

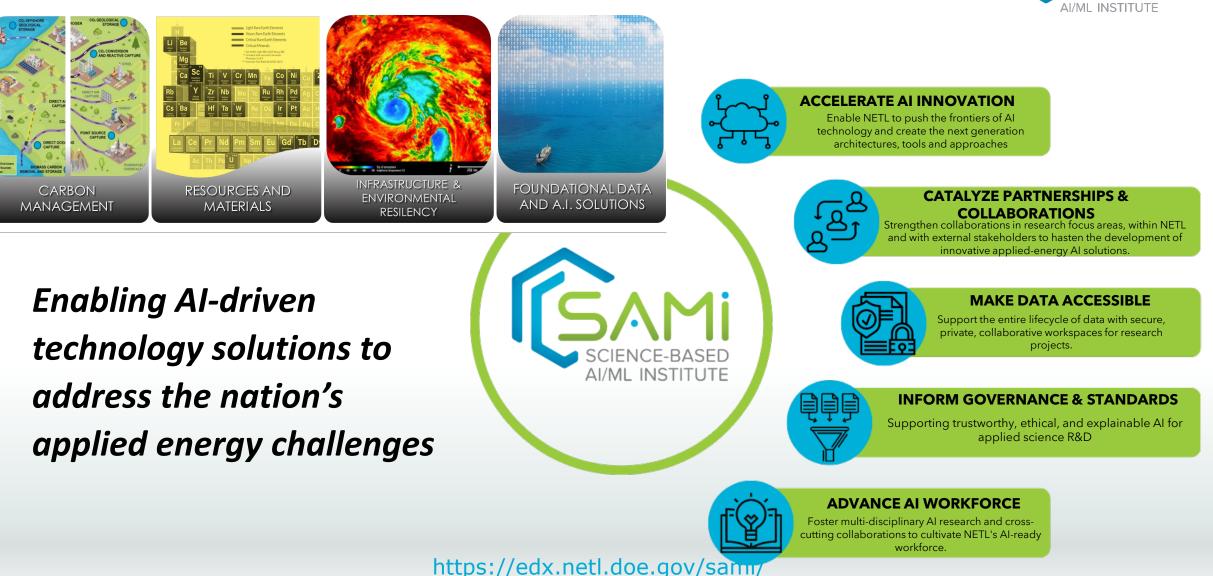
Innovating Next-Generation AI & Data Solutions for Offshore CCS Speaker: Kelly Rose,

Technical Director, NETL's AI/ML Institute, SAMI

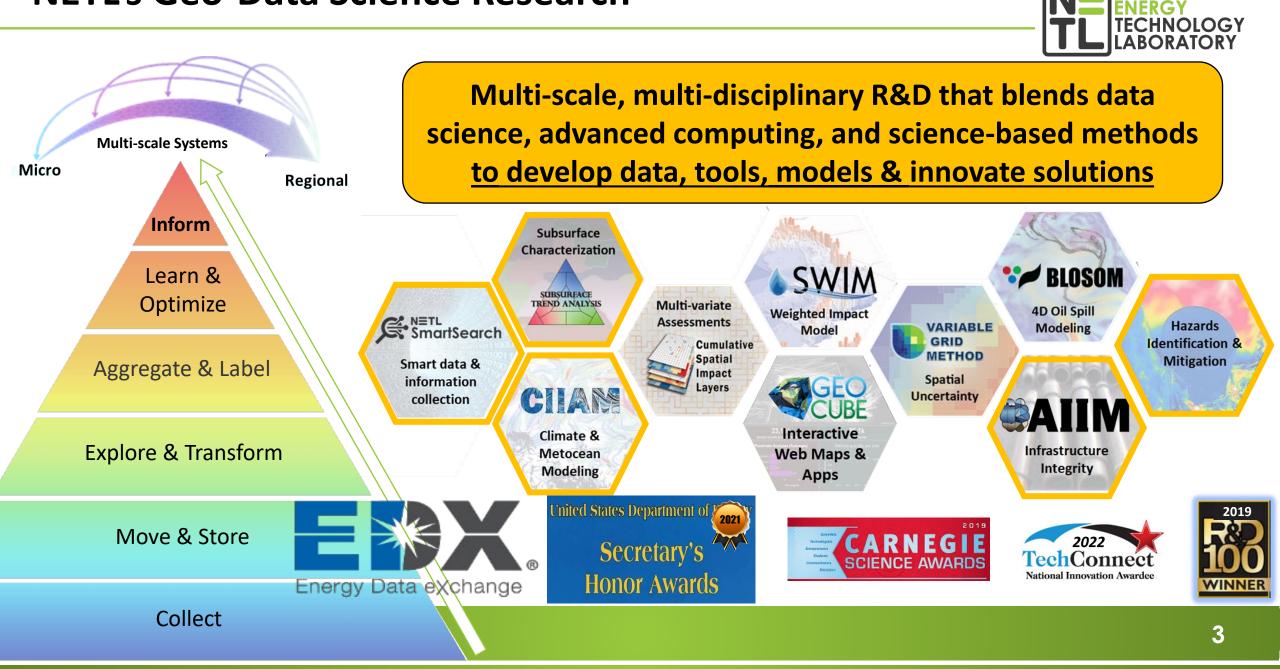
4/6/2023

Accelerating AI at NETL through SAMI

NETL's Science-based AI/ML Institute



NETL's Geo-Data Science Research



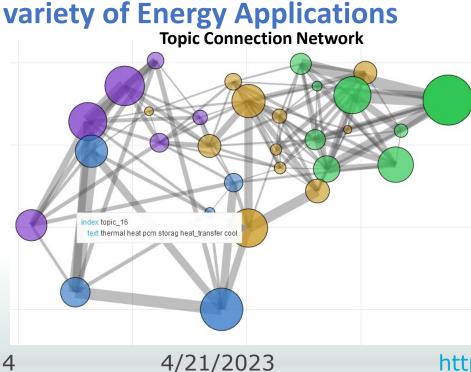
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SAMI-affiliated Research Highlights



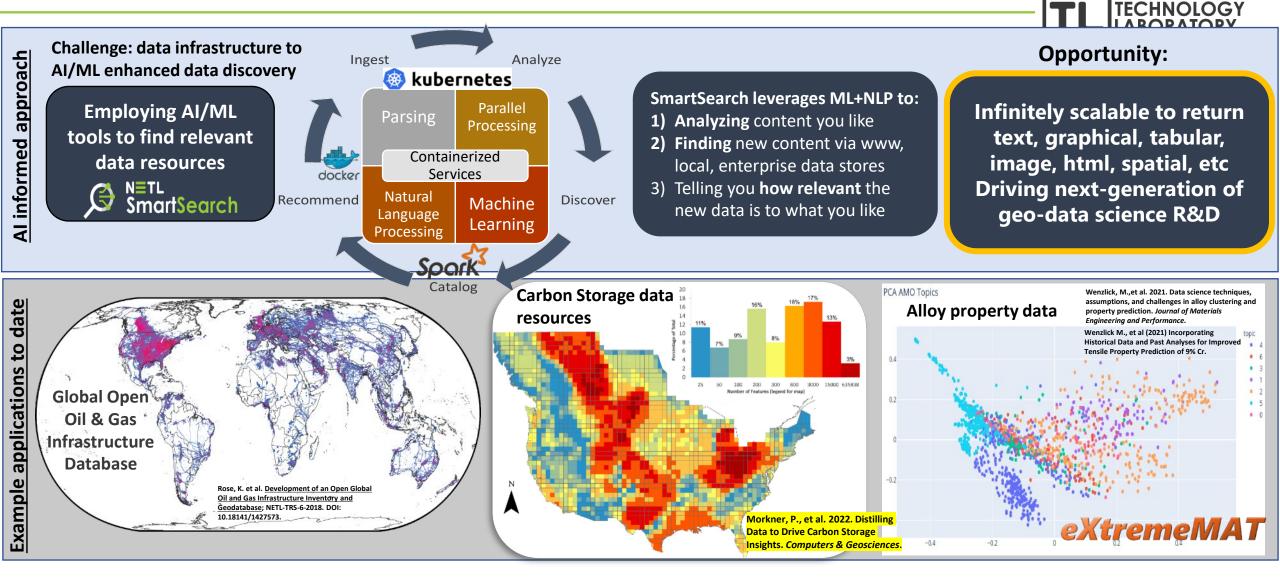
SAMI-affiliated research is at the leading edge of solving some of the most significant challenges applied energy

Topic Modeling & NLP for a



SmartSearch[©] Deep Learning/ **Generative AI for Data Discovery** Analyze Ingest 🛞 kubernetes Parallel Parsing Processing Containerized Services docker Natural Machine Recommend Language Discover Learning Processing Spark Catalog NATIONAL TECHNOLOGY

Digitalization, data management, & AI-informed data discovery



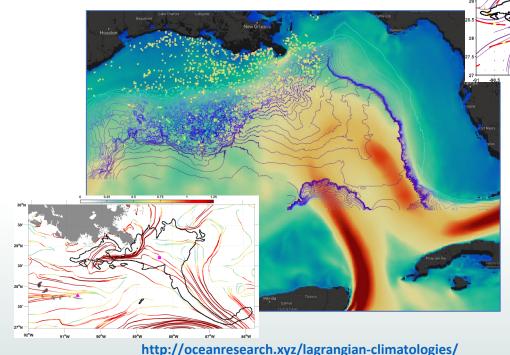
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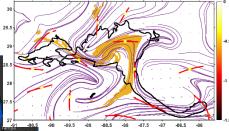
https://edx.netl.doe.gov/about

SAMI-affiliated Research Highlights

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Metocean modeling for advanced, adaptive forecasting of ocean systems





Climatological and Instantaneous Isolation and Attraction Models (CIIAM)

- **Award winning** model leverages the mathematical field of dynamical systems applied to geophysical fluids.
- Efficiently extracts climatological pathways and **trajectory patterns** from large velocity datasets.
- Leveraging of **unsupervised neural network learning**
- Identifies most influential instantaneous deformation patterns in fluid tracers bypassing inherent velocity errors.
- Used by research institutes in: USA, Mexico, Spain, UK, Brazil, India, Saudi Arabia, New Zealand.
 - Used for forecasting ocean plastic pollution, migrant boat locations, oil spill, and container ship loss trajectories, as well as fundamental ocean current patterns for transport and climate related insights

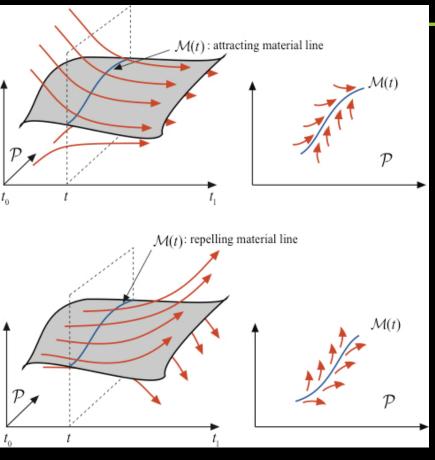
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Climatological Instantaneous Isolation and Attraction Model - CIIAM



https://edx.netl.doe.gov/dataset/ciam-climatological-isolation-and-attractionmodel-climatological-lagrangian-coherent-structures



Using concepts from the mathematical theory

of dynamical systems we find:

- most attracting pathways
- lack of attraction i.e. isolation



Duran, R.; Beron-Vera, F. J.; Olascoaga, M. J. <u>Extracting quasi-Steady Lagrangian transport patterns from the ocean</u> <u>circulation: An application to the Gulf of Mexico</u>. *Scientific Reports* **2018**, *8*, 10. DOI:10.1038/s41598-018-23121-y.

Gough, M. K.; Beron-Vera, F. J.; Olascoaga, M. J.; Sheinbaum, J.; Jouanno, J.; Duran, R. <u>Persistent Lagrangian</u> <u>Transport Patterns in the Northwestern Gulf of Mexico</u>. *Journal of Physical Oceanography* **2019**, 49, 353–367.



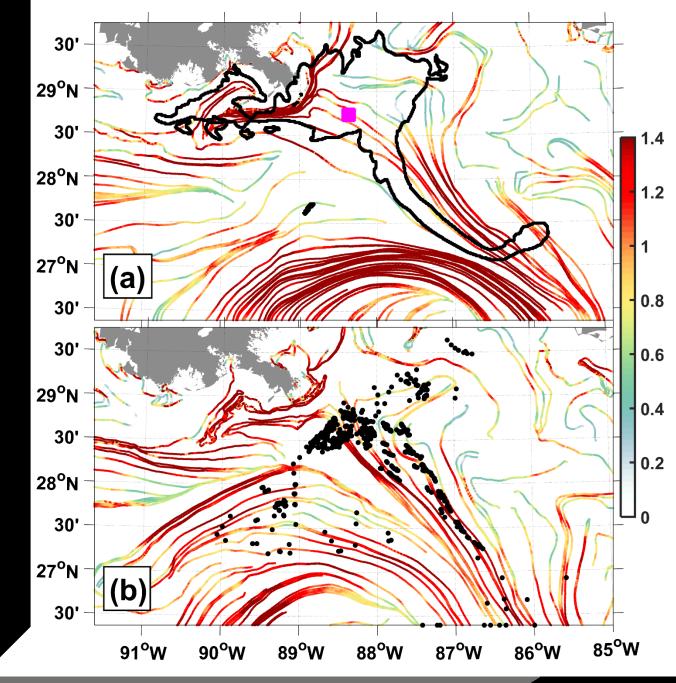
Solutions for Today | Options for Tomorrow



Predicts likely pathways

Oil from DwH in May 2010 stretches along May climatological attracting structures.

> Drifters released in July 2012, spread along July climatological attracting structures.





Used in domestic & international (Spain, Mexico, Brazil, etc) studies to:

- Predict changes in oceanographic currents
- Forecast fate and transport of refugee vessels
- Assess locations of sediment, chlorophyll, oil, and other particulates

Pathways: Red=attracting White=isolated

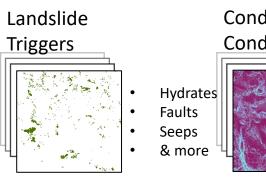


SAMI-affiliated Research Highlights

SCIENCE-BASED AI/ML INSTITUTE

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Artificial Intelligence (AI) Enhanced Workflow for <u>Natural Hazards Forecasting</u>

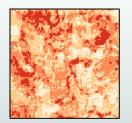


- Conducive Conditions
- Slope
- Curvature
- Sediment Type
- Geomorphology
- & more

Gradient Boosting Classifier
Artificial Neural Network







Output Landslide Susceptibility Map

https://edx.netl.doe.gov/sami/

https://edx.netl.doe.gov/sami **APPROVED FOR PUBLIC RELEASE**

catastrophic spills. Dyer, A., et al. Geohazard Analysis of Seafloor Landslide Potential for Infrastructure

Protection. In press https://www.researchsquare.com/article/rs-2070041/v1

Dyer, A.S., Mark-Moser, M., and Bauer, J., Submarine Landslide Susceptibility Mapping in the Northern Gulf of Mexico. In preparation.

Offshore Hazards include seabed instability, extreme wind/wave/current events, and earthquakes

Technology that integrates Artificial Intelligence and Machine Learning (AI/ML) methods with spatial data is being developed to forecast potential hazards to infrastructure

Benefits

- **Risk mitigation**
- Inform decommissioning and re-use strategies
- Reduce environmental and economic impacts

https://edx.netl.doe.gov/offshore

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ENERGY

Mexico

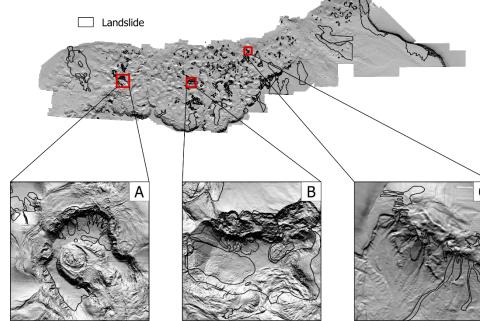
This photo from March 31, 2015, shows the wake of a supply vessel crossing an oil sheen in the Gulf of Mexico at the site of the former Taylor Energy oil rig, which was destroyed in 2004 by an underwater landslide triggered by Hurricane Ivan. PHOTOGRAPH BY GERALD HERBERT, AP PHOTO

SCIENCE | NEWS

Offshore Geohazard Forecasting

Hidden underwater landslides pose new dangers in the Gulf of

Seismic data show that earthquakes more than 600 miles away can trigger submarine mudslides that threaten offshore oil rigs and could lead to

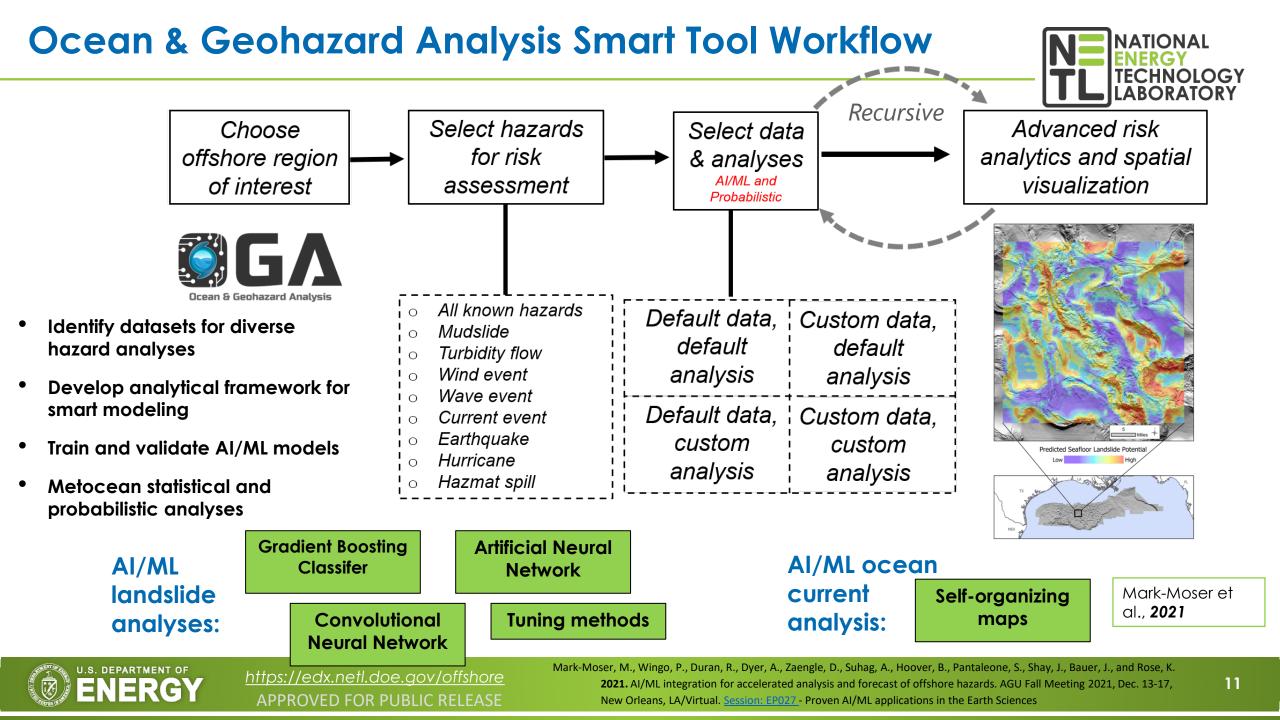












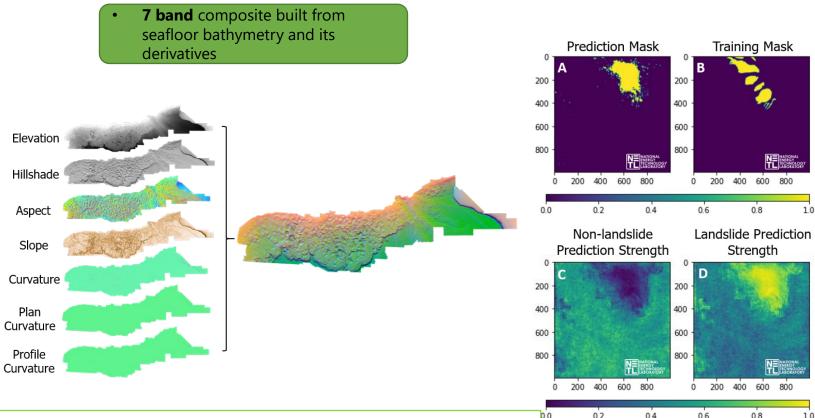
Landslide Detection





- Supervised computer vision modeling to identify historic landslides in high resolution bathymetry, decreasing time to locate and digitize training data
- Semantic segmentation deep learning framework developed using a Fully Convolutional Residual Network (ResNet50)

https://edx.netl.doe.gov/offshore



Mark-Moser et al., *in prep*, Integrated Artificial Intelligence/Machine Learning Smart Tool for Metocean and Seafloor Hazards: The Ocean & Geohazard Analysis Tool. NETL Technical Report Series.

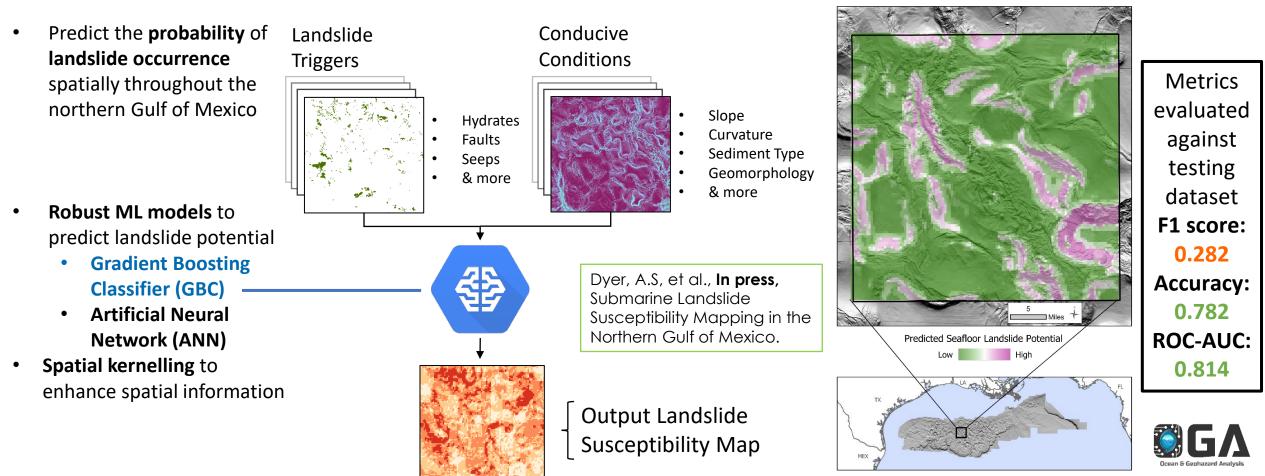


Landslide Susceptibility





GBC Model Prediction



https://edx.netl.doe.gov/sami









Key Takeaways

- AI/ML methods offer near-real time assessment of risks to offshore infrastructure from submarine landslides.
- Spatial workflow is generalizable, offering implications to accelerate other risk applications extending to other geohazard targets both offshore and onshore.

Challenges

- Landslides are **heterogeneous** in shape and structure, making them **difficult to identify** by computer models.
- Data availability throughout the Gulf of Mexico regarding seafloor properties is spatially sparse.



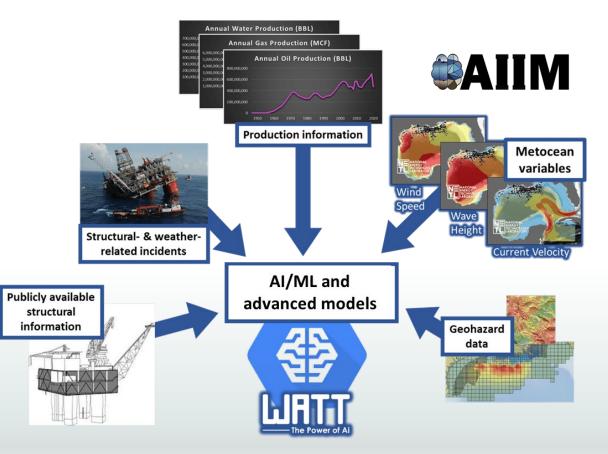


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Applied AI/ML Multi-Model Forecasting Infrastructure Integrity



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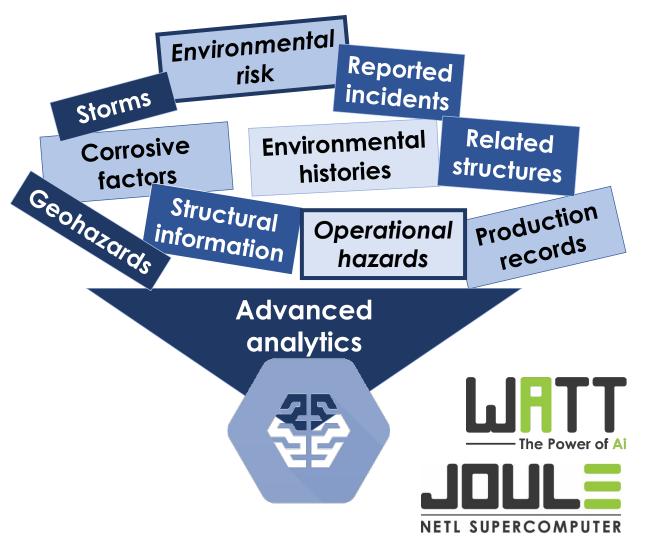
AIIM: <u>A</u>dvanced <u>I</u>nfrastructure <u>I</u>ntegrity <u>M</u>odel



AIIM utilizes big data, big data computing, multiple predictive machine learning (ML), spatiotemporal, and advanced analyses to **evaluate the current state of platforms, pipelines, and wells** in the U.S. Federal Waters of the Gulf of Mexico.

AIIM results can help:

- Identify assets vs. liabilities
- Inform life extension, remediation, & safe use strategies
- Assess infrastructure hazards and reuse potential for other energy sources
- Support environmental & operational risk prevention





AIIM Analytical Approach

NATIONAL ENERGY TECHNOLOGY LABORATORY

Metocean &

Biochemical

variables

Geohazard

data

Multiple Machine Learning (ML) and Advanced Modeling

Machine Learning Models (Dyer et al. 2022)

- Gradient Boosted Decision Trees (2 models)
- Artificial Neural Network (2 models)
- Bayesian Network

Advanced Analytics

- Geographically Weighted Regression
 (Nelson et al. 2021)
- Causality/Time Series Analytics

Why multiple models?

- Evaluate strengths vs. weaknesses
- Internal cross-validation

Identified **significant connections** among **biochemical** variables and **incidents**

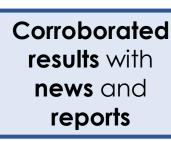
Annual Water

Incident

reports

Production

information



Structural

information

AI/ML &

Advanced

Modeling

The Power of Ai

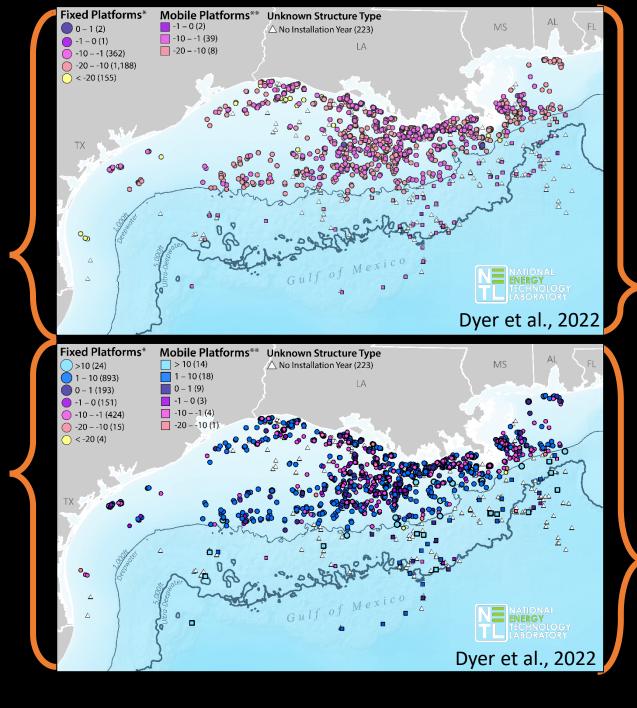
ML models capable of predicting **removal age <u>< 3 years</u>**



Predicting remaining platform lifespan

Gradient Boosted Regression Tree 97% accuracy 23 features

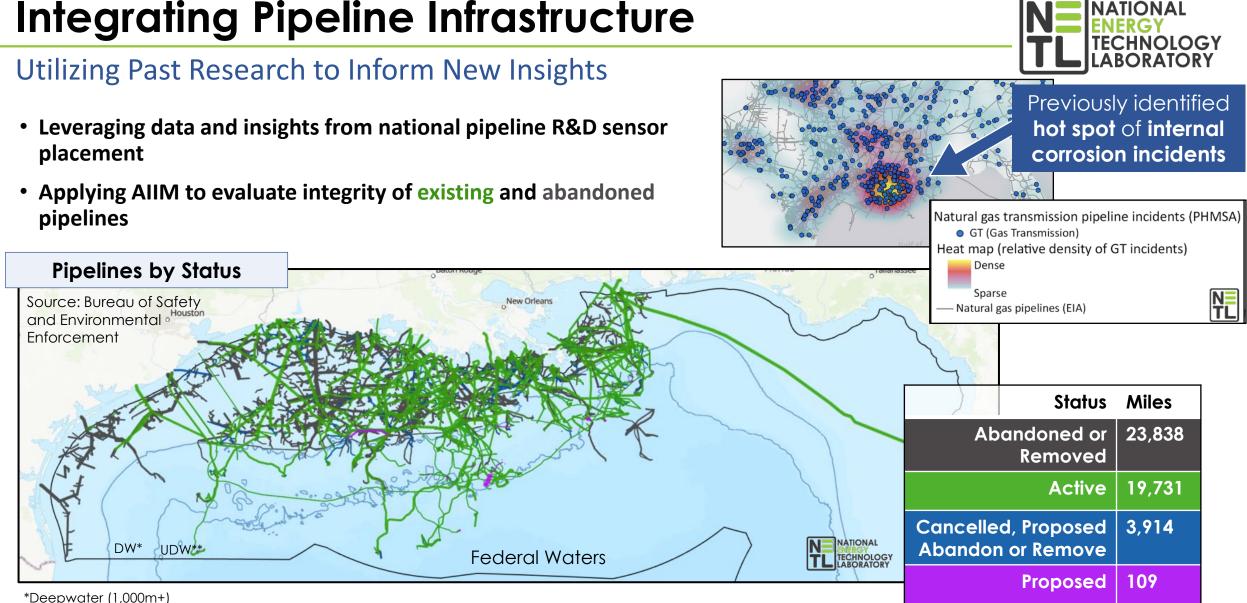
Artificial Neural Network 95% accuracy 792 features



Running *multiple models* allows us to *internally validate results*

> <u>Key Variables:</u> Metocean Production Structural Location

Key variables: Metocean Production Structural Location Incidents Geohazards



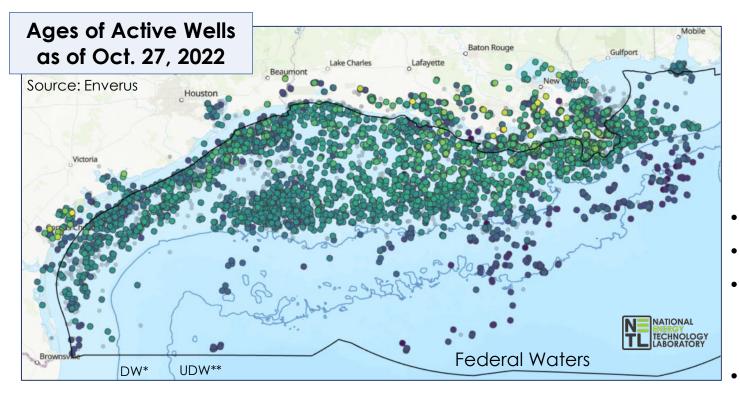
**Ultra-deepwater (5,000m+)



Integrating Well Infrastructure

Utilizing Past Research to Inform New Insights

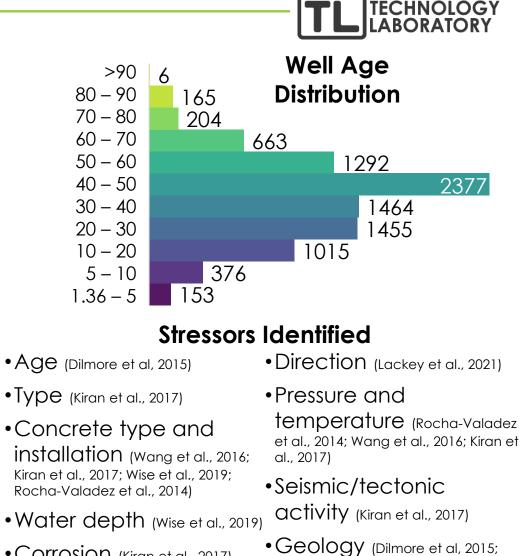
- Leveraging data and insights from onshore well integrity testing
- Evaluating well integrity for reuse potential



*Deepwater (1,000m+) **Ultra-deepwater (5,000m+)

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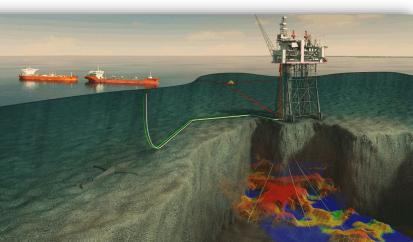
- Corrosion (Kiran et al., 2017)
 - https://edx.netl.doe.gov/offshore 20

Kiran et al., 2017)

AIIM Applications



Assess what infrastructure is available or could be reused to support offshore carbon sequestration



Legend
×

Pipelines

Pipelines

Gas_TG_4_20_18_Flag_Offshe

Buston

Plaforms

Plaforms

Past Incident

Severity_1

0.03 0.644

0.01 0.04

Understand what infrastructure could pose a risk to a project (example – preliminary

assessment with USCG)

What are the most traversed lease blocks by ship development to help traffic? users interrogate data & model results: What is the remaining lifespan of a platform? Alpha version Spring 2023 What is the What environmental history of a vulnerabilities exist in platform? the area? Lease block? **Pipeline?** Where are operational

risks more likely?



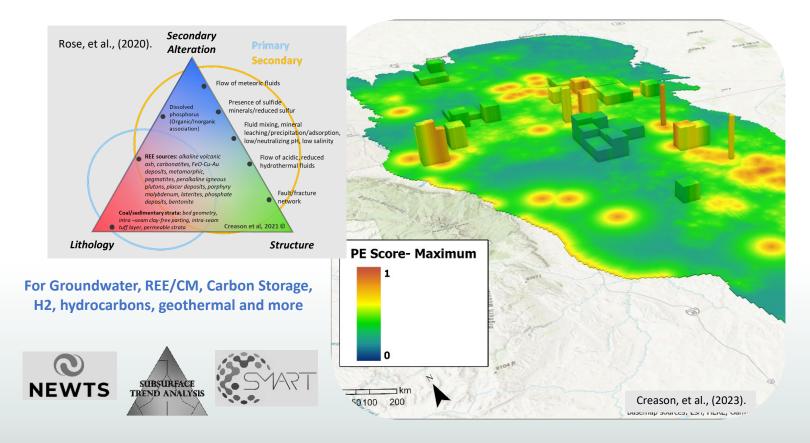


SAMI-affiliated Research Highlights

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Federated-AI modeling for improving Natural Resource Assessments



https://edx.netl.doe.gov/sami/

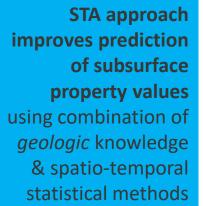


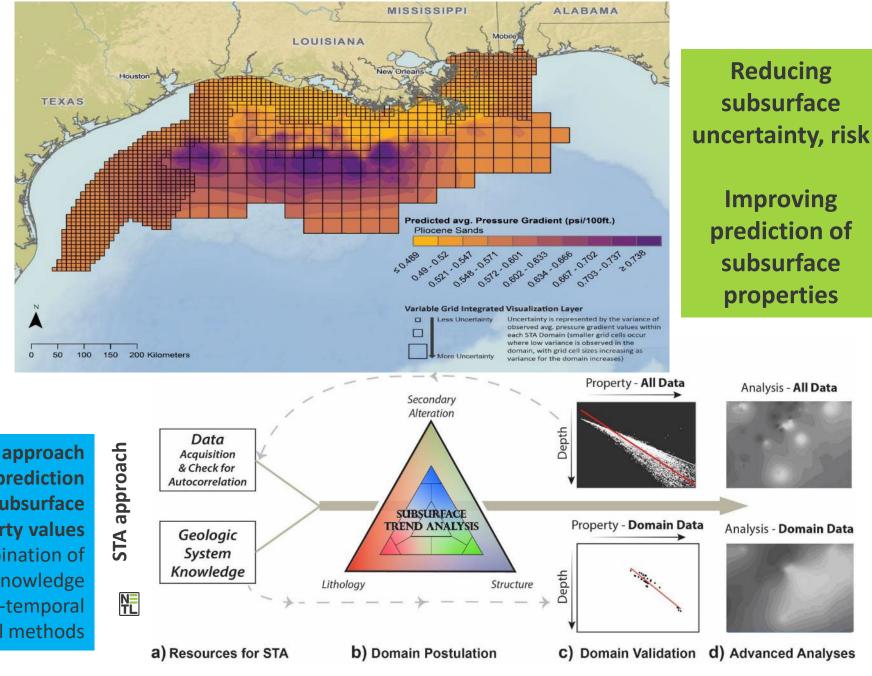
Subsurface Trend Analysis

Subsurface Hazards and Reservoir Resource Prediction

Rose, Bauer, Mark-Moser, 2021, Subsurface Trend Analysis, a Multi-Variate Geospatial Approach for Evaluation of Geologic Properties and Uncertainty Reduction, *Interpretation*.

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https:/edx.netl.doe.gov/offshore 23

Reframing Resources: Offshore CO_2 Storage in the Gulf of Mexico

Calculating safe resource storage potential to support decarbonization

Injected CO, Groundwater Caprock/Seal Chemosynthetic communities (tube worms) Fault Injected CO. the the Saline Formation Fault **Saline Formation**

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Offshore CO₂ Saline Storage Methodology

Built off the DOE CO₂ Storage Methodology for offshore saline systems

NETL

Goodman et al., 2016

Cameron et al., 2018

- Long-term volumetric estimation in saline formations
- Gigatons of CO₂ based on:
 - Area
 Density
 - Height Efficiency
 - Porosity

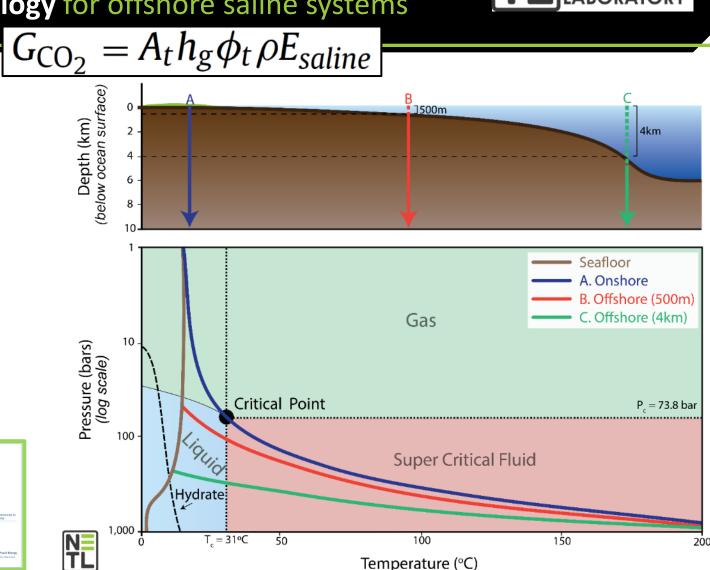
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In Offshore Systems:

- **CO₂** behaves differently • *Pressure, temperature, density*
- **Sediments** also behave differently
 - More porous & permeable

• Unlithified

NE ENERGY TECHNOLOGY LABORATORY

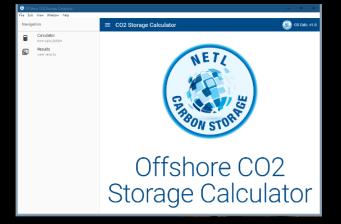






Offshore CO₂ Saline Storage Calculator

Romeo, L., et al IJGGC 2022



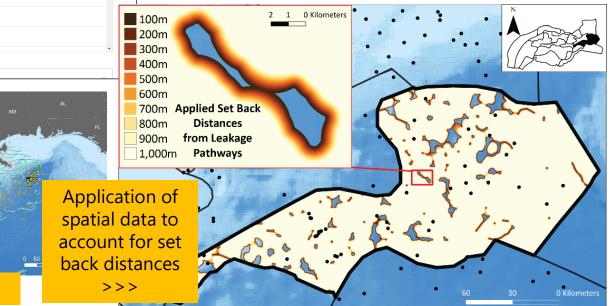
- Accounts for changes in CO₂ density given the overlying water column (Lemmon et al.)
- Enables the integration of setback distances from potential leakage pathways



CO2 Storage Calculator		_ 🗆 ×
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Porosity Efficiency range based on geologic factors from		
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Clastics Ec	olian	200m
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Leakage pathways

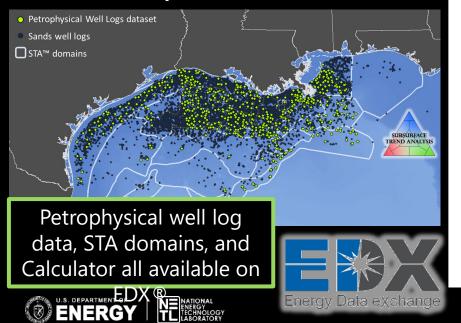
- Open-source and standalone
- Enables multi-scale assessments
- Leverages power of spatial data
- Flexible tool enables customization
 - 10-20 parameters
- Applicable to multiple **lithologies** and **depositional environments** in saline formations (Gorecki et al., 2009)

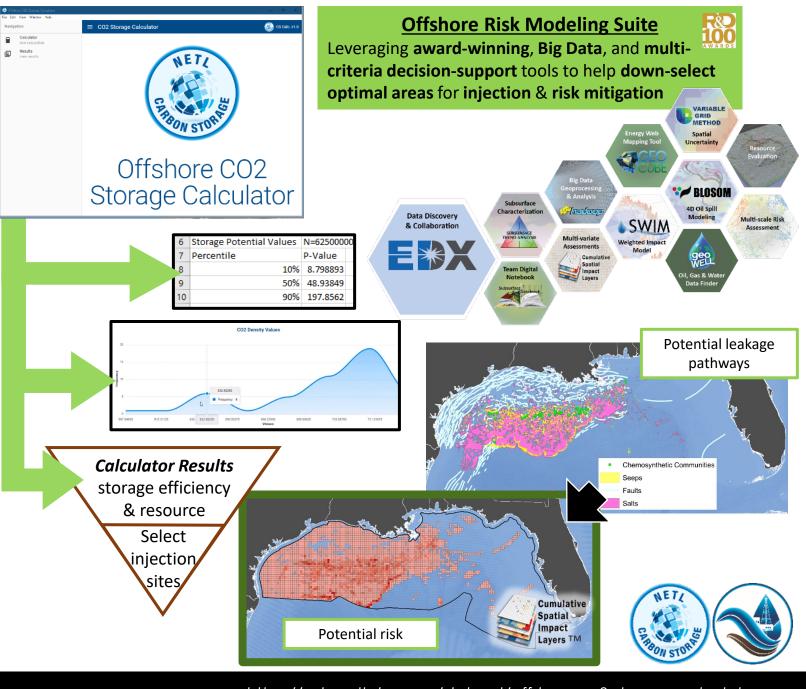


https://edx.netl.doe.gov/dataset/offshore-co2-storage-calculator 26

Improving Offshore CO₂ Capacity Estimates

- Offshore CO₂ Storage Calculator outputs <u>distributions</u> of CO₂ storage, data, stats, and graphs
- Enables multi-scale calculations
- Demonstrated by calculating resource distributions for geologic domains as defined by Subsurface Trend Analysis[™] (Mark-Moser et al., 2020)





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EDX DisCO2ver Platform

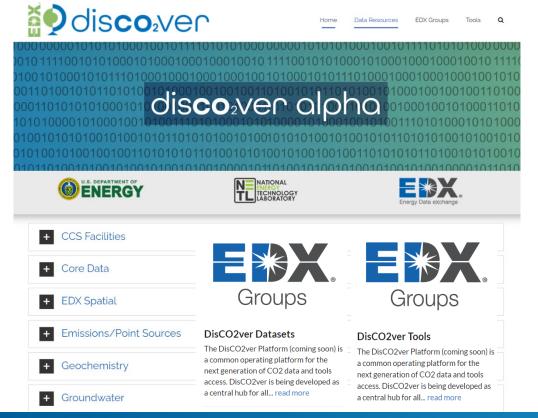
Digital Resources for the Carbon Storage Community

Near term (coming live, spring 2023):

EDX DisCO2ver Alpha Website

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 Static website hosting CCS specific data, tools, and resources for user community as we wait for DisCO2ver Beta to launch.







Long term (winter/spring 2024):

EDX DisCO2ver Beta Platform

https://edx.netl.doe.gov/

- Launch with EDX++ Deployment, expected Summer 2023
- **Dynamically** pull data from EDX into platform leveraging the EDX API
 - **Real time updates** to platform resources based on EDX query capabilities as submissions are published on EDX
 - Integration of cloud compute tools in future such as SmartSearch (out-year integration).

Database (NATCARB) is a geographic information system (GIS)-based tool for viewing carbon literature review performed to define the primary difference of the submission. The following submission of the submission. The following submission of the submission of the submission.	bis Do, Home Data Tools V⊖r			
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Additional Resources & References

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Innovating science-based, AI/ML solutions for applied energy challenges

Thank you!

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