Building an Analytical Framework to Measure Offshore Infrastructure Integrity, Identify Risk, and Strategize Future Use for Oil and Gas

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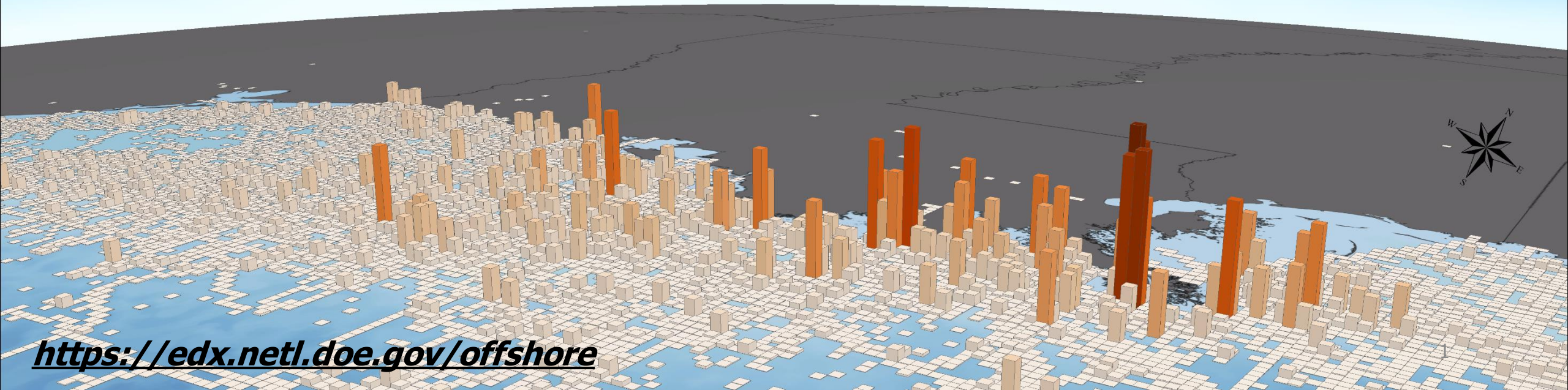

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Intelligent Risk Modeling for Offshore

Assessing Current and Future Infrastructure Hazards

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Identified need:

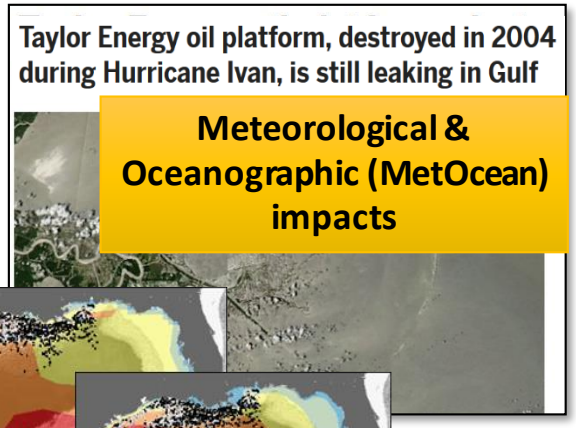
- **Extreme offshore environments** introduce **hazards** that can **impact the integrity & safety of infrastructure**
- Need for **novel methods and models** to ***assess existing infrastructure for future potential***

Approach:

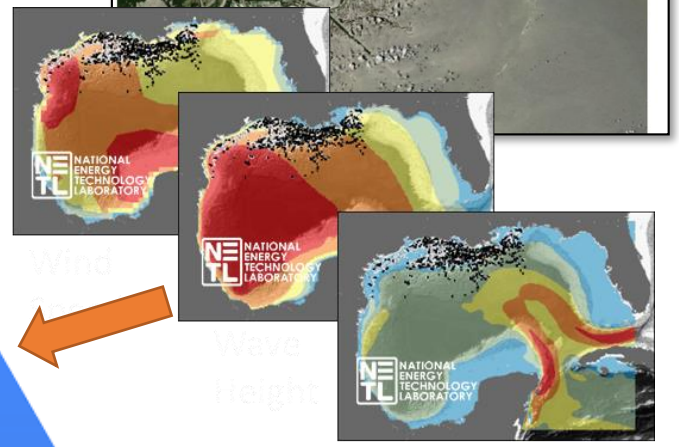
- Build **infrastructure dataset** integrating structural, environmental, & past incidents information
- Develop, test, and validate **advanced data-driven spatial, statistical, and Machine Learning (ML) models** to **quantify existing infrastructure integrity** and **improve prediction of performance**
- Release data and advanced analytical models into a **smart, online platform on Energy Data Exchange (EDX)**

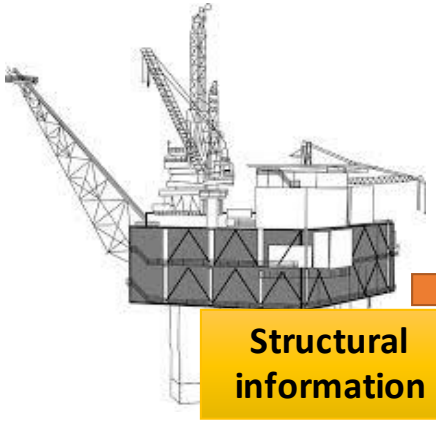
https://commons.wikimedia.org/wiki/File:Deepwater_Horizon_offshore_drilling_unit_on_fire.jpg

Structural and weather-related incidents



Meteorological & Oceanographic (MetOcean) impacts



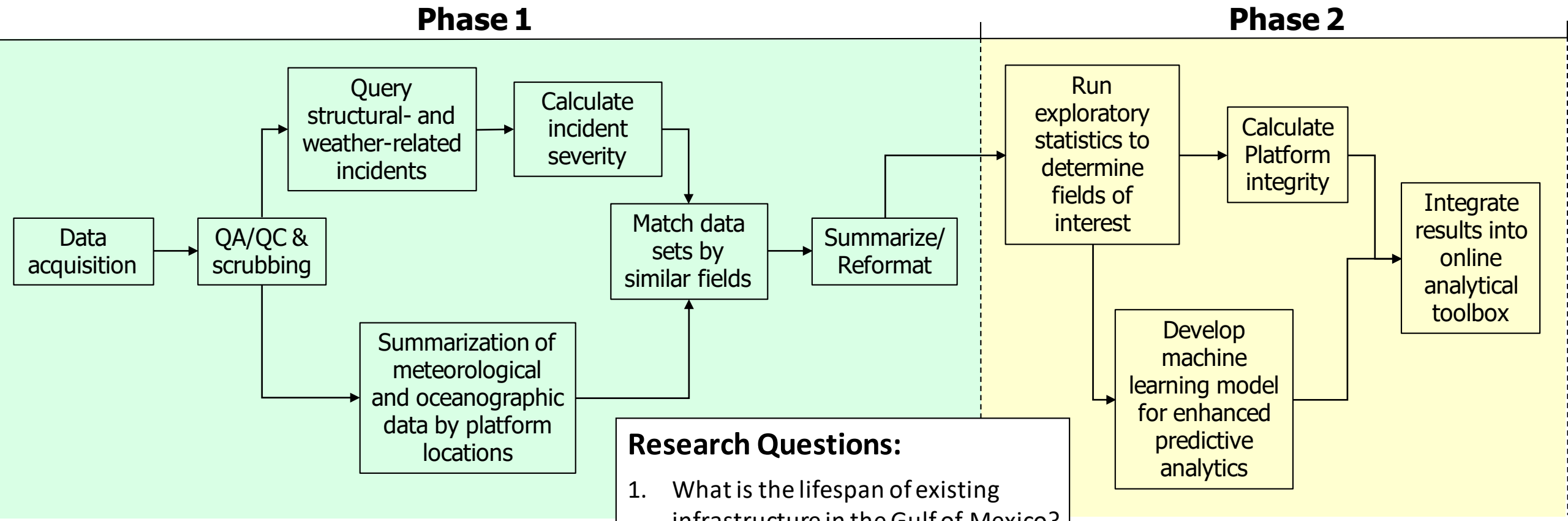


Structural information

EDX™ Energy Data eXchange

External Interest: API, BSEE, BOEM, EPA, DNV, Lloyd's Register, NOAA, Shell, SPE, USCG, and U.S. Steel

Methods and Workflow



Research Questions:

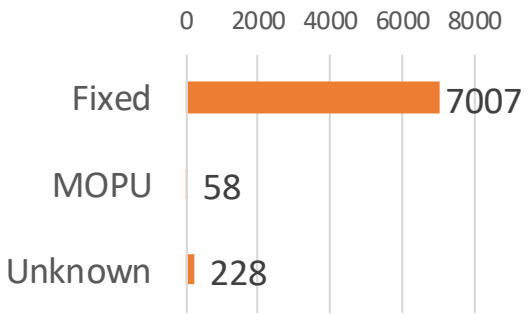
1. What is the lifespan of existing infrastructure in the Gulf of Mexico?
2. Where is risk/hazards likely to occur?

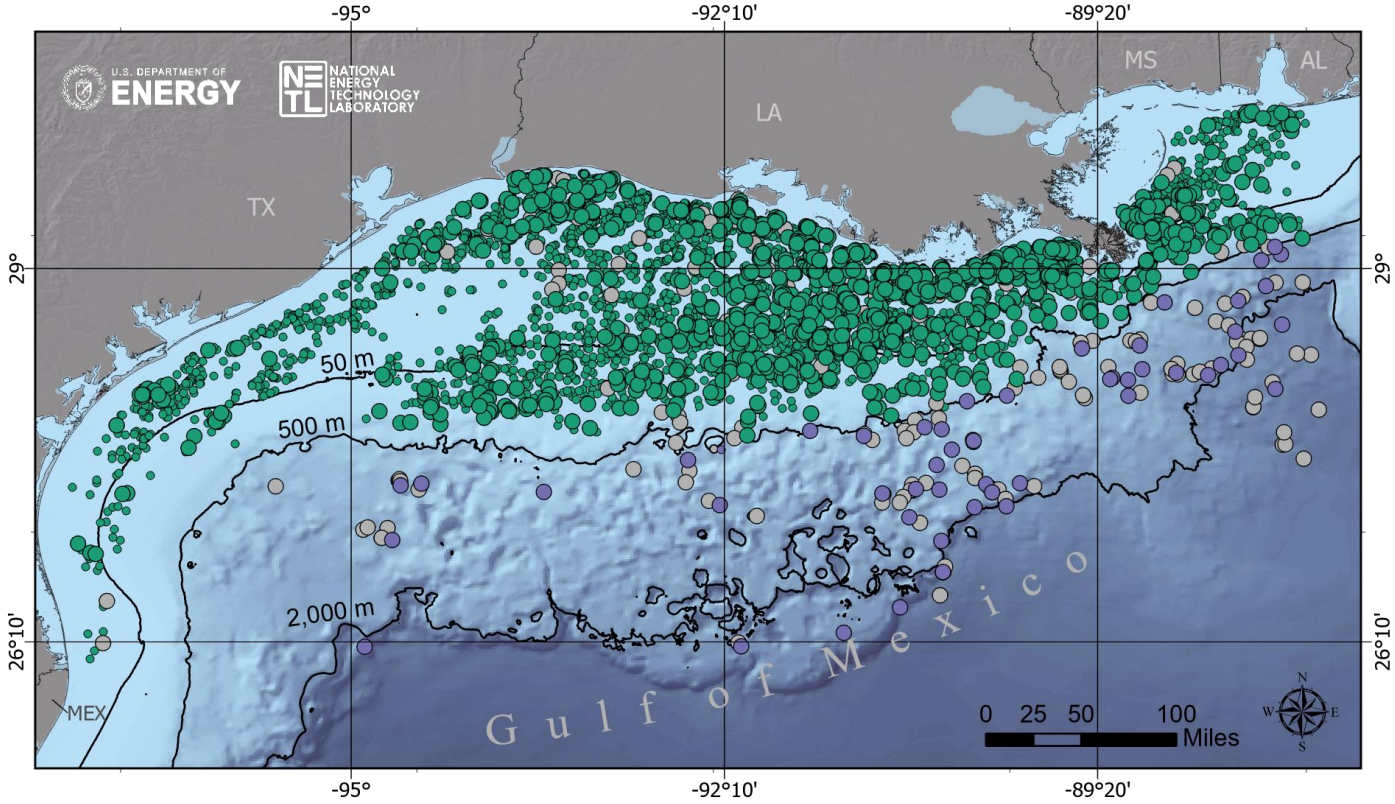
Infrastructure Data

Platform Records

- Source: Bureau of Ocean Energy Management (BOEM, 2020)

Platform Type Counts

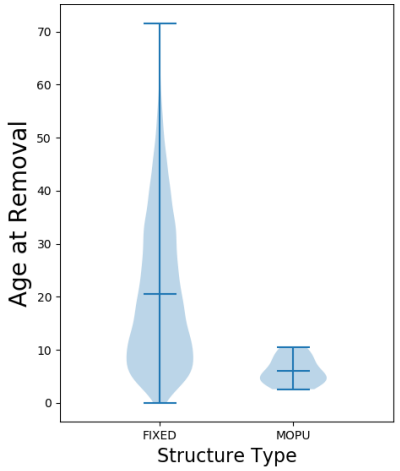


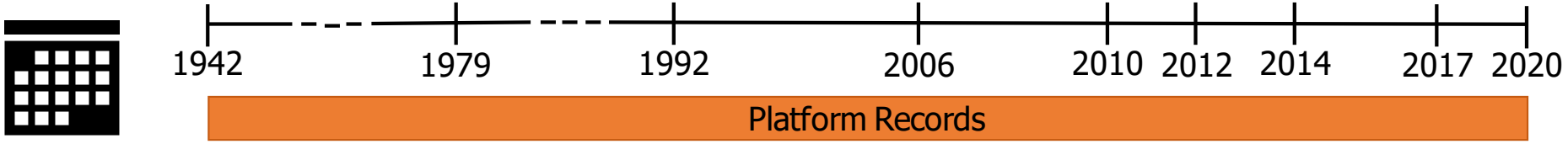


- Existing Platform
- Removed Platform

Platform Type

- Fixed
- Mobile Offshore Production Unit
- Unknown





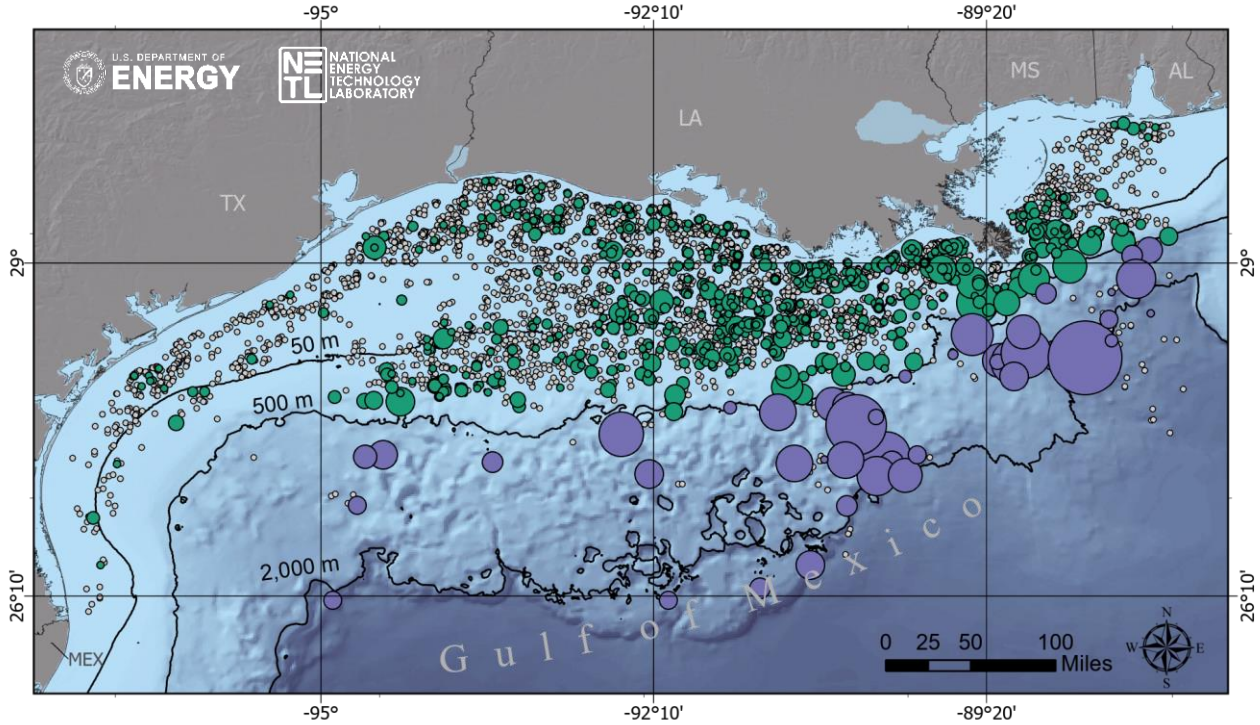
Bureau of Ocean Energy Management (2020). Platform/Rig Information.
Bureau of Safety and Environmental Enforcement (2017). Offshore incident statistics.
Unites States Coast Guard (2020). Incident Investigation Reports.

Incident Data

Incident Records

- Source: Bureau of Safety and Environmental Enforcement (BSEE, 2017)
- Source: U.S. Coast Guard* (USCG, 2020)

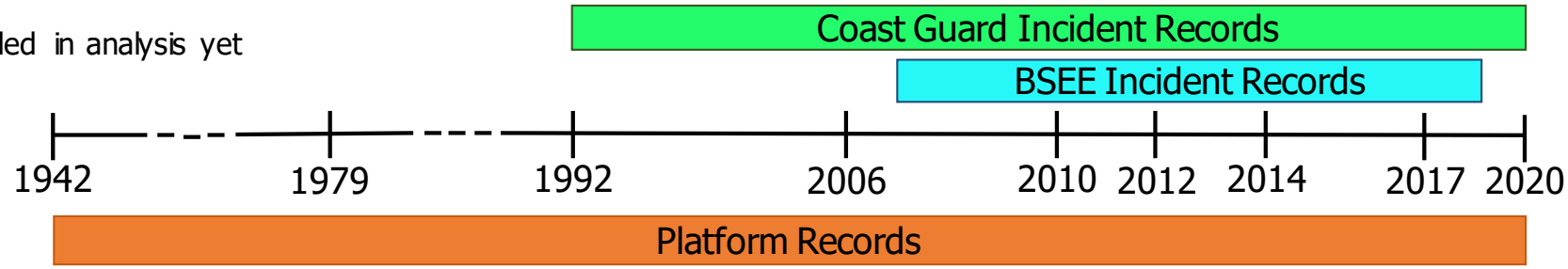
*Data not included in analysis yet



Platform Type
- Fixed
- MOPU

Number of Incidents
26
17
9
1

No Matched Incidents



Bureau of Ocean Energy Management (2020). Platform/Rig Information.
Bureau of Safety and Environmental Enforcement (2017). Offshore incident statistics.
Unites States Coast Guard (2020). Incident Investigation Reports.

MetOcean Data

Methods and Challenges

Cumulative Spatial Impact Layers

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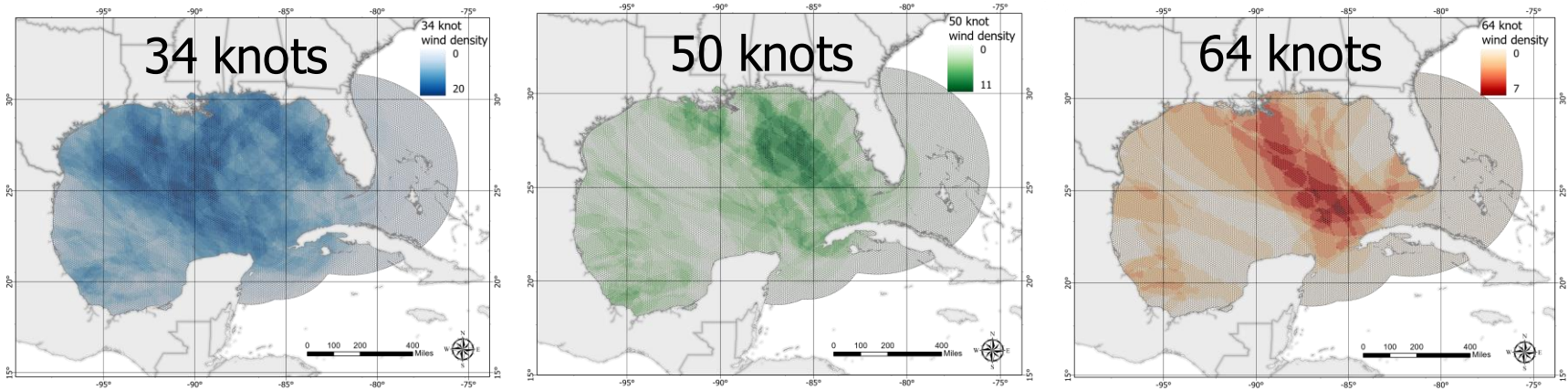
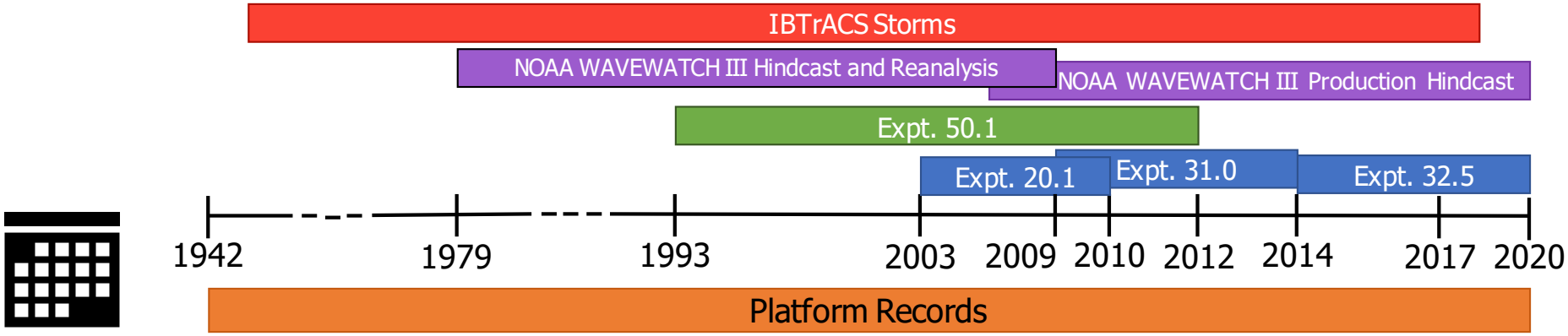
- HYCOM — GOMu0.04 — GOMI0.04
  - Water velocity (m/s)
- WAVEWATCH III
  - Wave height (m)
  - Wave period (s)
  - Wave power (kW)
  - Wave direction (°)
  - Wind speed (m/s)
- IBTrACS Storms
  - Storm/hurricane characteristics

Density of wind speed occurrences during historic storms



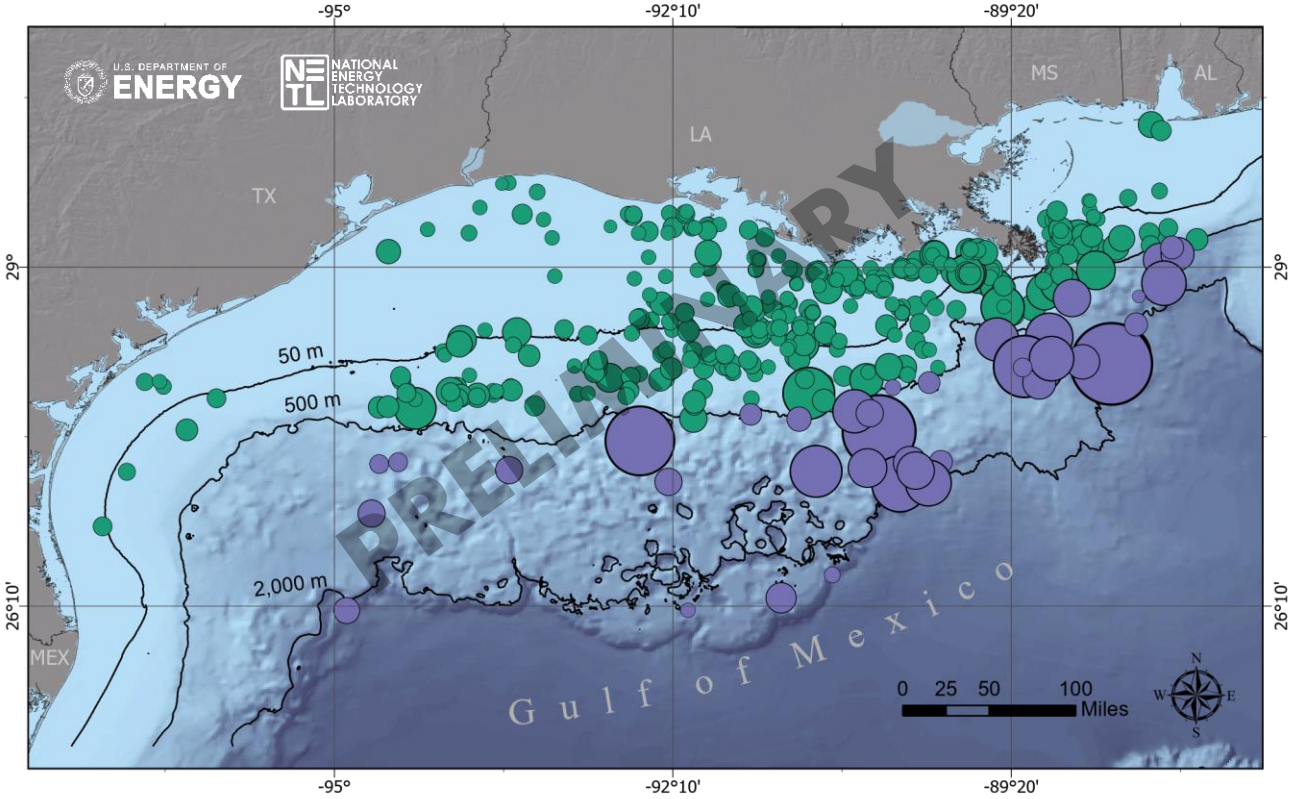


- 3-hour time steps (excluding storms)
- Same spatial and temporal resolution

Preliminary Analytics

Incident Severity

Current Offshore Oil & Gas Platform Incident Severity Ranking



Platform Type
- Fixed
- MOPU

Cumulative Incident Severity*

1
0.66
0.33
> 0

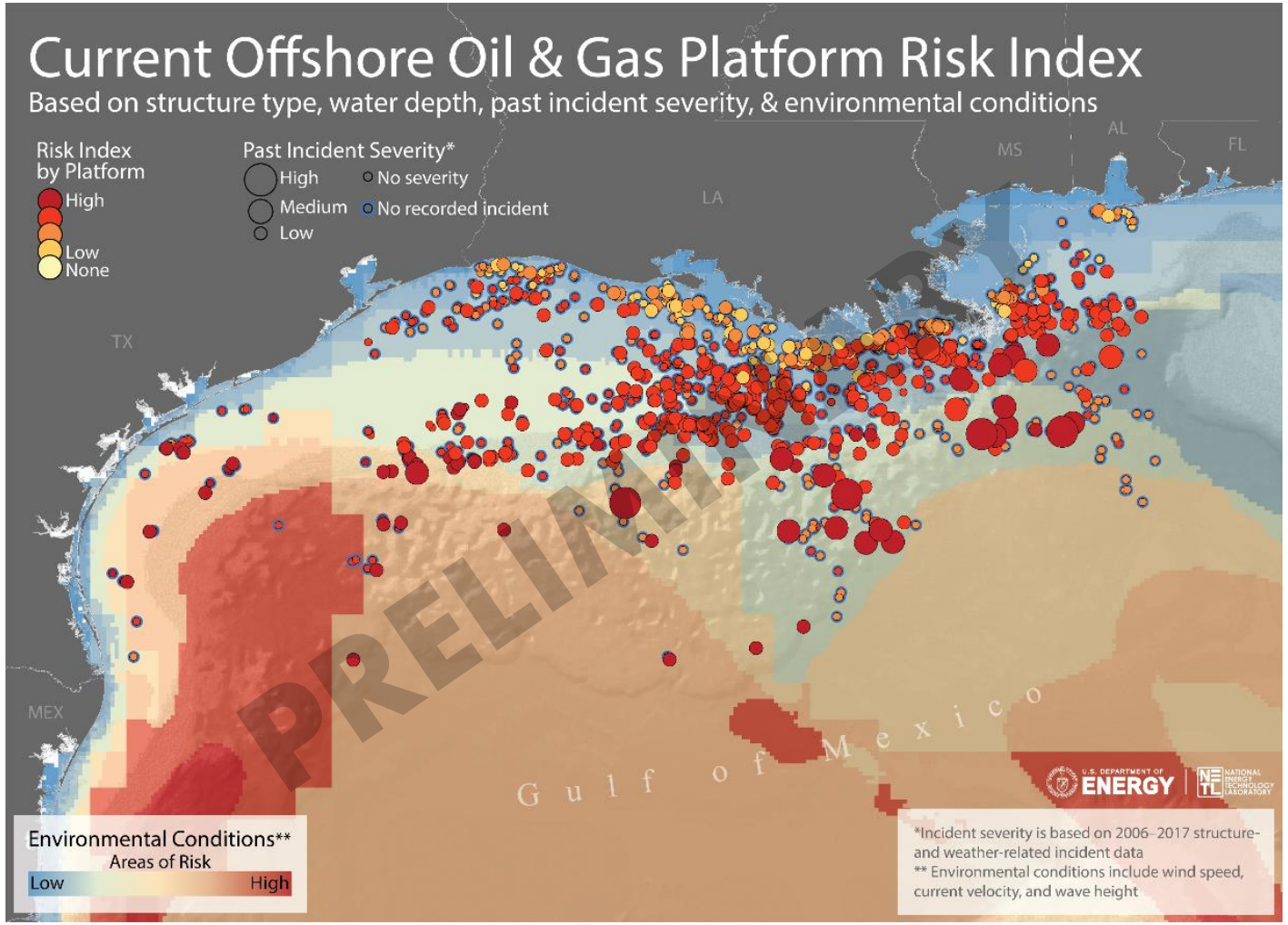
*Cumulative incident severity is based on structure- and weather-related incident data from 2006-2017 (BSEE, 2017; Nelson, et al., in prep). Incident severity summarized by platform that had one or more incidents reported, and then normalized to a scale of 0 -1.

Severity variables:

- Incident presence
- Fire explosion category
- Fire
- Explosion
- Loss of well control
- Collisions
- Hydrogen sulfide release
- Structural damage
- Required muster
- Equipment failure
- Spill release

Preliminary Analytics

Platform Integrity



Risk index of decommissioned platforms and applied to existing platforms

*Risk index variables:

- Current age minus average age at removal by type
- Water depth
- Incident severity
- Incident count
- Crane count
- Slot count
- Slot drill count
- Classified current velocity value
- Classified wave height value
- Classified wind speed value

*Picked using Kendall's Correlation, t-test, Chi-squared, and Kruskal Wallis statistics

Intelligent Risk Modeling

Predicting Integrity

Gradient Boosted Classifier

Artificial Neural Network

Geographically Weighed Regression

Predict age at removal for existing platforms

Bins

- 0-11 years
- 11-20 years
- 20-30 years
- 30-42 years
- 42-72 years

Intelligent Risk Modeling

Predicting Integrity

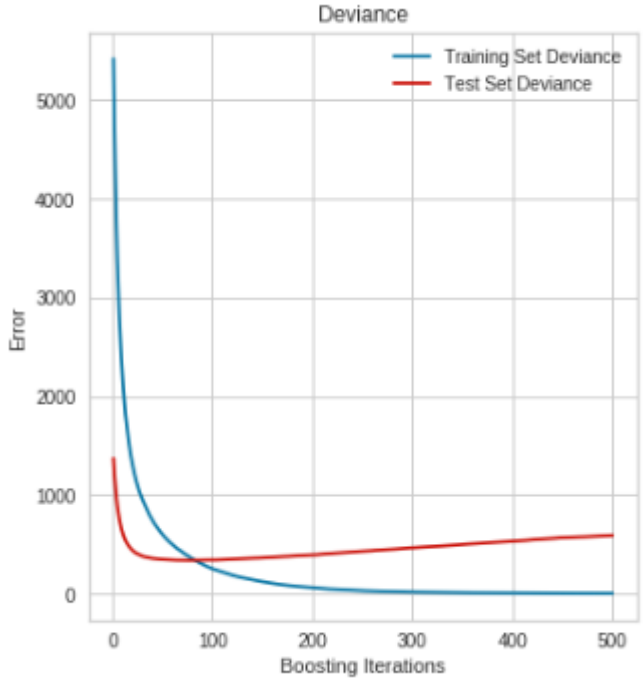
Gradient Boosted Classifier

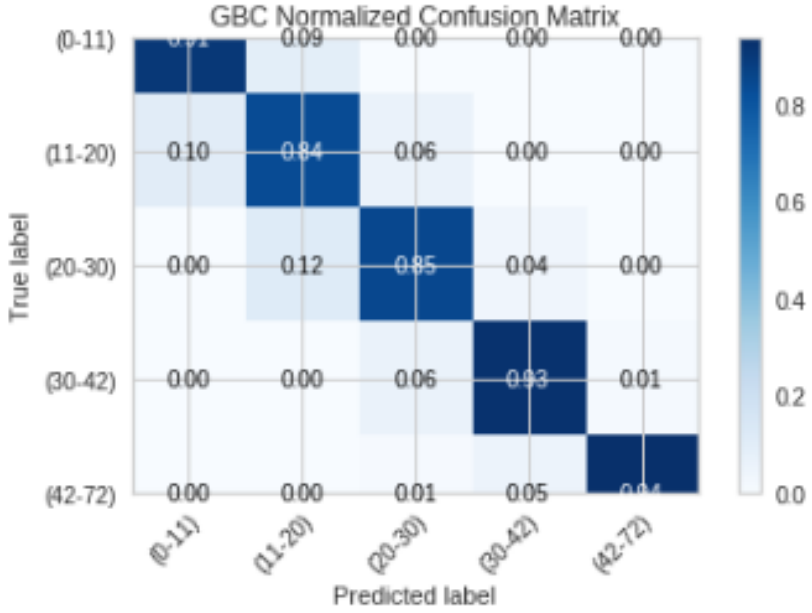
Artificial Neural Network

Geographically Weighed Regression

Training Set Score	87 %	Test Set Score	83 %

Overfitting





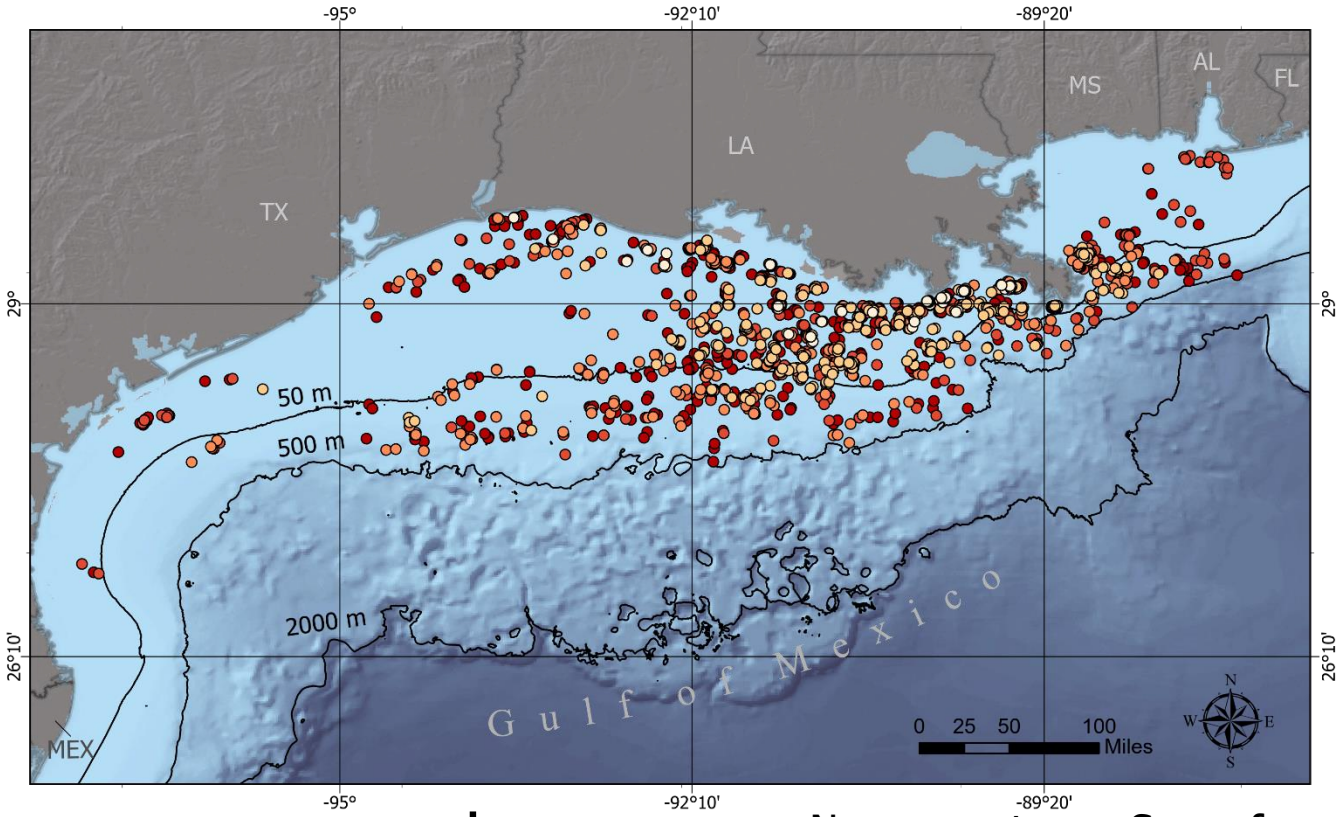
Intelligent Risk Modeling

Predicting Integrity

Gradient Boosted Classifier

Artificial Neural Network

Geographically Weighed Regression



Age at Removal Range (Years)

- 0-11
- 11-20
- 20-30
- 30-42
- 42-72

Most Important Features (Gini number)	# of cat. 1 hurricane impacts	None count of maximum reported wing gust	Sum of maximum sustained wind speed	Yearly average of cat. 1 hurricane impacts

Intelligent Risk Modeling

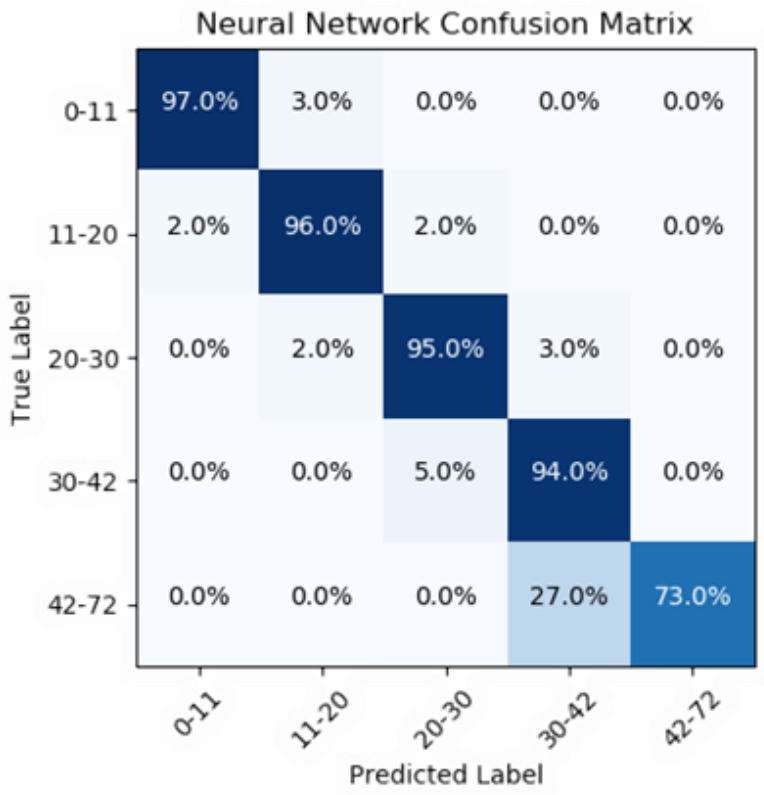
Predicting Integrity

Gradient Boosted Classifier

Artificial Neural Network

Geographically Weighed Regression

Training Set Score	89.3 %	Test Set Score	88.4 %



Intelligent Risk Modeling

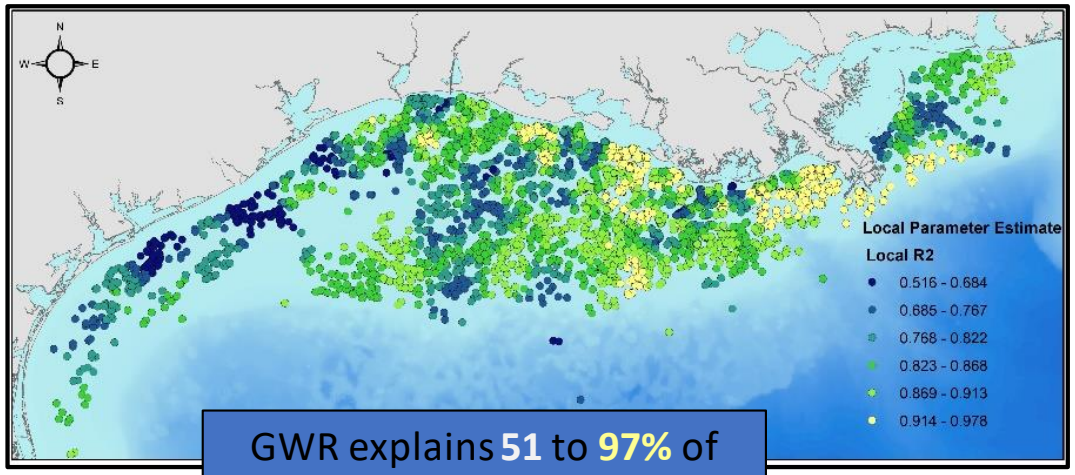
Predicting Integrity

Gradient Boosted Classifier

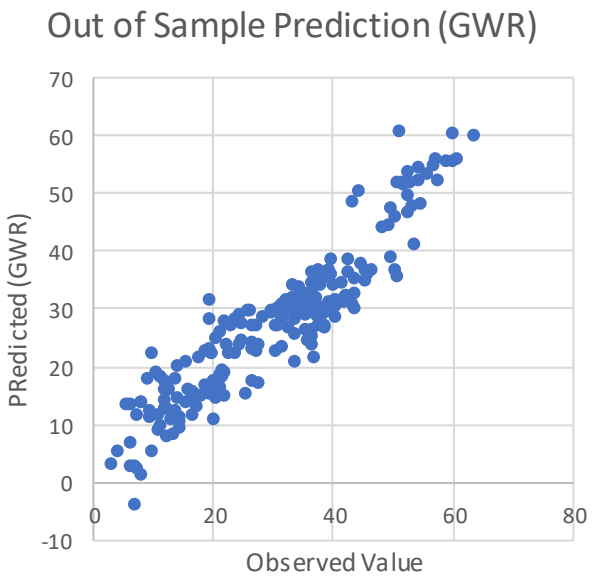
Artificial Neural Network

Geographically Weighed Regression

- Spatially predict existing platform age using **Geographically Weighted Regression**
- MetOcean variables are associated with both **positive** and **negative** GWR parameter estimates.
  - Spatially heterogeneous effects on age at removal



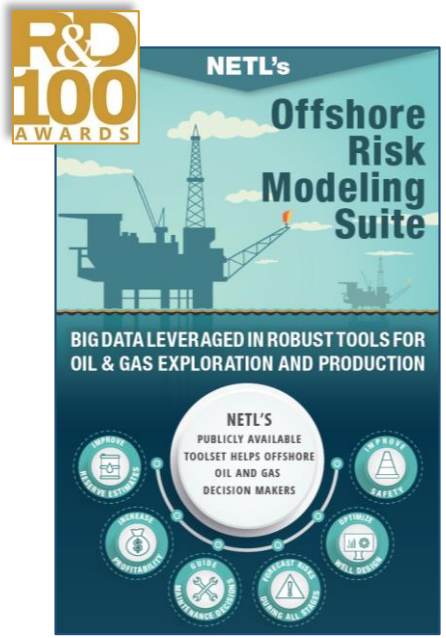
GWR explains **51** to **97%** of the variance in the data

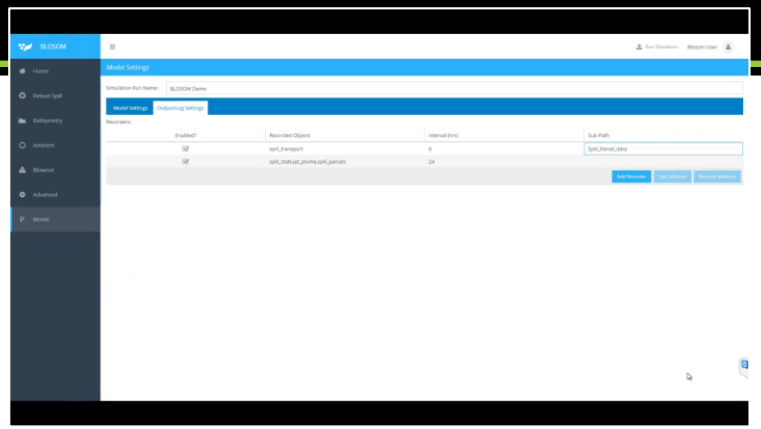


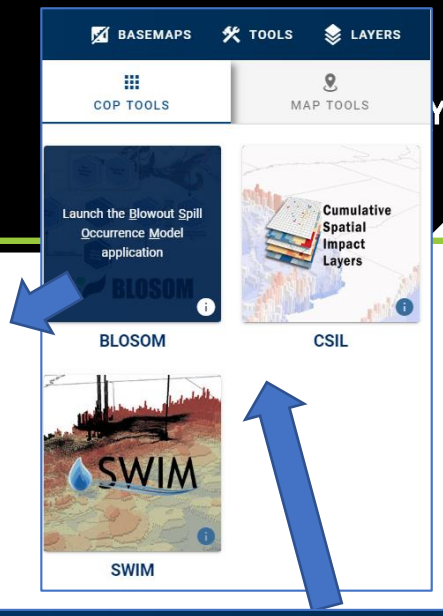
Intelligent Risk Modeling for Offshore

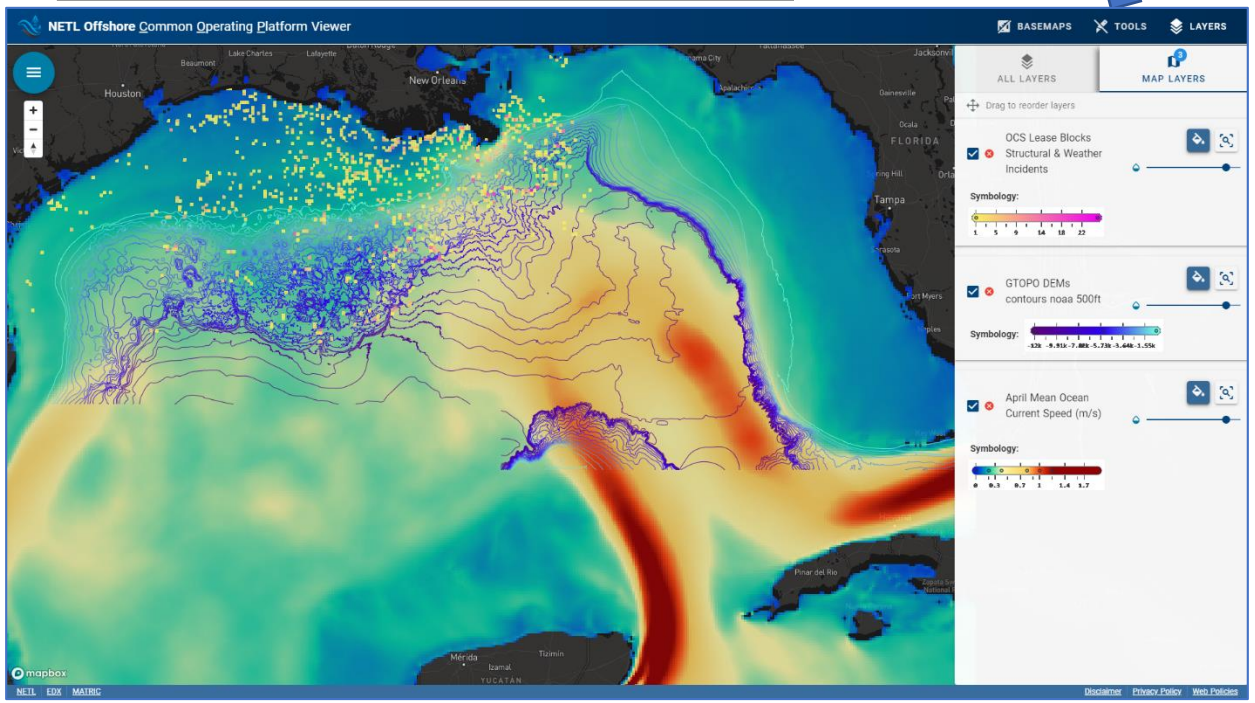
Access to improve industry models & predictions

- Integrate **ML, big data, and analytical outputs** with **online platform**
- Leverage **award-winning Offshore Risk Modeling Suite**
- Transform models into online tools to perform **real-time analyses** to **better understand offshore infrastructure integrity**
- Release tools and platform to stakeholders through **EDX**









EDX™
Energy Data eXchange

References

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- The WAVEWATCH III® Development Group (WW3DG) (2019). User manual and system documentation of WAVEWATCH III® version 6.07. Tech. Note 333, NOAA/NWS/NCEP/MMAB, College Park, MD, USA, 465 pp. + Appendices.
- Unites States Coast Guard (2019). Incident Investigation Reports. Retrieved from https://cgmix.uscg.mil/iir/.

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Thank you!

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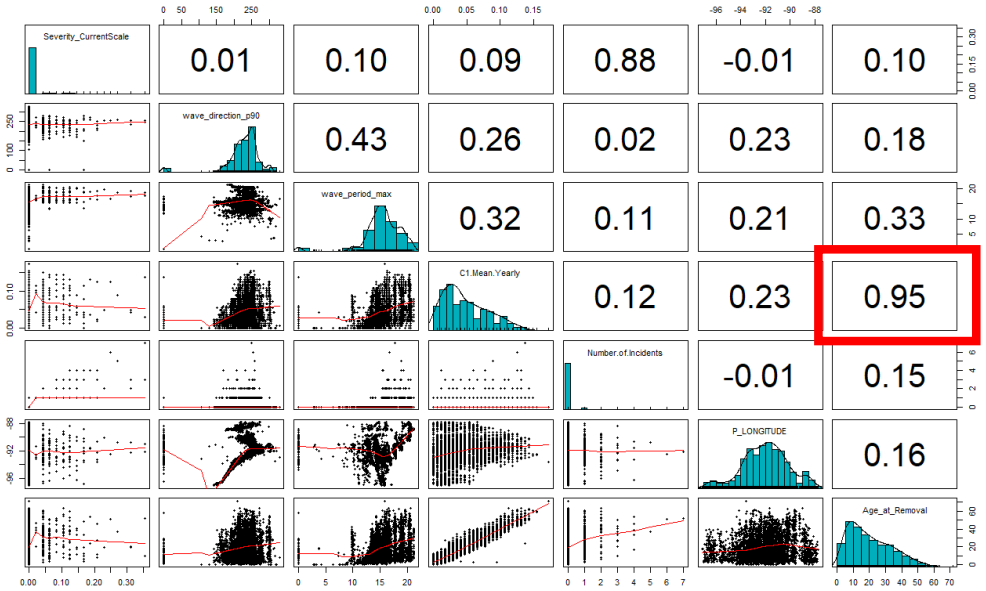
Task 3: Intelligent Risk Modeling for Offshore

Removal age & storm relationships

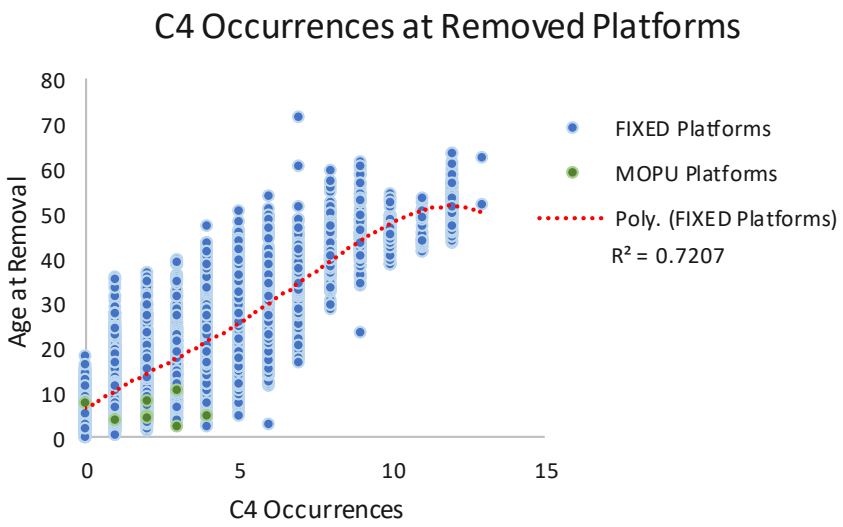
Key Variable Selection:

- Improved **understanding of operational platform lifespans**, by structure type, **to more accurately model expected lifespan**
- Platforms in areas of **more severe environmental conditions** are **removed on average 8 years sooner** than platforms in less severe areas (Spatial autoregressive model)



- **Model quality testing** on 40 variables (AIC)
- Strong relationship (0.95) between **hurricanes and removal age** (Pearson's Correlation)
- **Potential plateau** in the number of times a platform can sustain extreme hurricane conditions (Ordinary Least Squares regression)

***228 records missing key information



Task 3: Intelligent Risk Modeling for Offshore

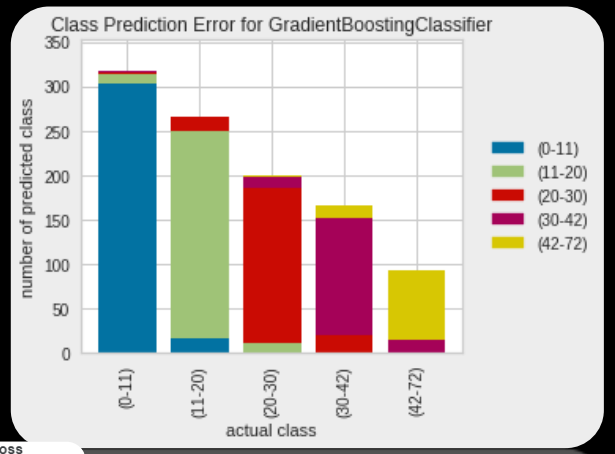
Key Findings & On-going Progress

Developing two machine learning models to:

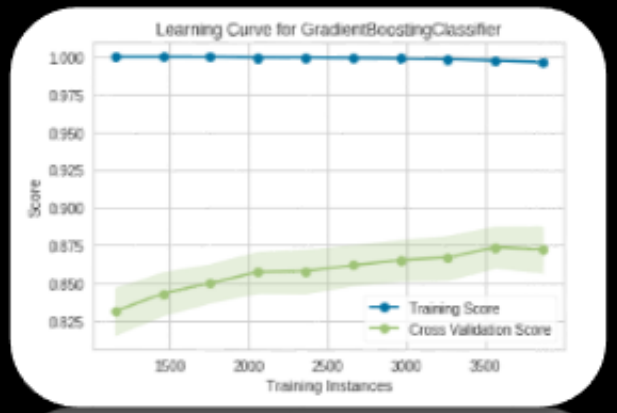
1. Predict life span for existing infrastructure using a Gradient Boosted Classifier
2. Characterize infrastructure integrity overtime using a Long Short-Term Memory Artificial Recurrent Neural Network (WATT)
    1. Accuracy calculated as correct/total is ~90% requiring no feature selection and model tuning
    2. With feature selection and heavy model tuning (>100 variations in parameters) accuracy reaches 93%
    3. Applies PyTorch to allow for quick changes to the model and fast training on available GPUs
    4. Automated scripts for model tuning and feature selection also speed up the testing of new models

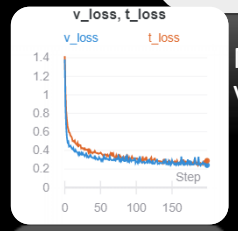
Both models are accurately predicting the age of removal for offshore platforms for 89% and 90% of offshore platforms

- Work continues to refine both models; to validation, reduce dimensionality and overfitting, and incorporating additional incident and metocean data



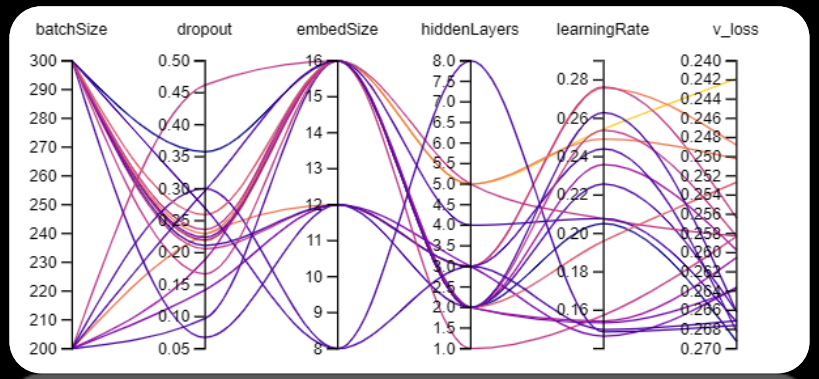
Evaluating model accuracy for ML model 1

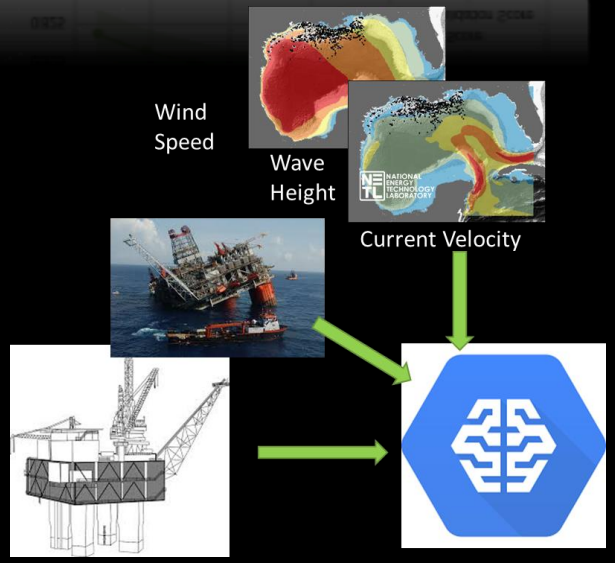




Neural Net Training and Validation Scores

Neural Net Model tuning results





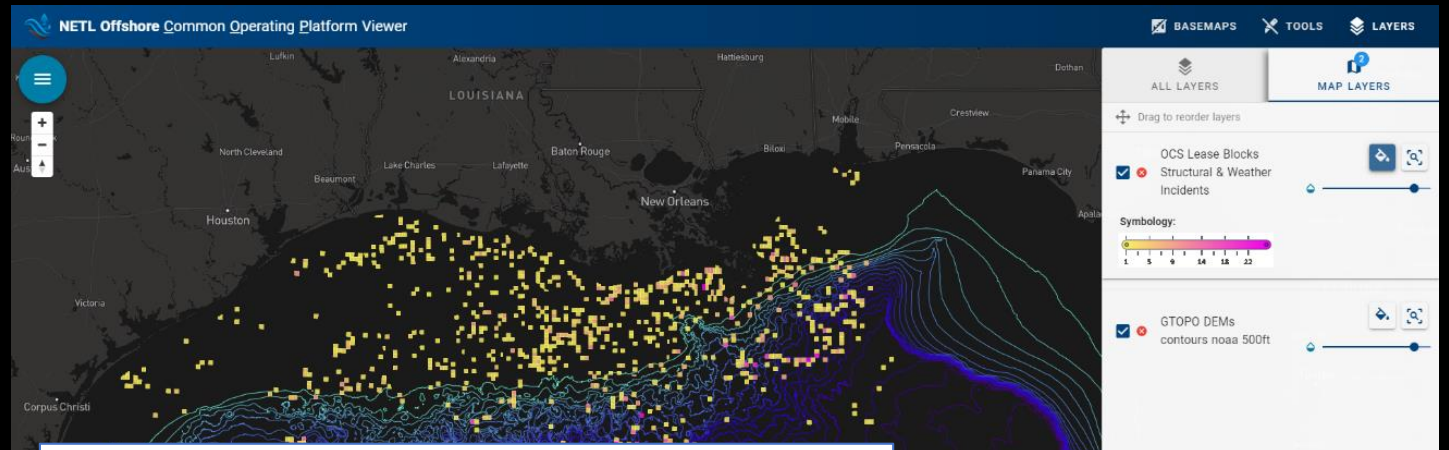
External Interest: API, BSEE, BOEM, EPA, DNV, Lloyd's Register, NOAA, Shell, SPE, USCG, and U.S. Steel

Task 3: Intelligent Risk Modeling for Offshore

Delivering novel resources for infrastructure integrity analytics

Key Accomplishments:

- Built comprehensive infrastructure dataset
- Identified key statistically-significant variables correlating to infrastructure lifespan
- Development of novel ML and advanced analytic models to predict existing lifespan and risk
- Technical report on intelligent analytics (*in progress*)
- Integration of data, models, ORM tools through interactive analytical platform



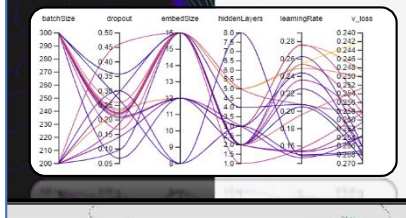
Values Delivered

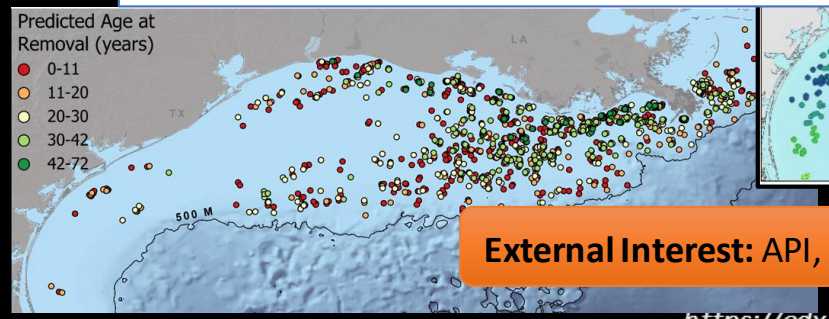
Understand ***existing infrastructure integrity***

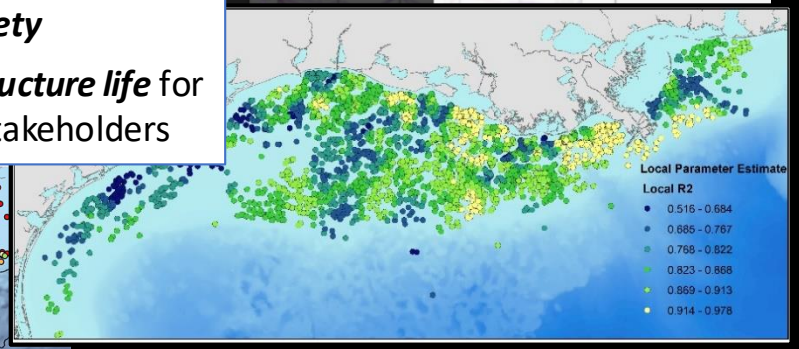
Improve infrastructure ***design & performance***

Minimize cost, maximize safety

Identify potential for ***extending infrastructure life*** for DOE, industry, regulators, and other stakeholders

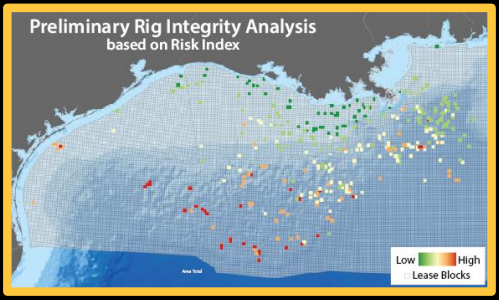






Next Steps

- Fill data gaps
  - Corrosion data
  - Resurrected historical incident data
  - Historical metocean data
- Refine & validate models
- Expand to rig integrity
- Full integration with ORM
- Release data & models on the online platform for real-time prediction & integrity assessments
- Publish manuscript on models for peer-review



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