Ocean & Geohazard Analysis

An AI/ML framework and Smart Tool to identify hazards to offshore infrastructure

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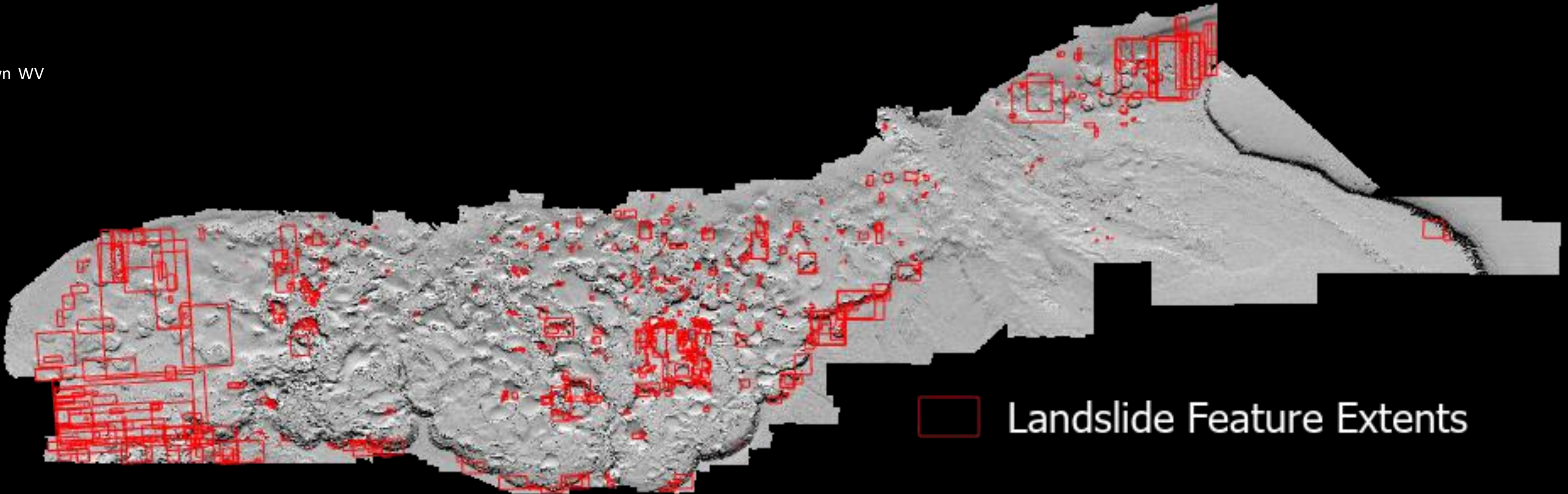
Virtual Project Review Meeting
Oct. 26th 2020



This Research was executed through the NETL Research and Innovation Center's Offshore Research field work proposal. Research performed by Leidos Research Support Team staff was conducted under the RSS contract 89243318CFE000003.

Offshore FWP, Task 6

Solutions for Today | Options for Tomorrow

U.S. DEPARTMENT OF ENERGY

Ocean & Geohazard Analysis

Advanced analytics to predict hazards to offshore infrastructure

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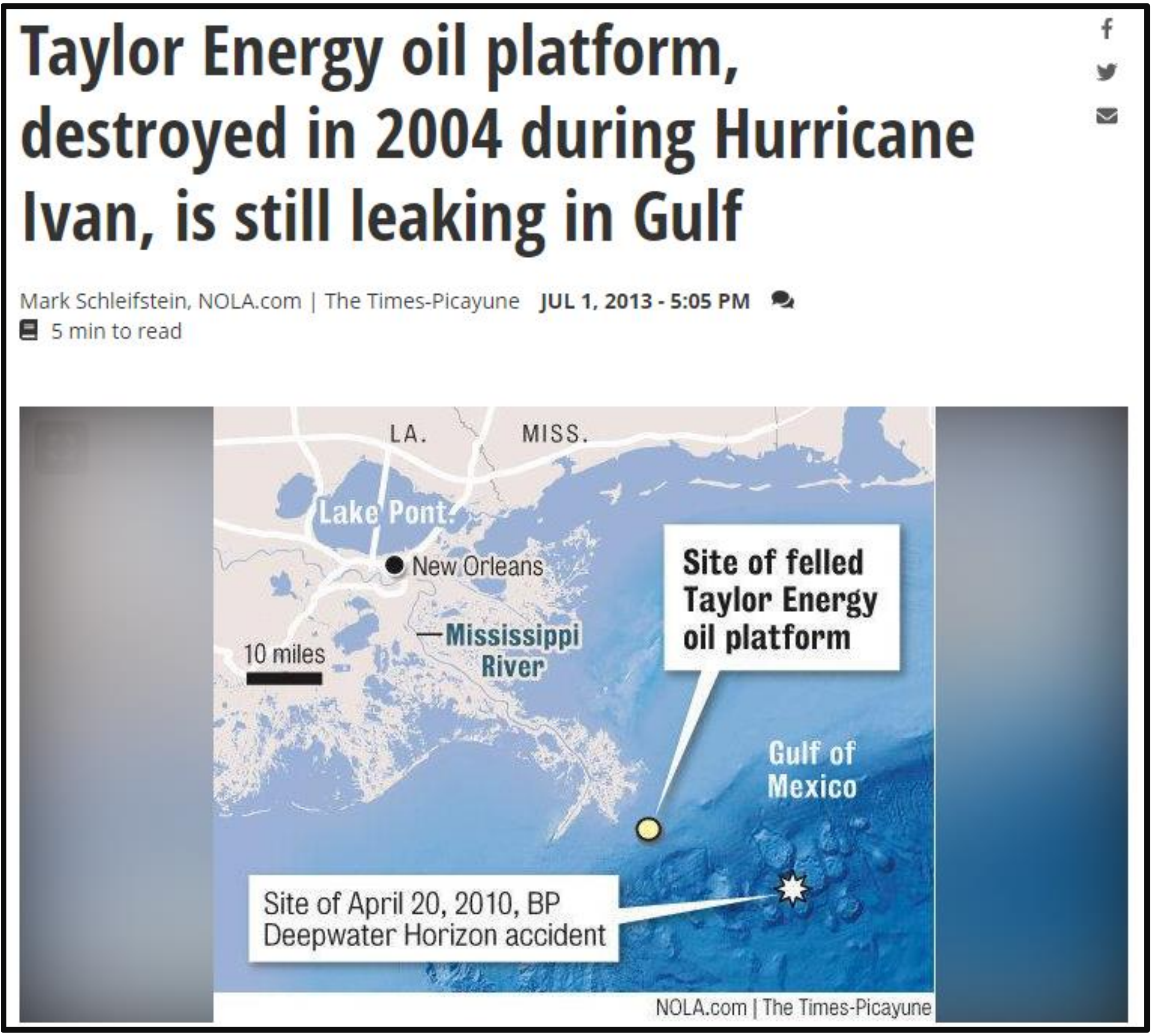

Taylor Energy oil platform, destroyed in 2004 during Hurricane Ivan, is still leaking in Gulf

Mark Schleifstein, NOLA.com | The Times-Picayune JUL 1, 2013 - 5:05 PM

5 min to read

Why is this work important?

Success and longevity of offshore operations depends on avoiding hazards.

Issue/R&D Need

- Technology that integrates big data and science-based analytics for offshore hazards does not exist.
- Advanced analytics can offer near real-time assessment of risks, and also forecast vulnerabilities.

Task 6: Infrastructure & Metocean technology

Motivation:

- Demand on offshore EEZ in the US and around the world is increasing.
- Offshore infrastructure is expected to increase 50–70% by 2028.
- Offshore structures include:
  - oil & gas
  - pipelines
  - renewable energies
  - bridges
  - tunnels
  - carbon storage
  - undersea internet cables

Data sources for examples:
A) A 1.4-Billion-pixel map of the Gulf of Mexico Seafloor. https://eos.org/science-updates/a-1-4-billion-pixel-map-of-the-gulf-of-mexico-seafloor
B) Bennett, R., Rochon, A., Schell, T., Bartlett, J., Blasco, S., Hughes-Clarke, J., Scott, D., MacDonald, A., and Rainey, W., 2004, Cruise report, Amundsen 2004-804: Beaufort Sea / Amundsen Gulf / Northwest Passage, June 23 -August 27, 2004: Geological Survey of Canada, Open File 5798, 111 p.
C) https://www.mathworks.com/matlabcentral/fileexchange/58320-demos-from-object-recognition-deep-learning-webinar

Offshore Unconventional FWP

Task 6 - Infrastructure and Metocean Technology

Research Problem:

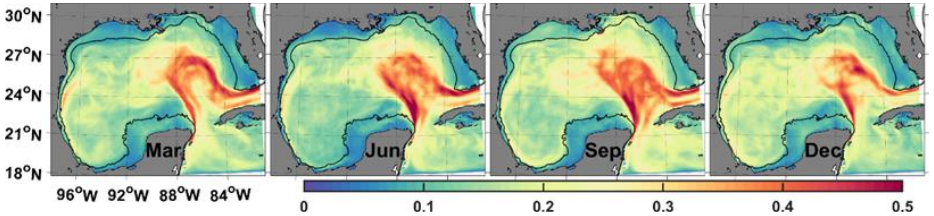
- Changes in the ocean environment (i.e., mudslides or burial from subsea currents, strong weather events or natural fluctuations) have been linked to **billions of dollars of impacts**.
- These events can have a significant effect on the **success and longevity** of offshore infrastructure, as well as affect **safety and cost** during exploration and production activities.

Research Approach:

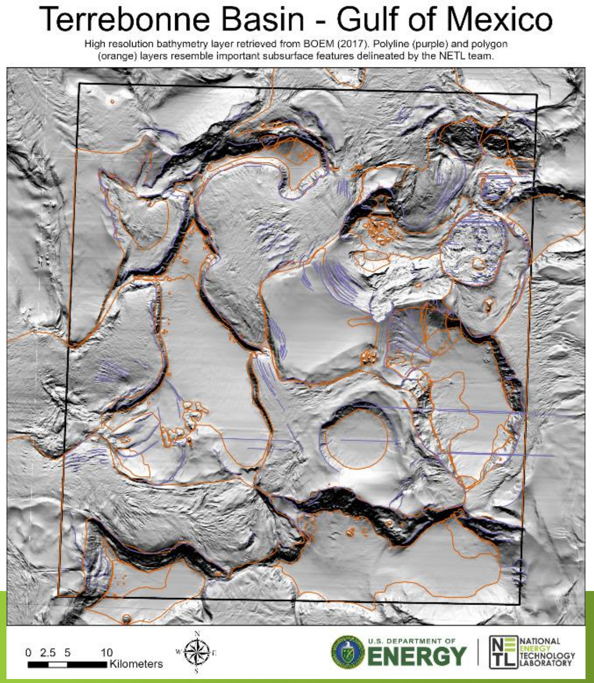
- Determine current state of knowledge regarding hazardous metocean and bathymetric conditions, and data availability regarding these conditions and historic events.
- EY19 - Evaluate if Ml/AI model can be developed to better identify current hazardous metocean and bathymetric conditions.
- EY 20 + - develop, train, and test ML/AI model to identify current conditions and forecast changes and vulnerability that may impact offshore infrastructure and operations.

Benefit:

- Improved characterization of seabed related hazards in the offshore environment will help to manage and minimize costs and risks during drilling and production operations, and help prevent catastrophic incidents.



Example of data collected:
Above - Avg. Bottom Current Velocity (12 yr. avg.)
Below – high-resolution bathymetric data and labeled hazards (in orange and purple)

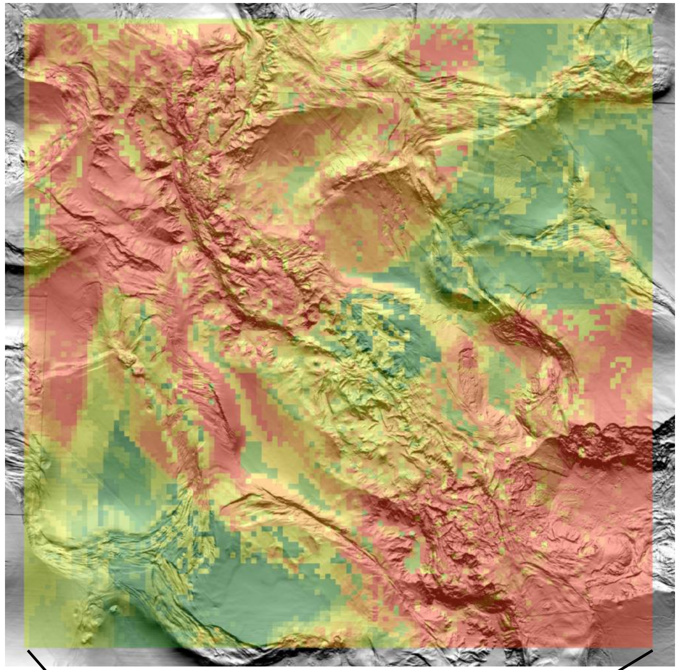


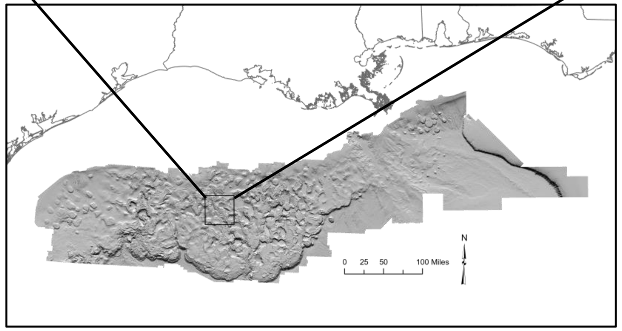
Task 6: Infrastructure & Metocean background

- Mississippi Delta region is one of the areas most hit by major hurricanes in the U.S.; all of GoM at high risk of extreme metocean events
- Mississippi River provides a steady source of unconsolidated sediments
- Many areas in GoM are densely populated with aging infrastructure in regions of metocean and geohazards
- Between 2004–2008, 181 structures and 1673 wells in GoM were destroyed by five hurricanes

Approach for Infrastructure and Metocean Technology: The Ocean & Geohazard Analysis Smart Tool

- Identify datasets for diverse hazard analyses
- Develop analytical framework for an **Ocean & Geohazard Analysis (OGA) Smart Tool**
- Train Machine Learning Models
- MetOcean statistical and probabilistic analyses
- Release data and models through the **online platform** hosted by **Energy Data eXchange (EDX)**





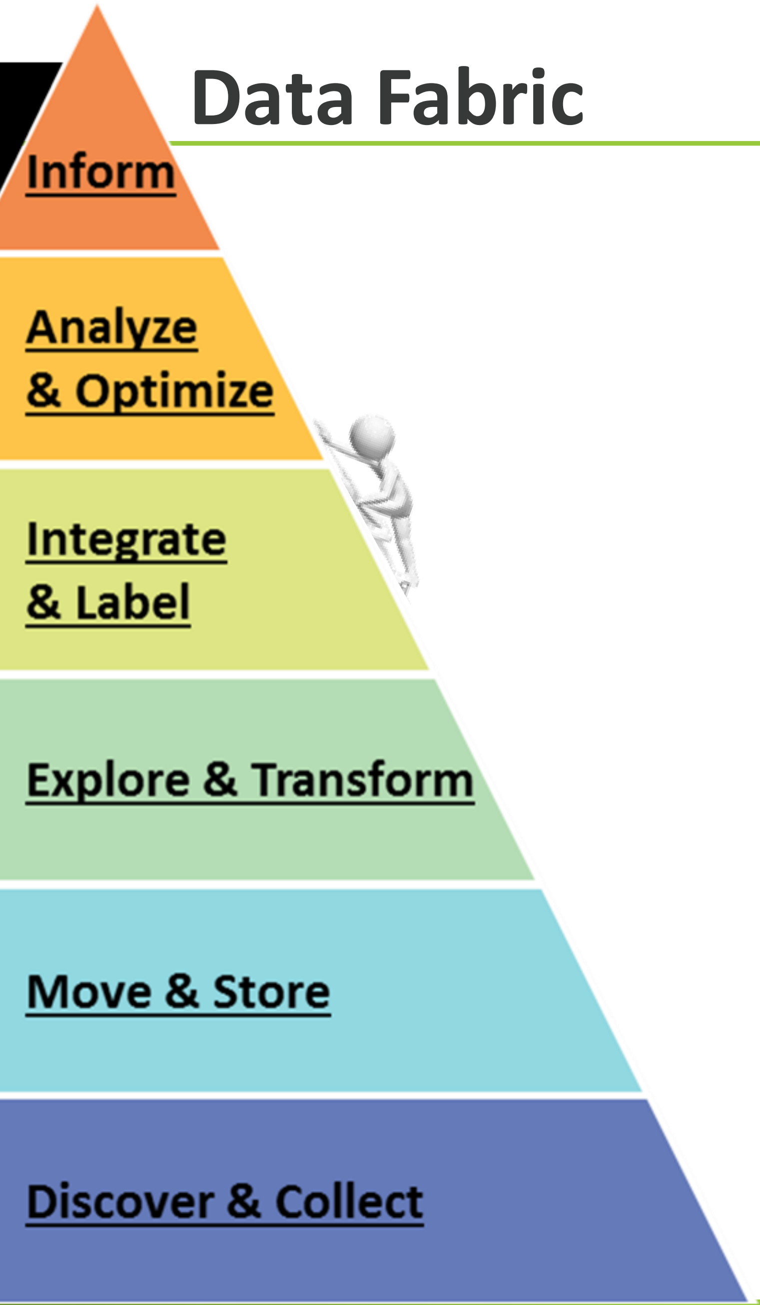
Ocean & Geohazard Analysis

Ongoing work:

Collect massive amounts of data, integrate from multiple sources to support analytics
- Digitizing old & unstructured data sets
- Aggregating all open-source data available nationally and internationally

Novel analyses of these datasets using:
- Machine Learning
- Nonlinear Dynamics
- Prediction Statistical Intervals
- Monte Carlo simulations

Data Fabric



Data Set	Source
BOEM bathymetry slope	BOEM, 2017
BOEM bathymetry curvature	BOEM, 2017
BOEM bathymetry profile curvature	BOEM, 2017
BOEM bathymetry plan curvature	BOEM, 2017
NOAA Coastal Relief Model (Vol, 3, 4, & 5)	NOAA National Geophysical Data Center
GEBCO 2020	GEBCO Compilation Group (2020))
SRTM15+ V2.1 and V2	NOAA National Centers for Environmental Information.
Northern Gulf Coast Digital Elevation Model	NOAA National Centers for Environmental Information.
Dominant sediment type	Buczkowski, et al., 2020 (usSEABED database)
Sediment age	
Vertical Sediment Accumulation Rate	Integrated Earth Data Applications (IEDA).
Sediment shear strength	Holcombe, L. & Holcombe, T., 2004
Geomorphology	Hance, et al., 2014
Faults	USGS Faults, Diegel et al, 1995
Sediment Thickness	
Sediment shear strength	Digitized from diverse sources
Digitized Landslides	Several sources
Ocean waves	Several sources
Ocean currents	Several sources
Wind	Several sources
IBTrACS Tropical Storms	NOAA
Ocean currents (bottom & surface)	Several sources
Landslide locations near Mississippi delta	Nodine et al 2007
Terrebonne Basin Mapping Area Landslides	NETL Team (Task 5/6)
Mass Wasting	Twichell (2005)
Slumps	BOEM (2016)
Flows	BOEM (2016)
Landslide locations near Mississippi delta	Nodine et al 2007 and others

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WATT The Power of Ai

JOULE NETL SUPERCOMPUTER

+ EDX Energy Data eXchange

FE's "Data Fabric" simplifies and integrates data management (EDX) with cloud and on-prem sci-compute to accelerate digital transformation

U.S. DEPARTMENT OF ENERGY

Ocean & Geohazard Analysis Smart Tool Workflow

Choose offshore region of interest → Select hazards for risk assessment → Select type of analysis ⇄ Advanced risk analytics and spatial visualization

Select hazards for risk assessment:

- ❑ All known hazards
- ❑ Mudslide
- ❑ Wind event
- ❑ Wave event
- ❑ Current event
- ❑ Erosion
- ❑ Earthquake
- ❑ Hurricane
- ❑ Hazmat spill

Select type of analysis:

Default data, default analysis	Custom data, default analysis
Default data, custom analysis	Custom data, custom analysis

Ocean & Geohazard Analysis

Landslide Detection

Locating critical parameters to identify mass wasting geohazards

Objective: Using high-resolution seafloor images, develop a data driven neural network model to identify the locations of submarine landslides.

Model Design

- We use as a base the Fully Convolutional ResNet101, a 101 layer network available with the PyTorch framework.
- The model performs semantic segmentation to create an output mask highlighting landslides given an input image.

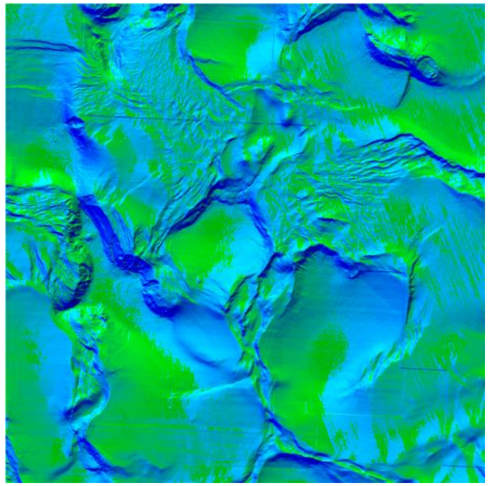
Challenges

- Imbalanced dataset - causes model to favor predicting no landslides. We hope to improve performance with higher penalties for missed landslide predictions.
- Small dataset, to overcome we augment our dataset by flipping rotating and scaling existing images.
- Most models are designed for 3 band input images (Red/Green/Blue) while the images we use have 7 bands. To overcome this we modify an existing model to accept the 7-band input image.

The model trains on Image and Mask pairs shown below.

It is given an input image and scored on how accurately it can produce a mask for the image.

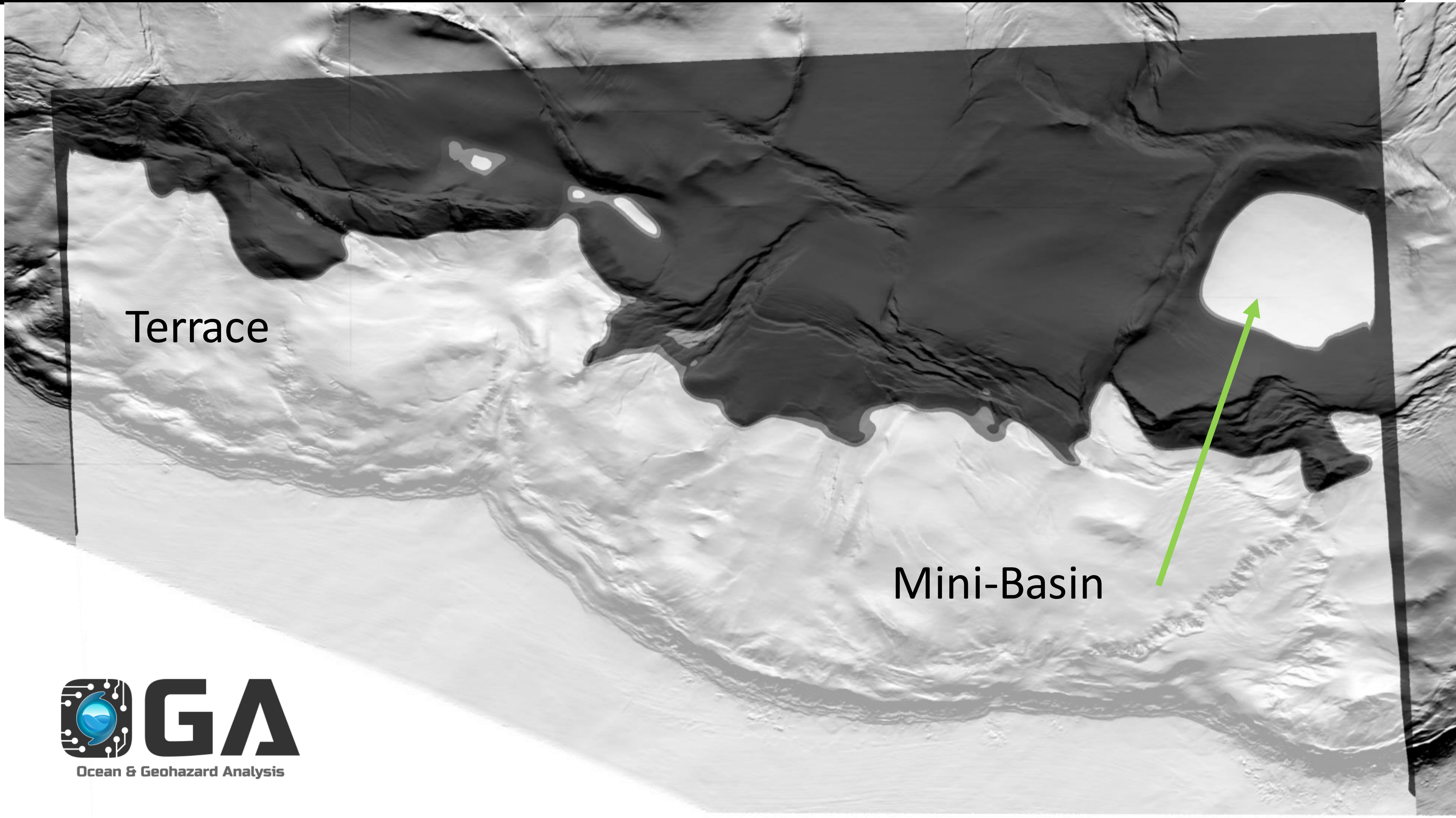
Training Image
*3 of 7 bands visualized



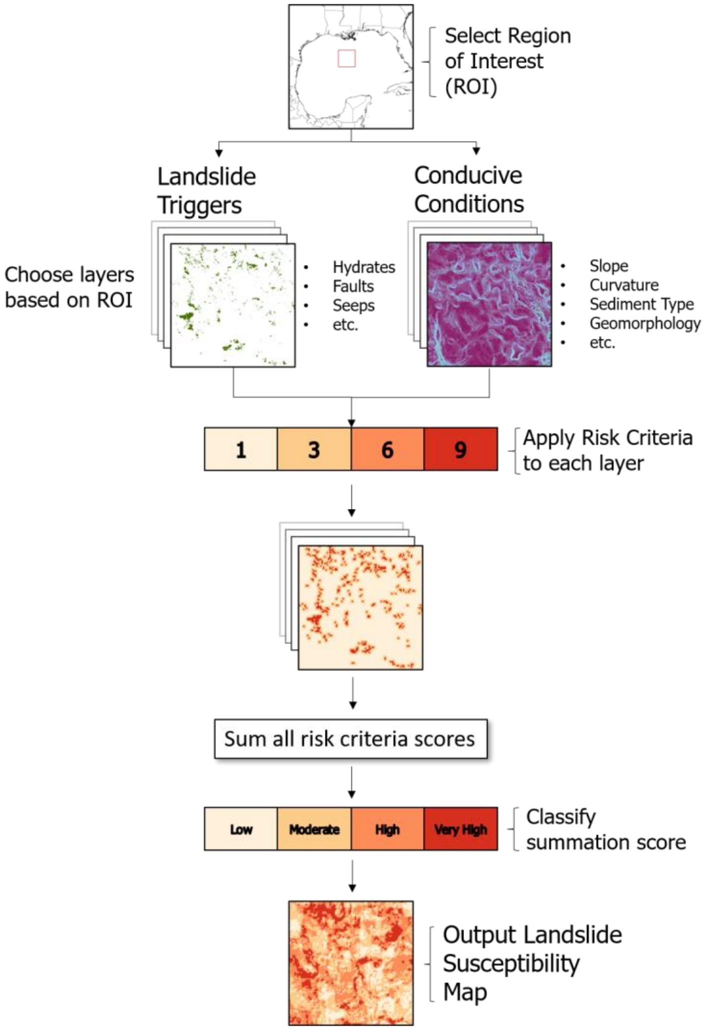
Training Mask

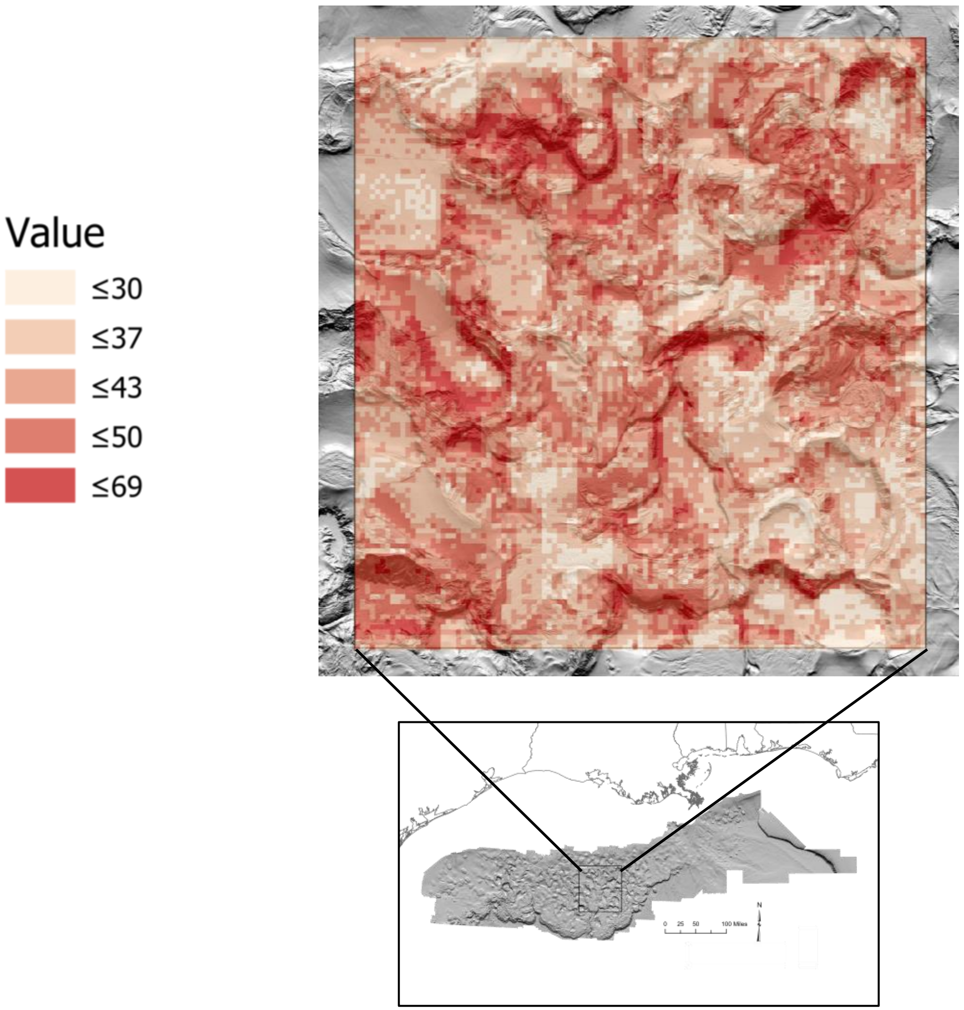
Landslide detection results

Current model output showing low likelihood of landslide (black) and high likelihood of landslide (white). Results show model identifying terraces and basins as high likelihood of landslide areas.



Landslide susceptibility assessment workflow



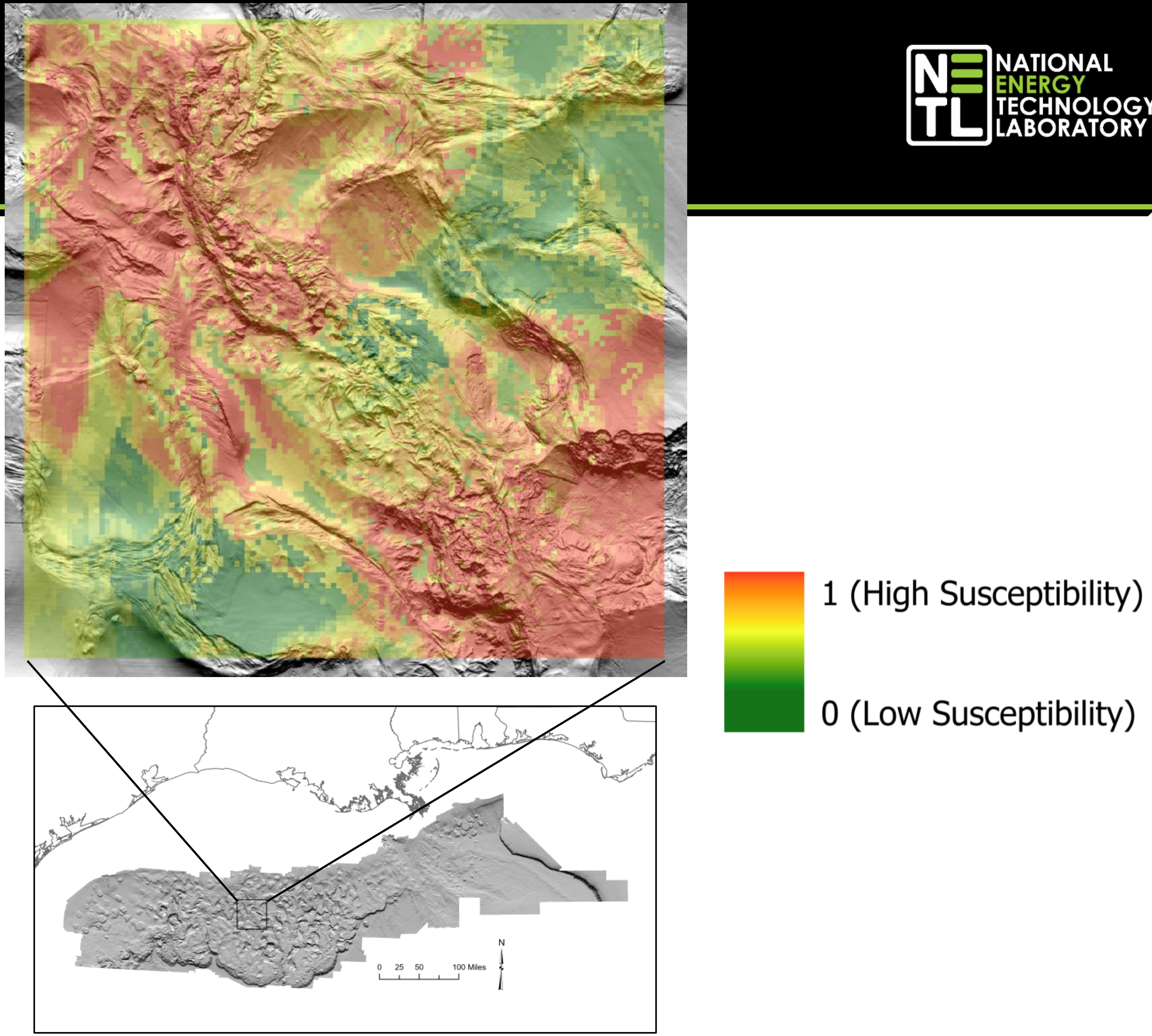


Landslide susceptibility
Machine Learning Approach

Utilizing the same input criteria along with common machine learning models to predict landslide susceptibility

- **Random Forests (at right)**
- **Gradient Boosting**
- **Decision Trees**

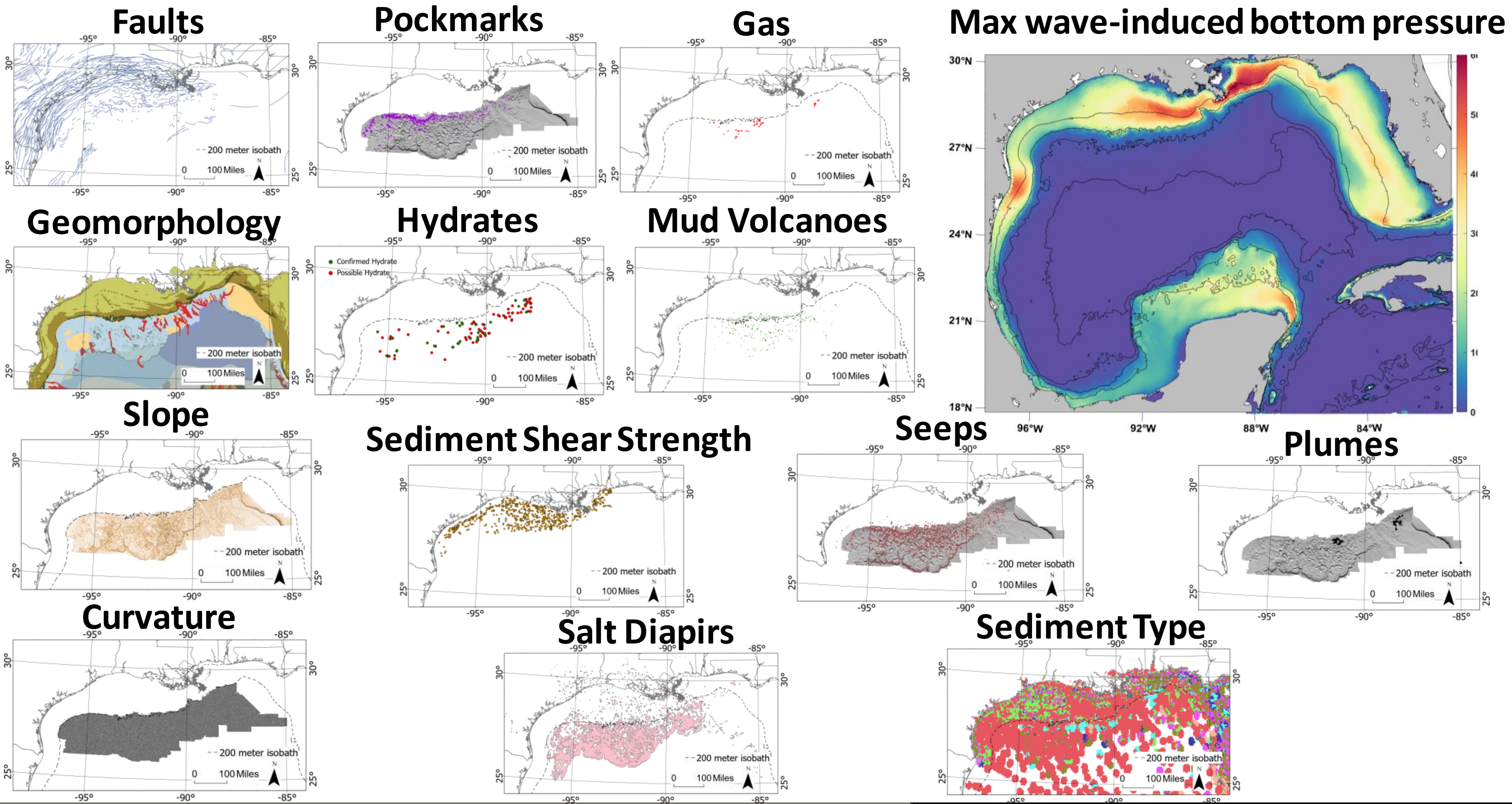
90% accuracy on test set



Landslide susceptibility
Diverse Approaches

Different approaches:

- GIS Layered Analysis
- Machine Learning Modeling
- Wave-induced bottom pressure vs sediment shear strength
- Erosion due to extreme bottom currents and waves



Advanced Probability and Statistics

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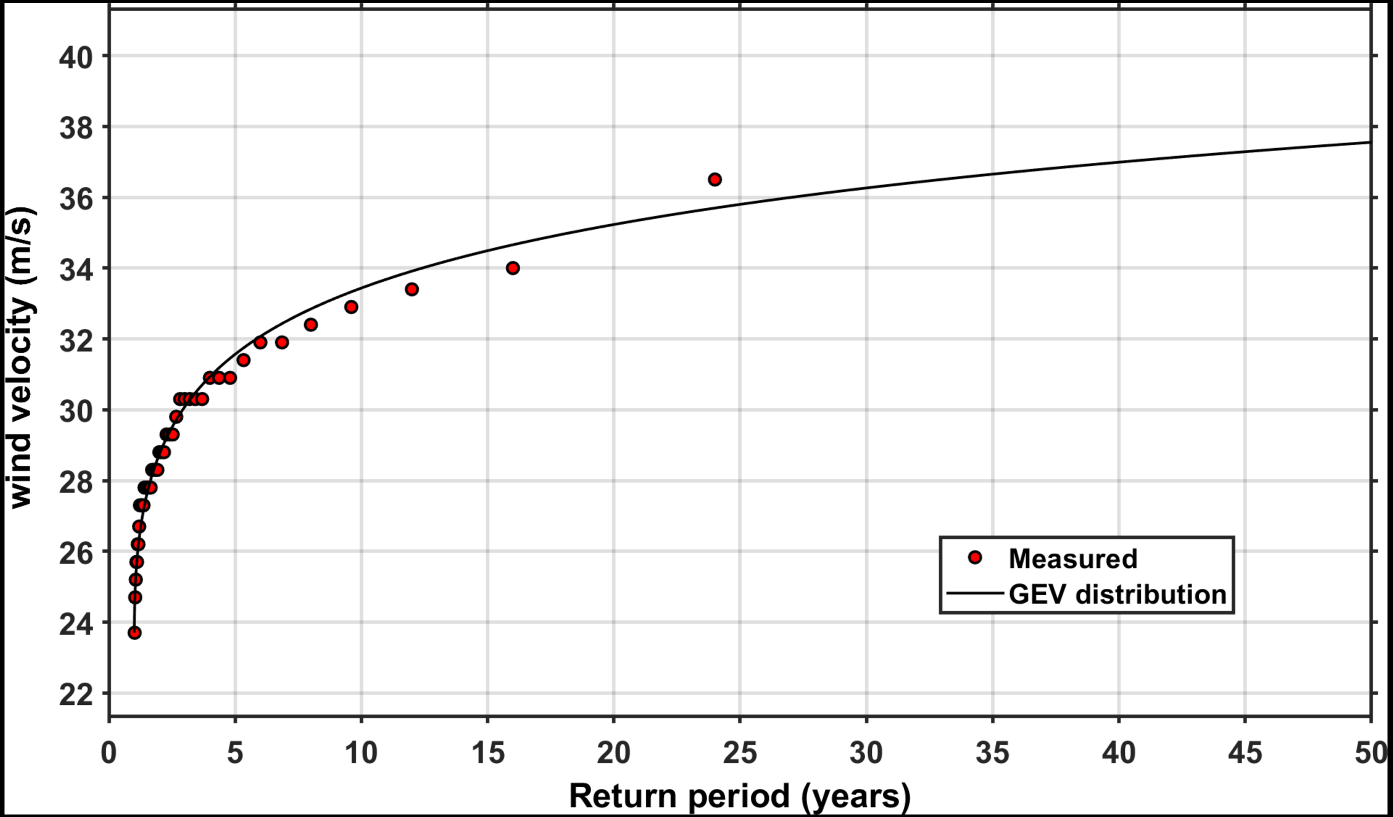
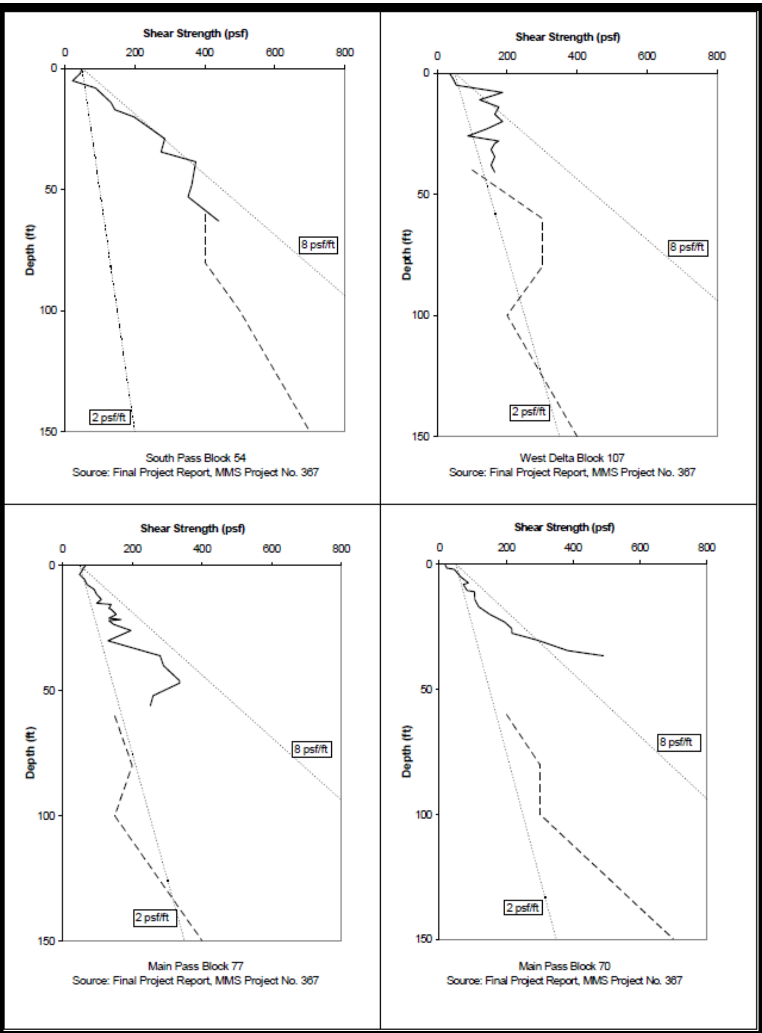
Generalized Extreme Value (GEV) distributions

$$G(z) = \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$



Prediction Intervals & Monte Carlo Simulations

$$\left[\underset{\sim}{x}_p,\ \ \widetilde{x}_p\right] = \left[\bar{x} + g'_{(\alpha/2;1-p,n)}s,\ \ \bar{x} + g'_{(1-\alpha/2;1-p,n)}s\right]$$

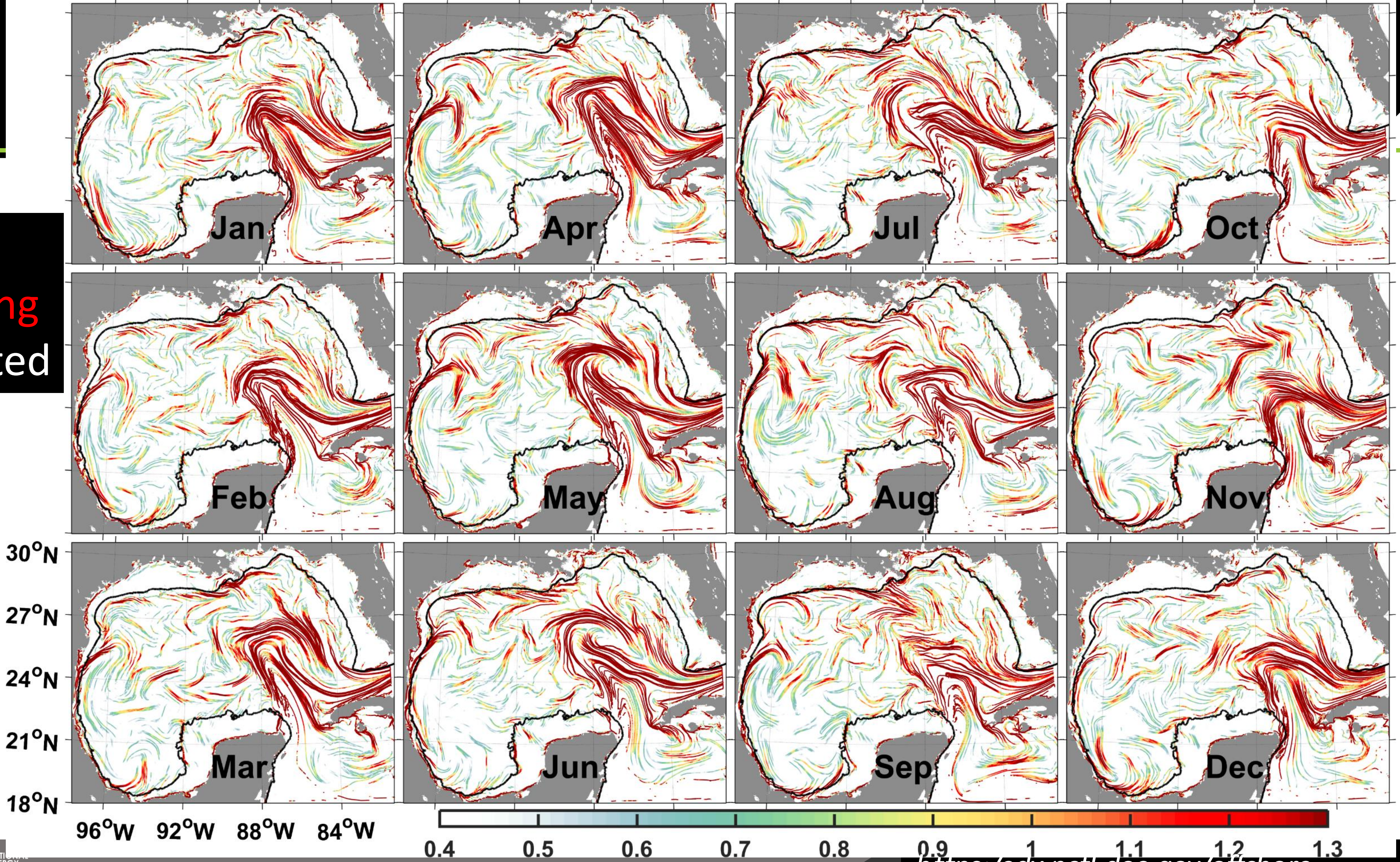


CIAM

Pathways:
Red=attracting
White=isolated

Large shelves are isolated:

- WFS
- LaTex
- Yucatan



NETL's Offshore Risk Modeling Metocean Simulation Tool, CIAM, Continues to Garner International Adoption/Use

Key Pubs:

- Duran, R.; Beron-Vera, F. J.; Olascoaga, M. J. Extracting quasi-Steady Lagrangian transport patterns from the ocean circulation: An application to the Gulf of Mexico *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 Persistent Lagrangian Transport Patterns in the Northwestern Gulf of Mexico *Physical Oceanography* **2019**, 49, 353–367.
- Duran, R., F. J. Beron-Vera and M. J. Olascoaga (2019).CIAM Climatological Isolation and Attraction Model–Climatological Lagrangian Coherent Structures DOI: 10.18141/1558781

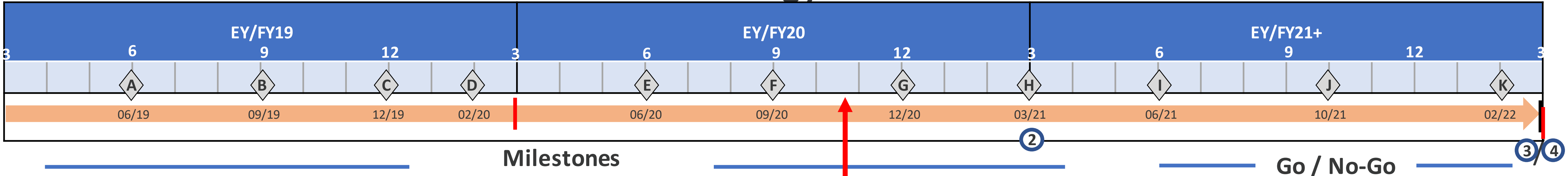
External CIAM Users

Country	Research Institute.	Study region	Status
Spain	ICM Marine Science Institute Spain.	Mediterranean	Work in progress
India	National Institute of Oceanography India	Gulf of Bengay surface	Preliminary results obtained
Mexico	Engineering & Coastal Processes UNAM Mexico	Tropical Atlantic surface	Preliminary results obtained
Brazil	National Institute for Space Research Brazil	Tropical Atlantic off Brazil coast surface	Peer-reviewed paper under review.
Mexico	CICESE Ensenada Center for Scientific Research and Higher Education, Mexico	Deep GoM	Maslo, A., et al. (2020). *Journal of Marine Systems*. https://doi.org/10.1016/j.jmarsys.2019.103267
Mexico	CICESE Ensenada Center for Scientific Research and Higher Education, Mexico	NW GoM Surface	Gough, M. K., et al . (2019). *Journal of Physical Oceanography* https://doi.org/10.1175/JPO-D-17-0207.1
Saudi Arabia	Red Sea Modeling and Prediction Group KAUST	Red Sea	Preliminary results obtained KAUST https://assimilation.kaust.edu.sa/Pages/Home.aspx
USA	UNC at Chapel Hill	Atlantic wind	Preliminary results obtained

Offshore Unconventional FWP

Key Team Members: PI – Jen Bauer, Kelly Rose - CO-PI – Makenzie Mark-Moser, Rodrigo Duran

Task 6 - Infrastructure and Metocean Technology



Number	Expected Completion Date	Description
EY19.6.A	06/19	Develop internal catalog documenting data resources collected.
EY19.6.B	09/19	Document libraries and software used to help collect, process, and label data.
EY19.6.C	12/19	Statistics summarizing metocean and bathymetric metadata.
EY19.6.D	02/20	Determine if sufficient data are available to support future work; if it is, plan to continue into EY/FY20.
EY20.6.E	06/20	Begin developing analytical framework plan for metocean and bathymetry data.
EY20.6.F	09/20	Outline analytical logic to support the development of a beta smart tool.
EY20.6.G	12/20	Draft presentation or report detailing current analytical framework.
EY20.6.H	03/21	Report current model evaluation offering details on model success.
EY21.6.I	06/21	List summarizing identified improvements and enhancements for analytical logic and smart tool.
EY21.6.J	10/21	Statistics demonstrating success of enhancements on key smart tool functions.
EY21.6.K	02/22	Evaluate TRL for smart tool and determine if additional development or enhancements are needed to obtain target TRL.
Additional milestones will be defined based off Go/No-Go decision.		

- End of EY/FY19: Ensure sufficient data are available to support future work; if it is, plan to continue into EY/FY20. Determined sufficient data are available to build robust ML/AI model (02/2020)
- End of EY/FY21: Evaluate TRL for smart tool and determine if additional development or enhancements are needed to obtain target TRL (4).

Chart Key

\# TRL Score | Go / No-Go Timeframe | Project Completion | Milestone

Ocean & Geohazard Analysis Smart Tool

Timeline (present to March 2021)

Upcoming Deliverables		
Date	Description	Status
03/21	Beta Smart Tool software version for internal release	On track

Upcoming Milestones		
Date	Description	Status
12/20	Draft presentation or report detailing current analytical framework	On track
03/21	Report current model evaluation offering details on model success	On track

Next steps

- Build out Smart Tool user interface
- Continue integrating datasets
- Train object detection algorithms
- Assess model accuracy and success

Publications & Presentations
Upcoming & Past

Publications

- Duran, R., T. Nordam, M. Serra and C. Barker (under review, 2020). Horizontal transport in oil-spill modeling. Book chapter in Marine Hydrocarbon Spill Assessments, Elsevier. https://arxiv.org/abs/2009.12954
- Nordam T., J. Skancke, R. Duran and C. Barker (under review, 2020). Vertical transport in oil spill modeling. Book chapter in Marine Hydrocarbon Spill Assessments, Elsevier. https://arxiv.org/abs/2010.11890
- Nordam, T. & R. Duran (in press, 2020). Numerical integrators for Lagrangian oceanography. Geoscientific Model Development. https://gmd.copernicus.org/preprints/gmd-2020-154/.
- Gouveia, M. B., R. Duran, J. A. Lorenzzetti, A. T. Assireu, R. Toste, L. P. de F. Assad and D. F. M. Gherardi (submitted, revision in progress, 2020). Persistent meanders and eddies lead to quasi-steady Lagrangian transport patterns in a weak western boundary current. https://arxiv.org/abs/2008.07620
- Zhang, R., P. Wingo, R. Duran, K. Rose, J. Bauer, R. Ghanem (2020). Environmental Economics and Uncertainty: Review and a Machine Learning Outlook. Oxford Encyclopedia of Environmental Economics. https://doi.org/10.1093/acrefore/9780199389414.013.572.
- Gough M. K., F. J. Beron-Vera, M. J. Olascoaga, J. Sheinbaum, J. Jouenno, R. Duran (2019). Persistent Lagrangian transport patterns in the northwestern Gulf of Mexico. J. Phys. Oceanogr., 49, 353–367, https://doi.org/10.1175/JPO-D-17-0207.1
- Duran, R., F. J. Beron-Vera, M. J. Olascoaga (2018). Extracting quasi-steady Lagrangian transport patterns from the ocean circulation: An application to the Gulf of Mexico. Scientific Reports, 8(1), 5218. https://www.nature.com/articles/s41598-018-23121-y

Upcoming Presentations

Duran, R., Dyer, A., Mark-Moser, M., Bauer, J., Rose, K., Zaengle. D., Wingo, P. A Geospatial Analytical Framework to Identify Seafloor Geohazards in the Northern Gulf of Mexico. AGU Annual Meeting 2020, Session: NH010 - Geohazards in Marine and Lacustrine Environments

Dyer, A., Zaengle, D., Mark-Moser, M., Duran, R., Bauer, J., Rose, K. accepted. Deep Learning to Locate Seafloor Landslides in High Resolution Bathymetry. AGU Annual Fall Meeting (Virtual), 2020. Session: NH007 - Data Science and Machine Learning for Natural Hazard Sciences II Posters.

Mark-Moser, M., Romeo, L., Rose, K., Wingo, P., Duran, R. submitted. Assessment of natural and engineered systems data using machine learning to reduce offshore operational risks. Offshore Technology Conference, 2021. Houston, TX.

Products available at https://edx.netl.doe.gov/offshore/

Key Takeaways

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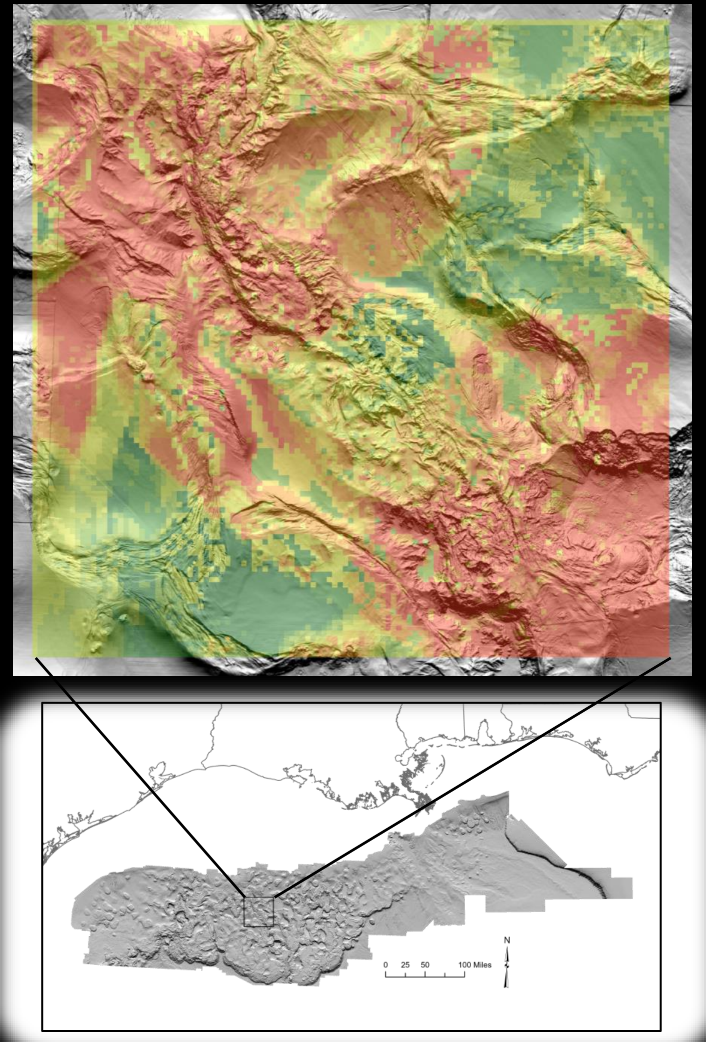
- **Technology that integrates big data and science-based analytics for offshore hazards does not exist**
- **Advanced analytics can offer near-real time assessment of risks but also forecast vulnerabilities**
- **Smart Tool:**
  - **adapts to data availability/quality**
  - **adapts to different regions**
  - **incorporates new analytics and datasets**

OGA
Ocean & Geohazard Analysis



Values Delivered

Advancing the current state of knowledge, improving infrastructure longevity, supporting offshore activities.

Improved characterization of seabed related hazards in the offshore environment will help to manage and minimize costs and risks during drilling and production operations, and help prevent catastrophic incidents.

Products available at https://edx.netl.doe.gov/offshore/

Disclaimer & Acknowledgement

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