Electric Power Infrastructure and Collaborative R&D on Desktop Wetland Identification

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ASWM Webinar: Investing in Resiliency: Intersectional Perspectives of Wetlands, Infrastructure, and Healthy Communities
May 18, 2021

Infrastructure – from Micro to Macro Scale

- Renewables on the landscape

Solar Plant in Southern Florida

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Solar Plant – Zooming Out

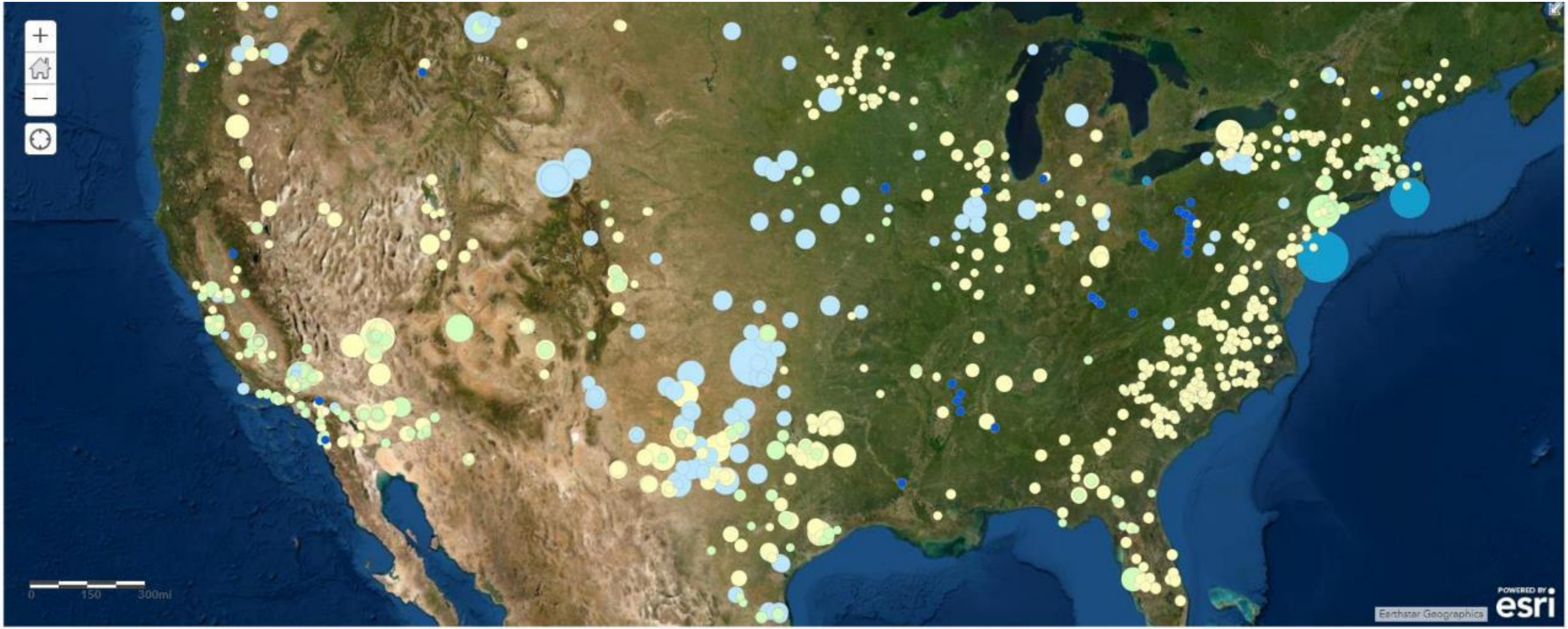
Solar Plant – Zooming Out

Wind in Southeast Texas

Wind – Zooming Out

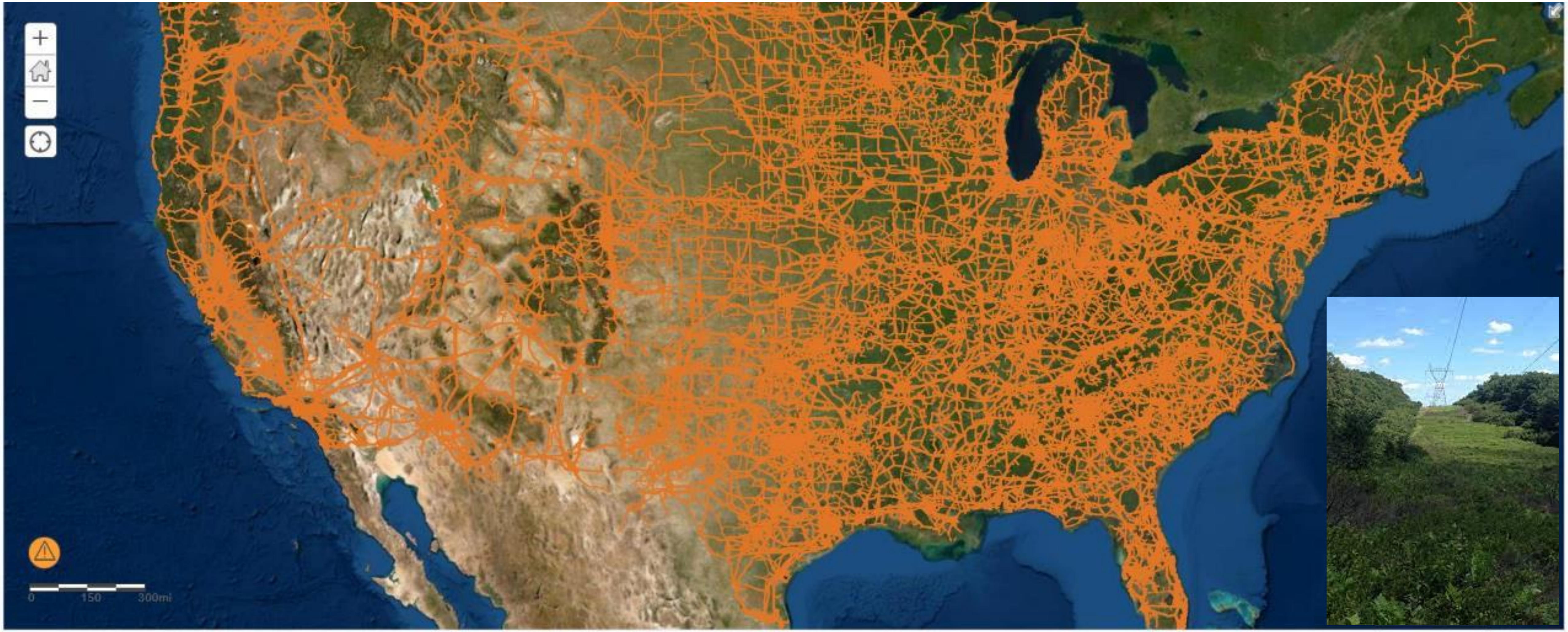
Planned Renewables

- Feb 2021 Energy Information Administration data (link)



Existing Electric Transmission Lines

- Homeland Infrastructure Foundation Level Database (link)



EPRI's Mission

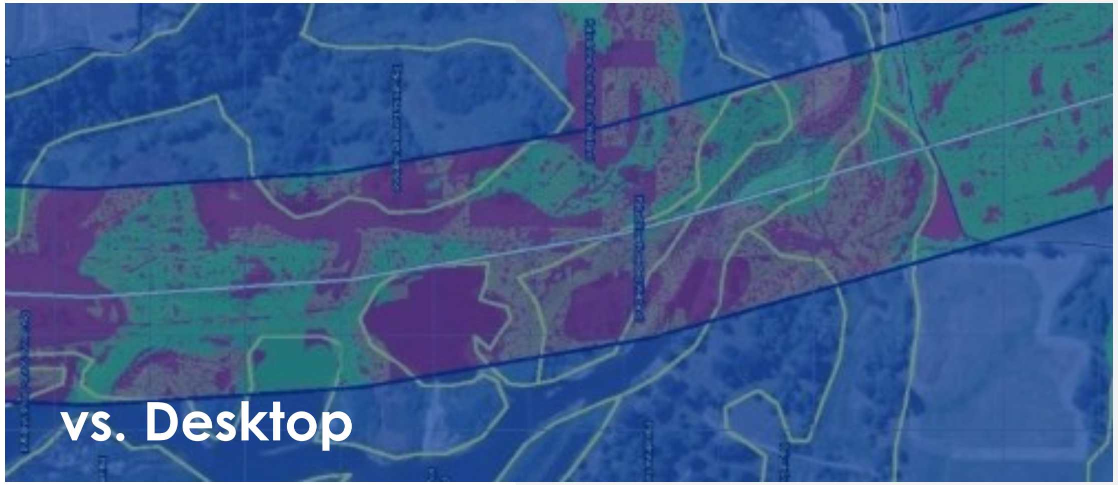
Advancing ***safe***, ***reliable***, ***affordable*** and ***environmentally responsible*** electricity for society through global collaboration, thought leadership and science & technology innovation

Independent, non-profit research organization

Desktop GIS Wetland Identification

Previous Research

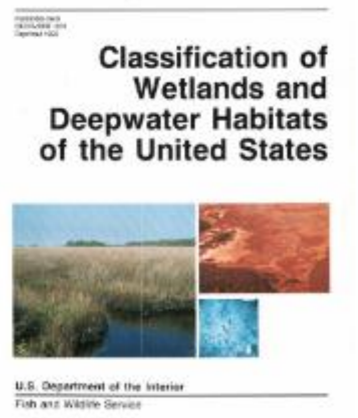
- **101-level:** brief of generally accepted methods
- **Peer review** of power company method
- **Literature review/discussion:** could a tool get you to 90% certainty?
- **Conceptual design** of tool
- **Value:** cost and time savings



“Additionality” and Automation over Standard Desktop ID

Must have	Like to have	Lower priority
Added accuracy over standard desktop identification of wetlands.	≥90% accuracy in identifying a wetland	
Automated component to desktop wetland identification (with consideration of wetland hydrology and hydric soils)	An indication of minimum-maximum extent or a “confidence interval” of parts of the wetland Application of machine learning (e.g., object-based image analysis) to automate identification	Understanding seasonal changes in wetlands, alerts / automation of wetland change detection
Classification of wetland type at a high level (e.g., marine, estuarine, riverine, lacustrine, palustrine)	Classification of wetland type to subsystem level	

- A note on identification, delineation, classification



What we heard: functionality companies would like to have in a tool

Data and Resolution

Must have	Like to have	Lower priority
At the minimum, bringing **up-to-date data into one place**; with timestamp and reference of data used	Automated updates of data on a regular basis	
Minimum of coarse support for early planning and siting (**resolution** of 10m may be acceptable for large scale right of way siting)	More accurate support for early planning and siting (≤10m preferred).	Ability to identify a <0.5 acre wetland
	Ability to **bring in shapefiles** of areas of interest, and to download data results from area of interest *(a "must have" for potential future expansion, but a "like to have" for prototype phase)*	

Must have	Like to have	Lower priority
User level of expertise: knowledgeable of GIS		User level of expertise: not knowledgeable of GIS
Watershed or county-level proof of concept/prototype	Regional proof of concept/prototype	National proof of concept/prototype

NASA Landsat (30m), weekly Truecolor May 10, 2019

Sentinel 2 (10m), weekly Truecolor May 23, 2017

Airbus Pléiades (0.5m), on demand Truecolor May 30, 2019

Collaborative Tool Development

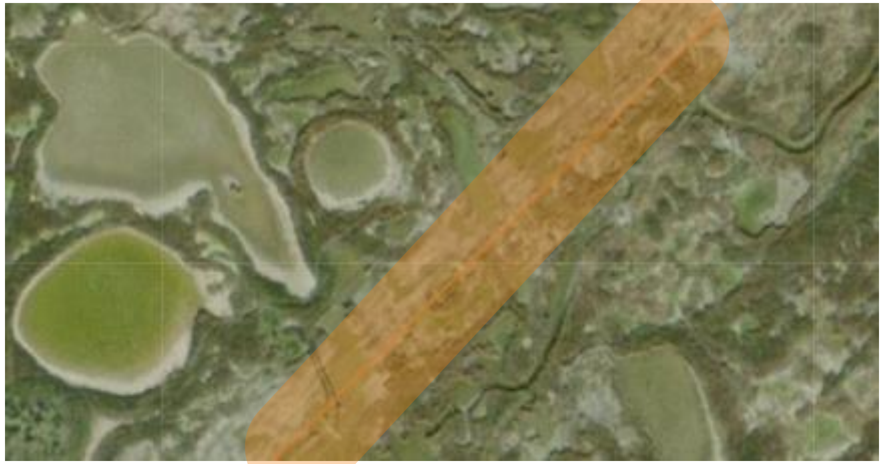
- RFP process
  - Shout out to applicants from St. Mary's University*, State University of New York*, Ducks Unlimited*, ICF, Chesapeake Conservancy
    (* = presented on ASWM webcasts)

- Chesapeake Conservancy's approach
  - Prototype web tool + method development
  - Artificial Intelligence (AI) based predictions
  - Goal:
    - Find a model with useful features that are widely available
    - Make it available for prediction in other areas

Method, Training Data, Geographic Areas

- UNet, a form of deep learning
  - Object based image analysis
  - Achieves 18% accuracy improvement over fully convolutional networks

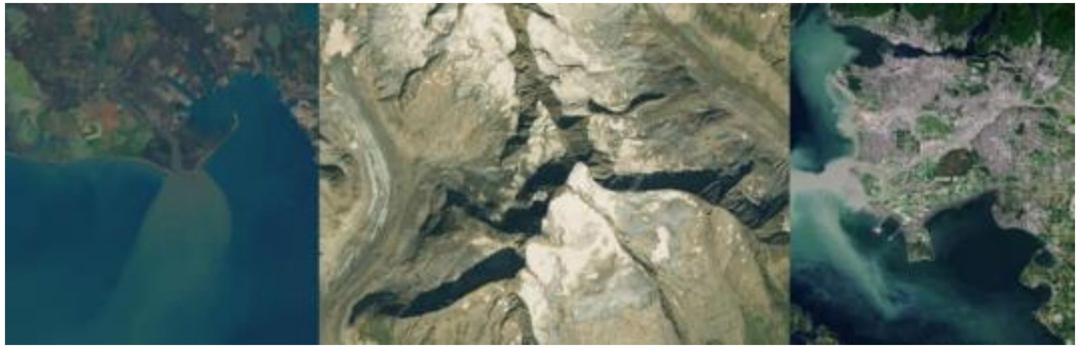
- Training data from areas of interest



Lesson learned: companies may have delineated wetland data, but may be unsuitable for training

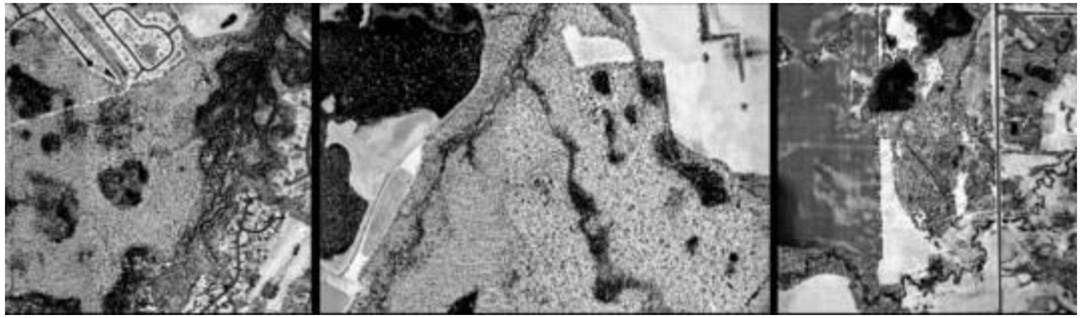
Data Inputs

- SENTINEL-2

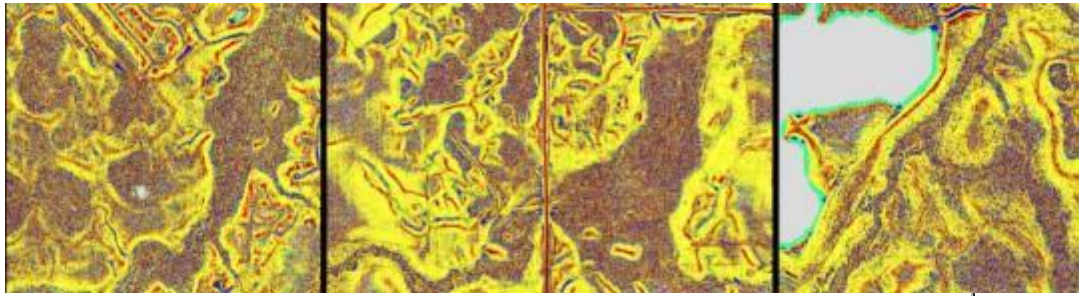


- NAIP

- LiDAR intensity

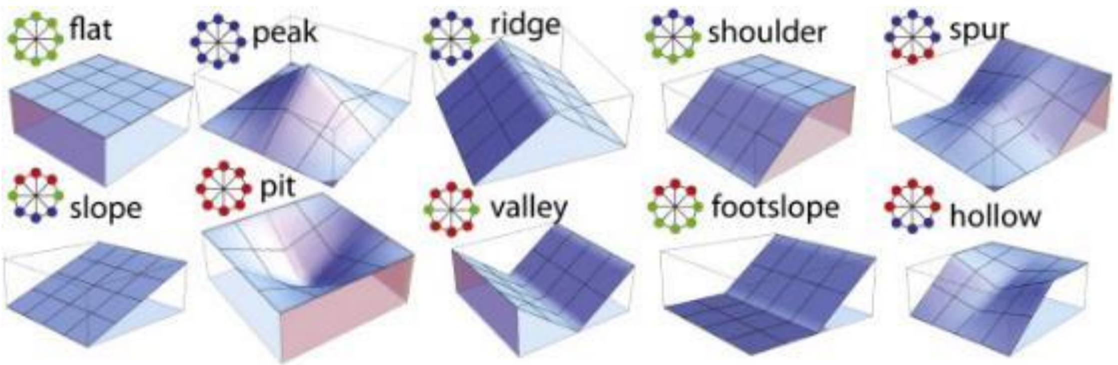


- Geomorphons

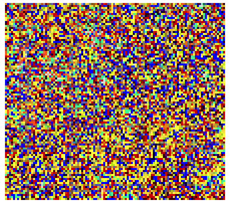


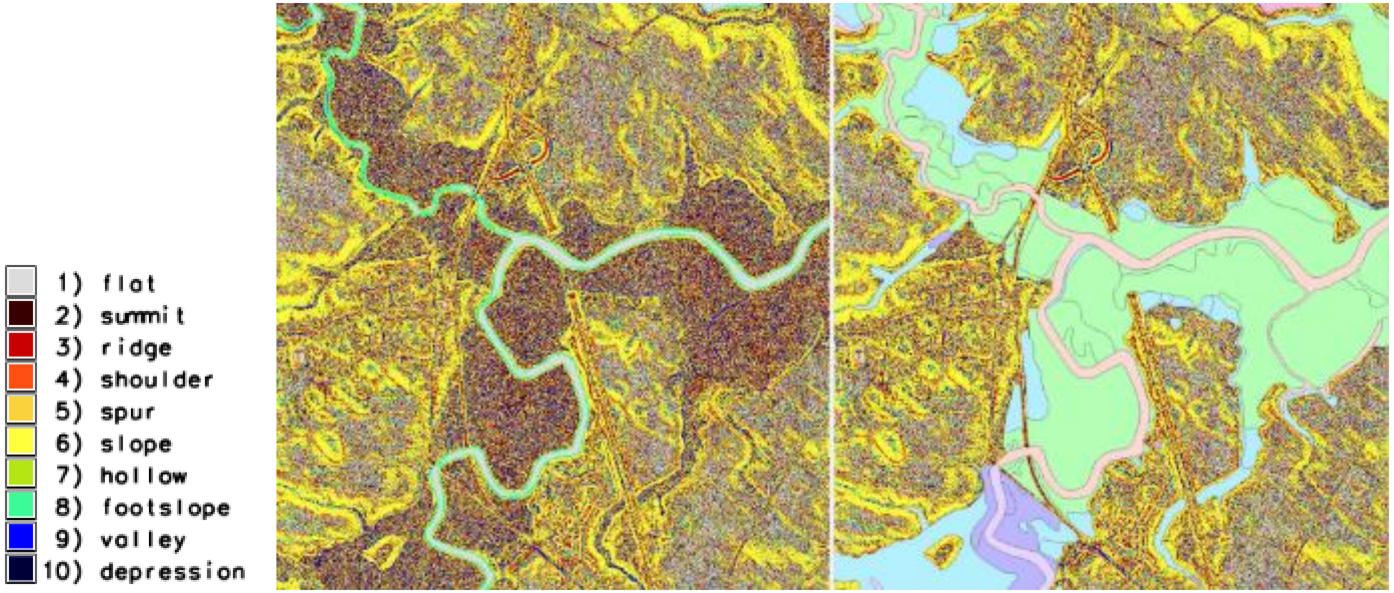
Geomorphons

- Landform classification approach derived from Lidar digital elevation models (DEMs)
- [Jasiewicz and Stepinski 2013]



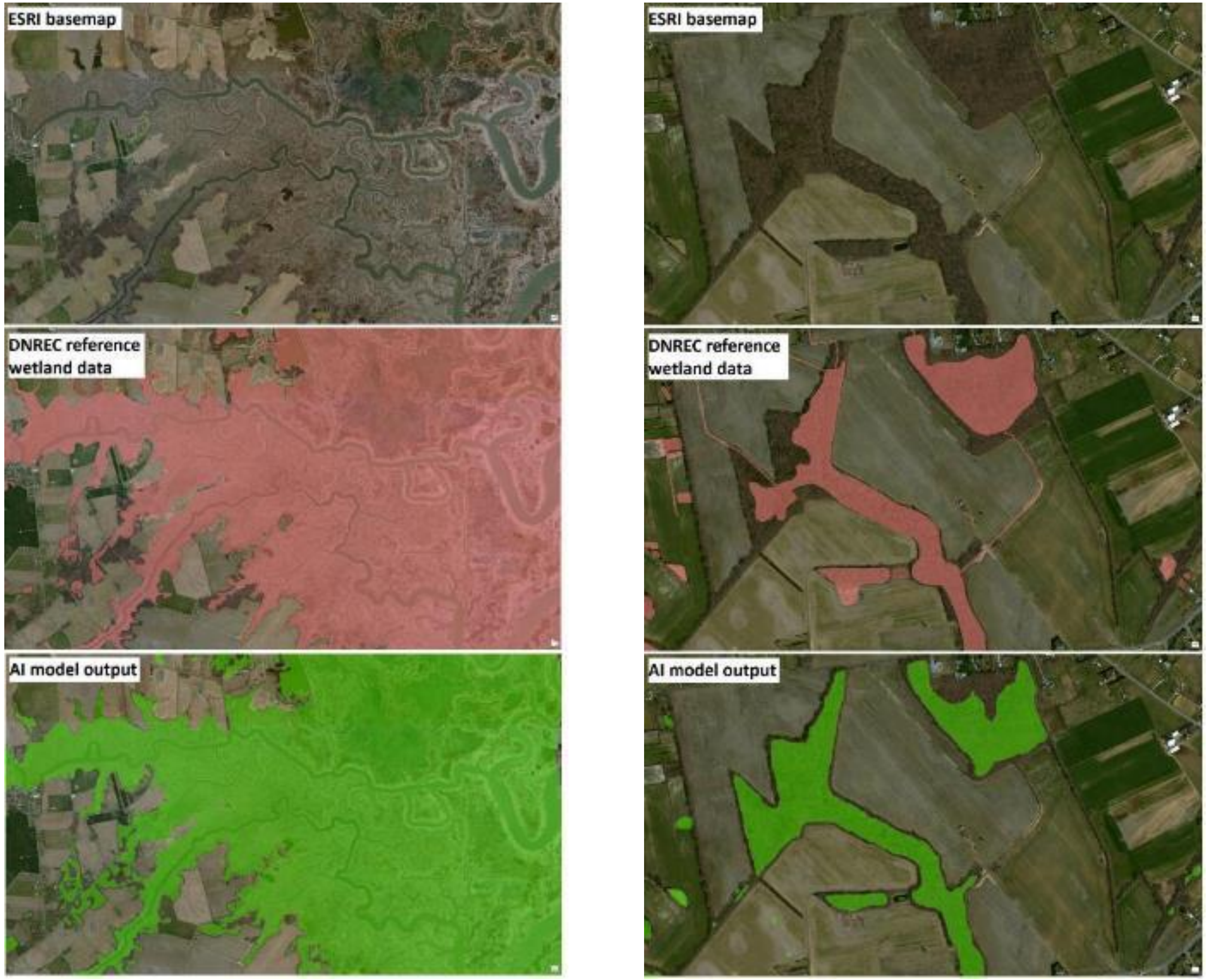
- Pattern in the noise





Results – DE Only

- Visual



Lesson learned: we 'broke Google' … there can be challenges with cloud based computing/storage/analytics platforms

Results – DE Only

- Performance stats
- Intersection over union
  - Relationship of probability of detection (recall) & precision of detection
  - IOU of >= 0.95 considered the best practices for industry standards
  - Routinely see state of the art detectors < 0.95 IOU
- Why a lower score is anticipated

Trained 4 models

Data Inputs of Model	IOU Score
Sentinel-2 & NAIP	81.4%
Sentinel-2 & NAIP +LiDAR	83.5%
Sentinel-2 & NAIP +Geomorphons	85.7%
Sentinel-2 & NAIP +Geomorphons +LiDAR	85.6%

TOOL DEMO

Next Steps

- Model refinement
  - Adding training data from NY, MN areas (July 2021)
- Publicize results
  - ArcGIS StoryMap
  - Demo video
  - Peer review article

StoryMap sneak peek

Next Steps

- Seek additional funding – *Your ideas appreciated!*
  - Support open source results
  - Support online tool access
  - Expand geographic area of model application
  - Incorporate additional training data?

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- EPRI member testing for potential tailoring (linear infrastructure)
  - *Other interest from organizations tackling linear infrastructure environmental issues?*

Green Infrastructure: ROI, Stacking, and Ecological Assets

Thank You!

Together...Shaping the Future of Electricity

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REFERENCE SLIDES

More about UNet

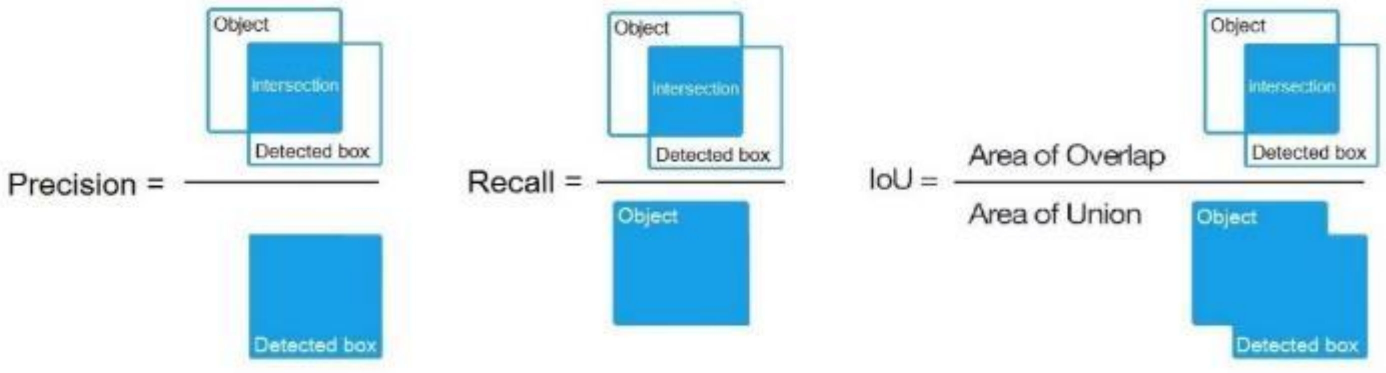
- Deep learning and Convolutional Neural Networks
- UNet
  - Segmentation – object detection with localization
  - Symmetric convolution and deconvolution pipeline
  - Deconvolution with up-sampling
- Wetland prediction by traditional machine learning
  - Very high accuracy with Lidar
  - Catch: high quality, controlled data, small area, a lot of manual/algebraic operation during data preprocessing
  - Very difficult and costly to scale up
- AI
  - feature extraction an autonomous process of the algorithm
  - less quality and less controlled data – okay to extract the dominant pattern
  - easy to scale up and high transferability across space and time

"U-Net takes advantage of the power of deep learning, but also considers contextual information and is able to perform image segmentation into classification categories (Ronneberger et al. 2015). U-Net is a major addition to the analytics of segmentation problems since the discovery of FCN [fully convolutional networks] by Long et al. (2015). Given the ~18% accuracy improvement with FCN in land cover classification compared to traditional machine learning with OBIA [object-based image analysis] (Liu et al. 2018), it is reasonable to expect even higher accuracy and better segmentation with our proposed U-Net model. U-Net is a sophisticated architecture for achieving semantic segmentation with computer vision. Segmentation works by identifying the edges pixel groups and labelling each pixel with a class. This is achieved by a series of algorithms: convolution, max pooling, up sampling, and final convolution (Ronneberger et al. 2015). Convolution and max pooling convert a high-resolution image to low resolution one, ensuring the detection of an object by observing surrounding pixels. Once an object is identified in a down sampled image, delineating the object in the original high-resolution image is achieved with up sampling."

- Chesapeake Conservancy

More about Model Evaluation / IOU

- Recall or Sensitivity
  - probability of detection
  - what fraction of data is recovered in the model prediction
- Precision
  - what fraction of predicted wetland is wetland in the data
- IOU < recall or precision
- IOU of >= 0.95 considered the best practices for industry standards
- State of the art detectors < 0.95 IOU



https://i.stack.imgur.com/JlHnn.jpg