NOAA Technical Memorandum NOS

Artificial Intelligence in Support of Coastal and Ocean Resilience

Silver Spring, Maryland
April 2023

noaa **National Oceanic and Atmospheric Administration**

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Artificial Intelligence in Support of Coastal Ocean Resilience

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1. INTRODUCTION

Coastlines and oceans are facing incredible challenges, from sea level rise to collapsing marine ecosystems (Sweet et al. 2022). To identify ways to enhance our adaptive capacity and climate resilience, the National Oceanic and Atmospheric Administration (NOAA) collects vast amounts of data through various networks, including satellites, aircraft, vessels, and monitoring systems (Figure 1), to provide science and information in support of a climate-smart nation. As NOAA masters big data storage and management, forward-thinking application of advanced forms of big data analytics will extract more value. In particular, implementing Artificial Intelligence (AI), which can provide automated cognitive capabilities across large volumes of data, gives NOAA the ability to apply the next level of analytics to address coastal resilience (i.e., simply storing and managing big data isn't enough for NOAA to get the most value from all that information). The big data analytics associated with AI will profoundly benefit climate analysis and coastal resilience, as large amounts of data are sifted in near real time- if not eventually in real time- thereby providing NOAA and especially its National Ocean Service (NOS) a level of analysis and productivity heretofore unknown to address complex scientific and multifaceted issues and gain actionable insight to support coastal intelligence and resilience.

Big data provides the raw material from which AI systems can derive insights. Many AI algorithms, most notably neural networks, have been available for decades. AI systems use data-driven algorithms and statistical models to analyze and find patterns in data rather than traditional rules-based approaches that follow explicit instructions. This paper focuses on NOS' ability to utilize the power of AI by providing some example applications for climate and coastal resilience and identifying directions for future development and implementation of AI to improve NOS' capabilities to identify and implement actions to address climate change and inform coastal resilience.

1.1. What is Artificial Intelligence?

Artificial Intelligence (AI) refers to computational systems able to perform tasks that normally require human intelligence, but with increased efficiency, precision, and objectivity. A subset of AI called machine learning (ML) refers to mathematical models able to perform a specific task without using explicit instructions, instead relying on patterns and inference. Deep learning (DL) is a subset of ML that utilizes artificial neural networks capable of learning from unstructured or newly added data. The use of labeled training data can further improve the AI predictive capability through supervised ML. NOAA AI Strategy (2020)

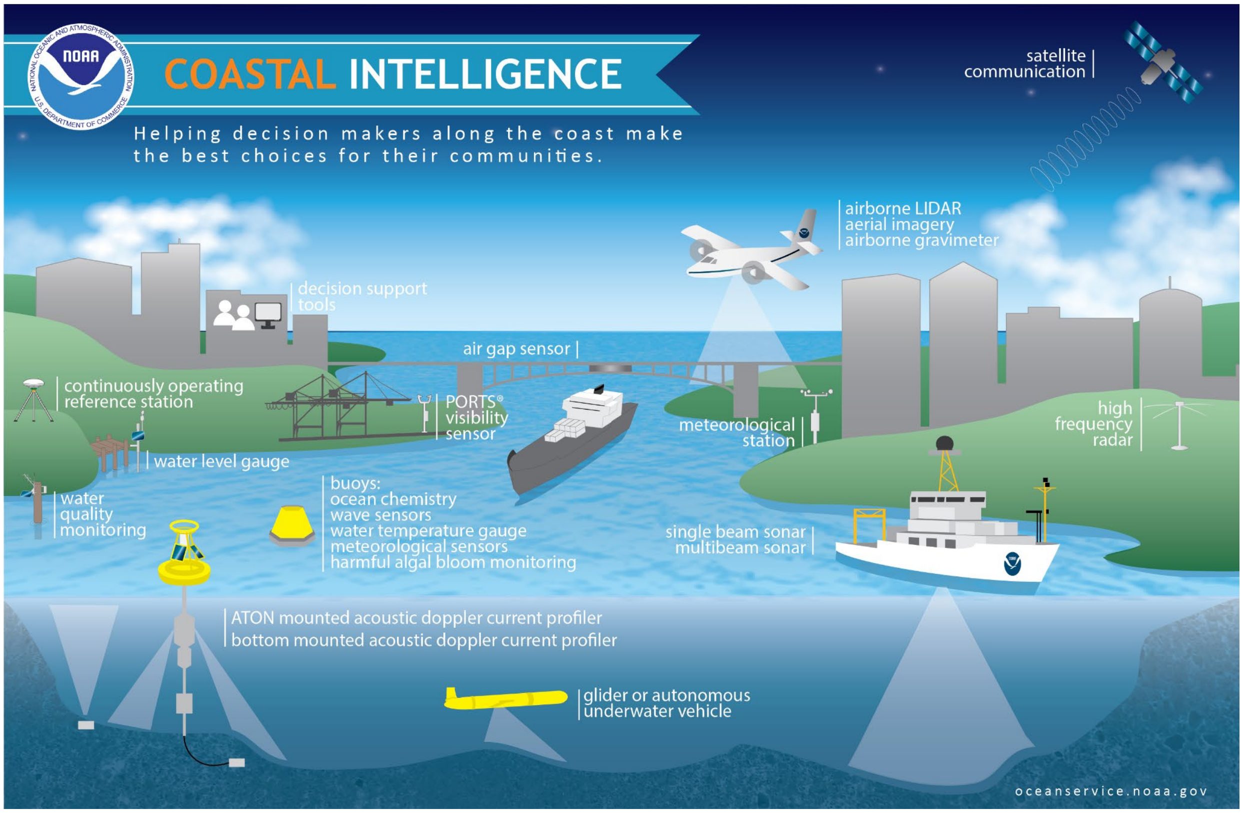

Figure 1. National Ocean Service's data streams that inform coastal intelligence capabilities.

2. EXAMPLES OF AI APPLICATIONS FOR COASTAL AND OCEAN RESILIENCE CURRENTLY IN OPERATION OR TRANSITIONING TO OPERATION

2.1 AI for Rip Current Detection

NOS, in partnership with the University of California, Santa Cruz, developed a ML approach for the automatic identification of rip currents with breaking waves. The ML approach uses a Faster Region-based Convolutional Neural Networks (R-CNN), a family of ML models for computer vision and specifically object detection (Figure 2), and a custom temporal aggregation stage to make detections of presence or absence of rip currents from still images/videos (from coastal imagery and webcams installed on the beach), with higher measured accuracy than both humans and other methods of rip current detection previously reported in the literature (Silva et al. 2021).

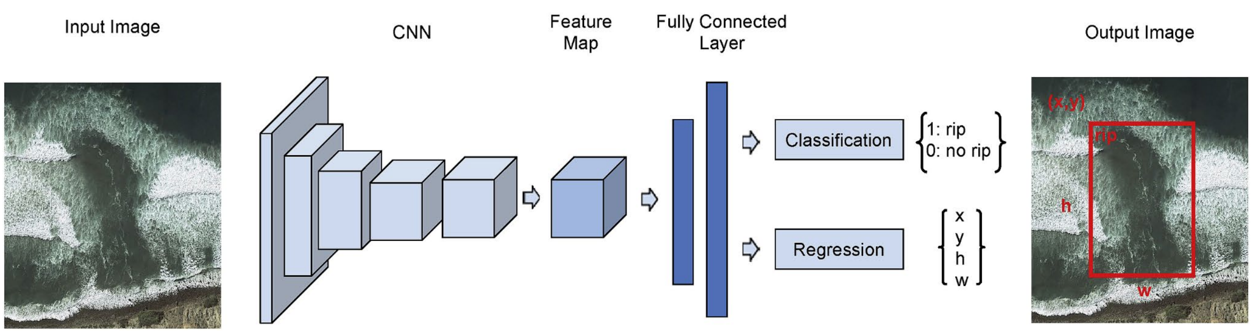

Figure 2. CNN workflow for rip current detection. (Source: CO-OPS)

2.2 AI for Testing Intervention Strategies to Enhance Coral Resilience to Climate Change

As a result of a National Academies of Sciences, Engineering, and Medicine recommendation (NASEM, 2019) to review and evaluate potential novel ecological and genetic coral interventions, NOAA's Coral Reef Conservation Program (CRCP) is supporting work identified in NOAA's Action Plan to increase coral resilience to climate change. An example of AI-focused work aimed at increasing coral resilience in the face of climate change is CoralNet, an operational AI enabled application designed to efficiently annotate coral reef images in support of the NOAA National Coral Reef Monitoring Program mission. The application is the result of collaboration between NOAA National Ocean Service, NOAA Fisheries, and many academic partners. CoralNet is able to perform automatic or manual coral taxa identification and significantly decreases survey processing time from months to weeks. Recently, the CoralNet architecture has been improved with new ML capabilities and expanded training data including Photogrammetric and Structure-From-Motion surveys, which has effectively reduced the operational product error rates by 22%. Users may access the product via the Application Programming Interface (API), which contains public classifier scripts that may be used in a wide range of projects.

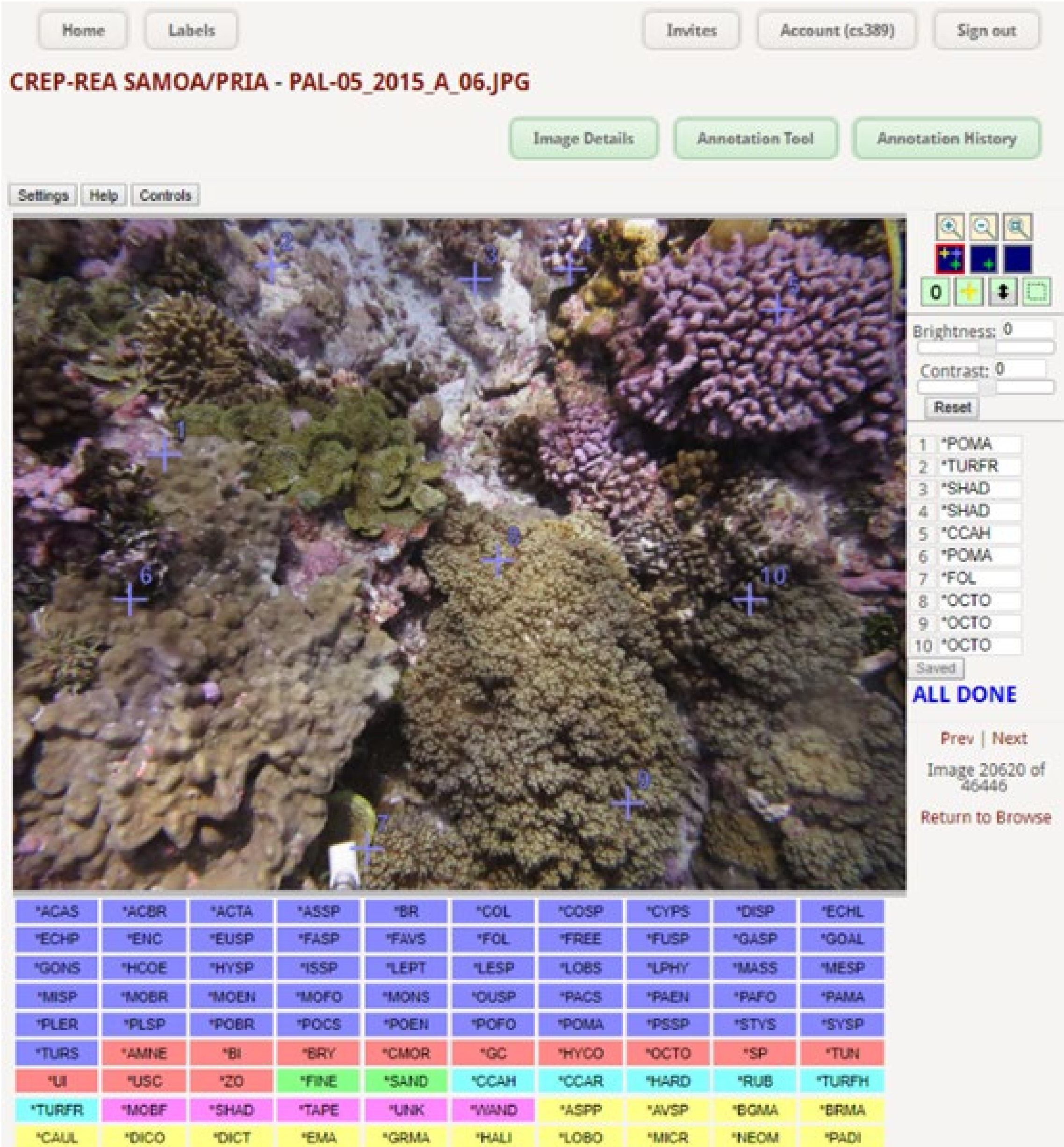

Figure 3. CoralNet is a software package that uses artificial intelligence to analyze benthic photos to classify corals. Image credit: NOAA Fisheries. NOAA Technical Memo: https://spo.nmfs.noaa.gov/sites/default/files/TMSPO208.pdf

2.3 AI for Advancing Coastal Mapping and Management

NOAA's Office for Coastal Management, through its Coastal Change Analysis Program (C-CAP), has developed the next generation of land cover data for the coastal United States, including the Great Lakes. This work has focused on the research and implementation of methodologies that increase the program's efficiency and impact. By applying AI through deep learning ML and DL algorithms using a U-Net convolutional neural network with ResNet-18 encoder in a cloud-based environment, these efforts have resulted in several high-spatial-detail land cover and habitat datasets, which serve to inform not only as proof of concept demonstrations but also as information guiding coastal management decisions at regional and local levels. The state of New Hampshire, for instance, has been utilizing saltmarsh habitat data produced through these efforts to better inform marsh resilience assessments and to inform the state's comprehensive marsh management planning.

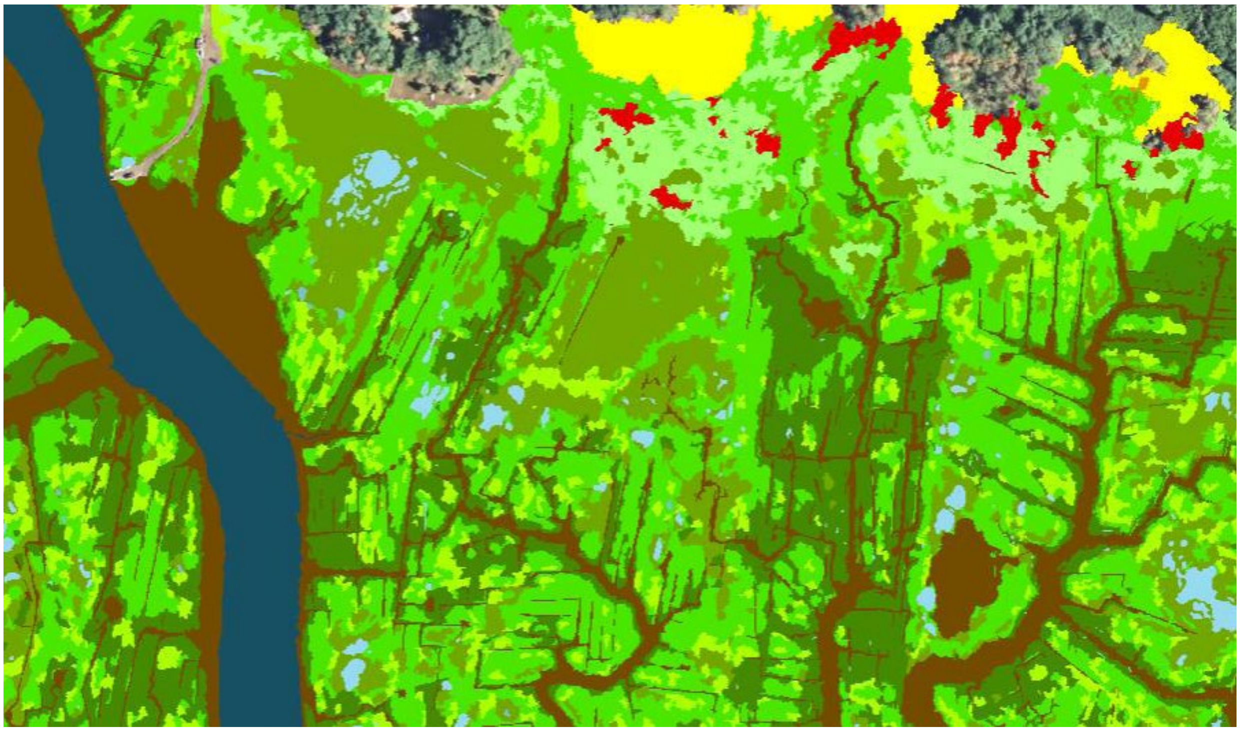

Figure 4. Saltmarsh habitat data (2013) for New Hampshire. Image credit: NOAA/NOS/OCM.

2.4 AI for Facilitating Citizen Science to Identify Harmful Algal Blooms

Blooms of the toxic microalga Karenia brevis occur seasonally in Florida, Texas and other portions of the Gulf of Mexico. Brevetoxins produced during Karenia blooms can cause neurotoxic shellfish poisoning in humans, massive fish kills, and the death of marine mammals and birds. Brevetoxin-containing aerosols are an additional problem, having a severe impact on beachgoers, triggering coughing, eye and throat irritation in healthy individuals, and more serious respiratory distress in those with asthma or other breathing disorders. Cell counts for Karenia brevis samples are typically completed manually by a technician using a laboratory microscope. The counts can take up to one week to complete and at the height of the bloom season are unlikely to be valid when published.

NOS National Centers for Coastal Ocean Science (NCCOS) in collaboration with the Gulf of Mexico Coastal Ocean Observing System (GCOOS), Texas A&M University, Texas Sea Grant, Mote Marine

Laboratory and Aquarium, Florida Department of Health and others partners developed the HABscope a tool designed to be usable by a volunteer (citizens) with minimal training and to provide real-time cell counts from the sampling location. The HABscope field kit consists of an Omax microscope, Apple iPod Touch, 3D printed adapter, StraightTalk hot spot, power supply, and case (See Figure 5). An app is loaded on the iPod Touch and provides sentinels with the ability to record a 30-second video and upload the video to a cloud server. When a video is uploaded to the server, it is first rotated for proper orientation and then run through the detection algorithm. The algorithm uses visual characteristics in the first pass to discriminate between particles of interest and detritus. Based on morphological characteristics, regions of interest (ROI) are identified. Each ROI is clipped from a frame and fed to a Google TensorFlow model. Using image recognition techniques each ROI is classified as 'Karenia' or 'Not Karenia'. Karenia cells are marked with a green target indicator. Other moving objects are marked with a red target indicator. The maximum number of visible cells is used to calculate cells/liter. The scale used in the calculation is self-generated by the algorithm. Testing against known cell quantities has shown that HABscope consistently provides cell counts within 20% of manual counts (Hardison et al. 2019).

HABscope

In Florida and Texas, citizen scientists are helping to protect public health and the economy by participating in the Red Tide Respiratory Forecast. The citizen scientists use HABscope, a portable microscope system with video and AI, to quickly analyze water samples for *Karenia brevis*, the organism that causes red tides in the Gulf of Mexico.

Left Photo: The HABscope system in the field. Right Picture: shows the AI program identifying Karenia brevis with the green squares. Image Credit: Mote Marine Laboratory and Robert Currier.

Figure 5. The HABscope setup. A photograph exhibiting the HABscope components and the machine learning algorithms. Credit: NCOOS and GCOOS (Hardison et al. 2019).

2.5 AI for High Resolution, Predictive Capacity for Monitoring Paralytic Shellfish Toxins Along the Gulf of Maine Coastline

Paralytic shellfish toxins (PSTs) are produced by several species of phytoplankton and can accumulate in shellfish and present a potentially lethal threat to consumers. Extensive blooms of the PST-producing organism, Alexandrium catenella, occur in the Gulf of Maine. The states of Maine, New Hampshire, and Massachusetts use considerable resources to conduct rigorous monitoring to ensure the safety of shellfish consumers and support shellfish producers. Each summer, shellfish beds are closed due to dangerous levels of PSTs along large stretches of the coast. The shellfish aquaculture and harvesting industries, vital components of a sustainable waterfront economy, are severely disrupted by these closures.

Disruptions caused by these HABs (or red tides) are likely to worsen with increasing aquaculture production, environmental pressures of coastal development, and climate change, necessitating improved HAB forecasts at finer spatial and temporal resolution (Grasso et al. 2019). A project funded through NCCOS developed a new ML approach for high-resolution forecasting of paralytic shellfish toxin accumulation. The forecast used a DL neural network to provide weekly site-specific forecasts of toxicity levels. The algorithm was trained on images constructed from a chemical fingerprint at each site composed of a series of toxic compound measurements. Under various forecasting configurations, the forecast had high accuracy, generally >95%, and successfully predicted the onset and end of nearly all closure-level toxic events at the site scale at a one-week forecast time. Tests of forecast range indicated a decline in accuracy at a three-week forecast time. Results indicate that combining chemical analytical measurements with new machine learning tools is a promising way to provide reliable forecasts at the spatial and temporal scales useful for management and industry (Grasso et al. 2019).

3. CHALLENGES & OPPORTUNITIES

3.1 Challenges

AI and ML methodologies have proven to be advantageous when applied to earth system data, however, challenges and limitations remain and deserve further attention. First and foremost, suitable access to ML technology remains a challenge. DL requires high computational intensity, thus requiring high-performance computational resources and long training times. For image processing for example, practitioners often work with large datasets of high-resolution images, requiring powerful GPUs and large storage capacities. While cloud-based services provide global access to high-performing computers, the internet connections and the pricing of these services may still hinder their use.

Once the AI technology is obtained, machine learning performance and accuracy will greatly depend on the quality of the data used in the analyses. Training data containing erroneous values or outliers may compromise the accuracy and effectiveness of machine learning techniques. While this is a problem for any data analysis method, it may be more difficult to notice and handle in deep learning models whose parameters are not easy to interpret. Users of Machine and Deep learning technologies should emphasize the importance of vetting data sources and quality by first performing robust quality control procedures on their training data.

Most importantly, building trust between the model providers and citizens will require transparency and accountability. The systems need to be understandable, explainable, and verifiable. These considerations need to be on the agenda right from the beginning of the development of any new ML-based system.

3.2 Opportunities

While many NOS offices have begun integrating AI and ML procedures into their operational or research work, the potential for further advances utilizing deep learning and neural networks exists. Advancing deep learning provides new opportunities to improve accessibility to data, training datasets, data enterprise architecture, and workflows to effectively use open source tools to ensure acceptable model performance for the end user. Deep learning carries major possibilities for improved monitoring, modeling, and reasoning to help decision-making. Improving monitoring methods (Mack et al. 2020) and emerging ocean observing technologies (Moustahfid et al. 2020) are creating a deluge of data that cannot be handled effectively with traditional and manual methods. Machine (Deep) learning presents a way to deal with these data, and through that, makes them more useful. Active learning approaches offer a way to minimize the labeling effort required from humans (Gal et al. 2017), lowering the bar to develop such a model.

For example, combining image analysis with spatio-temporal oceanographic data can yield much better spatio-temporal resolution that can complement any vessel-based monitoring efforts and enable better status assessment and faster detection of changes and anomalies. Deep learning-aided imaging of marine organisms (e.g., plankton, marine mammals, corals, sea birds, etc.) enables analysis of much larger datasets than previously possible and increased understanding of the oceans and their ecosystems.

We can also use AI/ML approaches to improve data quality for coastal resilience. CO-OPS is exploring using an AI approach for the quality control of water level data, aiming to drastically reduce manual human hours and speed up access to high-quality data.

In order to accelerate the implementation of deep learning applications and capacity development, robust partnerships with governments, academic institutions, and private companies will be required. Best practices and rigorous scientific evaluation by experts for scientific quality assurance will be needed to effectively advance the research and deployment of deep learning. Scientific information exchange and collaborations are critical for sharing knowledge and ensuring the integrity of scientific products as the tools and resources for deep learning applications. Improving deep learning organizational efficiencies in a cost-effective manner will deliver high quality and timely scientific products detailing the status of ocean resources.

4. CONCLUSION

Machine Learning and especially Deep Learning technologies are now seen as a silver bullet for solving many problems with marine scientific big data. We envision a future of ML/DL where processing and analysis of marine science data are accelerated to deliver high quality and timely scientific products. As shown in this short guidance document, several applications of ML may address needed responses to climate change. However, the use of this technology is not without significant challenges such as infrastructure accessibility, data quality, and public outreach. In order to overcome these complications and implement AI/ML technology as a standard tool in the workplace, the NOS AI/ML Working Group recommends the following:

5. RECOMMENDATIONS AND PATH FORWARD

To build AI/ML capacity to support NOS priorities for coastal resilience, coastal intelligence, and place-based conservation, NOAA aspires to achieve the following:

- Create AI/ML training opportunities for the NOAA workforce.
- Host a data science competition to leverage NOS climate data products and services.
- Increase collaboration among NOS line offices and programs by continued sharing of AI/ML/DL techniques and algorithms to improve efficiency. This will further advance NOS data processing and management capabilities to support coastal and ocean resilience and economic growth within the New Blue Economy.
- Identify NOS projects and programs that are interested in implementing AI/ML techniques and approaches.
- Support and implement AI ready data standards and best practices.
- Identify critical gaps in AI data readiness level and prioritize needs to fill such gaps.
- Develop projects to transition AI/ML pilot projects into operations, working closely with the Office of Research Transition and Application.
- Explore ways to implement cloud computing infrastructure (e.g., OCIO and collaboration with existing private sector partners) to improve access to computing resources needed for AI/ML-based applications.
- Participate in communities of practice to optimize use of AI to address challenges resulting from climate change.
- Form robust public and private partnerships involved with AI/ML to encourage knowledge transfer and sharing.

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REFERENCES

Grasso I., S. Archer, C. Burnell, B. Tupper, C. Rauschenberg, K. Kanwit, N. Record. 2019. The hunt for red tides: Deep learning algorithm forecasts shellfish toxicity at site scales in coastal Maine. Ecosphere. 10. 10.1002/ecs2.2960.

Guillou N. and G. Chapalain. 2021. Machine learning methods applied to sea level predictions in the upper part of a tidal estuary Oceanologia Volume 63, Issue 4, October–December 2021, Pages 531-544

Hardison D.R., W.C. Holland, R.D. Currier, B. Kirkpatrick, R. Stumpf, T. Fanara, et al. 2019 HABscope: A tool for use by citizen scientists to facilitate early warning of respiratory irritation caused by toxic blooms of Karenia brevis. PLoS ONE 14(6): e0218489. https://doi.org/10.1371/journal.pone.0218489

Hieronymus M., J. Hieronymus, F. Hieronymus. 2019. On the Application of Machine Learning Techniques to Regression Problems in Sea Level Studies. Journal of Atmospheric and Oceanic Technology. 36. 10.1175/JTECH-D-19-0033.1.

Kabir R., Borson N., Momen S., and Hossain M. Forecasting sea level rise using machine learning techniques, pp. 3, 2019.

Kumar, A. 2022. Machine Learning Use Cases for Climate Change. https://vitalflux.com/machine-learning-use-cases-climate-change/#Predicting_sea_level_rise

Moustahfid H. W. Michaels, B. Alger, A. Gangopadhyay and P. Brehmer. 2020. Advances in fisheries science through emerging observing technologies. ECO Magazine, special edition, July-August 2020, 34-37.

National Academies of Sciences, Engineering, and Medicine (NASEM). 2019. A Research Review of Interventions to Increase the Persistence and Resilience of Coral Reefs. Washington, DC: The National Academies Press. https://doi.org/10.17226/25279.

Nieves, V., Radin, C. & Camps-Valls, G. Predicting regional coastal sea level changes with machine learning. Sci Rep 11, 7650 (2021). https://doi.org/10.1038/s41598-021-87460-z

de Silva A. , I. Mori, G. Dusek, J. Davis and A. Pang. 2021. Automated rip current detection with region based convolutional neural networks, Coastal Eng., vol. 166, Jun. 2021, Available: https://www.sciencedirect.com/science/article/pii/S0378383921000193.

Tiggeloven, T., Couasnon, A., van Straaten, C. et al. Exploring deep learning capabilities for surge predictions in coastal areas. Sci Rep 11, 17224 (2021). https://doi.org/10.1038/s41598-021-96674-0

Tur R., E. Tas, A. Torabi Haghighi, A. Danandeh Mehr 2021. Sea Level Prediction Using Machine Learning. Water. 13. 3566. 10.3390/w13243566.

Sweet, W.V., B.D. Hamlington, R.E. Kopp, C.P. Weaver, P.L. Barnard, D. Bekaert, W. Brooks, M. Craghan, G. Dusek, T. Frederikse, G. Garner, A.S. Genz, J.P. Krasting, E. Larour, D. Marcy, J.J. Marra, J. Obeysekera, M. Osler, M. Pendleton, D. Roman, L. Schmied, W. Veatch, K.D. White, and C. Zuzak, 2022: Global and Regional Sea Level Rise Scenarios for the United States: Updated Mean Projections and Extreme Water Level Probabilities Along U.S. Coastlines.

NOAA Technical Report NOS 01. National Oceanic and Atmospheric Administration, National Ocean Service, Silver Spring, MD, 111 pp.