

Rethinking Coastal Ocean Observing, Intelligence, Resilience, and Prediction

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Introduction

As climate change accelerates the pace of oceanic and atmospheric shifts, the predictability of ocean processes, physics, ecosystems, water levels, and weather events becomes increasingly compromised. This heightened uncertainty undermines the effectiveness of today's AI-driven data analytics and modeling applications. These are hindered by the low resolution of critical *in-situ* data, required for their computations. Accurate weather, ocean, and ecosystem models are vital for predicting hurricane intensity, tracking, and impact, but they often fall short.

In-situ coastal ocean data collection systems are sparse, with significant gaps in coverage, particularly in crucial areas. The continental shelf regions, where hurricanes transition from the deep ocean to shallow coastal waters and pose significant threats to life and property, lack comprehensive multi-parameter baseline data collection and event-response capabilities.

The "Coastal Warning and Rapid Response Data Density System" (SeaWARRDD) is specifically designed to enhance hurricane forecast data collection by capturing comprehensive *in-situ* MetOcean+ data. It provides detailed insights into the ocean-atmosphere boundary layer and the water column below. SeaWARRDD's coordinated, multi-platform approach integrates essential stationary time-series data with mobile time-series data, offering both regional coverage and rapid-response adaptability to evolving events. Its capabilities include real-time mission control, data transmission, display, archiving, advanced analytics, and the development of tailored data products for specific end users. Our team, with decades of experience across the federal, state, academic, and private sectors, has been at the forefront of designing, developing, installing, and maintaining ocean monitoring and data collection systems, including in bays and estuaries.



Figure 1: SeaWARRDD Complete Vision with AI Processing and Comprehensive Observing Sensor Suites.

Hurricane Damage and Forecast Risk

Hurricane Ian struck West Florida in October 2022, killing 150 people and causing over \$113 billion in damage. Ian caught many by surprise due to deviations in track forecasts and unexpected rapid intensification, when a cyclone's top wind speeds increase by 35 mph or more within 24 hours. Initially forecast 3 days in advance to make landfall as a Category (Cat) 2 storm (110 mph), Ian instead rapidly intensified into a high-end Category 4 storm (155 mph) within 48 hours of landfall bringing catastrophic storm surges. This rapid intensification occurred as Ian moved over the West Florida Shelf (WFS), a broad region in the eastern Gulf of Mexico known for significant gaps in *in-situ* data. Crucially, no real-time water column density data (such as conductivity/salinity, temperature, and pressure/depth) were available along Ian's track to inform forecasting models.

Ian is not an isolated case. The WFS region has seen multiple hurricanes intensify beyond initial forecasts, including Michael (2018, Cat 1 to Cat 5), Idalia (2023, Cat 2 to Cat 4), and Helene (2024, Cat 3 to Cat 5, making landfall at Cat 4).

The Office for Coastal Management has highlighted the staggering financial impact of hurricanes on the United States, stating that "as of August 2023, tropical cyclones (or hurricanes) have caused the most damage in the US, totaling over \$1.3 trillion, with an average cost of \$22.8 billion per event" [1]. Additionally, NOAA emphasizes the critical need for enhanced hurricane forecasting and tracking capabilities. They note that "improving hurricane track and intensity forecast predictions is essential for protecting the public and reducing property damage. Early warning improvements in intensity and track forecasts for hurricanes greatly benefit public preparedness actions and emergency management decision-making" [2].

Missed hurricane forecasts are not unique to Florida; they are a global issue, especially

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in regions with limited *in-situ* data collection. Where data is sparse, uncertainty in forecasts is highest. Hurricane Otis (2023) provides a striking example. Otis rapidly intensified from a tropical storm to a Category 5 hurricane (165 mph) in just 12 hours before striking Mexico's coast and devastating Acapulco. Forecasts initially predicted only a tropical storm (50 mph) that would turn west and weaken, but instead, Otis unexpectedly turned east and grew into a catastrophic storm. The underlying conditions that fueled this rapid intensification were missed by forecasting models, primarily due to a lack of *in-situ* data. Relying on "synthetic ocean data" simply isn't effective in capturing these critical variables.



Figure 2: Damage from Tropical Cyclones (hurricanes) increasing with time, Science News Explores, August 2017

Accurate Ocean Data Needed for Hurricane Models

Accurate, high-density data is essential for developing precise machine learning models for hurricane prediction, as these systems are driven by complex, nonlinear interactions between atmospheric and oceanic conditions. Machine learning models rely heavily on the quality and quantity of input data, and high-resolution data enables more detailed feature extraction and pattern recognition. Key variables such as conductivity, temperature and depth (CTD), provide insights into the ocean's vertical structure, which is critical for assessing the thermodynamic state of the ocean. For instance, temperature gradients, particularly across the thermocline, influence the heat exchange between the ocean and atmosphere, directly affecting hurricane intensity. Conductivity data at multiple depths also informs salinity distribution, a key factor in ocean density and heat storage. These multivariate datasets, combined with atmospheric features like wind speed, humidity, and pressure, allow machine learning models to capture complex correlations and nonlinear interactions. High-density spatiotemporal data is crucial for identifying localized phenomena, such as ocean eddies and warm water pools, which can trigger rapid hurricane intensification. Training models on comprehensive datasets significantly enhances predictive accuracy, improving early warnings and disaster preparedness.

Supervised learning models, such as Random Forests, Gradient Boosting Machines (GBMs), and Support Vector Machines (SVMs), can effectively capture nonlinear relationships between these features and hurricane behavior. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are well-suited for spatiotemporal data analysis. CNNs can analyze gridded data, like sea surface temperature and depth-based conductivity, while RNNs or Long Short-Term Memory (LSTM) networks can capture temporal dependencies, such as the evolution of heat accumulation in ocean layers. By integrating these atmospheric and oceanographic variables, machine learning models can improve hurricane intensity and path prediction, enhancing disaster management strategies.

However, there is a notable lack of high-resolution, high-frequency oceanographic data, particularly from systems that capture temperature and conductivity across different ocean depths. This data gap has been widely recognized in academic research as a critical limitation. For instance, Glenn et al. highlight how the absence of real-time, high-frequency data restricts the ability to monitor hurricane progression through sea surface cooling patterns [3]. Similarly, when developing a Convolutional Neural Network (CNN) model to predict hurricanes in the Atlantic, Asthaa et al. had to oversample ground-truth data due to the limited availability of (in-situ) observations [4]. Moreover, as climate change alters hurricane dynamics, high-resolution, contemporary data is essential to understanding these evolving processes for accurate forecasting and modeling.

More accurate predictive models will significantly enhance relief efforts and resilience strategies by enabling more efficient resource allocation and improving rapid response capabilities. By accurately forecasting hurricane paths, intensities, and potential impacts, these models allow emergency management agencies to identify and prioritize high-risk areas for resource deployment, such as food, water, medical supplies, and personnel. Furthermore, precise predictions facilitate timely evacuation orders and proactive measures, thereby minimizing loss of life and property damage. With better-informed decisionmaking, responders can optimize logistics, ensuring that aid reaches the most affected regions quickly and effectively, ultimately strengthening community resilience in the face of natural disasters.

Hurricanes Develop Their Strength from the Ocean

Tropical cyclones, including hurricanes and tropical storms, are powerful weather systems fueled by Ocean Heat Content (OHC). The depth and stratification of warm water directly influence the amount of heat energy available for cyclone development, significantly impacting their formation and behavior. OHC is a critical metric in hurricane forecasting, representing the integrated vertical temperature from the sea surface to the depth where the water reaches 26°C (78.8°F). This is computed using altimeter-derived data on isotherm depths in the upper ocean relative to the 20°C layer.

Near the surface, ocean water is mixed by winds, waves, and currents, with heat from the sun also contributing. The depth of this mixed layer, typically extending up to 150 meters in the deep ocean and shallower in coastal zones, is vital for understanding ocean dynamics. Accurate data on thermoclines (rapid temperature changes), haloclines (rapid salinity changes), and pycnoclines (rapid density changes) can improve OHC calculations.

To assess OHC, the 26°C isotherm is often plotted, providing valuable insights for forecast models, including the calculation of Tropical Cyclone Heat Potential (TCHP). Verification and validation are done by comparing satellite-derived OHC data with *insitu* measurements from various sources. OHC and TCHP are critical factors, along with measurements and calculations of ocean-atmosphere heat flux, surface winds, humidity and moisture transport, surface ocean barrier layers, water-column stratification, mixedlayer depth, and ocean currents that transport heat.

Rapid Intensification

Rapid Intensification (RI) of hurricanes requires special attention. RI is defined as a wind speed increase of 35 mph or more within 24 hours. The frequency of RI events is rising and often catches weather models off guard, as today's climate change-driven hurricanes become more unpredictable.

Research indicates that regions within 400 km of coastlines have seen a significant rise in RI occurrences, with the number tripling between 1980 and 2020. Additionally, the thermodynamic environment has become more conducive to RI, with climate models suggesting that global ocean warming has played a key role in driving this trend [5].

Continental Shelf Coastal Influence

The influence of the continental shelf on hurricane development and rapid intensification is particularly important as storms traverse these near coastal regions while approaching land, posing threats to both people and property. Alarmingly, many storms deviate substantially from official forecasts while crossing continental shelves, intensifying even as the public is reassured with contrary information. Making things worse, by the time hurricanes reach the continental shelves they are typically within less than 48 hrs of impacting land, making last minute changes in the forecast too late for most decision making and preparations. Detailed advanced data on continental shelf conditions is required to anticipate effects on hurricane development. This represents a serious problem that requires immediate attention.

However, hurricane models base their TCHP and Potential Intensity (PI) calculations on OHC from deep ocean basins, largely due to the availability of Argo float data. *In*- situ OHC data is not generally available over continental shelf areas. Instead, OHC is interpolated from satellite SST measurements. The actual *in-situ* conditions are unknown (See Figure 12 below). Also lacking are accurate data on ocean layering, offshore forcing, surface boundary layer metocean interactions and dynamic changes of these conditions taking place across continental shelf regions in advance of a hurricane's arrival.

For example, Lewis J. Gramer et al. note that forecasters generally anticipate that tropical cyclones (TCs) experiencing significant vertical wind shear (VWS) will weaken, especially if ocean cooling is present. However, as TCs approach landfall, they can sometimes intensify despite ocean mixing, VWS, and adverse land interactions. Hurricane intensification is a complex issue involving nonlinear interactions between ocean and atmospheric conditions. Therefore, validating coastal downwelling models in future forecasts is crucial for accurately predicting TC intensity at landfall [6].

The SeaWARRDD Hurricane Data System

SeaWARRDD Technologies employs a coordinated multi-platform approach to gather the MetOcean data essential for advancing hurricane modeling. SeaWARRDD integrates critical stationary time-series data, necessary for trend analysis and model validation, with advanced "mobile time-series" data. This innovative combination extends the relevance of stationary measurements across a region and allows for on-the-fly adjustments in data collection to respond to emerging events.

For stationary time-series data, both at the surface boundary layer and in the water column below, state-of-the-art MetOcean+ RDSEA moored buoys are deployed, utilizing underwater "PRAWLER" CTD technology. Meanwhile, for mobile measurements, Nav2 MetOcean+ water-column current profile data is paired with mobile underwater OceanSCOUT Gliders, providing valuable insights into water column OHC and additional ocean physics data.



Figure 3: The SeaWARRDD System for Hurricane Measurements



Figure 4: Deployed RDSEA MetOcean Hybrid Buoy System, used for stationary time-series monitoring

1. RDSEA MetOcean+ Surface Buoy System

RDSEA's MetOcean+ Surface buoy system, a reliable design utilized for decades along the WFS of the eastern Gulf of Mexico and other coastal ocean regions, provides the essential "fixed-longterm-MetOcean-time-series" necessary for effective data input into both existing and newly developed ocean-weather-monitoring models [7] [8]. By integrating comprehensive surface meteorological monitoring with ocean water-column physics measurements (CTD along with ocean current speed and direction), stakeholers and end-users gain a complete understanding of the conditions in the deployment area [9] [10].

The PRAWLER system, a single CTD unit that freefalls downward and ascends along the mooring line using the buoy's surface wave motion for transport, continuously collects data and transmits it to the buoy controller through a process known as "induction". Additionally, water-column currents are measured using acoustic Doppler current profilers (ADCP). All data is transmitted in real time to beachside servers via the Iridium Satellite Network [11].



Figure 5: RDSEA MetOcean Hybrid Buoy System



Figure 6: Deployed Navocean Nav2 ASV, for mobility and rapid-response data collection

2. Navocean, Nav2 Sail and Solar Automated Surface Vehicle (ASV)

The Nav2 Sail and Solar ASV is designed to collect mobile timeseries data, complementing each stationary buoy system which in turn provides ground truth for ASV sensors. Its safe operation in most waterways enables nearshore coastal transects without hazard to navigation. The vehicle is not only capable of open ocean operations but is also small and lightweight, while accommodating a wide variety of payloads.

Featuring dual propulsion, the Nav2 is equipped with an electric thruster that serves as a backup in calm conditions or when higher speeds are required. Navigating



Figure 7: Nav2 ASV with Components and Associated Measurements

at an average speed of 3 km/h, the Nav2 ASVs can execute repeated survey patterns, extending from nearshore estuarine outflows across the WFS to buoy locations and beyond. Additionally, these ASVs can be redirected for targeted data collection in response to developing or approaching hurricanes.

Real-time data is transmitted back to the data portal via cellular and satellite networks [12]. The Nav2 has been successfully employed for research along the West Florida Coast [13] and nearby Lake Okeechobee [14].

3. McLANE PRAWLER

The PRAWLER (PRofiling crAWLER)

is a wave-actuated vehicle designed to traverse along the mooring wire, collecting data from the surface to the water column. It gathers a range of measurements, including CTD, optical backscatter, and dissolved oxygen.

Using wave motion and specialized ratcheting clamps, the PRAWLER moves along the wire, free-falling to the bottom of a user-programmed profiling range to collect data. The oscillation of the waves powers the vehicle's movement, while batterypowered sensors enable months of continuous data collection.



Figure 8: McLane PRAWLER and its conductivity, temperature, depth (CTD) system

4. Hefring Engineering OceanSCOUT Underwater Glider

The Hefring Engineering OceanSCOUT Underwater Glider is a new, compact, and highly efficient underwater glider equipped with CTD sensors.

By collecting ocean temperature and conductivity/salinity depth measurements, the OceanSCOUT can enhance the accuracy of hurricane intensity forecasts, especially when data is gathered from the upper hundred meters of the water column.

These gliders are specifically designed for deployment in shallow waters, allowing them to



Figure 9: Hefring Engineering's OceanSCOUT Glider

safely and autonomously collect essential information during storms. They transmit this data back to shore for real-time assimilation into operational models. The OceanSCOUT plays a critical role in the SeaWARRDD initiative by monitoring OHC in the water column and the coastal environment.

SeaWARRDD Data Portal

The SeaWARRDD system is capable of transmitting data sets at adjustable time intervals, ranging from minutes to hours, via Iridium satellite and cellular modems. These data sets will adhere to the scientific community's standards for quality assurance and archiving. All data will undergo thorough cleaning using updated calibration and validation procedures, and will be stored in the cloud along with associated metadata, ensuring secure access for end-users.

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Figure 10: Example of data collected from SeaWARRDD monitoring systems

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SeaWARRDD MetOcean Data Sets

Figure 11: Example Data Portal from NavOcean Inc.

SeaWARRDD Data End-users

SeaWARRDD data targets customers in the emerging and rapidly growing ocean-weather monitoring and modeling sector, which is increasingly driven by data-hungry AI modeling technology development. The transition of weather forecasting technology from government and academic institutions to the business sector has opened new opportunities and markets for SeaWARRDD data.

In addition to the business sector, the science, research, and education community, largely supported by government entities, remains a critical foundation for weather forecasting capabilities. This sector also represents a significant market for SeaWARRDD data. Our initial customer base will include businesses, research institutes, and state and federal programs in Florida and across the United States, with plans for international expansion to follow.

The following industries, programs, and entities support the SeaWARRDD WFS Plan and therefore represent potential customers:

- The Insurance/Re-Insurance Industries
- Catastrophe Bond (Cat-Bonds) and Investment Markets
- Ocean Weather forecast businesses
- NOAA National Hurricane Center (NHC)
- NOAA National Weather Service (NWS)
- NOAA National Center for Coastal Ocean Sciences (NCCOS)
- NOAA National Centers for Environmental Information (NCEI)
- NOAA HABs Observing System (HABSOS)
- NASA's Water Resources Applied Research Program
- FGCU Water School and Greater Caribbean Center for Ciguatera Research

- U.S. IOOS Regional Associations (RA's)
- Mote Marine Laboratory (MML)
- University of South Florida (USF), College of Marine Science
- The Florida Red Tide Mitigation & Technology Development Initiative
- Florida Blue-Green Algae Task Force
- South Florida Water Management District (SFWMD)
- Florida Atlantic University, Harbor Branch Oceanographic Institute (HBOI)
- Sanibel-Captiva Conservation Foundation/RECON Program
- Florida's Commercial Waterman's Conservation
- Florida Fish and Wildlife Conservation

SeaWARRDD Implementation

The initial target location for implementing SeaWARRDD is the Gulf of Mexico, specifically along the WFS. This region is significantly underserved in terms of *in-situ* ocean data collection, despite facing a high risk of hurricanes along the West Florida coast. Existing observing systems are ad hoc, lack continuity, and are slow to adopt new technologies, resulting in neglect due to inconsistent government funding. Consequently, public entities, business interests, and national, state, and regional managers are compelled to make critical decisions with limited data availability. This situation presents a significant opportunity for the private sector to forge a new path forward.

The WFS extends from the Mississippi Delta in the north to the Dry Tortugas in the south (Florida Keys). At nominally 250km wide, it is one of the broadest continental shelves on Earth. Florida boasts rich coastal and offshore biodiversity, and its low-lying geography, characterized by three dynamic coastlines, is unique in many respects. This attracts millions of visitors and residents to the region. However, these same unique qualities also render Florida highly vulnerable to impactful weather events, climate change, sea level rise (SLR), and environmental stressors stemming from significant population growth over the past few decades. The WFS is therefore an ideal location for SeaWAR-RDD to embark on this new initiative.

SeaWARRDD partners have identified high-priority regions within the WFS domain for the implementation of their *in-situ* data collection system. The plan involves initially establishing one complete SeaWARRDD observing system to demonstrate the viability of the business model. Following this, the initiative aims to expand to five full transect lines, comprising a total of ten systems, along the WFS. Additionally, there are plans for further expansion along the east coast.



Figure 12: SeaWARRDD MetOcean Transects to Address the Deficiency of Ocean Heat Content Data on the Continental West Florida Shelf

Conclusion

SeaWARRDD sets the stage for comprehensive, coordinated, multi-platform ocean data collection, transforming the science of hurricane forecasting and impact prediction. Current storms are outsmarting modelers, with significant deviations in track and intensity repeatedly catching coastal and inland communities by surprise. The lack of high-resolution *in-situ* MetOcean observing systems for the water column and boundary layer, particularly over continental shelf coastal areas, undermines the accuracy and reliability of hurricane modeling.

SeaWARRDD plans to implement its observing system in targeted high-value areas, beginning with the West Florida Shelf in the United States. Customized SeaWARRDD data sets, along with their derived analyses, models, and improved hurricane forecasts, will be provided to end-users across various sectors, including industry, science, and local communities. In the age of climate change, understanding the rapidly changing ocean environment is essential for the preservation and sustainability of the future, both locally and globally.

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SeaWARRDD Team and Author Biographies



Rick Cole: Founder, President, and Prin-RDSEA, Graduate of Florida Institute cipal, of Technology (FIT, Oceanography/Engineering), MTS/IMarEST/SUT Certified Marine Technologist (CMarTech). Has decades of sea-going, oceanography, ocean engineering, project development and management experience, as a veteran of the U.S. Navy, a former employee with NOAA (PMEL, Seattle, WA), the University of South Florida, College of Marine Science, and more recently, directing and managing projects with RD-SEA. Many of those years were spent developing, building, and managing the offshore component of Florida's Coastal Ocean Monitoring and Prediction System (USF-COMPS, WFS, Gulf of Mexico), 17 sites at its peak. Our "zoom-in" approach for Sea-

WARRDD builds upon knowledge gained from our work on COMPS and other international programs. Rick is also the Co-Chair of the MTS Buoy Technology Committee/Workshop (D. Peters, WHOI), and the General Chair of the IEEE-OES Currents, Waves, and Turbulence Measurements Conference (CWTMC). For more information please see; www.rdsea.com



Scott Duncan: Co-founder, Chief Designer and President of Navocean Inc., Scott has over 20-years of experience with design and fabrication of custom ASVs for ocean data collection. In 2000, he designed and built the first Navocean sail-powered prototype, the "mini'Nav-1", as proof-of-concept for the University of Washington, Applied Physics Laboratory (APL). The success of the mini-Nav led to demand for 2 mini semi-autonomous catamarans, funded by marine mammal research grants from the University of Washington and the University of British Columbia. Scott went on to receive grants from the Maine Technology Institute in collaboration with the Physical Oceanography Group at the University of Maine to further develop sail powered ASV prototypes, the original "Nav-2" and larger

"Nav-3". Scott has served as the Principal or Co-principal investigator of numerous ASV research projects including the recent Habs Assessment of Lake Okeechobee (HALO) project, in Florida, a year long detailed investigation of toxic algae deploying a Nav2 ASV with comprehensive innovative sensor suites across the lake. For more information, please see; www.navocean.com



Tim Mulvaney: Coastal Engineer and Machine Learning Engineer. Tim has five years of experience as a coastal modeller at AtkinsRéalis, specializing in using complex offshore datasets and advanced coastal modeling software to predict and simulate future extreme flood events. By transforming ocean monitoring datasets into industryleading coastal models, he has informed the design of coastal protection infrastructure such as breakwaters and artificial reefs. Recognizing the pivotal role of data, programming and artificial intelligence in coastal prediction, Tim further diversified and enhanced his skills with a master's degree in data science and a year as the lead machine learning engineer at Simo Capital Holdings. This combined

knowledge equips Tim with unique skills to apply advanced data analytics and machine learning techniques, including XGBoost and deep learning models, to develop predictive models for wave heights, long-term coastal erosion forecasting, and storm events across the UK. His understanding of ocean data and the automation of data processing and model execution using Python further optimizes model efficiency and reliability, while considering climate change impacts to enhance forecasting accuracy.