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Air-Sea Momentum, Heat, and Carbon Dioxide Fluxes in Shallow Coastal Ecosystems

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While there is a long history of research on the exchange of mass and energy between the atmosphere and the surface below it in open ocean and terrestrial settings, those exchanges are not well understood in shallow coastal ecosystems. This thesis addresses those exchanges observationally in two locations: an intertidal salt marsh and a shallow embayment. Direct covariance methods are used to measure turbulent fluxes of carbon dioxide, momentum, and heat. Additionally, the effect of light scattering on albedo and net shortwave heat flux is studied with a radiative transfer model for test cases representing a wide range of coastal systems: bright sand bottoms, seagrass canopies, and highly turbid waters.

Over the marsh, the observed fluxes depend on the timing of both solar noon and tidal inundation. Inundation suppresses the exchanges of momentum, carbon dioxide, sensible heat, and moisture. The inundation effect is greatest at midday. A carbon dioxide flux model incorporating these factors is developed and used to estimate the net vertical seasonal carbon exchange for the marsh system with and without inundation.

In the coastal embayment, the observed momentum and heat fluxes are compared to estimates generated by existing parameterizations. The COARE 3.5 bulk flux algorithm underestimates the observed wind stress, but estimates observed values well after a simple modification to the roughness length parameterization. Unexpectedly, the buoyancy flux estimated by COARE 3.5 is in good agreement with observations.
The radiative transfer model indicates a commonly used open-ocean parameterization of albedo provides a reasonable estimate of net shortwave heat flux in most shallow coastal waters with depths $> 1$ m. The exceptions are environments with bright sand bottoms or highly turbid water with total suspended matter concentrations $\geq 50$ g m$^{-3}$. In those cases, the albedo increases enough to substantially reduce net shortwave heat flux into the water. Guidance is provided to researchers who need to determine albedo in highly reflective or highly turbid conditions but have no direct observations.

This thesis illustrates the potential consequences of using parameterizations developed in non-coastal environments, and provides examples of how to modify the parameterizations for successful use in shallow ecosystems.
Air-Sea Momentum, Heat, and Carbon Dioxide Fluxes in Shallow Coastal Ecosystems

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APPROVAL PAGE

Doctor of Philosophy Dissertation

Air-Sea Momentum, Heat, and Carbon Dioxide Fluxes in Shallow Coastal Ecosystems

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Chapter 1

Introduction

In 2010, President Obama issued Executive Order 13547, establishing the National Ocean Policy for stewardship of the ocean, coasts, and the Great Lakes. In the same year, 39% of Americans lived in coastal counties and the population in these areas is expected to increase by 8% by 2020 (NOAA, 2017). Shallow coastal marine systems are simultaneously treasured by the public and among the systems most vulnerable to human activity and development. Air-sea momentum, heat, and carbon dioxide fluxes between the atmosphere and marine systems play an important role in determining the physical characteristics of these ecosystems; understanding them will help predict how the systems may respond to changing environmental conditions to inform sustainable management decisions. Much work on these fluxes has been done in terrestrial settings and in the open ocean, but in the complex, dynamic environment of the coastal boundary the fluxes are less explored.

This thesis examines the momentum, heat, and carbon dioxide fluxes in an intertidal salt marsh; momentum and heat fluxes in a shallow embayment; and the net shortwave radiative flux for three test cases: a bright sand bottom, a seagrass canopy, and highly turbid water.

This thesis is organized to facilitate the publication of each chapter individually. Therefore, introduction and conclusion chapters unify the overall theme of the work, and specific introductions and conclusions are presented for each chapter. All chapters investigate surface fluxes, but each chapter has a more specialized focus.
Chapter 2 addresses these questions:

1. How are the magnitude and direction of the vertical air-marsh momentum, heat, and carbon dioxide fluxes over an intertidal salt marsh dependent on the timing of solar noon and tidal inundation?

2. Can the net CO$_2$ flux be modeled as a function of irradiance, temperature, and inundation; and if so, what is the inundation effect on the seasonal carbon exchange of the marsh system and the air above it?

In situ instruments collected data for one year in the Freeman Creek salt marsh in Jacksonville, North Carolina, USA. The direct covariance (DC) method is used to calculate the turbulent fluxes and supporting measurements are used to calculate the radiative heat fluxes. Sediment and water temperatures, along with water level records on the marsh are used in conjunction with the CO$_2$ flux and solar irradiance measurements to develop a model of CO$_2$ flux. This model is used to gap-fill missing data and estimate an seasonal net vertical carbon exchange for the marsh system.

Chapter 3 addresses these questions:

1. Under what conditions does the COARE 3.5 bulk flux algorithm (Edson et al., 2013) accurately estimate wind stress in a shallow coastal embayment?

2. Can the COARE 3.5 bulk algorithm be modified to produce more accurate wind stress estimates in this shallow coastal embayment?

A floating platform was anchored for six months in the center of Mumford Cove, Groton, Connecticut, USA. The DC method is used to calculate observed wind stress, and bulk quantities are input to the COARE 3.5 bulk flux algorithm to generate bulk estimates of the wind stress. The bulk algorithm underestimates the observed wind stress. Data is subdivided into eight wind sectors, each corresponding with a different terrain type around the cove. For each wind sector a model of roughness length as a function of wind speed is derived. The empirically derived roughness length parameterization is used in place of the standard parameterization in COARE to improve wind stress estimates from the algorithm.

Chapter 4 addresses these questions:

1. Under what conditions does the COARE 3.5 bulk flux algorithm accurately
estimate buoyancy flux in a shallow coastal embayment?

2. Can the COARE 3.5 bulk algorithm be modified to produce more accurate buoyancy flux estimates in this shallow coastal embayment?

The buoyancy fluxes using the Mumford Cove data calculated using the DC method and the bulk algorithm are compared. Unlike the wind stress, the observed and estimated values are in good agreement. This chapter provides initial analysis and discussion of these unexpected results.

Chapter 5 addresses these questions:

1. Should changes be made to the parameterization of the shortwave surface heat flux (i.e. albedo) in coastal waters?

2. Under what conditions should investigators directly measure the albedo?

A sensitivity analysis using observations and models predicts the effect of light scattering on albedo and the net shortwave heat flux for three test cases: a bright sand bottom, a seagrass canopy, and highly turbid water. The albedo values from the test cases are compared to albedo using the commonly used parameterization by Payne (1972). Model results provide guidance to researchers who need to determine albedo in highly reflective or highly turbid conditions but have no direct observations.

Chapter 6 summarizes significant findings from each of the four main chapters and general conclusions and implications of this work are described.
Chapter 2

Surface Momentum, Heat, and Carbon Dioxide Fluxes in Freeman Creek Salt Marsh

Tidal salt marshes have been identified as significant carbon sinks per area (Chmura et al., 2003; Connor et al., 2001). The preservation and restoration of these ecosystems are being proposed as a method of carbon offset in the global carbon budget in the face of climate change (Chmura, 2013; Mcleod et al., 2011). The extent of future areal coverage of salt marshes in response to sea level rise is of concern (Kirwan and Guntenspergen, 2009; Nicholls, 2004; Morris et al., 2002). However, biophysical feedbacks and thoughtful management practices may allow many marshes to migrate, rather than disappear (Kirwan and Megonigal, 2013). To anticipate how environmental changes may affect the carbon and heat budgets in salt marsh systems, we must gain a better understanding of the processes that control the marsh carbon budget under current conditions.


2.1 Introduction

2.1.1 Salt Marsh Carbon Budget

A box model carbon budget of a salt marsh ecosystem includes the vertical exchange of carbon between the marsh and atmosphere due to uptake of carbon dioxide (CO$_2$) by photosynthesis and the release of CO$_2$ and methane (CH$_4$) by respiration; lateral import and export of carbon via sediment and particulate deposition and dissolved and particulate transport in porewater and overlying tidally exchanged waters; and storage in biomass and accumulated sediments (Figure 2-1). While CH$_4$ release plays a nontrivial role in the carbon budgets in some freshwater or oligohaline wetlands, methane respiration in mesohaline marshes comprises only $\sim 2\%$ of the combined CH$_4$ and CO$_2$ respiration, due to the abundance of sulfate in seawater which inhibits methanogenesis during the reduction of organic matter (Weston et al., 2014). Therefore, in mesohaline marshes, CO$_2$ flux provides a reliable estimate of total air-marsh carbon exchange. Lateral exchange may play an important role in the carbon budget of salt marshes, particularly those with high tidal amplitude (e.g. Wang et al., 2018, 2016), but is not the focus of this study. The air-marsh CO$_2$ exchange is the component of the salt marsh carbon budget we focus on in this study because the magnitude of carbon storage in marshes depends ultimately on net CO$_2$ exchange between the marsh and atmosphere. CO$_2$ fluxes measured at the air-marsh interface are used to estimate how much atmospheric carbon is incorporated into the marsh plants.

In this study, we are interested in both observing and modeling the vertical flux of carbon dioxide, $F_{CO_2}$, between the air and the marsh. To date, few studies to assess $F_{CO_2}$ have been done in salt marshes and even fewer have included momentum or heat fluxes as context.
2.1.2 Measuring Air-Marsh CO\textsubscript{2} Exchange with Community Chambers or the Direct Covariance Method

The community chamber method can be used to measure the uptake or release of CO\textsubscript{2} by the marsh (Weston et al., 2014; Neubauer et al., 2000). Chambers are placed over a small section (\(\sim 1\) m\textsuperscript{2}) of vegetation and the change in CO\textsubscript{2} concentration over several minutes is used to calculate the \(F_{CO_2}\) into the marsh at a given light intensity. Shade cloths are used to create lower light conditions and a fully darkened chamber is used to estimate the \(F_{CO_2}\) due to respiration alone. Typical chamber measurements consist of a small number of measurements per year, at a single site in the marsh with replicate chambers, during low tide in daytime. Because these data sets are temporally and spatially limited, they must be extrapolated to generate an annual carbon uptake rate.

Carbon dioxide exchange between the marsh and atmosphere can also be measured with direct covariance (DC) (i.e. eddy correlation) methods. Turbulent eddies are created in the atmospheric boundary layer when friction at the air-sea or land interface generates vertical shear in the wind profile (Stull, 1988). The coefficient of eddy viscosity is several orders of magnitude larger than molecular kinematic viscosity, and therefore turbulent exchange, rather than molecular diffusion, is responsible for most of the transfer of heat and gases between the air and marsh. The DC method can be used to measure the fluxes of momentum, heat and gases.

The DC method involves using a sonic anemometer and infrared gas analyzer mounted above the air-sea or air-land interface, sampling at 10 to 20 Hz, and correlating fluctuations in vertical wind velocity \(w'\) with fluctuations in horizontal wind velocity \(u'\) (or air temperature \(T'\), specific humidity \(q'\), carbon dioxide \(c'\)) to determine the vertical momentum \(\tau\) (sensible heat \(Q_H\), latent heat \(Q_E\), carbon dioxide \(F_{CO_2}\)) fluxes

\[
\tau = \rho_a w'u'
\] (2.1)
\[
Q_H = \rho_a c_p \bar{w}'T'
\]  
(2.2)

\[
Q_E = \rho_a L_v \bar{w}'q'
\]  
(2.3)

\[
F_{CO_2} = \rho_a \bar{w}'c'
\]  
(2.4)

where \(\rho_a\) is the density of air, \(c_p\) is the specific heat capacity of air, \(L_v\) is the latent heat of vaporization, the overbar denotes an appropriate time average, typically 30 minutes for terrestrial \(F_{CO_2}\) measurements (fluxnet.fluxdata.org), and prime indicates fluctuations about that time average. By meteorological convention downward fluxes are negative. Compared to chamber measurements, the DC method provides estimates of the \(F_{CO_2}\) at a much higher temporal resolution over a broader range of conditions (night and day, flooded and dry conditions), incorporates data from a larger area, and allows the \(F_{CO_2}\) to be evaluated in the context of heat and momentum fluxes.

Chamber studies comparing \(F_{CO_2}\) measurements during inundated and non-inundated periods indicated that there was no statistically significant effect of tidal inundation on GPP (Neubauer et al., 2000). This conclusion was applied to a more recent 4-year study of marshes along the Delaware River, and therefore annual C uptake estimates were based only on flux chamber data collected in non-flooded conditions (Weston et al., 2014). Recently, however, the DC method has been used in several salt marsh systems and in all cases showed that inundation decreases the exchange of \(F_{CO_2}\) between the air and the marsh (Forbrich and Giblin, 2015; Maffett et al., 2010; Kathilankal et al., 2008). Therefore, there is a need to resolve the differences in net CO\(_2\) uptake based on chamber and DC methods. In non-marsh systems, the fluxes of various greenhouse gases estimated by DC and chamber methods have been compared, with varying results (Krauss et al., 2016; Budishchev et al., 2014; Teh et al., 2011; Norman et al., 1997; Christensen et al., 1996). No study has yet compared DC measurements to chamber estimates in an intertidal salt marsh system.
After quality assurance, time series of fluxes calculated using the DC method will typically retain 40% to 80% of the fluxes (Papale et al., 2006). Gaps in the time series must be filled with modeled flux values before the time series is integrated to determine the seasonal or annual carbon exchange by the system. An accurate estimate of net C exchange is vital to an accurate salt marsh carbon budget (Section 2.1.1). The term Net Ecosystem Exchange \( NEE \) represents the net vertical exchange of CO\(_2\) between the air and the marsh. In a terrestrial environment without flooding, \( F_{CO_2} \) and \( NEE \) are equivalent. The time integrated \( NEE \) is used to estimate an annual or seasonal net carbon exchange of an ecosystem and the air above it. To model \( NEE \), observed \( F_{CO_2} \) is used to develop two separate models: one for gross primary production \( GPP \) and one for ecosystem respiration \( R_{eco} \), then \( NEE \) is calculated as

\[
NEE = GPP + R_{eco}.
\]  

\( GPP \) is the gross daytime \( F_{CO_2} \) and is modeled as a function of irradiance (e.g. Lasslop et al., 2010; Falge et al., 2001; Jassby and Platt, 1976). \( R_{eco} \) is the nighttime \( F_{CO_2} \) and is modeled as a function of air or sediment temperature (Lloyd and Taylor, 1994; Reichstein et al., 2005). Another model generates estimates of \( NEE \) as a function of photosynthesis, which is determined as a function of leaf area index (LAI) and photosynthetic photon flux density, and respiration, determined as a function of LAI and air temperature (Rastetter et al., 2010; Shaver et al., 2007). The Shaver et al. (2007) model is referred to as the PLIRTLE model due to its functional representation of \( NEE \): \( P(L, I)R(T, L) \) (Rastetter et al., 2010). The aforementioned models were developed for terrestrial environments and do not consider the effect of tidal flooding. Forbrich and Giblin (2015) modified the PLIRTLE model to incorporate the effect of inundation on \( NEE \) in a salt marsh using normalized difference vegetation index (NDVI) as an indicator of inundation, Reichstein et al. (2005) for components of the \( R_{eco} \) term, and Lasslop et al. (2010) to calculate reference values for both \( GPP \) and \( R_{eco} \) terms.
2.1.4 Air-Marsh Heat and Momentum Fluxes

In addition to quantifying the air-marsh carbon flux, we seek to understand the temporal variations in the vertical exchanges of momentum and heat in the marsh. Since turbulent exchange drives $F_{CO_2}$ at the air-marsh interface, analyzing variations in the momentum and heat fluxes also governed by turbulence will allow variations in $F_{CO_2}$ to be put into context beyond the physiological response of the biota. For example, sediment temperature has a strong effect on respiration and the air-marsh heat fluxes will have a strong effect on sediment temperature. The effects of flooding on heat fluxes into a marsh were briefly mentioned for the May-October 2007 dataset at the Virginia Coastal Reserve Long Term Ecological Research site (Kathilankal et al., 2008) and were evaluated in more detail for an 11-day dataset from a San Francisco salt marsh (Moffett et al., 2010), but a more comprehensive analysis will be possible with the longer time series from this project.

Net heat exchange across the air-marsh boundary, $Q_{net}$, is composed of six flux terms:

$$Q_{net} = Q_{SW\downarrow} + Q_{SW\uparrow} + Q_{LW\downarrow} + Q_{LW\uparrow} + Q_H + Q_E \quad (2.6)$$

where $Q_{SW\downarrow}$, $Q_{SW\uparrow}$ are downwelling and upwelling solar shortwave radiation, $Q_{LW\downarrow}$, $Q_{LW\uparrow}$ are downwelling and upwelling infrared longwave radiation, $Q_h$ is sensible heat flux, and $Q_E$ is latent heat flux. By meteorological convention, downward fluxes are negative. Pyranometers are used to measure both shortwave radiation fluxes, and a pyrgeometer is used to measure the downwelling longwave radiation flux. The Stefan-Boltzmann law for black-body radiation is used with the sea surface skin temperature or sediment surface temperature to calculate the upwelling longwave radiation flux. To account for the water temperature in the top few millimeters of the air-sea interface, a cool-skin adjustment of approximately -0.3 K can be made to the bulk water temperature (Fairall et al., 1996). Both $Q_H$ and $Q_E$ can be estimated using the DC method described in Section 2.1.2.
2.1.5 Scope Of This Project

The purpose of this project is to use *in situ* instruments and the DC method to calculate the observed vertical air-marsh momentum, heat, and carbon dioxide fluxes over an intertidal salt marsh; evaluate the dependence of the magnitude and direction of these fluxes on the timing of solar noon and tidal inundation; and use the observed CO$_2$ flux, irradiance, surface temperature, and water depth to develop models and estimate the total seasonal exchange of carbon between the air and the marsh.

The remainder of this chapter is organized as follows: Section 2.2 describes the study site, data collection, processing, and quality assurance methods; Section 2.3 reports our results on annual, monthly, and weekly time scales, Section 2.4 describes the development of the models used to estimate air-marsh CO$_2$ exchange, Section 2.5 provides estimates of seasonal carbon exchange per area of the Freeman Creek marsh system, and Section 2.6 concludes with a discussion.

2.2 Methods

2.2.1 Study Site

This study was conducted from 21 October 2015 - 4 October 2016 at the Freeman Creek salt marsh in Marine Corps Base Camp Lejeune, Jacksonville, North Carolina, USA (Figure 2-2 a) as part of the Coastal Wetlands Module (CW-4) of the Defense Coastal/Eastuarine Research Program (DCERP). The site is dominated by *Spartina alterniflora* and is inundated twice daily by the tide. The depth range of tidal water on the marsh is 0.9 m and the mean inundated depth is 0.2 m. Refer to the DCERP2 final report (dcerp.rti.org) for further detail on the species distribution and a digital elevation model.

2.2.2 Data Collection

Micrometeorological and supporting measurements to calculate marsh-atmosphere carbon, sensible and latent heat, and momentum fluxes were collected at a flux tower.
located at 34.594823° N, 77.251539° W (Figure 2-2 b,c). Sonic air temperature and three-dimensional wind velocities were measured by a sonic anemometer (Campbell Scientific CSAT-3), and carbon dioxide and water vapor molar concentrations were measured by an open path infrared gas analyzer (LI-COR Biogeosciences LI-7500). The CSAT-3 and LI-7500 were mounted 3.4 m above the marsh surface and the positive x-axis of the sonic anemometer pointed south. A data logger system (Campbell Scientific CR1000) recorded raw data at 20 Hz.

The following were sampled every 2 seconds and 1 minute means were recorded to the CR1000: air temperature, barometric pressure, and humidity (Vaisala PTU200), downwelling and upwelling shortwave radiation (downwelling: Kipp and Zonen CMP 21, upwelling: Eppley 8-48), and downwelling longwave radiation (Kipp and Zonen CG4).

Located ∼ 3 m southwest of the flux tower, pressure and temperature of the air or water were measured and internally logged at a water level sensor (Onset HOBO U20L-04). The water level sensor was positioned 0.02 m below the sediment surface from 21 October 2015 to 8 December 2015 and at 0.10 m above the air-sediment interface from 8 December 2015 to the end of the study. The elevation of the air-sediment interface at the water level sensor location was 0.08 m NADV 88 on 16 June 2016 (pers. comm., Anna Hilting, NOAA, 11 December 2017). Sediment temperatures were measured along a vertical array of buried temperature sensors (Onset HOBO U22-001). From 21 October to 8 December 2015 the temperature sensors were installed at 0.05 m, 0.08 m, and 0.2 m below the sediment surface, and from 8 December 2015 to the end of the study, temperature sensors were installed at depths of 0.005 m, 0.05 m, 0.1 m, 0.2 m, 0.3 m, 0.4 m, and 0.5 m below the sediment surface. The HOBO sensors logged measurements at 5 minute intervals from 21 October 2015 to 8 December 2015, and at 15 minute intervals for the remainder of the study.

Instruments were cleaned and data downloaded on 8 December 2015; 8 January, 28 March, 16 June, 4 August, and 4 October 2016. The last data download was completed days before the landfall of Hurricane Matthew, which damaged the flux
tower and prematurely ended data collection for this project.

Colleagues at the Virginia Institute of Marine Science collected community chamber $F_{CO_2}$ measurements in the Freeman Creek marsh near our flux tower in July and October 2015, and February, May and July 2016, and will independently generate carbon exchange estimates for the marsh to which our results may be compared. That comparison is not included in this dissertation.

2.2.3 Filling Missing Meteorological Data

The Vaisala PTU200 failed from 23 April - 4 August 2016 and various methods were used to estimate the missing air temperature, air pressure, and relative humidity measurements. Missing air pressure data was filled using a 1 year data set from New River Marine Corps Air Station KNCA (34.7073361° N, 77.4451639° W) obtained by request from the State Climate Office of North Carolina at NC State University, CRONOS database (climate.ncsu.edu/cronos). KNCA is located ∼ 20 km northwest of our Freeman Creek flux tower. Air pressure, air temperature, and relative humidity for a 2 m height above the 26 feet above sea level height of the KNCA station are reported hourly. Air pressure from KNCA and the Vaisala PTU200 for all overlapping times (October 2015-October 2016, excluding 23 April-4 August) are in excellent agreement and a best-fit linear equation was used to fill in hourly values for the missing air pressure measurements at Freeman Creek. Those hourly values were then linearly interpolated to 1 minute intervals in order to match the time intervals of the rest of the Vaisala PTU200 data.

Air temperature and relative humidity from KNCA did not have a consistent relationship with the observed Freeman Creek data. This was expected as local conditions are important for air temperature and relative humidity, but air pressure tends to have a larger spatial scale.

To fill the missing air temperature data at Freeman Creek, air temperature from the Vaisala PTU200 was plotted against the sonic anemometer air temperature for multiple solar irradiance classes (≤ 0, 0-10, 10-20, 20-50, 50-100, 100-200, 200-300, 300-400, 400-500, 500-600, 700-800, 900-1100 W m$^{-2}$) using data from 13-23 April.
and 5 August-28 September, but excluding 28 August-3 September due to atypical conditions during Hurricane Hermine. A best-fit linear equation was generated for each solar irradiance class and used to fill the missing air temperature data.

Relative humidity $RH$ can be calculated as

$$RH = \frac{q}{q_{sat}} \times 100\% \quad (2.7)$$

where $q_{sat}$ is the specific humidity of saturated air. Calculating $q$ requires virtual air temperature $T_v$, air pressure, and water vapor content (g m$^{-3}$). Virtual air temperature can be calculated using air temperature and observed specific humidity, where observed specific humidity is calculated using air pressure and relative humidity. Since we did not have observations of relative humidity, and therefore could not calculate virtual temperature, a different approach for estimating observed specific humidity was needed. We used sonic air temperature $T_s$ in place of $T_v$ in the observed specific humidity calculation, as the two quantities are closely related. Virtual air temperature is

$$T_v = T(1 + 0.61q) \quad (2.8)$$

while air temperature measured by the sonic anemometer is

$$T_s = T(1 + 0.51q). \quad (2.9)$$

The calculation of $q_{sat}$ usually uses air pressure and air temperature from the PTU200. We calculated $q_{sat}$ using air pressure and air temperature found by the techniques described above. When estimates of relative humidity are compared to Vaisala PTU200 observed relative humidity during the overlapping dates mentioned above, estimates and observations are within 5% relative humidity for 97% of the comparisons.
2.2.4 Calculating Water Level on the Marsh

The HOBO U20L-04 does not measure water level directly, but rather measures pressure on the sensor. In order to calculate water depth $h$, the barometric pressure $p_{\text{air}}$ signal must be removed from total pressure value $p_{\text{total}}$, then the remaining pressure signal converted to water column depth above the sensor using the hydrostatic equation, and finally the water depth must be adjusted for the mounting height of the sensor $z$:

$$h = (p_{\text{total}} - p_{\text{air}}) \rho_w g + z$$  \hspace{1cm} (2.10)

where $\rho_w$ is the density of seawater.

During the period 8 December 2015 to 4 October 2016, the water level sensor was deployed 0.10 m above the sediment interface. For times when the water depth was less than the sensor height, the water depth was determined as follows. Since the water level sensor was located 0.02 m below the sediment surface from October to December 2015, those data were used to determine the length of time required for the marsh to gain the first 0.15 m of water on the flood tide, and to lose the last 0.15 m of water on the ebb tide. Linear regressions to those data were then used in the 8 December 2015 to 4 October 2016 data set to produce water depth values for times when the water level was less than 0.10 m. The modified water level time series was then interpolated onto the 1-minute time intervals of the meteorological measurements. As a result we can more clearly identify time periods when the marsh was inundated over the full duration of this study.

2.2.5 Temperature Correction of HOBO Sensors

The temperature recorded by each of the HOBO sensors was corrected for bias, as previously determined by water bath calibration following Lentz et al. (2013). The bias correction ranged from -0.06°C to 0.06 °C.
2.2.6 Quality Assurance Filtering of Turbulent Data

Thirty-minute mean DC fluxes were calculated following a method commonly used in oceanography (pers. comm., J. Edson) whereby 10-minute means are calculated, then three 10-minute means are averaged to produce 30-minute means. Before calculating the 10-minute mean fluxes, spikes in the raw data were removed. Wind velocity components were rotated to align the 10-minute mean horizontal wind velocity with the streamwise direction and set the 10-minute mean cross-wind and vertical wind to zero. The Webb correction was applied to adjust for density effects on $Q_E$ and $F_{CO2}$ (Webb et al., 1980). Poor quality of LI-COR 7500 data results when the infrared beam is attenuated by rainwater, dew, or debris on the optical window. The automatic gain control value was used as a diagnostic measurement to indicate these conditions and values over 63 were used to exclude data. Additionally, if more than ten of the 12,000 possible 20 Hz sonic anemometer and LI-COR 7500 values per 10-minute period were missing, fluxes were not calculated for that period.

Stationarity

The DC method assumes stationarity, or invariance in turbulent conditions with time, over the averaging time. Stationarity of our data was evaluated on the 10-minute blocks of time used to make the original 10-minute means. Using $\chi$ to represent a parameter such as $u$ or $T_s$, the stationarity test compares the mean covariance over the whole averaging time interval (10 minutes), of $w'$ and $\chi'_{wi}$, to the mean covariance over several shorter intervals within that 10 minutes (four 2.5-minute periods), of $w'$ and $\chi'_{si}$. This stationarity test follows Foken and Wichura (1996) as seen in Equations 4.36 to 4.38 in Aubinet et al. (2012) and calculates the relative nonstationarity of the covariances $RN_{Cov}$:

$$RN_{Cov} = \left| \frac{w'\chi'_{si} - w'\chi'_{wi}}{w'\chi'_{wi}} \right|$$  \hspace{1cm} (2.11)

and when $RN_{Cov} < 0.3$, the time series is considered to be in steady state. For our dataset, the 30% threshold omits 5% of the data using $w'u'$ and 17% using $w'T_s'$.  

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The data is filtered for the threshold for both covariances and excludes 18% of the data.

**Integral Turbulence Characteristics**

The DC method only works if turbulent conditions exist. The ratio of the standard deviation of a turbulent parameter to its scaling parameter is nearly constant under turbulent conditions (Panofsky and Dutton, 1984). In Chapter 4.3.2.2 of Aubinet et al. (2012) evaluating this ratio is recommended as a good test of the development of turbulent conditions, and that reference provides two methods for filtering data based on these ‘integral turbulence characteristics’ (ITC). In these methods, equations for ratios that are functions of stability and use empirically-derived coefficients of ITC are compared to observed ratios by

\[
ITC_{\sigma} = \left| \frac{\frac{\sigma_{\chi}}{\lambda}}{\text{model}} - \frac{\sigma_{\chi}}{\lambda} \right|_{\text{measurement}} \quad (2.12)
\]

and if \(ITC_{\sigma} < 0.3\), well-developed turbulence can be assumed (Aubinet et al., 2012).

Using the first method with the coefficients and \(\frac{\chi}{L}\) restrictions from Table 4.2 in Aubinet et al. (2012) would lead to the elimination of 48% of the data that passed through the previous filtering. The omission of this large amount data is mainly because of the exclusion of positive values of \(\frac{\chi}{L}\) and would eliminate almost all of the nighttime data. Additionally, the observed \(ITC_{\sigma}\) for \(\frac{\sigma_w}{u^*}\) was \(\sim 0.4\), and over the threshold value (Figure 2-3).

The second method uses the coefficients and \(\frac{\chi}{L}\) restrictions from Table 1 in Thomas and Foken (2002) which are partially shown in Table 4.3 of Aubinet et al. (2012). With the \(ITC_{\sigma} < 0.3\) threshold, this method would omit 60% of the data that passed through the previous filtering with the \(\sigma_w\) test, 38% with the \(\sigma_u\) test, and 40% with the \(\sigma_{Ts}\) test, and 80% when of the data when the data is filtered to include the threshold for all three tests. The modeled ratios have more variability than the measured ratios (Figure 2-4).
Rather than following either of the ITC tests suggested in Aubinet et al. (2012) that rely on empirical equations that are functions of stability, we elected to use a more simple approach. The mean and standard deviation of the ratio of each of the quantities measured by the sonic anemometer (u, v, w, and $T_s$), to its appropriate scaling parameter ($u_*, T_{S*}$) were calculated. Data outside the limits of ± 2 standard deviations of the mean were omitted (Figure 2-5). This filtering technique omitted 5% of the data that passed through the previous filtering. When compared to exemplar ratios in Panofsky and Dutton (1984), their Table 7.1, the observed mean ratios of the Freeman Creek data are in excellent agreement (Table 2.1).

**Friction velocity threshold**

DC methods have been shown to underestimate $F_{CO_2}$ in forest systems during times of low turbulence, which leads to a systematic error since these conditions occur mainly during the night when there is a net efflux of CO$_2$ by the ecosystem (Aubinet et al., 1999; Goulden et al., 1996; Gu et al., 2005). As a consequence, $R_{eco}$ is underestimated because the $F_{CO_2}$ at ground level is not detected at the sensors above the canopy (Moncrieff et al., 1996). To reduce this systematic error, a $u_*$ threshold can be incorporated into data filtering. Whether or not this correction is necessary in the shorter canopy of a salt marsh is uncertain.

We followed Papale et al. (2006) to identify a $u_*$ threshold for our dataset. Observed nighttime $F_{CO_2}$ during non-inundated periods was first corrected for storage flux (Aubinet et al., 2001). The data set was then split into 3-month seasons to account for possible seasonal variation of vegetation structure (21 October - 31 December 2015, and in 2016, 1 January - 31 March, 1 April - 30 June, and 1 July - 30 September). The data for each season were split into six temperature classes of equal sample size according to quantiles, and for each temperature class, the set was split into 20 equally sized $u_*$ classes. Air temperature and sediment temperature classes were evaluated separately. The $u_*$ threshold is defined as the $u_*$-class where the average night-time flux reaches more than 99% of the average flux at the higher $u_*$-classes. The threshold is only accepted if for the temperature class, temperature
and \( u_* \) are only weakly correlated (|\( r \) < 0.4). The final threshold is defined as the median of the thresholds of the six temperature classes.

When this method was applied to our data, we did not see lower CO\(_2\) efflux (positive values) at low \( u_* \) classes for most of the temperature classes (Figures 2-6 to 2-9). Creating temperature classes using sediment temperature instead of air temperature did not substantially change the results, nor did using non-storage corrected \( F_{CO_2} \) (not shown). This indicates \( u_* \) filtering is not needed in this marsh ecosystem.

Additionally, we submitted our filtered data from non-flooded periods to the REddyProcWeb online tool (www.bgc-jena.mpg.de/bgi/index.php/Services/REddyProcWeb), which calculates a \( u_* \) threshold following Papale et al. (2006). REddyProcWeb provided a \( u_* \) threshold of 0.12 ms\(^{-1}\). Adding this to our filtering scheme would omit only 2% more of the data. Therefore, a \( u_* \) threshold is not included in the data filtering scheme for the Freeman Creek data.

**Limiting Wind Direction**

The mounting bracket and configuration of the CSAT3 sonic anemometer disturbs flow from certain wind directions relative to the sensors and can compromise the quality of the data. After referring to the data quality classification scheme in Foken et al. (2004), we elected to omit fluxes collected when the wind approached from \( > \pm 100^\circ \) from the +\( x \) axis of the sonic anemometer.

The drag coefficient \( C_D \) is calculated

\[
C_D = \frac{\overline{u'w'}}{U^2} \tag{2.13}
\]

where \( U \) is the mean wind speed. When plotted as a function of wind direction, \( C_D \) can reveal objects in the landscape, and this plot suggests our turbulent data may be compromised only from \( \sim 300^\circ \) to \( \sim 325^\circ \) (Figure 2-10). Thus, our decision to omit data from wind directions \( \pm 100^\circ \) from the +\( x \) axis of the sonic anemometer is conservative.
Flux Footprint

The position and size of the flux source area of the wind stress was estimated for every 30-minute flux using Flux Footprint Prediction (FFP) (Kljun et al., 2015). This flux footprint model is valid for a broad range of boundary layer conditions and generates the length, width, and shape of the footprint. It explicitly incorporates surface roughness length and assumes stationarity over the averaging period and horizontal homogeneity of the flow. Data were filtered to exclude fluxes collected when the flux footprint extended beyond 250 m in length. This flux footprint limit was chosen because the Intracoastal Waterway is 250 m from the flux tower. The area enclosed by a 250 m radius and the permitted wind directions incorporates a subset of Freeman Creek and its adjacent salt marsh (Figure 2-11).

We considered extending the extent of the flux footprint for fluxes associated with wind directions from 190-280°, to include a larger marsh footprint, but doing so added a negligible number of additional data points. We considered limiting the wind direction to 80-170° and the flux footprint length to 250 m so the source area would include exclusively marsh and not a combination of marsh and creek. However, this strict filtering scheme would eliminate 92% of the data that was collected.

Summary of Data Filtering

Overall, 67.4% of collected data were omitted from the analysis below. The percent of data excluded by each component of the filter ranges from 0.2% to 54.6% (Table 2.2). The wind direction filter eliminated the greatest percentage of the collected data due to variable dominant wind directions on seasonal and diurnal time scales.

2.2.7 Flux Calculations

The momentum, heat, and carbon dioxide fluxes were calculated for the filtered data following Equations 2.1 - 2.4, with the exception of the sensible heat flux. Since $\overline{w^\prime T^\prime}$ was not measured directly, $\overline{w^\prime T^\prime}$ was calculated as
\[
\overline{w'T'} = \overline{w'T_s'} - 0.51T(\overline{w'q'})
\]

(2.14)

where \(T\) is the mean air temperature, then \(\overline{w'T'}\) was used in Equation 2.2 to calculate \(Q_H\).

The calculations of \(Q_E\) using Equation 2.3 reflects the net vertical flux of moisture due to evapotranspiration. In this study, we do not attempt to separate the flux of latent heat into contributions from the evaporation of marsh surface water and transpiration by the marsh plants.

Net shortwave radiative heat flux was calculated with measurements from the upward- and downward-looking pyranometers

\[
Q_{SWnet} = Q_{SWdown} + Q_{SWup}
\]

(2.15)

and albedo \(\alpha\) was calculated

\[
\alpha = \frac{Q_{SWup}}{Q_{SWdown}}.
\]

(2.16)

Net longwave radiative heat flux was calculated as

\[
Q_{LWnet} = Q_{LWdown} + Q_{LWup}
\]

(2.17)

where \(Q_{LWup}\) was calculated

\[
Q_{LWup} = \epsilon \sigma T^4
\]

(2.18)

where \(\epsilon\) is the emissivity of the surface, \(\sigma\) is the Stefan-Boltzmann constant, and \(T\) is the surface temperature (K). Emissivity of seawater is 0.97 following Fairall et al. (1996) and emissivity of soil saturated with water is 0.96 (Van Bavel and Hillel, 1976). When the marsh was inundated with > 0.10 m of water, the temperature of the water level sensor was used as \(T\) and a -0.3 K cool-skin correction was applied. Otherwise the temperature measured 0.05 m below the sediment surface was used as \(T\). This mixture of temperature sources is henceforth referred to as ‘surface temperature’.
2.2.8 Atmospheric Transmission

Atmospheric transmission is the ratio of observed downwelling solar irradiance at the surface to the solar irradiance if there were no atmosphere (Payne, 1972). The no-atmosphere solar irradiance was calculated using the soradna1.m function in the MATLAB Air-Sea Toolbox (crusty.usgs.gov/sea-mat). Atmospheric transmission is used to filter data for clear-sky conditions in the monthly composites (Section 2.3.2).

2.3 Results

2.3.1 Annual Temporal Variability and Data Coverage

Over the duration of this study, the maximum observed 30-minute mean wind speed was 11.4 m s\(^{-1}\) and wind directions varied widely (Figure 2-12 a). Winds from the north generally occurred in the winter months, while dominant winds in summertime were from the southwest. After applying the data filters (Section 2.2.6), the maximum wind speed is 8.4 m s\(^{-1}\) and winds from the southwest dominate the data set (Figure 2-12 b). Wind speeds between 2 m s\(^{-1}\) and 4 m s\(^{-1}\) are most common (Figure 2-12 c).

An annual temperature cycle appears in all three records of temperature (Figure 2-13 a,b,d). Relative humidity and air pressure exhibit greater variation from October 2015 to June 2016, than from July to September 2016 (Figure 2-13 c,e). Data shown in Figure 2-13 a-e were not subjected to the filtering scheme. The scaling parameter \(\frac{\varphi}{L}\) is calculated with turbulent data, and the filtered data used in the analysis indicate both stable (positive \(\frac{\varphi}{L}\)) and unstable (negative \(\frac{\varphi}{L}\)) atmospheric conditions commonly occurred throughout the study (Figure 2-13 f).

The annual time series of filtered turbulent fluxes have more missing data in the winter than the summer due to the wind direction filter, but still provide information over the full year (Figure 2-14 a,b,d,f). The marsh \(F_{CO2}\) is small in magnitude in either direction from late January to early March, and shows a greater downward flux for the rest of the year (April through September), suggesting net autotrophy.
The sensible heat flux shows diurnal patterns, but is net upward for the year (Figure 2-14 b). Net shortwave radiative heat flux exhibits an annual cycle in response to the seasonally varying solar intensity, with minimum and maximum downward fluxes near the times of the solstices as expected (Figure 2-14 c). The latent heat flux is almost always upward, and increases from January to September (Figure 2-14 d). The longwave radiative heat flux alternates signs diurnally throughout the year, but is net upward overall (Figure 2-14 e). Wind stress is variable throughout the year and does not display any clear seasonal pattern (Figure 2-14 f).

2.3.2 Monthly Composites During Light Winds and Clear Skies

One of the objectives of this project is to determine how the magnitude and direction of the vertical air-marsh momentum, heat, and CO$_2$ fluxes are dependent on the timing of solar noon and tidal inundation. To address this objective, the fluxes and other variables were examined for each month in relation to the time of day and stage of inundation. Inundation classes are: water depth $\leq 0$ m (‘DRY’); 0 m $<$ water depth $\leq 0.2$ m (‘WET1’); 0.2 m $<$ water depth $\leq 0.4$ m (‘WET2’); water depth $> 0.4$ m (‘WET3’). In addition to the the previously described filtering methods, a wind speed range limit of 2 m s$^{-1}$ to 4 m s$^{-1}$ was applied to the data used in the monthly composite plots in order to minimize any confounding effects of atypical high or low wind speeds (see Figure 2-12 c). Data was also filtered to include clear-sky daytime values only, by requiring atmospheric transmission $> 0.6$ for midday and $> 0.3$ for the early and late portions of the daytime. These threshold values were chosen by examining the time series of downwelling solar irradiance and identifying atmospheric transmission values associated with smooth patterns of irradiance for that time of day.

Daily composites of $F_{CO_2}$ by month (Figures 2-15 and 2-16) support the patterns seen in the annual time series (Figure 2-14 a). Daytime downward and nighttime upward $F_{CO_2}$ decreases with the increasing depth of inundation to varying degrees from March through September. Daytime $F_{CO_2}$ often indicate the maximum CO$_2$ flux into the marsh during the growing season occurs mid-morning (Figure 2-16 f-k).

Monthly composites of $Q_H$ indicate the upward flux of sensible heat is generally
reduced with increasing depth of water on the marsh during daytime hours (Figures 2-17 and 2-18). The upward flux of latent heat is generally reduced with increasing depth of water on the marsh during daytime hours from March to August (Figures 2-19 and 2-20).

Monthly composites of albedo show there is little effect of inundation on the net shortwave radiative heat flux, and midday albedo is $\sim 0.07$ (Figures 2-21 and 2-22). The upward flux of longwave radiative heat is not consistently affected by increasing depth of water on the marsh (Figures 2-23 and 2-24).

Monthly composites of $\tau$ show there is no clear relationship between wind stress and depth of water on the marsh from November to February, but from March to September, increased water depth is often associated with decreased wind stress (Figures 2-25 and 2-26).

### 2.3.3 Weekly Means

Mean $F_{CO_2}$ in 7-day increments was estimated for daytime non-flooded periods, daytime inundated periods, nighttime non-flooded periods, and nighttime inundated periods, using water depth of $> 0.05$ m to define inundated periods (Figures 2-27). Periods of non-flooding are classified using water depth $\leq 0$ m. Nighttime data was defined by $Q_{SWdown} < 20$ W m$^{-2}$. Again, based on the non-gap filled time series the Freeman Creek marsh area appears to be net autotrophic for the entire year except in January.

For most of the *S. alterniflora* growing season of April to October weekly mean nighttime efflux of CO$_2$ from the marsh to the air is greater under non-flooded conditions than under inundated conditions (Figures 2-27, orange and blue). Weekly means of daytime uptake of CO$_2$ by the marsh rarely show a significant difference between non-flooded and inundated periods, except for March to May (Figures 2-27, green and yellow).
2.3.4 Air-Marsh CO₂ Exchange at Night

Nighttime $F_{CO_2}$ (i.e $R_{eco}$) is a function of both temperature and water depth (Figures 2-28 to 2-35, a). This relationship is evident using any of four reference temperatures: surface temperature, sediment temperature measured at 0.05 m below the sediment surface, temperature of the water level sensor, or air temperature.

The relationship of nighttime $F_{CO_2}$ with temperature and water depth is also evident when the entire time series (October 2015 to October 2016) or the growing season (April to October 2016) is used to generate the figures. The figures using the entire time series are discussed first. Regardless of the reference temperature used, from $\sim 10^\circ$C and above there are binned values representing each inundation class. The ‘DRY’ inundation class (Figure 2-28 to 2-31 a, orange) exhibits the greatest increase in $F_{CO_2}$ with temperature and begins increasing at $\sim 10^\circ$C, while the ‘WET1’ inundation class (cyan) begins increasing at $\sim 12^\circ$C and has $F_{CO_2}$ for the same temperature bin of $\sim 0.5 \mu$mol m$^{-2}$ s$^{-1}$ less than the ‘DRY’ values. $F_{CO_2}$ does not increase with temperature for the ‘WET2’ inundation class (green) until $\sim 22^\circ$C, and the ‘WET3’ inundation class (purple) shows $F_{CO_2}$ values of $\sim 0.5 \mu$mol m$^{-2}$ s$^{-1}$ in all bins. The ‘WET3’ inundation class includes the fewest number of observations per bin (Figure 2-28 to 2-31, b) and therefore has the largest error bars. Examining the figures using data from the growing season only, the decreased upward $F_{CO_2}$ with increasing depth is apparent over almost the full range of temperatures (Figure 2-32 to 2-35, a). Once water depth exceeds 0.2 m, the limit of the ‘WET1’ inundation class (cyan), $F_{CO_2}$ approaches 0 $\mu$mol m$^{-2}$ s$^{-1}$ for all but the highest temperature bins.

2.4 Modeling Net Ecosystem Exchange

In order to integrate $F_{CO_2}$ time series to calculate the total seasonal carbon exchange, the high quality observed $F_{CO_2}$ must be gap filled. This is accomplished by using observed $F_{CO_2}$, surface temperature, and solar irradiance to develop four models to represent the vertical CO₂ exchange during day and night for non-flooded and
inundated conditions.

2.4.1 Modeling $R_{eco}$ as a Function of Temperature in Non-Flooded Conditions

We seek to model non-flooded conditions first, and later develop a modified model to reflect the effect of inundation. Nighttime observed $F_{CO_2}$ and surface temperature data under non-flooded conditions only are used. The Lloyd and Taylor (1994) exponential model for $R_{eco}$ used in Reichstein et al. (2005) is fit to the data:

$$R_{eco\,dry} = R_{ref} \cdot e^{E_0 \left(\frac{1}{T_{ref} - T_0} - \frac{1}{T - T_0}\right)}$$  \hspace{1cm} (2.19)

where $R_{ref}$ is respiration at a reference temperature, $E_0$ is the free parameter that determines the temperature sensitivity of $R_{eco}$, $T_{ref}$ is 10°C, $T_0$ is -46.02°C, and $T$ is air or soil temperature. Using surface temperature as $T$, a weighted least squared regression in semilog space finds $E_0$ is 435 K and $R_{ref}$ is 0.247°C (Figure 2-36). The weighting scheme includes weighting by $\frac{F_{CO_2}^2}{\sigma^2}$ to account for performing a linear fit in semilog space. The structure of the error $\sigma$ is a percentage of the observed value, not a fixed value, and therefore the numerator and denominator of the weighting cancel each other. Due to some negative nighttime $F_{CO_2}$ values, we discard 6% of the nighttime $F_{CO_2}$ before performing the weighted linear regression. The modeled $R_{eco\,dry}$ has a smaller range (0 to 2.2 $\mu$mol m$^{-2}$ s$^{-1}$) compared to observed $R_{eco\,dry}$, which ranges from -0.7 to 3.7 $\mu$mol m$^{-2}$ s$^{-1}$ (Figure 2-37).

2.4.2 Modeling $R_{eco}$ as a Function of Temperature and Water Depth

To determine the inundation factor needed to model $R_{eco}$ when the marsh is flooded, Equation 2.19 is used to model $R_{eco}$ for all non-flooded and inundated conditions. The ratio of the observed $R_{eco}$ (i.e. nighttime $F_{CO_2}$) to modeled $R_{eco\,dry}$ decreases as a function of water depth on the marsh until a depth of $\sim$ 0.45 m, at which point the
ratio approaches zero (Figure 2-38, black).

An exponential equation was fit to the observed binned median values to generate a model for $R_{eco}$ during inundation called

$$R_{eco\, wet} = R_{eco\, dry} \times (A \times e^{-kh})$$  \hspace{1cm} (2.20)

where through linear fit in semilog space, $A$ is 1.02 and $k$ is 7.30. Equation 2.20 reproduces the ratio of the observed $R_{eco}$ to modeled $R_{eco\, dry}$ well except in the first depth bin (Figure 2-38, red). Observed values of the ratio in the 0.16 m water depth bin is lower than the exponential decay equation estimates. Therefore, Equation 2.20 will overestimate $R_{eco\, wet}$ for water depths $> 0$ m and $< \sim 0.05$ m.

Similar to $R_{eco\, dry}$ (Figure 2-37), modeled $R_{eco\, wet}$ has a smaller range (0 to $2 \mu$mol m$^{-2}$ s$^{-1}$) compared to observed $R_{eco\, wet}$, which has range from -2.7 to 14 $\mu$mol m$^{-2}$ s$^{-1}$, but most values of $R_{eco\, wet}$ are between -1 and 3 $\mu$mol m$^{-2}$ s$^{-1}$ (Figure 2-39).

**2.4.3 GPP as a Function of Irradiance and Water Depth**

Before $GPP$ models are created, we examine the observed $GPP$ as a function of both irradiance and water depth. The flux tower measures only the net CO$_2$ exchange, but an ‘observed’ $GPP_{obs}$ is calculated for daytime (irradiance $> 20$ W m$^{-2}$) as

$$GPP_{obs} = F_{CO_2} - R_{eco}$$  \hspace{1cm} (2.21)

where $F_{CO_2}$ is the observed flux and $R_{eco}$ is calculated with Equation 2.19 or 2.20. Since $R_{eco}$ is calculated as a function of temperature, temperature effects should not confound the relationship of $GPP$ and irradiance for different inundation classes.

Regardless of the time range of data used to create the figures, $GPP$ increases in magnitude with irradiance for all inundation classes, and the magnitude of $GPP$ at each irradiance bin decreases with increased depth of water on the marsh (Figure 2-40 a-c). The relationship between $GPP$ and irradiance appears more linear and the error bars have overlap when the October to October series is used, compared to using data from April to October (Figure 2-40 a,b). The timing of daylight and tides results in
few binned data points for inundated periods for July and August, but the general relationship shown in figures for the other time ranges can be seen (Figure 2-40 c).

The inundation effect on GPP occurs at all irradiance levels, and for the growing season, error bars between the ‘DRY’ and ‘WET1’ do not overlap once irradiance exceeds 250 W m$^{-2}$ (Figure 2-40 b). In the ∼ 650 W m$^{-2}$ irradiance bin, GPP for ‘WET1’ is 1 μmol m$^{-2}$ s$^{-1}$ smaller in magnitude than ‘DRY’, and ‘WET2’ is 2 μmol m$^{-2}$ s$^{-1}$ smaller in magnitude than ‘DRY’. From April to October, irradiance > 250 W m$^{-2}$ occurs for times between 0700 and 1700 EST (Figure 2-41) and suggest the inundation factor is important for the majority of daylight hours. Following Section 2.3.4, mean observed nighttime $F_{CO_2}$ indicates the inundation factor is important in the overnight hours as well (Figure 2-32 a).

### 2.4.4 Modeling GPP as a Function of Irradiance in Non-Flooded Conditions

The next model is for GPP under non-flooded conditions. This $GPP_{dry}$ is modeled following Lasslop et al. (2010)

$$GPP_{dry} = \frac{\alpha \beta I}{\alpha I + \beta}$$  \hspace{1cm} (2.22)

where $\alpha$ is the canopy light utilization efficiency (μmol C J$^{-1}$) and represents the initial slope of the light-response curve, $\beta$ is the maximum CO$_2$ uptake rate of the canopy at light saturation (μmol m$^{-2}$ s$^{-1}$) and $I$ is downwelling solar irradiance (W m$^{-2}$). Since the $GPP_{dry}$ vs. $I$ curve exhibits saturation of $GPP_{dry}$ at high $I$ during the growing season of April to October (Figure 2-40 b, orange), using data from this time period will yield more temporally accurate coefficients in Equation 2.22 for the growing season than if the entire time series is used. Optimized fit of the $GPP_{dry}$ vs. $I$ relationship between April and October finds $\alpha$ is -0.026 μmol C J$^{-1}$ and $\beta$ is -7.56 μmol m$^{-2}$ s$^{-1}$. Modeled values of $GPP_{dry}$ are in good agreement with $GPP_{obs}$ from -5 to 0 μmol m$^{-2}$ s$^{-1}$, and when observed GPP are < -5 μmol m$^{-2}$ s$^{-1}$, the model produces a nearly constant binned mean value of ∼ -5.8 μmol m$^{-2}$ s$^{-1}$ (Figure 2-42
2.4.5 Modeling \( GPP \) as a Function of Irradiance and Water Depth

Equation 2.22 is used to calculate a \( GPP_{dry} \) value for daytime periods under all inundation conditions and compared to \( GPP_{obs} \). Similar to \( R_{eco} \) (Figure 2-38), the ratio of \( GPP_{obs} \) to modeled \( GPP_{dry} \) decreases as depth of water on the marsh increases (Figure 2-43). However, the rate of decrease with depth for the \( GPP \) ratio is less than that of the rate of decrease with depth for \( R_{eco} \). When an exponential equation is fit to the observed binned median values to generate an exponential decay model for the \( GPP \) inundation factor

\[
GPP_{wet} = GPP_{dry} \times (A \times e^{-kh})
\]  

(2.23)

where \( A \) is 1.05 and \( k \) is 1.36 after a linear fit in semilog space. Equation 2.23 reproduces the ratio of the observed \( GPP_{obs} \) to modeled \( GPP_{dry} \) well except at depths greater than 0.5 m, where the ratio is overestimated (Figure 2-43, red). However, 94% of observed inundation depths for the full time series are < 0.5 m, so this discrepancy will not meaningfully affect the results. Modeled values of \( GPP \) underestimate observed \( GPP \) from -4.5 to 0 \( \mu \)mol m\(^{-2}\) s\(^{-1}\) by less than 1 \( \mu \)mol m\(^{-2}\) s\(^{-1}\), and the models produce a nearly constant value of \( \sim -5 \) \( \mu \)mol m\(^{-2}\) s\(^{-1}\) when observed \( GPP \) are < -5 \( \mu \)mol m\(^{-2}\) s\(^{-1}\) (Figure 2-44 a).

\( GPP \) is then modeled for all daytime periods under all inundation conditions using Equations 2.22 and 2.23. At this point, both \( R_{eco} \) and \( GPP \) have been modeled under all inundation conditions, and the models can be used to gap fill missing data from the observed \( F_{CO2} \) time series using Equation 2.5.

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2.5 Estimating Seasonal Carbon Uptake By the Freeman Creek Marsh System During the Growing Season

Sixty-three percent of the observed $F_{CO_2}$ time series between April and October 2016 require gap filling. Modeled NEE is used to gap fill the observed $F_{CO_2}$ time series (Figure 2-45 a). For comparison, the $F_{CO_2}$ time series was filled entirely with values generated by the wet and dry models, as appropriate (Figure 2-45 b, grey), and with values generated entirely by the dry models (Figure 2-45 b, red).

After gap filling, nineteen of 8933 30-min mean $F_{CO_2}$ values remain unfilled due to missing temperature, irradiance, or water depth data. The gap-filled time series is interpolated onto an uninterrupted time series from 1 April to 4 October 2016, and missing $F_{CO_2}$ are assigned values by linear interpolation.

The net vertical C exchange for the growing season is -220 g C m$^{-2}$ when the complete $F_{CO_2}$ time series gap filled by a combination of wet and dry models is integrated over time (Figure 2-46, solid black). In comparison, when the $F_{CO_2}$ time series is composed of NEE values modeled by wet and dry models and no observed $F_{CO_2}$, the net C exchange for the growing season is -209 g C m$^{-2}$ (Figure 2-46, dotted black). To quantify the effect of twice-daily inundation on the the net C exchange, a synthetic NEE time series is generated using $R_{eco\,dry}$ and $GPP_{dry}$ models only. When this marsh is modeled as being non-flooded, the net C exchange is -176 g C m$^{-2}$ (Figure 2-46, dotted red).

2.6 Discussion

The purpose of this project is to use in situ instruments and the DC method to calculate the vertical air-marsh momentum, heat, and carbon dioxide fluxes over an intertidal salt marsh; evaluate the dependence of the magnitude and direction of these fluxes on the timing of solar noon and tidal inundation; and use the observed
CO₂ flux, irradiance, surface temperature, and water depth to develop models and estimate the total seasonal exchange of carbon between the air and the marsh.

Our results reinforce certain aspects of existing literature and are contrary to others. This work continues to support the idea that inundation reduces air-marsh $F_{CO₂}$, wind stress, and sensible heat flux. Our findings on the effect of inundation on latent heat flux is contrary to observations by Kathilankal et al. (2008) and Moffett et al. (2010), who found $Q_E$ increased with inundation. Like Moffett et al. (2010) and contrary to Kathilankal et al. (2008), in our study it appears the reduction in $F_{CO₂}$ is a function of inundation depth. And contrary to Kathilankal et al. (2008), the inundation effect in Freeman Creek affects fluxes over much of the day, not just at midday flood tides. Additionally, this study provides winter estimates of these fluxes, which none of the the existing marsh DC studies provide.

The models for ecosystem respiration and gross primary production provide valuable information. Although inundation decreases $R_{eco}$ and $GPP$, the inundation effect is greater for $R_{eco}$. The twice-daily inundation of the marsh generates a larger apparent total vertical exchange of C than when the system is modeled as never being inundated. Even though the $GPP$ and $R_{eco}$ models do not fully capture the variability of the observed fluxes, the conclusion that an inundation effect exists and is a function of depth can be interpreted with confidence. The inundation effect cannot be due to limitations of the models. The decrease in $F_{CO₂}$ as a function of water depth is seen in the observed nighttime $R_{eco}$ before any modeling efforts are made. The conclusion from the chamber studies of Neubauer et al. (2000) that inundation does not affect $NEE$ is not valid in the Freeman Creek salt marsh.

In future work, all coefficients required to model $R_{eco}$ and $GPP$ could be calculated and optimized simultaneously. These coefficients will be calculated over shorter time intervals to accurately determine the temporal range over which each can be used. Other variables may be incorporated into the models for $GPP$, and $R_{eco}$. Time since inundation and time since sunset have already been evaluated and eliminated as important factors in determining $R_{eco\_dry}$ (not shown).

It is important to remember the terms $NEE$, $GPP$, and $R_{eco}$ originated in the
terrestrial flux community under the assumption that the instrumentation on the flux tower will measure ecosystem metabolism, and will represent the balance of photosynthesis and respiration of the vegetation and ground surface communities. This assumption is violated during inundation. The layer of flood water creates a barrier and prevents the signal from the efflux of CO$_2$ out of the sediments from reaching the instrumentation on the flux tower. The approximately exponential decay of the ratio of the observed $R_{eco}$ to modeled $R_{eco\,dry}$ (Figure 2-38, red) suggests the greatest reduction in $R_{eco}$ occurs right after flooding begins or ends. The continued reduction in $R_{eco}$ with increasing depth of water on the marsh may be due to the reduction in the exchange of CO$_2$ between the marsh plants and the air as a greater portion of the plants becomes inundated. Flux of CO$_2$ across the air-water boundary during the inundation period is likely to be insignificant, as the wind and current speeds at the interface are small and a surfactant-like ‘scum’ coats the surface of the water, all inhibiting the flux of CO$_2$ out of the water. Over the course of the inundation period, the concentration of CO$_2$ in the water increases, and on ebb tide, C is exported laterally out of the marsh system (Wang et al., 2018, 2016). The result is an apparent increase in the net uptake of CO$_2$ by the marsh during inundation. However, interpreting the net vertical exchange of CO$_2$ as measured by the flux tower over an inundated marsh as representing the balance of ecosystem photosynthesis and respiration would be incorrect. During inundation, the additional sources and sinks of CO$_2$ introduced by the layer of flood water must be considered.

This project focused on one element of a comprehensive carbon budget for an intertidal salt marsh, the vertical exchange of CO$_2$ between the marsh and overlying air. Standard methods used in terrestrial settings were applied and modified following existing literature for marsh settings to incorporate the effect of inundation on the vertical CO$_2$ flux. The terrestrial models did not fully capture the variability in the observations, particularly for daytime fluxes, and may result in the underestimation of the downward $F_{CO_2}$. Despite this, using these models with and without the incorporation of an inundation effect provides valuable insights on the magnitude of the lateral flux of C off the marsh, and contributes to continued advancements in the
modeling of salt marsh carbon budgets.
Table 2.1: Observed Integral Turbulence Characteristics (ratios of standard deviations of velocity components to friction velocity) Compared to Typical Values

<table>
<thead>
<tr>
<th>Ratio</th>
<th>Freeman Creek</th>
<th>Panofsky and Dutton (1984), their Table 7.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_u/u^*$</td>
<td>2.36</td>
<td>2.39 ± 0.03</td>
</tr>
<tr>
<td>$\sigma_v/u^*$</td>
<td>1.96</td>
<td>1.92 ± 0.05</td>
</tr>
<tr>
<td>$\sigma_w/u^*$</td>
<td>1.16</td>
<td>1.25 ± 0.03</td>
</tr>
</tbody>
</table>

Table 2.2: Percentage of all collected data omitted by each component of the filter

<table>
<thead>
<tr>
<th>Filter component</th>
<th>percent of data excluded</th>
</tr>
</thead>
<tbody>
<tr>
<td>automatic gain control (LI-COR 7500)</td>
<td>13.8</td>
</tr>
<tr>
<td>length of 20 Hz raw data record</td>
<td>0.2</td>
</tr>
<tr>
<td>stationarity test</td>
<td>18.5</td>
</tr>
<tr>
<td>integral turbulent characteristics test</td>
<td>28.8</td>
</tr>
<tr>
<td>wind direction</td>
<td>54.6</td>
</tr>
<tr>
<td>flux footprint length</td>
<td>3.7</td>
</tr>
<tr>
<td>all filter components combined</td>
<td>65.8</td>
</tr>
</tbody>
</table>
Figure 2-1: Conceptual box model of a salt marsh carbon budget.
Figure 2-2: Study site. a Portion of the east coast of the United States showing location of Freeman Creek (star). b Aerial view of Freeman Creek area with flux tower location (square). c Flux tower and additional instrumentation. Panels a and b by Melanie Fewings.
Figure 2-3: Comparison of modeled to measured ratios of integral turbulence characteristics (ITC). Modeled values were created using the equations in Table 4.2 of Aubinet et al. (2012). a Modeled ITC of horizontal wind. b Observed ITC of horizontal wind. c Modeled ITC of vertical wind. d Observed ITC of vertical wind.
Figure 2-4: Comparison of modeled to measured ratios of integral turbulence characteristics (ITC). Modeled values were created using the equations in Table 4.1 of *Thomas and Foken* (2002). 

a. Modeled ITC of horizontal wind. 
b. Observed ITC of horizontal wind. 
c. Modeled ITC of vertical wind. 
d. Observed ITC of vertical wind. 
e. Modeled ITC of sonic air temperature. 
f. Observed ITC of sonic air temperature.
Figure 2-5: Comparison of measured ratios of integral turbulence characteristics (ITC) (grey) and those filtered by omitting values beyond 2 standard deviations of the mean (black). a ITC of $u$ wind. b ITC of $v$ wind. c ITC of $w$ wind. d ITC of sonic air temperature.
Figure 2-6: Relationship of storage-corrected nighttime $F_{CO_2}$ during non-inundated periods to $u_*$ class in each of the six air temperature classes for 21 October-31 December 2015. Panels a-f show the relationship for each of the six air temperature classes. Panels b and d are blank because those air temperature classes failed the $|r| < 0.4$ test.
Figure 2-7: Relationship of storage-corrected nighttime $F_{CO_2}$ during non-inundated periods to $u_*$ class in each of the six air temperature classes for 1 January - 31 March 2016. Panels a - f show the relationship for each of the six air temperature classes. Panel d is blank because that air temperature class failed the $|r| < 0.4$ test.
Figure 2-8: Relationship of storage-corrected nighttime $F_{CO_2}$ during non-inundated periods to $u_*$ class in each of the six air temperature classes for 1 April - 30 June 2016. Panels a - f show the relationship for each of the six air temperature classes. Panels e and f are blank because those air temperature classes failed the $|r| < 0.4$ test.
Figure 2-9: Relationship of storage-corrected nighttime $F_{CO_2}$ during non-inundated periods to $u_*$ class in each of the six air temperature classes for 1 July - 30 September 2016. Panels a - f show the relationship for each of the six air temperature classes.
Figure 2-10: Drag coefficient as a function of wind direction. 

a. All collected values are shown (grey) as well as the subset of data used in the analysis for this project (black).

b. Vertical axis restricted to show a finer scale comparison of $C_D$. 

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Figure 2-11: Aerial view of the Freeman Creek area with 250 m and 500 m radii (red) around the flux tower. Straight lines from the flux tower represent the limits of permitted wind directions (80° to 280°).
Figure 2-12: Observed wind velocities measured at 3.4 m above the salt marsh on the Freeman Creek flux tower from 21 October 2015 to 4 October 2016. **a** All observed wind velocities. **b** Wind velocities associated with fluxes after data were filtered. **c** Histogram of wind speeds shown in b.
Figure 2-13: Annual time series of 30-min means collected from 30 October 2015 to 4 October 2016. 

- **a** Air temperature. 
- **b** Temperature of the sediment at 0.05 m below the sediment surface. 
- **c** Relative humidity. 
- **d** Temperature of the water level sensor during both non-flooded and inundated periods. 
- **e** Air pressure. 
- **f** Scaling parameter $\frac{z}{L}$.
Figure 2-14: Same as Figures 2-13 but 

a) $F_{\text{CO}_2}$ ($\mu$ mol m$^{-2}$ s$^{-1}$)

b) $Q_H$ (W m$^{-2}$)

c) $Q_{\text{SWnet}}$ (W m$^{-2}$)

d) $Q_E$ (W m$^{-2}$)

e) $Q_{\text{LWnet}}$ (W m$^{-2}$)

f) $\tau$ (N m$^{-2}$)

Figure 2-15: Carbon dioxide flux as a function of time of day and inundation depth by month. Inundation classes are: water depth \( \leq 0 \text{ m} \) (DRY, orange); \( 0 \text{ m} < \) water depth \( \leq 0.2 \text{ m} \) (WET1, cyan); \( 0.2 \text{ m} < \) water depth \( \leq 0.4 \text{ m} \) (WET2, green); water depth \( > 0.4 \text{ m} \) (WET3, purple). The top panels of a - e show monthly plots for November 2015 to March 2016. Error bars show \( \pm 2 \) standard errors about the mean. The bottom panels in a - e indicate the number of flux observations used to calculate each binned value.
Figure 2-16: Continuation of Figure 2-15 where f - k show monthly plots for April to September 2016.
Figure 2-17: Same as Figure 2-15 but for sensible heat flux.
Figure 2-18: Same as Figure 2-16 but for sensible heat flux.
Figure 2-19: Same as Figure 2-15 but for latent heat flux.
Figure 2-20: Same as Figure 2-16 but for latent heat flux.
Figure 2-21: Same as Figure 2-15 but for albedo. The horizontal axis has been limited to daytime hours in order to view the relevant values.
Figure 2-22: Same as Figure 2-16 but for albedo. The horizontal axis has been limited to daytime hours in order to view the relevant values.
Figure 2-23: Same as Figure 2-15 but for longwave radiative heat flux.
Figure 2-24: Same as Figure 2-16 but for longwave radiative heat flux.
Figure 2-25: Same as Figure 2-15 but for wind stress.
Figure 2-26: Same as Figure 2-16 but for wind stress.
Figure 2-27: Weekly mean $F_{CO_2}$.  

a Mean $F_{CO_2}$ in each 7-day increment was estimated for daytime non-flooded periods (yellow), daytime inundated periods (green), nighttime non-flooded periods (orange), and nighttime inundated periods (blue). Error bars indicate 95% confidence intervals as determine by bootstrapping. 

b The number of data points used to calculate each binned mean.
Figure 2-28: a Median nighttime $F_{CO_2}$ as a function of median surface temperature and water depth on the marsh using data from October 2015 to October 2016. Inundation classes are the same as in Figure 2-15. Error bars indicate 95% confidence intervals as determine by bootstrapping. b The number of data points used to create each binned value.
Figure 2-29: Same as Figure 2-28 but using sediment temperature measured at 0.05 m below the sediment surface.
Figure 2-30: Same as Figure 2-28 but using temperature measured at the water level sensor.
Figure 2-31: Same as Figure 2-28 but using air temperature.
Figure 2-32: Same as Figure 2-28 but using data from 1 April to 4 October 2016.
Figure 2-33: Same as Figure 2-32 but using sediment temperature measured at 0.05 m below the sediment surface.
Figure 2-34: Same as Figure 2-32 but using temperature measured at the water level sensor.
Figure 2-35: Same as Figure 2-32 but using air temperature.
Figure 2-36: Application of the Lloyd and Taylor (1994) exponential model for $R_{eco}$ using $F_{CO_2}$ and surface temperature from non-flooded nighttime observations. Observed (black) and model fit (grey).
Figure 2-37: Observed and modeled $R_{eco\,dry}$. Modeled values are from Equation 2.19 (black). Values are shown along a 1:1 line (black dashed).
Figure 2-38: Ratio of observed $R_{eco}$ to modeled $R_{eco\, dry\, modeled}$ as a function of water depth on the marsh. Ratios calculated with 30-minute mean flux values (grey), and binned median values of observed (black) and exponential fit (red) with 95% confidence intervals from bootstrapping.
Figure 2-39: Observed and modeled $R_{\text{eco wet}}$. Modeled values using Equations 2.20 and 2.20. Values are shown along a 1:1 line (black dashed).
Figure 2-40: \( GPP \) as a function of irradiance and inundation depth. Inundation classes are the same as in previous figures. The mean observed nighttime \( R_{eco} \) for each category is plotted at an irradiance equal to 0 W m\(^{-2}\). 

a) With data from 20 October 2015 to 4 October 2016. 
b) With data from 1 April 2016 to 4 October 2016. 
c) With data from 1 July 2016 to 31 August 2016. Error bars show the 95% confidence interval about the binned mean found by bootstrapping. Bins with fewer than 20 data points are not plotted.
Figure 2-41: Solar irradiance as a function of time of day. Irradiance for each 30-min mean solar irradiance from 1 April 2016 to 4 October 2016 (red), and reference irradiance of 250 W m$^{-2}$ (black line).
Figure 2-42: Observed and modeled $GPP_{dry}$. a 30-minute mean $GPP_{dry}$ values (grey) and mean binned $GPP$ (black). b Number of data points used to create each median binned value in a.
Figure 2-43: Same as Figure 2-38 but with ratio of $GPP_{\text{observed}}$ to modeled $GPP_{\text{dry}}$. 
Figure 2-44: Observed and modeled GPP. Same as Figure 2-42, but includes GPP at all inundation stages.
Figure 2-45: $NEE$ for 1 April - 4 October 2016. 

a. Observed $NEE$ (black) and $NEE$ modeled with wet or dry models, as appropriate (grey). 

b. Same $NEE$ modeled with wet or dry models, as appropriate from a (grey) and $NEE$ modeled dry models only (red).
Figure 2-46: Cumulative vertical carbon transfer for 1 April - 4 October 2016. Observed data gap-filled with wet and dry models (black). No observations, all values generated with wet or dry models, as appropriate (grey). No observations, all values generated with the dry models regardless of water level (red).
Chapter 3

Air-Sea Momentum Flux in Mumford Cove

3.1 Introduction

Understanding air-sea momentum and heat fluxes is vital to explaining and modeling the processes that govern stratification and water temperature in marine systems. Wind stress is the vertical flux of horizontal momentum between the air and water and results in surface waves and currents. When friction at the air-sea interface generates vertical shear in the wind profile, turbulent eddies are created in the atmospheric boundary layer (Stull, 1988). Since the coefficient of eddy viscosity is several orders of magnitude larger than molecular kinematic viscosity only a few centimeters above the water surface, turbulent exchange, rather than molecular diffusion, is responsible for most of the transfer of momentum and energy between the air and water. Direct measurements of turbulence in the atmospheric surface boundary layer provide the opportunity to determine how and when air-sea fluxes vary at a given location.

Wind stress is calculated using the direct covariance (DC) method or estimated using bulk formulae. The DC method uses field observations to calculate turbulent statistics from time series observations that resolve individual turbulent eddies. DC datasets are used to determine the transfer coefficient for momentum, known as the drag coefficient, which allows the development of bulk formulae. Bulk formulae allow
the turbulent fluxes to be estimated using more easily measured mean bulk quantities such as the mean wind speed.

Much work on these fluxes has been done in the open ocean. The state-of-the-art bulk flux algorithm COARE is based on the scaling laws of the Monin-Obukov Similarity Theory (MOST) and parameterizes the drag coefficient using a semi-empirical roughness length approach (Edson et al., 2013; Fairall et al., 2003, 1996). COARE provides estimates of momentum and heat fluxes using bulk measurements of air temperature, air pressure, relative humidity, wind speed relative to the surface current, sea surface temperature, and downwelling solar and long wave radiation. Originally developed as part of the Coupled Ocean-Atmosphere Response Experiment (COARE) in the western Pacific warm pool in an effort to reduce uncertainty in the total air-sea heat flux budget to less than 10 W m\(^{-2}\), the COARE algorithm has since been expanded to incorporate data sets from several field programs and can be used with confidence in open-ocean conditions at a wide range of latitudes and wind speeds. The latest version, COARE 3.5 (Edson et al., 2013), was developed using two datasets from the open ocean and two datasets from locations within 3-4 km of the coast, but for those datasets only data from open ocean fetch were used. COARE 3.5 provides improved wind stress estimates over a range of wind speeds and sea states compared to earlier versions.

Despite its development using open ocean, unlimited fetch data, the COARE bulk algorithm is used to estimate air-sea fluxes in coastal systems for lack of a better alternative. COARE is an option for the air-sea boundary layer in the Regional Ocean Modeling System (ROMS) and has been used in coastal applications (e.g., Sutherland et al., 2011; Whitney et al., 2016). In the Northeast Coastal Ocean Forecast System, which produces 3-day forecast fields of surface weather, surface icing, surface waves, water level, 3-D water temperature, salinity, and currents for the open ocean, shelf, and estuaries, inner bays, inlets, and harbors of the northeast US coastal region, COARE is used to calculate wind stress, sensible, and latent heat fluxes (Beardsley et al., 2013). A bulk flux algorithm for the coastal zone has yet to be developed, so COARE provides flux estimates that would otherwise be unavailable, or calculated
by other bulk formulae also developed in the open ocean (e.g. Smith, 1988; Large and Pond, 1981).

The accuracy of wind stress estimates by COARE for the nearshore environments being modeled is uncertain. Attempts to compare wind stress estimates from COARE using DC methods in coastal settings are limited but find that observed wind stress estimates are higher than those estimated by COARE (Fisher et al., 2015; Ortiz-Suslow et al., 2015; Brown et al., 2013; Valigura, 1995). These projects investigated the middle reaches of Chesapeake Bay, the dynamic New River Inlet (North Carolina), coastal Liverpool Bay (United Kingdom), and north Chesapeake Bay respectively. Constant values of the Charnock coefficient $\alpha$ (see Section 3.2.1) set to 0.016 (Valigura, 1995), 0.018 (Fisher et al., 2015; Lange and Højstrup, 2000), and 0.0185 (Brown et al., 2013) were used to generate satisfactory wind stress estimates with COARE. This modification accounts for the increased steepness of waves in coastal water at lower wind speeds because they tend to be shallow-, not deep-water waves.

Stationarity and homogeneity are basic assumptions of MOST: turbulent conditions are assumed to be invariant in time and space. These assumptions may be violated in coastal waters. Stationarity may be violated as winds arrive from various directions, their origins shifting from water with various fetch and depth to land with varying terrain. Diurnal cycles as well as land breeze and sea breeze conditions may strain the assumption of homogeneity.

The ability of COARE to accurately estimate wind stress in even shallower and more protected coastal waters than the above studies is unknown. This research project provided an opportunity to collect in situ data in a shallow, sheltered coastal embayment, calculate wind stress using the DC method, and compare it to estimates generated by COARE 3.5. With regard to net surface heat flux, which is also estimated by COARE, as part of the same experiment (Fogarty et al., 2018) demonstrated conditions when the albedo parameterization should be modified for use in coastal settings. The objectives of this chapter are to determine if and when the COARE bulk flux algorithm accurately estimates wind stress in this coastal environment, and when possible, modify the bulk algorithm to produce more accurate wind stress estimates.
The remainder of this chapter is organized as follows: Section 3.2 describes how wind stress is calculated; Section 3.3 introduces the study site and instrumentation; Section 3.4 explains data processing; Section 3.5 discusses how the roughness length parameterization in COARE 3.5 was modified; Section 3.6 compares observed and bulk-estimated values; and Section 3.7 presents a Discussion. Appendix A includes additional figures in support of the main results.

### 3.2 Calculating Wind Stress

Wind stress can be represented in several ways (Geernaert and Plant, 1990):

\[
\tau = -\rho_a \overline{u'w'} = \rho_a C_D U_r^2 = \rho_a u_\star^2 \tag{3.1}
\]

where \(\rho_a\) is density of air, \(\overline{u'w'}\) is the time-average covariance of the turbulent fluctuations of the streamwise component of the horizontal wind velocity \(u'\) and the vertical wind velocity \(w'\), \(C_D\) is the drag coefficient, \(U_r\) is the mean wind speed relative to the surface current, and \(u_\star\) is the Monin-Obukhov similarity scaling parameter for velocity, also known as the friction velocity. In this project, all turbulent statistics and bulk values are calculated using 10 minute means.

#### 3.2.1 Wind Stress Parameterization in COARE 3.5

The COARE bulk estimate of wind stress magnitude \(\tau\) depends on the roughness length \(z_0\). The log profile of mean wind speed will reach zero at some height above the ground \(z_0\), which represents the size of the eddies at the surface (Panofsky and Dutton, 1984). When the surface is rougher, \(z_0\) is larger. In COARE, \(z_0\) is calculated as (Edson et al., 2013; Fairall et al., 2003, 1996)

\[
z_0 = z_0^{\text{smooth}} + z_0^{\text{rough}} = \gamma \frac{\nu}{u_\star} + \alpha \frac{u_\star^2}{g} \tag{3.2}
\]

where \(z_0^{\text{smooth}}\) represents the roughness of an aerodynamically smooth ocean and \(z_0^{\text{rough}}\) represents the roughness due to surface gravity waves, \(\gamma\) is the roughness
Reynolds number for smooth flow, $\nu$ is the kinematic viscosity of air, $\alpha$ is the Charnock coefficient, and $g$ is gravitational acceleration.

COARE 3.5 provides a new parameterization of $\alpha$ compared to previous versions of COARE where

$$\alpha = 0.0017U_{10N} - 0.005$$  \hspace{1cm} (3.3)

and $U_{10N}$ is mean windspeed at 10 m above the air-sea interface adjusted to neutral atmospheric stratification. This parameterization of $\alpha$ is based on a linear fit of the 7 to 18 m s$^{-1}$ data in the four studies used in the development of COARE 3.5, and is applied to wind speeds 0 to 19 m s$^{-1}$. At wind speeds in excess of 19 m s$^{-1}$ a constant $U_{10N}$ of 19 m s$^{-1}$ is used in Equation 3.3.

Once $\alpha$ is calculated, COARE iterates six times to converge on a solution for $z_0$, $C_D$, and $u_*$. The drag coefficient is parameterized as a function of roughness length and atmospheric stability

$$C_D = \left( \frac{\kappa}{ln\left(\frac{z}{z_0}\right)} - \psi\left(\frac{z}{L}\right) \right)^2$$  \hspace{1cm} (3.4)

where $\kappa$ is the von Karman coefficient, $z$ is the measurement height of the wind speed, $\psi$ is a stability correction function, and $L$ is the Obukhov length.

Friction velocity $u_*$ is estimated as

$$u_* = S_r C_D^{1/2}$$  \hspace{1cm} (3.5)

where $S_r$ is the average wind speed relative to the surface \textit{(Fairall et al., 1996)}.

Wind stress $\tau$ is then estimated by

$$\tau = \frac{\rho_a u_*^2}{G}$$  \hspace{1cm} (3.6)

where $G$ is the gustiness parameter, which is formulated as the ratio of wind speed $S_r$ to vector-averaged wind $U_r$ \textit{(Beljaars and Holtslag, 1991)}.
COARE 3.5 also estimates the drag coefficient at neutral atmospheric stability $C_{DN}$, which enables comparisons between flux estimates collected in different stability conditions. Therefore, $C_{DN}$ is the parameter we refer to in the results when discussing the drag coefficient. Note $C_{DN}$ and $U_N$ are calculated for the observation height of 2.6 m, not the traditional 10 m height, since the adjustment to neutral conditions is a function of $z_0$. Maintaining the observed and neutral values at the same reference height, rather than scaling up to 10 m height, will avoid the effects of any inaccuracy in the conversion.

3.2.2 Calculating Wind Stress by the Direct Covariance Method

With the direct covariance method $\tau$ is calculated as

$$\tau = -\rho_a u'w'$$

as in Equation 3.1.

The drag coefficient can then be determined observationally from $\tau$ by

$$C_D = \frac{\overline{u'w'}}{U_r^2}$$

and the drag coefficient at neutral atmospheric stability by

$$C_{DN} = \frac{\overline{u'w'}}{U_N^2}$$

using the observed wind speed adjusted to neutral atmospheric conditions $U_N$, which is estimated by COARE 3.5.

Roughness length is then calculated from observations by solving for $z_0$ in

$$C_{DN} = \left(\frac{\kappa}{\ln\left(\frac{z}{z_0}\right)}\right)^2.$$  

Friction velocity $u_*$ is

$$u_* \equiv \left(-\overline{u'w'}\right)^{\frac{1}{2}}.$$
and is calculated for comparison to the COARE 3.5 estimate of $u_*$. 

The Obukhov length $L$ is calculated

$$L = \frac{-u_*^3 T_s}{\kappa gw' T_s}$$

and is used to calculate the scaling parameter $\frac{z}{L}$, which is used to filter the data (Section 3.4.5).

### 3.3 Study Site

We designed, constructed, and deployed a floating platform anchored in the center of Mumford Cove, Groton, CT, USA (41.324583° N, 72.019028° W) outfitted with instrumentation to provide the bulk inputs to COARE and to calculate wind stress and buoyancy fluxes by the direct covariance method (Figure 3-1). The platform was deployed 7 June-6 December 2016. Water depth at the platform ranges from 0.8-2 m over the tidal cycle and mean water depth is 1.5 m. The middle portion of the Cove is $\sim 500$ m wide. Terrain around the Cove varies (e.g. elevated forest, salt marsh, residential neighborhood, Cove entrance leading to Fishers Island Sound partially blocked by a sandspit).

A 6' x 8' pontoon platform was designed in order to increase platform stability in the shallow water and used instead of a traditional discus buoy. The 18" diameter foam pontoons (Gilman Corporation) and gridded fiberglass deck were through-bolted to a steel frame. The deck gridding allowed for modular arrangement of the instrumentation, power supply, and data logger. A length of chain was attached to the two corners of each short side of the steel frame from which an anchor chain and a 70 pound pyramid anchor (Dor-Mor, Inc.) was run off each midpoint. The platform was deployed with the long sides facing north and south to provide the most stable configuration relative to waves approaching from the longest fetch within the cove.

Measurements included downwelling and upwelling shortwave irradiance (Kipp & Zonen CMP21), downwelling longwave irradiance (Kipp & Zonen CG4), relative
humidity and air temperature (Vaisala HMP155A), barometric pressure (Campbell Scientific CS100). Output from these sensors was sampled every 2 seconds and mean values recorded at 1-minute intervals. Three-dimensional wind velocity and air temperature were recorded at 10 Hz by an ultrasonic anemometer (Gill Windmaster) positioned 2.6 m above the water surface. An attitude heading reference system (LORD MicroStrain 3DM-GX4-25) located next to the base of the sonic anemometer measured roll, pitch, yaw, and estimated 3D linear acceleration at 5 Hz. The data were recorded to a compact flash card on a data logger (Campbell Scientific CR1000 & CFM100). Additionally, water temperature and salinity were measured at 0.3 m below the water surface (Sea-Bird Electronics SBE 37-SMP); turbidity, chlorophyll and colored dissolved organic matter (CDOM) fluorescence were measured at 0.12 m below the water surface (Sea-Bird Electronics ECO Triplet-wB); and data were recorded internally at 15-minute intervals. Bottom pressure (Onset HOBO U20L-04) and water temperature (Onset HOBO U22-001) at multiple depths from the surface to 0.2 m above the bottom were internally recorded at 5 minute intervals at a separately anchored station ∼ 50 m north of the platform. Biweekly, the data card was retrieved and replaced, and the instruments were cleaned and inspected.

3.4 Data Processing

3.4.1 Wind Sectors

Subsets of the data were created using wind direction to filter for similar terrain types. The ‘MARSH’ wind sector includes data corresponding to wind directions clockwise from 345˚T to 10˚T where the approaching wind passed over the salt marsh before traveling over the water surface to the sonic anemometer on the platform. ‘HALEY’ (20˚T to 50˚T) consists of the wind approach that includes elevated forest then homes before reaching the Cove. ‘MCA’ (75˚T to 140˚T) and ‘GLP’ (145˚T to 165˚T) both include homes but are different in the composition and extent of vegetation. ‘MCA’ contains homes, trees, and Palmer Cove further to the east, while ‘GLP’ has homes,
trees, and marshes. ‘WATER’ (170°T to 205°T) is the wind sector most closely associated with an extended open-water fetch, although the sandspit on the western edge and the jetty on the eastern edge do interrupt the fetch. To the south of those intrusions is Fishers Island Sound which extends uninterrupted for at least 4 km. ‘BLUFF’ (220°T to 270°T) includes a portion of Bluff Point State Park where the elevation ranges from ~ 15 to 30 m above mean sea level, similar to the elevation of the forested area in the ‘HALEY’ wind sector. ‘BLUFF MAX’ (275°T to 310°T) is restricted to wind directions associated with flow over the highest elevations (up to 40 m) of the state park. The ‘NCHAN’ (315°T to 340°T) wind sector offers a land-based wind direction with extended fetch, as the wind travels along the narrow northern channel of the Cove before entering the middle portion of the Cove where the platform is located.

3.4.2 Flux Footprint Estimation

The platform was anchored near the middle of the central section of the Cove in order to provide a maximum fetch from all wind directions while remaining clear of the navigational channel. Fetch to the platform is at least 200 m from all wind directions (Figure 3-1a, red circle). When designing a micrometeorological instrumentation package to measure turbulent surface fluxes, it is common to assume the contributing fetch will extend 100 times the height of the sonic anemometer (Businger, 1986). Once data were collected, the position and size of the flux source area of the wind stress was estimated using Flux Footprint Prediction (FFP) (Kljun et al., 2015). This flux footprint model is valid for a broad range of boundary layer conditions and generates the length, width, and shape of the footprint. It explicitly incorporates surface roughness length and like MOST, assumes stationarity over the averaging period and horizontal homogeneity of the flow. Since we expect those assumptions to sometimes be invalid at our site, the FFP will be used as a qualitative tool.
3.4.3 Assessing Whether Motion Correction is Needed

Mumford Cove is a low energy environment and the magnitude of the motion of the pontoon was generally small. To determine whether motion correction methods following Edson et al. (1998) were necessary, the median standard deviation of each component of the platform’s motion was compared to that of the corresponding median standard deviation of the wind velocity. In all three dimensions, the standard deviation of the pontoon’s motion was at least an order of magnitude smaller than the standard deviation of the wind velocity. Therefore, no motion correction was performed.

3.4.4 Relative Wind Speed

In Mumford Cove, maximum tidal currents are < 0.05 m s$^{-1}$ (Applied Science Associates, 1987) and therefore we neglect the water motion and use mean wind speed for the wind speed input to COARE and as $U_r$ in Equation 3.8.

3.4.5 Data Filtering

Ten minute means of turbulent statistics and bulk variables were calculated for the entire time series. The data were initially filtered to exclude outliers and 10 minute sections during which the sonic anemometer record was missing more than ten of the 6000 records. For analysis, data were further filtered to exclude 10-minute means where $U_N$ was below 1 m s$^{-1}$ and $-2 < \frac{z}{L} < 2$ in order to reasonably expect MOST and the scaling parameter $u_*$ to be appropriate.

This simple filtering technique still allowed several large values to pass through the filter. Rather than adding arbitrary conditions to the filter, we chose to display the median rather than the mean of binned data in the figures in our results. While the large quantities skew the mean upward, the median provides a better representation of typical data values.
3.5 Modifying Roughness Length Parameterization in COARE 3.5

3.5.1 COARE 3.5 with a Constant Empirically-Derived Roughness Length

To evaluate the sensitivity of COARE wind stress estimates to the parameterization of \( z_0 \), the standard \( z_0 \) parameterization in COARE 3.5 (see Equation 3.2) was replaced with a value of \( z_0 \) representative of each wind sector. This was motivated by the results described below in Section 3.6.4. The values of \( z_0 \) were selected by examining the \( z_0 \) vs. \( U_N \) plots (see Section 3.6.4 and Figure 3-5) and choosing the median binned roughness length associated with the 3.5 m s\(^{-1}\) bin. This wind speed bin was chosen because the median windspeed for the time series was 3.6 m s\(^{-1}\) and therefore would provide the most characteristic roughness length for our data set. The resulting values of \( z_0 \) for each wind sector are listed in Table 3.1.

3.5.2 COARE 3.5 with an Empirically-Derived Equation for Roughness Length

For the ‘BLUFF’, ‘HALEY’, ‘GLP’, and ‘WATER’ wind sectors, empirically-derived equations for \( z_0 \) as a function of \( U_N \) were developed to evaluate the accuracy of the wind stress estimated by COARE under a more complex \( z_0 \) parameterization scheme than in Section 3.5.1. The equations for \( z_0 \) for these wind sectors are listed in Table 3.1 and each has an exponential decay function for wind speeds from 1 m s\(^{-1}\) to 4 m s\(^{-1}\) then a constant value for wind speeds above 4 m s\(^{-1}\). Equations were not derived for the other wind sectors because a simple equation was not able to be parameterized. Results from the four wind sectors tested are sufficient for drawing conclusions about this approach.
3.6 Results

3.6.1 Wind Velocities and Estimated Flux Footprints

Winds approached the platform from all directions and winds were generally weak, with 78% of observed wind speeds between 2 and 6 m s$^{-1}$ (Figure 3-2 a). The flux footprint prediction for each wind sector indicates at least 80% of the flux source area for the time series was within Mumford Cove (Figure 3-2 b).

3.6.2 Atmospheric Stability Conditions

The atmospheric surface boundary layer in Mumford Cove was generally unstable, even in summer; 77% of the analyzed fluxes occurred during conditions when $-2 < \frac{z}{L} < 0$ (Figure 3-3 a). The air-water temperature difference supported this instability because the water temperature was warmer than the air temperature for much of the experiment (Figure 3-3 b, black). In contrast, only $\sim$ 8 km southeast in 23 m of water, the water temperature measured at 1 m below the water surface (National Data Buoy Center Station 44060, www.ndbc.noaa.gov) was generally colder than the air temperature during the summer months (Figure 3-3 b, grey).

3.6.3 Observations and Bulk Estimates as a Function of Wind Direction

While setting $\alpha = 0.018$ has been successful in some coastal applications of COARE (see Section 3.1), this approach does not adequately modify COARE to produce accurate estimates in Mumford Cove (Figure 3-4, filled grey dots, all panels).

Roughness length calculated from observations (Equation 3.10) varies with wind direction and is up to three orders of magnitude greater than $z_0$ estimates from COARE (see Section 3.2.1) (Figure 3-4 a). The COARE estimate has no directional dependence and is $\sim 2 \times 10^{-5}$. The closest agreement between observations and the COARE estimate is in the ‘WATER’ and ‘NCHAN’ wind sectors where $z_0$ is $1 \times 10^{-4}$ and $2 \times 10^{-4}$ respectively. The least agreement is in the ‘BLUFF MAX’ sector where
$z_0$ is $2 \times 10^{-1}$. In ‘HALEY’ and ‘BLUFF’ $5 \times 10^{-3}$ is a typical value of $z_0$.

Observed $u_*$ is greater than the COARE estimated value for all wind directions (Figure 3-4 b). The directional dependence of both COARE estimated and observed $u_*$ results from the variation in median wind speed in each directional bin; $u_*$ is proportional to wind speed (Equation 3.1). Again, the greatest agreement between observations and COARE estimates occurs in the ‘WATER’ and the least agreement occurs in the ‘BLUFF MAX’ sector.

Observed $C_{DN}$ varies with wind direction and mirrors the terrain type surrounding the Cove (Figure 3-4 c). The largest observed value of $C_{DN} \times 1000$ is 5.6 and occurs at wind directions in ‘BLUFF MAX’. Wind directions associated with the similarly forested and elevated ‘BLUFF’ and ‘HALEY’ areas have a median $C_{DN} \times 1000 \sim 4$. ‘WATER’ and ‘NCHAN’ $C_{DN} \times 1000$ values are closer to COARE estimates, and are 1.5 and 1.8, respectively. The COARE estimates of $C_{DN}$ are a function of $z_0$ and stability only, have no directional dependence, and median values from COARE of $C_{DN} \times 1000$ are $\sim 1.1$.

Similar to $u_*$, the median observed wind stress $\tau$ is greater than the median COARE estimated value for all wind directions (Figure 3-4 d). The largest difference between observed and COARE estimated values of $\tau$ is $5 \times 10^{-2} \text{ N m}^{-2}$, a factor of 4.7, and occurs in the ‘BLUFF MAX’ wind sector while the closest agreement is in the ‘WATER’ wind sector, where the difference is $6 \times 10^{-3} \text{ N m}^{-2}$, a factor of 1.3.

### 3.6.4 Observations and Bulk Estimates by Wind Sector as a Function of Wind Speed

**Observations Compared to Standard Bulk Estimates**

The relationship of observed $z_0$ to $U_N$ varies from wind sector to wind sector (Figure 3-5, black in all panels). Observed $z_0$ is greater than COARE estimated $z_0$ for all bins and all wind sectors except the highest two wind speed bins in the ‘WATER’ sector. At the lowest wind speeds, the difference is as large as three orders of magnitude. The decay in observed $z_0$ over the first few wind speed bins that occurs in all but
the ‘MARSH’ and ‘LAND’ wind sectors is expected, since the \( z_0^{\text{smooth}} \) component dominates at low wind speeds and is inversely related to \( u_* \), which also decreases with wind speed. In all panels, the COARE estimates of \( z_0 \) have a minimum at the 3.5 m s\(^{-1}\) bin that reflects the fact that the parameterization of \( z_0 \) in COARE is transitioning from smooth to rough flow (Edson et al., 2013).

For all wind sectors, observed \( \tau \) is greater than COARE estimated \( \tau \) at almost every wind speed (Figure 3-6). The ‘WATER’ sector shows the best agreement between observations and COARE estimates, and the values are within less than 0.01 N m\(^{-2}\) of one another. The difference between observed and COARE estimated \( \tau \) values are similar across all wind speed bins for ‘NCHAN’, ‘MCA’, ‘GLP’, where the difference is \( \sim 0.02 \) N m\(^{-2}\). The difference increases with wind speed for ‘LAND’, ‘BLUFF’, ‘MARSH’, ‘HALEY’, ‘BLUFF MAX’, and the difference at the higher wind speed bins for each is between 0.05 N m\(^{-2}\) and 0.10 N m\(^{-2}\).

Observations Compared to Bulk Estimates Using a Fixed Empirical Roughness Length

Table 3.1 lists the empirical \( z_0 \) values used to modify the COARE parameterization of \( z_0 \) for each wind sector (see Section 3.5).

Parameterizing \( z_0 \) in COARE with an empirically-derived value for each wind sector improves COARE estimates of \( \tau \) and the resulting wind stress predictions are typically within 0.005 N m\(^{-2}\) of the observed value (Figure 3-7). The best agreement is for wind speed bins from 2 to 6 m s\(^{-1}\), while COARE overestimates \( \tau \) beyond the 95% confidence interval of the observed values for the 6 to 8 m s\(^{-1}\) wind speed bins in ‘BLUFF MAX’, ‘LAND’, and ‘MCA’. Using a single \( z_0 \) for each wind sector improved agreement between observations and COARE estimates over a range of wind speeds.

Observations Compared to Bulk Estimates Using an Empirical Equation for Roughness Length

Parameterizing \( z_0 \) in COARE with an empirically-derived equation for ‘HALEY’, ‘GLP’, ‘BLUFF’, and ‘WATER’ wind sectors (see Table 3.1) results in COARE esti-
mates of $\tau$ within $0.005 \text{ N m}^{-2}$ and $0.012 \text{ N m}^{-2}$ of the observed values, and within the 95% confidence intervals of nearly every binned value (Figure 3-8). If the 7.5 m s$^{-1}$ wind speed bin in ‘WATER’ is ignored, the COARE estimates and observed values of $\tau$ in ‘WATER’ are within $0.005 \text{ N m}^{-2}$ of each other as well.

**Observations Compared to All Three COARE Parameterizations**

Another way to visualize the improvements in the bulk estimation of $\tau$ by parameterizing $z_0$ in COARE with a fixed value or an empirically-derived equation is by comparing the results from both methods on the same plot (Figure 3-9). For all wind sectors, the original parameterization of $z_0$ in COARE (Figure 3-9, circles) underestimates wind stress. Using a fixed $z_0$ based on the median value of $z_0$ in the 3.5 m s$^{-1}$ wind speed bin for each wind sector (Section 3.6.4 and Table 3.1) results in COARE estimates of $\tau$ that generally fall on or near the 1:1 line when compared to the observed $\tau$ values (Figure 3-9, squares). Exceptions are the higher COARE estimated values in ‘NCHAN’, ‘BLUFF MAX’, ‘BLUFF’, and ‘MCA’, where COARE overestimates the observed $\tau$. The added level of complexity associated with deriving an equation to parameterize $z_0$ for each wind sector improves the COARE estimates more than using a single $z_0$ value for each wind sector in ‘WATER’, ‘Haley’, and ‘BLUFF’ sectors, but has little effect in ‘GLP’ (Figure 3-9, diamonds).

Appendix A includes plots as a function of $U_N$ similar to those in this Section but for $z_0$, $u_*$, and $C_{DN}$.

**3.7 Discussion**

The goal of this project was to determine if and when the COARE 3.5 bulk flux algorithm accurately estimates wind stress in a shallow coastal embayment, and to determine whether it was possible to modify COARE 3.5 to improve wind stress estimates in this environment. This project has three main findings. First, when winds approach from open water (i.e. ‘WATER’ wind sector), COARE 3.5 is reasonably accurate in estimating wind stress. Second, when approaching winds originate from
land, COARE 3.5 underestimates wind stress by up to 5.5x. Third, COARE 3.5 can be modified to produce accurate estimates of wind stress from all directions by replacing the parameterization of roughness length with a locally appropriate value.

Despite our concerns that the MOST assumptions of stationarity and homogeneity would be violated in Mumford Cove, the bulk algorithm performs well when only the roughness length is modified and 10-minute means are used. Whether or not this would hold true for all coastal sites is beyond the scope of this study.

This study reveals a counterintuitive piece of information about the atmospheric stability in shallow coastal waters. We tend to think of coastal waters in midlatitudes as being colder than air during the summer months. Warmer air overlying colder water encourages stable surface boundary layers. With this rationale, it is reasonable to expect mostly stable conditions in shallow water during the summertime. However, in Mumford Cove surface atmospheric conditions are mostly unstable because the very shallow water in the cove is warmer than the air for much of the deployment. This is true even when the atmospheric conditions only a few kilometers offshore are stable. Our observations are contrary to others from a study 2 km offshore of the island of Lolland, Denmark in 4 m of water in where the flow of warm air from relatively flat farmland land over cooler water produced stable conditions and reduced wind stress (Mahrt et al., 2001). The unstable conditions in Mumford Cove reduces the concern that the flux measurements at 2.6 m height above the water surface were decoupled from the fluxes at the air-sea interface.

The empirical $z_0$ values we find are likely specific to our site. The geometry of Mumford Cove and its surrounding terrain, combined with the typically weak winds, generates the roughness lengths we observe. Despite the FFP indication that at least 80% of the momentum flux source is from the water surrounding the platform, the drag coefficient and wind stress are clearly influenced by the land the wind blows over before arriving at the Cove.

Referring to a lookup table for roughness lengths for various terrain types is not useful for predicting which $z_0$ to select for each wind sector. For example in Figure 9.6 in Stull (1988), ‘forest’ is listed as having a roughness length of 1 m, but
‘BLUFF MAX’ had a maximum binned $z_0$ value of $2 \times 10^{-2}$ m. Likewise ‘many trees, hedges, few buildings’ is listed as having a roughness length of $\sim 3 \times 10^{-2}$ m, but ‘HALEY’, ‘MCA’, and ‘GLP’ have $z_0$ values of $5 \times 10^{-3}$ m, $2 \times 10^{-3}$ m, and $5 \times 10^{-4}$ m, respectively. ‘Off-sea wind in coastal areas’ has a roughness length of $1 \times 10^{-3}$ m, but ‘WATER’ and ‘NCHAN’ have $z_0$ of $1 \times 10^{-4}$ m, which is more like the ‘calm open sea’ roughness length in the figure. However, all of these seemingly incongruous $z_0$ values are qualitatively reasonable. Since the winds originate over land but then also flow over at least 200 m of water, the $z_0$ should be a hybrid of the $z_0$ for land terrain and water. The reason our observed $z_0$ over ‘WATER’ is smaller than the figure in Stull (1988) may be due in part to the weak winds, since the data used to compile the Stull figure are based on a wider range of wind speeds (Garratt, 1977).

The main conclusion of our investigation is that wind stress in a shallow coastal system can be successfully estimated using COARE after a simple modification to match $z_0$ to local conditions. Since $z_0$ values will be site specific, it may be valuable to temporarily deploy a turbulent flux measurement system in coastal sites that are frequently studied, for example the National Estuarine Research Reserve System sites, to inform the correct parameterization of $z_0$. Once representative data has been collected and an appropriate $z_0$ identified for each wind direction, the accurate estimate of wind stress by COARE 3.5 should be possible and would benefit a variety of research campaigns.

Feedback on this project has generated a question from researchers who work in larger coastal settings like Long Island Sound or the Gulf of Maine. The question is: At what distance offshore will the standard COARE 3.5 accurately estimate wind stress when the wind originates from land? In order to answer this question the research platform could be deployed at successively greater distances from shore until the appropriate distances under various conditions are identified. Additional instruments to measure waves and currents could be added to the platform. Ideally, the same project would be replicated at multiple sites to determine if a global recommendation can be made, or if local dynamics prohibit such a broad conclusion. Wind stress estimates from aircraft in the coastal zone of Duck, North Carolina, USA indi-
cate that for distances > 5 km offshore, the neutral drag coefficient was similar under offshore and onshore flow conditions (Sun et al., 2001).

The coastal ocean is a dynamic and complex environment. It is also the part of the ocean closest to our most densely populated and economically important regions. Understanding the processes that control the coastal ocean will benefit science and society by informing better management decisions. This project contributes to our growing understanding of air-sea fluxes in shallow waters.
Table 3.1: Empirical $z_0$ values used to modify the COARE parameterization of $z_0$

<table>
<thead>
<tr>
<th>Wind sector</th>
<th>fixed value for $z_0$ (m)</th>
<th>equation for $z_0$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLUFF</td>
<td>0.002</td>
<td>if $1 \text{ m s}^{-1} &gt; U_N &lt; 4 \text{ m s}^{-1}$, $z_0 = \exp(-1.4101U_N - 1.2075)$; if $U_N &gt; 4 \text{ m s}^{-1}$, $z_0 = 0.001$</td>
</tr>
<tr>
<td>BLUFF MAX</td>
<td>0.007</td>
<td>-</td>
</tr>
<tr>
<td>GLP</td>
<td>0.0005</td>
<td>if $1 \text{ m s}^{-1} &gt; U_N &lt; 4 \text{ m s}^{-1}$, $z_0 = \exp(-0.4299U_N - 5.9756)$; if $U_N &gt; 4 \text{ m s}^{-1}$, $z_0 = 0.001$</td>
</tr>
<tr>
<td>HALEY</td>
<td>0.004</td>
<td>if $1 \text{ m s}^{-1} &gt; U_N &lt; 4 \text{ m s}^{-1}$, $z_0 = \exp(-0.7682U_N - 2.9062)$; if $U_N &gt; 4 \text{ m s}^{-1}$, $z_0 = 0.004$</td>
</tr>
<tr>
<td>LAND</td>
<td>0.001</td>
<td>-</td>
</tr>
<tr>
<td>MARSH</td>
<td>0.001</td>
<td>-</td>
</tr>
<tr>
<td>MCA</td>
<td>0.002</td>
<td>-</td>
</tr>
<tr>
<td>NCHAN</td>
<td>0.0004</td>
<td>-</td>
</tr>
<tr>
<td>WATER</td>
<td>0.0002</td>
<td>if $1 \text{ m s}^{-1} &gt; U_N &lt; 4 \text{ m s}^{-1}$, $z_0 = \exp(-1.5U_N - 3.5)$; if $U_N &gt; 4 \text{ m s}^{-1}$, $z_0 = 0.0004$</td>
</tr>
</tbody>
</table>
Figure 3-1: Study site and research platform.  

a. Map of the Mumford Cove area (USGS, 1984). Research platform location (red triangle) and 200 m radius (red circle) indicating mean maximum extent of 80% of the turbulent fluxes as estimated by Flux Footprint Predictor (Kljun et al., 2015). 

b. Research platform outfitted with instrumentation needed to provide bulk inputs to COARE 3.5, calculate wind stress by the direct covariance method, and record platform motion.
Figure 3-2: Wind rose and flux footprint predictions. (a) Direction and speed of winds observed from June to December 2016. (b) Contour lines enclose 80% of the flux source area for each wind sector as estimated by Flux Footprint Prediction (Kljun et al., 2015).
Figure 3-3: Atmospheric stability in Mumford Cove. (a) Histogram of the scaling parameter $\frac{z}{L}$ values of the filtered data used in this project. (b) Water-air temperature differences in Mumford Cove over the entire experiment (black) and at NDBC Station 44060 in Long Island Sound for times during the experiment when data was available (red).
Figure 3-4: Observed (black), COARE estimated (open grey), and COARE estimated with $\alpha$ set to 0.018 (filled grey) values with respect to wind direction. 

a. Roughness length. 

b. Friction velocity. 

c. Neutral drag coefficient $\times 1000$. 

d. Wind stress. The median value of each 15° bin is shown with a 95% confidence interval as calculated by bootstrapping. Wind sector labels are shown at the top of panel a.
Figure 3-5: Observed (black) and COARE estimated (grey) values of roughness length as a function of equivalent neutral wind speed. The median value within each 1 m s$^{-1}$ bin is shown with a 95% confidence interval as calculated by bootstrapping. Black and grey dots are horizontally offset for ease of viewing. Bins with < 20 data points per bin are not shown.
Figure 3-6: Same as Figure 3-5, but for wind stress.
Figure 3-7: Same as Figure 3-6 but the $z_0$ parameterization in COARE was replaced with an empirical fixed value for each wind sector.
Figure 3-8: Same as Figure 3-6 but the $z_0$ parameterization in COARE was replaced with an empirical equation for each wind sector.
Figure 3-9: Wind stress estimates from standard COARE (circle), COARE with a fixed \( z_0 \) (square) and, when available, COARE with an empirical equation to parameterize \( z_0 \) (diamond), versus observed stress estimates. Data are the same as shown in Figures 3-6 - 3-8.
Chapter 4

Air-Sea Buoyancy Flux in Mumford Cove

This chapter follows closely from Chapter 3 and addresses the ability of COARE 3.5 to estimate buoyancy flux in Mumford Cove.

4.1 Calculating Buoyancy Flux

The buoyancy flux is closely related to the sensible heat flux, $Q_H$ (Fairall et al., 1996)

$$Q_H = \rho_a c_p \overline{w'T'} = -\rho_a c_p u_s T_s$$  \hspace{1cm} (4.1)

where $\rho_a$ is density of air, $c_p$ is the specific heat capacity of dry air, $\overline{w'T'}$ is the time-average covariance of the turbulent fluctuations of the vertical wind velocity and the air temperature, and $T_s$ is the temperature scaling parameter. By meteorological convention, negative values indicate downward fluxes.

Buoyancy flux incorporates the fluxes of both of temperature and moisture and is calculated

$$Q_B = \rho_a c_p \overline{w'T'} = -\rho_a c_p C_H U_r \Delta \theta_v = -\rho_a c_p u_s T_{s*}$$  \hspace{1cm} (4.2)

where the $T_s$ notation indicates the air temperature measured by the sonic anemometer, which is approximately equal to the virtual air temperature $T_v$; $C_H$ is the transfer
coefficient for sensible heat, which is assumed to be the same as the transfer coefficient needed in this equation; and $\Delta \theta_v$ is the sea-air virtual potential temperature difference.

Virtual air temperature is

$$T_v = T(1 + 0.61q) \quad (4.3)$$

where $q$ is the specific humidity of the air, while air temperature measured by the sonic anemometer is

$$T_s = T(1 + 0.51q). \quad (4.4)$$

The kinematic buoyancy flux using $T_v$ is related to the kinematic sensible heat flux $\overline{w' T'}$ as

$$\overline{w' T_v'} = \overline{w' T'} + 0.61 \overline{T (w' q')} \quad (4.5)$$

where $\overline{T}$ is the time-average air temperature, while the kinematic buoyancy flux using $T_s$ is related to the kinematic sensible heat flux as

$$\overline{w' T_s'} = \overline{w' T'} + 0.51 \overline{T (w' q')} \quad (4.6)$$

The temperature scaling parameter used in Equation 4.2 is calculated

$$T_{ss} = \frac{-\overline{w' T_s'}}{u_*} \quad (4.7)$$

and therefore is influenced not only by the kinematic buoyancy flux, but also by $u_*$. Note the negative sign causes $T_{ss}$ to be negative when the buoyancy flux is upward.

In COARE 3.5 both $u_*$ and $T_*$ are functions of $z_0$. Similarly to the way $u_*$ is estimated (Equation 3.5), $T_{ss}$ is

$$T_{ss} \approx -\Delta \theta_v C_H^{1/2}. \quad (4.8)$$
4.2 Results

4.2.1 Observations and Bulk Estimates as a Function of Wind Direction

Unlike the wind stress, which COARE underestimated (see Chapter 3), there was good agreement between observed and COARE estimated buoyancy fluxes. Agreement between observed and COARE estimated $T_s$ values varies somewhat with wind direction (Figure 4-1 a). The observed and COARE estimated buoyancy flux values are in good agreement and the least agreement is in the ‘WATER’ wind sector (Figure 4-1 b). These results were unexpected.

4.2.2 Observations and Bulk Estimates by Wind Sector as a Function of Wind Speed

Because COARE underestimates $u_*$ (Chapter 3) but produces good estimates of buoyancy flux (Section 4.2.1), by definition COARE generally overestimates the magnitude of observed $T_s$ (Figure 4-2). Parameterizing $z_0$ with a fixed empirical value for each wind sector (Table 3.1) improves the agreement between COARE estimates and observations of $T_s$ (Figure 4-3). Parameterizing $z_0$ with an empirical equation for each wind sector does little to further improve the agreement between COARE estimates and observations of $T_s$ (Figure 4-4).

With the exception of the ‘WATER’ and ‘MARSH’ wind sectors, the COARE estimated $Q_B$ is generally within the 95% confidence interval of the observed value (Figure 4-5). COARE overestimates $Q_B$ in the ‘WATER’ sector for wind speeds up to 6 m s$^{-1}$ by a maximum of 6.2 W m$^{-2}$, and in the ‘MARSH’ sector for wind speeds from 1 - 4 m s$^{-1}$ by up to 11 W m$^{-2}$ and from 6 - 7 m s$^{-1}$ by 20 W m$^{-2}$. Using empirical parameterizations for $z_0$ has little effect on the agreement between observed and COARE estimated values of $Q_B$ (Figure 4-6 and Figure 4-7).
4.2.3 Observations Compared to All Three COARE Parameterizations

Another way to visualize the improvements in the bulk estimation of $Q_B$ by parameterizing $z_0$ in COARE with a fixed value or an empirically-derived equation is by comparing the results from both methods on the same plot (Figure 4-8). The original parameterization of $z_0$ in COARE (Figure 4-8, circles) agrees well with observations in ‘BLUFF MAX’, ‘BLUFF’, ‘MCA’, ‘HALEY’, and ‘GLP’ sectors, and overestimates observed values in ‘WATER’ and ‘MARSH’ sectors. In the ‘NCHAN’ sector COARE underestimates negative values of observed $Q_B$, agrees well with observations from 0 W m$^{-2}$ to $\sim$ 50 W m$^{-2}$, and overestimates the observed values above $\sim$ 50 W m$^{-2}$.

Using a fixed $z_0$ based on the median value of $z_0$ in the 3.5 m s$^{-1}$ wind speed bin for each wind sector (Chapter 4, Section 6.4.2 and Table 1) does little to improve estimates in any of the wind sectors, and in ‘BLUFF MAX’ and ‘BLUFF’ results in slight underestimation of observed $Q_B$ by COARE (Figure 4-8, squares). The added level of complexity associated with deriving an equation to parameterize $z_0$ for each wind sector does not improve the COARE estimates more than using a single $z_0$ value in the case of ‘WATER’, ‘HALEY’, and ‘GLP’ sectors, and results in overestimation of observed $Q_B$ in the ‘BLUFF’ wind sector (Figure 4-8, diamonds).

4.2.4 Scaling Parameters

The buoyancy flux is a function of both $u_*$ and $T_{ss}$ (Equation 4.2). COARE tends to underestimate $u_*$ (Figure 4-9) but overestimate the magnitude of $T_{ss}$ (Figure 4-10), and the effects cancel each other.

The standard deviation of wind components should be constant when normalized by friction velocity, and typical values based on studies done over homogenous terrain are (Panofsky and Dutton, 1984)

$$\frac{\sigma_u}{u_*} \simeq 2.5 \quad (4.9)$$
\[
\frac{\sigma_w}{u_*} \cong 1.3 \tag{4.10}
\]

The ratios of the standard deviation of wind components to friction velocities were examined to determine if either the \(u'\) or the \(w'\) was more clearly responsible for the larger observed \(u_\ast\) (Figure 4-11 and Figure 4-12). In the ‘WATER’ wind sector, the observed and expected ratios are in good agreement, but are greater than expected for the other wind directions (Figure 4-11). The ratio of \(\sigma_w\) to \(\sigma_u\) is lower than expected, and suggests \(\frac{\sigma_w}{u_*}\) is relatively greater than the expected value compared to \(\frac{\sigma_u}{u_*}\) (Figure 4-12).

Unlike the ratios of standard deviations of wind components to friction velocity, there are few references in the literature to suggest a constant value of

\[
\frac{\sigma_{T_s}}{T_{s*}} \tag{4.11}
\]

that should be expected. Our observations of this ratio have a large variability, but binned median values are \(\sim -2 \text{ K}\) (Figure 4-13).

### 4.2.5 Daytime and Nighttime Observations and COARE Estimates of Buoyancy Flux

Comparing all wind sectors, there is not a consistent relationship between the daytime and nighttime estimated \(Q_B\) and observed \(Q_B\) (Figure 4-14). In ‘NCHAN’ and ‘BLUFF MAX’ wind sectors, the nighttime fluxes estimated by COARE are lower than the observed fluxes, but daytime fluxes estimated by COARE are often higher than the observed fluxes. In the ‘WATER’ and ‘MARSH’ sectors, both daytime and nighttime estimated \(Q_B\) are lower than the observed \(Q_B\), while in the remaining sectors all estimates fall nearly on the 1:1 line. However, the day-night difference in the departure of binned buoyancy fluxes from COARE predictions is not significant except in ‘BLUFF MAX’.
4.3 Discussion

The agreement between observed and COARE estimated buoyancy flux in Mumford Cove is not yet understood. The greatest discrepancy between the observed and COARE estimated $Q_B$ is in the ‘WATER’ wind sector, yet that is the sector in which the ratios of standard deviations of the wind velocity components to $u_*$, and the observed and COARE estimated stresses, are in the best agreement. In the future, it may be useful to calculate typical values of open ocean $\frac{\sigma_T}{T_*}$ to know if the Mumford Cove observations are different or similar.
Figure 4-1: Observed (black) and COARE estimated (grey) values with respect to wind direction.  

a. Temperature scaling parameter.  
b. Buoyancy flux. The median value for each 15° bin is shown with a 95% confidence interval as calculated by bootstrapping.
Figure 4-2: Observed (black) and COARE estimated (grey) values of the temperature scaling parameter as a function of equivalent neutral wind speed. The median value within each 1 m s\(^{-1}\) bin is shown with a 95% confidence interval as calculated by bootstrapping. Black and grey dots are horizontally offset for ease of viewing. Bins with < 20 data points per bin are not shown.
Figure 4-3: Same as Figure 4-2 but $z_0$ is parameterized with a fixed empirical value.
Figure 4-4: Same as Figure 4-2 but $z_0$ is parameterized with an empirical equation.
Figure 4-5: Same as Figure 4-2 but for $Q_B$. 
Figure 4-6: Same as Figure 4-5 but $z_0$ is parameterized with a fixed empirical value.
Figure 4-7: Same as Figure 4-5 but $z_0$ is parameterized with an empirical equation.
Figure 4-8: Observed buoyancy flux compared to estimates from standard COARE (circle), COARE with a fixed $z_0$ (square) and, when available, COARE with an empirical equation to parameterize $z_0$ (diamond). The median value within each bin is shown. Bins with < 20 data points per bin are not shown.
Figure 4-9: Observed friction velocity compared to estimates from the standard parameterization of COARE. The median value of each bin is shown. The median value of observed data is shown with a 95% confidence interval as calculated by bootstrapping. Bins with < 20 data points per bin are not shown.
Figure 4-10: Same as Figure 4-9 but with temperature scaling parameter.
Figure 4-11: Observed and literature-based ratios of the standard deviation of wind components to friction velocity. The figure is zoomed in to show the median binned values (circles) and error bars indicating the 95% confidence intervals, while the 10-min mean values (dots) are partially shown but some values are off the scale of this figure.
Figure 4-12: Same as Figure 4-11 but with observed and literature-based ratios of the standard deviations of the vertical wind speed to the streamwise horizontal wind speed.
Figure 4-13: Same as Figure 4-11 but with the ratio of the standard deviation of the sonic air temperature to the temperature scaling parameter.
Figure 4-14: Observed buoyancy flux compared to estimates from the standard parameterization of COARE for daytime and nighttime. Nighttime is categorized when solar irradiance < 20 W m\(^{-2}\). The median value of each bin is shown. The median value of observed data is shown with a 95% confidence interval as calculated by bootstrapping. Bins with < 20 data points per bin are not shown.
Chapter 5

The Influence of a Sandy Substrate, Seagrass, or Highly Turbid Water on Albedo and Surface Heat Flux

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The Influence of a Sandy Substrate, Seagrass, or Highly Turbid Water on Albedo and Surface Heat Flux

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Abstract

Sea-surface albedo is a combination of surface-reflected and water-leaving irradiance, but underestimates typically contributes less than 15% of the total albedo in open-ocean conditions. In coastal systems, however, the bottom substrate or suspended particulate matter can increase the amount of backscattered light, thereby increasing albedo and decreasing net shortwave surface heat flux. Here we present a sensitivity analysis using observations and models to examine the effect of shortwave irradiance on albedo and the net shortwave heat flux for three cases: a bright sand bottom, a seagrass canopy, and turbid water. After scaling to the full solar spectral range, daytime average albedo for the test cases is up to 0.20 and exceeds the value of 0.05 predicted using a commonly applied parameterization. Therefore, we suggest that the commonly applied albedo lookup table can be used in coastal heat flux estimates in water as shallow as 1 m unless the bottom substrate is highly reflective or the water is highly turbid. Our model results provide guidance to researchers who need to determine albedo in highly reflective or highly turbid conditions but have no direct observations.

1. Introduction

Effectively managing coastal resources requires an understanding and modeling of the physical processes that drive heating of the water and govern the health of these ecosystems. Inaccurate heating rate estimates in shallow waters cascade into poor estimates of temperature-dependent biological, chemical, and physical processes (Feng et al., 2015; Wang et al., 2012). Current air-sea heat flux parameterizations have not been tested in highly reflective or shallow water coastal ecosystems (≤ 10 m water depth) and may result in inaccurate estimates of coastal water temperature.

Net heat exchange across the air-sea boundary, $Q_{net}$, is composed of six flux terms:

$$Q_{net} = Q_{SWdown} + Q_{SWup} + Q_{LWdown} + Q_{LWup} + Q_{H} + Q_{E}$$

where $Q_{SWdown}$ and $Q_{SWup}$ are downwelling and upwelling solar shortwave radiation, $Q_{LWdown}$ and $Q_{LWup}$ are downwelling and upwelling infrared longwave radiation, $Q_{H}$ is sensible heat flux, and $Q_{E}$ is latent heat flux. By meteorological convention, downward fluxes are negative. Both shortwave fluxes can be measured by pyranometers, which are sensitive to irradiance over the spectral range 285 to 2,500 nm. In practice, usually only downwelling shortwave irradiance is measured and upwelling irradiance is estimated by multiplying the downwelling irradiance by an estimated albedo value. Albedo is the fraction of downwelling irradiance reflected or backscattered upward by both the sea surface and the water column. Downwelling longwave heat flux is measured by a pyrometer over a spectral range of 4,500–42,000 nm. Upwelling longwave heat flux is calculated using the sea-surface skin temperature in the Stefan-Boltzmann law for black-body radiation. Sensible and latent heat fluxes can be estimated using the direct covariance method or with bulk formulae (e.g., Edson et al., 2013). In this study, we examine the shortwave solar flux terms because incoming solar radiation is typically the largest source of ocean heating in the air-sea heat flux (e.g., Fewings & Lentz, 2011; Stewart, 2008).

Payne (1972) is a common parameterization of albedo. A lookup table indicates albedo as a function of atmospheric transmittance and solar altitude, and was developed using observations from pyranometers.
positioned over 20 m of water at the Buzzards Bay Entrance Light Station, MA, USA. Water-leaving irradiance was only 0.5% of downwelling irradiance in Buzzards Bay and the Sargasso Sea (Payne, 1971), leading Payne (1972) to conclude that, with a minimum observed albedo of 0.03, the water-leaving irradiance contributes no more than 15% of the albedo at any time. Therefore, the albedo parameterization is considered fairly insensitive to water column properties and is used broadly by the oceanographic research community. The Matlab Air-Sea Toolbox albedo.m file (crusty.usgs.gov/sea-mat/) computes ocean albedo following Payne (1972). Popular coastal and estuarine numerical circulation models have incorporated Payne (1972) as well. The net shortwave heat flux in the Finite Volume Community Ocean Model (Chen et al., 2004) uses the approach by Paulson and Simpson (1977), which incorporates the Payne (1972) albedo table and the assumption that water-leaving irradiance is 0.5% of downwelling irradiance. The COARE bulk flux algorithm uses a fixed albedo of 0.055 based on Payne (1972) (Edson et al., 2013; Fairall et al., 1996). COARE is an option for the air-sea boundary layer in the Regional Ocean Modeling System (ROMS) and is used in many coastal applications (e.g., Sutherland et al., 2011; Whitney et al., 2016). ROMS model results can be tuned to generate the best hindcasting of water temperature and salinity by selecting different "water types" and resulting absorption coefficients, but the albedo is not typically tuned (Wang et al., 2012).

In coastal water, water-leaving irradiance may be greater than assumed by Payne (1972) and result in a larger albedo. Concentrations of phytoplankton, colored dissolved organic matter (CDOM), and total suspended matter (TSM) are often higher in shallow coastal waters than in the open ocean and can influence the water-leaving irradiance by absorbing or scattering light. Submerged vegetation and the seafloor can further absorb and reflect light in coastal waters. Therefore, it is important to determine whether this widely used albedo parameterization is appropriate for shallow (<=10 m depth) coastal systems.

The water column is considered optically shallow when light reflected from the bottom substrate contributes to radiance measured above the sea surface. Optically shallow conditions are defined by the water clarity, bottom depth, and bottom composition (Dierssen & Randolph, 2013). Variability in albedo has been explored observationally and with radiative transfer models in optically deep open-ocean and shelf waters that contain phytoplankton and CDOM (Chang & Dickey, 2004; Jin et al., 2011; Ohlmann et al., 2000). However, these parameterizations do not consider highly scattering waters due to suspended sediments or optically shallow environments.

Researchers making observations of highly turbid or optically shallow systems have taken various approaches to estimating albedo: either accepting the error in net surface heat flux as a result of using Payne (1972), modifying existing albedo parameterizations, or measuring albedo directly at their study sites. For example, Payne (1972) was used to calculate net surface heat flux in a three-dimensional heat budget of the Duplin River in Georgia, despite the "high turbidity and generally brown color of the water" (McKay & Di Iorio, 2008). When calculating the heat budget for the optically shallow coral reef platforms in the eastern Red Sea, Davis et al. (2011) referred to HydroLight modeling and hyperspectral reflectance measurements over coral sand by Maritorena et al. (1994) and, as a result, added 0.10 to the Payne (1972) albedo values. In the ~0.5 to 2.5 m deep lagoon at the coral cay of Lady Elliot Island off Queensland, Australia, direct measurements provided a daytime average albedo (McCabe et al., 2010) that was substantially higher than Payne (1972) suggests.

The objectives of this study are to refine our understanding of albedo in coastal waters and determine (1) if changes should be made to the parameterization of the shortwave surface heat flux in these waters, and (2) under what conditions investigators should directly measure the albedo. Specifically, we investigated the influence of light scattering on albedo in three test cases representing common highly scattering coastal conditions: optically shallow water with a bright sediment bottom or submerged canopy of seagrass, and highly turbid waters with suspended particles. We investigated the change in net shortwave heat flux over the course of a day and the influence on albedo under these different scenarios using models and field data collected in a shallow embayment with eelgrass (Zostera marina).

The remainder of this paper is organized as follows: Section 2 describes the radiative transfer modeling and subsequent calculations; section 3 addresses the hyperspectral and broadband field measurements; section 4 considers the HydroLight model results and compares field measurements to modeled results and the Payne (1972) lookup table; and section 5 presents a discussion.
2. Radiative Transfer Modeling

2.1. Model Setup

We use the radiative transfer model HydroLight 5.2 © from Sequoia Scientific, LLC. (Mobley, 1994), which simulates radiation from 300 to 1,000 nm as it propagates into, within, and out of the water column. HydroLight includes parameterization for the absorption and scattering properties of various constituents in the water column and a bottom boundary. The bottom boundary is represented as a horizontal Lambertian surface with a constant benthic reflectance. HydroLight has been used in previous studies of albedo including Ohlmann et al. (2000) and Chang and Dickey (2004).

The model “base case” for the atmospheric and water column properties used in this study is similar to that of Ohlmann et al. (2000) and represents high incident irradiance and clear skies over the open ocean. Ohlmann et al. (2000) modified HydroLight to operate over the wavelength range of 250–2,500 nm in order to compare their results to Payne (1972). The resulting open-ocean albedo values agreed well with Payne (1972) (Ohlmann et al., 2000, Figure 15). Therefore, we expect any deviations from the albedo of our base case to also represent deviations from Payne (1972). In section 4.1.1, our results support this assumption.

The base case in this study is a “Classic” Case 1 inherent optical properties model where chlorophyll and CDOM are covarying and uses “clearest natural water” absorption coefficients by Smith and Baker (1981), seawater scattering coefficients by Morel (1974), and a chlorophyll concentration of 0.03 mg m\(^{-3}\), similarly to Ohlmann et al. (2000). Additionally, we use the Petzold average-particle phase function (Mobley et al., 1993) and include inelastic scattering options for chlorophyll fluorescence, CDOM fluorescence, and Raman scattering. All model runs are performed for solar zenith angles \(\theta\) of 0\(^\circ\), 20\(^\circ\), 40\(^\circ\), 60\(^\circ\), 80\(^\circ\); 0% cloud coverage; and wind speed of 2 m s\(^{-1}\). The bottom boundary is set to either infinite depth, eelgrass at 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.75, 1, or 5 m, or ooid sand at 0.5 or 5 m. Hyperspectral reflectance of eelgrass was measured in air with an ASD FieldSpec4 hyperspectral spectroradiometer over the wavelength range 350–2,500 nm following Dierssen et al. (2015) (Figure 1). The reflectance file was then trimmed to 350–1,000 nm and extrapolated for use as a bottom reflectance in HydroLight by assuming constant reflectance from 300 to 350 nm. The ooid sand reflectance file was produced with data taken near Horseshoe Reef, Lee Stocking Island, Bahamas (Lesser & Mobley, 2007) (Figure 1). In addition to the standard output, HydroLight was customized to separate reflectance just above the water surface, \(R_{\text{total}}(\lambda)\), into spectrally resolved reflectance

![Figure 1. Spectral reflectance of ooid sand collected near Horseshoe Reef, Lee Stocking Island, Bahamas (Lesser & Mobley, 2007) (magenta) and of eelgrass collected in Groton, CT, USA (green). Thick solid lines covering the range of 300–1,000 nm indicate the portion of the spectral reflectance used in HydroLight modeling for bottom reflectance parameterization. The gaps at ~1,800 to 1,900 and ~2,200 to 2,500 nm omit noise in the calculated reflectance due to near-zero downwelling irradiance at those wavelengths.](image-url)
due to surface glint $R_g(\lambda)$ and due to water-leaving irradiance $R_w(\lambda)$, where $\lambda$ is wavelength. All HydroLight output ranges from 300 to 1,000 nm with 5 nm resolution. Turbid conditions are not modeled in HydroLight, but rather are based on measured data from three highly turbid estuaries with a diversity of particle composition/type (Knaeps et al., 2015), and those methods are described in Appendix A.

While we parameterize sky conditions in HydroLight using the default input format of percentage cloud cover, Ohlmann et al. (2000) used atmospheric transmittance $T$ as their input and set $T = 0.78$ for the base case. Therefore, when comparing our model base case to Payne (1972), we use albedo values listed in the $T = 0.8$ row of the Payne (1972) lookup table.

The atmospheric radiative transfer model MODTRAN 5.3 (Berk et al., 2006) is used to generate spectrally resolved downwelling irradiance just above the water surface $E_d(\lambda, \theta)$ over 285–2,800 nm at the following $\theta$: 0, 20, 40, 60, 80. Using air mass type 9 in the midlatitude summer model to represent the observation site (Figure 2). Downwelling irradiance generated by MODTRAN agrees well with the downwelling irradiance generated by HydroLight; all points in the 300–1,000 nm wavelength range are within 0.1 W m$^{-2}$ nm$^{-1}$ and 88% are within 0.05 W m$^{-2}$ nm$^{-1}$. The downwelling irradiance from MODTRAN allows the HydroLight output to be extrapolated to the full shortwave solar wavelength range used in heat flux calculations (section 2.2).

Additional model runs were done to simulate the conditions of the 27 July 2016 hyperspectral field measurements (see section 3.1). In these runs, the settings match the base case except eelgrass canopy depth, $\theta$, and the chlorophyll concentration are set to match observed values at the times of data collection. The “low-tide” model run uses $\theta = 33$ and canopy depth of 0.2 m, and the “high-tide” model run uses $\theta = 42$ and canopy depth of 1 m. Both runs use a chlorophyll concentration of 3 g m$^{-3}$, as measured at the nearby research platform (see section 3.2).

### 2.2. Calculation of Modeled Albedo and Net Shortwave Heat Flux

The dimensionless total albedo is defined as

$$a(\theta) = \frac{E_{up}(\theta)}{E_d(\theta)}$$

where $E_{up}(\theta)$ is the spectrally integrated total upwelling irradiance just above the water surface and $E_d(\theta)$ is the spectrally integrated downwelling irradiance just above the water surface. The total albedo is defined...
this way rather than as a spectral average of the reflectance \( R_{\text{total}}(k; h) \) because simply averaging \( R_{\text{total}}(k; h) \) would neglect the variation with wavelength of the energy content of downwelling irradiance. Equation (2) allows albedo to be calculated as the ratio of total upwelling to total downwelling irradiance in units of \( \text{W m}^{-2} \), as in methods such as Payne (1972) that use pyranometer data to calculate albedo for air-sea heat flux budgets. For our purposes, \( E_u(t) \) must be separated into two terms to distinguish the fractions of albedo generated from surface glint and by water-leaving irradiance. Detailed methods used to calculate upwelling irradiance due to water-leaving irradiance and surface glint can be found in Appendix A.

The wavelength range of shortwave solar radiation used in heat flux calculations such as the COARE bulk algorithm is \( \approx 285 \) to \( 2,800 \) nm. The Kipp & Zonen model CMP21 pyranometers deployed in Mumford Cove (see section 3.2) are sensitive from \( 285 \) to \( 2,800 \) nm and each yield a single value for irradiance representing the total energy flux within that wavelength range. The Payne (1972) albedo lookup table is based on irradiance measurements using Eppley model 6–90 pyranometers, which are sensitive over a nearly identical wavelength range, \( 280 \)–\( 2,800 \) nm. Therefore, we calculate albedo for the wavelength range of \( 285 \)–\( 2,800 \) nm.

The net shortwave heat flux \( Q_{\text{SW net}}(t) \) is computed directly from spectrally integrated downwelling minus upwelling irradiance, or, using spectrally integrated downwelling irradiance and the total albedo:

\[
Q_{\text{SW net}}(t) = E_d(t) - E_u(t) = E_d(t)[1 - a(t)]
\]  

In order to compare modeled results with those using the commonly used albedo parameterization, values from the Payne (1972) lookup table for \( T = 0.8 \) are used to calculate \( a(t) \) and \( Q_{\text{SW net}}(t) \) for \( \theta = 0^\circ, 20^\circ, 40^\circ, 60^\circ, \) and \( 80^\circ. \) Note the lookup table uses solar altitude, not solar zenith angle; solar zenith angle equals \( 90^\circ \) minus solar altitude.

### 2.3. Calculation of Daytime Average Albedo and Total Daytime Net Shortwave Heat Flux

Daytime average values allow us to consider the total effect of increased albedo over the course of a day, rather than only the impact at discrete moments in time. As a simple way to estimate the daytime average albedo and total daytime net shortwave heat flux, we relate solar zenith angle to time of day based on a day with \( 12 \) h of daylight at the equator. The modeled \( E_{\text{u total}}(t) \) and \( E_d(t) \) for each solar zenith angle \( \theta \) are assigned to appropriate times throughout the day, and used to calculated the daytime average albedo

\[
x_{\text{day}} = \frac{\int_{2h}^{12h} E_{\text{u total}}(t) \, dt}{\int_{2h}^{12h} E_d(t) \, dt} \quad (4)
\]

and the total daytime net shortwave heat flux

\[
Q_{\text{SW net}} = \frac{\int_{2h}^{12h} Q_{\text{SW net}}(t) \, dt}{2h}
\]  

### 3. Fieldwork

#### 3.1. Hyperspectral Measurements of Irradiance and Albedo

On 27 July 2016, we collected spectrally resolved downwelling and upwelling irradiance from 350 to 2,500 nm with a hyperspectral spectroradiometer (ASD FieldSpec4 with 1 nm resolution) in Mumford Cove, Groton, CT, USA (Figure 3a). The FieldSpec4 was outfitted with a remote cosine collector held level 0.2 m above the water surface over moderately dense eelgrass (Figure 3). Measurements were collected at low tide under clear skies in late morning (\( \theta = 33^\circ \), 1100 EDT), when the eelgrass canopy was \( \approx 0.2 \) m below the water surface, blades angled toward horizontal (Figure 3b), and again near high tide in the afternoon (\( \theta = 42^\circ \), 1540 EDT), when the eelgrass canopy was \( \approx 1.0 \) m below the water surface and blades were generally vertical (Figure 3c). The measurements were made in an azimuthal direction facing toward the sun such that shadowing and reflectance from the boat were minimized. These measurements are used to calculate albedo following equation (A7) but using the 350–930 and 350–2,500 nm wavelength ranges.
3.2. Pyranometer Measurements of Irradiance and Albedo

A floating pontoon platform was anchored over water with low-density eelgrass and a dark mud bottom in the center of Mumford Cove from 7 June 2016 to 6 December 2016 (Figures 3a and 3d–3f). The top few meters of sediment consist of black mud in the central portion of the cove (Curewitz, 1992). Water depth at the platform location ranged from 0.8 to 2 m depending on the tidal stage. A suite of instruments on the platform included upward and downward-looking pyranometers (Kipp & Zonen CMP21) to directly measure downwelling and upwelling solar shortwave radiation over the water surface in the wavelength band from 285 to 2,800 nm. Downwelling and upwelling irradiance were measured every 2 s and the mean values

Figure 3. Fieldwork sites in Mumford Cove, Groton, CT, USA. (a) Map of Mumford Cove and the location of two field sites. (b) Eelgrass where hyperspectral measurements were collected, taken 27 July 2016 at the time of low tide measurements and (c) between low and high tide. (d) Pontoon platform with upward and downward-looking pyranometers. Red lines show 60° of nadir for the downward-looking pyranometer. Sparse eelgrass below pyranometers, taken (e) 8 August 2016 and (f) 8 September 2016.
were logged at 1 min intervals. Turbidity, CDOM, and chlorophyll fluorometry measurements were collected 0.12 m below the water surface every 15 min with a Sea-Bird Electronics/WET Labs ECO Triplet-wb. A motion sensor (LORD MicroStrain 3DM-GX4–25) measured the pitch and roll of the platform at 5 Hz. Evaluation of all data points indicates 96% of pitch and 99.5% of roll measurements were within ± 2.5° of vertical. In addition, the tilt response of the Kipp & Zonen CMP21 when tilted from 0° to 90° at 1,000 W m⁻² is < 0.2%. Therefore, we chose not to filter the data based on motion of the platform.

The two pontoon hulls and all metal surfaces facing the pyranometers were painted black to reduce signal contamination from reflected light off the pontoon platform (Figure 3d). The black paint used was Rust-oleum matte black FlexiDip Removable Rubber Coating, which has a low, spectrally flat reflectance in the visible and near-infrared wavelengths (350–2,500 nm) as measured by the Dierssen lab (B. Russell, personal communication, 2015). The pyranometers were positioned off the east side of the platform on a 1 m extension arm located 0.50 m above the water surface (Figure 3d). This placement was to ensure that the majority of light incident on the downward-looking pyranometer originated from the water column and was not influenced by the platform. Due to the cosine response of the planar sensor, the pyranometer is most sensitive to incoming irradiance within ± 60° of nadir, and the geometry of the extension arm was designed so the platform fell outside this viewing angle (Figure 3d, red lines). A second downward-looking pyranometer was deployed on the west side of the platform for 14 days to compare the upwelling light field on the two sides of the platform throughout the day. Interference in the upwelling radiation signal on the east side of the platform occurred after midday due to shadowing of the water column by the platform. Therefore, albedo is calculated for the morning hours only for the entire time series, following equation (A7) using the broadband $E_{\text{uw}}(\theta)$ and $E_{\text{g}}(\theta)$ from the pyranometers. The MATLAB Air-Sea Toolbox functions soradna1.m and albedo.m (crusty.usgs.gov/sea-mat) are used to find the Payne (1972) albedo values corresponding to the observed solar angles and atmospheric transmission calculated from the downwelling irradiance time series.

4. Results

4.1. Model Results

4.1.1. Modeled Albedo

To understand the differences in total albedo between test cases, it is useful to examine the spectral profiles of downwelling and upwelling irradiance and reflectance. For simplicity, we will examine the spectral profiles for $\theta = 0°$, as profiles for the other $\theta$ exhibit similar patterns (not shown). Downwelling irradiance incident on the ocean surface is the same for all test cases at $\theta = 0°$ (Figure 2, black line), while the water-leaving upwelling irradiance profiles just above the ocean surface vary by test case (Figure 4a). The contribution to the upwelling irradiance by surface glint is the same for each test case at $\theta = 0°$ (Figure 4a, black line), $E_{\text{uw}}(z, \theta)$ for each case is the sum of $E_{\text{uw}}(z, \theta)$ and $E_{\text{g}}(z, \theta)$ (Figure 4a, thick colored lines).

The open-ocean base case exhibits the smallest upwelling irradiance, peaking near 450 nm (Figure 4a, blue), as is expected of open-ocean water (Tyler & Smith, 1970). A bright ooid sand bottom positioned 0.5 m below the water surface produces the broadest and highest magnitude spectral peak in upwelling irradiance (Figure 4a, magenta). The Gironde estuary 105 g m⁻² produces the broadest and highest magnitude spectral peak in upwelling blue (Figure 4a, black), as is expected of open-ocean water (Tyler & Smith, 1970). A bright ooid sand bottom positioned near 750 nm due to reduced downwelling irradiance (Figure 2, black line) and increased atmospheric and water column absorption by water molecules, particularly at wavelengths near 750, 930, and 1,150 nm. For the base, ooid sand, and turbid cases, the majority of upwelling irradiance is largely in the visible (VIS) wavelength band, while for the test case with an eelgrass canopy at 0.05 m depth the near-infrared (NIR) waveband dominates upwelling light (Figure 4b).

The spectral profiles of total reflectance $R_{\text{total}}(\lambda, 0°)$ (Figure 4b) show the sum of $R_{\text{g}}(\lambda, 0°)$ and $R_{\text{uw}}(\lambda, 0°)$ and exhibit similar patterns to the water-leaving upwelling light profiles (Figure 4a). $R_{\text{total}}(\lambda, 0°)$ is smoother because the effects of the atmospheric gas absorption features that affect both the $E_{\text{g}}(\lambda, \theta)$ and $E_{\text{uw}}(\lambda, \theta)$ profiles tend to cancel in $R_{\text{total}}(\lambda, \theta)$. As the depth of the water column above the eelgrass canopy or ooid bottom increases, the upwelling irradiance at wavelengths greater than 700 nm diminishes since the
infrared light is preferentially absorbed by water molecules (Kirk, 1994). Moreover, the albedo shows distinct local minima in wavelengths related to enhanced liquid water absorption such as 750 and 980 nm. The modeled total albedo $\alpha(h)$ (equation (A7)) for all test cases exceeds that of the open-ocean base case at every $h$ and exceeds the Payne (1972) albedo values at all $h$ except 808° (Figure 6 and Table 1). The modeled open-ocean base case albedo estimates are slightly ($\approx 0.01$) higher than the Payne (1972) estimates, with the exception of $h = 80°$, where the open-ocean case is 0.05 lower. In section 4.2.2, we show that Payne (1972) albedo values also overestimate the field observations at large $h$ and discuss the field observations.

Figure 4. (a) Modeled upwelling irradiance just above the water surface for solar zenith angle $\theta$ of 0°. The black line indicates the contribution due to surface glint, which is the same for all test cases. Dotted lines indicate the water-leaving contribution for each case. The solid colored lines indicate the total upwelling irradiance for each case. Upwelling irradiance for wavelengths greater than 1,300 nm is not shown; the value is constant from 1,300 to 2,800 nm. (b) Upwelling irradiance within each radiation class for the examples in Figure 4a. The wavelength ranges for the four radiation classes are 285–400, 400–700, 700–1,400, and 1,400–2,800 nm, for ultraviolet (UV), visible (VIS), near infrared (NIR), and shortwave infrared (SWIR), respectively.

Figure 5. Spectrally resolved reflectance for the same cases shown in Figure 4a as well as ooid sand at 5 m and a seagrass canopy at 0.15, 0.25, and 0.50 m.
of albedo when $T/C_{21} = 0.8$ in Figure 6. Up to 6% more of the incoming shortwave energy is reflected out of the water column when eelgrass is present (Figure 6 and Table 1). As $h$ increases from 0° to 80° the albedo from open-ocean base case is 0.03–0.23, but when a seagrass canopy is positioned at 0.05 m depth, the albedo is 0.09–0.27. An ooid sand bottom at 0.5 m generates the highest albedo values in this study, which range from 0.18 to 0.34 as $h$ increases. Interestingly, the total albedo generated by ooid sand at 5.0 m depth is equivalent to that created by a seagrass canopy at 0.05 m. The total albedo value of the modeled turbid waters ranges from 0.06 to 0.30 and varies due to the composition of the suspended particle load in each of the three estuaries sampled.

Our open-ocean case agrees with the (Payne, 1971) conclusion that water-leaving irradiance contributes less than 15% of the albedo value (Figure 7). In contrast, the percentage of albedo due to water-leaving irradiance is much greater in the three test cases: 84% with an ooid sand bottom at 0.5 m, 68% with a seagrass

### Table 1

<table>
<thead>
<tr>
<th>Test Case</th>
<th>0°</th>
<th>20°</th>
<th>40°</th>
<th>60°</th>
<th>80°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payne (1972)</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.07</td>
<td>0.27</td>
</tr>
<tr>
<td>Open ocean</td>
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<td>0.04</td>
<td>0.04</td>
<td>0.08</td>
<td>0.23</td>
</tr>
<tr>
<td>Seagrass at 0.05 m</td>
<td>0.09</td>
<td>0.09</td>
<td>0.10</td>
<td>0.14</td>
<td>0.27</td>
</tr>
<tr>
<td>Seagrass at 0.50 m</td>
<td>0.05</td>
<td>0.05</td>
<td>0.06</td>
<td>0.10</td>
<td>0.23</td>
</tr>
<tr>
<td>Ooid sand at 0.5 m</td>
<td>0.18</td>
<td>0.18</td>
<td>0.19</td>
<td>0.22</td>
<td>0.34</td>
</tr>
<tr>
<td>Ooid sand at 5 m</td>
<td>0.09</td>
<td>0.09</td>
<td>0.10</td>
<td>0.13</td>
<td>0.27</td>
</tr>
<tr>
<td>Gironde estuary, TSM = 1.030 g m$^{-3}$</td>
<td>0.11</td>
<td>0.11</td>
<td>0.12</td>
<td>0.16</td>
<td>0.30</td>
</tr>
<tr>
<td>Gironde estuary, TSM = 411 g m$^{-3}$</td>
<td>0.11</td>
<td>0.11</td>
<td>0.12</td>
<td>0.16</td>
<td>0.30</td>
</tr>
<tr>
<td>Scheldt estuary, TSM = 402 g m$^{-3}$</td>
<td>0.08</td>
<td>0.08</td>
<td>0.09</td>
<td>0.13</td>
<td>0.27</td>
</tr>
<tr>
<td>Gironde estuary, TSM = 105 g m$^{-3}$</td>
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<td>0.08</td>
<td>0.09</td>
<td>0.13</td>
<td>0.27</td>
</tr>
<tr>
<td>Rio de la Plata estuary, TSM = 110 g m$^{-3}$</td>
<td>0.07</td>
<td>0.07</td>
<td>0.08</td>
<td>0.12</td>
<td>0.26</td>
</tr>
<tr>
<td>Scheldt estuary, TSM = 100 g m$^{-3}$</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>0.11</td>
<td>0.25</td>
</tr>
<tr>
<td>Scheldt estuary, TSM = 50 g m$^{-3}$</td>
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<td>0.06</td>
<td>0.07</td>
<td>0.11</td>
<td>0.25</td>
</tr>
<tr>
<td>Rio de la Plata estuary, TSM = 55 g m$^{-3}$</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>0.11</td>
<td>0.25</td>
</tr>
</tbody>
</table>
canopy at 0.05 m depth, and 65% for the 105 g m$^{-3}$ turbid water case from the Gironde estuary. As $h$
increases, the relative contribution of water-leaving irradiance to albedo decreases, but remains in excess of
15% even at $h = 80^\circ$ for the non-open-ocean test cases.

### 4.1.2. Modeled Daytime Average Albedo and Net Shortwave Heat Flux

Ooid sand bottoms, shallow seagrass canopies, or turbid water can all substantially increase the daytime
average albedo $a_{day}$ (Figure 8a). In the modeled day with 12 h of daylight, $a_{day}$ using Payne (1972) is 0.04
and for our open-ocean case it is 0.05, while for the other test cases $a_{day}$ ranges from 0.05 to 0.20. The greatest
increase in $a_{day}$ compared to the case using Payne (1972) is for ooid sand bottoms and the smallest
increase is for eelgrass at 5 m. Ooid sand bottoms at 0.5 and 5 m depth yield daytime average albedo of
0.20 and 0.11. The magnitude of $a_{day}$ diminishes with the depth of the eelgrass canopy, ranging from a maximum of 0.10 with eelgrass at 0.05 m depth to a minimum of 0.05 with eelgrass at 5 m deep.

Daytime average albeldos for the turbid cases vary with both TSM concentration and estuary. Greater TSM
concentrations generally create a higher albedo, and the Gironde estuary produces larger albedo values for
the same TSM concentrations ($\sim 100$ and $\sim 400$ g m$^{-3}$) compared to those from the Scheldt and Rio de la
Plata estuaries. Daytime average albedo ranges from 0.07 for TSM $\sim 50$ g m$^{-3}$ to 0.13 for TSM $\sim 1,000$ g m$^{-3}$.

As a result of increased albedo, ooid sand bottoms, shallow eelgrass canopies, and turbid water substan-
tially decrease the total daytime net shortwave heat flux $Q_{sw_{net,day}}$ (equation (5)) into the water compared to
estimates using Payne (1972) albedo values (Figure 8b). An ooid sand bottom reduces $Q_{sw_{net,day}}$ by 16 and
7% at 0.5 and 5 m, respectively. The presence of a seagrass canopy within 0.25 m of the surface reduces
$Q_{sw_{net,day}}$ by 3–6%. Turbid water with TSM $\sim 50$ g m$^{-3}$ reduces $Q_{sw_{net,day}}$ by 3–4%, while for TSM $\sim 1,000$ g
m$^{-3}$ the flux is reduced by 9%.

Over the course of a day, the greatest difference in the net shortwave heat flux $Q_{sw_{net}}(t)$ between estimates
using Payne (1972) albedo values and the test cases is at $\theta = 0^\circ$ (Figure 9, daylight hour 6). When the sun is
Figure 8. (a) Modeled daytime average albedo (equation (4)) from Payne (1972) (filled blue diamond), the open-ocean case (open blue diamond), seagrass canopy (green circles), and ooid sand bottom (magenta crosses) at multiple depths, and turbid water at various TSM concentrations from three highly turbid estuaries. (b) Similar to Figure 8a but for the percent change in modeled total daytime net shortwave heat flux into the water relative to total daytime net shortwave heat flux calculated using Payne (1972) albedo values. Vertical purple and brown lines show the range of values at a given TSM concentration in multiple estuaries. Data in the shaded boxes are independent of canopy or water depth.
higher in the sky, albedo values decrease (Figure 6), but the amount of incident irradiance is increased (Figure 2), resulting in the largest differences in $Q_{SW, net}(\theta)$ between cases occurring at small $\theta$.

### 4.2. Comparison of Albedo From Model, Fieldwork, and Existing Albedo Parameterization

#### 4.2.1. Comparison of Albedo From Model and Hyperspectral Measurements

To test how well HydroLight represents the effects of an actual seagrass canopy, we compare $R_{\text{total}}(\lambda, \theta)$ from the model to the spectrally resolved data collected in Mumford Cove (Figures 10a and 10b). Both the low- and high-tide measurements of $R_{\text{total}}(\lambda, \theta)$ exhibit peaks at wavelengths characteristic of the modeled $R_{\text{total}}(\lambda, \theta)$ of the water column with eelgrass (Figure 5), with a broad peak around 560 nm, and additional peaks near 710 and 810 nm in the low-tide measurements. We expect the observed dropoff of $R_{\text{total}}(\lambda, \theta)$ at higher in the sky, albedo values decrease (Figure 6), but the amount of incident irradiance is increased (Figure 2), resulting in the largest differences in $Q_{SW, net}(\theta)$ between cases occurring at small $\theta$. 

![Figure 9. Examples of modeled net shortwave heat flux throughout a day with 12 h of daylight. Negative values indicate heating of the water. Solar zenith angle $\theta$ corresponding to time of day for the chosen latitude (0°) is indicated at the top of the plot.](image)

![Figure 10. (a) Mean spectrally resolved total reflectance measured above the water surface at low tide (grey line, $n = 4$) and a ~0.2 m deep eelgrass canopy in Mumford Cove, Groton, CT, and generated by HydroLight using bottom reflectance set to 100, 50, and 25% of eelgrass reflectance (black lines). (b) Similar to Figure 10a but measured at high tide (grey line, $n = 5$) over ~1 m deep eelgrass canopy. Also shown are results from the HydroLight run using an infinite bottom rather than eelgrass at 1 m (dashed black line). Green arrows in both panels indicate peaks characteristic of total reflectance in model runs with eelgrass (Figure 5).](image)
wavelengths $>700$ nm, in contrast to Figure 1, due to the strong absorption by water at wavelengths $>700$ nm, as discussed in section 4.1.1. However, the magnitude of the observed peaks is smaller than predicted by the HydroLight model when the bottom reflectance is modeled as equal to 100% of the magnitude of eelgrass reflectance. When the bottom reflectance parameterization is modified to reduce the magnitude of the eelgrass reflectance to 25% of its full value, the resulting $R_{\text{total}}(\lambda, \theta)$ more closely matches the observations over moderately dense eelgrass (Figure 10, lower black line in each panel). This modification apparently better represents the three-dimensional canopy, with spaces between the seagrass blades and any dark sediment visible through gaps in the canopy that would have near-zero reflectance. We show spectral albedo at 100, 50, and 25% magnitude (Figures 10a and 10b) to show the range of values possible if a seagrass canopy is more dense and horizontally positioned than the observed canopy, for example in sites where the seagrass is nearly emergent at low tide.

The total albedo calculated from observed upwelling and downwelling irradiance $E_u(\lambda, \theta)$ and $E_d(\lambda, \theta)$ (equation (A7)) measured over the Mumford Cove eelgrass meadow is also lower than the total albedo predicted by HydroLight in the runs parameterized to match the field observations (section 2.1). At low tide, the observed total albedo for the 350–930 nm wavelength range is 0.04, while the model results integrated over the same wavelengths with eelgrass reflectance at 100% suggest the albedo should be 0.08. When eelgrass reflectance is set to 25% of its full value, total albedo is 0.05. At high tide, the mean observed total albedo over the 350–930 nm wavelength range is 0.05 at both 100% and 25% eelgrass reflectance, while the HydroLight model predicts a total albedo of 0.06. To determine whether these differences should be attributed to the way HydroLight represents seagrass, or to other parameterizations in HydroLight, we conducted an additional model run, replacing the eelgrass canopy with an infinitely deep bottom; this generated a total albedo of 0.05. The $R_{\text{total}}(\lambda, \theta)$ from the model run with an infinitely deep bottom parameterization suggests that overestimation of spectral albedo from 350 to 500 nm contributes slightly to the higher modeled total albedo (Figure 10b). However, most of the discrepancy between the observed and modeled total albedo with eelgrass at 0.2 or 1 m depth can be attributed to the absence of a strong eelgrass signal in the field data.

For comparison with Payne (1972) predicted values, total albedo is calculated using data from the full range of ASD data. Total albedo based on the ASD data collected at low tide is 0.03, and Payne (1972) indicates the albedo should be 0.04 for the same solar angle and observed atmospheric transmittance. The ASD spectral coverage is slightly narrower than Payne (1972) (350–2,500 nm rather than 280–2,800 nm), but these results suggest albedo over the Mumford Cove eelgrass meadow at low tide is comparable to Payne (1972).

At high tide, total albedo calculated with ASD data is 0.04 while Payne (1972) also indicates the albedo should be 0.04, again suggesting albedo in $\sim$1 to 2 m water depth in Mumford Cove is well represented by Payne (1972).

### 4.2.2. Comparison of Albedo From Pyranometer Measurements and Existing Parameterization

Pyranometer measurements of total albedo over the sparse eelgrass and dark mud bottom in Mumford Cove indicate that, despite the shallow physical depth of the water (0.8–2 m) and the typically optically shallow conditions, the observed albedo generally agrees well with the Payne (1972) lookup table. The agreement is best under clear skies ($T > 0.8$) and when the sun is high in the sky ($\theta < 45^\circ$) (Figures 11a and 11c). In Mumford Cove, land and trees obstructed the rising sun until it was $\sim$10° above the horizon, therefore data from $\theta > 80^\circ$ are omitted from these plots and calculations. The largest discrepancies between the pyranometer observations and Payne (1972) occur when the sun is low in the sky ($\theta > 45^\circ$) and clouds are present ($T < 0.8$) (Figures 11b and 11d).

Observed albedo is often higher than the values in the lookup table when the sun is near zenith, but is lower than the lookup table values when the sun is closer to the horizon. When skies are clear and $\theta < 30^\circ$, the observed albedo is higher than the Payne (1972) estimate 99% of the time (Figure 11c, red), and when $\theta$ is between 30° and 45°, observed albedo is higher 80% of the time (Figure 11c, yellow). However, once $\theta$ exceeds 45°, Payne (1972) tends to overestimate the albedo $\sim$90% of the time (Figure 11c, green, cyan, and blue). The lookup table also tends to underestimate observed albedo at all $\theta$ when atmospheric transmission is reduced by clouds ($T < 0.8$) (Figure 11d).

Another way to compare the observed and Payne (1972) albedo values is to evaluate how many of the paired values fall within 0.01 of each other. The two albedo values are in the greatest agreement at low solar zenith angles ($\theta < 45^\circ$) under clear skies ($T > 0.8$), where over 97% of the values are within 0.01 of
each other (Figure 12, open circles connected with dashed lines). Under both clear and cloudy skies, the
albedo values are in closest agreement at midday when \( h < 45^\circ \), when over 85% of the values fall within
0.01 of each other (Figure 12, circles connected by dashed lines). Agreement decreases as the sun
approaches the horizon.

Although the discrepancy between observed and Payne (1972) albedo at high \( h \) appears large, if we con-
sider the effect of the differences on the net shortwave heat flux instead of simply on the albedo, we see

Figure 11. (a) Observed albedo from pyranometers at Mumford Cove from June to December 2016 and estimated albedo from Payne (1972) for clear skies (atmo-
spheric transmittance, \( T > 0.8 \)). (b) Same as Figure 11a, but with \( T < 0.8 \). (c) Observed albedo compared to Payne (1972) albedo for various solar zenith angles. (d)
Same as Figure 11c but with \( T < 0.8 \).
our observed and Payne (1972) albedo values produce more similar results. We calculate the change in albedo required to produce a change in $Q_{\text{SWnet}}(\theta)$ equal to 10 W m$^{-2}$. We then determine, for five binned values of $h$, the percentage of observed albedo values that will produce less than a 10 W m$^{-2}$ change in $Q_{\text{SWnet}}(\theta)$ compared to the corresponding predicted Payne (1972) albedo values. For both atmospheric transmission conditions ($T/C_2 < 0.8$ and $T/C_2 > 0.8$), over 95% of observed albedo values satisfy the 10 W m$^{-2}$ restriction. At $h = 75^\circ$ to $80^\circ$, the observed and predicted values meet the restriction over 68% of the time (Figure 12, circles connected by solid lines). This analysis again suggests the Payne (1972) lookup table is suitable for use in a shallow cove with 1 to 2 m water depth.

5. Discussion

This study has three main findings. First, we used radiative transfer models HydroLight 5.2 and MODTRAN 5.3 and previously published reflectance data from highly turbid estuaries to perform a sensitivity analysis and predict the effect of highly reflective or backscattering waters on albedo. We find ooid sand bottoms; dense, horizontal near-surface seagrass canopies; and turbid water with TSM concentrations in excess of 50 g m$^{-3}$ substantially increase albedo and decrease net shortwave heat flux. Payne (1972) suggested water-leaving irradiance comprised at most 15% of upwelling irradiance, but we find that in these shallower or more turbid cases, water-leaving irradiance can generate up to 84% of the upwelling irradiance. Second, observations and the model indicate that although seagrass is highly reflective in the near infrared, it is unlikely to increase the daytime average albedo unless the seagrass blades are within 0.25 m of the water surface and are dense and horizontally oriented for the majority of the day. Third, the commonly used Payne (1972) albedo parameterization performs well compared to observed albedo in a shallow (1–2 m depth), low-turbidity embayment containing sparse eelgrass and dark sediment.

5.1. Defining a Significant Increase in Albedo

We find the daytime average albedo is higher, and net shortwave heat flux is lower, under all modeled scenarios compared to daytime average albedo modeled using the commonly applied Payne (1972) albedo lookup table. To determine what size error in albedo would cause a nonnegligible error in the net shortwave heat flux estimate, we compare to the known uncertainty in measured downwelling irradiance. The
expected error in daily mean measurements of downwelling shortwave radiation due to sensor and field errors is $-6 \text{ W m}^{-2}$, based on the accuracies of the pyranometers used on the Improved Meteorological system (Colbo & Weller, 2009). Using the daily average incoming shortwave radiation in that study, O(200 W m$^{-2}$), this is a 3% error in the measurement of daily downwelling irradiance. An increase in albedo of order 0.03 or greater will therefore cause nonnegligible reduction of the net shortwave heat flux into the water (equation (3)).

Test cases with ooid sand bottom at both 0.5 and 5 m, dense horizontal seagrass canopies shallower than 0.25 m, and turbid water with a TSM concentration $>50 \text{ g m}^{-3}$ exceed the 3% threshold (Figure 8). We focus the rest of the discussion on which test cases reduce the daily net shortwave radiation into the water by more than 3% relative to estimates using Payne (1972).

It is worth noting that $E_o(\theta)$ estimates from satellite reanalysis products have larger than a 3% bias when compared to surface observations, and the RMSE is also large (e.g., Yamada & Hayasaka, 2016; Zhang et al., 2016). For example, the North American Regional Reanalysis (NARR) 3-hourly values of solar shortwave radiation were systematically higher than ground observations by the Delaware Environmental Observing System and therefore NARR $E_o$ values were reduced by 20% before forcing ROMS for a Delaware Bay simulation (Wang et al., 2012). Therefore, if the highest level of accuracy in the net shortwave surface heat flux is required, satellite reanalysis products should not be used. Surface observations of downwelling and upwelling irradiance should be made directly. If this is not feasible, then surface observations of downwelling irradiance should be made and the albedo parameterized as skillfully as possible using Payne (1972) and the data in Figure 6. The daytime average albedo for each test case can be approximated from the mid-morning or midafternoon albedo value, in this case at $\theta = 45^\circ$ (Figures 6 and 8a). This result simplifies the amount of information required to estimate albedo in a given system, perhaps eliminating the need to collect albedo measurements over the full range of $\theta$.

### 5.2. Considerations When Modeling the Albedo of Seagrass Meadows

Calculations based on the model work indicate eelgrass canopies within 0.25 m of the surface will generate more than a 3% reduction in the net shortwave heat flux. However, the hyperspectral fieldwork indicates our HydroLight parameterization overestimates albedo in the presence of eelgrass when the bottom reflectance is parameterized entirely by the eelgrass spectral reflectance. Modeled and observed albedo are in better agreement when the bottom spectral reflectance uses an eelgrass spectral reflectance reduced in magnitude, presumably because the reduced reflectance better parameterizes the dark spaces in the canopy. The seagrass test cases therefore indicate the maximum effect of a seagrass canopy on the net shortwave heat flux, which should be more realistic if the canopies are dense and horizontally positioned.

HydroLight modeling is the most feasible first step to investigate the potential effect of eelgrass on albedo suggested by Figure 1, but a model able to resolve a 3-D eelgrass canopy is desirable for this type of analysis. Three-dimensional models for seagrass canopies have been developed (Hedley & Enriquez, 2010; Zhou et al., 2015; Zimmerman et al., 2015) and could be used to further evaluate the impact of leaf length, flow, orientation, epiphytes and sediment reflectance on the surface albedo. Another valuable experiment would be to repeat our albedo measurements over a horizontal near-surface seagrass canopy (e.g., Pacific Northwest off Washington and Oregon) or other types of aquatic vegetation (e.g., Sargassum mats) to further quantify variability in albedo due to submerged and floating aquatic vegetation.

### 5.3. Conditions Requiring an Albedo Parameterization Other Than Payne (1972)

Researchers working in locations with a bright bottom substrate such as ooid sand should be aware that albedo is likely to be much higher than the Payne (1972) parameterization and consider making direct measurements of albedo. Our modeled work is supported by the findings of McCabe et al. (2010) who observed the daytime average albedo was 0.135 over 0.5-2.5 m water depth in the lagoon at the coral cay of Lady Elliot Island off Queensland, Australia. In contrast, in the presence of highly turbid water, whether it is necessary to directly measure albedo will depend on the characteristics of the suspended material and the accuracy required for the application. Turbidity in Mumford Cove was typically low (97% of the readings are $<3$ NTU), therefore we cannot use the field data from Mumford Cove to test the effect of turbidity on albedo in these very shallow waters. The mass-specific absorption and scattering values and backscattering to scattering ratios of suspended material will vary from site to site. Research done in particularly bright
turbid environments, such as during whiting events in the Grand Bahamas Banks (Dierssen et al., 2009) may require directly measuring albedo. Otherwise, if the suspended material is not bright or the TSM concentration is less than 50 g m\(^{-3}\), the effort and expense of collecting the albedo data should be weighed against the acceptable error for the project. For example, in a 3-D heat budget of the Duplin River, which has highly turbid, brown water, there was an unexplained residual heat storage term (McKay & Di Iorio, 2008). It is possible that variations in albedo could account for part of that residual. It would be interesting to collect a time series of pyranometer and turbidity data over shallow water in multiple more turbid systems to quantify the albedo in these environments.

Our model results provide guidance to researchers who need to determine albedo in highly reflective or highly turbid conditions where no direct observations are possible. Figure 6 and Table 1 indicate albedo as a function of solar zenith angle for one of the most reflective bottom materials and for a range of TSM concentrations. Based on the characteristics of the research site, a specific albedo value may be chosen from our model results. Alternatively, our results may allow researchers to utilize a reasonable range of albedo values and quantify uncertainty in their net shortwave heat flux estimates.

5.4. Influence of Seagrass and Turbidity on the Total Net Surface Heat Flux

In addition to affecting the shortwave radiation, the presence of seagrass or turbid water has implications for other terms in the total net surface heat flux (equation (1)). Seagrass canopies partition the water column, creating a shallow surface layer that heats faster than the surface of a water column without seagrass (Zhang & Nepf, 2009). Likewise, turbid water absorbs incoming irradiance over a shallower depth than clear water, resulting in warmer surface water (Ramp et al., 1991; Zaneveld et al., 1981). Both these scenarios should increase sea-surface temperature (SST). The latent, sensible, and upwelling longwave heat fluxes are all functions of SST: heat flux out of the water generally increases as SST increases. Therefore, we expect environments with seagrass or turbid water to generate reductions in the total surface heat flux into the water beyond the effect of increased albedo.

6. Conclusions

This study indicates net shortwave radiative heat flux estimates using Payne (1972) and the COARE algorithm (Edson et al., 2013; Fairall et al., 1996) provide a reasonable estimate of albedo in most shallow coastal waters with depths \(\leq 1\) m. The exceptions are environments with bright sand bottoms or highly turbid water where TSM concentration \(\geq 50 \text{ g m}^{-3}\). In those cases, the albedo increases enough to substantially reduce net shortwave heat flux into the water. Improved confidence in parameterization of net shortwave air-sea heat flux will lead to more accurate estimation of coastal water temperatures and less uncertainty in numerical circulation models of shallow systems.

Appendix A: Detailed Calculation of Modeled Albedo

To extrapolate our model results to the larger wavelength range 285–2,800 nm, we separate the contributions of surface glint and water-leaving irradiance to the modeled albedo. We first calculate spectrally resolved upwelling irradiance just above the water surface \(E_{u_{\text{total}}} (\lambda, \theta)\), which is composed of upwelling irradiance from the water column \(E_{u_{\text{w}}} (\lambda, \theta)\) and due to surface glint \(E_{u_{\text{g}}} (\lambda, \theta)\)

\[
E_{u_{\text{total}}} (\lambda, \theta) = E_{u_{\text{w}}} (\lambda, \theta) + E_{u_{\text{g}}} (\lambda, \theta)
\]  
(A1)

where

\[
E_{u_{\text{w}}} (\lambda, \theta) = E_{\text{w}} (\lambda, \theta) R_{\text{w}} (\lambda)
\]  
(A2)

and

\[
E_{u_{\text{g}}} (\lambda, \theta) = E_{\text{g}} (\lambda, \theta) R_{\text{g}} (\lambda, \theta)
\]  
(A3)

\(E_{\text{w}} (\lambda, \theta)\) is generated by MODTRAN for the full wavelength range needed here, 285–2,800 nm. In contrast, the reflectance due to the water column \(R_{\text{w}} (\lambda)\) and reflectance due to surface glint \(R_{\text{g}} (\lambda, \theta)\) from HydroLight output and the hyperspectral field data have a more limited wavelength range (Figure A1). Therefore, we
extrapolate the spectrally resolved reflectance to 285–2,800 nm before calculating albedo and net short-wave heat flux. Below, we describe how the spectrally resolved reflectance is extrapolated.

The reflectance due to irradiance leaving the water column, $R_w(k)$, is nearly independent of solar zenith angle. Therefore, for the base, ooid sand bottom, and seagrass canopy test cases, we choose to extrapolate only $R_w(k; 0^\circ)$ from HydroLight and use the $h_{500}$ value for all $h(k)$ (Figure A2a). Because $R_w(k)$ is a nonlinear function of wavelength, we log-transform $R_w(300–320 \text{ nm})$, calculate the best fit straight line within that wavelength range, extrapolate to cover the 285–300 nm band, then transform back. Our results in the following sections are insensitive to the choice of extrapolation method because the 285–300 nm wavelength band contains a small fraction of the total downwelling irradiance (Figure 2). We assume $R_w(1,000–2,800 \text{ nm}) = 0$ based on the preferential absorption of infrared radiation by water molecules (Kirk, 1994).

For the turbid test cases, we use several spectrally resolved $R_w(350–2,500 \text{ nm})$ profiles measured with 1 nm resolution for varying levels of TSM (50–1,000 g m$^{-3}$) from the Gironde (France), Scheldt (Belgium), and Rio de la Plata (Argentina) estuaries (Knaeps et al., 2015). For each turbid condition, $R_w(350–380 \text{ nm})$ is extrapolated to 285–350 nm similarly to the HydroLight output above. Measured $R_w(k)$ is negligible for all turbid water cases for wavelengths greater than 1,300 nm and is set equal to zero in these calculations.

Surface glint $R_g(k; \theta)$ includes the contribution of light reflected from the direct solar beam $R_{g,direct}(k; \theta)$, which is spectrally flat in the UV, VIS, and NIR wavelengths, and reflected from diffuse skylight, $R_{g,diffuse}(k; \theta)$, which is blue-enhanced under clear skies:

$$R_g(k; \theta) = R_{g,direct}(k; \theta) + R_{g,diffuse}(k; \theta).$$

(A4)

We use a simple method to extrapolate the HydroLight $R_g(300–1,000 \text{ nm}, \theta)$ to 285–300 and 1,000–2,800 nm at each $\theta$: the value of $R_g(285–300 \text{ nm}, \theta)$ is set equal to the value of $R_g(300, \theta)$, and the value of $R_g(1,000–2,800 \text{ nm}, \theta)$ is set equal to $R_g(1,000 \text{ nm}, \theta)$ (Figure A2b). For comparison, we also determine $R_{g,direct}(300–1,000 \text{ nm}, 0^\circ)$ and $R_{g,diffuse}(300–1,000 \text{ nm}, 0^\circ)$ as described below, extrapolate each separately, then sum them to produce an extrapolated $R_g(285–2,800 \text{ nm}, 0^\circ)$.
To calculate $R_g$ direct (300–1,000 nm, $0^\circ$), we use the special case of Fresnel’s formula for normal incidence of unpolarized radiant energy to obtain a constant value of 0.021 (Mobley, 1994).

$R_g$ diffuse (300–1,000 nm, $0^\circ$) is calculated using $R_g$ direct (300–1,000 nm, $0^\circ$), $R_g$ (300–1,000 nm, $0^\circ$), and the diffuse downwelling irradiance just above the water surface $E_d$ diffuse (300–1,000 nm, $0^\circ$) output from HydroLight. First, we solve for $E_{g\text{ diffuse}}(\lambda, 0^\circ)$:

$$E_{g\text{ diffuse}}(\lambda, 0^\circ) = \frac{R_g(\lambda, 0^\circ)^2}{C_1} \frac{R_g(\lambda, 0^\circ)}{C_1}$$  \hspace{1cm} (A5)

and then $R_{g\text{ diffuse}}(\lambda, 0^\circ)$:

$$R_{g\text{ diffuse}}(\lambda, 0^\circ) = \frac{E_{g\text{ diffuse}}(\lambda, 0^\circ)}{E_{d\text{ diffuse}}(\lambda, 0^\circ)}$$  \hspace{1cm} (A6)

To extrapolate $R_{g\text{ diffuse}}$ (300–1,000 nm, $0^\circ$) to 285 nm, we assume $R_{g\text{ diffuse}}$ is constant from 285 to 300 nm, since Fresnel’s equation is accurate in the ultraviolet wavelengths (Mobley, 1994). However, the constant value from Fresnel’s equation is not accurate in the shortwave infrared (SWIR) wavelengths because the index of refraction of seawater decreases with increasing wavelength. The rate of change of the index of refraction in seawater in the SWIR is not known. To extrapolate $R_{g\text{ diffuse}}$ (300–1,000 nm, $0^\circ$) to 1,000 to 2,800 nm, the rate of decrease with wavelength in the index of refraction of freshwater in the SWIR is applied to the index of refraction of seawater, and Fresnel’s formula then used to estimate $R_{g\text{ diffuse}}$ (1,000–2,000 nm). $R_{g\text{ diffuse}}$ is extrapolated to 2,800 nm and $R_{g\text{ diffuse}}$ (300–1,000 nm, $0^\circ$) is extrapolated to 285–2,800 nm similarly to the way we extrapolated $R_g$ (A) above. These extrapolation techniques produce a decrease of $R_g(\lambda, 0^\circ)$ by 30% from 1,000 to 2,800 nm.

The above extrapolation technique for $R_g(\lambda, 0^\circ)$ yields a negligible difference in $R_g(285–2,800, 0^\circ)$ and the albedo calculations as compared to the simpler method of extrapolation assuming a constant value; the total albedo is insensitive to the method of extrapolation from 1,300 to 2,800 nm. This is due to the

Figure A2. (a) Examples of extrapolated spectral reflectance due to water-leaving irradiance for select cases for $\theta = 0^\circ$. Values generated by HydroLight (300–1,000 nm) are within the shaded box, and the water-leaving reflectance measured in a highly turbid estuary (350–2,500 nm) is within the dotted box. Extrapolated values are beyond the edges of the respective box boundaries. (b) Spectral reflectance due to surface glint at various solar zenith angles $\theta$. The contribution of light reflected from the direct solar beam (grey dotted), and that from diffuse skylight (grey dashed) are also shown for $\theta = 0^\circ$. Values generated by HydroLight (300–1,000 nm) are within the shaded box, and extrapolated values are beyond.
relatively small magnitude of downwelling irradiance for wavelengths greater than 1,300 nm (Figure 2). Therefore, in the following sections we use the simpler method of extrapolation.

After extrapolation, we see the largest component of spectral reflectance is due to the reflection from the water column for all but the open-ocean base case (Figure A2a): the black curve in Figure A2b is lower than all the curves in Figure A2a except the blue curve. The HydroLight model, and the field observations of highly turbid water, indicate \( R_g(\lambda) \) varies strongly with wavelength and test case (Figure A2a). \( R_g(\lambda, \theta) \) is blue enhanced and varies little with \( \theta \), with the exception of \( \theta = 80^\circ \). \( R_g(80^\circ) \) is red enhanced due to the increased scattering of blue light over the longer path length of light through the atmosphere at high \( \theta \) (Figure A2b, solid light grey line). \( R_g(\theta) \) and \( R_w(\lambda) \) are used to solve for \( E_{\text{sun}}(\lambda, \theta) \) and \( E_{\text{water}}(\lambda, \theta) \) in equations (A2) and (A3).

The dimensionless total albedo \( \alpha(\theta) \) for each model run is then calculated as

\[
\alpha(\theta) = \frac{\int_{285}^{800} (E_{\text{sun}}(\lambda, \theta) + E_{\text{water}}(\lambda, \theta)) d\lambda}{\int_{285}^{800} E_{\text{water}}(\lambda, \theta) d\lambda} = \frac{\int_{285}^{800} E_w(\lambda, \theta) d\lambda}{\int_{285}^{800} E_{\text{water}}(\lambda, \theta) d\lambda}
\]

(A7)

This allows us to distinguish the fractions of albedo generated from surface glint and by water-leaving irradiance, \( E_{\text{sun}}(\lambda, \theta) \) and \( E_{\text{water}}(\lambda, \theta) \), respectively.

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References
Chapter 6

General Conclusions

In this thesis, the vertical surface fluxes of momentum, heat, and carbon dioxide in shallow coastal ecosystems are investigated using observations and models. Improved understanding of these fluxes and how they should be parameterized is essential to accurately depicting the processes that govern these coastal environments. Overall, this thesis reveals that open-ocean and terrestrial models need modification before use in coastal environments.

Air-marsh momentum, heat, and carbon dioxide fluxes over an intertidal salt marsh are dependent on both the timing of solar noon and tidal inundation. Inundation suppresses the exchanges of momentum, CO$_2$, and sensible and latent heat between the marsh and the air above it. The effect of inundation increases with the depth of water on the marsh. After modifying standard models from the terrestrial DC community, a CO$_2$ flux model that accounts for the inundation effect is presented. This model allows the effect of inundation on the seasonal carbon uptake rate of the marsh to be quantified. When vertical exchange of CO$_2$ is modeled with inundation, the apparent net exchange from April to October is 19% larger than when modeled without the inundation effect. However, this ignores the likely increase in CO$_2$ concentration in the overlying water during the inundation period and the subsequent lateral export of C on the ebb tide. The discrepancy between the total net C exchange between the air and the marsh when the inundation effect is and is not incorporated provides a first-order estimate of the lateral flux of C between the marsh and adjacent
waters. The methods and results discussed in this thesis add to the relatively small body of literature dedicated to air-marsh CO₂ exchange, supporting some previous studies and contradicting others.

The standard parameterization of the COARE 3.5 bulk flux algorithm underestimates observed wind stress in a shallow embayment. The largest discrepancies are associated with winds that approach over the roughest terrain. Since COARE uses a semi-empirical roughness length parameterization, and the empirical data used to develop the algorithm were from the open ocean or coastal waters with unlimited fetch, the standard parameterization is not suitable to represent turbulent exchange very near the coast. When modified with an empirically-derived local roughness length parameterization, wind stress estimates from the algorithm are in good agreement with the observed wind stress in Mumford Cove.

Unexpectedly, the COARE 3.5 bulk flux algorithm estimates of buoyancy flux agreed well with observed buoyancy flux in the shallow embayment of Mumford Cove. The least agreement between bulk estimates and observed fluxes occurred for wind directions associated with the greatest fetch and access to open water. Examination of the ratio of the standard deviation of each wind velocity component to the friction velocity did not indicate the horizontal wind component is any more responsible for these results than the vertical wind component. Further analysis of the data is needed, as well as comparison of this data to data collected at open water stations.

Net shortwave radiative heat flux estimates using Payne (1972) and the COARE bulk flux algorithm provide a reasonable estimate of albedo in most shallow coastal waters with depths ≥ 1 m. The exceptions are environments with bright sand bottoms or highly turbid water with total suspended matter concentrations ≥ 50 g m⁻³. In those cases, the albedo increases enough to substantially reduce net shortwave heat flux into the water. Results of radiative transfer modeling presented in this dissertation can provide guidance to researchers who are unable to directly measure albedo in highly turbid waters or systems with bright sand bottoms. Improved confidence in parameterization of net shortwave air-sea heat flux will lead to more accurate estimation of coastal water temperatures and less uncertainty in numerical circulation
models of shallow systems.

Ultimately the goal of this thesis is to illustrate the potential consequences of using models and parameterizations developed with data from open ocean or terrestrial settings in a coastal environment, and to provide examples as to how those tools can be modified for successful use in shallow coastal ecosystems. The intended outcome of this work is to raise awareness of these issues among the coastal oceanography community so researchers may better understand the major assumptions and limitations of the tools they often use.
Appendix A

Appendix to Chapter 3: Additional Plots of $z_0$, $u_*$, and $C_{DN}$ as a function of $U_N$
Figure A-1: Number of data points per bin for all plots vs. $U_N$. Dashed line indicates the cutoff of 20 points per bin used to make Figures 3-5 - 3-9 and all of the plots in Appendix A and Chapter 4.
Figure A-2: Same as Figure 3-7 but for $z_0$. 

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Figure A-3: Same as Figure 3-8 but for $z_0$. 
Figure A-4: Same as Figure 3-5 but for $C_{DN}$. 
Figure A-5: Same as Figure 3-7 but for $C_{DN}$. 
Figure A-6: Same as Figure 3-8 but for $C_{DN}$. 
Figure A-7: Same as Figure 3-5 but for $u_*$.
Figure A-8: Same as Figure 3-7 but for $u_\ast$. 
Figure A-9: Same as Figure 3-8 but for $u_\ast$. 
Bibliography


