Atmospheric Compensation over Case II Waters: Simultaneous Aerosol and Water Constituent Retrieval

by

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Abstract

In many algorithms designed to retrieve water constituent concentrations, an assumption of negligible water-leaving radiance is made in the near infrared (NIR) wavelengths (750-950 [nm]). This allows fairly accurate atmospheric correction to be applied to the oceanic imagery. Given this assumption, it is possible to derive model estimates of aerosol type and density and compensate for its effects in other regions of the spectrum. Unfortunately this assumption is only valid in areas of very low total suspended sediment (TSS) concentrations, such as open ocean waters. Increased TSS load causes significant back-scattering within the water, increasing the water leaving signal in the NIR region, which confounds the compensation algorithms and incorrectly attributes all the effects entirely to aerosols. A possible solution to this problem is to model suspended sediment inherent optical properties (IOPs) in the NIR using the Ocean Optical Phytoplankton Simulator (OOPS) and couple this data using atmospheric and hydrologic radiative transfer models (MODTRAN and HYDROLIGHT, respectively). These models can be combined for a given sensor geometry to predict sensor reaching radiance and match the resulting spectra with actual image spectra. This is done including the NIR which should allow us to better characterize the sediment load. Look-up tables (LUTs) of radiances from modeled atmospheres and reflectances from modeled water allow us to make this an iterative process which can be optimized to give us the best match for the pixel in question. The products of this algorithm are the water constituent concentrations and the atmospheric parameters. This process has been implemented for AVIRIS hyperspectral imagery captured over the Rochester, NY embayment with reasonable success in atmospheric and constituent retrieval.

Contents

Intr	oducti	ion	1		
1.1	Overv	iew	2		
Bac	ckground				
2.1	Radia	tive Transfer	7		
	2.1.1	Radiance Reaching the Sensor	8		
		2.1.1.1 Energy Paths	9		
	2.1.2	Transmission	2		
		2.1.2.1 Absorption and Scattering in Water	4		
2.2	Atmos	spheric Compensation	6		
	2.2.1	In a Perfect World	6		
	2.2.2	Techniques For Atmospheric Compensation	6		
2.3	Remo	te Sensing Platforms	8		
	2.3.1	AVIRIS	8		
2.4	Spectr	cal Matching	22		
	2.4.1	Previous Work In This Area	22		
	2.4.2	Extending Spectral Matching Techniques 2	24		
	Intr 1.1 Bac 2.1 2.2 2.3 2.4	Introducts 1.1 Overv Background 2.1 Radia 2.1 2.1.1 2.1.2 2.1.2 2.2 Atmost 2.2.1 2.2.2 2.3 Remotion 2.4 Spectra 2.4.1 2.4.2	Introduction 1.1 Overview Background 2.1 Radiative Transfer 2.1.1 Radiance Reaching the Sensor 2.1.1 Energy Paths 2.1.2 Transmission 2.1.2 Transmission 2.1.2 Transmission 2.1.2.1 Absorption and Scattering in Water 2.2.2 Atmospheric Compensation 2.2.1 In a Perfect World 2.2.2 Techniques For Atmospheric Compensation 2.3.1 AVIRIS 2.4.1 Previous Work In This Area 2.4.2 Extending Spectral Matching Techniques		

3	Mo	eling	25
	3.1	Why Model?	25
	3.2	Modeling with MODTRAN	26
		3.2.1 Modtran LUT	27
	3.3	Modeling with HYDROLIGHT	29
	3.4	Water Constituents	30
		3.4.1 Suspended Solids	31
		3.4.2 Contribution to total water reflectance (TSS)	33
		3.4.3 Colored Dissolved Organic Material	34
		3.4.4 Chlorophyll	35
		3.4.5 Using OOPS to get HYDROLIGHT input parameters	37
		3.4.6 Hydrolight LUT	39
	3.5	Combining the Models to obtain Sensor-Reaching Radiance	41
4	Арр	roach	43
	4.1	Modeled Radiance	43
	4.2	Study Site and Ground Truth	46
		4.2.1 AVIRIS Dataset	51
		4.2.1.1 AVIRIS Signal-to-Noise Ratio	51
	4.3	Optimizing the Spectral Match	55
		4.3.1 Methods to Implement Optimization	57
		4.3.1.1 Method 1: No constraints	57
		4.3.1.2 Method 2: NIR First	58
		4.3.1.3 Method 3: New Starting Point	58
		4.3.1.4 Method 4: Low Starting Point	58

		4.3.1.5 Method 5: Constraints	59				
5	Res	ults and Discussion	61				
	5.1	Spectral Match	62				
	5.2	Constituent Concentrations	65				
		5.2.1 Atmospheric Output	68				
		5.2.2 Chlorophyll	70				
		5.2.3 Total Suspended Sediment	72				
		5.2.4 Colored Dissolved Organic Material	74				
	5.3	Comparison of Results to Previous Work	77				
6	Sun	nmary and Future Work	81				
	6.1	Future Work	82				
\mathbf{Li}	List of Figures 8						
\mathbf{Li}	st of	Tables	89				
Bi	bliog	graphy	91				
\mathbf{A}	HY	DROLIGHT Input Files	95				
	A.1	Chlorophyll Absorption and Scattering	95				
	A.2	CDOM Absorption	106				
	A.3	Total Suspended Sediment Absorption and Scattering	109				

CONTENTS

Chapter 1

Introduction

The quality of water is an important indicator of the health of the environment and is very important to the quality of human life. We depend upon clean water for drinking, bathing, day-to-day chores, and recreation, as well as for agricultural and industrial uses. Inland and coastal areas are especially important and vulnerable to us in this regard. The needs of a growing population place an ever-increasing demand upon the available freshwater supply. Monitoring is necessary to ensure that contaminants from point sources and excess runoff are detected so that remedial action may be taken to correct potentially harmful situations. Traditionally, water quality analysis has involved direct sampling of the areas in question. On-site monitoring is expensive and time-consuming, so it would be of great utility to develop a remote-sensing based monitoring and evaluation system to track changes in water quality in the coastal and littoral zones that is not dependent on frequent sampling of the study areas. Remote sensing methods can also reach areas that would be difficult to sample using traditional methods and provide greater spatial distribution information than direct sampling.

1.1 Overview

The purpose of this research is to develop and test a physics-based modeling method for extracting water constituent concentrations from hyperspectral imagery without first correcting the imagery atmospherically. This is desirable because current atmospheric correction methods are of questionable accuracy over coastal waters. Instead we will model both the water reflectance and the atmosphere using established radiative transfer models. This is desirable because water quality is of great importance to people throughout the world, particularly in coastal regions where many people live, work, and recreate. In order to accomplish this we have to model the effects of the atmosphere on the sensor reaching signal by characterizing the upwelled radiance (L_u) . Our assumption will be that the water constituents will produce a characteristic reflectance (ρ_w) based on the inherent optical properties of water and the concentration of the individual constituents. These constituents can be divided into three primary groups: colored dissolved organic material (CDOM), chloropyhll (CHL), and total suspended solids (TSS). Look-up tables (LUTs) will be developed combining the reflectance and atmospheric data sets.

Traditionally, retrieval of water constituent information has been conducted in two steps: application of an atmospheric correction algorithm to find the water reflectance, then use of a bio-optical algorithm to extract CHL, CDOM, and TSS concentrations. The first such algorithms were developed for use with open ocean imagery, where concentrations of constituents are typically low.

These algorithms are of limited use in near-shore situations because the assumption that water reflectance drops to zero in the NIR is not true in cases of high sediment concentrations. Since many of these algorithms rely on a band-ratio of pre-corrected reflectance data or a semi-analytic method that takes advantage of this assumed zero reflectance, the correction is not accurate when this is not true.(Gordon and Wang, 1994; Gordon, 1997; Gao et al., 2000)

Also, atmospheric correction using an empirical line method (ELM)(Smith and Milton, 1999) is often not practical. Ground reflectance measurements must be taken at the same time as the acquisition of the imagery, or highly accurate reflectance estimates of in-scene components must be made. These can be difficult or expensive to obtain. If such measurements are available, however, ELM is a very good method of atmospheric compensation.

Previous work in this area used an ELM to invert the sensor radiance to reflectance, then matched scene-derived reflectance spectra to modeled reflectance spectra attained through use of the **HYDROLIGHT** (Mobley and Sundman, 2000) radiative transfer model (Raqueño, 2004). The present research is aimed at reproducing, and/or improving upon, the results of this technique using a different modeling approach.

Whereas the previously mentioned project(Raqueño, 2004) did the spectral matching in reflectance, the aim of this thesis is to test the efficacy of a method of spectral matching in radiance space. Rather than using some form of atmospheric correction on the image data and matching to the resulting reflectance spectra, we will include various atmospheric models in the algorithm and match to the sensor reaching radiance. The attraction of this method is the possibility that we can reduce error in atmospheric correction and develop a more operational solution for the actual water constituent concentrations. This is important because > 95% of the signal in the VIS/NIR over water is due to the atmosphere. Any reduction in error in this region will make a large difference in the accuracy of our concentration estimates.

Unlike other studies, the spectral region of 700 - 950nm is included for the reason that we are assuming the majority of the change in water reflectance in this region is due to changes in the **TSS** concentration. One of the reasons ocean researchers assume negligible reflectance in this region is the low sediment concentrations found in Case I waters. We will demonstrate that the contribution to total ρ_w of CDOM and CHL is negligible in this region. It is part of our hypothesis that including this information will improve the retrieval of concentration values of all of the constituents.

One of the difficulties with this area of research is <u>not</u> that it is impossible to come up with a solution to the model-derived sensor-reaching radiance, but that there may be many solutions for each pixel. This aspect makes it necessary to provide constraints for the algorithm to prevent solutions that may not be physically possible(Defoin-Platel and Chami, 2007). For example, an area with a high **CHL** concentration would not usually have an extremely low sediment concentration.

The constraints are applied in two ways. First, when creating the look-up tables, upper limits approximating the upper limits of the ground truth samples were used. This limits the utility of this method to the data set we have, but other concentration ranges can be added later for a more robust LUT. Second, the interpolation/optimization routine can be told what minimum/maximum values to consider, and also where in the LUT to begin. For example, on a clear day we know that the visibility was greater than 10 km, so the program is set to ignore those values that are lower than that point.

That being said, it is difficult to constrain this process too much because of the nature of the area under study. Coastal regions often include a wide range of constituent values. Deep lake or ocean waters removed from shore usually exhibit low constituent concentrations. Closer to shore, one may encounter concentrations orders of magnitude higher, due to natural or agriculturally induced run-off, or from the turbid discharge from rivers and streams. The data set we are using was taken by the **AVIRIS** (Airborne Visible Infrared

1.1. OVERVIEW

Imaging Spectrometer) sensor (Vane et al., 1993) of the Rochester embayment and includes

the oligotrophic (relatively clear, nutrient-poor) waters of Lake Ontario, turbid discharge from the Genesee river, and the hypereutrophic (low visibility, nutrient-rich) waters of the various ponds and small bays in the area. This relatively wide range of concentrations makes this area a good test-bed for this algorithm, but also limits the constraints that can be applied. I will discuss methods of ensuring optimal matches in upcoming sections.

Chapter 2

Background

In this chapter I will outline the relevant theory behind the various parts of the algorithm we have developed to derive constituent concentration values from hyperspectral imagery. This will include a discussion of the relevant energy paths in radiative transfer theory, atmospheric compensation, a brief overview of scattering and absorption, and a look at some previous work in spectral-matching techniques over water.

2.1 Radiative Transfer

Radiative transfer is defined as the process of transmission of electro-magnetic radiation through a medium. As a beam of energy traverses a medium, it can lose energy through absorption, gain energy through emission, or energy can be re-directed through the process of scattering. In this section I will discuss the effects of the atmosphere and of water on the sensor-reaching signal.



Figure 2.1: Solar and self-emitted energy paths (labeled so as to be consistent with Schott (1997))

2.1.1 Radiance Reaching the Sensor

For passive remote sensing, where the sensor depends on naturally occurring radiation, we can divide the energy paths into two groups, those originating from solar radiation, and those resulting from the temperature of objects (self-emitted radiation). These paths are shown in Figure 2.1. Each of these paths can contribute some part of the total radiance $L(\lambda)$ reaching a sensor.

Irradiance is the rate at which the radiant flux is delivered to a surface; the surface in

2.1. RADIATIVE TRANSFER

question in this case being the outer limits of the atmosphere. Exoatmospheric irradiance $E'_{s\lambda}$ is the portion of the sun's radiance that reaches the Earth's outer atmosphere at each wavelength. Figure 2.2 illustrates the effect of even a fairly clear atmosphere on the



Figure 2.2: Example of irradiance spectra before and after being attenuated by a fairly clear atmosphere. (MODTRAN output)

irradiance reaching the ground between $.4\mu m$ and $2.5\mu m$.

2.1.1.1 Energy Paths

The energy paths that account for the solar portion of the total radiance reaching the sensor at each wavelength are represented by paths $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{G}$ from Figure 2.1. Path \mathbf{A} represents the photons from the sun that pass through the atmosphere, reflect off the target, and pass through the atmosphere again to reach the sensor. Path \mathbf{B} is the solar downwelled portion of the energy paths, sometimes referred to as skylight. This path represents photons that were scattered by the atmosphere before being reflected off of the target to the sensor. Path \mathbf{C} shows light that is scattered by the atmosphere into the

sensor without ever encountering the target. These upwelled photons increase the signal at the sensor without imparting any information about the surface of interest. Photons reflected off background objects (e.g. buildings), reflected further by the target surface and finally reaching the sensor are represented by path **G**. Significant background objects must be characterized for their contribution to total radiance. A shape factor, F, is included to represent the fraction of the sky that is open, while 1 - F represents the portion that is obscured by the background. We can also simplify matters by making an assumption that the target surface is approximately Lambertian (radiating equally in all directions). For nadir viewing over water, this is a fairly valid assumption. Thus, the total radiance reaching the sensor due to solar terms is:

$$L_{s\lambda} = L_A + L_B + L_G + L_C$$

or

$$L_{s\lambda} = \left\{ E_{s\lambda}' \cos \sigma' \tau_1(\lambda) \frac{r(\lambda)}{\pi} + F\left[E_{ds\lambda}\right] \frac{r(\lambda)}{\pi} + (1 - F)\left[L_{bs\lambda}\right] r(\lambda) \right\} \tau_2(\lambda) + L_{us\lambda} \quad (2.1)$$

Thermal effects can also contribute to the total radiance reaching a sensor. Objects with a temperature above absolute zero radiate energy in the form of self-emitted photons. Generally, the higher the temperature and the higher the emissivity of the object, the greater the number of photons emitted. In the area of the visible spectrum 400 - 700nm, the vast majority of the photons detected are of solar origin. At longer wavelengths (near 10 microns) the effect of the sun is negligible, and these self-emitted photons become very important in gaining information about targets. Paths **D**,**E**,**F**,**H** from Figure 2.1 illustrate these self-emitted sources. Path **D** shows photons self-emitted from a target that reach the sensor. These photons can be used to determine thermal property information about

2.1. RADIATIVE TRANSFER

the target. Path \mathbf{E} shows atmospherically generated photons that reflect from the target toward the sensor. Path \mathbf{F} also depicts atmospherically generated photons that radiate directly to the sensor. Path \mathbf{H} shows the line taken by photons thermally generated by a background object and reflected from the target to the sensor. The total radiance reaching the sensor due to self-emitted terms is:

$$L_{\varepsilon\lambda} = L_D + L_E + L_F + L_H$$

or

$$L_{\varepsilon\lambda} = \left\{ \varepsilon(\lambda) L_{T\lambda} + F[E_{d\varepsilon\lambda}] \frac{r(\lambda)}{\pi} + (1-F) [L_{b\varepsilon\lambda}] \frac{r(\lambda)}{\pi} \right\} \tau_2(\lambda) + L_{u\varepsilon\lambda}$$
(2.2)

Taken together, the total radiance reaching the sensor from all paths is:

$$L_{\lambda} = L_A + L_D + L_B + L_E + L_G + L_H + L_C + L_F$$

$$or$$

$$L_{\lambda} = \left\{ E_{s\lambda}' \cos \sigma' \tau_{1}(\lambda) \frac{r(\lambda)}{\pi} + \varepsilon(\lambda) L_{T\lambda} + F \left[E_{ds\lambda} + E_{d\varepsilon\lambda} \right] \frac{r(\lambda)}{\pi} + (1 - F) \left[L_{bs\lambda} + L_{b\varepsilon\lambda} \right] r(\lambda) \right\} \tau_{2}(\lambda) + L_{us\lambda} + L_{u\varepsilon\lambda}$$

$$(2.3)$$

In Equations 2.1, 2.2, and 2.3,

- L_{λ} total sensor-reaching radiance at a given wavelength
- $E_{s\lambda}^{\prime}$ exoat mospheric spectral irradiance
- $\sigma^{'}$ solar zenith angle from the normal to the target
- $\tau_1(\lambda)$ atmospheric transmission along the sun-target path
- $r(\lambda)$ total spectral reflectance of the target

- $\epsilon(\lambda)$ spectral emissivity of the target
- $L_T \lambda$ Planck radiance for a blackbody of temperature T at wavelength λ
- $E_{ds\lambda}$ solar downwelled irradiance (skylight)
- $E_{d\varepsilon\lambda}$ self-emitted downwelled irradiance (skylight)
- F shape factor for the obscuration of the target by background
- $L_{bs\lambda}$ reflected solar radiance for the background
- $L_{b\varepsilon\lambda}$ self-emitted radiance for the background
- $\tau_2(\lambda)$ atmospheric transmission along the target-sensor path
- $L_{u\lambda}$ upwelled or path radiance

The radiance due to thermal effects is a negligible part of the total radiance for the region of the electromagnetic spectrum we are studying, so the self-emitted terms can be eliminated from consideration in this case. In addition, areas such as open water have a shape factor of one, removing the (1 - F) terms and further reducing the equation to

$$L_{\lambda} = \left\{ E_{s\lambda}^{\prime} \cos \sigma^{\prime} \tau_{1}(\lambda) \frac{r(\lambda)}{\pi} + E_{ds\lambda} \frac{r(\lambda)}{\pi} \right\} \tau_{2}(\lambda) + L_{us\lambda}$$
(2.4)

2.1.2 Transmission

We are concerned with two different atmospheric transmissions. The first is the transmission along the sun-target path τ_1 , which can be defined as:

$$\tau_1(\lambda) = e^{-\delta_1(\lambda)} \approx e^{-\delta(\lambda) \sec \sigma}$$
(2.5)

where $\delta_1(\lambda)$ is defined to be the optical depth along the sun-target path, $\delta(\lambda)$ is the optical depth vertically through the atmosphere and σ is the solar zenith angle. Figure 2.3 illustrates how this calculation is implemented practically for an assumed stratified atmosphere.



Figure 2.3: Graphic showing the calculations for transmission in a stratified atmosphere. Each layer j is assumed to be homogeneous for each constituent i. The absorption cross section $C_{\alpha ij}$ and number density m_{ij} are considered to be constant for each path length z_j .

The second transmission loss we are concerned with is that from the target to the sensor

 τ_2 , which can be defined in similar terms:

$$\tau_2(\lambda) \approx e^{-\delta'(\lambda)\sec\theta}$$
 (2.6)

where δ' is the optical depth vertically from the target to the sensor altitude and θ is the view angle. The transmission terms τ_1 and τ_2 are modeled for this study using the **MODTRAN** radiative transfer program (Berk et al., 1989), as discussed more fully in Section 3.2.1.

2.1.2.1 Absorption and Scattering in Water

The radiance reaching the sensor from the water comes from two main sources: that which is reflected at the water surface; and that which is scattered back by the water molecules and matter suspended in the water. The only part that is of interest to us is the backscattered part, because the reflected part would have the same spectral composition as the light hitting the surface. Only the light that has gone into the water and been scattered back to our sensor has information about water constituents Cracknell (1981). The concept of spectral absorption, scattering, and transmission are illustrated in Figure 2.4. For an incident radiant flux, or power, $\Phi_i(\lambda)$, some part of it is absorbed, transmitted, and scattered by a given volume of water ΔV through length Δr . $\Phi_a(\lambda)$ is the portion absorbed, $\Phi_t(\lambda)$ is the portion transmitted with no directional change, and $\Phi_s(\lambda)$ is the portion scattered out of the water at an angle Ψ into solid angle $\Delta \Omega$ (Mobley, 1994). <u>Inherent</u> optical properties (IOP's) are properties that depend solely upon the medium through which the light is traveling. Inherent optical properties include the absorption coefficient, the scattering coefficient, the volume scattering function β , the index of refraction n, and the beam



Figure 2.4: Diagram of extinction components for an absorbing and scattering volume.(Mobley, 1994)

attenuation coefficient. This can be summed up in the equation:

$$c_{\lambda} = a_{\lambda} + b_{\lambda} \qquad [m^{-1}] \qquad (2.7)$$

where c_{λ} is the total beam attenuation coefficient, a_{λ} is the absorption coefficient, and b_{λ} is the total scattering coefficient. The total scattering coefficient b_{λ} is calculated by integrating the volume scattering function over all angles. The backscattering coefficient $b_{b(\lambda)}$ is similarly derived by integrating over the angles from 90° to 180°. <u>Apparent</u> optical properties depend both on the inherent optical properties and the light field in which they are measured. We are going to treat the water as an equivalent lambertian surface and derive an apparent reflectance using **HYDROLIGHT** (Mobley and Sundman, 2000) that we can then use to model a sensor-reaching radiance, when combined with radiance values

for each **MODTRAN**-derived atmosphere (Berk et al., 1999).

2.2 Atmospheric Compensation

2.2.1 In a Perfect World

In remote sensing we always hope that the signal from the target can be completely separated from the signal due to the intervening atmosphere. The atmospheric signal (path radiance) has no target information in it. Ideally, an atmospheric correction method would give us perfectly calibrated sensor radiance or target reflectance. If this is possible, then the resulting spectra can be used to characterize the target and give us specific information about it.

2.2.2 Techniques For Atmospheric Compensation

There are a variety of methods available to calculate the path radiance within a remotely sensed scene and minimize the effect of the atmosphere on visible and near infrared imagery. It is assumed when correcting high resolution scanner data that, due to the small field of view of the sensor, the atmospheric conditions within each scene are constant. As a result, the correction factor is a constant for each band of the dataset, although it may need to be adjusted for view angle due to lens falloff and other effects. Some of the most common methods to calculate the path radiance are: atmospheric measurements and modeling with sensor calibration, dark pixel subtraction, and spectral ratio techniques.

Atmospheric measurements and modeling involves the theoretical determination of the path radiance contribution of the atmosphere for the particular time of the overflight. Calculation of the contribution of the scattering to the reflected radiance requires that many atmospheric variables at the time of the overflight be recorded and put into theoretically derived equations to determine the effect of the atmosphere on each spectral band. Two such atmospheric modeling utilities are **MODTRAN** (Berk et al., 1989) and **6S** (E. et al., 1997). User-supplied radiosonde data may be used as input to **MODTRAN**, but the nearest regularly taken radiosonde to Rochester is at the Buffalo, NY airport, and its applicability 100 kilometers away is questionable.

Dark pixel subtraction is a technique which determines the pixel in the image with the lowest brightness value. This pixel is assumed to have near zero reflectance and therefore represents the upwelled radiance spectra for the scene. This method works well in scenes where there are pixels with deep, clear water, which have a very low reflectance in the near infrared. It is less accurate when the lowest scene reflectivity is elevated by even a few percent (Schott, 1997). This is similar to the technique used in **TAFKAA** (Gao et al., 2000), where the reflectance of water is assumed to go to zero at 865*nm*.

Spectral ratio techniques consist of a comparison of at least two known reflectance values with sensor recorded radiance values. Once the actual response and the recorded response values have been determined, linear regression can be used to determine the atmospheric effects for the overall image (Schott, 1997).

For scenes with sharp shadow lines, upwelled radiance can be solved for using the Piech and Walker sun-shadow method (Piech and Walker, 1974). This might be useful for near-shore imagery near large objects that can cast pixel-sized shadows.

None of these methods is fool-proof, and all are problematic when used over water, especially coastal and inland waters, where the assumption of zero reflectance in the NIR can invalidate the process. Which is why, in this research, we are going to omit this step and attempt to model the atmospheric effects directly.

2.3 Remote Sensing Platforms

Remote sensing platforms can vary considerably depending on their intended use. Those utilizing single-band, or pan imagery, depend on the total integrated radiance hitting a pixel. Corresponding gray tones are assigned based on the relative responses of the pixels in the array. These sensors have good spatial resolution due to the small pixel size possible for the individual element of the array. Multi-spectral sensors use filters or separate elements to capture data at specific wavelengths of the electro-magnetic spectrum. The bands are not contiguous in multispectral imagery, however, and cannot be used to define a spectral signature. Imaging Spectroscopy is the acquisition of images where for each spatial resolution element in the image a spectrum of the energy arriving at the sensor is measured. Hyperspectral imaging sensors use a diffraction grating to split the signal into separate , yet contiguous, wavebands. These are useful to explore the theory that materials can be identified by their unique spectral reflectance signature. These spectra are used to derive information based on the interaction of matter and energy expressed in the spectrum.

2.3.1 AVIRIS

The main data set under consideration in this study is AVIRIS imagery acquired on May 20, 1999. The overflight was at approximately 11:20 AM EDT. Ground truth collections were undertaken for the areas under the acquisition. Water samples were taken for many of the ponds and bays in the area, as well as for the Genesee River and the river plume extending into Lake Ontario. A brief description of AVIRIS follows.

AVIRIS is an acronym for NASA's Airborne Visible InfraRed Imaging Spectrometer. The main objective of the **AVIRIS** project is to identify, measure, and monitor constituents of the Earth's surface and atmosphere based on molecular absorption and particle scattering signatures. It is an optical sensor that delivers calibrated images of radiance in 224 contiguous spectral bands with wavelengths from 400 to 2500 nanometers [nm]. Each band is nominally on 10nm centers(Vane et al., 1993). A drawing of the sensor apparatus is shown in Figure 2.5 and the focal plane detectors setup is shown in Figure 2.6.

Use of this sensor for a collection over water offers a slight, yet important, inversion of usual practice for image acquisition. Usual practice is to acquire images with a high sunangle, in order to maximize the reflected signal reaching the sensor elements. A high sun angle increases the probability of solar glint in collections over water. This is undesirable because a pixel contaminated with solar glint has little information from the photons that have interacted with the water volume. We will have to choose the areas of study carefully to minimize this effect in our study. This will be discussed further in Section 4.2.1.



Figure 2.5: Drawing of AVIRIS Spectrometer(Vane et al., 1993)



Figure 2.6: Drawing of AVIRIS focal plane detectors showing spectral coverage from 400-2500 [nm](Vane et al., 1993)

2.4 Spectral Matching

With the advent of hyperspectral imagers, different methods of processing are available to researchers. Rather than comparing relative values from isolated bands, as is done with multi-spectral imagery, we can compare the overall shape of the spectral curves over a continuous range to achieve a better result.

2.4.1 Previous Work In This Area

A proof-of-concept study of spectral matching was carried out on a 2001 Hyperion data set of the western part of the Singapore Strait. Liew and Kwoh (Liew and Kwoh, 2003) used a 6S atmospheric model and the three-component water reflectance model (Sathyendranath et al., 1989) to create a LUT to match to the data set using an iterative chi-squared minimization. 6S (Second Simulation of the Satellite Signal in the Solar Spectrum) was developed by the Laboratoire d'Optique Atmospherique. The code permits calculations of near-nadir (down-looking) aircraft observations, non-lambertian surface conditions, absorbing gases, Rayleigh scattering, and aerosol scattering effects. The spectral resolution is 2.5 nm. The wavelength range of Liew and Kwoh's study was 450-700nm. The LUT was generated out to 905nm, but the wavelengths above 700 were not included in the minimization due to concerns about atmospheric absorption in the **NIR**. Comparison of results with SeaWiFS OC2 chlorophyll algorithm showed promise of better results with spectral matching methods than with traditional band ratio methods, especially in coastal waters.

A spectral matching technique was developed for extracting bottom classification and bathymetry information from hyperspectral imagery. Mobley, et al (Mobley et al., 2005) used a LUT and PHILLS (Ocean Portable Hyperspectral Imager for Low-light Spectroscopy) data to investigate shallow waters around Lee Stocking Island, Bahamas. They used EcoLUT (a trimmed-down version of Hydrolight used to speed processing) to model reflectances for various depths and bottom types and were able to get fairly consistent results. Retrieved bottom depths were within 5% and 0.5m of independently obtained depth measurements. The water they were dealing with was very clear, having CHL concentrations in the $0.1 \rightarrow 0.2mg/m^3$ range, with low concentrations of sediments and CDOM also. No attempt was made to extract concentration information in this study. The matching was done in the visible region (400-750nm). Mobley used **TAFKAA** (Gao et al., 2000) to do the atmospheric correction. In addition, a correction was performed on the PHILLS data in the form of an offset and gain adjustment, bringing the minimum spectrum down to zero beyond 650n. The stated reason for this was to correct for a systemic data problem that gave too high values in the red.(Mobley et al., 2005)

A similar technique utilizing an iterative spectral optimization algorithm (SOA) and coupled aerosol-water models was implemented using SeaWiFS (Sea-viewing Wide Field of view Sensor) data of the Middle Atlantic Bight (Chomko et al., 2003). This was a Case I water study, with very low constituent concentrations, and an assumption of negligible water reflectance at the SeaWiFS 765 and 865*nm* bands was made. For the low CHL, CDOM, and TSS concentrations of this area, this was a fairly valid assumption for ocean reflectance models. Difficulties were experienced due to problems with the algorithm getting "stuck" near its starting point for areas with suspected high CDOM concentrations, and also in the presence of absorbing aerosols. The authors state that the difficulty in extending this (SOA) technique to Case II (coastal and inland) waters is the elevated water reflectance in the NIR. They suggest possibly tuning the bio-optical models used for the particular body of water of interest.

Empirical methods for extracting information from remotely-acquired data are many

and varied. Most of them have been developed for use with open ocean data, for the problem of atmospherically correcting the data is more tractable there. Decoupling the oceanic and atmospheric optical signals using band-ratio information for SeaWiFS data is discussed in (Gordon and Wang, 1994). Good results are obtained for data sets of the Mid-Atlantic Bight, but it is stated that the algorithm breaks down in coastal and inland waters (Gordon, 1997).

2.4.2 Extending Spectral Matching Techniques

This effort to extract constituent concentrations using spectral matching techniques uses similar methods to those just mentioned, but with the addition of extending the matching to the **NIR** in order to improve accuracy in retrieved **CHL** and **TSS** concentration values.

Our current work is an extrapolation of the work done by Raqueño in (Raqueño, 2004) (Raqueño et al., 2000) with a few key changes and adjustments. Performing the matching in radiance space eliminates the need for atmospheric correction, while extending the wavelengths considered out to the **NIR** will achieve improved sediment retrieval. While this necessitates atmospheric modeling, it is hoped that this method will give comparable, if not improved results when compared to the earlier efforts. This will enable more easily realized constituent concentration studies to be conducted in near-shore areas where traditional ocean water algorithms are of limited use.
Chapter 3

Modeling

3.1 Why Model?

As outlined in the previous chapter, atmospheric correction is difficult in coastal areas. For this reason, this research will focus on modeling the atmospheric effects using MODTRAN to eliminate the need for this correction. In cases where the total radiance or reflectance is difficult or impossible to separate into its component parts we must often use a different approach to get the answers we need.

For the case in question, we have $L_{tot} = L_w + L_u$, where L_{tot} is the total radiance reaching the sensor, L_w is the water-leaving radiance, which is made up of the directly reflected solar irradiance and the reflected downwelled or sky radiance, and L_u is the upwelled radiance due to atmospheric scattering. Figure 3.1 shows the components of the sensor-reaching radiance. If we cannot properly account for the atmosphere or the reflectance of the water, we are stuck. However, a properly modeled atmosphere, when combined with a properly modeled water reflectance will result in the observed sensorreaching radiance. Paths **A**, the reflected solar component, and **B**, the reflected skylight



Figure 3.1: Graphic showing components of sensor-reaching radiance.

component, can also contain solar and sky glint, respectively. This will necessitate either the use of a glint removal process or careful selection of the study site to avoid areas of solar glint. Traditional atmospheric compensation algorithms treat sky glint as insignificant to total sensor-reaching radiance (Gordon and Wang, 1994). Therefore, the contribution of sky glint to the total sensor-reaching signal will be treated as negligible in this study.

3.2 Modeling with MODTRAN

The Space Vehicles Directorate of the Air Force Research Lab describes **MODTRAN** as:

The Moderate Resolution Transmittance (MODTRAN) Code calculates atmospheric transmittance and radiance for frequencies from 0 to 50,000 cm-1 at moderate spectral resolution, primarily 2 cm-1 (20 cm-1 in the UV). The

3.2. MODELING WITH MODTRAN

original development of MODTRAN was driven by a need for higher spectral resolution and greater accuracy than that provided by the LOWTRAN series of band model algorithms. Except for its molecular band model parameterization, MODTRAN adopts all the LOWTRAN 7 capabilities, including spherical refractive geometry, solar and lunar source functions, and scattering (Rayleigh, Mie, single and multiple), and default profiles (gases, aerosols, clouds, fogs, and rain). (Description taken from MODTRAN 4 Software Factsheet found at: http://www.kirtland.af.mil/library/factsheets/factsheet.asp?id=7915)

MODTRAN has been extensively verified and validated. In a comparison of radiance codes for climate modeling, MODTRAN was compared with three independent interferometer measurements of up-looking radiance and the overall agreement was excellent. MODTRAN UV radiance calculations were also compared with balloon measurements of transmitted solar energy to 40 km altitude. Comparisons of MODTRAN and integrating sphere data for visible and near-IR integrated solar radiation have also been conducted. Detailed validation of the MODTRAN code has also been performed recently using hyperspectral data from AVIRIS.(http://www.vs.afrl.af.mil/ProductLines/IR-Clutter/modtran4.aspx)

3.2.1 Modtran LUT

As a proof-of-concept, we will be using supplied default atmospheric aerosol models from MODTRAN to create our atmospheric look-up table, varying the aerosol type (urban, rural, maritime) and concentration through manipulation of the *VIS* parameter. More extensive modeling choices or user-supplied radiosonde data will probably be necessary in the future to make this a more accurate method. Since we are working with imagery from May of 1999, we will be using midlatitude summer as the seasonal setting.(Berk et al., 1999)

Table 3.1 shows the range of the parameters that will be changed for each MODTRAN run, the visibility (VIS) being changed by 1km for settings under 25km, and in 5km increments for settings from 25 - 70km. We also supply the time of day, day of year, latitude and longitude of the target area, ground altitude, and altitude of the sensor.

Aerosol	Visiblity(km)
urban	$1 \rightarrow 70$
rural	$1 \rightarrow 70$
maritime	$1 \rightarrow 70$

Table 3.1: Parameters for adjusting MODTRAN runs

MODTRAN is run twice for each setting. Once at 100% target reflectance to get downwelled and directly reflected solar terms to use with the modeled reflectance, and once at 0% to get an upwelled radiance unchanged by reflected adjacency effects. This yields an atmospheric LUT of 102 members. The resulting radiance curves are re-sampled to AVIRIS bandcenters in preparation for further processing.

Since MODTRAN does not output a downwelled term directly, it must be derived by taking the difference between the **GRND RFLT** and **DRCT RFLT** terms, which are, respectively, the total ground reflected radiance (sun and sky) and the directly reflected radiance (sun). It was originally thought that this would yield an accurate downwelled value when run at 100% target reflectance, for all of the downwelled would be in that term. But it was realized after the completion of these modeling runs that adjacency effects, or "trapping" are included in the **GRND RFLT** term and could cause the resulting difference term to be slightly too large, especially when run with multiple scattering. Also, the upwelled radiance obtained from the 0% MODTRAN run may result in a slightly lower than optimal estimate of this factor. Future water studies utilizing this technique may

find it better to run MODTRAN at a nominal reflectance curve simulating water target reflectance at each wavelength in order to minimize errors from this area.

Now that we have an atmospheric model we need to be able to estimate what is happening in the water to obtain a sensor-reaching radiance to use in our model.

3.3 Modeling with HYDROLIGHT

Hydrolight is a radiative transfer code designed to solve for the radiance distributions and derived quantities for natural water bodies.(Mobley and Sundman, 2000) We input the inherent optical properties (IOPs) of the water volume under study, including various water constituents, and get out spectral reflectance to combine with our atmospheric radiance spectra. Hydrolight also takes into account wind effects on the water surface, incorporating the Cox-Munk capillary wave slope statistics as described in (Mobley, 1994) to describe the surface reflection and transmission. This attenuates the amount of downwelling irradiance $E_d(\lambda)$ going into the water volume so that an accurate calculation can be made of the remote-sensing reflectance. This will enable us to model L_w , incorporating both volume reflectance and the averaged Fresnel reflectance from the water surface(Mobley, 1994). Mobley defines the remote sensing reflectance as:

$$R_{rs}(\theta,\phi;\lambda) \equiv \frac{L(z=a;\theta,\phi;\lambda)}{E_d(z=a;\lambda)} [sr^{-1}]$$
(3.1)

This is evaluated just above the air-water interface, as indicated by the depth z = a; E_d is the downwelled irradiance, and L is the water-leaving radiance. These are spectrally dependent quantities, as indicated by λ . In order to simulate a lambertian surface, we will multiply this by $\pi[sr]$, making a unitless apparent reflectance factor.

3.4 Water Constituents

The color of water is influenced by many factors. Water depth, chlorophyll concentration, sediments, and dissolved materials can all have an effect on the appearance of water. A classification scheme has been accepted by the ocean study community that divides water into Case I or Case II(Morel and Prieur, 1977). Case I waters are those in which phytoplankton and related material are the major contributors to optical variations in the water-leaving signal. Case II waters are influenced not only by phytoplankton, but also by other substances that vary independently of chlorophyll. While Case I makes up most of the world's water, coastal and inland waters are much more often Case II. Case II waters are optically much more complex, in that many different constituents can contribute to changes in the reflectance. Three main groupings will be discussed in the next sections. The methods developed for deriving the properties of open ocean waters cannot be used for these more complex cases, so new algorithms must be developed.(Sathyendranath, 2000)



Figure 3.2: Graph showing the spectral absorption coefficients for water constituents in Lake Ontario (Bukata et al., 1995) Dissolved organic carbon is yet another term for CDOM.

3.4.1 Suspended Solids

Suspended solids are of importance in the remote sensing of water because of the alteration of the signal due to increased scattering, especially in the NIR. Whereas deep ocean waters appear blue due to scattering in the 400-500nm region and strong absorption in the red (> 650nm), waters with high sediment loads can appear brownish-red due to an increased scattering in the red. This increased scattering continues into the near-infrared.

Suspended solids can include both organic and inorganic particles. Decaying plant and



Figure 3.3: Graph showing the spectral scattering coefficients for water constituents in Lake Ontario (Bukata et al., 1995) Dissolved organic carbon is not included for this because CDOM does not have appreciable scattering effects.

animal material as well as solids carried into the water body by run-off contribute to the total. Of interest to us is the particle size distribution in the water volume. Rather than using the Junge size distribution, which is commonly used by open ocean models, we will be using a log-normal size distribution, which has been found to better simulate natural conditions in near-shore regions. This is because terrestrial sediments approach log-normal in their size distribution and these, presumably, are what we will find in coastal areas and lakes due to runoff and natural eutrophication processes. A sediment sampling from

3.4. WATER CONSTITUENTS

Conesus Lake, near Rochester, New York, shows the validity of this assumption. This is illustrated in Figure 3.4. The samples were taken and analyzed by the Upstate Freshwater Institute and matched to a log-normal size distribution equation from the Ocean Optics Plankton Simulator (Kim, 2000) by Jason Hamel of RIT.



Figure 3.4: Plot of distribution of sampled sediments from Conesus Lake showing agreement with log-normal size distribution

3.4.2 Contribution to total water reflectance (TSS)

We are operating under the assumption that TSS is the major contributor to water reflectance in the NIR. This assumption is supported by the data reported by Bukata et al. (1995). This data is extrapolated to the NIR and used as inputs for the modeling of the spectral reflectance curves along with some adjustments made to account for local variation based on empirical data (see Section 3.4.5). A result of modeling runs done with **Hydrolight** (Mobley and Sundman, 2000) shows that increasing the TSS concentration causes an increased reflectance in the NIR (above 700nm.) When taken alongside the well-defined differences in the visible range (400 – 700nm), this gives us reason to hope we can discern these differences in the collected sensor data. Figure 3.5 illustrates this concept very well.



Figure 3.5: Graph showing water reflectance value due to TSS only. Wavelength is in nanometers (HYDROLIGHT output)

3.4.3 Colored Dissolved Organic Material

Colored dissolved organic matter (CDOM) is the optically measurable component of the dissolved organic matter in water. Also known as Chromaphoric Dissolved Organic Carbon, gelbstoff, yellow substance, humic matter. CDOM occurs naturally in aquatic environments primarily as a result of tannins released from decaying matter such as leaves (Sathyendranath, 2000). CDOM most strongly absorbs short wavelength light ranging from blue to ultraviolet, whereas pure water absorbs longer wavelength red light. Therefore, deep ocean water with little or no CDOM appears blue. The color of water will range through

green, yellow-green, and brown as CDOM increases. CDOM and chlorophyll both absorb in the same spectral range so it is difficult to differentiate between the two. Although



Figure 3.6: Graph showing water reflectance value due to CDOM only. Wavelength is in nanometers (HYDROLIGHT output)

variations in CDOM are primarily the result of natural processes, human activities such as agriculture, logging, effluent discharge, and wetland drainage can affect CDOM levels in fresh water and coastal regions. Figure 3.6 shows the effect on reflectance of adding various amounts of CDOM to pure water. For very high concentrations (such as $14.0m^{-1}$) it is easy to see that the absorption of light is almost total.

3.4.4 Chlorophyll

Chlorophyll presents us with a problem in that it exists both as a "free" constituent and as part of phytoplankton. In the free form (from the natural breakdown of organisms) it exhibits one set of scattering and absorption coefficients, while chlorophyll within living or whole organisms will exhibit different properties due to scattering effects from the internal and external structures of that specific organism. There are also interspecies differences to consider, as have been explored in (Kim, 2000). Figure 3.7 shows the results of **Hydrolight** simulations done with a scattering contribution in the NIR. In an effort



Figure 3.7: Graph showing the reflectance value due to chlorophyll only with scattering in NIR. Black line is spectra for pure water. Wavelength is in nanometers (HYDROLIGHT output)

to mitigate this effect, we will be using a scattering coefficient for chlorophyll (see Figure 3.8) that decreases exponentially in the NIR. This replaces the earlier curve which did a straight-line extrapolation from the last known data point. While we know that this is not exactly correct, we believe it is a workable approximation and a better representation of chlorophyll scattering than a straight line. This will probably result in slightly higher predicted TSS values for pixels with elevated NIR reflectance due to chlorophyll-containing phytoplankton being "classified" as suspended sediment.



Figure 3.8: Graph showing scattering coefficients of chlorophyll with exponential decay to zero vs. linear extrapolation

The result is that, while we can assume that the contribution to total reflectance from pure chlorophyll in the NIR is negligible, there is phytoplankton scattering that <u>will</u> contribute to the signal in the NIR that is linked to chlorophyll.

If we compare the resulting reflectance curves from the two sets of scattering coefficients (Fig. 3.7 vs. Fig. 3.9), we can see that the ρ_w values for the exponentially decayed case are insignificant in the NIR. This will result in most of the modeled reflectance in that region coming from the TSS concentration.

3.4.5 Using OOPS to get HYDROLIGHT input parameters

We will be using the Ocean Optics Plankton Simulator (**OOPS**)(Kim, 2000) to produce the absorption/scattering coefficients and the scattering phase functions of suspended solids needed for the **HYDROLIGHT** modeling runs. Coefficients for **CHL** and **CDOM** were



Figure 3.9: Graph showing the reflectance value due to chlorophyll with decreased scattering in NIR. Wavelength is in nanometers. (HYDROLIGHT output)

generated by taking the average values of the samples gathered in the ground truth collection and scaling them to represent differing concentrations. This was seen as being more representative of the conditions than using coefficients found in literature for biota and dissolved organic material that may not even be present in this body of water. **OOPS** is a visual, interactive tool to facilitate the investigation of the effect of changes in IOP's and their vertical distribution in the water column on the water-leaving radiance. Inputs to **OOPS** include the complex refractive index for the material in question, along with a size distribution function specifying maximum, minimum, mean, and standard deviation. Calcite has been chosen for this study as a representative mineral type. Output will be the absorption/scattering coefficients and the phase function for the wavelength range specified. Usual practice is to use the phase function at 550*nm* as a default setting.

3.4.6 Hydrolight LUT

To create the **LUT** of reflectance spectra, we take the sediment IOP's as modeled with **OOPS** and load them into **HYDROLIGHT** along with a concentration value. Absorption and scattering spectra are combined with constituent concentrations to produce scaled spectral absorption and scattering coefficients as illustrated in equations 3.2 and 3.3, respectively. The Fournier-Forand (F-F) function was used for mathematical estimations of the scattering phase function, with a back-scattering of 2.5 % rather than the HYDRO-LIGHT default of 1.8 %. This is the same back-scattering model used in (Raqueño, 2004), for the reason that the results were more easily reconciled with measured backscatter values in the turbid waters of the study area.

$$a(\lambda) = a_{water}(\lambda) + [CHL_{conc}]a_{chl}(\lambda) + [TSS_{conc}]a_{tss}(\lambda) + [CDOM_{conc}]a_{cdom}(\lambda)[m^{-1}]$$
(3.2)

$$b(\lambda) = b_{water}(\lambda) + [CHL_{conc}]b_{chl}(\lambda) + [TSS_{conc}]b_{tss}(\lambda)[m^{-1}]$$
(3.3)

where,

$a(\lambda)$	total spectral absorption coefficient
$a_{water}(\lambda)$	spectral absorption cross-section of pure water
$a_{chl}(\lambda)$	spectral absorption cross-section of CHL
$a_{tss}(\lambda)$	spectral absorption cross-section of TSS
$a_{cdom}(\lambda)$	spectral absorption cross-section of CDOM
$b(\lambda)$	total spectral scattering coefficient
$b_{water}(\lambda)$	spectral scattering cross-section of water
$b_{chl}(\lambda)$	spectral scattering cross-section of CHL
$b_{tss}(\lambda)$	spectral scattering cross-section of TSS

CHL_{conc}	constituent concentration
TSS_{conc}	constituent concentration
$CDOM_{conc}$	constituent concentration

These equations, combined, give us the total spectral beam attenuation $c(\lambda)$.

$$c(\lambda) = a(\lambda) + b(\lambda) \tag{3.4}$$

Note that **CDOM** is not included in the scattering equation (3.3) because it is assumed to have only absorption properties, with no significant scattering characteristics. Files of the absorption and scattering coefficients used in this research suitable for use with HYDROLIGHT will be included in an accompanying CD with this document.

We will be varying the concentrations of **CHL** and **CDOM** based on values obtained from the May 20, 1999 data collect. Ten values for each constituent will be included, covering the range of concentrations observed during the collect. The look-up table will be more heavily populated with lower concentrations, because greater differences in reflectance are generated by small increases in constituent concentrations at the lower end of the concentration scale than by small increases at higher concentrations. The final **LUT** will have 1000 reflectance curves. The concentration values used are distributed as shown in Table 3.3. The reflectance curves generated are re-sampled to match AVIRIS bandcenters.

$CHL(mg/m^3)$	TSS (g/m^3)	CDOM (m^{-1})
0.0	0.0	0.0
0.5	0.5	0.5
1.0	1.0	0.75
3.0	2.0	1.0
5.0	4.0	2.0
7.0	8.0	4.0
12.0	10.0	7.0
24.0	14.0	10.0
48.0	20.0	12.0
68.0	24.0	14.0

Table 3.3: Concentration Values used in HYDROLIGHT

3.5 Combining the Models to obtain Sensor-Reaching Radiance

As a proof of concept, a constituent concentration matching that of sampled data was run through **Hydrolight** and combined with modeled atmospheric radiance and transmission from **MODTRAN** to simulate a sensor-reaching radiance. The results of this are shown in Figure 3.10, plotted against a pixel from the same area as the ground truth collection from the AVIRIS overflight. Even with this rough approximation, we can see that the pixel spectral radiance is bracketed by the modeled data. This test run is important because it shows that our modeling technique is able to contain the test data. Optimization should now be able to zero in on a best match for the AVIRIS data. As can be seen in the graph (Figure 3.10), AVIRIS sensor response is low below 420nm. For this reason the matching algorithm will be restricted to the region between 420 and 950nm.

This section has laid out the basics of the modeling techniques that will be used in the spectral matching algorithm. The next section will offer refinements in the implementation and discuss the areas to be included in the study.



Figure 3.10: Sample of modeled radiances compared to **AVIRIS** radiance

Chapter 4

Approach

This technique combines a model of the atmosphere with a model of the water reflectance to simulate a sensor-reaching radiance. This simulated radiance is then matched to an actual sensor radiance and an error metric is calculated. Matching many simulated radiances in an iterative comparison allows us to find the combination of atmosphere and water reflectance that best matches the sensor radiance.

4.1 Modeled Radiance

The modeled radiance at each wavelength is described by the following:

$$L_{\lambda} = \left\{ E_{s\lambda}^{\prime} \cos \sigma^{\prime} \tau_{1}(\lambda) \frac{r(\lambda)}{\pi} + E_{ds\lambda} \frac{r(\lambda)}{\pi} \right\} \tau_{2}(\lambda) + L_{us\lambda}$$
(4.1)

as outlined in Section 2.1.1.1. Water reflectance $r(\lambda)$ is modeled for the same temporal period using **HYDROLIGHT** (see Section 3.3) with varying concentrations of chlorophyll, colored dissolved organic material, and representative sediments with a particle size distribution that approaches naturally occurring data (as shown in Figure 3.4). Once significant concentrations are achieved for each constituent (Case II waters) differentiation becomes problematic. Figure 4.1 illustrates this difficulty by showing that the Case I waters (where the constituent concentrations are low and mainly influenced by CHL) are well spaced and easily differentiated. The Case II waters, where concentrations are higher and constituents are well-mixed, are tightly grouped and difficult to separate. In other words, small differences at low concentrations result in reflectance values that are relatively easy to differentiate, while small differences at high concentrations result in reflectances that are very close to one another. This visualization is created using the ENVI N-Dimensional visualizer and a dataset of 640 reflectance values created using **HYDROLIGHT** using varying levels of **CHL**, **TSS**, and **CDOM**. Axes can then be rotated to illustrate degrees of separability within the dataset. The axis chosen best shows the separation between points representing low concentrations of constituents (Case I) and those representing higher concentrations (Case II).

While initially daunting, this illustration underscores the importance of accurate modeling. At this time, we are limiting the number of variables used to construct our look-up table (**LUT**)to three constituents and atmospheric modeling. This can be expanded to include separate phytoplankton species with differing scattering characteristics, for example. Further refinements and alternatives will be discussed in Section 6, when I will suggest directions for future work. We will assume for now that the present technique is sufficient to satisfy the minimum level for differentiation.



Figure 4.1: ENVI's N-dimensional visualizer allows us to see the difficulty in differentiating the reflectance due to constituent concentration variations in Case II waters

Ground truth for the areas examined with this test has been gathered, so we have a good idea of the TSS concentration range we need to generate the **HYDROLIGHT** reflectance data. We are using a fairly wide range of concentrations so that we can test this method in different areas of the images without biasing the outcome unfairly.

4.2 Study Site and Ground Truth

The area we are studying is in the Rochester Embayment of Lake Ontario. Specifically, we will be studying Long Pond, Cranberry Pond, Braddock's Bay, and a small area of Irondequoit Bay. These, along with the plume of Genesee River water in Lake Ontario, provide an astounding range of constituent concentrations within a relatively small area. Long Pond has relatively high **TSS** concentrations, and consequently, higher reflectance in the NIR. This pond was chosen because ground truth samples were taken at the time of the image acquisition and for the fact that the bottom is not detectable in the imagery, eliminating that parameter from consideration. Similarly, future work in modeling and measuring the benthic characteristics of this geographic area will extend the methods described in this research to areas where a sensor would detect the bottom. Figure 4.2 shows the approximate locations of the ground truth sampling for Long Pond on 5/20/1999.



Figure 4.2: Depth map of Long Pond (Makarewicz and Lampman, 1994). Sample locations added

The water sample collection involved three boats (Boston Whaler in the Genesee River, Lake Ontario and Irondequoit Bay, a canoe in Long Pond and Cranberry Pond, and a kayak in Braddock bay), a radiometer team, deployment of truth panels, and two spectrometer teams. Water samples, Secchi depths, and surface water temperatures were collected by each team on the water . Atmospheric parameters in the form of morning radiosonde released at the Buffalo Airport was acquired from the **NOAA** radiosonde database. Only the data regarding constituent concentrations will be used in this study, as we are modeling the atmosphere rather than trying to quantify it for the time of the collect, and in inverting the sensor data to reflectance. Future studies may use the radiosonde data as a starting point for creating an atmospheric **LUT**. It was decided for this study to use the standard atmospheric models included in the **MODTRAN** code.



Figure 4.3: Locations of sampling points on an image for the Rochester Embayment May 20, 1999 Collection. Bar graphs show relative magnitudes of the measured values. (Used by permission (Raqueño, 2004))

Figure 4.3 indicates the sample locations by different team icons and labeled by sample bottle ID. Detailed description of the processing of water samples collected can be found in (Raqueño, 2004), outlining the methods used to derive the inherent optical properties **IOP** which characterize the spectral absorption and scattering coefficients of each constituent independent of illumination conditions. These **IOP**s, verified and supplemented with data from the literature (Bukata et al., 1979; Makarewicz and Lampman, 1994) are used as input values for **HYDROLIGHT** (Mobley and Sundman, 2000) to generate modeled spectral reflectance values. Default inputs supplied by HYDROLIGHT as well as data from the literature will be used in cases where the optical properties could not be determined (Bukata et al., 1979). The collected ground truth will also be used for validation of the output of the spectral matching algorithm.



Figure 4.4: Map of western part of Rochester Embayment.(Makarewicz and Lampman, 1994)

4.2.1 AVIRIS Dataset

As discussed in Section 2.3.1, the reference data we are using comes from a collect carried out on May 20, 1999. Some pre-processing was necessary before the data could be used in the spectral matching algorithm. Two main collection flights were undertaken, one in an east-west line and one in a mainly north-south line. The north-south line was heavily contaminated with solar glint and was not used in this study. Fortunately, the river and the ponds thought to be most interesting to a constituent characterization study were well represented in the east-west line. Due to the sun-target-sensor geometry at the time of the collect, some sub-pixel glint is inevitable and will probably contribute to errors in retrieved constituent concentrations.

The data was subset to the VIS/NIR region of the spectrum, and some of the bands in the blue (below 419nm) were discarded due to low sensor response and signal-to-noise (SNR) effects that made them questionable. An overlap of bands caused by the design of the sensor required the removal of a redundant band at ~ 700[nm] The end result was a data set with 55 bands from 419-947[nm].

4.2.1.1 AVIRIS Signal-to-Noise Ratio

A 5X5 spatial averaging filter was applied to improve SNR and the image was masked to separate the land from the water. The averaging filter has the effect of lowering the instrument noise at the expense of spatial resolution. For a straight pixel aggregation, noise is decreased by a factor of \sqrt{n} , n being the number of pixels being averaged. In this case a gaussian low-pass kernel was applied with the intent being to reduce sensor noise while maintaining spatial resolution as much as possible. The improvement in this case is a roughly doubled SNR. The value of the trade-off of spatial resolution for improved SNR was discussed at the 9th AVIRIS Earth Science and Applications Workshop (Green and Boardman, 2000). With the very low reflectance of water, particularly in the NIR, the water-leaving radiance is correspondingly very small, so the trade-off of spatial resolution for improved SNR was deemed acceptable. Still, the possibility exists of the changes we are counting on to differentiate the spectral radiance curves being within the noise levels of the sensor. For the dataset under consideration in this study, the **SNR** was nominally 800 in the visible and about 360 at 2.2 microns (Green and Boardman, 2000). This number is achieved for a 50% reflectance target, so we can assume a lower **SNR** for a water target with single-digit reflectance values. In order to determine the observed **SNR**, an area of assumed uniform reflectance out in Lake Ontario was selected and the signal-to-noise ratio determined before and after applying the low-pass filter. The digital counts of a 100 pixel



(a) Image of AVIRIS collect area showing ROI(small red region)



(b) Filtered image (gaussian low-pass)

Figure 4.5: Scene-derived Signal-to Noise Ratio area

region of interest (**ROI**) were averaged and divided by the standard deviation (σ) to obtain

an accepted in-scene estimation of signal-to-noise ratio.

$$SNR = \frac{\overline{DC}}{\sigma} \tag{4.2}$$

The results of Equation 4.2 for both the raw and gaussian low-pass filtered images are shown in Figure 4.6. We can see a clear 2 : 1 increase in the **SNR**. A straight pixel aggregation would have up to a 5 : 1 increase, but the gaussian filter will preserve more spatial information in the image data and this is desirable in a study that purports to produce location-specific concentration maps.



Figure 4.6: Graph of scene-derived SNR

Continuing updates to the AVIRIS sensor have improved the SNR for current datasets, and newer noise reduction algorithms are being developed to help the processing of archived data such as the set we are using. Future work may include pre-processing the data with one of these algorithms, such as the wavelet-shrinkage noise reduction algorithm proposed in (Othman and Qian, 2006), which claims an 84% reduction in noise for a dataset from 2002.

4.3 Optimizing the Spectral Match

Once the modeled radiance curves have been generated, we can find the one that best matches the observed data. That curve will then tell us what the atmosphere and constituent concentrations were that produced it. Figure 4.7 shows how the radiance and reflectance from the **MODTRAN** and **HYDROLIGHT** simulations are combined to produce a modeled sensor-reaching radiance L_{mod} , which is then compared to hyperspectral sensor radiance L_{obs} to find the best-fitting spectral curve. The situation exists that



Figure 4.7: Illustration of modeled radiance generation using Modtran and Hydrolight

we will need to interpolate between two or more spectral curves to get the best estimation

of aerosol and constituent concentrations. That is, we may not have populated our **LUT** densely enough at the point of the match to give the needed radiance, so we make an assumption of linearity between the two closest points and interpolate to find the concentrations that would have given the correct radiance had we done that simulation. The dimensionality of the interpolator is derived from the number of variables to be considered in the algorithm. In the present case, we will be using four variables for interpolation. The fifth, **IHAZE**, is categorical and cannot be interpolated. Rather, we will interpolate to the best match in each **IHAZE** category and return the lowest **RMS** value. An interpolation/optimization program was written to carry out the fitting, using a root-mean-squared (RMS) error minimization to arrive at the best match. The error will be computed over the range $\lambda_0 \rightarrow \lambda_n$, which in this case is $419 \rightarrow 947nm$. Now we need a routine that will find the smallest error from a series of values. One such optimization is **AMOEBA**.

The AMOEBA function in IDL performs multidimensional minimization of a function Func(x), where x is an n-dimensional vector, using the downhill simplex method. AMOEBA is based on the routine amoeba described in section 10.4 of Numerical Recipes in C: The Art of Scientific Computing (Second Edition), published by Cambridge University Press. Basically, amoeba searches for a vector that returns a minimum error according to user-supplied inputs. Initial values within the range of the parameters are supplied as a starting point for the iterations. If a minimum is found, AMOEBA returns an n-element vector corresponding to the function's minimum value. If a minimum within the given tolerance is not found within the specified number of iterations, AMOEBA returns a scalar value of -1. Results are returned with the same precision (single- or double-precision floating-point) as is returned by the user-supplied function to be minimized. (source: *IDL* Reference Guide)

4.3.1 Methods to Implement Optimization

4.3.1.1 Method 1: No constraints

This method is the most hopeful. Assuming that the modeled radiance spectra of the water are accurate and can be differentiated, the algorithm is given no constraints for possible constituent concentrations and a starting point at the mean of each concentration range. Figure 4.8 shows the process flow for this approach.



Figure 4.8: Overview of simultaneous extraction algoritm

4.3.1.2 Method 2: NIR First

Here we match in the NIR first to lock in TSS concentration and atmosphere, then use the visible region (400-700nm) to optimize the rest of the constituents as seen in Figure 4.9. This approach is based on the assumption that there is enough information in the NIR to allow a reasonable match based on just the radiance due to increased reflectance from the suspended sediments in the water. Assuming this is correct, we can lock in that value for each pixel in the image. Since we also get atmospheric information with this match, we lock in those values also, and re-run the algorithm over the visible bands to predict the remaining constituent concentrations. For this method we also used a mean starting point. The results of these trials were inconsistent produced overly simplified output maps, leading us to discard it in favor of one with more consistent and realistic spatially variant output.

4.3.1.3 Method 3: New Starting Point

For this method, the algorithm was run once over the image (as in Method 1) to get an initial output, then the output concentration files were read back into a modified program that used each value to change the starting point for a second optimization.

4.3.1.4 Method 4: Low Starting Point

This method came about from the idea that the LUT was populated in a biased manner. That is, the lower values were more heavily represented, because small initial changes in concentration brought about the most obvious changes in volume reflectance, and therefore, water-leaving radiance. Setting the starting point at the mean value could have the effect of skewing the result. In setting an unrealistic starting point, the possibility of finding



Figure 4.9: Modification of algorithm for NIR-first match

a local rather than global minimum was increased. Dropping the starting point into the lower range of the LUT can avoid this and improve the results.

4.3.1.5 Method 5: Constraints

Rather than use a large portion of the image that has many water types in it, a smaller area is considered that encompasses just one body of water at a time. So rather than having to consider the entire range of the LUT, we can limit it to the extrema of concentrations of the individual body of water under consideration. This would entail using a priori information to set the limits for each pond or river. Another approach would entail an initial run through the algorithm to set an AEROSOL value, taking the average output for the ponds area and locking it in for another iteration to obtain constituent concentration output.

As the purpose of this investigation was to cover as broad an area as possible, this technique was not implemented; but this may be useful in regions where the constituent concentration ranges have been previously established through sampling.

Each of these methods was implemented and the results compared with the values obtained from laboratory evaluation of samples from the various bodies of water in the study. Method 4 was determined by this to have the greatest probability of success and is the technique used for the results discussed in the concluding sections of this study.
Chapter 5

Results and Discussion

This investigation began with the expectation of finding a good match between modeled and observed data. As with many such endeavors, results have been mixed and need exploration and interpretation. The performance of the algorithm is evaluated by comparing the output (predicted) constituent concentrations to laboratory measurements of water samples taken from the study areas.

Analysis of the samples collected in May 1999 from the study areas in the Rochester Embayment (Long Pond, Cranberry Pond, Braddock Bay, Irondequoit Bay, and the Genesee River plume) showed a wide range of chlorophyll, suspended sediment, and CDOM concentrations between each body of water (Raqueño, 2004). These widely varying concentrations make this area a good test bed to determine the performance of our algorithm. Studies completed in 1990 and 1994 by Dr. Joseph Makarewicz of the Aquatic Sciences program in SUNY Brockport confirm the persistent trophic states of the bay and ponds shown In Figure 4.4 on page 50 (Makarewicz and Lampman, 1994; Makarewicz et al., 1990). Successful implementation of this spectral matching algorithm could allow for estimation of the trophic status of water bodies using remote sensing techniques to supplement in situ sampling.

5.1 Spectral Match

One side benefit of this technique is that we can reconstruct the input image using our modeled data. Obviously, the closer we can get to an exact spectral match , the closer the visual match will be. Figure 5.1 shows a comparison between the input and output spectral radiance values for three pixels from the Genesee river and plume. These matches were accomplished using the low starting point method discussed in Section 4.3.1.4. Agreement between the modeled and observed curve is fairly close. The spectral shape of each is similar, and the amplitude is close. Data from a pixel further out in Lake Ontario is included for comparison purposes, as is a mixed pixel (shown in red) to show an intermediate case. In both instances, the match between modeled and observed data is good. Reconstruction of the image data using the modeled radiance is shown for a visual comparison.

In Figure 5.2(a) we see the original input sub-image of the Genesee river mouth with the reconstructed image shown in 5.2(b). The reconstructed image is composed of the pixels that have the best matching spectral radiance values as determined by the matching algorithm. Despite minor differences in the output image, we can see that the reconstruction is faithful to the original input.

5.1. SPECTRAL MATCH



Figure 5.1: Comparison of radiance (input vs. output) for Genesee River and sediment plume. Lake pixel (green) added for comparison.



(a) Input Image of Genesee River mouth



(b) Output Image of Genesee River mouth (modeled data)

Figure 5.2: Reconstruction of plume image from modeled radiance

Image reconstruction and Spectral matches for an image showing three bodies of water in the study area are shown in Figures 5.3 and 5.4. Long Pond, Cranberry Pond, and Braddock Bay are very important to this study because they encompass a wide range of constituent concentrations verified by ground truth collection. Figure 5.4 shows a close agreement between observed and modeled spectral radiance curves for pixels in each of these water bodies. Each image was run through the algorithm several times to prevent spurious results. Minor variations did occur, but the output values were mainly consistent across the several runs.



(a) Input Image of Braddock's Bay, Cranberry Pond, and Long Pond



(b) Output Image (modeled data)

Figure 5.3: Reconstruction of ponds image from modeled radiance



Figure 5.4: Comparison of radiance (input vs. output) for three ponds in Rochester Embayment

While the visual reconstruction of an image does not indicate that the algorithm was successful, it does encourage the expectation of success and suggest that modeled data can be used to create images of water based on input constituent concentration levels. This may be useful to model the appearance of toxic spills, plankton blooms, or seasonal sediment loading. The close agreement of the images shown in Figure 5.3 is gratifying, as it shows that the modeled reflectances and atmospheric transmissions are close enough to simulate observed data.

5.2 Constituent Concentrations

Each successful completion of the algorithm outputs image files based on the constituent concentration levels that rendered the lowest RMS for each pixel. The output concentration

maps resulting from Method 4 (4.3.1.4) are shown in Figure 5.5. The files are color mapped using ENVI's EOS A color table. For each map, purple and blue indicate low values, while red to dark burgundy indicate higher values.

A root mean square error was computed for each constituent, based on the difference between predicted and measured values, as indicated by:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} \left([C_{pred}]_i - [C_{obs}]_i \right)^2}{n}}$$
(5.1)

where,

$$[C_{pred}]_i$$
 predicted value for location i
 $[C_{obs}]_i$ observed (measured) value for location i
 n number of locations

This will result in an absolute **RMS** error expressed in the concentration units of the constituent. A more realistic measure may be the **RMS** expressed as a percentage of the total range of the constituent concentration. That is:

$$[RMS]\% = \frac{100}{[range]} \sqrt{\frac{\sum_{i=1}^{n} \left([C_{pred}]_i - [C_{obs}]_i \right)^2}{n}}$$
(5.2)

5.2. CONSTITUENT CONCENTRATIONS



Figure 5.5: Output Concentration Maps

Table 5.1 is a compilation of output from Method 4 as discussed in Section 4.3.1.4. Data from the output maps corresponding to the ground truth collection locations were gathered using ENVI's ROI (region of interest) tool. 4X4 or 5X5 pixel ROIs were used, depending on shore proximity (sometimes the larger ROI would intersect with shore pixels and invalidate the data.) The mean of the ROI was then used to determine the constituent concentration for the area. No points are included for comparison with open lake regions

	Sample	$\operatorname{CHL}\left[\frac{mg}{m^3}\right]$		$\mathrm{TSS}\left[\frac{g}{m^3}\right]$		CDOM[1/m@350nm]	
SITE	Site ID	Lab	predicted	Lab	predicted	Lab	predicted
	A22	64.15	65.80	22.67	22.85	6.15	9.00
Long Pond	A18	62.37	64.30	21.33	23.52	6.09	3.83
	A20	62.37	63.70	23.33	23.05	6.10	8.48
~	A23	6.24	2.43	3.67	1.03	4.81	2.36
Cranberry Pond	A19	5.35	2.17	2.67	0.89	4.86	2.90
	A6	5.35	9.44	6.80	4.95	9.02	9.05
	A4	6.68	6.07	10.50	5.08	7.96	9.24
Braddock Bay	A5	7.13	9.00	10.67	8.88	9.10	10.21
	A3	5.35	4.71	6.00	6.41	12.80	12.68
Genesee River Plume	A25	4.28	3.45	10.00	12.27	2.75	1.96
Irondequoit Bay	A27	19.60	21.89	15.30	13.28	4.12	1.42

due to the lack of ground truth data for those areas.

Table 5.1: Table of laboratory and predicted values for ponds in the Rochester Embayment

5.2.1 Atmospheric Output

The output of the aerosol map (see Figure 5.5(d)) was treated somewhat differently than the other concentration maps. Rather than small sample regions, the areas of the ponds, including Braddock's Bay, were combined into one ROI to determine the modeled visibility measured in kilometers. The result was a mean visibility of $28.15 \, km$ (std. dev. 2.11). This was consistent with the output of an image of Irondequoit Bay, which had a mean of $30.05 \, km$ (std. dev. 2.51). For both images, the aerosol maps had a range from $22.5-37 \, km$. This figure includes the results for the total water area, including the area of Lake Ontario visible in the test image. Homogeneous areas within Long Pond and Braddock's Bay were compared and found to have a mean of $26.3 \, km$ and a standard deviation of 0.84. The pixelto-pixel variation within these areas was mainly gradual, on the order of 0.1 to $0.2 \, km$. The larger variations across the entire image may be due to small regions of glint adding to the radiance reaching the sensor. It is encouraging that two bodies of water, with completely different constituent loading, have such a close similarity in the aerosol map output. The categorical parameter, **IHAZE**, was consistent throughout the results, always returning a value of "3", which indicates the urban aerosol model used by **MODTRAN** (Berk et al., 1999).

The results from Cranberry Pond are more problematic. As we can see from the output map (Figure 5.5(d), the aerosol result for this pond is higher than for the two nearby water bodies (Braddock Bay and Long Pond), as indicated by the large patch of green in the output map. The mean for Cranberry is 31.1 km with a standard deviation of over 2.0 km. These inconsistent values may be due to bottom reflectance. Since the bottom type was not modeled in our **LUT** as a variable, any radiance change due to bottom reflectance would evidence itself in one or more of the modeled variables. The ground truth notes for this pond mention the Secchi disc "bottoming out" in one measurement, and the Secchi depth in another measurement was very close to the recorded depth (within 0.1m).

Since we do not have atmospheric data specific to the Rochester embayment, the consistency of the aerosol (visibility) results is a good indicator of the quality of our results. Large pixel-to-pixel variations would indicate an atmosphere that varies too much to be realistic.

In the next sections we will examine the results of the in-water constituent concentration retrieval.

5.2.2 Chlorophyll

The output concentration map for **CHL** (5.5(a)) shows the relative concentrations based on color scale. These maps can be queries using **ENVI**s Region of Interest (**ROI**) or Pixel Locator tools for the value at a given location. The values for areas where samples were acquired was determined and recorded in Table 5.1. We would expect, for a successful result from the algorithm, that the output values for Long Pond would be high, and the values for ponds with lower sampled concentrations to be low. This is what the output map shows when the values are plotted in bar graph form. Figure 5.6 indicates a fairly close agreement between modeled and observed data. To further illustrate this agreement, a scatter plot of the data points for each water body is shown in Figure 5.7. A one-toone trendline is included in this graph to indicate the distance the data points are from a perfect match.

Error analysis of the data points using Equation 5.1 shows an absolute RMS error of 2.33 $\left[\frac{mg}{m^3}\right]$. In terms of percent error of the concentration range, Equation 5.2 results in a value of 3.43% for a range of 0.0-68.0 $\left[\frac{mg}{m^3}\right]$. There is a very real possibility that we have underpopulated our **LUT** in terms of concentration levels of **CHL**, however. Long Pond may have concentration levels well above the top value 68.0 $\left[\frac{mg}{m^3}\right]$. Makarewicz reports that samples taken in May of 1988 were in the range of 130.0 $\left[\frac{mg}{m^3}\right]$ (Makarewicz et al., 1990). In our attempt to simply bracket the sampled values, we may have forced the algorithm to underestimate the concentrations in some parts of Long Pond. This would help explain the solid dark red appearance of the output map for this area.

The agreement of the output map with the historical trophic states of the study areas (Makarewicz et al., 1990; Makarewicz and Lampman, 1994) shows that the algorithm is able to distinguish high concentrations of chlorophyll from low with relatively good



accuracy in this data set.

Figure 5.6: Bar graph of laboratory vs predicted values for Chlorophyll. Site IDs as specified in Table 5.1 and Figure 4.3



Figure 5.7: 1:1 Plot of laboratory vs predicted values for Chlorophyll

5.2.3 Total Suspended Sediment

In a similar fashion to the **CHL** analysis, the output concentration map for **TSS** (5.5(b))shows the relative concentrations based on color scale. This map can be queried using **ENVI**s Region of Interest (**ROI**) or Pixel Locator tools for the value at a given location in the same way. The values for areas where samples were acquired was determined and recorded in Table 5.1. Figure 5.8 indicates a fairly close agreement between modeled and observed data in Long Pond, Irondequoit Bay, and the Genesee plume. To further illustrate this agreement, a scatter plot of the data points for each water body is shown in Figure 5.9. A one-to-one trendline is include in this graph to indicate the distance the data points are from a perfect match. Lower than expected values in Cranberry Pond could indicate contamination due to bottom reflectance, causing a higher than expected atmospheric (AEROSOL) result, and a subsequent lowering of output constituent concentration value. Cranberry Pond is problematic in all of the output map values, however, and an argument can be made to exclude the results of that pond on the grounds that bottom reflectance is contaminating the results. As the desired product is an algorithm that can function in a wide variety of conditions, we have left the data points in the results in the hope that an improved future model including bottom reflectance can lower the discrepancies.

Error analysis of the data points using Equation 5.1 shows an absolute RMS error of 2.34 $\left[\frac{g}{m^3}\right]$. In terms of percent error of the concentration range, Equation 5.2 results in a value of 9.77% for a range of 0.0-24.0 $\left[\frac{g}{m^3}\right]$. While not exact, when compared to errors from studies of ocean water, and considering that the values are derived from a remote sensing system, this result is still encouraging. As in the **CHL** case, we may have underpopulated our **LUT** in terms of concentration levels of **TSS**. Long Pond may have concentration levels of sediment above the top value of 24.0 $\left[\frac{g}{m^3}\right]$ used in our study. Samples taken in

May of 1988 in two feeder streams (Black Creek and Northrup Creek) (Makarewicz et al., 1990) support an argument for an expanded **LUT**. Again, in our attempt to simply bracket the sampled values, we may have forced the algorithm to underestimate the concentrations in some parts of Long Pond.

With the exception of some data points, the agreement of the output with the observed trophic states of the study areas shows that the algorithm is able to distinguish high concentrations of total suspended sediment from low with relatively good accuracy in this data set.



Figure 5.8: Bar graph of laboratory vs predicted values for Total Suspended Sediment. Site IDs as specified in Figure 5.1



Figure 5.9: 1:1 Plot of laboratory vs predicted values for Total Suspended Sediment

5.2.4 Colored Dissolved Organic Material

The output concentration map for **CDOM** (5.5(c)) also shows the relative concentrations based on color scale. This map can be queried using **ENVI**s Region of Interest (**ROI**) or Pixel Locator tools for the value at a given location in the same way. The values for areas where samples were acquired was determined and recorded in Table 5.1. Figure 5.10 shows a more varied agreement between modeled and observed data in Long Pond, Irondequoit Bay, the Genesee plume and Cranberry Pond. In the area of highest concentrations (Braddock Bay), agreement with sampled data is quite close. To illustrate this agreement, a scatter plot of the data points for each water body is shown in Figure 5.11. A one-to-one trendline is include in this graph to indicate the distance the data points are from a perfect match. Close agreement of data points in Braddock Bay suggest that the algorithm can predict with good accuracy the relative concentration levels. Again, Cranberry Pond is problematic in that it is giving lower than expected values.

Error analysis of the data points using Equation 5.1 shows an absolute RMS error of $1.90 \left[\frac{1}{m}@350nm\right]$. In terms of percent error of the concentration range, Equation 5.2 results in a value of 13.54% over a range of $0.0\text{-}14.0 \left[\frac{1}{m}@350nm\right]$. As in the **CHL** and **TSS** case, we may have underpopulated our **LUT** in terms of concentration levels of **CDOM**. Braddock Bay may have concentration levels of **CDOM** above the top value of $14.0 \left[\frac{1}{m}@350nm\right]$ used in our study.

While this is not as encouraging as the chlorophyll and sediment results, the algorithm is able to distinguish high concentrations of colored dissolved organic matter from low with relatively good accuracy in this data set. High areas are generally reported as high , while low concnetrations result in a lower predicted output. Better understanding and improved modeling of the effects of **CDOM** absorption on water-leaving reflectance could bring about in an improvement on these results.



Figure 5.10: Bar graph of laboratory vs predicted values for Colored Dissolved Organic Material. Site IDs as specified in Figure 5.1



Figure 5.11: 1:1 Plot of laboratory vs predicted values for CDOM

5.3 Comparison of Results to Previous Work

In an evaluation of a new technique it is advantageous to be able to compare results with previous efforts that have the same intent. Two previous studies have attempted to extract water quality parameters for the ponds in the Rochester area.

(Raqueño, 2004) used the same **AVIRIS** dataset to extract water constituent concentrations of the ponds of the Rochester Embayment, also using an AMOEBA-based optimization scheme. His piecewise method of optimization applied AMOEBA fitting sequentially over localized spectral regions of the dataset, fixing TSS with the red region match, CHL and TSS with the green, and CDOM, CHL, and TSS with the blue. This matched the constituents with their assumed spectral regions of greatest influence. Differences with the method of the current study include the use of an ELM (empirical line method) inversion to reflectance space, eliminating the necessity of matching the atmospheric parameters, and the exclusion of spectral bands including the near-infrared. It was with his assistance and constant encouragement that the current technique was developed, with the desire that improved results could be obtained.

Tables 5.2, 5.3, and 5.4 show a point -by-point comparison of constituent concentration results for the two methods. The tables show the results compared against ground truth sample concentrations with error being expressed as percent of the assumed concentration range. Mean error for all sample sites is shown in red at the bottom of each table.

We can see that there is variation in the accuracy of the results from site to site, but the overall error in the current values shows a definite improvement from the 2004 study. Most improvement is seen in the CHL and TSS results, with a small decrease in total error seen for CDOM results.

		(Chlorophyll			
	Sample		2004		2010	
SITE	Site ID	$\operatorname{Lab}\left[\frac{mg}{m^3}\right]$	predicted	err	predicted	err
	A22	64.15	31.00	48.75	65.80	2.43
Long Pond	A18	62.37	53.00	13.78	64.30	2.84
	A20	62.37	57.00	7.90	63.70	1.96
	A23	6.24	13.00	9.94	2.43	5.60
Cranberry Pond	A19	5.35	16.00	15.66	2.17	4.68
	A6	5.35	0.59	7.00	9.44	6.01
	A4	6.68	6.50	0.26	6.07	0.90
Braddock Bay	A5	7.13	6.30	1.22	9.00	2.75
	A3	5.35	12.00	9.78	4.71	0.94
Genesee River Plume	A25	4.28	4.10	0.26	3.45	1.22
Irondequoit Bay	A27	19.60	19.00	0.88	21.89	3.37
Average error		(percent of range)		16.84		3.43

Table 5.2: Comparison of predicted CHL values for ponds in the Rochester Embayment between (Raqueño, 2004) and Simultaneous Extraction technique

Total Suspended Sediment						
	Sample		2004		2010	
SITE	Site ID	$\operatorname{Lab}\left[\frac{mg}{m^3}\right]$	predicted	err	predicted	err
	A22	22.67	19.2	14.46	22.85	0.75
Long Pond	A18	21.33	19.5	7.62	23.52	9.13
	A20	23.33	17.6	23.88	23.05	1.17
	A23	3.67	3.2	1.96	1.03	11.00
Cranberry Pond	A19	2.67	2.8	0.54	0.89	7.42
	A6	6.80	15.00	34.17	4.95	7.71
	A4	10.50	8.7	7.50	5.08	22.58
Braddock Bay	A5	10.67	9.00	6.96	8.88	7.46
	A3	6.00	11.00	20.83	6.41	1.71
Genesee River Plume	A25	10.00	15.5	22.92	12.27	9.46
Irondequoit Bay	A27	15.30	14.8	2.08	13.28	8.42
Average error		(percent o	f range)	16.72		9.77

Table 5.3: Comparison of predicted TSS values for ponds in the Rochester Embayment between (Raqueño, 2004) and Simultaneous Extraction technique

Colored Dissolved Organic Material						
	Sample		2004		2010	
SITE	Site ID	$\operatorname{Lab}\left[\frac{mg}{m^3}\right]$	predicted	err	predicted	err
	A22	6.15	3.90	16.07	9.00	20.36
Long Pond	A18	6.09	2.5	25.64	3.83	16.14
	A20	6.10	5.30	5.71	8.48	17.00
	A23	4.81	4.76	0.36	2.36	17.50
Cranberry Pond	A19	4.86	4.74	0.86	2.90	14.00
	A6	9.02	5.05	28.36	9.05	0.21
	A4	7.96	10.50	18.14	9.24	9.14
Braddock Bay	A5	9.10	10.30	8.57	10.21	7.93
	A3	12.80	9.60	22.86	12.68	0.86
Genesee River Plume	A25	2.75	1.70	7.50	1.96	5.64
Irondequoit Bay	A27	4.12	3.60	3.71	1.42	19.29
Average error		(percent o	f range)	15.81		13.54

Table 5.4: Comparison of predicted CDOM values for ponds in the Rochester Embayment between (Raqueño, 2004) and Simultaneous Extraction technique

Percent Extraction Errors								
OLI Blue Band Simultaneous								
Cranberry Pond	Cranberry Pond							
CHL 5.55 5.14								
	TSS	12.9	9.21					
	CDOM	32.9	15.75					
Long Pond								
CHL 6.1 2.41								
	TSS	4.4	3.68					
	CDOM	42.5	17.83					

Table 5.5: Comparison of extraction errors for ponds in the Rochester Embayment between (Gerace, 2010) and Simultaneous Extraction technique

(Gerace, 2010) also extracted constituent concentrations during the course of his evaluation of LANDSAT'S OLI (Operational Land Imager) sensor. In this he resampled the AVIRIS data to the nominal bands of the OLI and extracted values also using a multidimensional LUT/optimization technique. Due to the methods employed, a point-by-point comparison is not possible, as it was in the previous discussion. Comparing the average errors for the two ponds considered in his method, we can see that the OLI Blue Band method does fairly well for CHL and TSS values, but poorly for CDOM extraction. This is explained by the low SNR in the blue region and calibration issues with the AVIRIS sensor. This situation is exacerbated by the limited number of bands available for this technique, rendering CDOM concentration matching difficult. Table 5.5 shows that the overall error of the Simultaneous Extraction method is lower than that of the OLI Blue Band method, although the OLI method has very good results for a multiband sensor technique.

Chapter 6

Summary and Future Work

This problem has been in place for several decades and has been problematic for coastal regions because of the complexity of the problem. While ocean researchers have to deal with very low concentrations of water quality constituents, investigators in littoral zones have to consider that the concentrations may span several orders of magnitude in a relatively small spatial area. Atmospheric correction algorithms that have been used to process ocean imagery break down or are of limited use in coastal regions.

The process that we have used here has shown an ability to model complex waters while simultaneously modeling the atmosphere, producing a simulated sensor-reaching radiance that allows us to derive the constituent concentrations. It is very promising that the model's prediction and the real data have the same spectral shape, enabling reconstruction of the image data. Constituent concentration results have been achieved that agree, to a great extent, with sampled data from the study site. This is our goal, and when we can reconstruct the image data almost exactly, we'll know that our various models are as correct as we can make them.

6.1 Future Work

While the results attained with this technique are quite good for a proof of concept, there are many points that can be improved upon for more accurate results in the future.

One of the improvements we can make is that the models we are using, both Hydrolight and MODTRAN, have fundamental plane parallel assumptions for the scene elements that make our algorithm prone to discrepancies when compared to real scenes. This will become more important as improvements are made to the spatial resolution of the datasets available for water remote sensing research.

The optimization technique, AMOEBA, that we used may also be improved upon. Future work should explore the use of several different optimization techniques (simulated annealing or a genetic algorithm, for example) to check consistencies in the different solutions. This may mitigate the possibility of arriving at local minima in the solution space. The optimization technique could also include spectral weighting techniques to take advantage of the specific regions affected most by the various constituents.

Further refinements to the creation of atmospheric LUTs using MODTRAN are necessary to correct errors in L_d (downwelled radiance). The two-pass method used in this study may result in a larger value due to adjacency effects and can be improved upon using userspecified reflectance files for the target and background. Also, when available, accurate radiosonde data can be substituted for the default MODTRAN atmospheres used for the construction of the current LUTs. In addition to using more accurate data for establishing an atmospheric starting point, an initial optimization run can be used to determine the atmospheric parameters (VIS and IHAZE) for the study and use these values in a second run to determine the constituent concentrations.

Consideration should be given to the implementation of a glint reduction algorithm in

the preparation of the dataset for processing, depending on the angle of image acquisition. Glint can have a severe effect on the accuracy of the extracted constituent concentration values.

This work used limited constituent models. Future models could vary CHL further by including different species of phytoplankton that have differing absorption and scattering characteristics. Sediment types could also be varied according to locally known mineral loads and particle size distributions. Further investigation of the scattering characteristics of sediment and phytoplankton in the NIR would also help refine our model. Both of these constituents could be modeled with varying depth concentrations if differentiation between surface and depth concentration plumes can be determined.

List of Figures

2.1	Solar and self-emitted energy paths (labeled so as to be consistent with	
	Schott (1997))	8
2.2	Example of irradiance spectra before and after being attenuated by a fairly	
	clear atmosphere. (MODTRAN output)	9
2.3	Graphic showing the calculations for transmission in a stratified atmosphere.	
	Each layer j is assumed to be homogeneous for each constituent i . The	
	absorption cross section $C_{\alpha ij}$ and number density m_{ij} are considered to be	
	constant for each path length z_j	13
2.4	Diagram of extinction components for an absorbing and scattering vol-	
	ume.(Mobley, 1994)	15
2.5	Drawing of AVIRIS Spectrometer(Vane et al., 1993)	20
2.6	Drawing of AVIRIS focal plane detectors showing spectral coverage from	
	400-2500 $[nm]$ (Vane et al., 1993)	21
3.1	Graphic showing components of sensor-reaching radiance	26

3.2	Graph showing the spectral absorption coefficients for water constituents in	
	Lake Ontario (Bukata et al., 1995) Dissolved organic carbon is yet another	
	term for CDOM	31
3.3	Graph showing the spectral scattering coefficients for water constituents in	
	Lake Ontario (Bukata et al., 1995) Dissolved organic carbon is not included	
	for this because CDOM does not have appreciable scattering effects	32
3.4	Plot of distribution of sampled sediments from Conesus Lake showing agree-	
	ment with log-normal size distribution	33
3.5	Graph showing water reflectance value due to TSS only. Wavelength is in	
	nanometers (HYDROLIGHT output)	34
3.6	Graph showing water reflectance value due to CDOM only. Wavelength is	
	in nanometers (HYDROLIGHT output)	35
3.7	Graph showing the reflectance value due to chlorophyll only with scattering	
	in NIR. Black line is spectra for pure water. Wavelength is in nanometers	
	(HYDROLIGHT output)	36
3.8	Graph showing scattering coefficients of chlorophyll with exponential decay	
	to zero vs. linear extrapolation	37
3.9	Graph showing the reflectance value due to chlorophyll with decreased scat-	
	tering in NIR. Wavelength is in nanometers. (HYDROLIGHT output) $\ . \ .$	38
3.10	Sample of modeled radiances compared to AVIRIS radiance	42
4.1	ENVI's N-dimensional visualizer allows us to see the difficulty in differenti-	
	ating the reflectance due to constituent concentration variations in Case II	
	waters	45

4.2	Depth map of Long Pond (Makarewicz and Lampman, 1994). Sample loca-	
	tions added	46
4.3	Locations of sampling points on an image for the Rochester Embayment May	
	20, 1999 Collection. Bar graphs show relative magnitudes of the measured	
	values. (Used by permission (Raqueño, 2004))	48
4.4	Map of western part of Rochester Embayment.(Makarewicz and Lampman,	
	1994)	50
4.5	Scene-derived Signal-to Noise Ratio area	52
4.6	Graph of scene-derived SNR	53
4.7	Illustration of modeled radiance generation using Modtran and Hydrolight .	55
4.8	Overview of simultaneous extraction algoritm	57
4.9	Modification of algorithm for NIR-first match	59
۳ 1		
5.1	Comparison of radiance (input vs. output) for Genesee River and sediment	
	plume. Lake pixel (green) added for comparison.	63
5.2	Reconstruction of plume image from modeled radiance $\ldots \ldots \ldots \ldots$	63
5.3	Reconstruction of ponds image from modeled radiance \ldots	64
5.4	Comparison of radiance (input vs. output) for three ponds in Rochester	
	Embayment	65
5.5	Output Concentration Maps	67
5.6	Bar graph of laboratory vs predicted values for Chlorophyll. Site IDs as	
	specified in Table 5.1 and Figure 4.3	71
5.7	1:1 Plot of laboratory vs predicted values for Chlorophyll	71
5.8	Bar graph of laboratory vs predicted values for Total Suspended Sediment.	
	Site IDs as specified in Figure 5.1	74

5.9	1:1 Plot of laboratory vs predicted values for Total Suspended Sediment	74
5.10	Bar graph of laboratory vs predicted values for Colored Dissolved Organic	
	Material. Site IDs as specified in Figure 5.1	76
5.11	1:1 Plot of laboratory vs predicted values for CDOM	76
A.1	Plot of spectral absorption coefficients for CHL	96
A.2	Plot of spectral scattering coefficients for CHL	101
A.3	Plot of spectral absorption coefficients for CDOM	106
A.4	Plot of spectral absorption coefficients for Total Suspended Sediment	109
A.5	Plot of spectral scattering coefficients for Total Suspended Sediment	110

List of Tables

3.1	Parameters for adjusting MODTRAN runs	28
3.3	Concentration Values used in HYDROLIGHT	41
5.1	Table of laboratory and predicted values for ponds in the Rochester Embay-	
	ment	68
5.2	Comparison of predicted CHL values for ponds in the Rochester Embayment	
	between (Raqueño, 2004) and Simultaneous Extraction technique	78
5.3	Comparison of predicted TSS values for ponds in the Rochester Embayment	
	between (Raqueño, 2004) and Simultaneous Extraction technique	79
5.4	Comparison of predicted CDOM values for ponds in the Rochester Embay-	
	ment between (Raqueño, 2004) and Simultaneous Extraction technique	79
5.5	Comparison of extraction errors for ponds in the Rochester Embayment	
	between (Gerace, 2010) and Simultaneous Extraction technique	80
A.1	Input CHL Absorption Coefficients For HYDROLIGHT Simulations $\ . \ . \ .$	97
A.2	Input CHL Absorption Coefficients For HYDROLIGHT Simulations–part 2	98
A.3	Input CHL Absorption Coefficients For HYDROLIGHT Simulations–part 3 $$	99
A.4	Input CHL Absorption Coefficients For HYDROLIGHT Simulations–part 4	100

A.5	Input CHL Scattering Coefficients For HYDROLIGHT Simulations 1	02
A.6	Input CHL Scattering Coefficients For HYDROLIGHT Simulations–part 2 . 1	.03
A.7	Input CHL Scattering Coefficients For HYDROLIGHT Simulations–part 3 . 1	04
A.8	Input CHL Scattering Coefficients For HYDROLIGHT Simulations–part 4 . 1	105
A.9	Input CDOM Absorption Coefficients For HYDROLIGHT Simulations 1	107
A.10	Input CDOM Absorption Coefficients For HYDROLIGHT Simulations–part 21	08
A.11	Input TSS Absorption Coefficients For HYDROLIGHT Simulations–OOPS	
	generated	.11
A.12	Input TSS Scattering Coefficients For HYDROLIGHT Simulations–OOPS	
	generated	.12

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Appendix A

HYDROLIGHT Input Files

The following tables show the values used for modeling spectral reflectance using HYDRO-LIGHT and OOPS.

A.1 Chlorophyll Absorption and Scattering

Tables A.1, A.2, A.3, and A.4 show the absorption coefficients used as inputs to HYDRO-LIGHT for the reflectance simulations used in this research. These values are derived from measured values taken from the Rochester embayment on May 20, 1999 and scaled such that a(450nm) = 0.50 to correspond with chlorophyll absorption curves from the literature. Figure A.1 shows a plot of the coefficients for illustrative purposes.



Figure A.1: Plot of spectral absorption coefficients for CHL
	1						,		
$\lambda(\text{nm})$	abs	λ	abs	λ	abs	λ	abs	λ	abs
290	0.128077	323	0.0649985	356	0.0437625	389	0.043157	422	0.0558204
291	0.123918	324	0.0665615	357	0.0432894	390	0.0434517	423	0.0560402
292	0.11976	325	0.066188	358	0.0432741	391	0.0439684	424	0.0564111
293	0.115601	326	0.0621174	359	0.0432569	392	0.044163	425	0.0559847
294	0.111442	327	0.0609866	360	0.0453757	393	0.0437026	426	0.0557121
295	0.107284	328	0.0620989	361	0.0454535	394	0.0437418	427	0.0565578
296	0.103125	329	0.0605508	362	0.0443631	395	0.0445422	428	0.0578152
297	0.0989668	330	0.0600061	363	0.0445175	396	0.0443434	429	0.057661
298	0.0948082	331	0.0607837	364	0.0448903	397	0.0441056	430	0.057126
299	0.0906497	332	0.055281	365	0.0445429	398	0.045273	431	0.0586933
300	0.0864911	333	0.0538281	366	0.0426942	399	0.0461144	432	0.0601306
301	0.0823326	334	0.0577395	367	0.0425096	400	0.0459653	433	0.0598083
302	0.081009	335	0.0531472	368	0.0425713	401	0.0455832	434	0.0597909
303	0.0734366	336	0.0537061	369	0.0416076	402	0.0452132	435	0.0598612
304	0.0770474	337	0.0558877	370	0.0424918	403	0.0454125	436	0.0605167
305	0.0817166	338	0.053881	371	0.0427891	404	0.0458626	437	0.0608478
306	0.0715372	339	0.0561191	372	0.0421452	405	0.0468896	438	0.0602749
307	0.0681478	340	0.0555438	373	0.0423332	406	0.047711	439	0.0596956
308	0.0691625	341	0.0545635	374	0.0428175	407	0.0479798	440	0.0599439
309	0.0710385	342	0.0589099	375	0.0424118	408	0.0491651	441	0.0601288
310	0.0750636	343	0.0600001	376	0.0428978	409	0.0504785	442	0.0587797
311	0.0767433	344	0.0562754	377	0.0431905	410	0.050727	443	0.0578204
312	0.0722777	345	0.0510046	378	0.0442921	411	0.0505997	444	0.0574621
313	0.0684088	346	0.0482201	379	0.0452389	412	0.0513139	445	0.0569723
314	0.0775185	347	0.0482778	380	0.0442525	413	0.0524362	446	0.0551089
315	0.073964	348	0.0458908	381	0.043693	414	0.0530084	447	0.053286
316	0.0659659	349	0.0431512	382	0.0436612	415	0.0531006	448	0.0524722
317	0.0724147	350	0.0463549	383	0.0444306	416	0.054059	449	0.0510158
318	0.071782	351	0.0477505	384	0.0446908	417	0.0548313	450	0.05
319	0.0666088	352	0.0488066	385	0.0440213	418	0.0542466	451	0.0495415
320	0.0714594	353	0.0465837	386	0.0436429	419	0.053871	452	0.0483128
321	0.0706554	354	0.042367	387	0.0447575	420	0.0538818	453	0.047082
322	0.063329	355	0.0436385	388	0.0442847	421	0.0549861	454	0.0458171

Table A.1: Input CHL Absorption Coefficients For HYDROLIGHT Simulations

$\lambda({ m nm})$	abs	λ	abs	λ	abs	λ	abs	λ	abs
455	0.04469	488	0.0334727	521	0.0194472	554	0.00969207	587	0.00863265
456	0.0441704	489	0.0329128	522	0.0191731	555	0.00936727	588	0.00875548
457	0.0436772	490	0.0327874	523	0.0185442	556	0.00919397	589	0.00853945
458	0.043288	491	0.0330238	524	0.0180555	557	0.00905533	590	0.00859392
459	0.0428096	492	0.0326664	525	0.0178579	558	0.00869526	591	0.00879703
460	0.0428029	493	0.0324024	526	0.0174976	559	0.00839566	592	0.00864516
461	0.0420534	494	0.0319693	527	0.0170058	560	0.00838824	593	0.00870095
462	0.041258	495	0.0314725	528	0.0167815	561	0.00828498	594	0.00913417
463	0.0416517	496	0.0311028	529	0.0159296	562	0.00815298	595	0.00906527
464	0.0416018	497	0.0307266	530	0.0153081	563	0.00813879	596	0.00900882
465	0.0405674	498	0.0300147	531	0.0149899	564	0.0079883	597	0.00905204
466	0.0398532	499	0.0294019	532	0.0146578	565	0.00821356	598	0.00913411
467	0.0396736	500	0.0288593	533	0.0147068	566	0.00862852	599	0.00916835
468	0.0393063	501	0.0284173	534	0.0146487	567	0.0086806	600	0.0090515
469	0.0390045	502	0.0284731	535	0.0138848	568	0.00869095	601	0.0088175
470	0.0383845	503	0.0281475	536	0.0135045	569	0.00823415	602	0.00923479
471	0.0378868	504	0.02795	537	0.01347	570	0.00775694	603	0.00996043
472	0.0376321	505	0.0274873	538	0.0132369	571	0.0080332	604	0.00964556
473	0.0372633	506	0.0267082	539	0.0129298	572	0.00803823	605	0.00934697
474	0.0368934	507	0.025787	540	0.0122634	573	0.00807043	606	0.00950974
475	0.0367049	508	0.0249729	541	0.0122548	574	0.00830263	607	0.01011
476	0.0365304	509	0.0251642	542	0.0123635	575	0.00838943	608	0.0101005
477	0.0361859	510	0.0252525	543	0.0121962	576	0.00820728	609	0.00978133
478	0.0356546	511	0.0246769	544	0.0122355	577	0.00804056	610	0.0100682
479	0.0352872	512	0.0239783	545	0.0115581	578	0.00826648	611	0.010247
480	0.034994	513	0.0233597	546	0.0106524	579	0.00825062	612	0.0103018
481	0.0345963	514	0.0227739	547	0.0107881	580	0.00831102	613	0.0104521
482	0.034436	515	0.0218247	548	0.0111495	581	0.00856794	614	0.0107118
483	0.0342864	516	0.0215426	549	0.0110339	582	0.00867449	615	0.0108639
484	0.0348232	517	0.0211907	550	0.0107722	583	0.00872945	616	0.0109778
485	0.0350503	518	0.0206175	551	0.0106038	584	0.00898368	617	0.0109987
486	0.0345614	519	0.0203868	552	0.0102597	585	0.00893686	618	0.010769
487	0.0339555	520	0.0195854	553	0.00986429	586	0.00852472	619	0.0109809

Table A.2: Input CHL Absorption Coefficients For HYDROLIGHT Simulations–part 2

$\lambda({ m nm})$	abs	λ	abs	λ	abs	λ	abs	λ	abs
620	0.0111736	653	0.0110248	686	0.0181143	719	0.00105587	752	0.000253259
621	0.0110866	654	0.0110777	687	0.0167875	720	0.000970225	753	0.000119209
622	0.0112463	655	0.0114857	688	0.0153586	721	0.000900714	754	0.000119209
623	0.0116271	656	0.0117241	689	0.0141098	722	0.00130508	755	0.000194365
624	0.0118188	657	0.012125	690	0.0128892	723	0.001276	756	0.000194365
625	0.0117108	658	0.0128803	691	0.0119374	724	0.00108465	757	0.000194365
626	0.0119102	659	0.0133625	692	0.0110427	725	0.00106979	758	0.000194365
627	0.0118279	660	0.0135732	693	0.0101619	726	0.000568639	759	0.000130984
628	0.0117673	661	0.0140785	694	0.0086621	727	0.000258094	760	0.000130984
629	0.0121338	662	0.0147456	695	0.00732307	728	0.000452467	761	0.000130984
630	0.0123476	663	0.01527	696	0.00658599	729	0.000518249	762	0.000130984
631	0.0122571	664	0.0163247	697	0.00579818	730	0.000475528	763	0.000215731
632	0.011739	665	0.0177328	698	0.00545775	731	0.000592027	764	0.000186077
633	0.0117444	666	0.0183491	699	0.00508097	732	0.000582977	765	0.000107988
634	0.011885	667	0.0187599	700	0.00453382	733	0.000479747	766	8.64E-05
635	0.0117667	668	0.019388	701	0.00428591	734	8.27 E-05	767	8.64E-05
636	0.0119688	669	0.0197808	702	0.00384094	735	0.000155961	768	8.64E-05
637	0.011997	670	0.0209332	703	0.00304189	736	0.000444593	769	0.000228951
638	0.0119948	671	0.0215718	704	0.00274437	737	0.00052365	770	0.000228951
639	0.012084	672	0.0215657	705	0.00270713	738	0.000626987	771	0.000252192
640	0.0122135	673	0.0219011	706	0.00240357	739	0.000371637	772	0.000252192
641	0.0119917	674	0.0221241	707	0.00243146	740	8.36E-05	773	0.000252192
642	0.0114093	675	0.0226847	708	0.00241044	741	3.30E-06	774	0.000252192
643	0.0109376	676	0.0229074	709	0.00219248	742	6.45 E-05	775	0.000167052
644	0.0107925	677	0.0225562	710	0.00197887	743	0.000396982	776	0.000167052
645	0.0108667	678	0.0225992	711	0.0017827	744	0.00085504	777	0.000167052
646	0.0113429	679	0.0227457	712	0.00162333	745	0.000687883	778	0.000167052
647	0.0116131	680	0.0219468	713	0.00145156	746	0.000474471	779	0.000167052
648	0.0109333	681	0.0213336	714	0.00115292	747	0.000400725	780	0.000167052
649	0.0105947	682	0.0209599	715	0.00109396	748	0.000400725	781	0.000167052
650	0.0107755	683	0.0202555	716	0.00150271	749	0.000431704	782	0.000167052
651	0.0110397	684	0.0195301	717	0.00180036	750	0.000431704	783	0.000167052
652	0.0112134	685	0.018821	718	0.00148078	751	0.000253259	784	0.000264001

Table A.3: Input CHL Absorption Coefficients For HYDROLIGHT Simulations–part 3

$\lambda({ m nm})$	abs	λ	abs	λ	abs	λ	abs	λ	abs
785	0.0002640	818	0.0005186	851	0.0005186	884	0.0005186	917	0.0005186
786	0.0002640	819	0.0005186	852	0.0005186	885	0.0005186	918	0.0005186
787	0.0002640	820	0.0005186	853	0.0005186	886	0.0005186	919	0.0005186
788	0.0002640	821	0.0005186	854	0.0005186	887	0.0005186	920	0.0005186
789	0.0002640	822	0.0005186	855	0.0005186	888	0.0005186	921	0.0005186
790	0.0002640	823	0.0005186	856	0.0005186	889	0.0005186	922	0.0005186
791	0.0006943	824	0.0005186	857	0.0005186	890	0.0005186	923	0.0005186
792	0.0005361	825	0.0005186	858	0.0005186	891	0.0005186	924	0.0005186
793	0.0004513	826	0.0005186	859	0.0005186	892	0.0005186	925	0.0005186
794	0.0001455	827	0.0005186	860	0.0005186	893	0.0005186	926	0.0005186
795	0.0001455	828	0.0005186	861	0.0005186	894	0.0005186	927	0.0005186
796	0.0001455	829	0.0005186	862	0.0005186	895	0.0005186	928	0.0005186
797	0.0005186	830	0.0005186	863	0.0005186	896	0.0005186	929	0.0005186
798	0.0005186	831	0.0005186	864	0.0005186	897	0.0005186	930	0.0005186
799	0.0005186	832	0.0005186	865	0.0005186	898	0.0005186	931	0.0005186
800	0.0005186	833	0.0005186	866	0.0005186	899	0.0005186	932	0.0005186
801	0.0005186	834	0.0005186	867	0.0005186	900	0.0005186	933	0.0005186
802	0.0005186	835	0.0005186	868	0.0005186	901	0.0005186	934	0.0005186
803	0.0005186	836	0.0005186	869	0.0005186	902	0.0005186	935	0.0005186
804	0.0005186	837	0.0005186	870	0.0005186	903	0.0005186	936	0.0005186
805	0.0005186	838	0.0005186	871	0.0005186	904	0.0005186	937	0.0005186
806	0.0005186	839	0.0005186	872	0.0005186	905	0.0005186	938	0.0005186
807	0.0005186	840	0.0005186	873	0.0005186	906	0.0005186	939	0.0005186
808	0.0005186	841	0.0005186	874	0.0005186	907	0.0005186	940	0.0005186
809	0.0005186	842	0.0005186	875	0.0005186	908	0.0005186	941	0.0005186
810	0.0005186	843	0.0005186	876	0.0005186	909	0.0005186	942	0.0005186
811	0.0005186	844	0.0005186	877	0.0005186	910	0.0005186	943	0.0005186
812	0.0005186	845	0.0005186	878	0.0005186	911	0.0005186	944	0.0005186
813	0.0005186	846	0.0005186	879	0.0005186	912	0.0005186	945	0.0005186
814	0.0005186	847	0.0005186	880	0.0005186	913	0.0005186	946	0.0005186
815	0.0005186	848	0.0005186	881	0.0005186	914	0.0005186	947	0.0005186
816	0.0005186	849	0.0005186	882	0.0005186	915	0.0005186	948	0.0005186
817	0.0005186	850	0.0005186	883	0.0005186	916	0.0005186	949	0.0005186
								950	0.0005186

Table A.4: Input CHL Absorption Coefficients For HYDROLIGHT Simulations–part 4

Tables A.5, A.6, A.7, and A.8 show the chlorophyll scattering coefficients used as inputs to HYDROLIGHT for the reflectance simulations used in this research. This curve utilizes data from (Bukata et al., 1979), and is extrapolated into the NIR for our purposes. A plot of the coefficients is shown in Figure A.2.



Figure A.2: Plot of spectral scattering coefficients for CHL

$\lambda(\text{nm})$	scat	λ	scat	λ	scat	λ	scat	λ	scat	λ	scat
290	0.128	323	0.128	356	0.128	389	0.128	422	0.1184	455	0.105
291	0.128	324	0.128	357	0.128	390	0.128	423	0.1176	456	0.105
292	0.128	325	0.128	358	0.128	391	0.128	424	0.1168	457	0.105
293	0.128	326	0.128	359	0.128	392	0.128	425	0.116	458	0.105
294	0.128	327	0.128	360	0.128	393	0.128	426	0.1152	459	0.105
295	0.128	328	0.128	361	0.128	394	0.128	427	0.1144	460	0.105
296	0.128	329	0.128	362	0.128	395	0.128	428	0.1136	461	0.105
297	0.128	330	0.128	363	0.128	396	0.128	429	0.1128	462	0.105
298	0.128	331	0.128	364	0.128	397	0.128	430	0.112	463	0.105
299	0.128	332	0.128	365	0.128	398	0.128	431	0.1115	464	0.105
300	0.128	333	0.128	366	0.128	399	0.128	432	0.111	465	0.105
301	0.128	334	0.128	367	0.128	400	0.128	433	0.1105	466	0.105
302	0.128	335	0.128	368	0.128	401	0.128	434	0.11	467	0.105
303	0.128	336	0.128	369	0.128	402	0.128	435	0.1095	468	0.105
304	0.128	337	0.128	370	0.128	403	0.128	436	0.109	469	0.105
305	0.128	338	0.128	371	0.128	404	0.128	437	0.1085	470	0.105
306	0.128	339	0.128	372	0.128	405	0.128	438	0.108	471	0.1052
307	0.128	340	0.128	373	0.128	406	0.128	439	0.1075	472	0.1054
308	0.128	341	0.128	374	0.128	407	0.128	440	0.107	473	0.1056
309	0.128	342	0.128	375	0.128	408	0.128	441	0.1068	474	0.1058
310	0.128	343	0.128	376	0.128	409	0.128	442	0.1066	475	0.106
311	0.128	344	0.128	377	0.128	410	0.128	443	0.1064	476	0.1062
312	0.128	345	0.128	378	0.128	411	0.1272	444	0.1062	477	0.1064
313	0.128	346	0.128	379	0.128	412	0.1264	445	0.106	478	0.1066
314	0.128	347	0.128	380	0.128	413	0.1256	446	0.1058	479	0.1068
315	0.128	348	0.128	381	0.128	414	0.1248	447	0.1056	480	0.107
316	0.128	349	0.128	382	0.128	415	0.124	448	0.1054	481	0.1073
317	0.128	350	0.128	383	0.128	416	0.1232	449	0.1052	482	0.1076
318	0.128	351	0.128	384	0.128	417	0.1224	450	0.105	483	0.1079
319	0.128	352	0.128	385	0.128	418	0.1216	451	0.105	484	0.1082
320	0.128	353	0.128	386	0.128	419	0.1208	452	0.105	485	0.1085
321	0.128	354	0.128	387	0.128	420	0.12	453	0.105	486	0.1088
322	0.128	355	0.128	388	0.128	421	0.1192	454	0.105	487	0.1091

Table A.5: Input CHL Scattering Coefficients For HYDROLIGHT Simulations

$\lambda({ m nm})$	scat	λ	scat								
488	0.1094	521	0.1133	554	0.1194	587	0.121	620	0.121	653	0.1114
489	0.1097	522	0.1136	555	0.1195	588	0.121	621	0.1209	654	0.1112
490	0.11	523	0.1139	556	0.1196	589	0.121	622	0.1208	655	0.111
491	0.1101	524	0.1142	557	0.1197	590	0.121	623	0.1207	656	0.1108
492	0.1102	525	0.1145	558	0.1198	591	0.1211	624	0.1206	657	0.1106
493	0.1103	526	0.1148	559	0.1199	592	0.1212	625	0.1205	658	0.1104
494	0.1104	527	0.1151	560	0.12	593	0.1213	626	0.1204	659	0.1102
495	0.1105	528	0.1154	561	0.12	594	0.1214	627	0.1203	660	0.11
496	0.1106	529	0.1157	562	0.12	595	0.1215	628	0.1202	661	0.1095
497	0.1107	530	0.116	563	0.12	596	0.1216	629	0.1201	662	0.109
498	0.1108	531	0.1161	564	0.12	597	0.1217	630	0.12	663	0.1085
499	0.1109	532	0.1162	565	0.12	598	0.1218	631	0.1198	664	0.108
500	0.111	533	0.1163	566	0.12	599	0.1219	632	0.1196	665	0.1075
501	0.1111	534	0.1164	567	0.12	600	0.122	633	0.1194	666	0.107
502	0.1112	535	0.1165	568	0.12	601	0.1219	634	0.1192	667	0.1065
503	0.1113	536	0.1166	569	0.12	602	0.1218	635	0.119	668	0.106
504	0.1114	537	0.1167	570	0.12	603	0.1217	636	0.1188	669	0.1055
505	0.1115	538	0.1168	571	0.1201	604	0.1216	637	0.1186	670	0.105
506	0.1116	539	0.1169	572	0.1202	605	0.1215	638	0.1184	671	0.1045
507	0.1117	540	0.117	573	0.1203	606	0.1214	639	0.1182	672	0.104
508	0.1118	541	0.1172	574	0.1204	607	0.1213	640	0.118	673	0.1035
509	0.1119	542	0.1174	575	0.1205	608	0.1212	641	0.1174	674	0.103
510	0.112	543	0.1176	576	0.1206	609	0.1211	642	0.1168	675	0.1025
511	0.1121	544	0.1178	577	0.1207	610	0.121	643	0.1162	676	0.102
512	0.1122	545	0.118	578	0.1208	611	0.121	644	0.1156	677	0.1015
513	0.1123	546	0.1182	579	0.1209	612	0.121	645	0.115	678	0.101
514	0.1124	547	0.1184	580	0.121	613	0.121	646	0.1144	679	0.1005
515	0.1125	548	0.1186	581	0.121	614	0.121	647	0.1138	680	0.1
516	0.1126	549	0.1188	582	0.121	615	0.121	648	0.1132	681	0.0995
517	0.1127	550	0.119	583	0.121	616	0.121	649	0.1126	682	0.099
518	0.1128	551	0.1191	584	0.121	617	0.121	650	0.112	683	0.0985
519	0.1129	552	0.1192	585	0.121	618	0.121	651	0.1118	684	0.098
520	0.113	553	0.1193	586	0.121	619	0.121	652	0.1116	685	0.0975

Table A.6: Input CHL Scattering Coefficients For HYDROLIGHT Simulations–part 2

$\lambda({ m nm})$	scat	λ	scat	λ	scat	λ	scat	λ	scat
686	0.097	719	0.0590000	752	0.0045238	785	0.0017593	818	0.0010920
687	0.0965	720	0.0575000	753	0.0043182	786	0.0017273	819	0.0010795
688	0.096	721	0.0550000	754	0.0041304	787	0.0016964	820	0.0010674
689	0.0955	722	0.0525000	755	0.0039583	788	0.0016667	821	0.0010556
690	0.095	723	0.0500000	756	0.0038000	789	0.0016379	822	0.0010440
691	0.094	724	0.0475000	757	0.0036538	790	0.0016102	823	0.0010326
692	0.093	725	0.0450000	758	0.0035185	791	0.0015833	824	0.0010215
693	0.092	726	0.0425000	759	0.0033929	792	0.0015574	825	0.0010106
694	0.091	727	0.0400000	760	0.0032759	793	0.0015323	826	0.0010000
695	0.09	728	0.0375000	761	0.0031667	794	0.0015079	827	0.0009896
696	0.089	729	0.0350000	762	0.0030645	795	0.0014844	828	0.0009794
697	0.088	730	0.0325000	763	0.0029688	796	0.0014615	829	0.0009694
698	0.087	731	0.0300000	764	0.0028788	797	0.0014394	830	0.0009596
699	0.086	732	0.0275000	765	0.0027941	798	0.0014179	831	0.0009500
700	0.085	733	0.0250000	766	0.0027143	799	0.0013971	832	0.0009406
701	0.084	734	0.0225000	767	0.0026389	800	0.0013768	833	0.0009314
702	0.083	735	0.0200000	768	0.0025676	801	0.0013571	834	0.0009223
703	0.082	736	0.0175000	769	0.0025000	802	0.0013380	835	0.0009135
704	0.081	737	0.0150000	770	0.0024359	803	0.0013194	836	0.0009048
705	0.08	738	0.0125000	771	0.0023750	804	0.0013014	837	0.0008962
706	0.0785	739	0.0118750	772	0.0023171	805	0.0012838	838	0.0008879
707	0.077	740	0.0105556	773	0.0022619	806	0.0012667	839	0.0008796
708	0.0755	741	0.0095000	774	0.0022093	807	0.0012500	840	0.0008716
709	0.074	742	0.0086364	775	0.0021591	808	0.0012338	841	0.0008636
710	0.0725	743	0.0079167	776	0.0021111	809	0.0012179	842	0.0008559
711	0.071	744	0.0073077	777	0.0020652	810	0.0012025	843	0.0008482
712	0.0695	745	0.0067857	778	0.0020213	811	0.0011875	844	0.0008407
713	0.068	746	0.0063333	779	0.0019792	812	0.0011728	845	0.0008333
714	0.0665	747	0.0059375	780	0.0019388	813	0.0011585	846	0.0008261
715	0.065	748	0.0055882	781	0.0019000	814	0.0011446	847	0.0008190
716	0.0635	749	0.0052778	782	0.0018627	815	0.0011310	848	0.0008120
717	0.062	750	0.0050000	783	0.0018269	816	0.0011176	849	0.0008051
718	0.0605	751	0.0047500	784	0.0017925	817	0.0011047	850	0.0007983

Table A.7: Input CHL Scattering Coefficients For HYDROLIGHT Simulations–part 3 $\,$

851 0.000791667 884 0.000620915 917	0.000510753
852 0.000785124 885 0.000616883 918	0.000508021
853 0.000778689 886 0.000612903 919	0.000505319
854 0.000772358 887 0.000608974 920	0.000502646
855 0.000766129 888 0.000605096 921	0.0005
856 0.00076 889 0.000601266 922	0.000497382
857 0.000753968 890 0.000597484 923	0.000494792
858 0.000748031 891 0.00059375 924	0.000492228
859 0.000742188 892 0.000590062 925	0.000489691
860 0.000736434 893 0.00058642 926	0.000487179
861 0.000730769 894 0.000582822 927	0.000484694
862 0.000725191 895 0.000579268 928	0.000482234
863 0.000719697 896 0.000575758 929	0.000479798
864 0.000714286 897 0.000572289 930	0.000477387
865 0.000708955 898 0.000568862 931	0.000475
866 0.000703704 899 0.000565476 932	0.000472637
$867 ext{ 0.000698529 900 } ext{ 0.00056213 933 }$	0.000470297
$868 ext{ 0.000693431 901 } ext{ 0.000558824 934 }$	0.00046798
$869 ext{ 0.000688406 902 } ext{ 0.000555556 935 }$	0.000465686
870 0.000683453 903 0.000552326 936	0.000463415
871 0.000678571 904 0.000549133 937	0.000461165
872 0.000673759 905 0.000545977 938	0.000458937
873 0.000669014 906 0.000542857 939	0.000456731
874 0.000664336 907 0.000539773 940	0.000454545
875 0.000659722 908 0.000536723 941	0.000452381
$876 \qquad 0.000655172 909 0.000533708 942$	0.000450237
877 0.000650685 910 0.000530726 943	0.000448113
878 0.000646259 911 0.000527778 944	0.000446009
879 0.000641892 912 0.000524862 945	0.000443925
880 0.000637584 913 0.000521978 946	0.00044186
881 0.000633333 914 0.000519126 947	0.000439815
$882 \qquad 0.000629139 915 0.000516304 948$	0.000437788
883 0.000625 916 0.000513514 949	0.00043578
950	0.00043379

Table A.8: Input CHL Scattering Coefficients For HYDROLIGHT Simulations–part 4

A.2 CDOM Absorption

A plot, Figure A.3 , and list of absorption coefficients, Tables A.9 and A.10, show the values used as input to HYDROLIGHT. Note that the coefficients are normalized with respect to the value at 350nm.



Figure A.3: Plot of spectral absorption coefficients for CDOM

A.2. CDOM ABSORPTION

Table A.9: Input CDOM Absorption Coefficients For HYDROLIGHT Simulations

λ (nm)	abs	λ	abs	λ	abs	λ	abs	λ	abs
290	3 32591	333	1 37506	376	0.606793	419	0 269439	462	0.123082
200	3.02001	334	1.34897	377	0.595786	420	0.209400 0.264241	463	0.120002 0.121044
291	3.18506	335	1.32319	378	0.555100 0.584371	421	0.204241 0.259655	464	$0.121044 \\ 0.118598$
292	3.10000 3.11779	336	1.02019 1 29822	379	0.504071 0.572854	422	0.255000 0.25517	465	0.116661
294	3 05226	337	1.27386	380	0.512001 0.561337	423	0.250482	466	0.114623
295	2.98703	338	1.25001	381	0.550839	424	0.245386	467	0.112686
296	2.92241	339	1.22708	382	0.540444	425	0.240901	468	0.110954
297	2.85973	340	1.20435	383	0.530354	426	0.236621	469	0.109119
298	2.79909	341	1.18172	384	0.520671	427	0.232238	470	0.107386
299	2.73987	342	1.1592	385	0.511091	428	0.227958	471	0.105654
300	2.68412	343	1.13769	386	0.501816	429	0.223677	472	0.104023
301	2.62705	344	1.11782	387	0.492134	430	0.219396	473	0.102189
302	2.56906	345	1.09754	388	0.482757	431	0.215319	474	0.100558
303	2.51595	346	1.07715	389	0.473482	432	0.211141	475	0.0989271
304	2.46479	347	1.05738	390	0.464208	433	0.207166	476	0.0971944
305	2.41424	348	1.03771	391	0.455341	434	0.203293	477	0.0956656
306	2.36481	349	1.01977	392	0.447187	435	0.199522	478	0.0941368
307	2.3168	350	1	393	0.439033	436	0.195853	479	0.09271
308	2.27023	351	0.979005	394	0.430472	437	0.192184	480	0.091385
309	2.22497	352	0.960863	395	0.42242	438	0.188413	481	0.0903658
310	2.17993	353	0.943435	396	0.41498	439	0.185049	482	0.0892447
311	2.13579	354	0.926516	397	0.407031	440	0.181788	483	0.0875121
312	2.09289	355	0.909088	398	0.399387	441	0.178221	484	0.0858813
313	2.0513	356	0.892067	399	0.39215	442	0.174857	485	0.0846583
314	2.01003	357	0.875454	400	0.384608	443	0.172004	486	0.0834353
315	1.96803	358	0.858739	401	0.377372	444	0.16915	487	0.0826199
316	1.92747	359	0.841311	402	0.370136	445	0.16599	488	0.0814988
317	1.88803	360	0.8248	403	0.363409	446	0.162729	489	0.0800719
318	1.84848	361	0.809919	404	0.35709	447	0.159569	490	0.0784412
319	1.81006	362	0.794733	405	0.350465	448	0.156716	491	0.0771162
320	1.7749	363	0.779446	406	0.344146	449	0.154066	492	0.0759951
321	1.74065	364	0.764667	407	0.337827	450	0.151518	493	0.0744663
322	1.706	365	0.750093	408	0.331304	451	0.148766	494	0.0734471
323	1.67165	366	0.735926	409	0.324781	452	0.146014	495	0.0725298
324	1.63853	367	0.721759	410	0.318768	453	0.143874	496	0.0721222
325	1.60663	368	0.707592	411	0.312959	454	0.141326	497	0.0713068
326	1.57524	369	0.693731	412	0.307251	455	0.138574	498	0.069778
327	1.54425	370	0.680481	413	0.302155	456	0.136332	499	0.0690646
328	1.51398	371	0.667538	414	0.296244	457	0.134089	500	0.0682492
329	1.48483	372	0.654492	415	0.290536	458	0.131541	501	0.0673319
330	1.45619	373	0.641752	416	0.284727	459	0.128891	502	0.0666185
331	1.42796	374	0.629827	417	0.279427	460	0.126547	503	0.0657012
332	1.40105	375	0.61831	418	0.274739	461	0.124917	504	0.0645801

Table A.10: Input CDOM Absorption Coefficients For HYDROLIGHT Simulations–part 2

$\lambda(\text{nm})$	abs	λ	abs	λ	abs	λ	abs	λ	abs
505	0.0638667	548	0.0349214	591	0.0179008	634	0.00923764	677	0.00281669
506	0.0633571	549	0.0341061	592	0.017697	635	0.00913572	678	0.00261285
507	0.0626436	550	0.0333926	593	0.0171874	636	0.00872804	679	0.00302053
508	0.0617263	551	0.0330869	594	0.0167797	637	0.00842228	680	0.00302053
509	0.0602995	552	0.0326792	595	0.0166778	638	0.00842228	681	0.00302053
510	0.059586	553	0.0323734	596	0.0162701	639	0.00832036	682	0.00281669
511	0.0590764	554	0.0314562	597	0.0160663	640	0.00791268	683	0.00271477
512	0.0580572	555	0.0308446	598	0.0156586	641	0.00791268	684	0.00251093
513	0.0569361	556	0.0305389	599	0.0153528	642	0.00791268	685	0.00240901
514	0.0566304	557	0.0300293	600	0.0148432	643	0.00791268	686	0.00230709
515	0.0557131	558	0.0294178	601	0.0145375	644	0.00760692	687	0.00240901
516	0.0548977	559	0.0288062	602	0.0142317	645	0.00740308	688	0.00240901
517	0.0539804	560	0.0287043	603	0.0143336	646	0.00730116	689	0.00230709
518	0.0530632	561	0.0285005	604	0.0142317	647	0.00719924	690	0.00210325
519	0.052044	562	0.0280928	605	0.013824	648	0.00709732	691	0.00189941
520	0.0512286	563	0.0275832	606	0.0135183	649	0.00679156	692	0.00149174
521	0.0509228	564	0.0269717	607	0.0134164	650	0.00668965	693	0.00149174
522	0.0504132	565	0.0264621	608	0.0129068	651	0.00648581	694	0.0012879
523	0.0500056	566	0.0262582	609	0.0128048	652	0.00658773	695	0.00149174
524	0.0490883	567	0.0258506	610	0.0131106	653	0.00668965	696	0.0012879
525	0.0480691	568	0.0256467	611	0.0127029	654	0.00618005	697	0.000982136
526	0.0470499	569	0.0251371	612	0.0123972	655	0.00567045	698	0.000778298
527	0.0463364	570	0.0248314	613	0.0120914	656	0.00556853	699	0.000676377
528	0.0458268	571	0.0247294	614	0.0123972	657	0.00556853	700	0.000676377
529	0.0454192	572	0.0244237	615	0.0120914	658	0.00536469	701	0.000370618
530	0.0452153	573	0.0237103	616	0.0115818	659	0.00505893	702	0.000472537
531	0.0452153	574	0.0230987	617	0.0111741	660	0.00465125	703	0.000268697
532	0.0445019	575	0.022793	618	0.0111741	661	0.00465125	704	0.000574458
533	0.0431769	576	0.0225891	619	0.011276	662	0.00495701	705	0.000472537
534	0.0424635	577	0.0224872	620	0.0111741	663	0.00475317	706	6.49E-05
535	0.0417501	578	0.0220795	621	0.0111741	664	0.00485509	707	6.49E-05
536	0.0411385	579	0.0216719	622	0.0106645	665	0.00465125	708	0
537	0.0404251	580	0.0213661	623	0.0107664	666	0.00454933	709	0
538	0.0395078	581	0.0210603	624	0.0108684	667	0.00434549	710	0
539	0.0389982	582	0.0203469	625	0.0107664	668	0.00424357	711	0
540	0.0386925	583	0.020245	626	0.0102568	669	0.00383589	712	0
541	0.0380809	584	0.0197354	627	0.010053	670	0.00363205	713	0
542	0.0373675	585	0.0194296	628	0.00974724	671	0.00363205	714	0
543	0.0365521	586	0.0190219	629	0.00974724	672	0.00383589	715	0
544	0.0363483	587	0.0190219	630	0.00964532	673	0.00383589	716	0
545	0.0361445	588	0.0186143	631	0.00933956	674	0.00363205	717	0
546	0.035431	589	0.0184104	632	0.00944148	675	0.00383589	718	0
547	0.0351253	590	0.0181047	633	0.00933956	676	0.00342821	719	0

A.3 Total Suspended Sediment Absorption and Scattering

The Ocean Optics Particle Simulator (OOPS) uses complex refractive index and a particle size distribution function as input, and outputs absorption and scattering coefficients and a scattering phase function that can be used as inputs into HYDROLIGHT to generate spectral reflectance. Tables A.11 and A.12 show the coefficients used in the generation of the data used in this research. Figures A.4 and A.5 illustrate these coefficients. Any further inputs needed to reproduce the results found in this thesis can be found on the accompanying data CD.



Figure A.4: Plot of spectral absorption coefficients for Total Suspended Sediment



Figure A.5: Plot of spectral scattering coefficients for Total Suspended Sediment

Table A.11: Input TSS Absorption Coefficients For HYDROLIGHT Simulations–OOPS generated

-	$\lambda(\text{nm})$	abs	λ	abs
	350	0.005237457	650	0.002922269
	360	0.005106826	660	0.002870749
	370	0.004987535	670	0.002846965
	380	0.004841762	680	0.002807601
	390	0.004754751	690	0.002751924
	400	0.004642283	700	0.00272348
	410	0.004504131	710	0.002671414
	420	0.004422552	720	0.002650153
	430	0.004331266	730	0.002621507
	440	0.004224031	740	0.002566231
	450	0.00413454	750	0.002548412
	460	0.004058995	760	0.002497006
	470	0.003970326	770	0.002467087
	480	0.003898504	780	0.002454605
	490	0.003813934	790	0.002418896
	500	0.003749875	800	0.002377239
	510	0.003674469	810	0.002349869
	520	0.003603376	820	0.002323419
	530	0.003529135	830	0.002293622
	540	0.003484429	840	0.002262937
	550	0.003401785	850	0.002246487
	560	0.003356304	860	0.002217194
	570	0.003296769	870	0.002199085
	580	0.003259145	880	0.00216943
	590	0.003203184	890	0.002144735
	600	0.003157621	900	0.002125863
	610	0.00308938	910	0.002101861
	620	0.003048804	920	0.002075346
	630	0.003012824	930	0.002051663
	640	0.002962716	940	0.002032909
			950	0.002013868
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$\lambda(\mathrm{nm})$	abs	λ	abs
350	0.26715918	650	0.28064396
360	0.26768956	660	0.28079984
370	0.26831653	670	0.28121204
380	0.26885044	680	0.28153557
390	0.26950796	690	0.28186356
400	0.26968285	700	0.28234802
410	0.27010112	710	0.28274098
420	0.27104303	720	0.28321312
430	0.2712308	730	0.28383814
440	0.27154487	740	0.28392878
450	0.27203471	750	0.28459351
460	0.27269356	760	0.28454409
470	0.27320544	770	0.28493155
480	0.27352272	780	0.28540552
490	0.27398731	790	0.28530478
500	0.27448653	800	0.28543741
510	0.27487933	810	0.28544285
520	0.27515232	820	0.28600129
530	0.2757653	830	0.28611105
540	0.27661294	840	0.28602466
550	0.27629627	850	0.28683667
560	0.27706265	860	0.28743955
570	0.27692628	870	0.28779696
580	0.277751	880	0.28810086
590	0.27817066	890	0.28849727
600	0.27869994	900	0.28893319
610	0.27914197	910	0.28926657
620	0.27962401	920	0.28954314
630	0.27999763	930	0.2898168
640	0.28034999	940	0.29010999
		950	0.29036911

Table A.12: Input TSS Scattering Coefficients For HYDROLIGHT Simulations–OOPS generated