{g}(\lambda)$, and bottom reflectance all can affect the inversion of $b_{bp}(\lambda)$ from $R_{rs}(\lambda)$ in the green region. Sun glint can introduce a bias in the $R_{rs}(\lambda)$ values that the inversion method could interpret as an increase in the $b_{bp}(\lambda)$ reference value. While the $K_{d}(\lambda)$ is not greatly affected by sun glint or bottom reflectance, the other factors along with wave focusing can influence its inversion of $b_{bp}(\lambda)$. The $b_{bp}(\lambda)$ value has a much smaller contribution in the Kdopt model than the $R_{rs}(\lambda)$ inversions making errors in inverting $b_{bp}(\lambda)$ due to environmental factors larger. While these other factors may result in some errors for the $R_{rs}(\lambda)$ inversions, they can be very significant for a $K_{d}(\lambda)$ inversion of $b_{bp}(\lambda)$.

Some general trends are notable in the $b_{bp}(\lambda)$ analysis. The three $R_{rs}(\lambda)$ inversions may be weighting the ideal value towards their values because of the similarity in approaches for determining the $b_{bp}(\lambda)$ coefficient and using $R_{rs}(\lambda)$ as input for determining their $b_{bp}(\lambda)$ reference value. However, the $R_{rs}(\lambda)$ inversions also have the highest signal to noise ratios for $b_{bp}(\lambda)$ so it could be the case that they are more accurate. Rrsopt and QAA are even more similar in method for determining $b_{bp}(\lambda)$ than MODIS and may result in the statistics for those methods usually being close in value. Rrsopt and QAA have the best results under the NF, NB, NBLCLZ, and MODNB filter. For the filters with bottom contribution, HS6 usually has the best results. MODIS usually has results a little poorer than other two $R_{rs}(\lambda)$ inversions for the first four filters because Rrsopt and QAA iterate $b_{bp}(550)$ to determine it while MODIS uses an empirical algorithm. Kdopt is usually the furthest from the ideal value for $b_{bp}(\lambda)$ but shows some promise when outliers are removed. Kdopt and the HS6 sometimes have similar statistical results but the similarity between Kdopt and the HS6 may simply be that they are equally poor in their results since their methods for determining $b_{bp}(\lambda)$ are not similar.
Figure 5.23. Regression and correlation analysis of $b_{\text{ip}}(\lambda)$ versus ideal values using the NF filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.24. Percent error and outlier analysis of $b_{bp}(\lambda)$ under the NF filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.25. Regression and correlation analysis of $b_{\text{bp}}(\lambda)$ versus ideal values using the NB filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.26. Percent error and outlier analysis of $b_{bp}(\lambda)$ under the NB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.5.2. Ideal Conditions $b_{bp}(\lambda)$

MODIS algorithm has the slope closest to one under ideal conditions using the NBLCLZ filter (Figure 5.27) but still has high percent error statistics (Figure 5.28). Kdopt and the HS6 both have poor performances under this filter due to their lower path length and sensitivity relative to that of the $R_{rs}(\lambda)$ inversions. All of the $R_{rs}(\lambda)$ inversions have similar spectral shapes in plots of slope and intercept and have high correlations with the ideal value. This indicates that they are probably well correlated with each other spectrally. The intercepts and slopes for Rsopt and QAA are very close in magnitude adding to the evidence that their similar approaches give similar values.

The error statistics under the NBLCLZ filter again show that the MODIS $b_{bp}(\lambda)$ value is from 40 to 50% greater than the ideal value just like under the NB and NF filters (Figure 5.28). This indicates that the difference is not due to environmental factors like percent cloud cover, high solar zenith angles, or bottom reflectance but due to a difference in method from the QAA and Rsopt. The HS6 is the opposite of MODIS under this filter and is about 40 to 60% below the ideal value. The error in the HS6 is probably due to it reaching the accuracy of the instrument in some of the clear waters.

Under the MODNB filter the waters are the clearest and the $R_{rs}(\lambda)$ inversions have the best regression results (Figure 5.29). MODIS is using the semi-analytical only algorithm and its regression against the ideal value has changed. Under the previous three filters the MODIS values had a slope just below one and a positive intercept. Under the MODNB filter it has a slope above unity and a negative intercept. The three $R_{rs}(\lambda)$ inversions have correlations close to 1 while Kdopt and the HS6 are near zero. The results indicate that the longer path lengths and greater sensitivity of the $R_{rs}(\lambda)$ inversion are best for this clear water.

The error terms again indicate MODIS has an about 40 to 50% greater value for $b_{bp}(\lambda)$ under the MODNB filter (Figure 5.30). The statistics for Rsopt and QAA indicate that they are very similar to the ideal value. Whether this is because they are close to the actual value or they give very similar results and weight the ideal value towards their $b_{bp}(\lambda)$ result is not clear without further study. Its possible that most of the time MODIS is the higher of the values for $b_{bp}(\lambda)$ and Kdopt and the HS6 are the lower values. This would leave Rsopt or QAA as the likely median value.
Figure 5.27. Regression and correlation analysis of $b_{bp} (\lambda)$ versus ideal values using the NBLCLZ filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.28. Percent error and outlier analysis of $b_{bp}(\lambda)$ under the NBLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.29. Regression and correlation analysis of $b_{\text{bp}}(\lambda)$ versus ideal values using the MODNB filter.  A. Slope of linear regression of each method versus ideal value.  B. Intercept of linear regression of each method versus ideal value.  C. Correlation between ideal value and each method.
Figure 5.30. Percent error and outlier analysis of $b_{pq}(\lambda)$ under the MODNB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.5.3. Bottom Reflectance Only $b_{bp}(\lambda)$

Under the filters with significant bottom reflectance only, $R_{rsopt}$, $K_{dopt}$, and the HS6 were used to determine the ideal $b_{bp}(\lambda)$ value since MODIS and QAA do not account for bottom reflectance. The results under both all conditions (BT) and the ideal conditions (BTCLCLZ) are very similar (Figures 5.31 and 5.33). QAA and $R_{rsopt}$ have high slopes near 2, MODIS and $K_{dopt}$ are close to unity or well below it, and HS6 was near zero in slope. MODIS and QAA have a high positive intercept, with $K_{dopt}$ and the HS6 in between, and $R_{rsopt}$ had a negative intercept. Under correlation analysis, QAA and $R_{rsopt}$ are near 1, MODIS was near 0.5, and the HS6 and $K_{dopt}$ were below 0.5. There is no clear statistical best in regression analysis. Based on regression slope and intercept, $K_{dopt}$ would be best but based on correlation $R_{rsopt}$ and QAA would be best.

The percent error and outlier analysis provides gives more information regarding the regression results (Figures 5.32 and 5.34). The HS6 despite having poor regression results and correlation is the only method with low percent and absolute percent error. In addition, it has low outliers relative to the other methods. $R_{rsopt}$ is second best while the percent error for MODIS and QAA are well above 100%. $K_{dopt}$ is third lowest in error terms but is near or above 100% error. It appears that the HS6 is probably the closest to the actual value but has poorer regression values because of influence by a few outliers.

Possibly bottom reflectance is producing an overestimate for the $R_{rs}(\lambda)$ inversions by misinterpreting the reflectance from the bottom as $b_{bp}(\lambda)$. Since most of the areas with significant bottom reflectance have a white sand bottom, it would have a similar reflectance for the wavelengths the $R_{rs}(\lambda)$ inversions use to determine $b_{bp}(\lambda)$. The light reflected off the bottom would be affected by the scattering within the water column as it heads to the surface. The $R_{rs}(\lambda)$ inversions are probably detecting the scattering within the water column but adding some bottom reflectance to it resulting in an overestimate that would still correlate well with the ideal $b_{bp}(\lambda)$. If the ideal value is close to the actual value then $R_{rsopt}$ and QAA result in double the value for $b_{bp}(\lambda)$ when the bottom contribution to $R_{rs}(\lambda)$ is significant.

The HS6 is the best method for measuring $b_{bp}(\lambda)$ when bottom is present but has some outliers keep it from having a good regression result. Several large outliers in the same direction especially at the minimum or maximum values in the data set can affect the slope of a least squares linear regression fit. The HS6 occasionally reached noise level when in the very clear waters off the Bahamas. This was apparent when examining the data because the instrument gave approximately the same value for several casts in the clearest waters. While the HS6 has a modulated signal from its light sources, it can be affected by bright ambient light. To minimize this affect, the instrument was pointed downward. In the Bahamas the bottom was very bright white aragonite sand that could have reflected enough sunlight during shallow casts to interfere with the HS6 measurement. However, when testing the different sources of IOP input for the bottom albedo model (Chapter 7) it was found that using the HS6 $b_{bp}(\lambda)$ data produced results closer to measured values than the ideal value or $R_{rsopt}$.
Figure 5.31. Regression and correlation analysis of $b_{bp}(\lambda)$ versus ideal values using the BT filter. 
A. Slope of linear regression of each method versus ideal value. 
B. Intercept of linear regression of each method versus ideal value. 
C. Correlation between ideal value and each method.
Figure 5.32. Percent error and outlier analysis of $b_{bp}(\lambda)$ under the BT filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.33. Regression and correlation analysis of $b_{wp}(\lambda)$ versus ideal values using the BTLCLZ filter.  A. Slope of linear regression of each method versus ideal value.  B. Intercept of linear regression of each method versus ideal value.  C. Correlation between ideal value and each method.
Figure 5.34. Percent error and outlier analysis of $b_{bp}(\lambda)$ under the BTLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.5.4. Discussion of $b_{bp}(\lambda)$ Comparisons with Ideal

$R_{ss}(\lambda)$ optimization had the best performance overall in determining $b_{bp}(\lambda)$ under most conditions without bottom according to regression and error analysis. The QAA model was second best. MODIS was close but didn't perform as well as the QAA model. While all three models use an empirical approach to determine the spectral coefficient for $b_{bp}(\lambda)$, only MODIS uses an empirical function for the $b_{bp}(550)$ reference value. It appears that even the limited iterations performed by the QAA model are all that is necessary for improving the inversion of $b_{bp}(\lambda)$ from $R_{ss}(\lambda)$.

The Hydroscat-6 has agreement with the $R_{ss}(\lambda)$ inversions for $b_{bp}(\lambda)$ at 412 nm for the NB filter. Under this filter, high zenith values and high cloudiness were not excluded but stations with significant bottom contribution were. As the wavelengths increased the Hydroscat-6 did significantly worse in comparison. This error at longer wavelengths may mean that high solar zenith angles and high cloudiness affect the empirical spectral determination by $R_{ss}(\lambda)$ inversions producing errors of similar magnitude and direction. High clouds could create more diffuse downwelling irradiance affecting the average cosine of the downwelling irradiance. Higher solar zenith angles would lower the path length for the $R_{ss}(\lambda)$ measurement giving less signal for $b_{bp}(\lambda)$ in the measurement. The higher solar zenith angle would also affect the average cosine of the upwelling light producing errors due to path length elongation. Since scattering affects the average cosine too, it would make it more difficult to invert $b_{bp}(\lambda)$ from $R_{ss}(\lambda)$ since most inversion models are parameterized for solar zenith angles less than 45°. In addition to the areas where bottom is present, the HS6 may be the better method for determining $b_{bp}(\lambda)$ under solar zenith angles greater than 46° and cloudiness greater than 80%.

The Hydroscat-6 did poorly under the NBLCLZ conditions compared to the $R_{ss}(\lambda)$ inversions. Under ideal conditions for $R_{ss}(\lambda)$ measurements, the longer path length seemed to be a better method of determining $b_{bp}(\lambda)$. According to the manufacturer’s specifications, the Hydroscat-6 has a noise level range of 0.0002 m$^{-1}$ to 0.00002 m$^{-1}$. This lower range is achieved under low ambient light levels but at high light levels (bright sun) the noise level increases by an unspecified amount. The HS6 determines $b_{bp}(\lambda)$ based on a $\beta_p(\lambda)$ measurement at 140° by multiplying the result by 2*Pi and 1.08. This conversion gives $b_{b}(\lambda)$ within ±10% of the actual value and includes the known backscattering due to water. If the worst error of 10% is assumed then the error for $b_{bp}(\lambda)$ increases as it becomes lower relative to the pure seawater backscattering. Using calculated particulate backscattering values and the Morel seawater backscattering values (Morel 1974) over a range of $b_{b}(525)$ from 0.05 to 0.0005 m$^{-1}$ demonstrates that a positive 10% error in the backscattering values including seawater can result in an error for $b_{bp}(525)$. This error for $b_{bp}(\lambda)$ ranges from 10.23% at the $b_{b}(525)$ of 0.05 m$^{-1}$ and increases exponentially to 33.4% at the lower $b_{b}(\lambda)$ value. Under clearer water conditions, the Hydroscat-6 may have more error if there is a very different phase function than what was used to calculate the factor for converting from $\beta(140^\circ,\lambda)$ to $b_{b}(\lambda)$. The $R_{ss}(\lambda)$ values will have an increasing signal from $b_{b}(\lambda)$ under clearer skies,
lower attenuation, and lower solar zenith angles leading to better inversion results under the NBLCLZ and MODNB filters.

$K_d(\lambda)$ optimization performed the worst for $b_{bp}(\lambda)$ inversions under most conditions. This result was expected since $b_{bp}(\lambda)$ makes up about 5% of the $K_d(\lambda)$ value. Downwelling irradiance measurements also have a lower effective path length than $R_{ns}(\lambda)$ measurements resulting in lower signal to noise ratios. Wave focusing, if not completely corrected, would have a large effect on a $b_{bp}(\lambda)$ result from $K_d(\lambda)$ inversion since it increases the error in the $K_d(\lambda)$ value. As error increases due to wave focusing the error in the estimation of the coefficient for $b_{bp}(\lambda)$ increases since the wave focusing error changes the spectral shape of the $K_d(\lambda)$ value. Backscattering is a larger portion of the signal at 532 to 555 nm than at other wavelengths and the iterative fitting process could underestimate backscattering in that region if focusing events are more dominant. If defocusing events dominate the profile then backscattering could be overestimated.

Changes in cloud cover or solar zenith angle affect the average cosine of downwelling irradiance and affect the $K_d(\lambda)$ inversions more than from $R_{ns}(\lambda)$ inversions. The change in the average cosine can be interpreted as a change in backscattering under the $K_d(\lambda)$ optimization algorithm. Under perfect conditions where the $K_d(\lambda)$ is not in error due to wave focusing and the average cosines of upwelling and downwelling irradiance are known, the inversion of $b_{bp}(\lambda)$ from $K_d(\lambda)$ should be reasonable. The coefficient and intercept can be determined directly from Preisendorfer's equation with a direct measurement of $\tilde{\mu}_p(\lambda)$. A very slowly descending instrument package (descent rate of < 0.01 m/sec) that measured both the average cosine and below water irradiance reflectance would be able to determine a more accurate $b_{bp}(\lambda)$ value. The poor accuracy of the $K_d(\lambda)$ optimization inversion of $b_{bp}(\lambda)$ was expected due to the low signal of $b_{bp}(\lambda)$ in the $K_d(\lambda)$ values combined with environmental factors that result in errors for $K_d(\lambda)$.

A problem with this statistical analysis is there needs to be a more independent reliable standard to determine $b_{bp}(\lambda)$ than any of the methods in this study. The $R_{ns}(\lambda)$ methods appeared to vote together. Their agreement may be due to the higher signal to noise in the $R_{ns}(\lambda)$ measurement or due to the similarity of the $R_{ns}(\lambda)$ inversion methods. The $K_d(\lambda)$ method had some problems that made it unreliable due to low signal by $b_{bp}(\lambda)$. The Hydrosat-6 relies on an empirical relationship that may introduce error into the determination of $b_{bp}(\lambda)$ and has a lower accuracy in very clear waters. There exist methods that require very intensive laboratory procedures to determine $b_{bp}(\lambda)$ that might improve statistical closure if employed in future research.

An approach to better test the backscattering of the methods would be select a site that has a water column that is well mixed within one attenuation depth and use proven laboratory equipment to also determine backscattering. The Brice-Phoenix was an early device that gave information on particulate scattering at specific angles (Carder 1970). Laser scanning devices using diffraction within a sample can give some information on particle sizes that can be used to determine $b_{bp}(\lambda)$ (Agrawal and Potsmith 1989). A coulter counter could also provide some information on small particle sizes. With a
measured particle size distribution, Mie theory could be used to estimate $b_{bp}(\lambda)$ based on assumptions about particle shape and index of refraction. Combining several in situ instruments that measure scattering at different angles to better determine the volume scattering function might better approach to determine $b_{bp}(\lambda)$. An instrument that was deployed but the data were not used in this study was the VSF meter. The VSF meter measures backscattering for a single wavelength at several angles (Moore et al. 2000). Analysis of the VSF output could possibly yield a better backscattering value for comparison with the other methods. A combination of the VSF with the Hydrosocat-6 may possibly might even give the best results for $b_{bp}(\lambda)$ (Reynolds et al. 2006). The use of other methods for determining $b_{bp}(\lambda)$ would improve the statistical analysis for determining backscattering.

An inversion using Hydrolight might also provide a better estimate of $b_{bp}(\lambda)$. Using an accurate $a_{ww}(\lambda)$ as input while incrementing the $b_{bp}(\lambda)$ levels until the $R_{rs}(\lambda)$ and $K_d(\lambda)$ measurements matched the output of Hydrolight might give a closer value to the actual $b_{bp}(\lambda)$. This approach would require very good simulation of the downwelling light field. Using stations where above water measurements of $E_d(\lambda)$ were collected and cloudiness was low might provide a better irradiance input into Hydrolight. The biggest problem with this approach would be that it would require a large amount of computer time and setup time. The benefit is that it could provide closure to the $b_{bp}(\lambda)$ methods using the existing data set.

5.6. Comparisons of $a_g(\lambda)$ to Idealized Values

5.6.1. Unfiltered and No Bottom Filters $a_g(\lambda)$

Path length and the method of determining the coefficient for $a_g(\lambda)$ are the big factors for this IOP. MODIS has the result closest to 1, the intercept closest to 0, and the highest correlations under the $a_g(\lambda)$ NF filter (Figure 5.35). The ac9 only does well for the 412 and 440 nm wavelengths then rapidly drops off in value as the wavelengths increase. The signal to noise ratio decreases rapidly with $a_g(\lambda)$ measurements and the 25 cm path of the ac9 does not provide the sensitivity of the AOP measurements. Rrs opt is the only technique with a negative intercept. Rrs opt is assumes a set spectral coefficient for $a_g(\lambda)$ and could have influence from CDOM fluorescence. Kd opt iterates the coefficient and would have less influence from CDOM fluorescence than the $R_{rs}(\lambda)$ inversions but could have errors associated with iteration of the slope coefficient. Spectral errors in the $K_d(\lambda)$ values due wave focusing or incorrect estimates of $\tilde{n}(\lambda)_d$ could result in an incorrect $a_g(\lambda)$ coefficient. MODIS uses a higher coefficient for an initial determination of $a_g(\lambda)$ and a lower coefficient for calculated $a_g(\lambda)$ at longer wavelengths. Kd opt does well for the regression analysis but has a poor correlation. Specag with the shortest path length does somewhere in between the $R_{rs}(\lambda)$ inversions and the other methods.
The percent error under all the filters for \(a_g(\lambda)\) exhibit logarithmically increasing values with increasing wavelength (Figure 3.36). The error at the longest wavelengths is usually above 100%. Almost all oceanic \(a_g(\lambda)\) values logarithmically decrease as a function of wavelength. The result is that for wavelengths of 555 nm or longer, the \(a_g(\lambda)\) may be below the accuracy of the instrument for the direct measurements or masked by other IOP values in the AOP inversions. The \(a_g(\lambda)\) values were so low during the CoBOP cruise that even some measurements at 400 nm were not above the noise level for the ac9 and Specag.

The median \(a_g(\lambda)\) values of each method for the entire data set are very different from each other. The ac9 has the highest value at 0.011 m\(^{-1}\), which is right at the instrument's accuracy of 0.01 m\(^{-1}\), and the Specag has a median of 0.004 m\(^{-1}\), which is below its accuracy. For comparison, the median for Rrsopt is 0.004 m\(^{-1}\), for MODIS is 0.006 m\(^{-1}\), and for Kdopt is 0.006 m\(^{-1}\). The inversion algorithms have an advantage because they are only estimating \(a_g(\lambda)\) at 400 or 440 nm and using a decaying log slope equation (Equation 3.1) to extrapolate it to other wavelengths. Using this equation guarantees that they will never have negative values at the longer wavelengths. The ac9 and Specag both had over 9% of their \(a_g(\lambda)\) values below zero at 555 nm and had to have them filtered out before statistical analysis. As the wavelengths increase, the differences between the methods become greater due to lower accuracy for ac9 and Specag along with spectral coefficient differences in the inversion algorithms. The best wavelength range to compare these methods is from 412 to 510 nm because above that the signal to noise ratio is too low for any method to be trusted.

The method used to determine the spectral coefficient for Kdopt resulted in improved values under the NF filter but probably contributed to outliers in some instances. The method of iterating the \(a_g(\lambda)\) coefficient probably result in Kdopt having a higher number of outliers that increased in percentage with wavelength due to errors in estimating the slope coefficient. The iteration of the slope coefficient was performed separately from the iteration to determine the other unknowns to minimize errors but it may not have done enough. Under the unfiltered data set, some of the high solar zenith angles, wave focusing in shallow waters, and cloudiness may have been interpreted as a change in the \(a_g(\lambda)\) slope coefficient by the model. The other methods only had a few outliers at the shorter wavelengths.

The removal of a few outliers might bring the ac9 regression slopes much closer to one under the NF filter for \(a_g(\lambda)\) (Figure 3.36). A few stations may have some errors due to bubbles in the ac9 flow tube or clogged filters bringing the values for the ac9 down. While the ac9 lacks the sensitivity of the other methods it makes separate measurements at the longer wavelengths. The Rrsopt inversions are limited to determining the value at one shorter wavelength then extrapolating it to longer wavelengths. The Rrsoprt method can have problems due to an error at one wavelength affecting all the other wavelengths. The ac9 has less dependence between the measurements at each wavelength and an error at one wavelength won't necessarily affect the other wavelengths. If the error is due to bubbles in the ac9 it will affect all wavelengths but if
the error is due to a film on one or its nine filters, it will only affect that particular wavelength. Despite the poorer performance of the ac9 relative to the other methods, its values at the shorter wavelengths are may be good if a few outliers are removed.

MODIS again has the best regression results for \( a_g(\lambda) \) under the NB filter (Figure 5.37). MODIS has the best correlation results and the numbers are similar to those under the NF filter. The removal of the stations with a significant bottom contribution resulted in a greater amount of divergence from zero at shorter wavelengths for intercept by all methods. Only MODIS remained close to zero. The intercepts logarithmically approach zero as the wavelengths increase. This divergence is probably the result of different approaches for estimating the spectral coefficient of \( a_g(\lambda) \). Different spectral coefficients would result in intercepts further from zero that approach zero as the wavelengths became longer and \( a_g(\lambda) \) became smaller.

Rrsopt has low error terms for \( a_g(\lambda) \) under the NB filter and based on its low number of outliers it probably would have done better under the regression analysis if the outlier values were excluded (Figure 5.38). The error terms reflect the path length of the measurement. Rrsopt, MODIS, and Kdopt are lowest in error terms in that order. The ac9 had few outliers from 412 to 510 nm indicating that a few bad stations probably increased its percent error and removing those values may result in significant improvement for the ac9 over the shorter wavelengths.

MODIS has low outliers for 412 and 440 nm under the NB filter but spikes up to greater than 50% outliers for wavelengths greater than 440 nm (Figure 5.38). While the regression, correlation, and error results for MODIS are good, the outliers at the longer wavelengths indicate a potential problem due to selection of the second slope. MODIS \( a_g(\lambda) \) values are close to unity in slope versus the ideal value but are just far enough off that the slopes are not within the 10% range. This indicates that despite being within the range the values at the longer wavelengths are off by a small but consistent factor. The coefficient selected for the calculation of the \( a_g(\lambda) \) values is probably slightly too low under the conditions of the NB filter resulting in good agreement at 412 and 440 nm but less at longer wavelengths. CDOM fluorescence may not be as big a factor under some of the less than ideal conditions due to lower direct sunlight. The compensation for it by the higher coefficient under MODIS may introduce some errors under those conditions. The \( a_g(\lambda) \) coefficient used for first calculating the \( a_{ph}(\lambda) \) and \( a_g(400) \) value was 0.018 and the value for calculating \( a_{nw}(\lambda) \) and \( a_g(\lambda) \) was 0.16. A slight increase in value to 0.017 or 0.0165 may result in improving the MODIS values at longer wavelengths. However, the outlier method is just one of the statistics. Another possibility is the inclusion of higher cloudiness and solar zenith angles are affected the \( a_g(\lambda) \) inversions using MODIS by affecting the average cosine. The less direct and more diffuse light could change the spectral values of \( \bar{p}(\lambda) \) and may cause a slight multiplicative error in \( a_g(400) \). While MODIS has a consistent factor that keeps it from having a slope within the ±10% range of the ideal, the difference in slope is not large and MODIS still has the best results for \( a_g(\lambda) \) under the NB filter.
Figure 5.35. Regression and correlation analysis of $a_g(\lambda)$ versus ideal values using the NF filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.36. Percent error and outlier analysis of $\alpha_g(\lambda)$ under the NF filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.37. Regression and correlation analysis of $a_g(\lambda)$ versus ideal values using the NB filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.38. Percent error and outlier analysis of $a_\theta(\lambda)$ under the NB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.6.2. Ideal Conditions $a_g(\lambda)$

MODIS has the best statistics under the ideal conditions for AOP measurements for $a_g(\lambda)$ values under the NBCLLZ filter (Figure 5.39). Rsopt has a much higher regression slope and its difference in intercept from zero is more pronounced. The poorer performance of Rsopt may be due to increased CDOM fluorescence. Under these conditions there is more direct sunlight reaching depth stimulating more fluorescence that would show up in the water leaving radiance. Despite its smaller path length, Specag was second best for regression under this filter followed by Kdopt. The Specag only exhibited poor regression results at 676 nm where possibly some bad filtering techniques allowed some chlorophyll to contaminate the sample. Chlorophyll absorbs strongly at 676 nm and using a high vacuum pressure during filtering can result in rupture of phytoplankton cells releasing some chlorophyll into the dissolved sample.

The percent error results using the NBCLLZ filter are similar to the results under the NB filter but the outliers exhibit larger differences from the previous two filters (Figure 5.40). MODIS has zero outliers for all wavelengths while the other methods have high outliers. Comparing this to the outliers using NB filter provides evidence that the reason for the high outliers for MODIS under the NB filter is a problem with high zenith angles and cloudiness. MODIS is an algorithm for inverting $R_{rs}(\lambda)$ from satellite imagery (like the MODIS satellite). Satellite imagery is masked by clouds and usually not collected at high zenith angles so the MODIS algorithm normally does not have to deal with them in its inversions. This results demonstrates that the MODIS algorithm using the higher $a_g(\lambda)$ coefficient to calculate the initial $a_g(400)$ and $a_{p0}(\lambda)$ works well under the conditions where MODIS was designed to work.

MODIS and Rsopt have almost identical regression and correlation values under the MODNB filter for $a_g(\lambda)$ (Figure 5.41). Kdopt has good regression results under this filter. Path length is the dominant factor under this filter since it represents the clearest waters. Both the ac9 and Specag perform poorly for regression and correlation under this filter.

The error terms are similar to the other filters but the outliers are different under the MODNB filter for $a_g(\lambda)$ (Figure 5.42). Rsopt has the lowest percent error followed by MODIS and Kdopt. Only MODIS imagery and Rsopt have low outliers at for 412 and 440 nm. Rsopt rapidly increases in value to some of the highest outlier values for 488 nm and longer. This indicates that while Rsopt is close to the ideal value at 412 and 440 nm, its coefficient for $a_g(\lambda)$ is wrong. The coefficient used for Rsopt was 0.018 and probably was too high for most of these waters since Rsopt has a slightly negative percent error. Kdopt has low outliers at 532 nm and longer. Kdopt probably has the opposite case from Rsopt, the coefficient is right but the $a_g(440)$ values used to calculate $a_g(\lambda)$ were too high. MODIS may also have high coefficient for $a_g(\lambda)$ and it might have problems with the high solar zenith angle and cloudiness that was included under this filter.
5.39. Regression and correlation analysis of $a_g(\lambda)$ versus ideal values using the NBLCLZ filter.  
A. Slope of linear regression of each method versus ideal value.  
B. Intercept of linear regression of each method versus ideal value.  
C. Correlation between ideal value and each method.
Figure 5.40. Percent error and outlier analysis of $a_g(\lambda)$ under the NBLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.41. Regression and correlation analysis of $a_g(\lambda)$ versus ideal values using the MODNB filter.  
A. Slope of linear regression of each method versus ideal value.  
B. Intercept of linear regression of each method versus ideal value.  
C. Correlation between ideal value and each method.
Figure 5.42. Percent error and outlier analysis of $a_g(\lambda)$ under the MODNB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.6.3. Bottom Reflectance Only $a_g(\lambda)$

With bottom reflectance included under the BT filter for $a_g(\lambda)$, the ac9 and Specag have the best regressions (Figure 5.43). The problems with the AOP methods are similar as under the BT filter for $b_{bp}(\lambda)$. Increased bottom influence can be interpreted by the model as decreased $a_g(\lambda)$. Even though Rssopt takes into account bottom albedo, it can still affect inversions of IOPs that have spectrally increasing or declining values. MODIS was not designed to work with significant bottom reflectance so its performance is no surprise. Kdopt was expected to perform better but has the poorest regression and correlation results. Kdopt $a_g(\lambda)$ inversions were probably affected by wave focusing, higher cloudiness and higher solar zenith angles under this filter.

Rssopt and Specag have the lowest percent error terms under the BT filter for $a_g(\lambda)$ but Rssopt has some of the largest outliers for 488 and higher (Figure 5.44). Specag has the lowest percent outliers but the ac9 is close indicating a few outlier cause problems for the ac9. The filtered ac9 can have some problems in shallow waters since it is more difficult to clear bubbles from the flow tube. Shallower waters, especially along the West Florida Shelf, have much more particles that could fill the pores of the filter used with the ac9. These two factors may be responsible for the errors in the ac9 $a_g(\lambda)$ values.

The regression results under the BTLCLZ filter for $a_g(\lambda)$ are show that ac9 and Specag have the best results (Figure 5.45). Both Rssopt and Kdopt have good results for 412 nm but decrease in slope at longer wavelengths but have intercepts that are spectrally flat. Kdopt and Rssopt are getting the right reference value for $a_g(\lambda)$ but are not using the right coefficient. The presence of the bottom limits the path length advantage of the AOP methods and the higher signal to noise ratios usually found in shallow waters helps the ac9 and Specag in obtaining better measurements for $a_g(\lambda)$.

The percent error statistics have Specag and Rssopt performing the best for the BTLCLZ filter for $a_g(\lambda)$ (Figure 5.46). Kdopt has a low percent error at 412 and 440 nm but is above 60% error for absolute percent error at those wavelengths. This indicates that while it is around the ideal value, it is evenly under and over the value for all the stations. Using the iterative approach to determining the coefficient for $a_g(\lambda)$ may not be a good method for Kdopt in shallow regions. It may be best to use a set coefficient when the irradiance sensor cannot get below the depths of severe wave focusing.

The ac9 and Specag have low outliers overall and the AOP inversions have high outliers under the NBLCLZ filter for $a_g(\lambda)$ (figure 5.46). There is a spike in outliers at 488 nm by the ac9 while MODIS dips to almost zero outliers. MODIS initially has a regression slope much larger than unity but declines to near unity at 488 and then is below unity indicating a spectral slope problem (Figure 5.45). About half the ac9 outliers at 488 nm were from the first CoBOP cruise to the Bahamas. The ac9 used for $a_g(\lambda)$ during that cruise had problems with degradation of its optical filters and had to be repaired after the cruise. The 488 nm filter was one of those replaced. This demonstrates
that inter-comparisons between these methods are a way to determine problems with instruments.

Figure 5.43. Regression and correlation analysis of $a_g(\lambda)$ versus ideal values using the BT filter.  
A. Slope of linear regression of each method versus ideal value.  
B. Intercept of linear regression of each method versus ideal value.  
C. Correlation between ideal value and each method.

Figure 5.43. Regression and correlation analysis of $a_g(\lambda)$ versus ideal values using the BT filter.  
A. Slope of linear regression of each method versus ideal value.  
B. Intercept of linear regression of each method versus ideal value.  
C. Correlation between ideal value and each method.
Figure 5.44. Percent error and outlier analysis of $a_g(\lambda)$ under the BT filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.45. Regression and correlation analysis of $a_g(\lambda)$ versus ideal values using the BTLCLZ filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.46. Percent error and outlier analysis of $a_g(\lambda)$ under the BTLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.6.4. Discussion of $a_g(\lambda)$ Comparisons with Ideal

MODIS has the best inversion for the unfiltered data. This is surprising in one respect because the MODIS algorithm does not compensate for some of the external environmental variables. The change to the MODIS algorithm using the higher estimated CDOM coefficient for initial inversion and then a lower value for the output IOPs seems to give this algorithm an advantage in determining $a_g(\lambda)$ over the Rrs optimization and QAA models. MODIS continued to have the best inversion results for all filters except those where only bottom was present. Under conditions where bottom reflectance was significant, MODIS had regression slopes approaching two at shorter wavelengths then declining to below one at longer wavelengths. Without correcting for the bottom contribution, the bottom influence was calculated as lower $a_g(\lambda)$ and or higher $b_{bp}(\lambda)$ resulting in errors in $a_g(\lambda)$ for MODIS. MODIS did the best under the unfiltered data and performed better that Rrs($\lambda$) optimization for $a_g(\lambda)$ inversions except where bottom was present.

The higher $a_g(\lambda)$ coefficient used in the MODIS algorithm compensates for increased upwelling radiance associated with CDOM fluorescence and improves $a_{ph}(\lambda)$ values for Rrs($\lambda$) inversions. Using a fulvic acid dominated fluorescence efficiency equation in Hydrolight and an $a_g(\lambda)$ coefficient of 0.016 results in an increase in Rrs($\lambda$) that has a peak around 450 to 500 nm near the Soret peak for chlorophyll a absorption (Hawes 1992). Without correction, this peak would produce an error under estimating the phytoplankton absorption coefficient. This increase in fluorescence will also affect $b_{bp}(\lambda)$ inversions. MODIS is possibly less affected for $b_{bp}(\lambda)$ than the Rrs optimization model since the MODIS algorithm uses an empirical approach for $b_{bp}(\lambda)$ while Rrs optimization iterates $b_{bp}(400)$. Rrs optimization still returns good inversions for $a_{ph}(\lambda)$ without taking into account CDOM fluorescence because it compensates for the fluorescence by increasing $b_{bp}(\lambda)$ and decreasing $a_g(\lambda)$ instead of decreasing $a_{ph}(\lambda)$. The MODIS approach is best for high CDOM waters where fluorescence is a problem.

Kdopt performed well under the MODNB and NBLCLZ filters for $a_g(\lambda)$ but did poorly under the other filters. Higher clouds and zenith angle affected the $a_g(\lambda)$ inversion from Kd($\lambda$) values. The initial testing where $a_{uw}(\lambda)$ was inter-compared under varying degrees of cloudiness and zenith angles using the K-W statistic indicated that Kd($\lambda$) was more affected than Rrs($\lambda$) by these parameters. Changes in the average cosine would affect the spectral shape of the $a_g(\lambda)$ values under the iteration method used for the $a_g(\lambda)$ coefficient. The iteration of the $a_g(\lambda)$ coefficient seems to work well for ideal conditions but had problems under other conditions due to increased cloudiness and higher solar zenith.

Under the regression analysis, the Kd($\lambda$) optimization performed poorly for bottom conditions. While it performed well under the nonparametric analysis, it appears that it has a significant number of outliers that increase in number with increasing wavelength. Correction for wave focusing is more difficult in shallow environments.
since the depth may be too shallow to get below the depths where wave focusing is a significant effect. The result can be a spectral shift in the values. Since outliers affect the nonparametric technique less than the regression analysis, it seems that adjusting the model for the conditions may improve it. In shallow regions, the $a_g(\lambda)$ coefficient should be set to an estimated value instead of iterated.

The ac-9 is only reliable from 412 to 510 nm for $a_g(\lambda)$ measurements. The accuracy of the ac-9 is $\pm 0.01$ m$^{-1}$ for a well-calibrated instrument. The values at wavelengths beyond 510 nm were usually below the level of accuracy. A solution to this error is fit the logarithmic spectral curve for $a_g(\lambda)$ though the first 3 to 4 wavelengths of the ac-9. However, the ac-9 was one of the best methods under the regression analysis for determining $a_g(\lambda)$ when bottom was present. Despite its lower optical path compared to the AOP inversions, the ac-9 has no interference with the bottom due to changes in the geometric light field. The more direct measurement is sometimes better under these conditions.

The high error for ac-9 $a_g(\lambda)$ under most filters is due to outliers. Problems with bubbles and flow rate can result in data from and ac-9 that is very different from the actual value. Removing the outliers does improve the statistical agreement to the idealized data. The presence of the outliers indicates the complexity of deployment of this type of instrument especially with a 0.2 µm filter inline. Later improvements to the method resulted in a lower number of outliers. The higher error for the ac-9 appears to be a function of some really bad outliers from earlier deployments that if removed will significantly lower the error.

The spectrophotometric technique for $a_g(\lambda)$ has high error under conditions with low bottom contribution to $R_{rs}(\lambda)$. There are three reasons for this error, low path length, bad technique, and variations in $a_g(\lambda)$ over depth. The spectrophotometer has only a 10 cm path cell giving it the shortest path length of any of the instruments. This results in a lower signal to noise for the instrument. During one of the main cruises used in this study, a student that was just learning the technique may have not performed it properly. The samples were improperly filtered resulting in some contamination by particles. The spectrophotometric measurements use seawater collected from a specific depth at a specific point in time. If there exists a change in $a_g(\lambda)$, either in magnitude or spectrally, over depth then the value would not be similar to the other methods, which are integrated over depth. All or some of these problems could result in the high error and outliers for the deeper waters.

Changing IOPs over depth can be a significant problem for AOP inversions in coastal environments. The outflow from a river can have high CDOM concentrations with a lower $a_g(\lambda)$ coefficient and can form at layer over the top of more saline oceanic waters that typically have lower $a_g(\lambda)$ coefficients. During the formation of a seasonal thermocline higher CDOM concentrations usually occur in the deeper cooler waters with lower concentrations at the surface. Hypersaline bays like Florida Bay can have outflows on the shelf waters that are high in CDOM with low $a_g(\lambda)$ coefficients that will sink
below the more oceanic waters. All of these environmental conditions will present problems for AOP inversion models that can lead to errors in their IOP results.

5.7. Comparisons of $a_{ph}(\lambda)$ to Idealized Values

5.7.1. Unfiltered and No Bottom Filters $a_{ph}(\lambda)$

The Specaph method has the best regression results for $a_{ph}(\lambda)$ values under the NF filter but has low correlation at 555 nm (Figure 5.47). While the ac9, HS6, and Specag have much shorter path lengths, the Specaph method has a fairly long effective path length. By taking samples from a particular depth and concentrating them on a glass fiber filter, the $a_{ph}(\lambda)$ measurements using the Specaph approach have an effective path length of meters to tens of meters long. The Specaph method does not have problems with other absorbing components masking the measurement value or environmental conditions affecting the measurement. The Specaph measurement does have problems in that it represents only a point in the water column. If $a_{ph}(\lambda)$ values change with depth then this technique may not represent the water column value. The Specaph requires an empirical correction for scattering within the filter pad that results in increased path length for the measurement. This correction can result in errors for the value that could be the reason for the poor correlations for Specaph at 550 nm. Another factor for the poor correlations is that the absorbance values at 550 nm are very low and may be near the accuracy limit of the spectrophotometer used for these measurements resulting in more noise at the middle wavelengths.

Rrsopt, Kdopt, and MODIS have poor regression results under the NF filter for $a_{ph}(\lambda)$ but correlations above 90% (Figure 5.47). Kdopt and Rrsopt track closely in magnitude and spectral shape for both slope and intercept. This agreement between Rrsopt and Kdopt is due to both techniques using a similar approach to determining $a_{ph}(\lambda)$ by iterating a shape factor. Both algorithms used the same values for the shape factors that were based on filter pad measurements from the three study areas. MODIS has a different approach using generalized values that correspond to different phytoplankton pigment packaging. The MODIS equations were based on the analysis of an extensive library of $a_{ph}(\lambda)$ filter pad measurements from around the globe. The use of the $a_{ph}(\lambda)$ filter pad measurements to parameterize the AOP inversion algorithms means that there is more dependence between the methods than in previous statistical comparisons. Rrsopt and Kdopt will have more dependence on the filter pad method than the MODIS algorithm because they are using some of the actual measurements in this study to determine the shape factor for $a_{ph}(\lambda)$.

None of the techniques has low percent error terms or outliers for $a_{ph}(\lambda)$ under the NF filter except for MODIS at 510 nm (Figure 5.48). The only good regression results for MODIS were at 510 nm where it was near unity in slope and zero in intercept. The percent error for Specaph and Kdopt are especially high at 532 to 555 nm. MODIS takes into account pigment packaging by using different factors for $a_{ph}(\lambda)$ based on nitrate...
depletion temperatures. This approach may serve to better estimate the $a\text{ph}(510)$ values instead of using the shape factors like $K\text{dopt}$ and $R\text{rsopt}$.

Under the NB filter for $a\text{ph}(\lambda)$, Specaph again has the best regression results but low correlation at 532 to 555 nm (Figure 5.49). $R\text{rsopt}$ and $K\text{dopt}$ are further apart in value but have similar spectral shapes. $K\text{dopt}$ does not perform as well as $R\text{rsopt}$ since $R\text{rsopt}$ has a longer effective path length. MODIS has a slope well below one and probably has problems due to the less than ideal conditions and inclusion of the default algorithm. With the removal of the stations with significant bottom contribution, $K\text{dopt}$ and $R\text{rsopt}$ no longer have the spike up in slope at 532 and 555 nm observed under the NF filter nor does MODIS have the spike in slope value at 532 nm. This indicates that the bottom contribution, which would be significant at 532 nm, may have affected these values under the NF filter.

The Specaph and $K\text{dopt}$ both have spikes in value at 532 to 555 nm for absolute percent error using the NB filter (Figure 5.50). $R\text{rs}(\lambda)$ measurements would have the longest path length in this region and $K\text{dopt}$ and Specaph may be affected by a low signal to noise over the green wavelengths. $K\text{dopt}$ generally has the highest error and this probably due to the low path length compared to the $R\text{rs}(\lambda)$ inversions and greater path length and signal to noise of the Specaph. The outliers are lower for $K\text{dopt}$ than under the NF filter and all methods have around 40% outliers. The $R\text{rs}(\lambda)$ values exhibit a spike in outliers at 650 nm. The MODIS value at this wavelength is an extrapolation so higher error is expected for it. The $R\text{rsopt}$ outlier values are up near 80% at 650 nm and the percent error indicates an overestimate by $R\text{rsopt}$ for $a\text{ph}(650)$. Since $R\text{rsopt}$ did not exhibit the same spike for $a\text{g}(\lambda)$ or $b\text{bp}(\lambda)$ it may be due to spectral factors related to sun glint.
Figure 5.47. Regression and correlation analysis of $a_{ph}(\lambda)$ versus ideal values using the NF filter.  
A. Slope of linear regression of each method versus ideal value.  
B. Intercept of linear regression of each method versus ideal value.  
C. Correlation between ideal value and each method.
Figure 5.48. Percent error and outlier analysis of $a_{ph}(\lambda)$ under the NF filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.49. Regression and correlation analysis of $a_{\text{ph}}(\lambda)$ versus ideal values using the NB filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.50. Percent error and outlier analysis of $a_{ph}(\lambda)$ under the NB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.7.2. Ideal Conditions $a_{ph}(\lambda)$

Rrsopt and Specaph have the best regression results but Kdopt is greatly improved over the previous filters under the NBLCLZ filter for $a_{ph}(\lambda)$ (Figure 5.51). The improvement in Rrsopt and Kdopt regression values under the ideal conditions indicates that high solar zenith angle and cloudiness do have some effect on the inversion of $a_{ph}(\lambda)$ by the iterative models. MODIS has the slope furthest from one and it is probably due to the errors from its default empirical algorithm.

Kdopt has the highest percent error terms because the $R_{rs}(\lambda)$ methods have the longest path lengths under the ideal conditions (Figure 5.52). Both Specaph and Kdopt exhibit spikes in percent error at 532 to 650 nm probably due to low signal to noise for Kdopt and packaging effects for the Specaph surface measurements. The high outliers for Specaph may be due to it being a measurement at a single depth. The integration of the water column $a_{ph}(\lambda)$ values by the AOP inversions may produce difference from the ideal value for the Specaph values. Rrsopt has a high number of outliers and approaches 100% for 555 to 650 nm wavelengths. The correlation between error and environmental factors presented later in this section indicates a negative correlation between solar zenith angle and absolute percent error at the longer wavelengths for Rrsopt $a_{ph}(\lambda)$. By using the different filters and statistics, a conclusion can be reached, the main cause of Rrsopt's $a_{ph}(650)$ outliers is probably sun glint which occurs at lower solar zenith angles. MODIS and Kdopt have relatively low outliers from 412 to 555 nm indicating that a removing less than 20% of the stations would improve their regression results.

Under the MODNB filter for $a_{ph}(\lambda)$ the water is the clearest and Rrsopt has the best results (Figure 5.53). Specaph and MODIS are close seconds. MODIS now is only using the semi-analytical portion of the model and has much better regression results. Kdopt is has the poorest regression results due to a shorter path length than the other methods. Kdopt even has much worse results at the longer wavelengths.

The absolute and signed percent error terms indicate that MODIS slightly underestimates the ideal $a_{ph}(\lambda)$ value for 412 to 532 nm but generally has the lowest error terms for all except the extrapolated values under the MODNB filter (Figure 5.54). Kdopt and Specaph have very high error at 532 nm. This error may be due to packaging effects not captured by the single near surface Specaph measurement and low signal to noise for the Kdopt $a_{ph}(532)$. The ideal value could also be biased due to errors in the same direction for the $R_{rs}(\lambda)$ inversions. Rrsopt again exhibits high number outliers at 555 and 650 nm that are likely due to sun glint. MODIS has a high number of outliers at the extrapolated value of 555 nm but this is an extrapolated value. Excluding the two wavelengths where there are extrapolated values and MODIS has the lowest mean number of outliers.
Figure 5.51. Regression and correlation analysis of $a_{ph}(\lambda)$ versus ideal values using the NBLCLZ filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.52. Percent error and outlier analysis of $a_{ph}(\lambda)$ under the NBLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.53. Regression and correlation analysis of $a_{ph}(\lambda)$ versus ideal values using the MODNB filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.54. Percent error and outlier analysis of $a_{ph}(\lambda)$ under the MODNB filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.7.3. Bottom Reflectance Only $a_{ph}(\lambda)$

Specaph and Rrsopt have the best regression results for $a_{ph}(\lambda)$ under the BT filter (Figure 5.55). MODIS has very poor regression results with slopes near zero, high intercepts, and low correlations. The performance of MODIS is not unexpected since it was not set to work with significant bottom reflectance. Unlike $b_{bb}(\lambda)$ and $a_{g}(\lambda)$ when bottom is present, Rrsopt has good results for $a_{ph}(\lambda)$. The spectral shape of the $a_{ph}(\lambda)$ curve is different enough from the spectral albedo of the bottom that its signal is unique for the iterative Rrsopt method. Kdopt suffers from wave focusing due to the shallower depth but does improve its regression results at longer wavelengths.

Kdopt has a low percent error but high absolute percent error indicating that it is around the ideal value but there is a lot of noise in the inversion for $a_{ph}(\lambda)$ under the BT filter (Figure 5.56). Rrsopt and Specaph are the lowest in error. Rropt has zero outliers from 412 to 510 nm indicating that is was the median value for most stations at those wavelengths. Kdopt has high outliers of near 80% for 412 to 510 nm but rapidly drops to near 20% for the longer wavelengths. This indicates that the spectral affects of wave focusing are affecting the $a_{ph}(\lambda)$ inversions from $K_d(\lambda)$ in the shorter wavelengths.

Rrsopt has the best results for regression and correlation analysis for $a_{ph}(\lambda)$ under the ideal conditions with significant bottom contribution (Figure 5.57). Specaph is second best in regression results but has higher percent error terms (Figure 5.58). Kdopt has higher percent error terms under this filter than under the less than ideal conditions providing further evidence for wave focusing problems interfering with $a_{ph}(\lambda)$ inversions from $K_d(\lambda)$. Under the ideal conditions the sun would be closer to zenith and the light would enter the water closest to the vertical. The water column is shallow and the irradiance sensor cannot go to the depth where the focused rays becomes scattered and mixed. The effects of wave focusing would be greatest under these conditions. Rrsopt has high outliers at 650 nm possibly due to sun glint. It appears that wave focusing affects $K_d(\lambda)$ inversions for $a_{ph}(\lambda)$ in the short wavelengths while Rrsopt has affects from sun glint on its inversions at the long wavelengths.
Figure 5.55. Regression and correlation analysis of $a_{ph}(\lambda)$ versus ideal values using the BT filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
Figure 5.56. Percent error and outlier analysis of $a_{ph}(\lambda)$ under the BT filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
Figure 5.57. Regression and correlation analysis of $a_{ph}(\lambda)$ versus ideal values using the BTLCLZ filter. A. Slope of linear regression of each method versus ideal value. B. Intercept of linear regression of each method versus ideal value. C. Correlation between ideal value and each method.
5.58. Percent error and outlier analysis of $a_{ph}(\lambda)$ under the BTLCLZ filter. A. Mean of the percent difference from the ideal value. B. Mean of the absolute value of the percent difference from the ideal value. C. Percent outliers determined by removing high error values until the regression slope versus the ideal value was near unity.
5.7.4. Discussion of $a_{ph}(\lambda)$ Comparisons with Ideal

Under Regression analysis, the filter pad method performs the best overall for the NF and NB filters. The regression results exhibit a large spread in values under the less than ideal conditions with the filter pad method being the closest to 1 for slope. There is the possibility of the two iterative models voting together. Kdopt and Rrsopt use the same shape factors for $a_{ph}(\lambda)$ and their slopes and intercepts under the regression analysis followed the same spectral pattern for the unfiltered data. However, Kdopt and Rrsopt did not have similar spectral patterns for the regression analysis under the other filters. It is not clear if they coincidently followed the same pattern under these two filters or they match in regression results because of the similar approaches and model factors.

The good results for the Specaph method were not surprising since it has the longest effective path length of the methods not based on AOPs. To determine the effective path of the measurement, the volume filtered in cubic meters is divided by the area of coverage of the particles on the filter pad. The measurement is then multiplied by a Beta factor that takes into account the scattering through the glass fiber filter pad increasing its path length (Mitchell and Kiefer 1988). The Beta factor is typically around 2 in value indicating that it the path of the light through the filter pad is double the length of the straight path through the pad. These values combine to give an effective path length for the filter pad method from above 1 to over 20 meters for the areas in this study. Like AOP values, the filter pad method usually increases its path length as attenuation decreases. Generally, in clearer waters, more water has to be filtered to achieve optimum optical density on the filter pad for a measurement resulting in an increase in effective path length (Fig. 5.60). This longer path results in a high signal to noise ratios without masking of the signal by other substances or influences from external environmental factors.
With the exception of the two bottom only filters, there are a low correlation values for Specaph from 532 to 555 nm. One possibility is that the Beta factor that is used to empirically determine the path length elongation in the filter pad method is wrong. The 532 to 555 nm region is an area of low optical density in a filter pad absorbance spectrum. The Beta factor is empirically fit over a range of absorbance values. If the optical density is below the range of the fit, then the filter pad $a_{ph}(\lambda)$ measurements may be inaccurate at that wavelength. The filter pads for $a_{ph}(\lambda)$ under the CoBOP project had problems with achieving ideal optical density in the 532 to 555 nm region. The pores in the filters tended to stop up before the pad had reached the ideal optical density. During the 1999 CoBOP cruise, 25 out of 49 pads had absorbance values below 0.04 at this wavelength. CoBOP also may have had different species of phytoplankton than used in the original calculation of the equation for the Beta factor. The Bahamas Banks are dominated by small dinoflagellates according to some surveys of that area (Agard et al. 1995). These organisms may have different optical properties from the phytoplankton used to parameterize the beta factor in this study and require a different beta factor. The Beta factor or filtering technique may have produced errors around 555 nm for $a_{ph}(\lambda)$.

The AOP $a_{ph}(\lambda)$ inversions could have errors in the 532 to 555 nm region that bias their values in the same direction. The 532 to 555 nm wavelength is affected by scattering or bottom reflectance in the AOP inversions. The $a_{ph}(\lambda)$ values selected for calculating the $a_{ph}(\lambda)$ curves under Rrsopt and Kdopt may not be representative of the phytoplankton species for the study and could result in errors. The actual absorption spectrum may have packaging effects that lead to a different absorption than the
parameters used in the model at the 532 to 555 nm wavelength. The error due to packaging can also be applied to the filter pad \(a_{ph}(\lambda)\) since the samples were usually collected near the surface. However, since MODIS used a set of parameters for \(a_{ph}(\lambda)\) that was different from the \(K_d(\lambda)\) and \(R_{rs}(\lambda)\) optimization, the filter pad method may be the source of the error in this wavelength region.

MODIS \(a_{ph}(\lambda)\) values did improve to second best under the MODNB filter under regression analysis for \(a_{ph}(\lambda)\). Only the Semi-Analytical method for MODIS was included under this filter resulting in a less empirical approach. However, none of the methods were very good at \(a_{ph}(555)\) under the MODNB filter. The filter pad method had a regression slope of near 2 while the AOP inversions were near 0. This may be further evidence that the change in \(a_{ph}(555)\) with changes in packaging or pigments over depth results in problems with comparison to the filter pad method.

Comparing the filter pad results for the FSLE4 cruise where there was a bottle sample taken at three different depths illustrates the changes in \(a_{ph}(555)\) versus \(a_{ph}(440)\) at different depths. A change in depth from about 1.5 m below the surface to 25.3 m below the surface resulted in a 39.04% change in the \(a_{ph}(555)\) to \(a_{ph}(440)\) ratio and a 52.11% change in \(a_{ph}(555)\) value. The AOP measurement may reflect the increased relative value of \(a_{ph}(555)\) at depth if that depth is optically shallow enough to influence \(R_{rs}(\lambda)\) but the surface filter pad may not.

A caveat to the change in \(a_{ph}(440)\) relative to \(a_{ph}(555)\) is the amount of CDOM fluorescence. CDOM fluorescence at this region would act in an opposite affect on \(R_{rs}(\lambda)\) and to a lesser extent \(K_d(\lambda)\) as an increase in the \(a_{ph}(440)\) to \(a_{ph}(555)\) ratio. To resolve the issue, known values of CDOM fluorescence at individual sites would have to be compared to known values of \(a_{ph}(\lambda)\) over depth using an exact model like Hydrolight to determine the extent of the factors. Either packaging effects or CDOM fluorescence could produce errors in all the IOPs in this wavelength region. It seems likely that the errors at 555 nm for \(a_{ph}(\lambda)\) are due to a combination of sources of error and further research is needed to determine the significance of each source of error.

The filter pad did best under most filters for \(a_{ph}(676)\). Since water absorption at 676 nm is not a factor for the filter pad method, it has the best signal to noise ratio of any method at this wavelength for \(a_{ph}(\lambda)\). \(R_{rs}(\lambda)\) optimization and MODIS both do well for the filters that are not bottom only at 676 nm. Both methods have slopes close to the filter pad method. Under bottom conditions the \(R_{rs}(\lambda)\) inversions have more difficulty at 676 nm and the \(K_d(\lambda)\) optimization method does better. This difference for the \(R_{rs}(\lambda)\) inversions is possibly an artifact of the bottom reflectance especially in shallow bright bottom. It may cause the \(R_{rs}(\lambda)\) inversions to slightly decrease their \(a_{ph}(\lambda)\) reference value to compensate for increased reflectance resulting in errors at 555 nm. The \(K_d(\lambda)\) optimization method is usually not able to fit its model curve for wavelengths greater than 600 nm and it is relying on the values at shorter wavelengths to determine 676 nm based on the \(a_{ph}(\lambda)\) shape factor so it is surprising that it does much better. Since the
filter pad value at 676 nm is better, it underscores the need for multiple techniques when working under less than ideal conditions such as those with a significant bottom contribution.

One of the difficulties with the $K_d(\lambda)$ optimization method was determining the average cosine of down welling irradiance and errors in estimating this term could result in errors in separation of $a_{ph}(\lambda)$ and $a_g(\lambda)$ from $a_{nw}(\lambda)$. Both scattering ratios and cloudiness had significant spectral correlation with absolute percent error in $a_{ph}(\lambda)$. The main effect of these errors would be in determination of average cosine. Backscattering is more difficult to estimate from $K_d(\lambda)$ since it only makes up 5% of the signal. The average cosine across the air-water interface can be estimated based on Snell's law but it is more difficult at depth without *a priori* knowledge of scattering or a direct measurement. Wave focusing has a spectral effect resulting in errors in average cosine. The magnitude of $a_g(\lambda)$, under less than ideal conditions, can be in error resulting in errors in $a_{ph}(\lambda)$. If there is a tradeoff in value between $a_g(\lambda)$ and $a_{ph}(\lambda)$ in the blue wavelengths then $a_{nw}(\lambda)$ can be close to right but both $a_g(\lambda)$ and $a_{ph}(\lambda)$ can have errors.

5.8. Absolute Percent Error Correlations with Parameters

5.8.1. Correlations with $a_{nw}(\lambda)$

Under the NF filter and several other filters, there was a negative correlation between the solar zenith angle and the AOP inversion models (Figures 5.61, 5.62, 5.65, and 5.71). As the solar zenith angle decreased the error increased. Solar zenith angles of 45° or less are generally considered the best for low sun glint, surface reflectance, and sufficient water leaving radiance, but that may have to be reconsidered with the higher errors due to sun glint at lower zenith angles. A lower range limit may need to be set. $K_d(\lambda)$ has increased wave focusing at lower angles and also exhibited a negative correlation with solar zenith angle under several filters. The sun being closer to nadir will result in greater penetration of the light under wave focusing conditions. $K_{dopt}$ and $R_{rsopt}$ have less of a problem with negative correlations with zenith angle for $a_{nw}(\lambda)$ as compared to the more empirical models. The problems experienced with low solar zenith angle under $a_{nw}(\lambda)$ seem to occur more in conjunction with increased cloudiness and not under the ideal condition filters.

The ac9 had some correlations with environmental factors that should not have any influence on it but may be related to other factors. The ac9 has a negative correlation with solar zenith angle under the NB filter and the NBLCLZ filter (Figures 5.66 and 5.69). The ideal value may be biased because of the affects on the AOPs resulting in similar errors in the same direction. The ac9 has some positive correlations with increases in bottom reflectance contributions under the NF, BT, and BTLCLZ filter usually at or between 488 to 555 nm (Figures 5.63, 5.75, and 5.78). The Spec does not have correlations with bottom reflectance contribution except at 412 nm under the BT filter. While this correlation could be a bias in all the AOP methods affecting the ideal value for the ac9 but the correlation is likely because bottom contribution to $R_{rs}(\lambda)$
generally increases with shallower waters. The ac9 has troubles with the clearance of bubbles from its flow tubes and one method of clearance is to send the instrument deeper to about 30 m to where the bubbles are compressed and can be forced from the tubes. The shallower waters with significant bottom reflectance may not be deep enough to clear the flow tubes in the ac9. The correlation is really between the ac9 and depths less than 30 m and is especially problematic in clear waters.

The Spec has of correlations with \( a_{nw}(\lambda) \) absolute percent error and various parameters at 650 nm for the all the filters but only a few correlations at other wavelengths. The main correlations at 650 nm for the spec were with negative with \( a_{nw}(440) \), \( c_{nw}(440) \), and \( b_{bp}/c_{nw}(440) \) and positive for \( b_{bp}/a_{nw}(440) \) and \( b_{bp}/b_{p}(440) \) (Figures 5.63, 5.66, 5.69, 5.72, 5.75, and 5.78). The negative correlations indicate that the Spec increases in error at 650 nm as the attenuation and absorption become lower and the particulate scattering relative to attenuation becomes lower. The lowest \( a_{nw}(\lambda) \) values generally occur at 650 nm. At this wavelength the optical density of the filter pad may be below the minimum value for the Beta correction and the spectrophotometric \( a_{g}(650) \) values are well below the accuracy of the instrument. Lower particulate scattering to attenuation may mean that \( a_{g}(650) \) is a greater contribution to the \( a_{nw}(650) \) value than \( a_{p}(650) \) resulting in higher error due to the lower accuracy of the spectrophotometric \( a_{g}(\lambda) \) measurement. The backscattering ratios could also indicate problems with the beta factor in clear waters. The lowest attenuation waters in this study were around the Bahamas where the phytoplankton species population was composed primarily of small dinoflagellates. The fine aragonite sand in the Bahamas could be resuspended and clog the filter pores before a large enough quantity of water could be filtered to achieve the required absorbance on the filter pad. These aragonitic particles also have a higher \( b_{bp}/a_{nw}(440) \) and \( b_{bp}/b_{p}(440) \) explaining the positive correlation between error and those ratios. If the beta factor was not sufficient to account for the scattering in the filter by the different phytoplankton species or the aragonite particles, then it could cause the error at 650 nm. While the absolute percent error correlations for the Spec at 650 nm could simply be that it is the only method that is correct, it appears possible that this is a wavelength where it has errors due to environmental factors.

MODIS has positive correlations with significant bottom reflectance but negative correlations with \( b_{p}/c_{nw}(440) \) under filters, NF, BT and BTLCLZ (Figures 5.61, 5.73, 5.76). As scattering decreases relative to attenuation, more of the bottom reflectance might increase due to a lower return path to the surface for the light. For this study percent bottom contribution is slightly correlated \( (r^2 = 0.56) \) with \( b_{p}/c_{nw}(440) \). The stations with the highest bottom reflectance were in the Bahamas and these stations also had the lowest \( b_{p}/c_{nw}(440) \). It is likely the correlation is simply with the increased bottom reflectance and not the \( b_{p}/c_{nw}(440) \) ratio. The absorption becomes a larger portion of the attenuation due to the observed high \( a_{g}(\lambda) \) relative to \( a_{nw}(\lambda) \) in the waters around Lee Stocking Island, Bahamas decreasing the \( b_{p}/c_{nw}(440) \) ratio by increasing the attenuation. This correlation is more \( b_{p}/c_{nw}(440) \) correlating with shallower waters in this study that it is correlating with absolute percent error for MODIS.
MODIS also has positive correlations with $b_{bp}/a_{nw}(440)$ and $b_{bp}/b_{p}(440)$ but negative with $b_{p}/c_{nw}(440)$ for several wavelengths under the NB, and NBLCLZ filters but not for MODNB (Figures 5.64, 5.67, and 5.70). Unlike the correlation with percentage of bottom contribution and $b_{p}/c_{nw}(440)$, this appears to be a correlation based on the use of the empirical portion of the MODIS algorithm instead of the semi-analytical portion. The empirical portion is for waters with higher chlorophyll concentrations that were removed using the MODNB filter. Based on this correlation, the empirical portion of the MODIS algorithm does have problems in waters that are probably Case II waters. As backscattering increases as a proportion of the component absorption or particulate scattering, the absolute percent error increases. As particulate scattering decreases as a proportion of the component attenuation, the absolute percent error increases. This water probably has high CDOM and high backscattering but overall lower particulate scattering. The area with high backscattering ratios but low $b_{p}/c_{nw}(440)$ was in the Bahamas. These optical characteristics were water close enough to shore to receive the higher CDOM but far enough offshore that they are more dominated by smaller phytoplankton species with higher backscattering efficiencies.

The $K_d(\lambda)$ inversions have correlations between percent error for several wavelengths and parameters that represent water clarity and cloudiness. The $K_d(\lambda)$ inversions have some correlations with bottom reflectance but this more a correlation with the increased water clarity and shallower bottoms. Under these cases the irradiance sensor may not get deep enough below the areas of high wave focusing so that a polynomial fit can correct the wave focus values. This correlation is higher than a correlation with depth because it also factors in the water clarity. $KdKirk$ has negative correlations with $a_{nw}(440)$ for the longer wavelengths especially under the NF, NB, and MODNB filters (Figures 5.62, 5.65, and 5.71). $KdKirk$ is the most empirical of the $K_d(\lambda)$ inversions and will have more problems under conditions that are not ideal, waters that do not match the estimated $b_{bp}/a_{nw}(\lambda)$ ratios, and waters that do not have phase functions close to the Petzold phase function. Cloudiness also shows up more as a percent error correlation more under the $K_d(\lambda)$ inversions than under the $R_{rs}(\lambda)$ inversions. The problems with $K_d(\lambda)$ and cloudiness were observed under the K-W nonparametric tests.

$KdOpt$ has several percent error correlations with different parameters at 412 nm including the $b_{bp}/a_{nw}(440)$ and $b_{bp}/b_{p}(440)$ ratios (Figures 5.62, 5.65, 5.68, and 5.71). While it is not exactly clear why it has so many different error correlations at this wavelength under several of the filters, it may be because of the method of iterating the $a_g(\lambda)$ coefficient. While both $KdOpt$ and $Rrsopt$ determine the a reference value $a_g(\lambda)$, $KdOpt$ iterates over a set range to determine the best $a_g(\lambda)$ coefficient. Because the iterative models focus on minimizing the differences between the two measured and modeled curves over most of the spectrum, they are not just determining the reference value based on one wavelength. Since the $a_g(\lambda)$ is higher with decreasing wavelength, combining the iteration of the coefficient and reference may result in errors that will affect the 412 nm region more under $KdOpt$. Conditions where the scattering ratios are distinctly different or cloudiness is high may exacerbate the errors in estimating both the reference and coefficient for $a_g(\lambda)$. While $b_{bp}(\lambda)$ is not a large factor in the $K_d(\lambda)$
inversion equation, the $b_{bp}/a_{nw}(440)$ and $b_{bp}/b_{p}(440)$ ratios could be indicators of changes in the average cosine of downwelling irradiance because of changes in scattering. The combined effects of $b_{bp}(\lambda)$ attenuating downwelling irradiance and the effect of $b_{bp}(\lambda)$ on the average cosine could possibly make $b_{bp}(\lambda)$ a bigger factor in inversions from $K_d(\lambda)$ but will require much more research to determine whether this valid.

Other correlations have explanations that are more obvious. $K_d(\lambda)$ inversions, MODIS (under the BT and BTLCLZ filters), and the ac9 sometimes have negative percent absolute error correlations with $a_{nw}(440)$, $c_{nw}(440)$, and chlorophyll concentrations (Figures 5.68 and 5.72). Chlorophyll was found under many of these tests to have similar correlation values as $a_{nw}(440)$ so it is acting as a proxy for absorption at 440 nm (Figures 5.64 and 5.72). Chlorophyll concentrations could act as an indicator for $aph(440)$ when it is by itself in correlation with a method. The $K_d(\lambda)$ and ac9 values have more error as absorption and attenuation decrease because the signal to noise ratio is also declining and the longer path length $R_{rs}(\lambda)$ inversions are better. QAA, KdLoisel, and MODIS were not designed to take into account the bottom contributions to $R_{rs}(\lambda)$ and have errors when it is significant (Figures 5.61 and 5.62). Even the less than 10% bottom contribution under the non-bottom filters can contribute to some error. $R_{rs-opt}$ and MODIS under the NB and NBLCLZ filters exhibit error correlations with bottom contribution even though the bottom contribution is less than 10% (Figures 6.64 MODIS and 5.76 Rrs-opt).
Figure 5.61. Percent error correlations with environmental parameters under the NF filter for $a_{\text{nv}}(\lambda)$ inversion from $R_{\text{rs}}(\lambda)$. 

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Figure 5.62. Percent error correlations with environmental parameters under the NF filter for $a_{nw}(\lambda)$ inversion from $K_d(\lambda)$. 

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Figure 5.63. Percent error correlations with environmental parameters under the NF filter for $a_{nw}(\lambda)$ direct measurements.
Figure 5.64. Percent error correlations with environmental parameters under the NB filter for $a_{nw}(\lambda)$ inversion from $R_{rs}(\lambda)$. 

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Figure 5.65. Percent error correlations with environmental parameters under the NB filter for $a_{nv}(\lambda)$ inversion from $K_d(\lambda)$.
Figure 5.66. Percent error correlations with environmental parameters under the NB filter for \( a_{nv}(\lambda) \) direct measurements.
Figure 5.67. Percent error correlations with environmental parameters under the NBLCLZ filter for \(a_{nw}(\lambda)\) inversion from \(R_{rs}(\lambda)\).
Figure 5.68. Percent error correlations with environmental parameters under the NBLCLZ filter for $a_{nw}(\lambda)$ inversion from $K_d(\lambda)$. 
Figure 5.69. Percent error correlations with environmental parameters under the NBLCLZ filter for $a_{nv}(\lambda)$ direct measurements.
Figure 5.70. Percent error correlations with environmental parameters under the MODNB filter for $a_{nw}(\lambda)$ inversion from $R_{rs}(\lambda)$. 
Figure 5.71. Percent error correlations with environmental parameters under the MODNB filter for $a_{nw}(\lambda)$ inversion from $K_d(\lambda)$. 

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Figure 5.72. Percent error correlations with environmental parameters under the MODNB filter for $a_{nw} (\lambda)$ direct measurements.
Figure 5.73. Percent error correlations with environmental parameters under the BT filter for $a_{nw}(\lambda)$ inversion from $R_{rs}(\lambda)$. 

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Figure 5.74. Percent error correlations with environmental parameters under the BT filter for $a_{nw}(\lambda)$ inversion from $K_d(\lambda)$. 
Figure 5.75. Percent error correlations with environmental parameters under the BT filter for $a_{nw}(\lambda)$ direct measurements.
Figure 5.76. Percent error correlations with environmental parameters under the BTLCLZ filter for \( a_{nw}(\lambda) \) inversion from \( R_{rs}(\lambda) \).
Figure 5.77. Percent error correlations with environmental parameters under the BTLCLZ filter for $a_{nw}(\lambda)$ inversion from $K_d(\lambda)$.
5.8.2. Correlations with $b_{bp}(\lambda)$

The bottom contribution correlates with absolute percent error under most filters for $b_{bp}(\lambda)$. Even the less than 10% contribution has an effect on the determination of $b_{bp}(\lambda)$ from $R_{s,opt}$ (Figure 5.81). QAA seems to be affected the most when bottom was above 10% (Figures 5.76, 5.87, and 5.88). The bottom is most visible in the middle wavelengths where the attenuation is lowest and most models use that to fit the bottom contribution. By iterating the $b_{bp}(555)$ value QAA and $R_{s,opt}$ may be more likely to include the bottom contribution as $b_{bp}(\lambda)$ under conditions where the contribution is small. By using an empirical approach, MODIS may not have the same errors in $b_{bp}(\lambda)$. 

Figure 5.78. Percent error correlations with environmental parameters under the BTLCLZ filter for $a_{nw}(\lambda)$ direct measurements.
This does not mean that MODIS has the best approach for determining $b_{bp}(\lambda)$ from $R_{rs}(\lambda)$ when bottom is present but it did have regression results that were closer to unity as compared to the QAA and Rrs$^{opt}$ inversions when bottom contribution to $R_{rs}(\lambda)$ was significant.

QAA has a positive correlation between absolute percent error for $b_{bp}(\lambda)$ and $a_{nw}(440)$ under the NB filter but a negative correlation under the MODNB filter (Figures 5.81 and 5.85) and a negative spectral correlation with chlorophyll under the BT filter (Figure 5.87). The QAA model appears have problems with absorption under conditions where solar zenith angle or cloudiness is high resulting in errors in $b_{bp}(\lambda)$ with increasing absorption. The MODNB filter results in low-chlorophyll low-attenuation waters and as the absorption value decreases the QAA has more error under this filter (Figure 5.85). Under the NBLCLZ filter and under the NB filter, QAA has positive correlations with $b_{bp}/a_{nw}(440)$ and $b_{bp}/b_{p}(440)$ but negative with $b_{p}/c_{nw}(440)$ for several wavelengths (Figures 5.81 and 5.83). Like MODIS, the QAA model may not be able to compensate for changes in parameters like the Q factor under coastal water that are high back scattering but have low particulate scattering. Even though Rrs$^{opt}$ and QAA have similar approaches to inverting $R_{rs}(\lambda)$ for $b_{bp}(\lambda)$, the QAA model has a more empirical approach to determination of the "g" coefficient and does not do as many iterations for determining the reference values for $b_{bp}(\lambda)$. This more empirical approach makes it computationally faster but makes it more sensitive to conditions that are not ideal.

$K_{d}$opt has a positive spectral correlation with $a_{nw}(440)$ and chlorophyll but a negative correlation with $b_{p}/c_{nw}(440)$ under the NB filter for $b_{bp}(\lambda)$ (Figure 5.82). This correlation gives information that was already suspected, that $K_{d}$opt has problems determining $b_{bp}(\lambda)$ when its signal is small relative to absorption. The percentage of $b_{bp}(\lambda)$ contributing to the $K_{d}(\lambda)$ signal is only about 5%. As absorption increases in value relative to scattering, the percent error for the inversion using $K_{d}$opt increases.

The HS6 has several positive correlations with $b_{bp}/a_{nw}(440)$ and $b_{bp}/b_{p}(440)$ (Figures 5.80, 5.82, 5.86, 5.87, and 5.88). This increase in absolute percent error could be due to problems with the AOP inversions under these environments biasing the ideal values in the same direction. However, it may be a problem with the assumption that total backscattering is $1.08 \pi b(140^\circ)$. The HS6 actually only measures backscattering at a $140^\circ$ but extrapolates it all backscattering angles based on an empirical assumption that usually can estimate backscattering to within 10%. The higher backscattering ratios are often indicative of smaller particles. These particles may not fit the relationship used by the HS6 for the estimating total backscattering. The result is that under these conditions, the HS6 may need a different empirical function to more accurately estimate $b_{bp}(\lambda)$. 

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Figure 5.79. Percent error correlations with environmental parameters under the NF filter for $b_{bp}(\lambda)$ inversion from $R_n(\lambda)$. 

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Figure 5.80. Percent error correlations with environmental parameters under the NF filter for $b_{bp}(\lambda)$ from HS6 and Kdopt.
Figure 5.81. Percent error correlations with environmental parameters under the NB filter for $b_{bp}(\lambda)$ inversion from $R_{rs}(\lambda)$.
Figure 5.82. Percent error correlations with environmental parameters under the NB filter for $b_{np}(\lambda)$ from HS6 and Kdopt.
Figure 5.83. Percent error correlations with environmental parameters under the NBLCLZ filter for \( b_{bp}(\lambda) \) inversion from \( R_{rs}(\lambda) \).
Figure 5.84. Percent error correlations with environmental parameters under the NBLCLZ filter for $b_0(\lambda)$ from HS6 and Kdopt.
Figure 5.85. Percent error correlations with environmental parameters under the MODNB filter for $b_{bp}(\lambda)$ inversion from $R_{rs}(\lambda)$. 
Figure 5.86. Percent error correlations with environmental parameters under the MODNB filter for $b_{bp}(\lambda)$ from HS6 and Kdopt.
Figure 5.87. Percent error correlations with environmental parameters under the BT filter for $b_p(\lambda)$ for QAA and HS6.
Figure 5.88. Percent error correlations with environmental parameters under the BTLCLZ filter for $b_{bp}(\lambda)$ Rrs opt, QAA, and HS6.
5.8.3. Correlations with $a_g(\lambda)$

Kdopt absolute percent error for $a_g(\lambda)$ had positive correlations with $c_{nw}(440)$ and cloudiness under all the filters with no significant bottom contribution to reflectance (Figures 5.89, 5.92, 5.93, and 5.95). The correlations either started lower at 440 or 488 nm and increased slightly with wavelength. Under MODNB there were also similar magnitude correlations with Chlorophyll concentrations and $a_{nw}(440)$. While the NBLCLZ filter was considered low cloudiness, it used at 80% or greater cloudiness as its filter point. This correlation may be the reason for the lower agreement for the $K_d(\lambda)$ inversions with increasing cloudiness using the K-W nonparametric statistics. Since there is no correlation with these parameters at 412 nm, they are not affecting the reference value for $a_g(\lambda)$. This error correlation is possibly an effect from the Gordon Normalization (Gordon 1989). Even though the diffuse light values used in the Gordon Normalization were calculated using the cloudiness correction in Hydrolight, it may not have properly modeled it. As cloudiness increases the light becomes more diffuse. As attenuation increases the light becomes less at depth. Kdopt $a_g(\lambda)$ does not have a similar correlation when the bottom contribution is significant indicating that this is probably an effect on the geometric light field at depth. Kdopt method cannot compensate for the longer path length of light in conjunction with greater attenuation. While the problem with the model is not clear without further testing, the average cosine of downwelling irradiance is probably competing with the spectral slope coefficient of $a_g(\lambda)$.

MODIS and Rrsopt both had negative correlation at the longer wavelengths with solar zenith angles using the NB, NF, NBLCLZ, and MODNB filters (Figures 5.89, 5.92, and 5.95). In addition, MODIS had negative correlations with solar zenith angles at 412 and 440 nm using the BT filter (Figure 5.97) and Rrsopt had negative correlations under the BTLCLZ filter. MODIS always correlated with 412 and 440 nm but continued out to 555 nm under the NF and NB filters. Rrsopt never had correlations at 412 nm but had correlations from either 440 or 488 to 532 or 555 nm. This error is likely due to sun glint but affects each $R_{rs}(\lambda)$ inversion model in different ways because of their different $a_g(\lambda)$ slope coefficients.

Solar zenith angle was a significant affect on $a_g(\lambda)$ as all AOP methods had correlation with it and $a_g(\lambda)$ under some filters. Even Specag had correlations under every filter except for BTLCLZ. This correlation indicates that the solar zenith angle affected all the AOP methods introducing an error in the ideal value. This error in $ag(\lambda)$ usually occurred at a wavelength greater than 412 nm.

While MODIS had several positive correlations with $a_g(\lambda)$ absolute percent error and bottom contribution to reflectance under the NF, BT, and BTLCLZ filters (figures 5.89, 5.97 and 5.99), Rrsopt only had correlations at 412 to 488 nm under the NB filter (Figure 5.92). Rrsopt had correlation with bottom contribution and absolute percent error using the NB filter for $a_{nw}(\lambda)$ and $b_{np}(\lambda)$ despite the contribution being less than 10% (Figures 5.64 and 5.81). A low bottom contribution to reflectance is detectable under the
RrsOpt model but it does seem to produce errors in the IOP values when conditions are not ideal or the water has a higher chlorophyll concentration.

MODIS had positive $a_g(\lambda)$ error correlations with $b_{bp}/b_p(440)$, $b_{bp}/a_{nw}(440)$ and chlorophyll concentrations under the NB and NBLCLZ filter at 412 and 440 nm (Figures 5.92 and 5.93). This looks similar to the correlations under for $a_{nw}(\lambda)$ the backscattering ratios. This correlation appears under the filters where bottom contribution to $R_{rs}(\lambda)$ is not significant and MODIS includes the default algorithm in the mix. These correlations appear to indicate a path length problem with the default algorithm because of the error associated with the scattering ratios.

Specag and filtered ac-9 had negative correlations with $a_{nw}(440)$ and $a_g(\lambda)$ absolute percent error. Specag was spectral for MODNB while the ac-9 was at 412 and 440 nm (Figure 5.96). This was probably due to low signal to noise from the lower path length instruments. MODIS had a negative correlation with $a_{nw}(\lambda)$ for the entire spectrum under the MODNB filter and RrsOpt had negative $a_g(\lambda)$ error correlations with $a_{nw}(\lambda)$ for 532 to 650 (Figure 5.95). KdOpt had positive error correlations for 488 to 676 with $a_{nw}(\lambda)$ under the MODNB filter. Except for KdOpt, all the methods had some signal to noise problems for $a_g(\lambda)$ in the clearest waters. KdOpt had problems with too high of an absorption producing errors in $a_g(\lambda)$. 
Figure 5.89. Percent error correlations with environmental parameters under the NF filter for $a_d(\lambda)$ from AOP inversions.
Figure 5.90. Percent error correlations with environmental parameters under the NF filter for $a_g(\lambda)$ from Specag.

Figure 5.91. Percent error correlations with environmental parameters under the NB filter for $a_g(\lambda)$ from Specag.
Figure 5.92. Percent error correlations with environmental parameters under the NB filter for $a_{g}(\lambda)$ from AOP inversions.
Figure 5.93. Percent error correlations with environmental parameters under the NBLCLZ filter for $a_d(\lambda)$ from AOP inversions.
Figure 5.94. Percent error correlations with environmental parameters under the NBLCLZ filter for $a_g(\lambda)$ from Specag.
Figure 5.95. Percent error correlations with environmental parameters under the MODNB filter for $a_g(\lambda)$ from AOP inversions.
Figure 5.96. Percent error correlations with environmental parameters under the MODNB filter for $a_g(\lambda)$ direct measurements.
Figure 5.97. Percent error correlations with environmental parameters under the BT filter for $a_g(\lambda)$ from AOP inversions.
Figure 5.98. Percent error correlations with environmental parameters under the BT filter for $a_g(\lambda)$ direct measurements.
Figure 5.99. Percent error correlations with environmental parameters under the BTLCLZ filter for $a_g(\lambda)$ from AOP inversions.
For $a_{ph}(\lambda)$ MODIS has positive correlations between absolute percent error and $b_{bp}/a_{nw}(440)$ and $b_{bp}/b_{p}(440)$ but negative with $b_{p}/c_{nw}(440)$ for most wavelengths under the all filters but except for MODNB. These correlations are similar to those for $a_{nw}(\lambda)$ and $a_{g}(\lambda)$ percent error. Because the semi-analytical MODIS exhibits few correlations with the scattering ratios, it is the default band ratio algorithm that is having the most difficulty with $a_{ph}(\lambda)$. This error seems to occur when optical properties are very different from Case 1 waters. At 650 nm, MODIS has fewer correlations with the scattering ratios but this is an extrapolated value. MODIS is at a disadvantage in this comparison, though. Kdopt and Rrsopt use known shape factors for $a_{ph}(\lambda)$ based on the filter pad measurements from each of the 3 locations leading to dependencies among their results. MODIS requires no \textit{a priori} knowledge of the area and is designed for large pixel satellite images collected around the globe. The empirical portion of MODIS will only be used for high chlorophyll regions so this does not indicate an error for most of the regions where the MODIS algorithm is used for $R_{rs}(\lambda)$ inversions from satellite data.

Kdopt has more correlations between absolute percent error for $a_{al}(\lambda)$ and factors that affect the light field above the surface. Under the NF filter, Kdopt has correlations with solar zenith angle for 412 to 488 nm and cloudiness for 532 to 676 nm. Under the NB and MODNB filter there were also correlation with both, but only negative
correlation with solar zenith angle under the NBLCLZ filter. Kdopt for the $a_{\text{ph}}(\lambda)$ inversion appears more susceptible to the diffuse light from increased cloud cover and spectral shifts from wave focusing at lower zenith angles. Kdopt percent error had a spectral correlation with bottom contribution to reflectance under the BT filter and for the short wavelengths under the BTLCLZ filter. Part of this may be that the $a_{\text{ph}}(\lambda)$ methods from the $R_{ns}(\lambda)$ inversions are much better since Kdopt has the shortest path length of the AOP inversions. As presented earlier, the quantitative filter pad method for $a_{\text{ph}}(\lambda)$ has a very long effective path length and it may even exceed the path length for the $K_d(\lambda)$ measurement if a shallow bottom limits the depth for the profile of $E_d(\lambda)$ to determine $K_d(\lambda)$. Even though cloudiness did seem to cause problems for the Kdopt inversion for $a_{\text{ph}}(\lambda)$, this may not be a factor where the Kdopt model failed but a case where the $R_{ns}(\lambda)$ inversions and the Specaph methods were just that much better under those conditions.

While the $b_p/c_{nv}(440)$ values do correlate with bottom contribution to reflectance, there were some correlations with absolute percent error for $a_{\text{ph}}(\lambda)$ under conditions with little bottom influence for the AOP inversions. For total scattering divided by attenuation, this term is called single scattering albedo or probability of photon survival. If the ratio is close to one, then the photon is more likely to be scattered while if the ratio is lower the photon is more likely to be absorbed. For the inversion of $a_{\text{ph}}(\lambda)$, it appears that under most filters there is a negative correlation between the $b_p/c_{nv}(440)$ ratio and percent error for AOP based models. As the chance for survival of the photon goes down, the effective path length of the AOP value decreases. This results in a lower signal to noise for the AOP inversion. For waters that are high in CDOM or have particles that are low in scattering, the AOP inversions for $a_{\text{ph}}(\lambda)$ experience more error.
Figure 5.101. Percent error correlations with environmental parameters under the NF filter for $a_{ph}(\lambda)$ from AOP inversions.
Figure 5.102. Percent error correlations with environmental parameters under the NF filter for $a_{ph}(\lambda)$ filter pad method.

Figure 5.103. Percent error correlations with environmental parameters under the NB filter for $a_{ph}(\lambda)$ filter pad method.
Figure 5.104. Percent error correlations with environmental parameters under the NB filter for $a_{ph}(\lambda)$ from AOP inversions.
Figure 5.105. Percent error correlations with environmental parameters under the NBLCLZ filter for $a_{ph}(\lambda)$ from AOP inversions.
Figure 5.106. Percent error correlations with environmental parameters under the MODNB filter for $a_{ph}(\lambda)$ from AOP inversions.

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Figure 5.107. Percent error correlations with environmental parameters under the MODNB filter for \( a_{ph}(\lambda) \) filter pad method.

Figure 5.108. Percent error correlations with environmental parameters under the BT filter for \( a_{ph}(\lambda) \) filter pad method.
Figure 5.109. Percent error correlations with environmental parameters under the BT filter for $a_{\text{ph}}(\lambda)$ from AOP inversions.
Figure 5.110. Percent error correlations with environmental parameters under the BTLCLZ filter for \( a_{ph}(\lambda) \) from AOP inversions.
5.9. Problems with Making Comparisons Between Methods

The comparisons in this study may not be fair to all the AOP inversion models since some were better designed for these environmental conditions in this study. Some of the AOP inversions models tested in this study were at a disadvantage to the other inversion models due to data not collected. Bottom reflectance was possibly an influence at 46 of the 126 stations in this study and the only \( R_{rs}(\lambda) \) inversion model that took it into account was the Lee et al. \( R_{rs}(\lambda) \) optimization algorithm (Lee et al. 1998, Lee et al. 1999). The geometric underwater light field may be influenced by cloud cover and zenith angle affecting all AOPs in a similar manner biasing the ideal IOP values. Some of the models were created to work with the limited wave bands available from satellites and are being compared to models that use hyperspectral data putting them at a disadvantage. The limitations of the some of these models were expected and were factored into the comparisons.

The inversion model by Loisel et al. required below water irradiance reflectance \( r_{rs}(\lambda)0^- \), as an input (Loisel et al. 2001). Only downwelling irradiance was collected below water not upwelling radiance. To substitute for the \( r_{rs}(\lambda)0^- \), \( R_{rs}(\lambda) \) with an empirical function (Carder et al. 1999) to correct for the air water interface and irradiance to radiance ratio (Q factor) was substituted. This substitution introduced errors into the algorithm since they use \( r_{rs}(\lambda)0^- \) in a function to determine scattering and the average cosine of scattering. The portion of the model to determine \( b_{op}(\lambda) \) wasn't even used since

![Figure 5.111. Percent error correlations with environmental parameters under the BTLCLZ filter for \( a_{ps}(\lambda) \) filter pad method.](image-url)
it would have resulted in very large errors without including a measured $r_{ns}(\lambda)$. The Loisel et al. model is not expected to function as well as the Kd optimization model because of this missing input.

The $R_{rs}(\lambda)$ inversion models had difficulties in estimating $b_{bp}(\lambda)$ when bottom contributions to $R_{rs}(\lambda)$ were significant. The QAA and MODIS algorithm were not parameterized to take into account the bottom albedo. The $R_{rs}(\lambda)$ optimization algorithm took into account the bottom but, like the other $R_{rs}$ inversions, it used an empirical model to determine the spectral slope of $b_{bp}(\lambda)$. The $b_{bp}(\lambda)$ value generally affects the spectral shape of the $R_{rs}(\lambda)$ curve in the areas of lowest absorption. This usually falls into the green area of the spectrum around 532 to 555 nm. The combined affects of bottom reflectance and backscattering are hard to separate resulting in errors in $b_{bp}(\lambda)$ from $R_{rs}(\lambda)$ inversion algorithms even if they take into account the bottom contribution. The $R_{rs}$opt method has a set spectral shape for the bottom albedo that is only controlled by a factor. The albedo is based on pure sand and increases almost linearly with wavelength. Actual measurements of bottom albedo can have variations in shape spectrally that are non linear or have a different intercept if linear. These variations can result in further errors in $b_{bp}(\lambda)$ values from the $R_{rs}$ optimization model. The in situ $b_{bp}(\lambda)$ measurements from the HS6 had to be used to achieve reasonable results for the bottom albedo inversion instead of the $R_{rs}$opt $b_{bp}(\lambda)$ values due to problems with inverting $b_{bp}(\lambda)$ from $R_{rs}(\lambda)$ in areas where there is significant bottom reflectance. The presence of significant bottom reflectance in the $R_{rs}(\lambda)$ signal results in lower accuracy for the inverted $b_{bp}(\lambda)$ values.

The $K_d(\lambda)$ measurements had the most noticeable effects from zenith angle. A lower solar zenith angle resulted in errors in $K_d(\lambda)$ that increased with wavelength. The higher the sun was in the sky the greater magnitude of the wave focusing. Wave focusing affects the $K_d(\lambda)$ primarily in the longer wavelengths since these are normally attenuated by water absorption, the sudden focusing allows them to penetrate deeper. $E_d(\lambda)$ drops off rapidly at the wavelengths greater than 600 nm due to water absorption and there are fewer readings to fit a curve through resulting more noise in $K_d(\lambda)$ values. For $K_{dopt}$ this error can show up at other wavelengths than those most affected by wave focusing because it does an iterative fit to most of the visible spectrum. This zenith angle effect on wave focusing especially hurts the $K_d(\lambda)$ inversion models that rely more on empiricism.

The $R_{rs}(\lambda)$ error sometimes increases with lower solar zenith angles. When the sun is higher there is a greater amount of specular reflection (sun glint) on the surface of the water. This results in a bias to the $R_{rs}(\lambda)$ spectra making it appear higher than normal. The $R_{rs}$opt algorithm can correct some for errors due to sun glint by subtracting off a bias that is determined through iteration but the other $R_{rs}(\lambda)$ inversion models do not do this. If the reflectance is too much it can increase the whole spectra but especially affect the red end and none of the models can correct for this. The inclusion of sun glint will most affect the inversion for $b_{bp}(\lambda)$ resulting in an underestimate since it's spectral shape is flatter than $a_{pi}(\lambda)$ or $a_g(\lambda)$. Both high and low solar zenith angles can affect $R_{rs}(\lambda)$
inversion accuracy but the lower solar zenith angles appear to be a bigger factor than first thought.

Sometimes sun glint can be minimized by use of a different technique or processing method for collecting the $R_{rs}(\lambda)$ data. One alternative is to try to collect the $R_{rs}(\lambda)$ at an angle different from the usual 30°. Sometimes a 40 to 45° angle for view angle of the radiance spectrometer can result in less sun glint. In some cases, sun glint results in a saturation of the reading by the spectrometer. The spectrometer takes an initial scan to determine how long to integrate the reading. If the movement of the water from waves or swells results in a change in the amount of sun glint during the actual scan the result can be a reading that is the maximum allowed due to saturation of the detector. The standard procedure used in collecting the $R_{rs}(\lambda)$ was for 3 sets of one scan of the grey card, three scans of water radiances, and one scan of sky radiance. The saturated scan is then excluded. However, if the scan is higher in value but not saturated, it introduces a bias to the $R_{rs}(\lambda)$ values if it is not noticed during processing. This bias can affect all $R_{rs}(\lambda)$ inversion techniques. While attempts are made to minimize sun glint in $R_{rs}(\lambda)$ measurements, it can still have some effects.

Cloudiness had a minimal effect on $R_{rs}(\lambda)$ but had a noticeable effect on $K_d(\lambda)$. A $R_{rs}(\lambda)$ scan collected under partly cloudy skies can exhibit a lot of noise with small spikes in value over the spectrum but can still have an overall shape that can be inverted if smoothed or used in a hyperspectral algorithm. The only affect is minimally on the $b_{bp}(\lambda)$ and not the $a_{nys}(\lambda)$. The effect on $K_d(\lambda)$ was more pronounced. The change in the average cosine of downwelling irradiance affects the $K_d(\lambda)$ inversions resulting in an overestimate of absorption. The $E_d(\lambda)$ is lower due the longer path and lower surface irradiance. The lower subsurface irradiance results in fewer depths for curve fitting to determine $K_d(\lambda)$ resulting in a less accurate value due to cloudiness.

The $K_d(\lambda)$ optimization algorithm was able to compensate somewhat for cloud cover by using Gordon's normalization for $K_d(\lambda)$ (Gordon 1989). Hydrolight has a simple algorithm that takes the input from Radtran (Gregg and Carder 1990, Mobley 1994) and adjusts the direct and diffuse ratios for cloudiness. These direct and diffuse irradiance ratios are used in Gordon's normalization algorithm to remove the effects of the average cosine due to solar zenith angle and diffuse sky irradiance leaving only the average cosine due to scattering. While this technique cannot accurately compensate completely for partly cloudy skies, it did improve the results for the $K_d(\lambda)$ optimization method. Further improvement in model results was made under cloudy conditions by having the average cosine of downwelling irradiance spectrally vary under the $K_d(\lambda)$ optimization algorithm. This allowed the model to compensate for changes in spectral average cosine due to cloudiness with an iterated value for the magnitude to compensate for the increase in diffuse downwelling irradiance. The $K_d(\lambda)$ optimization algorithm was able to compensate some for the effects of cloudiness while the other $K_d(\lambda)$ inversion algorithms were more limited.
Several of the models were originally parameterized to use only specific wavelengths. These models are at a disadvantage when compared to models that use hyperspectral input data. This is most notable in the red end of the spectrum where there is low signal. The KdKirk and the KdLoisel Models do not take into account spectral variations in $b_\theta(\lambda)$ or $a(\lambda)$ that are outside expected levels. The MODIS $R_{\text{rs}}(\lambda)$ inversion algorithm is parameterized to function at the MODIS satellite wavelengths. The QAA model is parameterized to use only 440 and 550 nm wavelengths in the version used in this study. One advantage to these models using these wavelengths is that satellites and some oceanographic instruments only collect data at specific optical wavelengths. However, when there is hyperspectral data available, the models that use a fitting method to the spectral curve are expected to outperform the others. In the case of the $K_d(\lambda)$ inversions, there is a much lower signal at the longer wavelengths, but the $K_d(\lambda)$ optimization algorithm uses a fit at all wavelengths and filters out the longer wavelengths that are obvious errors. The use of a hyperspectral fit means that the $K_d(\lambda)$ optimization method performs better than either of the other models at the longer wavelengths. The models that are designed to use hyperspectral data were able to compensate for spectral changes in in situ values while the others are more limited.

Field comparisons introduce more errors than laboratory or artificial data when comparing AOP inversions to more direct IOP measurements so the best closure to the ideal value is around 20% for this study. The artificial data used for other closure experiments for AOP models does not contain possible operator error, instrument failure, or instrument accuracy limitations. The surface waves are ideal structures in data from the Hydrolight model and do not contain sea foam or floating debris like field conditions. The input data under idealized modeled conditions usually doesn't include partial cloud cover, low solar zenith angles, or sun glint. Hydrolight does not even simulate fish schools swimming over the submersible downwelling irradiance sensor or doing profiles in schools of thimble jellyfish. Since the conditions are rarely absolutely perfect in the field and this study assumes that no model or method is the absolute truth under any conditions, it is not surprising that the best closure achieved by any model or method was 20%.

Most closure experiments premise one method as most accurate and then compare the other measurements to it. While this approach can achieve much greater closure than 20%, it does present some problems. Using a single method assumes that it is independent from the other methods and is close to the actual value. Dependence can vary between the measurements and models depending on how and where the models were parameterized and the data collected. The $R_{\text{rs}}(\lambda)$ and $K_d(\lambda)$ optimization models might have dependencies based on how close the $a_{\text{ph}}(\lambda)$ measurements are to the filter pad values that were used to calculate the shape factors. The $a_{\text{ph}}(\lambda)$ inversions might have more dependencies if they are adjusted based on measurements from the same area. The measurements from a surface water sample when there is a change in optical properties over depth will not have the same result as a profile over depth. Most closure experiments examine areas with less optical variability than those in this study and consider a single measurement to be the truth.
5.10. Best Methods

Overall the best method for determining IOPs under most conditions was the $R_{rs}(\lambda)$ optimization algorithm. $R_{rs}(\lambda)$ measurements provide the longest path length of light to determine signal. The inversion models and techniques for measuring $R_{rs}(\lambda)$ have progressed to the point where they are good alternatives for \textit{in situ} measurements. In optically clear waters, the $R_{rs}(\lambda)$ inversions have better signal to noise ratios than any of the more direct IOP measurements except for the quantitative filter pad technique. However, under certain conditions, the other techniques are better. The Hydroscat-6 is better for determining $b_{bp}(\lambda)$ in waters where the bottom reflectance is greater than 10% of the $R_{rs}(\lambda)$ signal. For $a_{aw}(\lambda)$ in areas with greater than 10% bottom reflectance, the $K_d(\lambda)$ optimization method was the best when doing inversions to determine albedo. Overall $R_{rs}(\lambda)$ optimization was the best method but under certain conditions, wavelengths, and IOP types other methods proved better.

The mean absolute percent error as averaged over the first six wavelengths are listed at the end of this chapter. They can give a little idea about which method did best under each filter but should be viewed with caution. For example under the $a_{aw}(\lambda)$ bottom filters $KdKirk$ and $KdLoisel$ appear to be some of the best inversions. Because these tables are for the first three wavelengths it does not show that they sharply increase in error immediately at the next one or two wavelengths. These tables do not show that while Specag appears to have low absolute percent error when the bottom contribution is significant that it also has poor regression results under those filters. So while this can provide a little insight into which model performed best it would be best to check the other statistics before using that method for analysis of an environmental problem.
Table 5.2. Mean absolute percent error for $a_{sw}(\lambda)$ from 412 to 555 nm. *QAA is a mean of 440 and 555 nm not a mean over six wavelengths like the other values.

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<tr>
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<td>176.91</td>
<td>59.68</td>
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<td>15.38</td>
<td>81.38</td>
<td>16.02</td>
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</tr>
<tr>
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<td>226.31</td>
<td>107.49</td>
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<td>214.94</td>
<td>83.62</td>
<td>57.44</td>
<td>72.26</td>
<td>32.05</td>
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Table 5.3. Mean absolute percent error for $b_{sp}(\lambda)$ from 442 to 589 nm.

<table>
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<th>MODIS</th>
<th>QAA</th>
<th>Rsopt</th>
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<tr>
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<td>82.58</td>
<td>40.02</td>
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<td>NB</td>
<td>47.34</td>
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Table 5.4. Mean absolute percent error for $a_{g}(\lambda)$ from 412 to 555 nm.

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<th>MODIS</th>
<th>Rsopt</th>
<th>Specag</th>
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Table 5.5. Mean absolute percent error for $a_{pl}(\lambda)$ from 412 to 555 nm.

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6. Improvements to Instruments and Methods

6.1. Analytical Versus Empirical Models

The more analytical models were hypothesized to produce better results and the statistical comparisons support that hypothesis, with a few exceptions, was supported. The analytical models do have disadvantages when compared to the more empirical models since they require more a priori knowledge of a study region. There is some empiricism required even for the methods that are more direct. All of the direct IOP measurements require corrections for path length elongation, attenuation, or scattering. The inversion models varied as to their degree of empiricism. For the K_d(\lambda) inversions, the K_d(\lambda) optimization model was the least empirical followed by the Kd Loisel Model, and the Kd Kirk model. The ranking from least to most empirical for the Rrs inversions are R_{rs}(\lambda) optimization, MODIS semi-analytical, QAA, and the MODIS default band ratio model. The inclusion of empiricism in all methods is one of the reasons why it is difficult to determine absolute truth in the value of the IOPs.

The best illustration of the degree of empiricism as a contribution to error are the regression statistics for a_{ww}(\lambda) under the filters MODNB and NBLCLZ. Under the NBLCLZ filter, the K_d(\lambda) models exhibit a larger diversion from a regression slope of one at the longer wavelengths due to less signal but have median values overall that are close to one. However, the K_d(\lambda) optimization method is the only K_d(\lambda) inversion method that comes close to zero intercept at the longer wavelengths. R_{rs}(\lambda) optimization has the median slope closest to one under the NBLCLZ method while MODIS and the QAA model have median slopes much different from one. Under the MODNB filter, where only the semi-analytical model for MODIS is used, MODIS improves its regression results and tracks closer to the values for the less empirical R_{rs}(\lambda) optimization algorithm. The degree of empiricism of these methods corresponds almost directly to the regression results under the ideal conditions.

The ac-9 uses four different empirical or estimated corrections to correct absorption values. It uses the ratio of the initial estimate of scattering at a given wavelength to scattering at 715 nm times the absorption value at 715 nm to estimate a correction for internal losses of signal. In addition to that correction, there is an empirical correction for internal temperature shifts in the ac-9 that would affect its photocells. The ac-9 also uses an empirical relationship to correct for the difference between the temperature and salinity of the pure water used for calibration and the in situ values. Even the direct ac-9 IOP measurements rely on some empiricism to correct for errors and path length elongation.
Each of the spectrophotometric methods uses an empirical or estimated correction. The filter pad method uses an empirical equation called the beta factor to correct for path length elongation. The beta factor is based on the expected types and sizes of particulate matter present in the sample. The correction is limited to a minimum and maximum value of absorbance based on the range of its empirical fit. Even the spectrophotometric CDOM absorption measurements assume that the 750 nm value is all scattering and that scattering is spectrally flat to correct for internal scattering within the cuvette. Even the laboratory direct IOP measurements require empiricism.

The Hydroscat-6 uses three empirical equations in processing the output. During calibration, an empirical relationship is established at each wavelength to correct for attenuation along the path of the signal. The Hydroscat-6 uses an empirical equation for the backscattering due to seawater that is about half the value determined by Morel's research. The instrument measures backscattering at an angle of 140° but estimated total backscattering through an empirical relationship. Total backscattering is estimated by multiplying the $b_b(\lambda, 140^\circ)$ by pi and 1.08. The assumption is that the total backscattering is equal to 8% more than if integrated over a hemisphere. The three empirical corrections for the Hydroscat-6 can have a significant affect on its $b_b(\lambda)$ value if any of those assumptions are not met.

The $K_d(\lambda)$ optimization algorithm is the least empirical of the $K_d(\lambda)$ inversions algorithms. The $K_d(\lambda)$ optimization model is based on Preisendorfer's formulation of the relations between $K_d(\lambda)$ and IOP values (Preisendorfer 1961). If the average cosines are known and the $K_d(\lambda)$ values are perfect, then the model should give the close to the exact value for $a_{nw}(\lambda)$ and $b_{bp}(\lambda)$. The empiricism in this model arises from determining the average cosines of upwelling and downwelling light. The $K_d(\lambda)$ Loisel model uses the below water irradiance reflectance and above water average cosine of downwelling irradiance to empirically estimate the average cosine and then determines $a(\lambda)$ empirically. The Kirk $K_d(\lambda)$ inversion is most empirical and requires an estimate of the $b(\lambda)$ to $a(\lambda)$ ratio along with the average cosine of above surface solar zenith angle to determine $a(\lambda)$ from $K_d(\lambda)$. Both the Kirk and Loisel $K_d(\lambda)$ inversions perform well at shorter wavelengths from 400 to about 500 nm. However, they have problems at the longer wavelengths due to lower signal and the lack of spectral variations in their parameters. The Kirk $K_d(\lambda)$ inversion performs well enough at 440 nm that it was used to initialize the absorption values for the iteration process in the $K_d(\lambda)$ inversion algorithm. The $K_d(\lambda)$ optimization algorithm is the least empirical of the three $K_d(\lambda)$ inversion algorithms and provided the best inversion results for $K_d(\lambda)$ under the most conditions and wavelengths.

The $R_{rs}(\lambda)$ inversions consist of actually 4 models. The $R_{rs}(\lambda)$ optimization model is the least empirical followed by the MODIS semi-analytical, the QAA, and the MODIS default algorithm. The $R_{rs}(\lambda)$ inversion algorithm breaks the path of the light into two components, $rrs(\lambda)$ due to the water column and the $rrs(\lambda)$ due to the bottom albedo. Empirical relationships with absorption and backscattering are then used to determine the
light field geometry while the rest of the values are determined through iteration. The MODIS semi-analytical algorithm uses an iterative process to determine \( a(\lambda) \) but relies on an empirical algorithm for \( b_{bp}(\lambda) \) at the reference wavelength. The QAA model uses only three iterations to solve for \( a_{nw}(440, 550) \) and \( b_{bp}(440, 550) \). All three models use an empirical relationship to determine the coefficient for \( b_{bp}(\lambda) \). MODIS has a default algorithm for high chlorophyll areas that uses ratios of \( R_{rs}(\lambda) \) at specific wavelengths to empirically determine \( a(\lambda) \). The MODIS default algorithm is the most empirical of the \( R_{rs}(\lambda) \) inversion algorithms.

The use of empiricism and the accuracy of the methods make it difficult to determine the real value of the IOPs. The AOP inversions have greater accuracy at most wavelengths in optically clear waters due to the longer path length the light travels. However, the empiricism in some of these models may cause spectral inaccuracies at longer wavelengths where path length is reduced as observed for the Kirk and Loisel \( K_d(\lambda) \) inversion models. While the direct methods have fewer empirical assumptions, most have lower accuracy when the signal to noise ratio is lower due their shorter path length.

The use of empirical methods in the direct measurements means that it is difficult to get an absolute measure of the IOPs. If it were possible to provide these corrections from first principles, then the limitation would be simply the accuracy of the instrument. As it stands, most of these corrections are small but some of them can have a large influence on smaller values. The ac-9 \( a_{nw}(650) \) measurement can be in error by over 50% due to a 5% error in the \( a_{nw}(715) \) value used in the correction algorithm. This error is part of the reason why the ac-9 performs best in areas of higher absorption. The \( a_{nw}(715) \) value is usually very low and may be below the accuracy limit of the ac-9. Because of this low value, the magnitude of the \( a_{nw}(715) \) from the ac-9 may be more a function of instrument noise than scattering in low attenuation waters.

While AOP methods perform best at the shorter wavelengths (412 and 440 nm), there are assumptions in these models that can affect their accuracy at the longer wavelengths. If the phytoplankton absorption spectra in the optimization models are not representative of the study area, then there could be spectral differences at the longer wavelengths. Since the \( K_d(\lambda) \) optimization and \( R_{rs}(\lambda) \) optimization use the same phytoplankton shape factors, it could mean that they might be biased in a similar manner. This would bias the median ideal value used to compare against the other models. If the spectral coefficient for \( b_{bp}(\lambda) \), if wrong, its could affect the AOP inversions spectrally. Its effect is smaller than that for \( a_{ph}(\lambda) \) but it can have an effect in the 530 to 555 nm range where \( a(\lambda) \) is low. The slope coefficient for CDOM is assumed to be constant in all inversion algorithms except for \( K_d(\lambda) \) optimization. If this coefficient is wrong then it can affect the spectral inversion results especially at green wavelengths in the 500 to 555 nm range. Despite higher signal-to-noise ratio at longer wavelengths it would be an error to assume that the AOP inversions are always the most accurate under every condition.
None of these methods achieves the perfection of a pure first principle approach to measuring IOPs. The common assumption that the more direct methods are always the most accurate was disproven by the statistical results. The R_{\text{t}}(\lambda) optimization method was best under most of the tested conditions in determining the IOP values. The statistical results indicate areas of weakness in all the methods under certain conditions. By examining the statistical results, it is possible to determine some approaches that might improve these methods and lessen inaccuracies due to empirical assumptions or environmental parameters.

6.2. Improvements to K_{d}(\lambda) optimization

The K_{d}(\lambda) optimization model was developed during the course of this study. It proved to be the best of the K_{d}(\lambda) inversions but not as reliable under all conditions for some IOP inversion results as the R_{\text{t}}(\lambda) inversions. The best results were for a_{\text{inw}}(\lambda) inversions under ideal conditions. Some improvements in future versions of this model may increase its accuracy. These improvements can be divided into two categories, better E_{d}(\lambda) measurement techniques and making the algorithm more analytical.

Wave focusing is one problem that confounds the measurement of down-welling irradiance below the sea surface. The correction for wave focusing does have some flaws. When using a modeled value for the near surface value it relies on the accuracy of the input values to the Hydrolight model. Unless there is an above water measurement that can be properly used as a reference to match the above water downwelling irradiance in the model, there may be errors in the Hydrolight model result. Since the determination of large increases in value using a depth versus E_{d} graph is slightly subjective, there can also be errors introduced. The smaller wave focusing events could still be biased towards a focus or defocus, since it depends on when the irradiance meter is sampling relative to focus or defocus events. If there are not enough measurements at the surface to average the focusing out, it could have a bias one way or another.

The K_{d}(\lambda) optimization method had negative correlations between solar zenith and absolute percent error for many IOP inversions. The closer the sun is to zenith, the more direct becomes the lens effect of the wave. Alternatively, the closer the sun to the horizon, the less light is available at depth due to a longer path length of the solar irradiance. The best conditions for E_{d}(\lambda) were when the sun was approximately between 15° and 45° zenith. Since wave focusing affects the spectral nature of the light by sending more light at longer wavelengths to depth, this in turn affects the separation of a_{g}(\lambda) and a_{p}(\lambda) from a_{\text{inw}}(\lambda) by over or under estimating the magnitude of a_{g}(440), the a_{g}(\lambda) coefficient, and the magnitude of a_{p}(440). The correction for wave focusing is more critical with the sun at a low zenith angle than when it is closer to the horizon.

Several IOP results from K_{d}(\lambda) inversions had a strong correlation with bottom reflectance and absolute percent error using the K_{d}(\lambda) optimization method. At first it was suspected that this might be due to internal reflectance from upwelling irradiance
reflected off the bottom. Hydrolight model results demonstrated that this was not the case but that a greater percentage of up-welled light was actually transmitted through the air water interface with a greater bottom albedo. This increase in transmittance demonstrates that there is less internal reflectance at the surface with a Lambertian bi-directional reflectance (BDRF) for the bottom than for water column where the bottom is well below the 1% light level. Near the bottom there can be some increase in light resulting in a "C" shape to the $E_d(\lambda)$ profile due to reflectance by a bright bottom. The increase in light near the bottom is due to scattering forcing the light reflected off the bottom back in the downward direction. However the bright bottom does not seem to affect the inversions since the third order polynomial fit for the $E_d(\lambda)$ over depth compensated for this increase near the bottom. The increased fraction of bottom reflectance in the total reflectance value is correlated with the optical depth of the water column. Generally, the greater the bottom contribution to below surface reflectance, the shallower and clearer the water column. The main factor is that, for a shallow water column, the instrument cannot descend below the level of high wave focusing. Once the light becomes diffuse enough due to scattering over depth, wave focusing ceases to be a significant factor and the polynomial fit through the unfocused deeper layer smoothes the focusing in the upper water column. The correlation between $K_d(\lambda)$ optimization error and percentage of bottom reflectance for several IOP values actually represents a correlation with increased wave focusing errors.

A byproduct of wave focusing is saturation of the downwelling irradiance measurement when the integration time is too long. The Spectrix downwelling irradiance sensor takes an initial scan and the magnitude of this initial measurement determines how long the shutter will stay open to achieve an adequate signal. If this initial scan occurs during a defocus event and the actual sample occurs during a focus event, the result may be an over exposure leading to saturation of the spectrometer. These saturated scans are taken as indications of the possibility of wave focusing. If only a few wavelengths are saturated, it can be corrected by interpolating the saturated values using an unsaturated scan at the nearest depth but if the numbers of saturated wavelengths are greater than 75 out of 512 total then the scan is not used. The number of discarded scans is used as a proxy for severity of wave focusing. To force the curve fit through the modeled sub-surface value, the number of modeled sub-surface values added are equal to the number of discarded saturated scans. While this does improve the quality of the data especially in the longer wavelengths, it is not as good as collecting real data near the surface.

The greatest improvement in accuracy for $K_d(\lambda)$ measurement is greater $E_d(\lambda)$ sampling near the surface. This would require an active control of the rate of descent for the instrument package so that it would stay just below the surface longer. While the rate of decent can be controlled by attachment to a winch, this approach requires the instrument package to be located close to a vessel and would result in the vessel shadowing the instrument. If the seas are significant, a hard wire attachment to a vessel can result in rapid changes in depth, both up and down, for the instrument during a measurement. Under extreme cases the changes in depth can be several meters resulting in a smearing of $E_d(\lambda)$ over depth and less accuracy in $K_d(\lambda)$. Active control of the
descent rate coupled with isolation from the movement of the platform would provide the best method of increasing near surface $E_d(\lambda)$ measurements.

The best method is to place the downwelling irradiance meter on a ROV, move the vehicle away from the vessel, and then slowly lower it through the water column. The problem with this method is that a ROV is very expensive to purchase and operate. A ROV requires several knowledgeable personnel to deploy and maintain it. ROVs require a much longer time to prepare and deploy than a vertical profiling package. These platforms are usually more limited in their payload capacity and can carry fewer instruments than a profiling package. They require adjustment to trim the vehicle any time the payload weight is changed so that it is balanced in the water column. This limits changes in instrumentation during a research cruise. Though they are the ideal platform, they are not ideal in ease and cost of deployment.

A slow descent, free falling profiling package that is near neutral buoyancy is a good compromise between a ROV and attaching a profiling package to the ship wire. It has some drawbacks. If the buoyancy is adjusted properly a free falling package can collect data with a very high resolution over depth. The package can also drift away from the ship minimizing ship shadow. Since its attachment to the vessel is loose, it is not pulled up and down in the water column smearing the depth of the $E_d(\lambda)$ measurement. However, it does not allow for slowing descent near the surface to collect a greater number of measurements to better resolve wave focusing and improve signal to noise at the longer wavelengths. A more active method of controlling descent is needed.

A vertical profiling package with an active control for buoyancy would be the ideal setup. An extremely slow descent (<0.01 m/s) near the surface would give enough measurements to aid in removing the effects of wave focusing. The BSOP profiler (Langebrake et al. 2002) uses a method of active buoyancy control by pumping a fluid from one reservoir to another. This method would be better than other methods using compressed air and a bladder. The bubbles from the release of the air could possibly interfere with down welling irradiance measurements by scattering light. The control would not have to be large and would only require a fine adjustment in the buoyancy. The active buoyancy control could be autonomous, receiving depth input from a pressure sensor and slowly descending for the first 10 meters then descending at a greater rate to depth. The cost of such a system would be moderate compared to the instrumentation and would greatly improve the $E_d(\lambda)$ measurements.

Measurements from a scalar down welling irradiance sensor would improve the $K_d(\lambda)$ optimization accuracy. The ratio of scalar downwelling irradiance to planar downwelling irradiance ($E_{0d}(\lambda)/E_d(\lambda)$) is defined as the average cosine of the angle of downwelling light. Knowing the average cosine of downwelling irradiance at a single wavelength or PAR would improve the inversion from $K_d(\lambda)$ by removing one unknown. While there is some spectral variation to the average cosine, it is small compared to the spectral variation of the IOPs. A simple model could estimate the slope of the spectral change in the average cosine of downwelling irradiance using the measurement as an
intercept if $E_{0d}(\lambda)$ was only collected at a single wavelength. This measurement would eliminate the need for Gordon's normalization to remove the average cosine due to skylight and solar zenith angle. The average cosine under cloudy conditions is difficult to model but would be directly measured using this approach.

The scalar $E_{0d}(\lambda)$ sensor data could be compared to the planar sensor data to determine the extent of wave focusing. A scalar measurement is less affected by a wave-focusing event since it collects light evenly from all directions over a hemisphere while a planar collector collects light as a function of the cosine of the down-welling irradiance. Knowledge of a wave focus or defocus event can aid in filtering the near surface data so that it is not biased towards focusing or defocusing. It would then provide a truer balance to improve a curve fit through the data. Testing this configuration just below the surface would lead to an idea of how to determine when wave focusing is occurring.

Shadowing of the irradiance sensor is another problem with the measurement of $E_d(\lambda)$. While ship shadows can be avoided with proper deployment, some shadowing cannot be avoided. During one cast a large school of amberjack was observed swimming over the sensor. During another cruise, a school of dolphins became curious about the instrument package and swam around it shading the instrument. Problems with swimming creatures or floating algae are difficult to control and can only be noticed if there is someone observing the package descent or there is a camera on board the package recording the descent. A method proposed to further prevent ship shadow was a float attached to the package allowing it to drift away from the ship. Once away from the ship, a release is triggered allowing the instrument package to sink thus avoiding any chance of shadowing by the vessel.

An alternative to the direct measurement of the average cosine is a more analytical approach to modeling it. The Heney-Greenstein phase function uses the average cosine of scattering as input to the function (Henyey and Greenstein 1941). Using $b_0(\lambda)\rightarrow b(\lambda)$ ratios, it is possible to invert the Heney-Greenstein function and determine the average cosine due to scattering. This result can possibly be used to estimate the average cosine of downwelling irradiance for the $K_d(\lambda)$ optimization model making it more analytical. While this approach does require additional instrumentation, the ac-9 and the Hydroscat 6 provide this information within the instrument package used in this study. The Gordon normalization routine removes the average cosine of downwelling irradiance due to above surface conditions and the Heney-Greenstein equation could provide the average cosine due to scattering.

Using the change in $E_d(\lambda)$ value across two depths where IOPs remain constant may also give some information on the average cosine of downwelling irradiance. Once the loss due to absorption and backscattering is accounted for, the change should be primarily due to changes in the path elongation of the downwelling irradiance. It may be possible to model this resulting in an estimate of the average cosine. Another optical sensor such as a beam attenuation meter could provide information on whether there is a significant change in optical properties between the two depths. If the optical properties
are constant then solving the Preisendorfer equations for $K_d(\lambda)$ between two depths could give the change in the average cosine of down-welling irradiance. This approach requires further study but may be able to create a more analytical approach to modeling the average cosine and inverting the $K_d(\lambda)$ for IOPs by examining the changes in $E_d(\lambda)$ over an area of constant IOPs.

Another approach that could increase accuracy is to use the inversion algorithm at several depths. The $K_d(\lambda)$ value used in the model is the result of a fit to the depth where the instrument reached its accuracy limit for that particular wavelength. While using the water-column total $K_d(\lambda)$ values seems to minimize noise and provide an average value comparable to the $R_{rs}(\lambda)$ inversions, the average cosines are different at each wavelength due to shallower depths of penetration of light, resulting in greater spectral differences in value. If the fit to determine $K_d(\lambda)$ through the $E_d(\lambda)$ values was done for the same depth, the fit would have to occur at a shallow depth due to water absorption limiting the penetration of light at longer wavelengths. Using a shallow depth would limit the curve fit for $K_d(\lambda)$ to the region most influenced by wave-focusing and would miss changes in inherent optical properties deeper in the water column. A 10 m $K_d(\lambda)$ value was tested and found to result in less accurate inversions compared to the fit to depth. The average cosine was iteratively solved in the $K_d(\lambda)$ optimization method and an empirically determined spectral slope spectral slope was used to extrapolate that value to other wavelengths. However, it may be better to run the algorithm at several depths where the average cosine of down-welling irradiance is more constant spectrally. Instead of determining $K_d(\lambda)$ for the water column, $K_d(\lambda)$ would be determined by changes between two individual depths over a smoothed $E_d(\lambda)$ profile. The $K_d(\lambda)$ optimization routine could then be run at several depths to obtain an IOP profile that could be integrated to compare to the $R_{rs}(\lambda)$ inversions. The model would have to limit the fit to just the wavelengths at that depth where the $E_d(\lambda)$ measurement is above noise level. This change in method is computationally more intensive but has the added benefit of providing changes in absorption and backscattering at each depth.

The Gordon normalization portion of the Kd optimization algorithm can be made more analytical. Instead of modeling the direct and diffuse above surface downwelling irradiance, it could be directly measured by shading the direct sunlight from the irradiance meter during a surface measurement. This shading would provide a more accurate diffuse irradiance estimate especially during cloudy periods. When using Gordon's normalization, Gordon's original algorithm called for including waves using a formulation by Cox and Monk but that was not used in this correction (Gordon 1989). It should be tested to observe if it improves the algorithm. Another improvement would be to use the results from a Hydrolight run instead of Gordon's empirical approach. In the absence of a scalar irradiance sensor, the subsurface water average cosine from Hydrolight would be a more accurate normalization than Gordon's especially with a measurement of direct and diffuse solar irradiance as input.

While the iteration of the $a_d(\lambda)$ coefficient improved the model results under most conditions it was possibly a source of error under other conditions. When there was a
large amount of wave focusing, the iteration possibly introduced additional errors. Under conditions of high wave focusing, such as a shallow cast or sun near zenith, the model may be improved by locking the $a_g(\lambda)$ coefficient to a set value that is representative of the $a_g(\lambda)$ for the study area. The $K_d(\lambda)$ optimization exhibited significant error correlation between IOP values and cloudiness. This error in the IOP values is probably the result of the downwelling irradiance being more diffused and the average cosine of down-welling irradiance not being estimated properly. Under these conditions some of the error in the average cosine may affect the iteration of $a_g(\lambda)$ and the coefficient may need to be locked to one value. A more detailed analysis under different conditions is needed to develop a criteria for locking the $a_g(\lambda)$ coefficient.

6.3. Improvements to Loisel K$_d(\lambda)$ inversion

The $K_d(\lambda)$ optimization method compensated for the downwelling direct and diffuse light by using Gordon's normalization method. This method should normalize the $K_d(\lambda)$ values to a black sky and sun at zenith. Using this method for input into both the Loisel and Kirk $K_d(\lambda)$ inversion models should improve them slightly. Currently the Loisel model relies on an empirical relationship with below water remote sensing reflectance to estimate the average cosine. The Kirk model uses the solar zenith angle as input to estimate the average cosine. If Gordon's normalization functions properly then these models would only have to compensate for the change in downwelling average cosine due to scattering.

The Loisel $K_d(\lambda)$ inversion model in this study was hampered by using an above water remote sensing reflectance instead of the below water value. The above water value was empirically converted to a below water value based on the method of Carder et al. (1999). However, it still would not be as exact as having an actual below water measurement. The Loisel model does offer a method for separating the $a_{ph}(\lambda)$ and $a_g(\lambda)$ values from $a_{nw}(\lambda)$ in addition to calculated scattering. Since it performed poorly for the $a_{nw}(\lambda)$ inversion, the other values were not calculated. The model results probably would have been better with the below water reflectance but that data was not collected during this study.

6.4. Improvements to Hydroscat-6

One major problem with the Hydroscat-6 is that the processing of the data uses a different backscattering from seawater than the Hydrolight model. The Hydroscat-6 processing method results in total backscattering as estimated from the backscattering at a single angle of 140° using an empirical factor. When Hydrolight takes this data in for modeling it separates it into component of particulate and water backscattering. While running the model it was noticed that some of the Hydroscat data was creating errors in some of the lower attenuation waters. The Hydrolight model uses seawater backscattering values based on a model by Andre Morel (Morel 1974). These $b_{bw}(\lambda)$ were sometimes higher than the total backscattering from the Hydroscat-6 processing. Using the Hydroscat-6 values resulted in a negative particulate backscattering causing an
error in the Hydrolight model. To correct for this, the backscattering due to sea water used by the Hydroscat processing program had to be subtracted from the Hydroscat-6 $b_b(\lambda)$ values and the Morel values added to it. This correction resulted in no errors and produced the best results for the albedo inversions.

This correction to the Hydroscat-6 processing also calls into question the approach by the manufacturer that suggests that Morel's seminal work on backscattering for pure seawater was too high. It indicates that a spectral parameter in the HOBI Labs processing method is slightly off by the magnitude of the difference between Morel's $b_{bsw}(\lambda)$ values and those used by HOBI Labs. This may be a factor related to their $1.08*2*\pi$ value for converting the $\beta(\lambda)$ at $140^\circ$ to total $b_b(\lambda)$. The relationship of $\beta(\lambda,140^\circ)$ to $b_b(\lambda)$ may also have a bias that varies spectrally instead of just a factor.

### 6.5. Improvements to MODIS Algorithm

The change in the way the MODIS algorithm deconvolves $a_{nw}(\lambda)$ into $a_g(\lambda)$ and $a_{ph}(\lambda)$ was demonstrated to be an improvement on the algorithm. For the initial process, the $a_g(\lambda)$ coefficient was set at 0.018. The $a_{ph}(\lambda)$ result is then added to an $a_g(\lambda)$ value calculated using the resulting $a_g(400)$ and a lower $a_g(\lambda)$ coefficient of 0.016 to give an $a_{nw}(\lambda)$ value. This change resulted in better agreement with the ideal value for $a_{nw}(\lambda)$.

This change in the algorithm also improved the $a_{ph}(\lambda)$ inversion and the $a_g(\lambda)$ inversion results. The higher coefficient compensated for CDOM fluorescence by lowering $a_g(\lambda)$ absorption at the affected wavelengths. A correction like this needs to be made a part of the MODIS algorithm.

The initial coefficient and second coefficient were determined by statistical analysis of the MODIS results for several combinations of CDOM coefficients. Further research is need to determine the magnitude of difference between the two coefficients for $a_g(\lambda)$. Measurements need to be examined to determine how much is needed to compensate for CDOM fluorescence and under what conditions. Questions like the effect of solar zenith angle on the magnitude of CDOM fluorescence need to be addressed. The correlation of CDOM fluorescence with CDOM concentration is another question. The effect of photobleaching needs to be included too (Kramer 1979). Since most of these casts were on the continental shelf, the CDOM was expected to be less photobleached than CDOM found in offshore waters. The magnitude of the correction may need to be tied to the expected CDOM coefficient. A higher coefficient like those found in offshore waters might only require a correction of 0.001. During several of the research cruises in this study, another researcher was measuring spectral fluorescence. Combining the $R_{nw}(\lambda)$ data, IOP data, and this fluorescence data will an aid in determining how best to make the correction for CDOM fluorescence.

The $b_{pp}(\lambda)$ intercept is locked at an empirically determined value for MODIS, while the other methods use an iterative process. Under several conditions MODIS did not produce results as close to the other methods for $b_{pp}(\lambda)$. Further analysis is needed
but it does appear that, under the filters without significant bottom reflectance contributions to \(R_{er}(\lambda)\), the iterative approach to \(b_{bp}(\lambda)\) is more accurate. MODIS has a factor offset from the ideal value for \(a_{anw}(\lambda)\) and is about 40% higher for \(b_{bp}(\lambda)\). The offset to the \(a_{anw}(\lambda)\) value might be corrected by a better method of determining \(b_{bp}(\lambda)\). The QAA model only uses a couple of iterations to determine \(b_{bp}(\lambda)\) and does not require an increase in computational requirements. An improvement to MODIS may be to use a similar approach for \(b_{bp}(\lambda)\) as found in the QAA model.

MODIS has significant spectral correlations with scattering ratios when the default algorithm is included for \(a_{ph}(\lambda)\) and \(a_{anw}(\lambda)\). The MODIS algorithm has a negative correlation with \(b_p(440)/c_{nw}(440)\) but positive correlations with \(b_{bp}(440)/b_p(440)\) and \(b_{bp}(440)/a_{nw}(440)\). Under the MODNB filter, that only uses the semi-analytical data from MODIS, there are very few correlations with any of the parameters. This difference in correlation indicates that the empirical default MODIS algorithm can lead to errors when backscattering is a higher portion of the IOPs but total scattering is a lower percentage of attenuation. One possibility is that the algorithm is switching to the default when it would be better using the more accurate semi-analytical approach. Many of the study sites have high \(a_g(\lambda)\) values relative to \(a_{anw}(\lambda)\). This high CDOM to absorption ratio could cause the algorithm to categorize these sites as high chlorophyll and switch to the default algorithm. Further review of the data is necessary to determine exactly the affect of this on the MODIS algorithm and how it could be corrected.

### 6.6. Improvement to the ac-9

The ac-9 is currently the most popular instrument for high resolution sampling of \(a_{anw}(\lambda)\) over depth. A new instrument using an integrating sphere may change this but it needs to go through the rigorous testing that the ac-9 has been through. The ac-9 could be improved in ways that increases its accuracy and stability. The method for deploying this instrument has changed to compensate for some of the problems with using this instrument but some additional equipment and procedures could improve the deployment of this instrument.

One of the biggest weaknesses in the ac-9 is the use of a quartz-halogen light source. The ac-9 works by projecting light through a rotating filter wheel and into a flow tube where change in radiance at a given wavelength is then determined by a photocell at the other end of the tube. The lamp takes a few minutes to warm up and stabilize before any measurements can occur. The lamp produces a lot of heat resulting in a large temperature correction for the internal electronics. The heat possibly contributes to degradation of the filters over time. If the ac-9 is not placed in a water bath when operating on bench top for an extended length of time the internal temperature can easily rise above 40° C. The lamp has a lower output at shorter wavelengths. The output at 412 nm is about half that at 555 nm but the absorption at 412 nm is usually many times that at 555 nm. The output is lowest where absorption is the highest resulting in lower signal to noise at those wavelengths. The lamps age requiring regular calibration as the
output shifts spectrally. Modern high output LEDs would make a better source light than the quartz-halogen lamp.

LED lamps are now capable of white light output due to phosphorescent coatings and would make a good replacement for the quartz-halogen lamp in the ac-9. The LED lamps are more stable than a quartz halogen lamp and power up to a maximum output rapidly. The LED lamps would generate less heat allowing bench top operation for an extended period of time without a bath to cool the instrument. The internal temperature correction wouldn't have to be applied over as wide of a range. LEDs use less power resulting in longer battery life for mooring deployments. A combination of LEDs could provide light output at wavelengths centered around the filters in the rotating filter wheel giving more output at the measured wavelengths instead of focusing on a white light source. LED lamps would make the instrument a more stable, energy efficient, and give it a lower operating temperature.

The filters in the ac-9 are on a rapidly rotating wheel that operates at about 6 hz. The filters degrade over time due to a film that slowly forms over them. The manufacturer is not clear on what causes this film. The degradation of the filters is one reason that the instrument requires a daily calibration and regular factory maintenance. The wheel itself is a mechanical part that may eventually fail. Vibrations to the instrument can cause tiny movements in the filter wheel resulting in noise in the data. The instrument is so sensitive to vibration that stomping hard on a floor near the instrument can cause a jump in its output values. The filters wheel is a weak point in the ac-9.

The wheel could be replaced by a series of LEDs at wavelengths centered at the measurement wavelengths. It would require a more complex optical setup but they would provide an interface with lower mechanical parts for failure. Another possibility would be for the manufacturer to find a better quality filter. There are literally hundreds of manufacturers of optical filters for every sort of application or condition. If the cause of the filter failure resides in the filters themselves, then there should be a manufacturer that has addressed this problem. Alternatively a cooler light source may minimize the filter problems.

A vexing problem with the ac-9 is the clearance of small bubbles from the instrument. Air bubbles trapped in the flow tubes can result in a large amount of scattering rendering the data useless. As the bubbles bounce around in the tube, the values often reach the maximum possible for the instrument. To clear out bubbles, great care is made during the plumbing of the intake and exhaust path for water pumped through the instrument. The data output is monitored to determine if there are spikes in the values that are indicative of bubbles before the data from the instrument is logged. If there is a difficulty clearing the ac-9 near the surface, it can be sent to depths of around 20 to 30 m to compress the gas bubbles aid in clearing them from the instrument. Some design or deployment changes may make it easier to purge bubbles from the instrument.
Filling the ac-9 flow tubes with water before deployment might make it easier to clear bubbles once it is deployed. It would require a device to close the intake tubes for the ac-9 and open it once it is deployed. The caps on the inlet tubes would protect against air being forced into the instrument’s flow path as it is being lowered into the water. The flow path could be filled from the bottom inlets using a pressurized reservoir forcing out the bubbles. The o-rings on the flow tubes would need regular maintenance to insure that water doesn't leak from them while the instrument is sitting on deck and a more secure system would be needed for attaching the flow tubes. The caps on the inlets wouldn't require an electronic release mechanism. The release could be a float well above the instrument package that pulls a release pin or a tag line that pulls the pin. A similar device could be developed for the filtered ac-9 that releases a reservoir full of deionized water that the filter is stored in. This would provide a simple and inexpensive method of purging the bubbles from the ac-9.

A high volume pump for purging bubbles from the ac-9 followed by a low volume pump for sampling could reduce air bubble scattering. Either a two-speed pump or a valve with a separate high volume pump could be used to purge the instrument. The high-speed pump would create enough force to pull the bubbles through the instrument but could not be used during regular deployment due to turbulence related density shifts in the incoming water that can increase scattering. The filtered ac-9 would require a valve on the inlet to bypass the filter during a purge by a high-speed pump because pulling a large amount of seawater through the filter could cause it to prematurely clog. This setup would require additional plumbing and electronics but would be more convenient than priming with water before deployment.

The path of the water through the flow tubes could be improved to aid in removing bubbles. It might be a better design to bevel the outlet at the top of the flow tube to allow the bubbles to flow up and out of the instrument. The current design has a flat surface with the outlet near level to the plane of the window covering the detector at the top of the tube. If the window was a little further down in the tube, then a sloped area leading up to the outlet could be used to allow bubbles to flow outward. Several designs could be tested with a clear glass tube to determine the best design for clearance while retaining the maximum reflective surface of the absorption tube. The original ac-9 design was modified by the addition of larger diameter exit tubes for the flow and resulted in fewer problems with bubbles. A new design for the flow tubes might improve purging of air bubbles without extra procedures or new equipment.

The output from the filtered ac-9 may be improved by calibrating the instrument with a filter in place. The filter restricts the flow through the instrument and changes in the flow rate do affect the calibration and clearance rate. The ac-9 is found to produce its best results with a flow rate of greater than one liter per minute. At a higher rate there may be turbulence related scattering. At a lower rate, there may be problems with clearance of bubbles and aliasing of the values versus depth. The calibration is most effective when a similar flow rate is used for both calibration and deployment. Some of the differences due to scattering by turbulence will be compensated for by the calibration
if the rates are similar. Using a setup with the filter in place in a sealed polycarbonate container that has a valve for degassing the container would better match the flow conditions the instrument will experience during deployment.

An inline flow meter on the outflow ac-9 can determine the clearance rate of the instrument and compensate for aliasing. An inline flow meter will allow knowledge of the clearance rate and how it might change during the deployment. The depth for the sample can be adjusted based on the clearance rate and a more accurate profile of absorption or attenuation can be obtained. The flow meter can aid in determining the ideal flow rate for a particular setup. The meter can be calibrated under a variety of flow conditions and a calibration adjustment for each rate determined. The calibration under different rates would especially benefit the filtered ac-9 since the flow rate will change as particles fill up the filter pores. Monitoring the flow rate would reduce aliasing and improve calibration values.

The post processing of the ac-9 uses a correction for the scattered light in the absorption tube that might be improved by using data from other instruments. Backscattered and some forward scattered light is lost by the ac-9 on the absorption tube. Using backscattering measurements from the Hydroscat-6 may assist in some of the correction for the absorption tube by providing a more exact measurement of the loss due to backscattering. The remaining scattering loss in the absorption tube is primarily due to forward scattering at angles that are refracted by the glass window protecting the detector in the absorption tube and could be corrected in using the ratio method of Zaneveld 1994.

The post processing for the attenuation tube could take into account the near forward scattering. The acceptance angle of any attenuation meter is not limited to only light scattered in the same direction as the source. A limited acceptance angle like that would be almost impossibly tiny to build, require precise alignment with the source, and need a sensitive detector. Therefore, most manufacturers use an aperture that allows light at more angles than absolute 0°. The acceptance angle for the ac-9 is 0.93° ± 0.07°. A model could estimate the amount of forward scattering not counted as attenuation to improve the attenuation results. The error can range from 5% to 20% underestimate for the ac-9.

One method for estimating the near forward scattering would be to use the \( \beta_{bp}(\lambda) \) to \( \beta_p(\lambda) \) ratio to model the phase function using the Heney-Greenstein (1941) method. It might still slightly underestimate the forward scattering but it would probably be by such a small amount that it would not make a major difference in the values. Another approach would be to use a multiple angle scattering meter like the VSF to estimate the phase function and determine forward scattering. The attenuation tube of the ac-9 could be calibrated using a known scattering standard such as polystyrene beads. An empirical correction for the losses by forward scattering could be determined and applied for the ac-9. This correction combined with a correction for backscattering for the absorption tube should improve the results from the ac-9.
6.7. Improvements to Quantitative Filter Pad Method

One of the biggest problems with the filter pad method during this study was obtaining sufficient optical density on the filters to make the beta correction valid. Most beta corrections are fit for values within a specific range of optical densities (Bricaud and Stramski 1990). However, in waters, such as those in the Bahamas, the filter pads would stop up before they achieved the lower limit for optical density. Transparent material such as small zooplankton or transparent exo-polymers (TEP) might be responsible for clogging the pores of the filter (Allredge et al. 1993). Another possibility could be precipitation of calcium carbonate particles.

A way to determine the source of the clogs in the filters would be to examine the filter pads after they become clogged under a high-powered microscope. If the problem is due to transparent zooplankton or TEP then a fine zooplankton mesh screen may remove them from the sample. Since they absorb little to no visible light, removal would not significantly affect the absorption result from the filter pad. If the problem is due fine calcium carbonate particles, then maybe adjusting the pH of the sample a little lower might keep more in solution. Adjusting the pH would have to be carefully tested under controlled laboratory conditions to assure that it would not dissolve absorbing particles. These changes might allow for a greater optical density under conditions of non-absorbing material clogging the filter pores.

The beta factor is usually based on the dominant species assemblage of phytoplankton. The common method for determining a Beta factors is to take a concentrated monoculture of phytoplankton and measure the absorption within a cuvette in very accurate bench top spectrophotometer (Bricaud and Stramski 1990, Cleveland and Weidemann 1993). The same culture is then filtered onto a glass fiber filter and the path length elongation due to light scattered by particles through the filter pad and the optical density measured. The measurements are repeated for up to hundreds of different phytoplankton species. The equation for this correction is determined through an empirical fit of optical density to actual absorption measured from the concentrated sample for all the species.

Some Beta factors are more appropriate for estuaries where there are large diatoms while others are designed for open ocean waters where there are smaller chlorophytes and cyanobacteria. Other phytoplankton can have unusual indices of refraction due to their physical composition. *Trichodesmium* and coccolithophores can scatter light more than some of the other phytoplankton (Subramanian et al. 1999, Ackleson et al. 1994). Usually a beta factor is used that represents a diverse assemblage of phytoplankton species unless the composition is known. Under certain conditions these may not be representative of the phytoplankton species and could produce some errors in the filter pad measurement. Ideally the researcher would determine the dominant types of phytoplankton and then select a beta factor specific for those species. Determination of species composition could be either through direct counts under a microscope or by examining the pigment composition of the sample. Alternatively, a review of data
collected by researchers that examined species or pigment composition for the study site could provide some information about the phytoplankton species assemblage. The filter pad data in this study used a general-purpose beta factor (Carder et al. 1999). The statistical agreement especially at some of the lower absorption values might have been improved with a beta factor more representative of the phytoplankton species composition.

A surface measurement was used for comparing the results from the filter pad method to the results from AOP models in this study and it may not give the same result. While the absorption value from the surface is the most dominant influence on the AOP values, it may not be representative of lower depths if there is a change in packaging, species composition, or detritus particles. The AOP measurement represents an integrated value over depth and the discrete samples represent a single point. The filter pad measurement may represent a closer value to the AOP inversion results if multiple depths are collected and then the depths interpolated and integrated to give a value comparable to the AOP inversions. A chlorophyll and backscattering profile can be used to indicate the best sample depths for both pigmented and detrital particles. The profiles could aid in interpolation of the filter pad method. If the signal to noise ratio is high enough, an ac-9 profile could be used to interpolate the filter pad method resulting in a hyperspectral profile for absorption.

6.8. Improvements to Spectrophotometric $a_g(\lambda)$

The spectrophotometric dissolved organic absorption measurements could benefit from an instrument with a longer path length. A path length longer than the 10 cm cuvette would increase signal to noise providing more signal for sample collected from waters with very low absorptions. A spectrophotometer with a folded path was proposed by Peacock (1992) and would have made these measurements more accurate. A recent innovation is the submersible integrating sphere by HOBI Labs. It uses multiple bounces of the light within a sphere that has a Lambertian reflective surface to increase path length while reducing scattering errors (Kirk 1995). It could be a better instrument for determining absorption by dissolved substances with higher accuracy. Some of the spectrophotometric measurements have increasing noise at longer wavelengths due to low signal. A long path instrument would have more signal-to-noise especially at the longer wavelengths.

Like the filter pad measurements, the $a_g(\lambda)$ measurements could be improved by more samples at depth. Unless the water column is well mixed, $a_g(\lambda)$ will vary some over depth. The changes can be both in magnitude and spectral slope. Photobleaching near the surface results in a higher coefficient for the logarithmic spectral equation for $a_g(\lambda)$ (Twardoski and Donaghay 2002). The deeper waters may also have a higher coefficient due to decomposition of the dissolved organic matter. Any near shore measurements could have more terrestrial humic substances making up the CDOM, which typically has a lower coefficient than the fulvic CDOM offshore (Carder et al. 1989). As estuarine waters mix with offshore waters they are usually less saline and stay at the surface.
However, an inversion was noticed at the Bahamas sites where higher salinity warmer high CDOM waters from the banks were denser than the offshore waters and formed a bottom layer (Otis et al. 2004). All these conditions may result in a surface sample not being comparable to an AOP inversion result that represents and integral of the values over depth. A CDOM fluorescence meter would indicate the depths necessary for sampling to interpolate the bench top spectral measurements over depth. It would indicate changes in CDOM concentration or composition where sampling could take place. As with other single depth measurements, the lack of samples at deeper depths limits the comparison to \( R_{rs}(\lambda) \) inversions for \( a_g(\lambda) \).

### 6.9 Improvements to \( R_{rs}(\lambda) \) Optimization Algorithm

\( R_{rs}(\lambda) \) optimization could benefit from similar changes made to the MODIS algorithm. A compensation for CDOM fluorescence would improve \( a_g(\lambda) \) values. \( R_{rs}(\lambda) \) optimization optimizes both \( a_g(\lambda) \) and \( b_{bp}(\lambda) \) and may need to empirically set \( b_{bp}(\lambda) \) under certain conditions. The bottom albedo model used in \( R_{rs}(\lambda) \) optimization may need an additional parameter to reflect actual albedo measurements. The \( a_{ph}(\lambda) \) shape factors could benefit from a model that ties them to nitrate depletion temperatures like MODIS. However, despite a few possible changes, this algorithm proved to be the most robust of the AOP inversion algorithms.

A problem with the \( R_{rs}(\lambda) \) optimization method is that the \( a_g(\lambda) \) and \( b_{bp}(\lambda) \) values can have similar effects on the shape of the modeled Rrs curve. An increase in \( a_g(\lambda) \) gives a similar result spectrally as a decrease in \( b_{bp}(\lambda) \). Normally this doesn't result in a large error but under some conditions it can create problems. When there is significant bottom contribution, \( b_{bp}(\lambda) \) and \( a_g(\lambda) \) appear to be less accurate for \( R_{rs}(\lambda) \) optimization because there is a trade off for bottom albedo and \( b_{bp}(\lambda) \) or \( a_g(\lambda) \). Solar zenith angle and cloudiness can also affect the inversion for \( b_{bp}(\lambda) \) and \( a_g(\lambda) \). Under conditions where these effects could be significant, it may be better to determine \( b_{bp}(\lambda) \) empirically instead of iterating it's value to prevent interference with the \( a_g(\lambda) \) inversion.

CDOM fluorescence appears to affect the \( R_{rs}(\lambda) \) optimization algorithm in a different manner than the MODIS algorithm. Because \( R_{rs}(\lambda) \) optimization iterates \( b_{bp}(\lambda) \), it appears to compensate for CDOM fluorescence by increasing \( b_{bp}(\lambda) \). Instead of using the two \( a_g(\lambda) \) coefficients like used for MODIS, it may be better under \( R_{rs}(\lambda) \) optimization to either adjust \( b_{bp}(\lambda) \) or come up with an spectral CDOM fluorescence term tied to \( a_g(\lambda) \) values. The \( b_{bp}(\lambda) \) values could use a lower slope followed by a higher slope for the actual calculation in a manner similar to what was used for MODIS. Another method that could be explored for all \( R_{rs}(\lambda) \) inversions is to tie the magnitude of the CDOM absorption and downwelling irradiance to a value for spectral CDOM fluorescence. Directly correcting for CDOM fluorescence would be the most analytical method for correcting \( R_{rs}(\lambda) \) inversions. Either of the approaches could correct for CDOM fluorescence in the \( R_{rs}(\lambda) \) optimization inversions.
CDOM fluorescence could produce errors to the empirical relationship for the spectral coefficient for $b_{bbp}(\lambda)$. All the Rrs inversions use an empirical relationship at wavelengths that would be affected by significant CDOM fluorescence. Rrs optimization uses the ratio of $R_{rs}(440)$ to $R_{rs}(490)$. QAA uses the ratio of $R_{rs}(440)$ to $R_{rs}(555)$. Further study is needed but under high CDOM conditions, the relationship may not be the same as for low CDOM conditions. Either the slope needs to be adjusted based on a CDOM fluorescence compensated $R_{rs}(\lambda)$ or different wavelengths need to be selected for the $b_{bbp}(\lambda)$ coefficient.

Another improvement for the $R_{rs}(\lambda)$ optimization method might be to vary the $a_{ph}(\lambda)$ shape factor as a function of temperature similar to the method used by MODIS. Packaging usually varies from onshore to deeper waters. The temperature factor, a distance from shore, or $a_{nw}(\lambda)$ might serve as a method to shift the shape factor from larger more estuarine phytoplankton to smaller more open ocean phytoplankton. Ideally, one would have direct measurements of $a_{ph}(\lambda)$ to use if the $R_{rs}(\lambda)$ measurements are collected aboard a ship. The direct measurement could then be used for the shape factor. When using satellite data it is not always possible to have a ship taking direct measurements. The $a_{ph}(440)$ to $a_{ph}(676)$ ratios are usually more affected by changes in packaging (Kirk 1975). A scaling factor could shift the spectral ratios to better match the changes in packaging. MODIS uses the nitrate depletion temperature with its more empirical approach but has better results at $a_{ph}(676)$ under the semi-analytical algorithm. $R_{rs}(\lambda)$ optimization could benefit from this approach.

$R_{rs}(\lambda)$ optimization, like all the AOP inversions, had problems at sites where bottom reflectance was a significant proportion of the $R_{rs}(\lambda)$ signal. Actual albedo measurements demonstrate that not only is a factor needed but a bias is required too. The spectral measurements show that most albedo over sand is close to linear with a positive slope under the visible wavelengths (next chapter). A linear fit through this measurement shows not only a change in slope but also a change in intercept is needed for different sand bottoms with similar slopes. This change may be due to the different amounts of organic material on the bottom absorbing more at shorter wavelength. Differences in mineragenic composition of the bottom cannot be ruled out without some testing. The $R_{rs}(\lambda)$ optimization model could be parameterized to include an iterated bias over a limited range along with a slope for the bottom. Further measurements along with analysis of bottom composition could lead to a relationship between the magnitude of the albedo at a specific wavelength and the slope of the spectral albedo. Using a better albedo both spectrally and in magnitude would improve the IOP inversions especially for $a_{g}(\lambda)$ and $b_{bbp}(\lambda)$.

6.10. Improvements to Kirk and QAA models

The QAA and Kirk models were not criticized as much as the other models since they represent mostly empirical algorithms. These algorithms are useful when computational resources need to be conserved or a simple estimate is needed. Both models could benefit from some of the suggested changes in similar algorithms but it
would result in increasing their complexity and computational requirements. The Kirk $K_d(\lambda)$ and QAA $R_{\text{in}}(\lambda)$ models can be used to improve the more analytical optimization models by giving initial input values. The $K_d(\lambda)$ Kirk model was used to estimate the initial absorption value for the $K_d(\lambda)$ optimization model and improved the algorithm results. The approach from QAA model can be used to better estimate the $b_{bp}(\lambda)$ values for the MODIS algorithm with little additional computational requirements. Small changes like using the Gordon normalization for input into the $K_d(\lambda)$ inversion and not iterating the $b_{bp}(\lambda)$ reference value when bottom is present for the QAA model would give some improvement to these algorithms.
7. Bottom Albedo

7.1. Introduction

Now that closure has been achieved, it is possible to utilize combinations of the different measurements and methods to gather more detailed optical information. One way to do this is to use the IOP values and combine them in a numeric model that can relate them to the AOP values. With these relationships other AOP values that were not directly measured can be determined. Hydrolight is a unique model in that its solution to the radiative transfer equation is exact if the input data to the model is accurate (Mobley 1994). The inputs to the Hydrolight model are the IOP values and the downwelling solar irradiance. The outputs are the AOPs such as $R_{rs}(\lambda)$ and $K_d(\lambda)$. By comparing the output AOPs from Hydrolight to the measured values, the quality of the input IOPs can be tested. The $E_d(\lambda)$ measurements can also be used to assure that the parameters for solar input for Hydrolight are correct. Under the conditions with significant bottom contribution to the reflectance value, $K_{dopt}$ is best for $a_{bs}(\lambda)$ and the HS6 is best for $b_{bp}(\lambda)$. With input of these values into Hydrolight, it is possible to extrapolate other optical properties such as average cosines and bottom albedo.

The $R_{rs}(\lambda)$ optimization method provided an interesting formula for determining albedo. Spectral albedo inversions using the $R_{rs}(\lambda)$ optimization algorithm did not produce useful results because the reflectance from the bottom was so small relative to the model uncertainties that the result was noise. However, the formulation of the $R_{rs}(\lambda)$ optimization model did give an example of how to invert $R_{rs}(\lambda)$ values to obtain bottom albedo. The optimization method separates subsurface irradiance reflectance into two components. One component is due to the water column and the other is that due to the light reflected off the bottom. Each has a diffuse attenuation factor empirically set to estimate the change in average cosine and attenuation along the path. The bottom path diffuse attenuation factor is a function of depth and the iterated IOP values. This factor is multiplied by the albedo at each wavelength. Therefore, a black bottom (albedo = 0) should represent the water column only and a white bottom (albedo = 1) would give the bottom component with 100% reflectance. If it is assumed that the factors determining the transmittance across the air water interface are close to the same with the black bottom and white bottom, then a measurement of $R_{rs}(\lambda)$ can be used instead of the subsurface remote sensing reflectance values.

This approach does make another big assumption. It assumes the bottom has a Lambertian reflectance. Albedo is the planar irradiance leaving a flat surface divided by the planar irradiance impacting that surface. $R_{rs}(\lambda)$ is radiance leaving the water divided by the irradiance entering the water. This means that $R_{rs}(\lambda)$ is only looking at one angle.
while a true albedo measurement would collect radiance from all the angles. This approach is actually measuring part of the Bi-direction Reflectance Distribution Function (BRDF, Nicodemous et al, 1977). The BRDF is the radiance reflectance of all angles of light leaving a surface over a unit hemisphere at all possible angles of radiant light striking the surface. This is an extremely difficult measurement because it requires precise knowledge of the source and reflected light for a given surface at several angles that can be interpolated to determine this function. A Lambertian reflector appears to reflect light evenly to the observer from all angles as function of the average cosine of the radiance striking the surface. While the assumption of a Lambertian reflector greatly simplifies the inversion, it may result in inaccuracies if the bottom is not close to Lambertian in BRDF. The Rsopt model assumes a Lambertian BRDF as it divides the albedo by Pi in equation 7.1. A recent study has pointed out that for a fairly flat uniform bottom assumption of a Lambertian BRDF will only introduce about 10% error under most angles of source and reflected light (Mobley et al. 2003).

There are several benefits of this approach for deriving albedo values from Rrs(λ) and IOP measurements. The algorithm doesn't require expensive or complicated equipment. With an aircraft or towed radiometer; the method can provide albedo values for a large area. The method can provide output over many wavelengths. Many models start out assuming an estimate of the albedo and then attempt to match the values to that. This method doesn't require an a priori estimate of the albedo value. This model, if the assumptions are correct, will give a close estimate of the albedo for any bottom type.

The measurements required for the albedo inversion are absorption, attenuation, and backscattering along with an above water Rrs(λ). The depth of the water column should also be known. If the water column is well mixed optically, then surface measurements will suffice for the IOPs. The equipment can be as simple as a pair of attenuation meters, a 2 channel backscattering meter, and a radiometer along with surface samples collected for spectrophotometric absorption values. The best results would come from a profile of reflectance using a radiometrically calibrated downwelling irradiance meter in conjunction with a radiometrically calibrated upwelling radiance meter, an ac-9, Hydroscat-6, and acoustic bottom sounder. A profiling package would be required at locations where there are significant changes in optical properties over depth. A flow through optical system would complement the profiling. When changes in optical properties are noticed in the flow through, an optical profile could be collected. Either of these approaches is simpler than anchoring the ship for hours while divers measure small areas of the bottom with hand held radiance meters or a team of technicians deploy an ROV.

One of the more intriguing approaches is to use this method in conjunction with an aircraft mounted radiometer to measure reflectance over a large region. This approach would allow the mapping of the bottom albedo for a large area of interest (Dierrson et al. 2003). Alternatively, the radiometer could be towed behind the vessel or deployed on an AUV (English et al. 2006). The towed or AUV method would give a much smaller view of the bottom but would give a much greater resolution and eliminate the atmospheric
attenuation correction associated with air borne sensors. Either of these approaches could provide the baseline for environmental monitoring of a region with a shallow benthic community.

7.2. Bottom Albedo Inversion Method

The path of light to the bottom and back to the surface can be broken up into the path due to interaction with the water column only and the light that reaches the bottom and returns to the surface. The $R_{rs}(\lambda)$ optimization algorithm uses a method that sums both components of $r_{rs}(\lambda)$. The equation can be simplified to equation 7.1.

$$r_{rs}(\lambda) = r_{rs}(\lambda) \text{ (water column)} + \frac{\rho}{\pi} r_{rs}(\lambda) \text{(bottom)}$$  \hspace{1cm} \text{Equation 7.1}

The Greek letter, $\rho$, represents the bottom albedo. If the bottom absorbed all light, only the water column $r_{rs}(\lambda)$ to that depth would be measured and the bottom would have an albedo of zero. If the bottom reflected light, then it would have both the water column $r_{rs}(\lambda)$ and the $r_{rs}(\lambda)$ from the bottom. If closure is achieved between the AOPS and IOPs based upon the previous statistics, then the IOPs can be used as input into the analytical forward model, Hydrolight, to determine the bottom albedo. If the difference in transmittance across the air water interfaces is insignificant for different bottom albedo values, it can be assumed to be a constant and the above water $R_{rs}(\lambda)$ can be used. A Hydrolight model gives us the water column only $R_{rs}(\lambda)$ using a black bottom (albedo of 0). A second run using a white bottom (an albedo of 1) gives us both water column and bottom reflectance $R_{rs}(\lambda)$. Subtracting the $R_{rs}(\lambda,\text{black})$ from both the measured $R_{rs}(\lambda)$ and the $R_{rs}(\lambda,\text{white})$ leaves us with only the bottom contribution. Taking a ratio of the two factors of $R_{rs}(\lambda)$ provides the albedo.

$$\text{albedo}(\lambda) = \frac{R_{rs}(\lambda,\text{measured}) - R_{rs}(\lambda,\text{black})}{R_{rs}(\lambda,\text{white}) - R_{rs}(\lambda,\text{black})}$$  \hspace{1cm} \text{Equation 7.2}

The IOP value from all 126 stations used in this study were divided into five groups based on attenuation at 440 nm. The mean IOP values at 440 nm from each of these groups were used with different bottom albedos and solar zenith angles as input to the Hydrolight model to test the albedo inversion (Table 7.1). The resulting Hydrolight data use IOP values that were similar in relationship to each other as actual field data but without the accuracy limits of the instruments or techniques. The 5 sets of IOP values were run through Hydrolight simulations with bottom albedo values of 0, 10, 20, 30, 40, 50, 60, 80, and 100. Three different solar zenith angles of 15°, 45°, and 60° were used in the simulations. This synthetic data set was used to test the effectiveness of the model and the limits under which it was applicable if all the input data were perfect. The limits of diffuse attenuation, beam attenuation, solar zenith angle, and depth were tested to determine where the model functioned correctly and where it had errors. The resulting limits were then compared to the albedo inversions based on measured values to determine if they were applicable.
Table 7.1. Mean values of inherent optical properties from study locations. The IOP data from all stations were ranked and split into 5 groups according to attenuation values. The high $b_b(440)/b(440)$ ratio from the 2nd quintile is due to resuspended or precipitating aragonite particles at the CoBOP near shore stations.

<table>
<thead>
<tr>
<th>Quintile</th>
<th>$b_b(440)/b(440)$</th>
<th>$c_{nv}(440)$ $\text{m}^{-1}$</th>
<th>$a_{nv}(440)$ $\text{m}^{-1}$</th>
<th>$b(440)$ $\text{m}^{-1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>0.027</td>
<td>0.076</td>
<td>0.022</td>
<td>0.054</td>
</tr>
<tr>
<td>2nd</td>
<td>0.060</td>
<td>0.124</td>
<td>0.037</td>
<td>0.087</td>
</tr>
<tr>
<td>3rd</td>
<td>0.027</td>
<td>0.185</td>
<td>0.042</td>
<td>0.143</td>
</tr>
<tr>
<td>4th</td>
<td>0.021</td>
<td>0.264</td>
<td>0.050</td>
<td>0.214</td>
</tr>
<tr>
<td>5th</td>
<td>0.023</td>
<td>0.764</td>
<td>0.189</td>
<td>0.575</td>
</tr>
</tbody>
</table>

The albedo inversion results were compared to known bottom albedo measurements. These measurements included the sand, sea grass, green algae, brown algae, and red algae albedo values provided with the Hydrolight model (Figure 7.1 A). Nine direct measurements taken of albedos of sand bottoms near the 10 m isobath off Sarasota, FL were also compared (Mazel 1997, McIntyre 2003) to the inversion results (Figure 7.1B). The measured albedos were collected at close to the same time and area as the FSLE 3 cruise data used in this study (See Table 2.3 in Chapter 2). The closest match was determined by the lowest total absolute percent error of the modeled albedo values from a measured albedo values. The matched albedos were adjusted over the spectrum using a factor and a bias if the correlation with one of the measured albedos was greater than 0.5 but the percent error was greater than 20%. The scaling was limited to the range of slope and intercepts of albedo value versus wavelength calculated for the 9 measured sand bottoms in Figure 7.1 B.
Figure 7.1. Measured albedo values compared to albedo inversion results. A. Measured values used in the Hydrolight model. B. Measurements made using a submersible hand-held radiometer off the West Florida Shelf.
7.3. Inversion Results

There were errors associated with the bottom albedo inversion using Equation 7.2 that increased in shallower environments with higher albedo values (Figure 7.2). Analysis of Hydrolight runs with varying bottom albedos revealed that the light reflected off a bottom with a Lambertian BRDF and a shallow water column resulted in a higher average cosine of upwelling irradiance than for an infinitely deep bottom (Maritorena et al. 1994). This produced a non-linear function for \( R_{rs}(\lambda) \) versus bottom albedo. Holding all conditions constant except for bottom albedo, it was observed that bottom albedo correlated with a \( R_{rs}(\lambda) \) fit using a second order polynomial function \((r^2 > 0.99 \ n = 8, \ \text{Equation 7.3})\). Using a third Hydrolight modeling run with an albedo of 50\% \((R_{rs}(\lambda_{\text{grey}}))\) was enough to obtain a correlation of 0.98 which compensated for the non-linearity resulting from lower internal reflectance. While it may be possible to come up with a function to compensate for the change in average cosine, it was less complex to use the polynomial fit with a third model run.

\[
albedo(\lambda) = X_1^2 R_{rs}(\lambda, \text{Meas}) + X_0 R_{rs}(\lambda, \text{Meas}) + C(\lambda) \quad \text{Equation 7.3}
\]

The measured albedo values from the West Florida Shelf were mostly linearly increasing values with wavelength for \( \lambda < 600 \text{ nm} \). Normalizing these values at 550 revealed that they not only had different slopes but different intercepts (Figure 7.3). The differences are possibly a function of the coverage of the sand with biological material such as detritus, bacteria, or algae. A pure sand albedo is approximately linear in the same manner as these measurements but has a much large magnitude. The absorption by detritus has a decaying log slope that is much higher in shorter wavelengths than longer ones. A covering of detritus across the bottom could serve to lower the albedo values at shorter wavelengths resulting in a nearly linear spectral shape with a much lower slope and different intercept. This change in slope and intercept means that \( R_{rs}(\lambda) \) inversions that take into account the bottom albedo need both a bias and multiplicative factor to adjust the albedo values. This spectral linear relationship means that it is not easy to compare measurements from different locations and times with the model results. The scaling of these sand albedo values was limited to the range of slopes and intercepts observed in the measured albedo values.
Figure 7.2. Comparison of ratio method to polynomial method using Hydrolight generated data. The ratio method averages 7.1% less than the input green algae albedo while the polynomial fit average 7.5% higher over 400 to 625 nm.

Figure 7.3. Measured West Florida Shelf albedos and Hydrolight sand albedo normalized to their 550 nm values.
Of the 126 stations, 86 are shallow enough that some reflectance from the bottom could be a part of the $R_{ns}(\lambda)$ measurement. All were processed using the albedo inversion. Only 46 of the 86 stations have sufficient bottom reflectance in the $R_{ns}(\lambda)$ measurement for depth analysis using the $Rrsopt$ algorithm. Only 23 of the stations have $Rrsopt$ inversion results for depth that were within 20% of the actual depth and only 13 stations within 10% of the actual depth. The IOP data and $R_{ns}(\lambda)$ from the 86 stations were input into Hydrolight to determine if they could provide a realistic bottom albedo value. The modeled data were run at 10 nm increments from 400 to 700 nm at albedos of 0, 0.5 and 1.

The albedo inversion had matches within 20% for at minimum 3 wavelengths (10 nm increments) for 30 stations. There are seven stations where the $R_{ns}(\lambda)$ inversion algorithm did not find the bottom but the albedo inversion was able to provide an albedo result (ECO2, F3005, F3014, F4006, F4012, LK204, and LK205). The best matches were in the optically clear waters in the Bahamas with the poorest matches in the more turbid waters off the West Florida Shelf (Figures 7.4 and 7.5). The bottom contribution was not significant in the Puget Sound stations. Sixteen stations had matches to an albedo that did not require scaling. Fourteen of those stations were off the West Florida shelf near the location where some of the bottom albedo measurements were collected (Figures 7.6 to 7.8). Of the 86 stations put through the model, 30 produced albedo inversion results that are within 20% of measured albedo values from other studies at 3 or more wavelengths.
Figure 7.4. Albedo inversion results and similar measured albedos: 1998 Bahamas stations. Any values to the right of the solid blue line and to the left of the dashed blue line are greater than 2 optical depths. Values less than or equal to zero were not plotted since they were not considered a real result.
Figure 7.5. Albedo inversion results and similar measured albedos: 1998-1999 Bahamas stations. Any values to the right of the solid blue line and to the left of the dashed blue line are greater than 2 optical depths. Values less than or equal to zero were not plotted since they were not considered a real result.
Figure 7.6. Albedo inversion results and similar measured albedos: 11/99 to 07/00 West Florida Shelf stations. Any values to the right of the solid blue line and to the left of the dashed blue line are greater than 2 optical depths. Values less than or equal to zero were not plotted since they were not considered a real result.
Figure 7.7. Albedo inversion results and similar measured albedos: 07/00 to 11/00 West Florida Shelf Stations. Any values to the right of the solid blue line and to the left of the dashed blue line are greater than 2 optical depths. Values less than or equal to zero were not plotted since they were not considered a real result.
Figure 7.8. Albedo inversion results and similar measured albedos: 2001 West Florida Shelf Stations. Any values to the right of the solid blue line and to the left of the dashed blue line are greater than 2 optical depths. Values less than or equal to zero were not plotted since they were not considered a real result.
7.4. Accuracy of the Albedo Inversion Algorithm

Hydrolight is an exact numerical model but has a limit due to the number of significant digits it can calculate and still be able to complete the calculation in a reasonable time. For certain combinations of input factors, the model would not produce a result for albedo. In these cases the surface $R_{rs}(\lambda)$ signal from the backscattered irradiance just above the bottom was lower than the noise in the model due to the rounding of very small numbers. While this accuracy is not the same as accuracy using actual data, it does provide an upper limit to determine the conditions under which the Hydrolight model is limited in calculating a bottom albedo.

To determine the environmental conditions at which this model is applicable, the synthetic data set created using Hydrolight was compared to various combinations of AOPs, IOPs, depths, and bottom albedo values. The magnitude of the albedo did not have an influence on whether the albedo can be modeled. The factor that indicated the noise level was the optical depth as calculated by $K_d(\lambda)$ multiplied by the depth of the water column resulting in a unit-less number indicating the penetration of light to depth (Kirk 1994). There are some differences in the literature over the term optical depth. Kirk (1994) defines it as used in this study but Mobley (1994) defines it as the beam attenuation times the depth. $K_d(\lambda)$ times depth is more useful for determining the limits for albedo inversions since it combines absorption, backscattering, and $\mu$ into one term. The optical depth is useful because it can give both maximum depth if the $K_d(\lambda)$ value is known and can give maximum $K_d(\lambda)$ if the depth is known. An optical depth of 3.2 appears to be the cutoff point using the artificial data set (Figure 7.10). If the $K_d(\lambda)$ value for an area is 0.1 m$^{-1}$ then dividing the 3.2 limit by it would give a maximum depth of 32 meters. Likewise if the depth is 10 meters, dividing the optical depth of 3.2 by 10 m would give a maximum $K_d(\lambda)$ value of 0.32 m$^{-1}$. By raising the base of the natural logarithm (e) to negative of the maximum optical depth then multiplying by 100 gives the minimum percent of downwelling irradiance reaching the bottom necessary to determine albedo as 4.1%. Field data are rarely as accurate as the Hydrolight modeled values so 3.2 optical depths should be considered the theoretical limit.
Figure 7.9. Absolute percent error for albedo at 440 nm using the Hydrolight generated data set. All quintiles of IOPs, solar zenith angles, and bottom albedos are included in this graph.

When using actual field data the maximum optical depth at which the bottom albedo could be reasonably determined was 1.5 to 2.0 (Figure 7.11). The percent difference from the input albedo noticeably increased above 3.2 optical depths. A value of 3.2 to 3.0 might be the highest useful optical depth under ideal environmental conditions with very precise instrument data but an optical depth of 2 is probably the most practical limit. At an optical depth of 2 only 1.8% of the light reaching a bottom with 100% reflectance would make it back to the surface. Based on the comparison of environmental parameters, the accuracy of the IOP input into Hydrolight and $R_{rs}(\lambda)$ measurements limits the accuracy of the model to about 2 optical depths. Albedo inversions using actual data were achieved for optical depths as high as 4 but the agreement between the measurements and the modeled values became significantly noisier above 2 optical depths. Plotting the cumulative percentage of values with agreement of 20% or less revealed that there is an inflection point at 2 optical depths after which the fraction with good agreement significantly declines (Figure 7.12). There is another inflection point at 1.2 optical depths but it reflects a leveling of the change in the percentage of good agreement. Until testing with a larger data set is available, 2 optical depths is probably the practical limit.
Figure 7.10. Plot of absolute percent difference from best match measured albedos versus albedo inversion results at 440 nm. This is based on actual field data.

Figure 7.11. Cumulative percentage of matches that are 20% or less than the given optical depth at 440 nm. This data set is based on the actual field data. The percent difference is based on the best match to measured values where the albedo result was greater than zero.
Based on the Hydrolight modeled data set, an optical depth based on beam attenuation (Mobley 1994) at 440 nm could also function as a limit. The correlation between error and a diffuse attenuation optical depth or beam attenuation optical depth is 0.86 for both. The upper limit for the model data using beam attenuation based optical depth is 15.28 and noise starts to occur at 6.20 (Figure 7.13). This information could be useful for field exercises where a submersible downwelling irradiance meter is not available. As with the other modeled results this represents a theoretical limit not the practical limit as determined from field measurements.

Figure 7.12. Absolute percent error versus optical depth as calculated using attenuation for Hydrolight generated data set. This method of calculating optical depth is also referred to as attenuation length. All quintiles of IOPs, solar zenith angles, and bottom albedos are included in this graph.

The change in average cosine is a much more significant effect than the magnitude of the albedo value. Instead of light continuing to depth and being backscattered, the light is cut off at a certain depth and either reflected back towards the surface or absorbed. If the bottom is close to Lambertian in reflectance, then the average cosine of the light reflected off the bottom is 0.5. This means that the downwelling irradiance, as a function of the attenuation by the bottom, is returned less diffusely than if there were no bottom. This results in a greater percentage of light being transmitted across the air water interface (Maritorena et al. 1994) instead of lost to internal reflectance. Even a black bottom affects the average cosine if it is shallow enough. A dark bottom cuts off the light before it reaches depth and undergoes multiple scattering events. The average cosine is a function of a shallower water column where $\bar{\mu}(\ddot{\lambda})$ is
greater due to a shorter path to the surface. The limit to this albedo inversion is independent of the actual albedo but relies on whether there is sufficient signal from the water column at a depth just above the bottom.

The Q factor is the ratio of subsurface upwelling irradiance to subsurface upwelling radiance at depth and varies as a function of the bottom albedo (Figure 7.14). The Q factor exhibits significant variation as a function of albedo resulting in a hyperbolic curve. As the albedo value increase, the ratio of radiance to irradiance increases. This increase in the Q factor is due to two factors: the increased amount of downwelling irradiance that is reflected up due to the bottom, and the change in angle of the upwelled radiance to a more direct path to the surface. The more direct path will result in lower attenuation and less chance of internal reflection at the surface.

![Figure 7.13. Rrs(440) and below-surface Q factor at 440 nm versus albedo values for middle quintile IOPs and 10 m bottom depth.](https://example.com/figure7.13)

A ratio equation using modeled Rrs(λ) values with albedos of 0 and 1 is a close approximation but results in a slight error depending on the change in Q factor for different albedo values. The fit for the Rrs(440) values to albedo for the median values in this study, had r² values of over 99% for both a linear and second order polynomial fit. However, the differences between the measured and modeled values can be large for the linear fit especially at smaller albedo values. Because of a bias in the regression line, the middle quintile of IOP values the linear fit had a 170% error predicting an albedo of 0.5% while a second order polynomial had a 4% error. The ratio method is not good for small albedo values due to the nonlinear relationship between albedo and Rrs(λ).
Due to the possibility of problems with the fit of the second order polynomial curve to albedo values below 10%, a second set of modeled data was created with 12 total values by adding four values between the albedo values of 0 and 10. Additional albedo values of 0.5, 1.7, 2.8, and 5 were included with the original group using the 3rd quintile of IOP values, a 15° solar zenith angle, and 10 m depth. Using 12 albedo values resulted in similar statistics but higher percent differences at some lower albedo values. At an albedo value of 0.5, the fit through 12 albedo values had a percent error of 4.14% while the fit through three albedo values had a percent error of 0.81%. The extra values probably would have better results with a higher order polynomial equation but that was not necessary since using the three values provides an error of less than 1%. The three point albedo value fit was used instead of a larger number of computationally intensive Hydrolight runs at more albedo values since the greater number of values did not improve the results when using a second order polynomial fit.

The optical depth limit of 2 was not always a perfect predictor of when the albedo inversion could be achieved. With values at greater than two optical depths removed, the CoBOP stations had about 68% of the possible wavelengths within 20% of the reference albedo values. The West Florida Shelf stations had 50% within 20% of the reference albedo values. Station F4006 on the West Florida Shelf has matches within 20% at 5 wavelengths from 460 to 510 nm but the whole spectrum is outside the optical depth limit of 2. The optical depth limit was not a perfect predictor of model success but only one station had realistic inversion values that were seriously outside it.

7.5.Sources of Error

There are some liabilities to this approach. The data collected must be of very high quality. The use of several different instruments can compound the error from each. The method assumes that the bottom is Lambertian in reflectance and may have some errors if the BRDF for the bottom substrate differs much from a Lambertian BRDF (Voss et al. 2003, Mobley et al. 2003). In addition to very good IOP input, the model requires very good meteorological data so that the input solar radiation is a close match to the actual down welling irradiance for determining transitions across the air water interface.

Accurate data are crucial for the success of the polynomial approach to bottom albedo modeling. Most instruments are accurate to within 10% of the actual value at best. Since the method requires the use of $R_{rs}(\lambda)$, $a_{nw}(\lambda)$, $c_{nw}(\lambda)$, and $b_{op}(\lambda)$, there are four instruments that can contribute to errors in the resulting albedo if they are too far from the actual value. The error in instrument accuracy is most likely the reason why the technique is limited to 2 optical depths using real data but is usable up to 3.2 optical depths for the Hydrolight simulated data. This also is the most likely reason for some high error values at optical depths below 2 when using the real data.

Some of the inversions clearly have inaccurate data as inputs. The inversion from station ST103 has a deviation from the measured value from 400 to 475 nm that has a decaying slope logarithmic shape (Figure 7.4). The error could be due to a low $a_{g}(\lambda)$
value, too high $b_{bp}(\lambda)$ value, or too much skylight in the $R_{rs}(\lambda)$ signal. Adjusting the values or trying different instruments might improve this inversion. However, without an absolute measurement of this bottom, it can't definitely be defined as any one cause. Adjusting the $a_{aw}(\lambda)$ up by 30% and the $b_{bp}(\lambda)$ value down by 20% brought the values closer to one another in the longer wavelength range but did not significantly effect the area that was already matched. This test at one station indicates that the inversion is pretty robust in the regions of strongest signal.

The meteorological data could introduce errors if there is a problem with the estimate. Hydrolight can use direct measurements also as input if the separation of direct and diffuse light is first determined by shading the sun from the above water radiance meter. Without knowledge of the direct and diffuse irradiance values, the best way to input the down welling solar irradiance into Hydrolight is to first match the above water values to a direct measurement that is synchronous with the $R_{rs}(\lambda)$ measurement. Hydrolight uses the Radtran solar irradiance model as one of its inputs (Gregg and Carder 1990). The Radtran algorithm can be coded in either Matlab or Excel in such a way as to allow the values to be iterated until a match is achieved with a direct measurement. This match would minimize one source of error for the inversion.

Actual measurements of radiance from different zenith and azimuthal angles indicate that most bottoms are not purely Lambertian in reflectance (Voss et al. 2003). In one particular direction there is usually a "hot spot" where more radiance is emitted. However, most bottom albedos do come close to Lambertian especially after attenuation through the water column. Mobley et al. (2003) estimate that assuming a Lambertian bottom albedo will only introduce errors of 10% in modeled $R_{rs}(\lambda)$ values. This is an area where further research is needed. After compiling how different bottom types respond to light, it may be possible to estimate the bi-directional reflectance distribution function based on the bottom type. Another method that might help in determining the BRDF is through using this albedo inversion method but taking several $R_{rs}(\lambda)$ measurements at different angles. The BRDF could be calculated by looking at the differences in albedo from several different points. The albedo value from this albedo inversion is valid for the solar zenith angle, solar azimuth angle, and view angle of the radiance sensor for this $R_{rs}(\lambda)$ measurement. It just may not be as accurate under different angles if the bottom is assumed to be Lambertian in reflectance.

Since the $R_{rs}(\lambda)$ value collected in the field represents the effects from a three dimensional bottom it could influence the overall albedo inversion. Most models assume that bottoms have one set albedo and BRDF but in reality, they can vary widely over a short range. Sand waves trap detritus resulting in darker patches in troughs while there are light areas at the peaks (Carder et al. 2003). The slope of the bottom especially for a rapidly changing bottom can result in different albedo values even if Lambertian (Mobley and Sundman 2003). Adjacency effects can cause errors. These occur where the reflectance from two different bottom types merge together in the water column due to scattering. This smearing of the two albedos can make it difficult to determine the actual bottom albedo for a given location (Mobley and Sundman 2003, Farmer 2005).
albedo is a mix of different patches of albedo values with different BRDF functions so this method cannot completely remove the water column attenuation to reveal a sharp, color, spectral, image of the bottom.

High solar zenith angles were associated with errors in the albedo inversion. High zenith angles can lead to increased sun glint resulting in error in the $R_{rs}(\lambda)$ measurement. The assumption of Lambertian reflectance may not be valid for higher solar zenith angles. The light striking the surface at an angle close to the horizon may not give the same percentage of reflectance towards a radiometer angled 30° from nadir when compared to the sun being more directly overhead. In examination of the stations where there were albedo inversion results it was determined that at only 15% of the stations with a solar zenith angle of less than 30° was an error of greater than 30% at 440 nm observed while at 85% of those with solar zenith angles of greater than 37° was an error greater 30% found (there were no stations with solar zenith angles between 30° and 37° that produced an albedo result). Examination of the areas that were possibly shallow enough to have some bottom influence on the $R_{rs}(\lambda)$ values revealed that at 96% of the stations with no results were found either solar zenith angles greater than 30° or optical depths at 440 nm greater than 2. Of the stations with no result, 63% had both high zenith angle and high optical depth while only 10% of stations with results had this combination. To reliably achieve a bottom albedo inversion, both optical depths less than 2 and a low solar zenith angle are needed.

Further research is needed to determine the maximum solar zenith angle for the technique. A controlled experiment at a single location with a known bottom albedo would be necessary to fully understand the sources for the problems with high solar zenith angle. Sun glint may be a major factor in causing errors in the inversion. Since the average cosine of upwelling irradiance is the primary indication of bottom albedo, the error at larger zenith angles may be function of a change in $\bar{\mu}_i(\lambda)$ due to the zenith and scattering in the water column. To determine if the change in $\bar{\mu}_i(\lambda)$ produces the error further research is needed. Based on the actual data, $R_{rs}(\lambda)$ values collected at greater than 37° should be suspect when albedo inversions are attempted.

Unfortunately optical data collected in the field is never absolutely perfect, so the practical limit of this method is a much lower optical depth than indicated by modeled data. There were no synchronous measurements of the albedo values at any of the stations in this study to confirm the model results, so this limit may not be as low. The known albedo values consisted of standard measurements used in the Hydrolight model and measurements collected just offshore from Sarasota, Florida. The $R_{rs}(\lambda)$ could contain excessive skylight or sun glint that could cause errors in the values. Since only the integrated value was used, the IOP input values could cause errors if the values change significantly over depth. It is difficult to statistically analyze the limit of the model based on the results using real data from this study. Further testing of the algorithm with bottom albedo measurements collected in synchrony with the $R_{rs}(\lambda)$ and IOP values are required before a more definitive limit can be established.
7.5. Applications for Albedo inversions

The uses for a real spectral bottom albedo could be many. Many surveys are performed with color video cameras. Most cameras only have 3 colors, red, green, and blue. While three wavelengths can be used for some colorimetric identification of objects below the surface, spectral data can provide a more quantitative identification. If the bottom is covered with a photosynthetic organism like sea grass or algae, the spectral shape of the albedo may give some indication to the type of organism. If the object is a manmade device, such as submersible vehicle, it would be very difficult to exactly match it's color and reflectivity to the substrate making it detectable using a spectral radiometer. This technique could be useful for applications ecological mapping to port security.

The biggest drawback to using this technique with hyperspectral imagery would be the need for a less processor intensive version of the Hydrolight model combined with a very powerful computer. A faster version of Hydrolight has been created for use with Phills imagery to generate look up tables to determine bathymetry and bottom type (Mobley et al. 2005). They involve matching the $R_{rs}(\lambda)$ to a set of preset values using estimated IOP data in conjunction with known albedo values. The change in average cosine values with changes in depth and albedo would require model runs for each wavelength and IOP values using bottom albedo values of 0, 0.5, and 1. The wavelength range could be lowered if the depth is such that attenuation by water would increase the optical depth to greater than 2. While taking a large amount of computer time, this method is feasible even for high-resolution imagery.

If the IOPs are constant over the area of interest then a series of regressions could be calculated for the albedo fits at 0, 0.5, and 1 over the depth range of the area. For coral reef off the Florida Keys, the depth range might be 1 to 20 meters. Instead of doing Hydrolight runs for each depth, runs could be determined for several depths and a second order polynomial equation calculated for each of those depths. A second regression using a logarithmic or polynomial fit is calculated for each of the terms as they change over depth. A correction for slight changes in solar zenith angle during the time of collection could further increase the accuracy of the results. To map the albedo of an area, it may only require as little as 12 Hydrolight runs to get this matrix. The computer time would not be a concern with this approach.

The best time for mapping the albedo of an area would be during a period of constant IOPs with lower attenuation such as a high tide. Since the areas where this technique would be applied are most often near shore, a flood tide would provide the lowest attenuations. A flood tide would usually bring in clear offshore waters. The peak of high tide when the currents slow down may be the best time for mapping most regions. A problem could be possible resuspension of sediment caused by an incoming tide if the current is strong enough. The tidal period should be an important consideration in mapping an area especially if there is a significant change in optical properties with the tide.
A 3 dimensional color map of a coral reef could be created using this technique. A hyperspectral-scanning imaging sensor like the Phills (Davis et al. 1999, Lesser 2007), a side scan sonar system, and a flow through optical system could provide a high resolution color map of a coral reef region. A lower cost method could use a towed balloon with miniature black and white cameras using narrow band pass filters for several important wavelengths (Dave English, personal communication). Such a map would be invaluable to coral reef ecologists and natural resources officials. It would provide a baseline for future research and could be used to quantify coral coverage. A spectral three-dimensional image could be used to identify hazards to coral reefs such as bleaching, cyanobacterial blooms, or black band disease. The spectral values could identify species of corals based on pigments through fourth derivative analysis of the spectral shape. Currently reef systems worldwide are in decline. Management practices need to be geared to addressing the reefs in the greatest decline. By initially identifying the problems in these areas, more efficient allocation of resources and policy changes could be targeted to the individual reefs. A three-dimensional spectral baseline map would provide a tool to focus restoration and preservation efforts.

Homeland security could benefit from spectral maps of specific bottom areas. Monitoring a harbor from below the surface can be very complex. It usually requires active systems like sonar. Coverage of a large area would be difficult. If the attenuation is low enough, the area could be monitored optically using the bottom albedo inversion technique. An object of interest could be camouflaged from a video camera since it only sees 3 colors across a narrow range. Camouflaging an object so that it spectrally blends in with the water column or bottom would be much more difficult. This difficulty would be compounded as the object moves across the bottom. An active camouflage system that changes in spectral reflectance would be difficult to implement.

To provide real time indications of a change in the bottom, an initial mapping of the area could be performed to determine the albedo using an approach similar to the mapping of the reef area. A faster model like the R_{ss} optimization routine could then be combined with the known albedos and depths. The iterative portion of the model would not need to be run if the IOP inputs were provided in real time through moorings. The resulting R_{ss} spectra could then be compared to measurements from a tethered balloon or autonomous air craft with an algorithm to detect outliers in bottom albedo. The outliers could then be examined in more detail and determined if they represent a possible threat. Surveys at set intervals would be required to update the bottom albedo values depending on seasonal changes in the bottom albedo due to changes in benthic biological organisms or sediment deposits. This system would provide a real time tool for monitoring the large area of a port without a need for a large array of acoustic moorings, a fleet of ships, or a fleet of AUVs.

Sea grass coverage has declined in some areas due to anthropogenic influences and needs to be monitored for restoration efforts. Tampa Bay experienced a severe decline in sea grass coverage during the early 70s (Dawes et al. 2004). Efforts the last couple of decades have succeeded in restoring several of these areas. Monitoring sea
grass using a radiometer can be difficult due to changes in patterns (Zimmerman 2003). Changes in current can result in more of the leaf being visible due to the grass either laying over or standing up. Changes in epiphytes on the grasses can change their albedo. Changes in coverage or sediment between the grasses can also change the albedo. A spectral albedo would make it easier to separate these changes in a sea grass bed. Other algorithms require *an a priori* input of sea grass and sand albedos and attempt to estimate coverage based on the proportion of those values. With knowledge of the IOP values and depths, spectral values could be determined and then deconvolved into sand or grass areas to get coverage estimates (Diersson et al. 2003). The resulting sea grass coverage along with spectral changes due to epiphytes could be estimated from this method.
8. Conclusions

An analytical inversion of an AOP measurement can be more accurate than the more direct measurement for determining IOP values under many environmental conditions. The AOP inversions are especially accurate for low attenuation waters without a significant bottom contribution. This study assumed that no method was an absolutely perfect measurement of the selected inherent optical property but instead let statistics determine the best method. Instead of a single measurement, an idealized data set based on a nonparametric analysis of the different methods was assumed to represent the best value for the water column IOP tested. The $R_{rs}(\lambda)$ optimization algorithm performed the best under the most conditions for most of the IOP comparisons due to its analytical approach and longer effective path length. Both the quantitative filter pad method and $R_{rs}(\lambda)$ were best for determining $a_{ph}(\lambda)$ depending on conditions. The MODIS algorithm was best for determining $a_{p}(\lambda)$ when using its semi-analytical approach combined with an initial higher value for the $a_{g}(\lambda)$ coefficient. The $K_d(\lambda)$ optimization model was best for $a_{nw}(\lambda)$ and the Hydroscat-6 was best for $b_{gw}(\lambda)$ when the bottom contribution to $R_{rs}(\lambda)$ was significant. The percent error terms had correlations with parameters that revealed areas for improvement for most methods. The closure of results among the methods provided an approach for determination of spectral bottom albedo using $R_{rs}(\lambda)$.

The longer the effective path length of light in the method, the better the accuracy of the method in low attenuation waters. The closure study demonstrated that under conditions where there was no bottom present, the $R_{rs}(\lambda)$ inversions were more accurate than the $K_d(\lambda)$ inversions for calculating $a_{nw}(\lambda)$ due to an optical path length that is much larger than that of the $K_d(\lambda)$ values. The $K_d(\lambda)$ optimization method was more accurate than the ac-9 for $a_{nw}(\lambda)$. $K_d(\lambda)$ values have path lengths of several meters while the ac-9 has a path length of only 0.25 m. The exception for the more direct methods was the $a_{ph}(\lambda)$ measurements using the quantitative filter pad method where effective path length can exceed 20 m for clear water and volumes of over 4 liters are filtered. The increase in signal to noise from an increased optical path length more than compensates for the empirical assumptions made in AOP inversions for clear waters.

Low solar zenith angle can affect both $K_d(\lambda)$ inversions and $R_{rs}(\lambda)$ inversions. Under ideal conditions there were significant negative correlations with solar zenith angle and error from $K_d(\lambda)$ inversions for primarily 412 to 555 nm and error $R_{rs}(\lambda)$ inversions for primarily 532 to 676 nm. $K_d(\lambda)$ values are affected by increased wave focusing and $R_{rs}(\lambda)$ value are affected by sun glint when the sun is nearer to zenith. For solar zenith angles less than 15° more $K_d(\lambda)$ measurements are needed near surface to smooth out
wave focusing. \(R_{rs}(\lambda)\) measurements may need to be collected at different view angles than the standard 30° observation zenith angle to possibly minimize glint at low solar zenith angles. The ideal angles appear to be between 15° and 45° based on the data set used in this study. The lower solar zenith angles resulted in greater error for the AOP values than the higher angles.

The \(R_{rs}(\lambda)\) inversion models were less accurate when bottom reflectance was greater than 10% of the total \(R(\lambda)\) for most IOPs. The exception was the \(R_{rs}(\lambda)\) optimization for \(a_{ph}(\lambda)\) values when bottom was present. While \(R_{rs}(\lambda)\) optimization statistically did well for \(a_{nv}(\lambda)\) under optimal conditions and significant bottom contribution to reflectance, it did not perform as well when used for albedo inversions under the same conditions. However, because the \(R_{rs}(\lambda)\) optimization algorithm takes into account the bottom albedo, it did perform well for inversion of \(a_{ph}(\lambda)\) when bottom reflectance was significant. Since the \(a_{ph}(\lambda)\) values do not have a spectral shape that decreases with increasing wavelength as does \(b_{bp}(\lambda)\) or \(a_{g}(\lambda)\), it does not appear to be as influenced by bottom reflectance.

The \(K_d(\lambda)\) optimization method, developed in this study gave the best result of the \(K_d(\lambda)\) inversions tested. The model is based on Preisendorfer's definition of \(K_d(\lambda)\) and would give very accurate results for absorption values if the data were perfect and the average cosine of downwelling irradiance known. The \(K_d(\lambda)\) optimization results have errors primarily due to wave focusing and empirical determination of the average cosine of downwelling irradiance. \(K_d(\lambda)\) optimization did not perform well for \(b_{bp}(\lambda)\) due to the low signal from \(b_{bp}(\lambda)\) in the \(K_d(\lambda)\) measurement but it did get closer to the ideal value when a number of outliers was removed. The \(a_{nv}(\lambda)\) results from the \(K_d(\lambda)\) optimization method were the best input for the albedo inversion algorithm. The \(a_{nv}(\lambda)\) and \(a_{ph}(\lambda)\) results from \(K_d(\lambda)\) optimization, while not the absolute best, were good under most conditions. Generally, the longer path length of the \(R_{rs}(\lambda)\) values gave them a greater signal to noise ratio than the \(K_d(\lambda)\) values. The \(K_d(\lambda)\) optimization method does provide the best inversion of \(K_d(\lambda)\) values to obtain IOPs.

The MODIS semi-analytical algorithm proved the best method of the \(R_{rs}(\lambda)\) inversions for determining \(a_{g}(\lambda)\). The CDOM fluorescence contribution to \(R_{rs}(\lambda)\) affects the inversion of \(a_{ph}(\lambda)\) by increasing \(R_{rs}(\lambda)\) around 440 nm and \(b_{bp}(\lambda)\) by increasing \(R_{rs}(\lambda)\) around 555 nm. The MODIS algorithm, using a higher coefficient for the \(a_{g}(400)\) equation, increased the modeled \(R_{rs}(\lambda)\) value at lower wavelengths to correct for the CDOM fluorescence. A lower coefficient was then used after the model run to calculate the \(a_{nv}(\lambda)\) and \(a_{g}(\lambda)\), resulting in better agreement with the idealized values. This change in the method could be applied to other \(R_{rs}(\lambda)\) inversions to improve them in areas where CDOM fluorescence is expected to be significant.

The level of empiricism is a tradeoff that limits the accuracy of a model but requires less \textit{a priori} knowledge of the study area and lower computational needs. The ranking of the accuracy of the AOP inversion proceeded from least empirical to most
empirical. Of the four $R_{sr}(\lambda)$ inversions, $R_{sr}(\lambda)$ optimization was the most accurate, followed by MODIS, QAA, and MODIS default band ratio algorithm. For the $K_d(\lambda)$ inversions, $K_d(\lambda)$ optimization was best followed by $K_d$ Loisel and $K_d$ Kirk. The more direct IOP methods required some empirical functions to correct for errors. The ac-9 uses a ratio of estimated scattering to correct for losses in the absorption tube. The filter pad method uses an empirical function to correct for path length elongation. The Hydroscat-6 uses an empirical function to correct for attenuation and convert $b_b(\lambda, 140^\circ)$ to $b_b(\lambda)$. Every method in this study employs some form of empiricism, the level of which affects the accuracy of the method.

There are some exceptions to the level of empiricism and accuracy of the algorithms since the complexity of the more analytical algorithms can sometimes lead to errors. The MODIS algorithm performed better than the $R_{sr}$ optimization algorithm for $a_{ms}(676)$. The better accuracy for MODIS may be due to adjustment of the phytoplankton absorption factors based on nitrate depletion temperatures to account for changes in packaging. The fits at longer wavelengths for some of the methods represent extrapolations based on fits at the shorter wavelengths due to decreased signal to noise caused by water absorption at the longer wavelengths. MODIS uses an empirical function based on $a_{ph}(440)$ and water temperature to estimate $a_{ph}(676)$ that gave it very good results at that wavelength. While generally a more analytical approach is better, a more empirical approach can yield better results under certain condition.

The results for $R_{sr}(\lambda)$ inversions in this study indicate some improvement to the algorithms. To compensate for CDOM fluorescence, all the $R_{sr}(\lambda)$ algorithms would benefit from using a larger CDOM slope coefficient for the initial iterative fit or a correction function that fits the emission from CDOM fluorescence. While it is standard practice to measure $R_{sr}(\lambda)$ at zenith angles less than $45^\circ$, higher zeniths should be avoided to limit sun glint. Under most conditions, the MODIS algorithm could benefit from the simple iteration method used to determine $b_{bp}(\lambda)$ by the QAA algorithm. When bottom contribution is significant, the $R_{sr}(\lambda)$ optimization method can be improved by basing the $b_{bp}(\lambda)$ value on an empirically determined value similar to the approach used by the MODIS algorithm.

The $K_d$ optimization method can be improved by changes in measurement technique. Lower solar zenith angles lead to greater wave focusing and need to be compensated for by increasing near surface measurements of $E_d(\lambda)$. Collection of scalar downwelling irradiance synchronous along with planar measurement would provide a direct measurement of the average cosine of downwelling irradiance and eliminate an empirical equation in the algorithm. The coefficient for $a_g(\lambda)$ needs to be locked to a specific value under certain conditions. However, if wave focusing is minimized and the average cosine of downwelling irradiance measured, solution to the CDOM slope coefficient could be iterated. By minimizing the effects of wave focusing and measuring the average cosine of downwelling irradiance, the $K_d(\lambda)$ optimization method would be improved.
The more direct IOP measurements can be improved through changes in instrument design and path length corrections. The ac-9 can be improved by designs that would improve water flow through the instrument resulting in fewer entrapped bubbles. The ac-9 needs a better light source that is more stable and produces lower heat. An LED light source and longer path length may improve the instrument. The Hydroscat-6 needs a better post processing routine that uses Morel's (1974) salt-water scattering equations instead of assuming half the Morel (1974) values. The filter pad method could use beta factors that were more appropriate to the species composition of the study area. The spectrophotometric \( a_g(\lambda) \) measurements need a longer path length instrument to achieve a higher signal to noise ratio. When comparing the spectrophotometric methods to profiles or AOP inversions, a larger number of samples need to be collected over depth and interpolated between to achieve an integrated water column value for the IOPs. These improvements could bring some of the more direct methods closer to the AOP inversions in clear waters.

The use of Hydrolight derived \( R_{rs}(\lambda) \) values using input IOPs derived from \( K_d(\lambda) \) inversions and the Hydroscat-6 provided for determination of spectral bottom albedo values from the measured \( R_{rs}(\lambda) \). While the method does not require a priori knowledge of the bottom type, it does require accurate knowledge of \( R_{rs}(\lambda) \), \( a_{aw}(\lambda) \), \( b_{bp}(\lambda) \), and depth for the water column. The algorithm is simpler than a direct measurement of the bottom albedo and can be used over a wider spatial area. Since the algorithm assumes the bottom is a Lambertian reflector it may have errors at other angles for benthic surfaces with a bi-directional reflectance distribution function that is very different from isotropic. The algorithm functions best for optical depths based on \( K_d(\lambda) \) times geometric depth that are less than 2 and solar zenith angles that are less than 30°. This optical depth translates into a maximum depth of 20 m if the \( K_d(\lambda) \) is 0.1 m\(^{-1}\). However, greater depths and diffuse attenuation values may be possible with more accurate measurements. The algorithm is independent of the magnitude of the bottom albedo since it is a function of the change in the average cosine of irradiance by the presence of a bottom versus a deep-water column. Determining the color of the bottom would be useful in estimating the health of coral reefs and sea grass coverage. Spectral bottom albedo values are one of the resulting optical properties that can be determined through the relationships between the different methods studied in this project as determined through the closure approach.
List of References


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