AI / ML for Chesapeake Bay Science and Management

Promise, Gaps, and Cost

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Structure:

🟢 Applied Now 🟡 Promising 🔴 Uncertain 📚 Training Gap ⚡ AI's Cost

Setting the Stage

Credit: NASA/USGS/Landsat 5

Why now?

The Chesapeake region has over 100 years of climate and monitoring data. AI/ML offers new ways to extract insight from it.

The February 2025 STAC AI/ML Workshop (Zhang et al., Pub. 25-005).

Applied Now

Already informing Bay decisions

Promising

Proof of concept

Still Uncertain

Real potential, honest unknowns

Two issues:

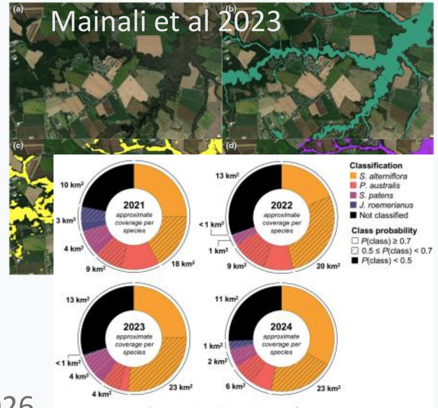
- **The Training Gap**
- **AI's Own Environmental Footprint**

Applied Now

Takeaway: these work because data are abundant, targets are measurable, and validation benchmarks exist.

Habitat & Wetland Mapping

- Chesapeake Conservancy CNN model — 94% wetland identification accuracy.
- Tidal marsh species classified from PlanetScope + random forest, 93% agreement. Coffer et al 2026

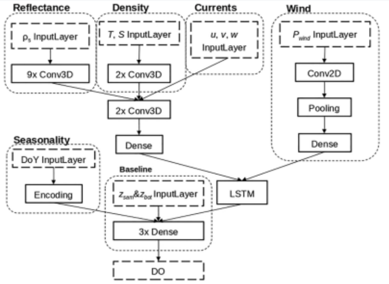


Coffer et al 2026

Fig. 6. Approximate minimum species coverage for 2021–2024.

Hypoxia & Dissolved Oxygen Forecasting

- NOAA/NASA LSTM + CNN daily dissolved oxygen in Bay main stem from satellite reflectance + hydrodynamic model output.
- Earlier random forest model.
- Gap: predict DO well but cannot answer scenario questions without running the mechanistic model
- *Zheng et al. 2024 · Ross & Stock 2019*



Streamflow from Trail Camera Images (USGS Flow Photo Explorer)

- Deep Learning model trained on user-annotated image pairs estimates relative streamflow hydrograph from low-cost trail cameras.

- *Goodling et al 2025*

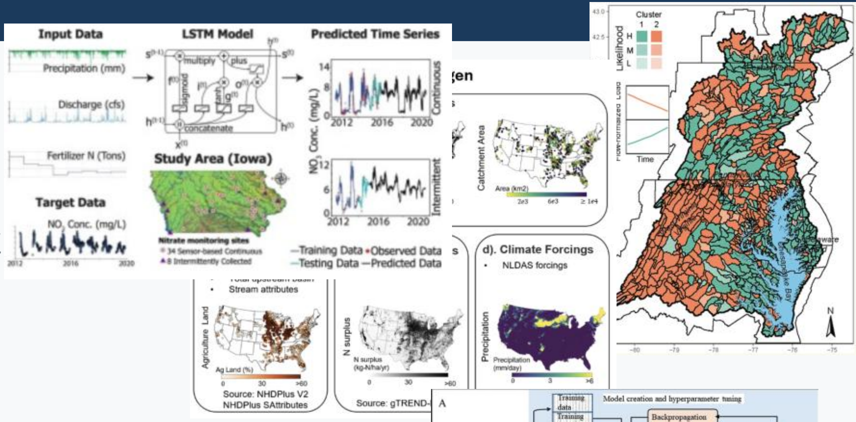
Image Analysis for Oyster Restoration & Aquaculture Monitoring

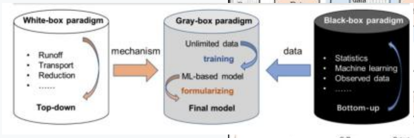
- Computer vision automating spat counts, reef structure scoring, and aquaculture condition assessment
- Natural fit: high-volume visual data, repeatable targets.
- *Xu et al 2025 IEEE Sensors*

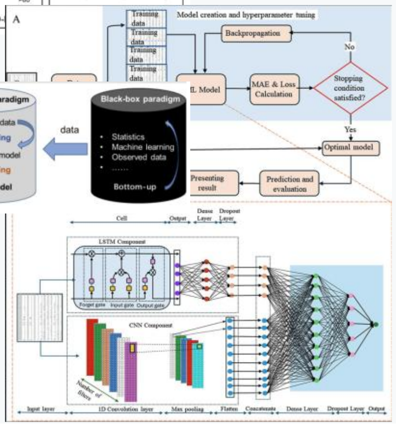
Mechanical engineering doctoral student Michael Xu tests sonar imaging of oyster shells in a UMD tank. The research team he's working with plans to use sonar as part of an imaging system that will employ artificial intelligence to spot oysters in murky environments.

Promising

Key theme: the science is ahead of the institution. Barriers are regulatory and institutional, not technical.







Nutrient Trend Attribution & Legacy N/P

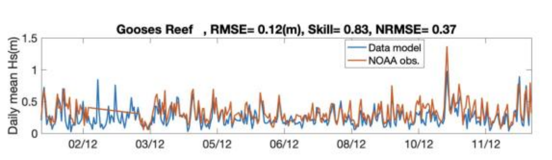
- Random forest models identify regional N & P trend drivers.
- Legacy N (ELEMeNT-N framework): decade-long lags between BMP implementation and Bay response
- *Zhang et al. Water Res. 2022; ERL 2023 · Chang, Van Meter et al. ERL 2021 · Saha et al. Sci. Total Environ. 2023 · IWAND-Nitrogen, Sci. Data 2026*

BMP Verification & Future Land Use

- Paired treated and untreated fields with AI/ML to determine BMP impact.
- Satellite + ML detects cover crops, riparian buffers, and tillage intensity.
- Gap: regulatory defensibility. TMDL accounting requires auditable reasoning; e.g. CBLCM uses regression rather than AI
- *Thapa et al 2025 Ecol. Informatics, Liu et al 2024 J. Hydrology, Claggett & McDonald et al. JAWRA 2023*

Coastal Flooding & Sea Level Rise

- Operational "Digital Twin" ensemble at Annapolis: R^2=0.997, validated on 369 extreme events over 6 years — required a Bay-specific correction factor of 0.337.
- LSTM-SAM: transfer learning for storm surge at data-scarce gauges.
- Princeton/GFDL: AMOC-linked sea level predictable 8 years ahead.
- Gap: point predictions ≠ spatial inundation maps emergency managers actually need.
- *Shahabi & Tahvildari, Coast. Eng. 2024, Magoulick Environ. Model. Softw. 2026 · Daramola et al. W 2025 · Gu et al Climate and Atm. Sci 2024 · Shen et al Earth and Space Sci.2024*



Still Uncertain

Key theme: the most dangerous place for AI is where it sounds confident but is extrapolating into territory it has never seen.

Living Resources & Scenario Planning

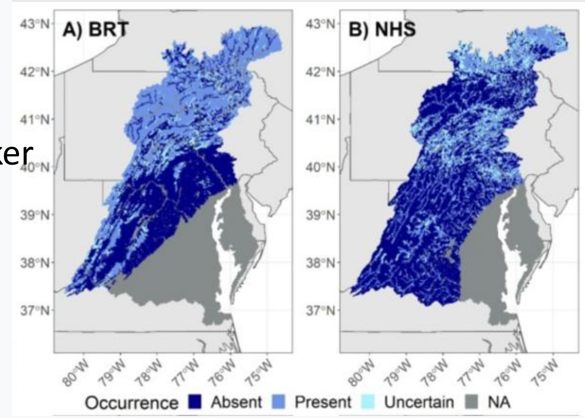
ML models are interpolators, not extrapolators.

- Biological sample sizes are small relative to needs
- Interannual variability in Bay fish populations is high
- Uncertainty quantification is not a current AI/ML strength
- Novel climate scenarios push to the edge of training data

Blue crab, striped bass, forage fish habitat modeling under future climate: early stage.

Maloney et al. USGS 2022 · Woods et al. USGS (STAC 2025)

Brook Trout
Northern Hog Sucker



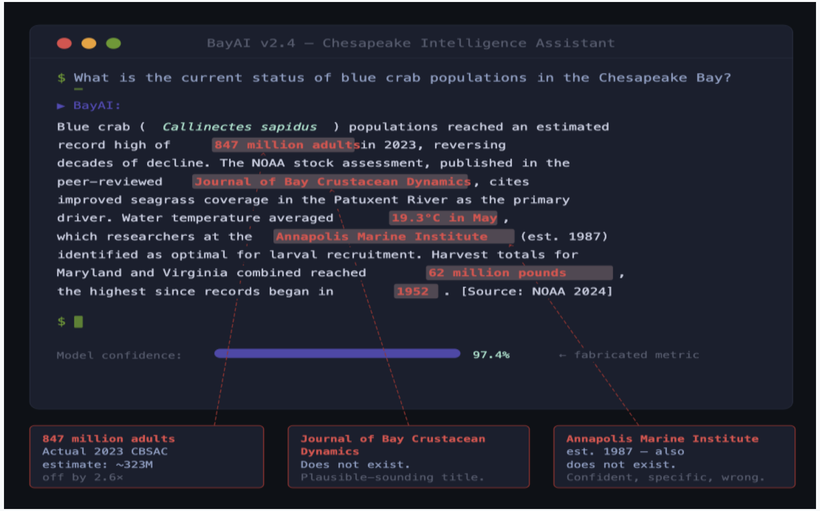
Generative AI & LLMs for Bay Decision Support

Evidence base for Gen AI/LLM can improve management decisions?

- LLMs are good at synthesis; weak at causal reasoning
- Hallucination risk is real
- Institutional liability of AI-generated management

near-term use: documentation, synthesis, stakeholder communication — not model-based decision support.

Guo et al, CERF 2025



The Training Gap

Do we really want good models that nobody understands?

The Risk

Model adoption should be informed by skill AND by insight.

In a non-stationary environment, AI models may confidently predict outside their training

What's Needed

Environmental scientists need training in AI tools AND in how to interrogate them: understanding uncertainty, diagnosing failure modes, recognizing when a model is extrapolating.

Data scientists need ecological and management context to build tools that are actually useful.

UMCES CGC SCIPE

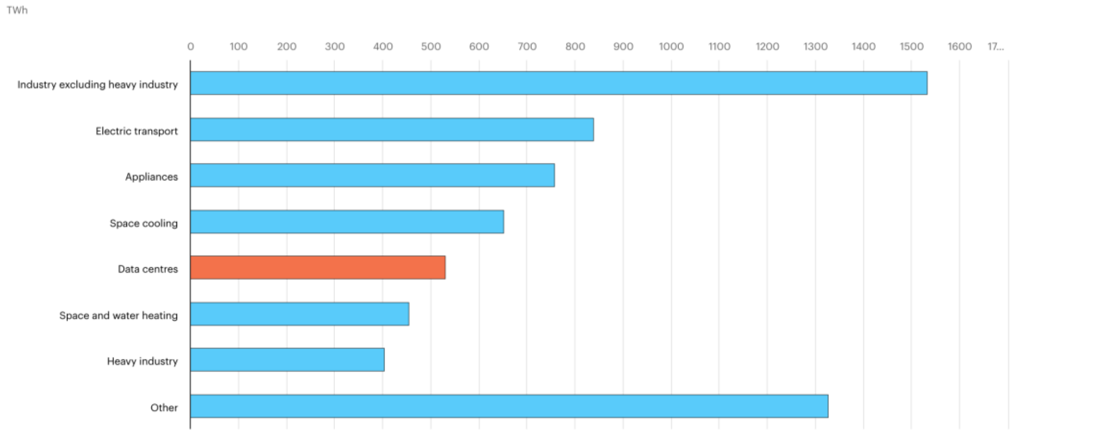
The NSF funded CGC-SCIPE Program at UMCES pairs data scientists with environmental scientists — bidirectional training.

Institutional response: the science is available; the training pipeline is the gap.

STAC recommendation: 'Invest in training and literacy programs so scientists, managers, and decision makers can effectively use and interpret AI/ML tools' (Zhang et al. 2025, Pub. 25-005) · SHAP: Lundberg & Lee, NIPS 2017

⚡ AI's Own Environmental Footprint

The conversation we're not having



https://www.iea.org/reports/energy-and-ai/energy-demand-from-ai

4.4% of US energy goes to Data Centers
half of that goes to AI (projected in 2028)
2024 United States Data Center Energy Usage Report Shehabi et al.

80-90% of compute power is for inference not training.
Per prompt ~ 6,706 joules ~ 400 ft of ebike riding.

https://www.technologyreview.com/2025/05/20/1116327/ai-energy-usage-climate-footprint-big-tech/

1. Are we accounting for the carbon and water footprint of our models when evaluating their net benefit to restoration?
2. Does a Deep Learning model that marginally improves a hypoxia forecast justify its energy cost if a simpler model gets 80% of the way there?
3. Should we be asking this question systematically?