Evaluating the Accuracy of HawkEye Ocean Color Imagery: Comparative Study of Satellite-Derived and In Situ Measurements

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# Introduction

## Importance and Vulnerabilities of Coastal Estuarine Environments

Coastal estuarine environments, where freshwater and marine realms converge, epitomize unique ecological and biogeochemical dynamism. These zones play indispensable roles in the life cycles of myriad aquatic species, serving not only as nursery grounds but also as critical habitats throughout various life stages (Beck et al, 2001; Nagelkerken, 2007; 2013).

Economically, coastal estuaries are invaluable. Their productivity underpins an estimated annual value of US$2.5 trillion, bolstering fisheries, aquaculture, and tourism sectors (Hoegh-Guldberg et al, 2015). For instance, coral reefs, beyond their ecological grandeur, serve dual roles: as formidable economic assets and as natural defenses against climatic adversities, shielding coastal areas and fostering other pivotal ecosystems like seagrass beds and mangroves (Barbier, 2014). Seagrasses act as biological bulwarks against wave energy, especially during low tide scenarios, and secure sediment with their extensive root networks, aiding in coastal erosion prevention (Fonseca and Cahalan, 1992; Hemminga and Nieuwenhuize, 1990). Furthermore, beach and dune systems, through their root infrastructure, retain soil and counteract erosion, safeguarding numerous coastal assets, as well as providing a defense against coastal flooding (Doody, 2013; Barbier, 2014).

In the biogeochemical arena, coastal estuaries excel as pivotal carbon reservoirs. These wetlands, some of the most productive ecosystems globally, sequester an estimated 5 to 87 Tg of organic carbon annually (Mcleod et al, 2011). Intriguingly, macroalgae, traditionally perceived as having minimal carbon burial potential due to their substrate preference, have been identified as significant contributors to global carbon burial, particularly when they colonize soft sediments (Macreadie et al., 2019).

Beyond their tangible values, coastal estuarine environments resonate deeply with local communities, offering recreational, cultural, and aesthetic significance (Ghermandi et al, 2011). Yet, alarmingly, these keystone ecosystems are confronted with escalating anthropogenic pressures, from pollution and overfishing to climate perturbations and sea level rise. For instance, mangrove ecosystems have contracted by 35%, with some regions experiencing annual loss rates as high as 3.6%, mainly due to habitat destruction through human encroachment (Valiela et al, 2001; Kathiresan and Bingham, 2001). Analogously, many tropical warm-water coral reefs have witnessed precipitous declines of at least 50% over the past three to five decades (Hoegh-Guldberg et al., 2017). The subsequent degradation could have profound repercussions.

## Expanding Horizons of Ocean Color Remote Sensing

Encompassing approximately 70% of Earth’s surface, the oceans, while indispensable, have traditionally presented considerable challenges for detailed study. The advent of remote sensing technologies has revolutionized our comprehension of marine domains by delivering comprehensive data on diverse oceanic attributes. Prior to this technological leap, oceanographic data predominately relied on point-based measurements, such as those from ships, providing limited temporal and spatial snapshots, which were insufficient to capture mesoscale variability (Carr et al., 2006). Remote sensing has augmented our capacity to discern sub-mesoscale features, like oceanic fronts and eddies, and even intricate micro-scale phenomena essential for marine ecological dynamics (Belkin, 2021). Specifically, ocean color remote sensing has been instrumental in estimating global phytoplankton concentrations, thus informing chlorophyll a levels and primary productivity. While invaluable for open ocean studies, its accuracy wanes in coastal and estuarine regions due to interferences from optically active components such as colored dissolved organic matter (CDOM) and suspended sediments

The essential role of photosynthesis in the global carbon cycle is unequivocal. Astonishingly, marine ecosystems, with a mere phytoplankton biomass of around 1 Pg, contribute to 46% of global net primary production, approximating an annual mean of 48.5 Pg C (Field et al., 1998). The foundational premise of ocean color remote sensing is the correlation between the intensity and spectral distribution of visible light reflected off the water surface and the underlying biogeochemical processes (Smith and Baker, 1978). Emphasis has invariably been on chlorophyll a, a phytoplankton pigment, whose absorption in the visible spectrum modulates the ocean’s hue, turning it more greenish with rising concentrations (O’Reilly and Werdell, 2019). Since NASA’s maiden space-born ocean color sensor launch, Coastal Zone Color Scanner (CZCS), in 1978, there have been monumental strides in our grasp of phytoplankton distribution across oceanic expanses, facilitating monitoring from seasonal and interannual scales (Delgado et al., 2015; Chen et al., 2022)

The purview of ocean color remote sensing has evolved, transcending mere chlorophyll estimations. Enhanced technology now accurately quantifies other marine constituents like total suspended matter, CDOM, and particulate inorganic carbon. Additionally, its applications now span diverse marine habitats, monitoring environmental perturbations in both pelagic and coastal zones (Dierssen and Randolph, 2012).

## Challenges of Remote Sensing in Coastal Biogeochemical Dynamics

Coastal regions, despite accounting for only a fraction of the world’s oceanic area, are crucial nodes in the biogeochemical processes underpinning marine productivity. Accounting for 75-90% of global suspended riverine input and roughly 15% of marine primary production, coastal regions are hotspots for biogeochemical transformations (Loisel et al., 2013). Suspended particulate matter (SPM), a composite of organic and inorganic constituents, modulates light penetration and nutrient dynamics, thus influencing phytoplankton production. The intricate and variable nature of coastal zones, however, impedes a holistic comprehension of their contributions to global carbon fluxes. Persistent ambiguities regarding organic matter export from the coast underscore the imperative to elucidate the roles of SPM, particulate organic carbon (POC), dissolved organic carbon (DOC), and chlorophyll (Chl) within marine biogeochemical cycles (Bauer and Druffel, 1998; Hedges et al., 1997; Hedges, 1992, Schlünz and Schneider, 2000). Traditional data collection methodologies, including oceanographic cruises and in situ time series, while indispensable, are constrained by spatial and temporal limitations, coupled with substantial financial and labor costs. Conversely, remote sensing promises expansive spatial and temporal coverage, yet grapples with challenges related to depth resolution and accuracy, necessitating in situ validation (Miller and McKee, 2004; Doxaran et al., 2009; Vanhellemont and Ruddick, 2014, Ody et al., 2016).

Coastal remote sensing is mired in complexities arising from the multifarious nature of the coastal environment. Issues such as photon reflection from adjacent landmasses, sediment resuspension in littoral zones, and ocean floor reflection are significant impediments to the accurate estimation of marine bio-optical properties (Loisel et al., 2013). Terrestrial fluxes from riverine sources, instrumental in molding nutrient gradients, light availability, phytoplankton activity, and pollutant dissemination, remain inadequately quantified (Häder and Gao, 2015). Effective monitoring of SPM is vital for deciphering sedimentary dynamics and facilitating ecologically informed coastal management. Yet, the multifarious influences shaping SPM distribution at river mouths, ranging from fluvial attributes to seasonal shifts and coastal conditions, are often insufficiently captured due to data paucity. Furthermore, the coastal milieu, replete with reflective minerals and high concentrations of particulate organic matter, can obfuscate satellite-derived signals, confounding atmospheric corrections and bio-optical algorithm outputs (IOCCG, 2000; 2006). Intermittent cloud cover further exacerbates this by misidentifying turbid zones as clouded regions, thus truncating data continuity (Loisel et al., 2013). The pronounced heterogeneity inherent to coastal zones amplifies these complications. Collectively, these impediments accentuate the need for refined methodologies and enhanced tools tailored to coastal remote sensing exigencies.

# Literature Review

## Review of Ocean Color Missions

NASA’s maiden foray into Earth observation can be traced back to the 1960s with initiatives like TIROS and NIMBUS, primarily oriented towards meteorology. The spark for ocean color (OC) observations was kindled when a 1970 publication in Science revealed the potential of airborne measurements to discern near-surface Chl concentrations (Clarke et al., 1970). This revelation galvanized a burgeoning community in marine optics and ocean biology/ecology, aspiring to harness the potential of satellite-based OC observations.

The Coastal Zone Color Scanner (CZCS), operational from 1978 to 1986, heralded a new era in marine remote sensing. As a singular OC instrument aboard the Nimbus-7 satellite, it boasted six bands, emphasizing wavelengths centered on 443, 520, 550, 670, and 750 nm and a thermal IR band at 11.5 um (NASA). The Nimbus Experiment Team supported the CZCS initiatives by developing algorithms for atmospheric correction (AC) and bio-optical data product derivation (Gordon et al., 1983). McClain et al.’s (1984) assessment of these algorithms, juxtaposing in situ Chl measurements with CZCS-derived data values across the Gulf Stream, revealed remarkable congruence. Although Nimbus-7 sensors were considered a proof-of-concept, collaborative endeavors with the Skidaway Institute of Oceanography yielded SEAPAK, a software suite for CZCS data manipulation, consequently enticing a wider research community. SEAPAK was eventually superseded by the SeaWiFS Data Analysis System (SeaDAS) (Baith et al., 2001).

The Sea-viewing Wide Field-of-view Sensor (SeaWiFS), aboard the OrbView-2 spacecraft (formerly SeaStar) from 1997 to 2010, incorporated 8 distinct bands centered on the 412, 443, 490, 510, 555, 670, 765, and 865 nm wavelengths collected data with a 1.1 km spatial resolution (NASA). In response to CZC’s sensor attrition challenges, NASA innovated calibration methodologies for the SeaWiFS mission, including deploying the Marine Optical Buoy (MOBY) off Lanai, Hawaii, and pioneering lunar calibration for ongoing sensitivity assessments (Barnes et al., 2001). These novel calibration approaches have since been adapted to ensure NASA OC missions (Franz et al., 2012).

The Moderate Resolution Imaging Spectroradiometer (MODIS), aboard the Aqua and Terra satellites since 1999, supports diverse environmental inquiries with its 36 spectral bands ranging from 412 nm to 14.3 um. Of these, nine are quintessential for OC studies, centered on wavelengths 412, 443, 488, 531, 547, 667, 678, 748, and 869 nm, at 1 km spatial resolution, with the MODIS-Aqua proving more robust for marine applications due to calibration discrepancies with MODIS-Terra (NASA; Franz et al., 2008; Kwiatkowska et al., 2008).

Under the aegis of the European Space Agency (ESA), the Copernicus initiative launched the Sentinel-3 satellite series, with two active and two prospective missions. Equipped on the Sentinel-3A and Sentinel-3B, the Ocean and Land Colour Instrument (OLCI), encompasses 21 spectral bands ranging from 400 to 1020 nm and provides 300 m full spatial resolution (NASA).

The Operational Land Imager (OLI), aboard the Landsat-8 satellite since 2013, offers 30 m spatial resolution with spectral bands at 440, 475, 550, 655, 865, 1370, 1610, 2200, and a panchromatic band at 590 nm (US Geologic Survey, n.d.). While primarily designed for terrestrial inquiries, OLI’s bands span the blue to green region of the visible spectrum and include two bands in the near-infrared (NIR) to shortwave IR (SWIR), making it compatible with the AC process, and subsequently has been proven to be useful in OC science (Franz et al., 2015; Vanhellemont and Ruddick, 2014; 2015).

## The SeaHawk/HawkEye

The 2018-initiated SeaHawk CubeSat mission, supported by luminaries such as Gene Feldman and the Ocean Biology Processing Group (OBPG), epitomizes a transformative paradigm in OC remote sensing by pioneering cost-effective Earth Observation (EO) endeavors. The mission’s core instrument, the HawkEye sensor, created by Alan Holmes with Cloudland Instruments, redefines miniaturization in OC instruments.

Distinct from traditional EO satellites, SeaHawk’s design emphasizes efficiency. Its compact and lightweight stature of 10 x 10 x 30 cm3 and 3 kg weight stands in stark contrast to Orbview-1’s larger 50 x 50 x 200 cm3 frame and 309 kg weight. Furthermore, its rapid development span of two years and the modest budget of $1.7 million is significantly leaner compared to OrbView-1’s decade-long, $100 million undertaking (https://www.eoportal.org/satellite-missions/seahawk-1#seahawk-1-cubesat-ocean-color-mission).

Notably, SeaHawk’s efficiency doesn’t trade off performance. The HawkEye instrument, despite its condensed 1U size, embodies an advanced sensor configuration with 4 linear arrays and 8 bands akin to SeaWiFS. It achieves an impressive spatial resolution of 120 m, an eightfold enhancement from SeaWiFS’s 1000 m while maintaining a commensurate signal-to-noise ratio (SNR). Given the ocean’s inherent darkness, wherein up to 90% of light detected in some bands is not -ocean-originated, maximizing SNR is paramount. HawkEye employs a 4X oversampling methodology in tandem with an aggregation of three chroma channels. This technique amplifies the SNR by the square root of 12, a result both theoretically and empirically corroborated. An additional 2 x 2 binning process further refines SNR, ensuring spectral resolutions akin to SeaWiFS but with a fourfold enhancement in spatial detail (Holmes et al., 2018).

While SeaWiFS was instrumental in providing global OC data, its resolution often fell short for detailed observations of localized marine zones like estuaries. HawkEye, with its superior spatial resolution, bridges this gap. Its spectral alignment with SeaWiFS ensures data consistency, but its nimble, cost-effective design, rooted in CubeSat technology and off-the-shelf commercial components, signifies technological progress. Thus, HawkEye doesn’t supplant missions like SeaWiFS; it augments them, offering a more granular perspective of intricate marine ecosystems. With the promise of scalability through potential constellation launches, SeaHawk delineates a promising trajectory for affordable, high-resolution marine monitoring endeavors (Jeffrey et al., 2018)

## Atmospheric Correction

Atmospheric correction (AC) serves as a crucial computational step for ensuring that bio-optical models and pigment algorithms harness oceanic conditions without atmospheric interferences. This process distills the water leaving radiance (*L*w)from the total radiance (*L*t) registered by the satellite sensor at the top of the atmosphere (TOA). Such a step is imperative, given the intricate interplay between solar radiation and Earth’s atmosphere, influencing the light’s trajectory and characteristics reaching satellite sensors. Inaccurate AC can severely compromise the veracity of OC mission outputs.

The observed upwelling radiance (*L*u) is an amalgamation of:

1. *L*a, atmospheric contribution, from solar radiation scattering by atmospheric gases and aerosols.
2. *L*r, surface-reflected radiance, depicts sunlight reflected by the water's surface.
3. *L*w, water-leaving radiance, represents the light that has permeated the ocean surface, interacted with marine constituents, and scattered upwards.

Conceptually, this interrelation can be depicted as:

A diagram of a sun and waves

Description automatically generated with medium confidence

Figure 1: A model of contributions to the observed upwelling radiance above the sea surface (Mobley, Ocean Optics Web Book: Atmospheric Correction, The Atmospheric Correction Problem)

This model serves as an aggregate framework but lacks detail. A more nuanced theoretical representation is as follows:

A diagram of a ray of light

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Figure 2: Qualitative illustrations of the various processes contributing to the total TOA radiance (Mobley, Ocean Optics Web Book, Atmospheric Correction: The Atmospheric Correction Problem)

Here, *L*R signifies Rayleigh scattering, factoring in sky reflectance *L*sky­, whichincorporates reflectance by the sea surface. *L*A consolidates aerosol *L*a and aerosol-gas *L*aR contributions, *L*g denotes sun glint, and *L*wc represents sun/sky radiance by whitecaps and foam. The transmittance factors *T* and *t* modulate these contributions.

*T*, or direct transmittance, considers near-collinear paths between the solar source and the observing sensor. It signifies the fraction of light traversing the atmosphere without scattering. An illustrative equation for an off-nadir viewing direction θv is:

Here, τ is the atmospheric optical depth along a nadir path. This formulation indicates that as the viewing angle deviates from the zenith, atmospheric traversal increases, subsequently diminishing *T*.

Diffuse transmittance *t* encompasses multi-directional scattered or emitted radiance, influenced by the atmospheric characteristics and the angular distribution of *L*w:

Here, *L*w is the water-leaving radiance at the sea surface and is the water-leaving radiance that reaches the TOA.

A diagram of a sun glint

Description automatically generated

Figure 3: Illustration of sun glint as seen from the TOA, which is described by a direct transmittance (left), and water-leaving radiance as seen from the TOA, which is described by a diffuse transmittance (right) (Mobley, Ocean Optics Web Book, Atmospheric Correction: Atmospheric Transmittances)

Further refined AC procedures incorporate gaseous transmittance and polarization correction:

Here, *t*dv is the diffuse transmittance along the sensor’s line of sight. Two types of gaseous transmittance are considered: *t*gv pertains to the attenuation of light due to atmospheric gases in the sensor’s viewing direction, and *t*gs to the direction of solar illumination. *f*p is the polarization correction factor (Mobley, 2020)

In OC retrieval, atmospheric contributions can account for up to 90% of TOA radiance, particularly in shorter wavelengths such as blue (IOCCG, 2010). Classical algorithms like Gordan and Wang’s (1994) leverage the “black pixel” postulate for the near-infrared (NIR) band, presuming NIR wavelengths to have negligible oceanic contributions. While efficacious for oligotrophic waters, this fails in optically complex waters like coastal and turbid regions (Siegel et al., 2000; Ruddick et al., 2000; Stumpf et al., 2003). Innovative correction strategies for such waters have emerged, either adjusting NIR radiance with parameters like chlorophyll a or sediment concentrations (Lavender et al., 2005; Siegal et al., 2000) or employing models concurrently solving aerosol and backscattering properties (Ruddick et al., 2000). Modern methodologies also utilize shortwave infrared (SWIR) bands, enhancing AC in multifarious waters (Wang et al., 2007; 2011; Hu et al., 2012).

## Bio-Optics

Ocean color remote sensing harnesses bio-optical properties to illuminate facets of marine ecosystems and biogeochemical dynamics. These properties delineate how light interacts with waterborne constituents, encompassing phytoplankton, suspended sediments, and DOC. Grounded in bio-optical principles, specialized pigment algorithms have been formulated to interpret radiometric data, allowing the elucidation of water’s biogeochemical attributes like phytoplankton concentration, non-algal particles, and CDOM (Werdell et al., 2018). Such analytical paradigms have propelled forward our grasp on key research domains, including carbon cycling (Allison et al., 2010; Siegel et al., 2014), oceanic productivity (Saba et al., 2011), and phytoplankton diversity (Westberry et al., 2016).

Bio-optical studies are anchored in two cardinal optical property categories: Inherent Optical Properties (IOP) and Apparent Optical Properties (AOP). IOPs, devoid of any dependencies on the incidence angle or intensity of light, represent attributes of water and its suspended constituents. Key processes encapsulated within IOPs include absorption *A*(λ), scattering *B*(λ), and transmittance *T*(λ), articulated as:

Conforming to the energy conservation principles, these parameters abide by:

A diagram of a mathematical equation

Description automatically generated

Figure 4: Geometry used to define inherent optical properties (Mobley, Ocean Optics Web Book, Inherent and Apparent Optical Properties: Inherent Optical Properties)

Within the IOP geometric framework, light interactions with a diminutive water volume, ΔV, with thickness Δr, can be encapsulated. Given a collimated monochromatic light beam with spectral radiant power Φ­i(λ) scattered at an angle ψ, the energy conservation becomes:

Concurrently, the absorption coefficient α(λ) and scattering coefficient *b*(λ) represent rates of light absorption and scattering per unit distance:

Their summation yields the beam attenuation coefficient *c* (λ), which captures the totality of light propagation through a medium:

Complimenting IOPs, AOPs provide empirical metrics describing water’s appearance, amalgamating ambient light conditions with the bio-optical paradigm. Among paramount AOPs is Remote Sensing Reflectance (*R*rs), denoted as:

Herein, *L*w denotes the water-leaving radiance, and *E*d represents the downwelling irradiance. It is critical to distinguish between irradiance (*E*)—a scalar quantity representing radiant power received by a surface per unit area (W m-2)—and radiance (*L*)—a vector quantity portraying radiant power in a specific direction per unit solid angle per unit projected area (W m-2 sr-1).

The irradiance reflectance (*R*) demarcates the fraction of downwelling irradiance *E*d (which is considered a known quantity: solar constant plus atmospheric correction), reflected as upward irradiance (*E*u). *f* is a conversion factor that relates *R* to :

*R* is a ratio that is modulated by factors like solar inclination, water turbidity, scattering mechanisms, and absorption spectra of marine constituents. *Q* is the conversion factor that relates *E*u to *L*u:

Serving as a nexus between IOPs and AOPs, *R*rs­ standardizes water-leaving radiance, thus simplifying inter-comparisons across varying light scenarios. These equations can be related as:

Or more succinctly:

This intricate interplay between IOPs and AOPs not only facilitates accurate oceanic parameter retrieval but also amplifies our holistic grasp on marine biogeochemistry and ecosystem dynamics (Mobley, 2020).

## Pigment Algorithms

Pigment algorithms serve as computational frameworks that convert remote sensing reflectance *R*rs(λ) into geophysical variables, prominently chlorophyll a (Chl) concentration. These variables are essential proxies for assessing marine ecosystem health, underpinning endeavors in fisheries management, water quality monitoring, and recreational activities (IOCCG, 2008). Nonetheless, a salient constraint arises from satellites predominantly capturing surface waters, potentially misrepresenting sub-surface biomass distributions (Hill and Cota, 2005). Two primary algorithmic archetypes for deriving Chl from *R*rs(λ) are empirical and semi-analytical algorithms (SAAs).

Empirical Ocean Color (OC) algorithms hinge on the statistical nexus between *R*rs(λ) and concurrent in situ Chl observations. Pioneered by Clark et al. (1970), renowned models such as OC2, OC3M, and OC4 have since emerged. Specifically, the OC4 algorithm, tailored for SeaWiFS, computes Chl using the ratio of blue (*R*rs(443), *R*rs(490), *R*rs(510)) to green light (*R*rs(555) reflected from the sea (O’Reilly et al., 1998; 2000):

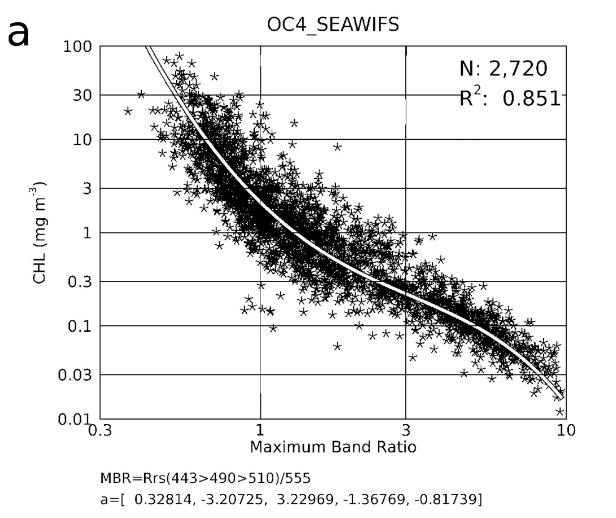


Figure 5: High chlorophyll concentrations are associated with low blue over green reflectance. Relatively clear water would be to the right on the x-axis (O’Reilly and Werdell, 2019)

Rooted in robust datasets of paired in situ Chl and *R*rs(λ) measurements, this third-order polynomial model, however, remains vulnerable to calibration disparities, atmospheric correction, or other noise perturbations (McClain, 2009; Dierssen, 2010). Although proficient in Case 1 waters—where phytoplankton predominantly influence optical properties—empirical algorithms often falter in Case 2 coastal waters. Here, other optically active constituents like CDOM and TSM introduce complexities and can skew results (Sathyendranath et al., 1999; Prieur and Sathyendranath; Dierssen et al., 2006; Schofield et al., 2004; Dowel, 2012).

Alternative empirical methodologies include *R*rs(λ) line-height models (Hu et al., 2012), red-edge ratio linear methods (Moses et al., 2012), and machine learning techniques such as artificial neural networks (Doerffer and Schiller, 2007). NASA’s Ocean Biology Processing Group notably employs the OC3/OC4 band ratio algorithms across OC missions, with the NASA bio-Optical Marine Algorithm Dataset (NOMAD) (O’Reilly et al., 2000; NASA Ocean Color; Werdell and Bailey, 2005). A pivotal enhancement came in 2014, integrating the OC3/OC4 algorithm with the ocean color index (OCI) to refine Chl estimations in oligotrophic waters (Chl < 0.3 mg/m3) (Franz, 2014).

The interference of CDOM and TSM on the normalized water-leaving radiance (*nLw*) complicates accurate Chl determinations via empirical algorithms (IOCCG, 2006). Mitigating this, SAAs have emerged, amalgamating in situ IOP databases specific to specific aquatic regions with radiative transfer theoretical frameworks (Lee et al., 2002; Maritorena et al., 2002; Sathyendranath et al., 2001). Delineating IOPs, SAAs offer insights into the total absorption and backscattering coefficients (*a*(λ)), *b*b(λ), respectively) of water (*a*w(λ), *b*w(λ)) and a diverse range of marine constituents, including phytoplankton (*a*ph(λ), *b*ph(λ)), detrital matter or non-algal particles (*a*d(λ)), *b*d(λ)), and CDOM (*a*CDOM(λ) or *a*g(λ)) (IOCCG, 2006):

Notable strategies to derive IOPs encompass both top-down and bottom-up approaches, with algorithms such as the Quasi-Analytical Algorithm (QAA), adopting the former and the Generalized Inherent Optical Property (GIOP) model and the Garver-Siegel-Maritorena (GSM) model embracing the latter (Lee et al., 2002; Mishra et al., 2014; Rotta et al., 2021). Accurate parameter estimations in SAA often hinge on inversion methods, like the nonlinear least squares optimization, typically using the Levenberg-Marquardt optimization method, to fit the observed *R*rs(λ) spectrum. SAAs can be further classified into different categories depending on their approach to spectral data interpretation, including direct linear inversion, spectral deconvolution, and bulk inversion (Werdell et al., 2018).

# Objectives

1. Obtain high-resolution ocean color imagery from HawkEye, MODIS, OLCI, and OLI spanning the Cape Fear River Estuary that overlaps temporally with R/V Cape Fear in situ data collection cruises. This imagery will serve as a basis for evaluating HawkEye’s performance against in situ water parameter measurements captured by the Acrobat and handheld spectroradiometer.
2. Investigate the spatial variability of Chl concentrations within the CFRE. This will entail integrating in situ and satellite-derived measurements, targeting regions proximate to Wilmington and the mouth of the Masonboro Inlet. Analyze the intricacies captured by HawkEye that were potentially overlooked by the lower resolution satellites.
3. Execute a comprehensive match-up analysis, juxtaposing satellite observations with their in situ counterparts to evaluate the accuracy and reliability of satellite-derived measurements. This assessment will leverage statistical metrics such as R2, RMSD, MAPD, CV, Bias) to quantify discrepancies.
4. Synthesize, scrutinize, and disseminate the research outcomes through a prominent scientific journal. The methodologies and data sets will be made open source to be shared with the broader scientific community to promote HawkEye’s capabilities and encourage its increased utilization in related studies.

# Materials and methods

## Study site description

The study was conducted in two distinct regions along the Cape Fear River Estuary (CFRE) on the southeastern coast of North Carolina: the Cape Fear River proximate to Wilmington (34.0836, -77.9331) and the mouth of the Masonboro Inlet near Wrightsville Beach (34.181, -77.798). The selected area is of particular interest because of the significant discharge of the Cape Fear, which drains a large portion of the state’s groundwater, rich in nutrients from upstream CAFOs.

A map of the ocean

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Figure : Study area in southeastern North Carolina

A map of a sea

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Figure 7: Seven transects where in situ measurements were taken at the mouth of the Masonboro Inlet

The Cape Fear River Basin (CFRB), one of North Carolina’s entirely contained river basins, is a nexus of human activity and nature. It commences with the confluence of the Deep and Haw rivers and culminates in a 35-mile-long coastal estuary. Ecologically, the estuary is a sanctuary for marine biodiversity, including juvenile fish, crabs, and shrimp, and habitats for various endangered and threatened species. As North Carolina’s most industrialized basin, it houses one-fifth of the state’s populace, encompassing major urban areas like Durham-Chapel Hill, Fayetteville, and Wilmington. Growth in human and livestock populations has augmented nutrient flows into waters. The CFRB is unparalleled in terms of industrial livestock agriculture, boating the highest density of Concentrated Animals Feeding Operations (CAFOs) globally, producing over 10 million hogs, 16 million turkeys, and 300 million chickens annually (NC.gov; capefearriver.org).

Satellite data acquisition and processing

In this study, satellite data were acquired from a suite of platforms encompassing MODIS Aqua, Sentinel 3A and 3B OLCI, Landsat 8 OLI, and SeaHawk HawkEye, specifically targeting the Lower CFRE and Masonboro Inlet vicinity. This acquisition was facilitated through the Ocean Color Web (<https://oceandata.sci.gsfc.nasa.gov/>), supported by the OBPG at NASA-GSFC. Emphasis was placed on selecting imagery proximate to the dates of in situ water sampling, particularly May 3rd and 5th, 2023.

The data were processed from level-1A to level-2 using SeaDAS v8.10, employing the l2gen incorporated within the software package, and then to Level-3 with the l2bin. The checked flags to exclude invalid data include: ATMFAIL, LAND, HILT, HISATZEN, STRAYLIGHT, CLDICE, COCCOLITH, LOWLW, CHLWARN, CHLFAIL, and NAVWARN. For the May 3rd transect along the Cape Fear River, 1 satellite image was sourced from both OLI and Sentinel 3B OLCI, both dated May 3rd. Regrettably, other satellite platforms either lacked coverage or produced data marred by dense cloud obscuration for the target region on this date. The May 5th Masonboro Inlet expedition availed of a broader dataset: 2 HawkEye images (May 6th and May 7th), a Sentinel 3A OLCI image (May 7th), 2 Sentinel 3B OLCI images (May 5th and 7th), and a MODIS image (May 7th). Notably, only 1 suitable imagery dated May 5th was accessible from these satellite sensors, primarily due to the aforementioned lack of coverage or cloud interference.

A rainbow colored map of the sea

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Figure : Aqua-MODIS, May 7

Figure : S3A-OLCI, May 6

Figure : HawkEye, May 7

Though it is advantageous to in situ data collection and satellite overpass coincide temporally, the absence of significant meteorological perturbations between May 5-7, 2023, coupled with the system’s modest tidal variability, suggests the water quality metrics would exhibit relative temporal stability (Han & Jordan, 2005). This assumption is corroborated by prior studies that have achieved satisfactory outcomes despite greater temporal discrepancies between satellite and in situ datasets (Baban, 1997).

## In situ remote sensing reflectance (Rrs)

The remote sensing reflectance (*R*rs) was determined utilizing the HR-512i handheld spectroradiometer from Spectra Vista CorporationTM. This spectroradiometer encompasses 512 optical channels spanning 350 nm and 1050 nm, allowing measurements of downwelling surface irradiance (*E*s), as well as profiles for downwelling irradiance (*E*d) and upwelling radiance (*L*u). Data acquisition and preliminary processing were carried out with the SVC PC Data Acquisition Software. The *R*rs(λ), if not directly available, was computed from irradiance reflectance or water-leaving radiances, via:

Here, represents the downwelling spectral irradiance just above the water surface. In deriving *L*w (λ), we adhered to established ocean optics protocols, as described by Mueller et al. (2000):

In this equation, *L*u(λ, 0-) is below-surface water-leaving radiance, signifies the Fresnel reflectance index of seawater, andw is the Fresnel refractive index of seawater. The above-surface downwelling irradiance, was derived as:

Where α represents the Fresnel reflection albedo due to solar radiation, and is extrapolated from the profile (Tilstone et al., 2013).

In situ measurements

During our survey on May 3, 2023, The R/V Cape Fear navigated the Cape Fear River, while on May 5, 2023, the vessel ventured through the mouth of the Masonboro Inlet extending slightly offshore near Wrightsville Beach. Throughout these voyages, we employed the Acrobat system, a versatile marine research platform engineered by Sea Sciences Inc. Despite its lightweight frame (approximately 30 lbs. without instrumentation), the Acrobat seamlessly accommodates a range of standard research instruments and facilitates real-time data acquisition. To this platform, we integrated the Seabird SBE 25 plus Sealogger CTD, along with a suite of auxiliary sensors:

• Seabird SBE 4 Conductivity Sensor

• Seabird 43 Oxygen Sensor

• Seapoint Chlorophyll Fluorometer

• Seapoint Ultraviolet Fluorometer

• Seapoint Turbidity Meter



Figure : The Acrobat with payload of auxiliary instruments

On May 5, we noted the malfunctioning of the CDOM sensor (Seapoint Ultraviolet Fluorometer), while the turbidity sensor’s performance was observed to be 14% below its specified range. It’s pertinent to mention that this observation isn’t a reflection on the quality of Seapoint sensors; rather, it underscores the age of these instruments, being original components of the Acrobat and in operation for over 15 years.

In tandem with the aforementioned, the R/V Cape Fear is equipped with the SBE 21 SeaCAT Thermosalinograph, a flow-through measuring apparatus situated near the ship’s seawater intake. Paired with an AC-powered interface box close to a computer, this device not only provides power and an isolated data interface but also integrates a NMEA 0183 port, which appends navigational data. Primarily, the thermosalinograph has been calibrated to render accurate readings of sea surface temperature and conductivity while in transit. Data obtained is concurrently archived and transmitted to a computer in real time. The thermosalinograph system further incorporated auxiliary sensors:

• Seapoint Chlorophyll Fluorometer

• Seapoint Ultraviolet Fluorometer

• Seapoint Turbidity Meter

The surface layer of the water column, represented by the top 10 m, was chosen to derive the best estimates of Chl concentration for comparison with satellite observations. The Chl concentration discerned from satellite radiometry closely approximates a weighted average of the water column’s first optical depth, particularly when there’s vertical inhomogeneity. The weighting function hinges on the layer’s optical characteristics (Sathyendranath et al., 1989; Zaneveld et al., 2005; Gordon and Clark, 1980). Based on this understanding, the averaged Chl concentration of the initial 10 m was utilized for evaluating satellite-derived Chl data (Sathyendranath et al., 2019).

## Match-up analysis and accuracy evaluation

In situ measurements will be paired with their respective satellite observations through proximity-based latitude and longitude identification. The central pixel of the satellite data will be aligned with the in situ point, and a surrounding 3 x 3 pixel matrix, centering the in situ data point, will be analyzed. Key statistical metrics from this matrix, such as mean, median, and coefficient of variation, will be recorded for reference.

The accuracy of each satellite sensor will be statistically evaluated using five metrics: coefficient of determination (*R*2), Root Mean Square Difference (*RMSD*), Mean Absolute Percentage Difference (*MAPD*), Coefficient of Variation (*CV*), and bias (δ). These metrics are formulated using the differences between estimated () and measured ( values of remote sensing reflectance (*R*­rs ). The equations are (*N* is the number of data points) (Wang et al., 2022):

# Preliminary Results

In the study conducted at the Masonboro Inlet’s mouth, Chl concentration contour plots were generated for each transect (Figure 8). The values ranged from 0.0 μg/L to 2.19 μg/L. The path taken by the Acrobat through the water column was interpolated linearly to depict the water column’s properties through the extent of each transect. These contour plots were subsequently stacked side by side to offer a comprehensive view, maintaining their orientation corresponding to the water column (Figure 9). To contextualize these observations, bathymetry data from the transect locations were incorporated reference (Figure 10). The depicted Chl concentrations exhibit vertical inhomogeneity and are believed to be well within the first optical depth of coastal euphotic zone. Analogous plots with be generated for the Cape Fear River cruise.

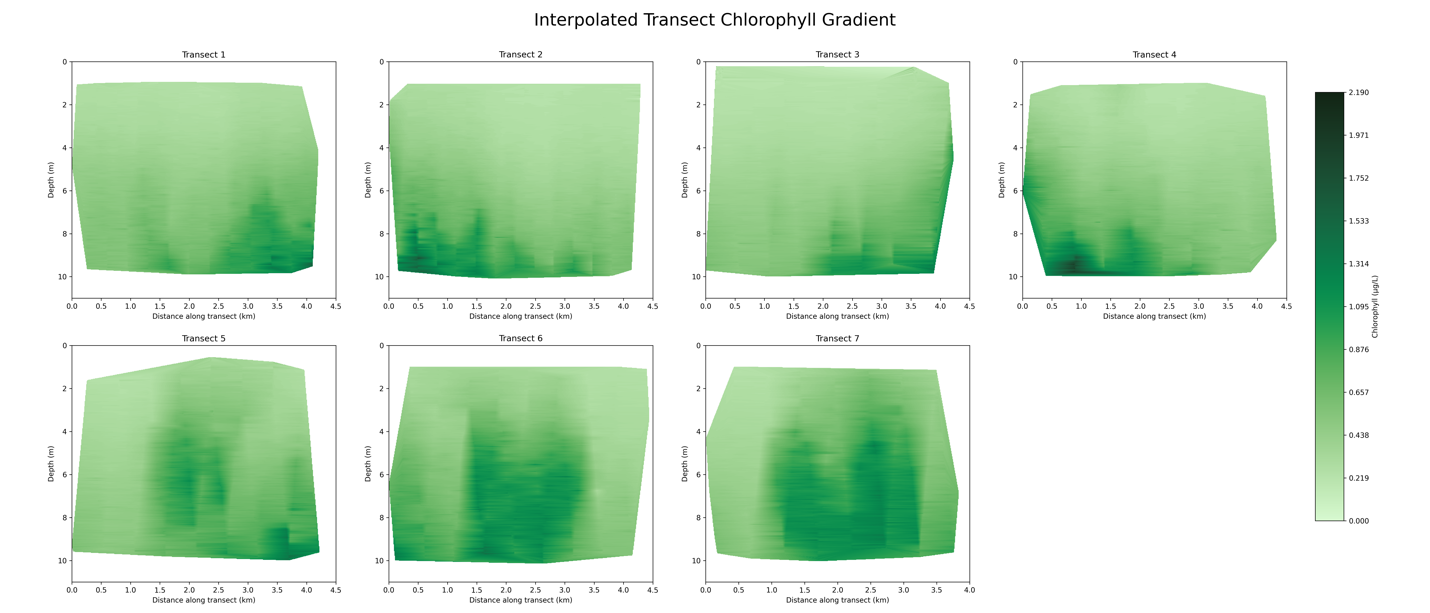


Figure 13: Interpolated chlorophyll concentrations along each transect at the mouth of the Masonboro Inlet

A graph of green squares

Description automatically generated

Figure 14: The 7 transects stacked side by side.

A green and grey gradient

Description automatically generated

Figure 15: Example of the Chl measurements with the bathymetry data added for reference.

# Academic Plan

For my research thesis, I intend to work on the following future tasks:

* Process and analyze handheld spectroradiometer data and obtain *R*rs at locations along the transects for both R/V Cape Fear research outings.
* Spatially bin satellite imagery to 3 x 3 pixel matrixes along the transects.
* Average the depth data of in situ chlorophyll within the first 10 m of the water column for comparison with satellite observed data.
* Pair satellite-derived data bins with their corresponding in situ observation averages based on latitude and longitude coordinates, centering the in situ data in the bins.
* Conduct a statistical analysis to assess the consistency and accuracy of the satellite-derived data against in situ measurements. Quantify the discrepancies.
* Synthesize all findings, comparisons, and analyses in a comprehensive document and clearly articulate the details of the observations, methods, and results.
* Write and defend the thesis.

As for my academic plan, I have taken all required coursework and hours after this semester, so I will do continuous enrollment for the remainder of my time at UNCW. My timeline with some of the major tasks is as follows\*:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Task | Sept-Oct 2023 | Nov – Dec 2023 | Jan – Feb 2024 | Mar – Apr 2024 | May – July 2024 |
| Write and Defend Oral Prospectus |  |  |  |  |  |
| Data Preparation |  |  |  |  |  |
| Match-up Analysis |  |  |  |  |  |
| Statistical Evaluation |  |  |  |  |  |
| Write and defend the thesis |  |  |  |  |  |

\* If graduating by July 2024 for a total of 24 months in the program

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