Leveraging deep learning and data science for the conservation and restoration movement

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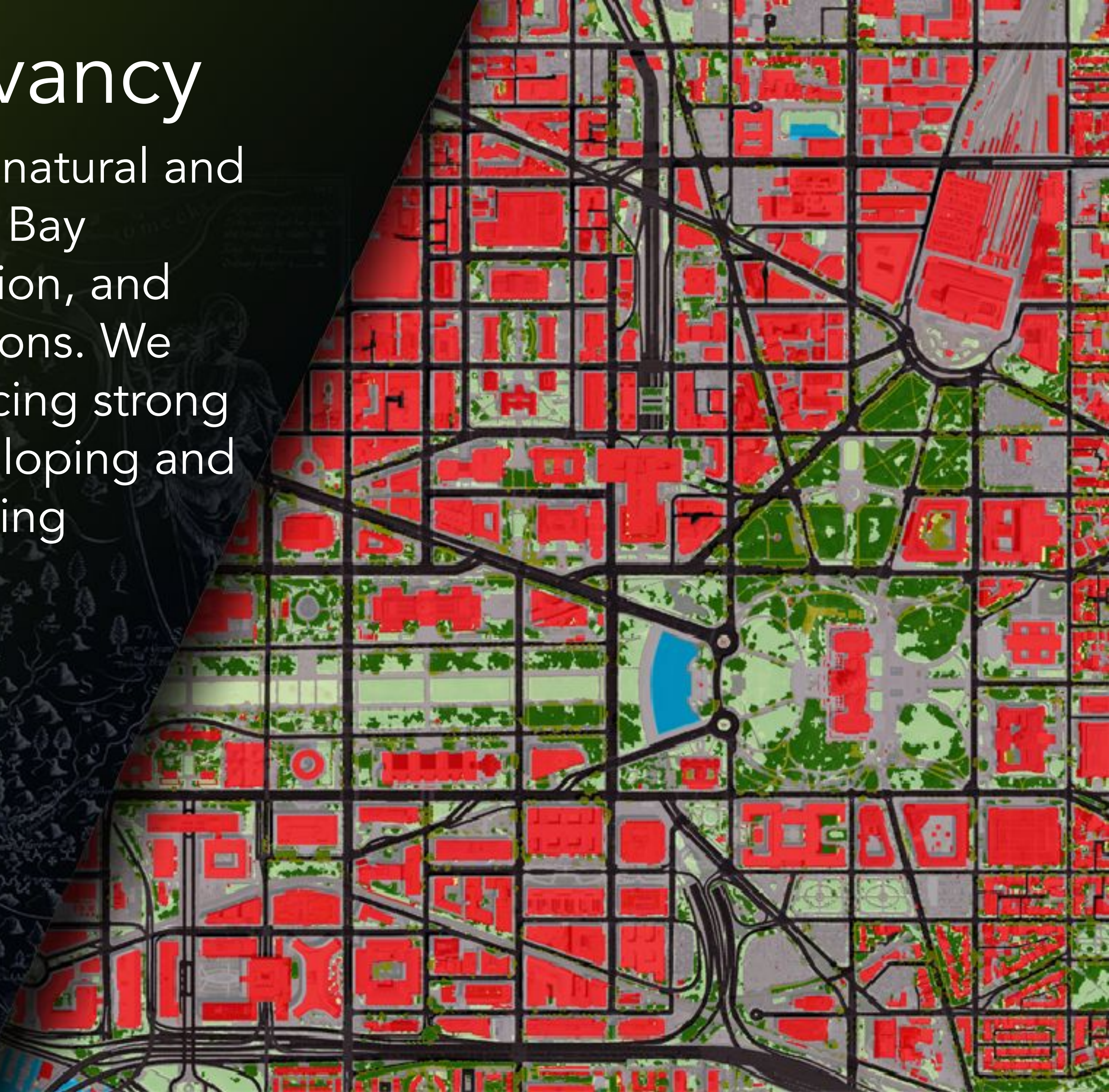
Chesapeake Conservancy

Mission: To conserve and restore the natural and cultural resources of the Chesapeake Bay watershed for the enjoyment, education, and inspiration of this and future generations. We serve as a catalyst for change, advancing strong public and private partnerships, developing and using new technology, and empowering environmental stewardship.

2023-2030 Goal:
To conserve and restore 30% of the Chesapeake Watershed by 2030 with emphasis on landscapes of significant ecological and cultural value, to engage and empower diverse conservation leaders, and build the foundation of an enduring institution.



High-resolution Data
Planning at the Parcel Scale

Land Use Conversion

2013 NAIP

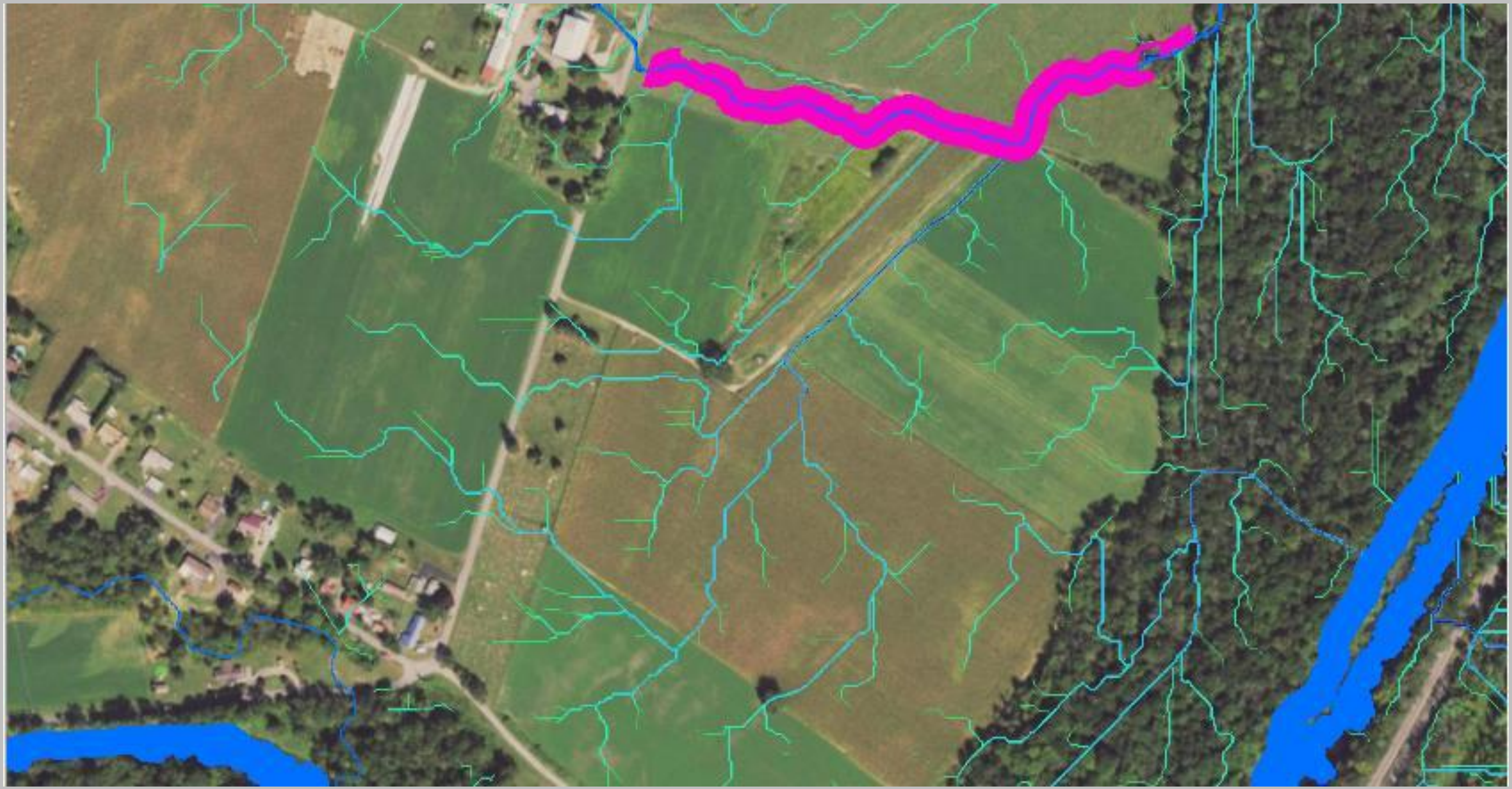
2013 Land Cover

- Water
- Wetlands
- Forest
- Shrubland
- Herbaceous Vegetation
- Barren
- Structures
- Impervious
- Roads
- Tree Canopy over Structures
- Tree Canopy over Impervious Surfaces
- Tree Canopy over Impervious Roads

2013 Land Use

- Impervious, Road
- Impervious, Non-Road
- Tree Canopy over Impervious
- Water
- Tidal Wetlands
- Floodplain Wetlands
- Other Wetlands
- Forest
- Tree Canopy over Turf
- Mixed Open
- Fractional Turf (small)
- Fractional Turf (med)
- Fractional Turf (large)
- Fractional Impervious
- Turf Grass
- Agriculture

Restoration



Deep Learning and Data Science for Conservation and Restoration

Chesapeake Conservancy

Microsoft Game Day ad

Deep Learning (AI) and Data Science in Conservation

What is AI?

Why use AI?

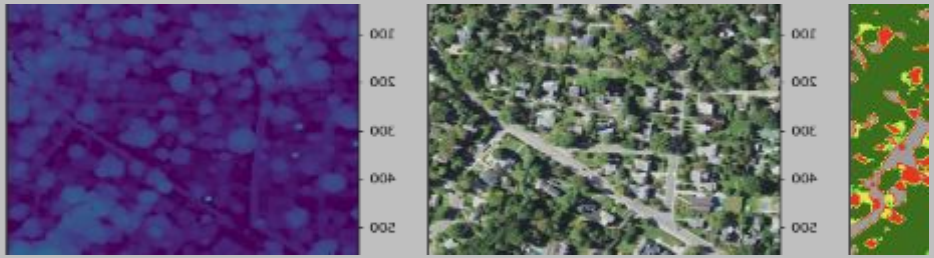
When to use AI?

When NOT to use AI?

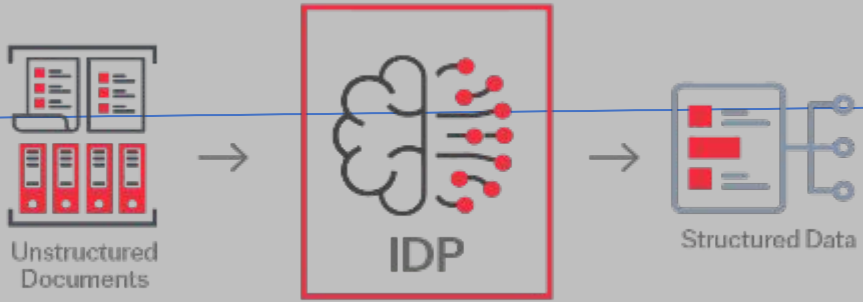
How can AI help?

What is AI? Types of AI

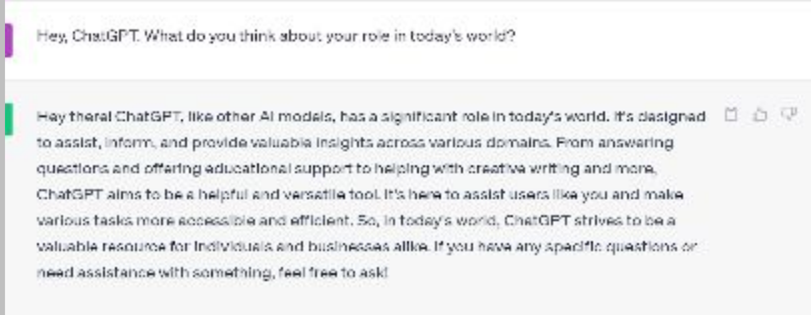
Traditional



Out of the Box

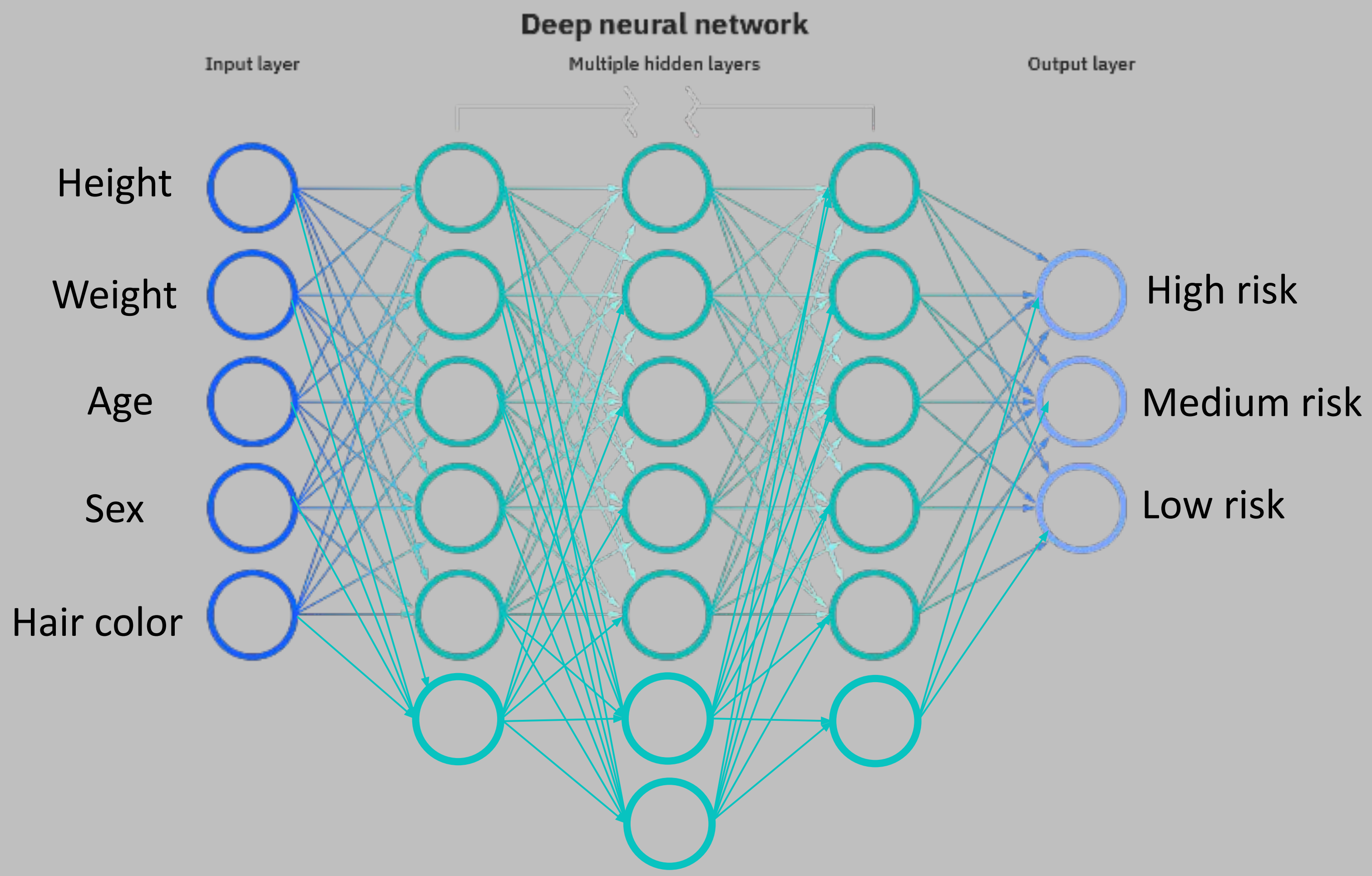


Custom



Generative

Deep Learning (AI)

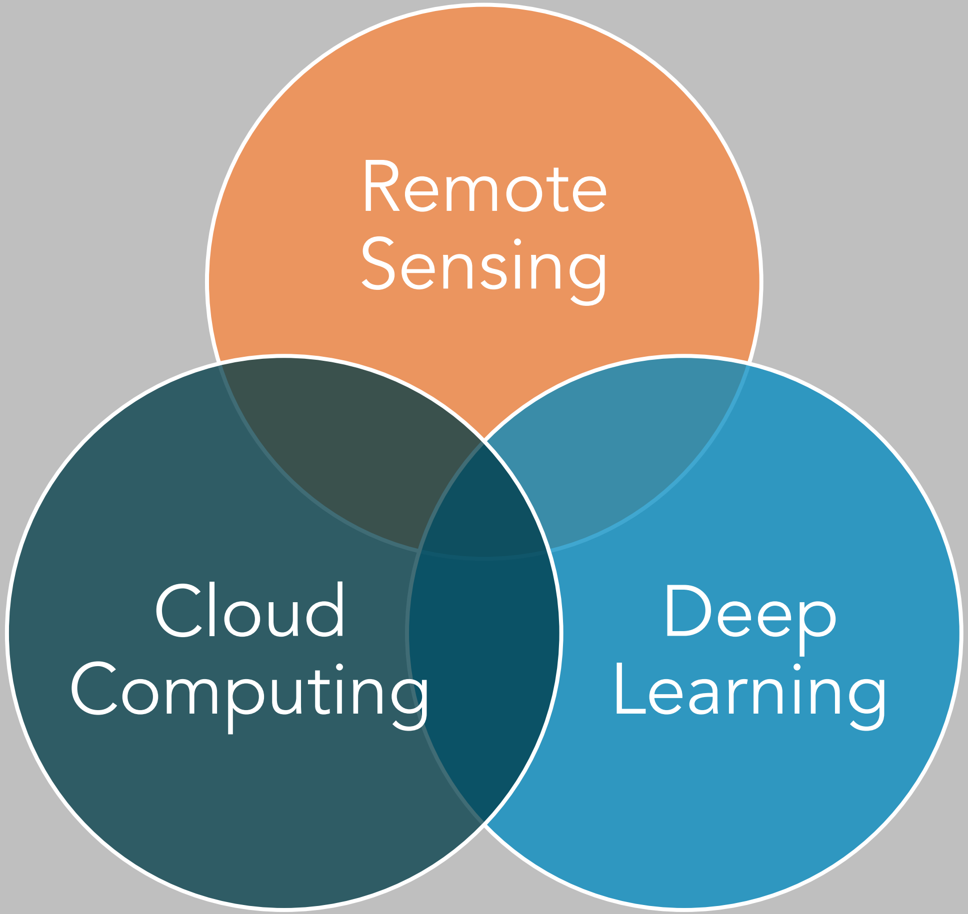


Good at learning non-linearities, conditionality, complex interactions

Why Use AI?

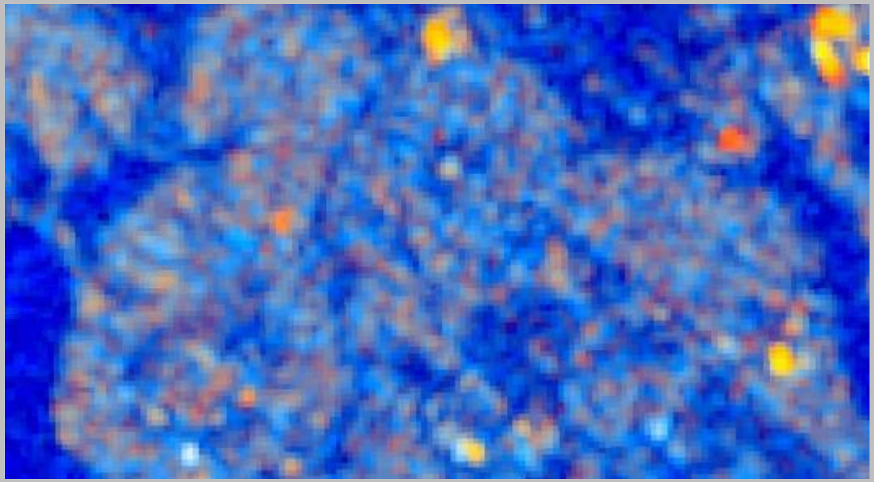
1. Effectively leverage big data
2. Improve accuracy
3. Solve old problems
4. Answer new questions

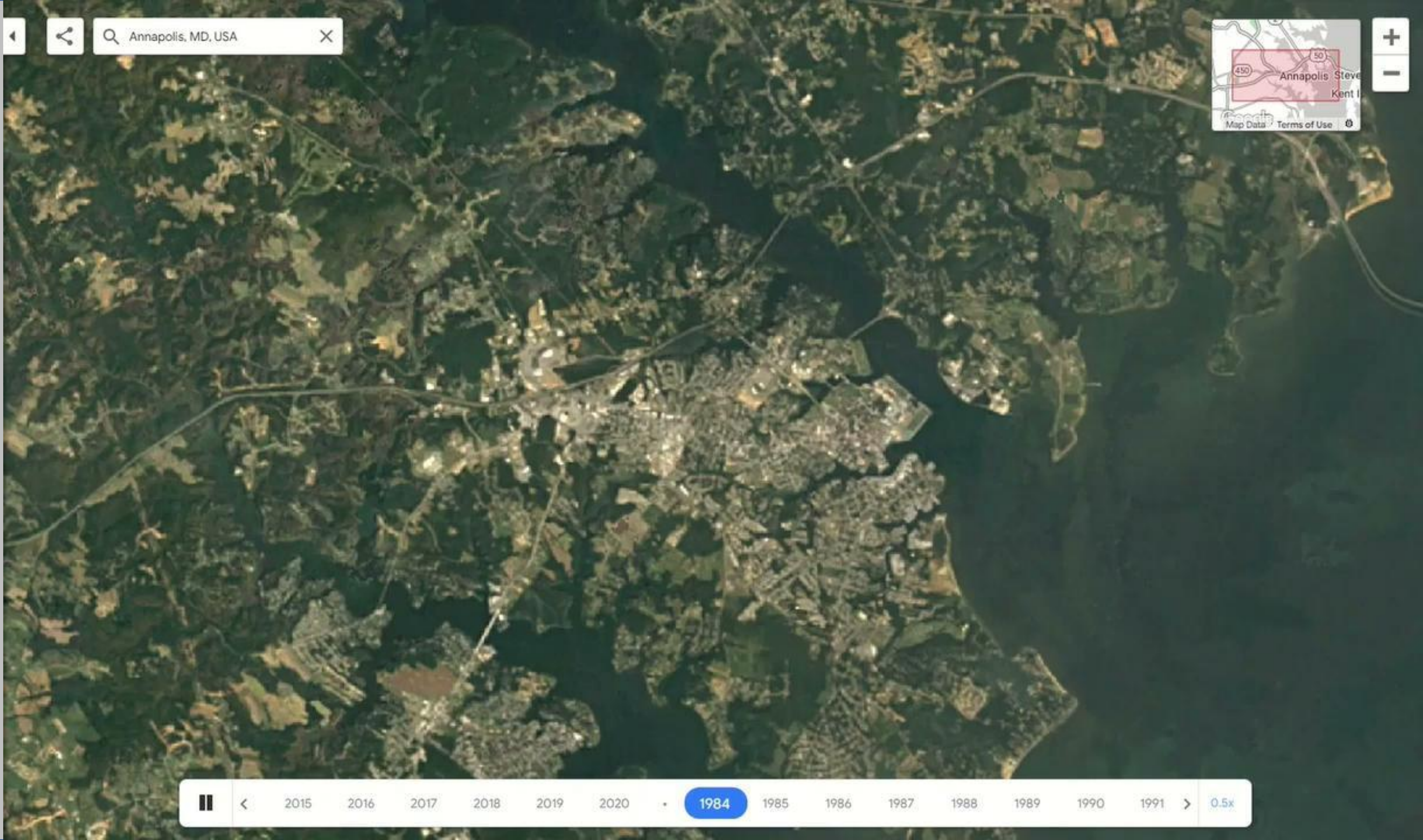
How to utilize deep learning



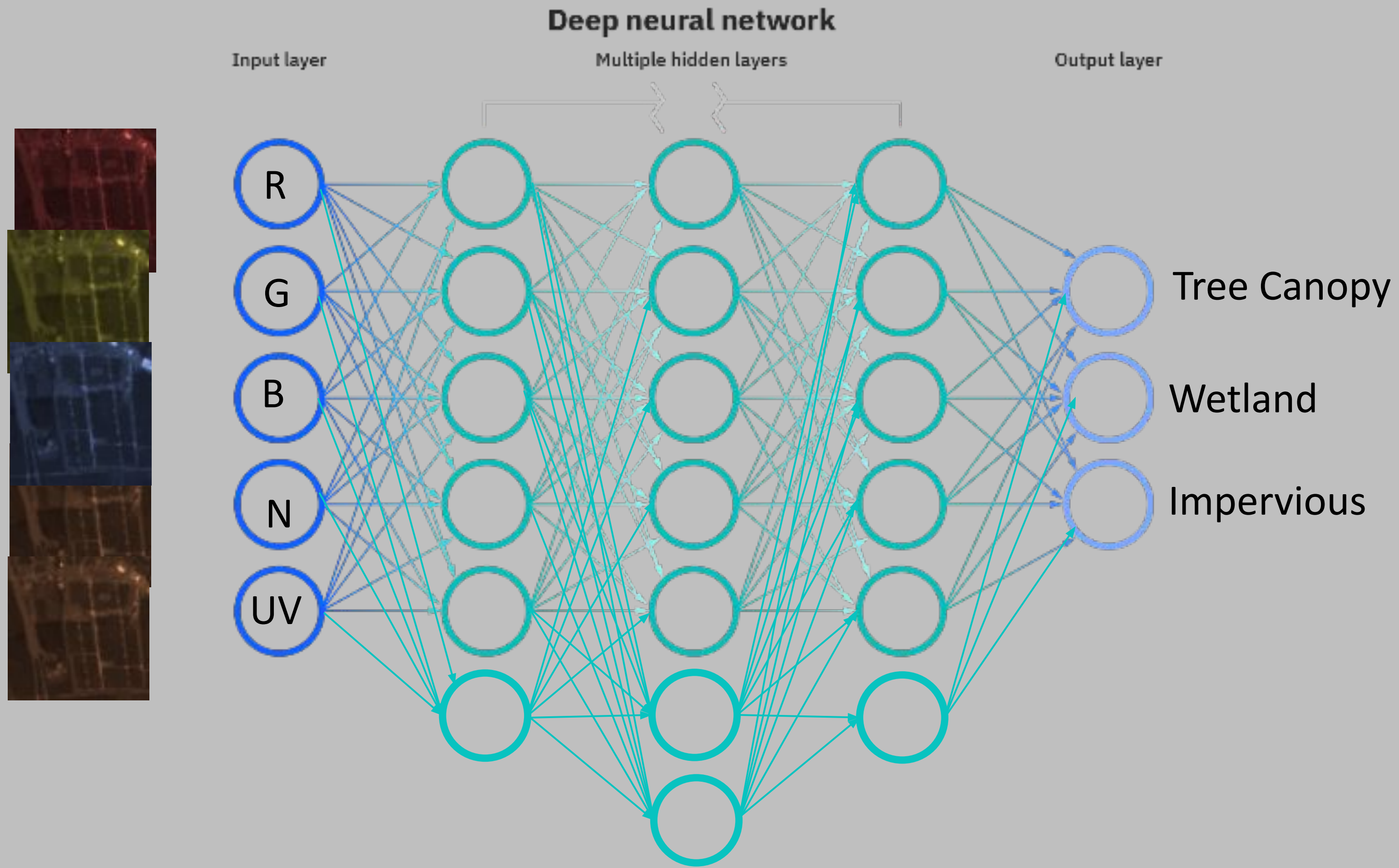
Big Data - remote sensing

1. Data about Earth's surface
2. Collected by satellite or plane
3. Can have multiple 'bands'
4. Many types of data (radar, lidar, etc.)



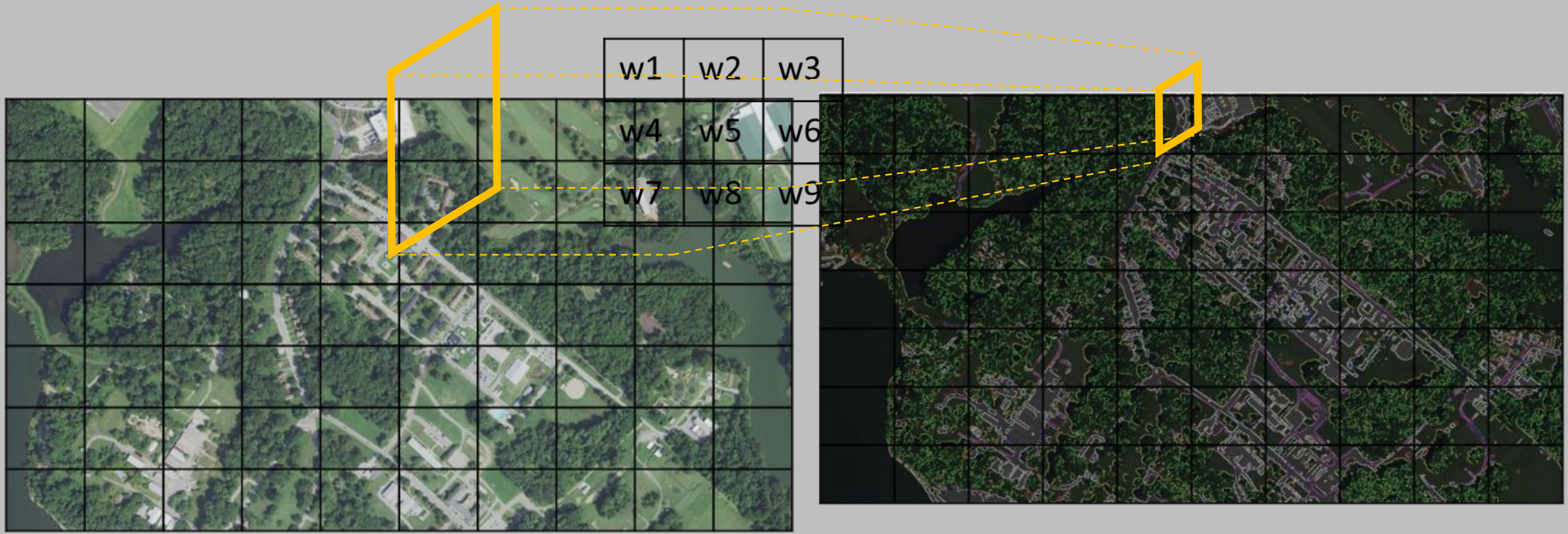

Annapolis, MD, USA
Annapolis
Map Data
Terms of Use
2015
2016
2017
2018
2019
2020
1984
1985
1986
1987
1988
1989
1990
1991
0.5x

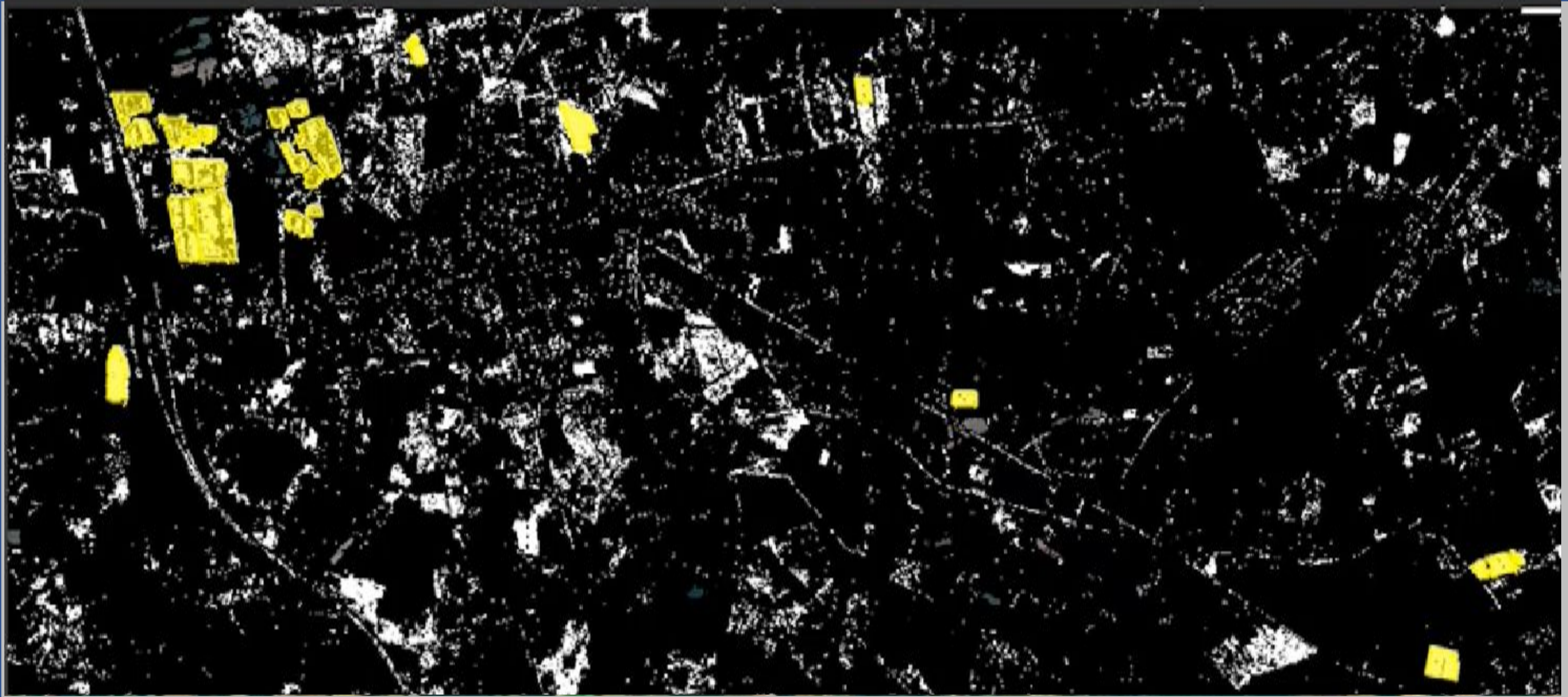
Why use AI? Remote sensing

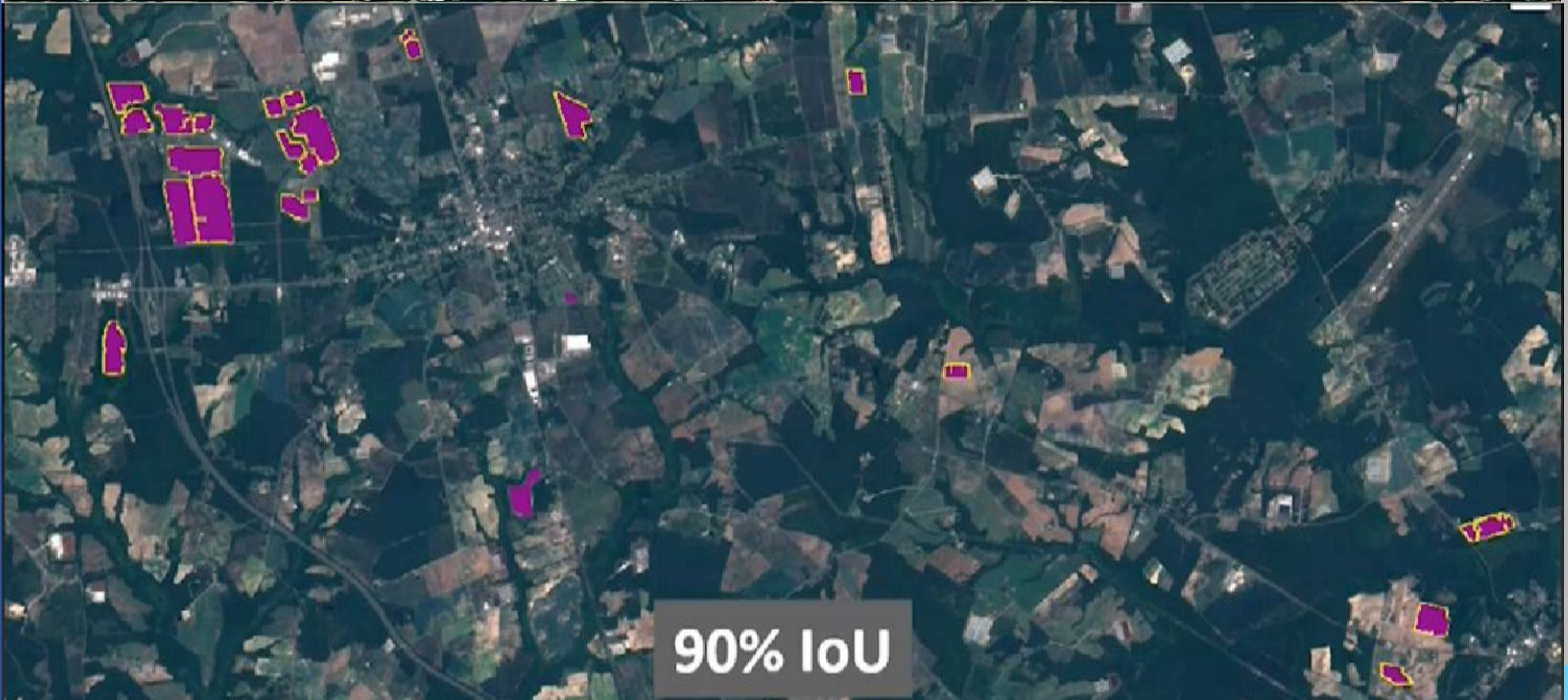


Good at learning non-linearities, conditionality, complex interactions

Why use AI? Recognizing spatial patterns







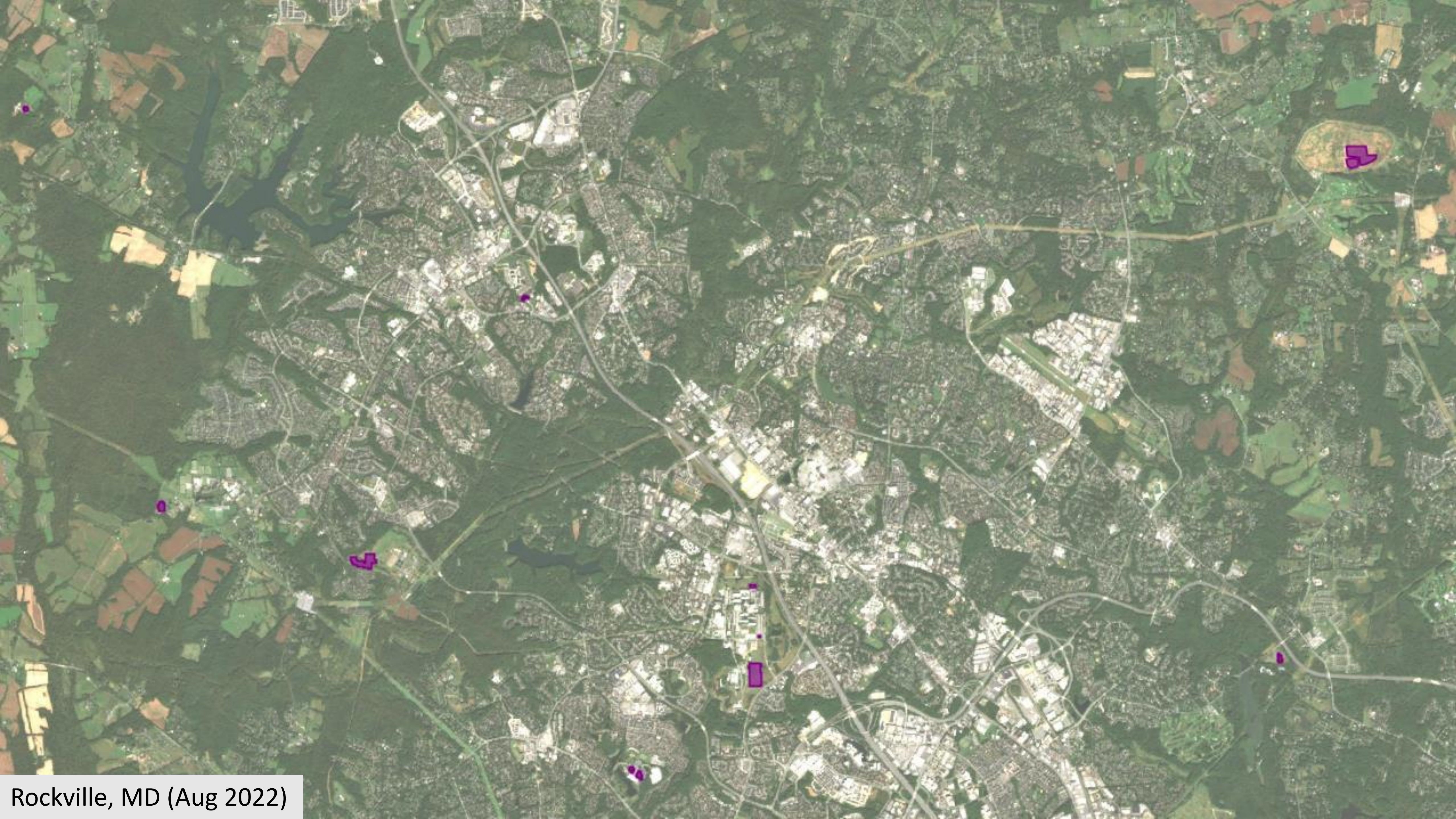
Traditional Machine Learning (ML) – evaluates pixels independently

- Real solar arrays
- ML identified solar arrays
- Deep-learning identified solar arrays

Deep learning – uses the shape and context of objects in images

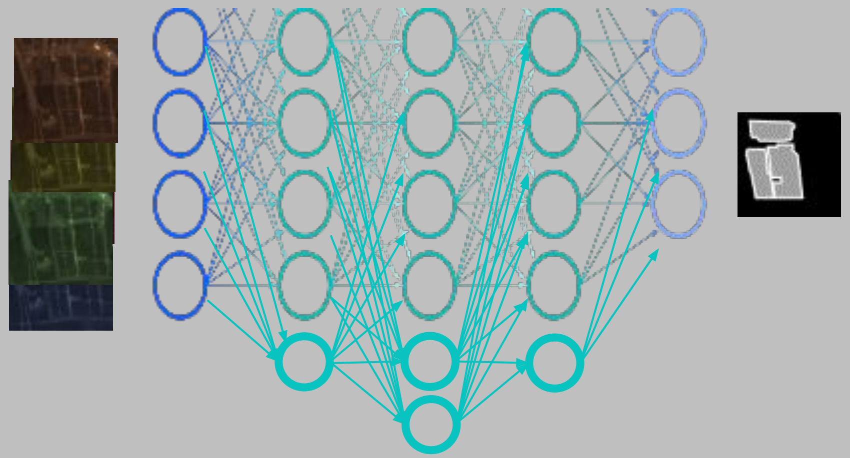
Why use AI? To answer new questions: Solar development in the Chesapeake

1. Where are ground mounted solar arrays? (AI)
2. What land uses transitioned into solar? (Not AI)
3. Where is solar most likely to go next? (Not AI)



Rockville, MD (Aug 2022)

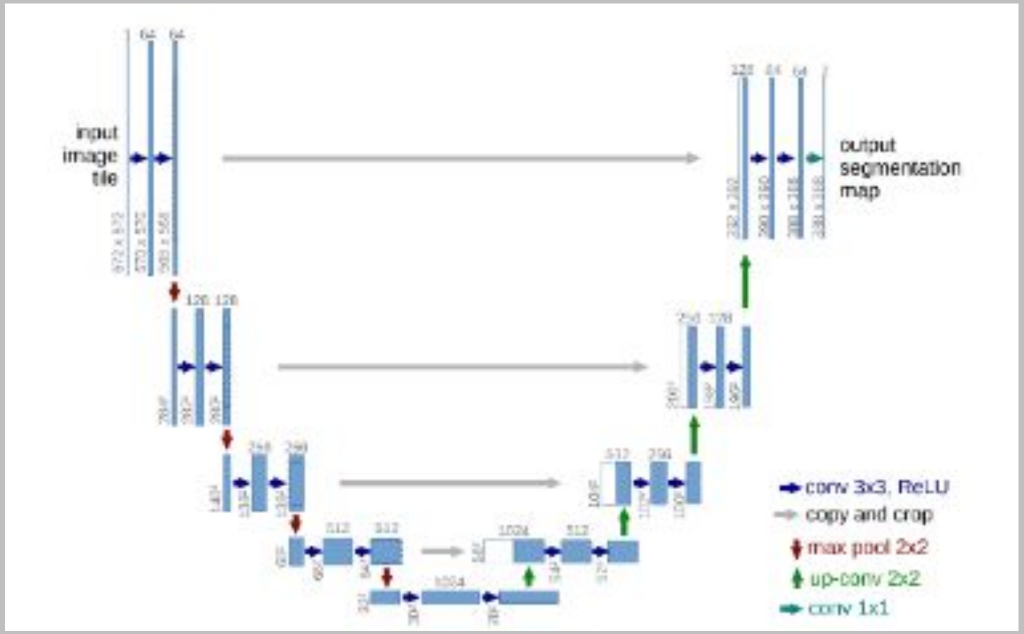
AI Solar Mapping



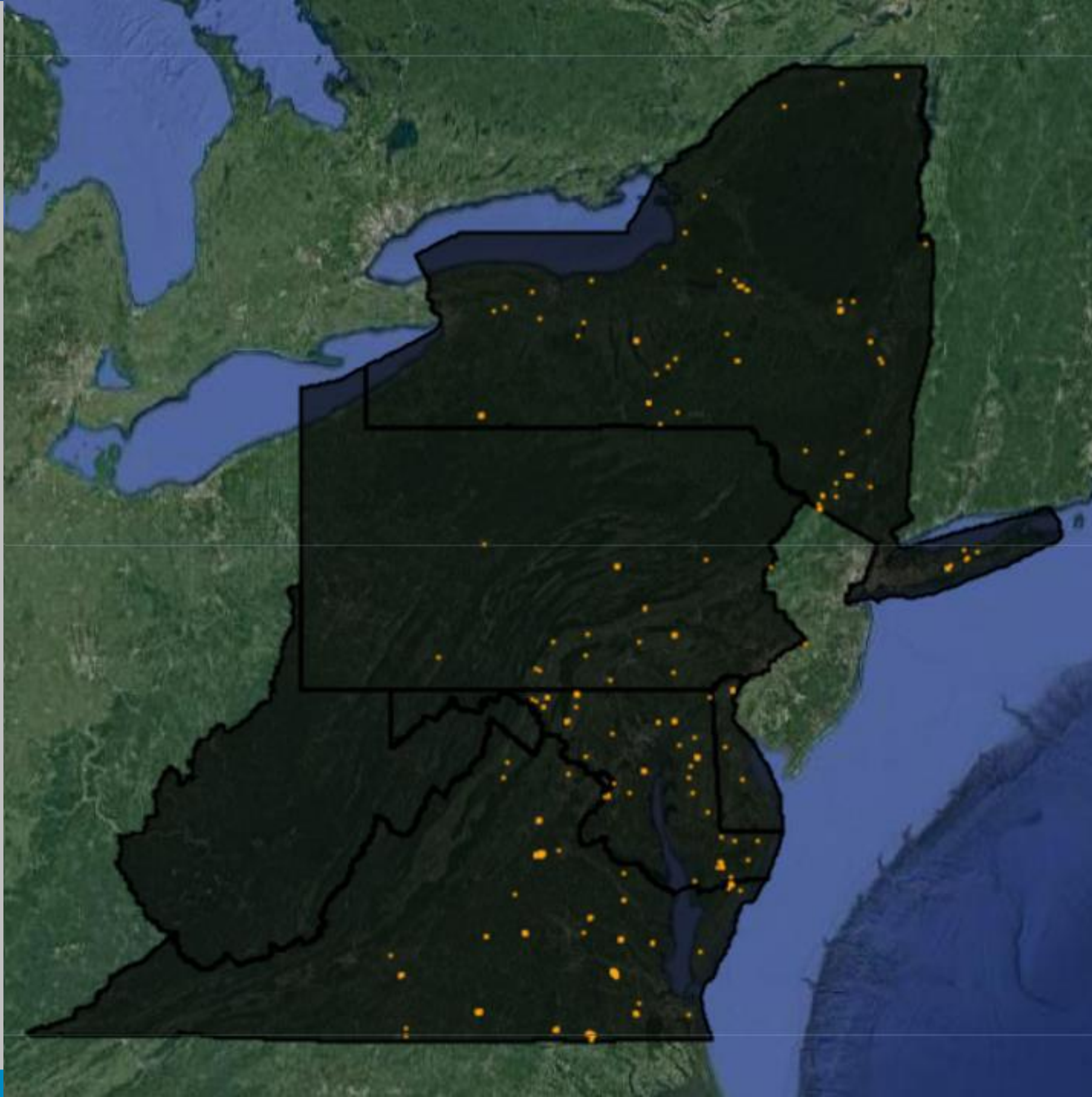
Map all solar arrays in DC, DE, MD, PA, NY, VA, WV

Each year from 2017 - 2021

AI Solar Mapping



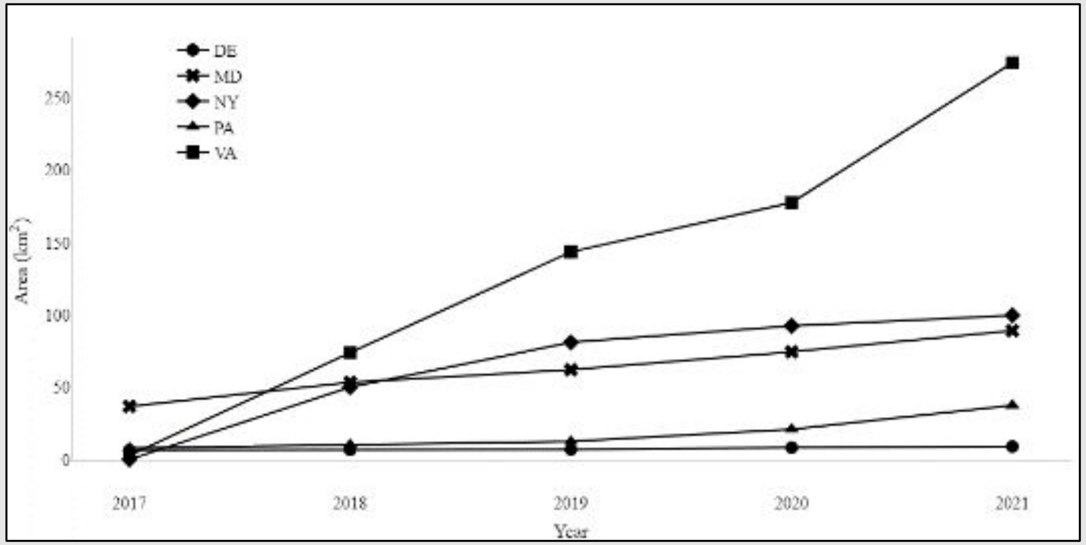
Recall: 90.2%
Precision:
90.1%
IoU: 85.6%

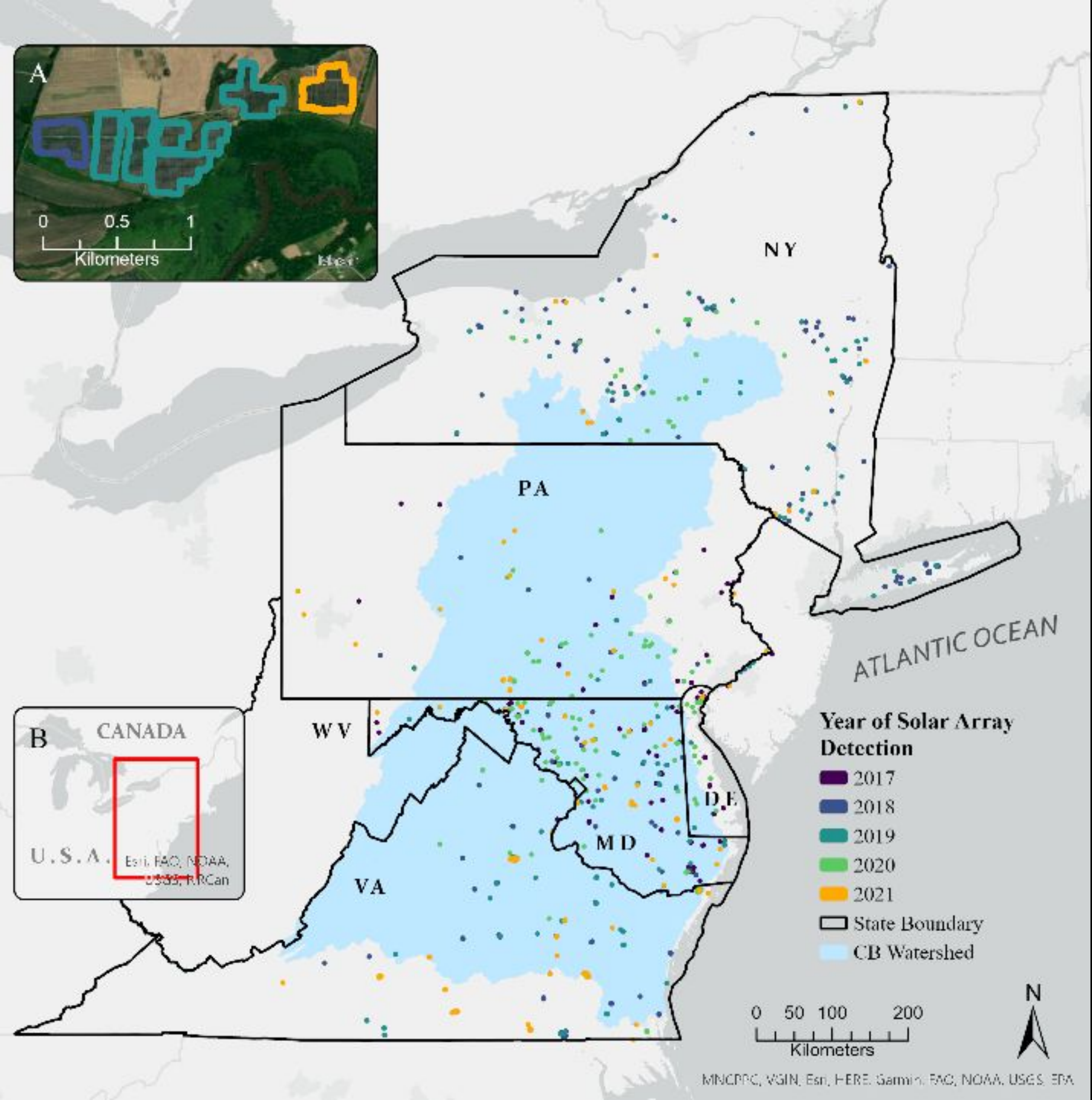


Solar analysis

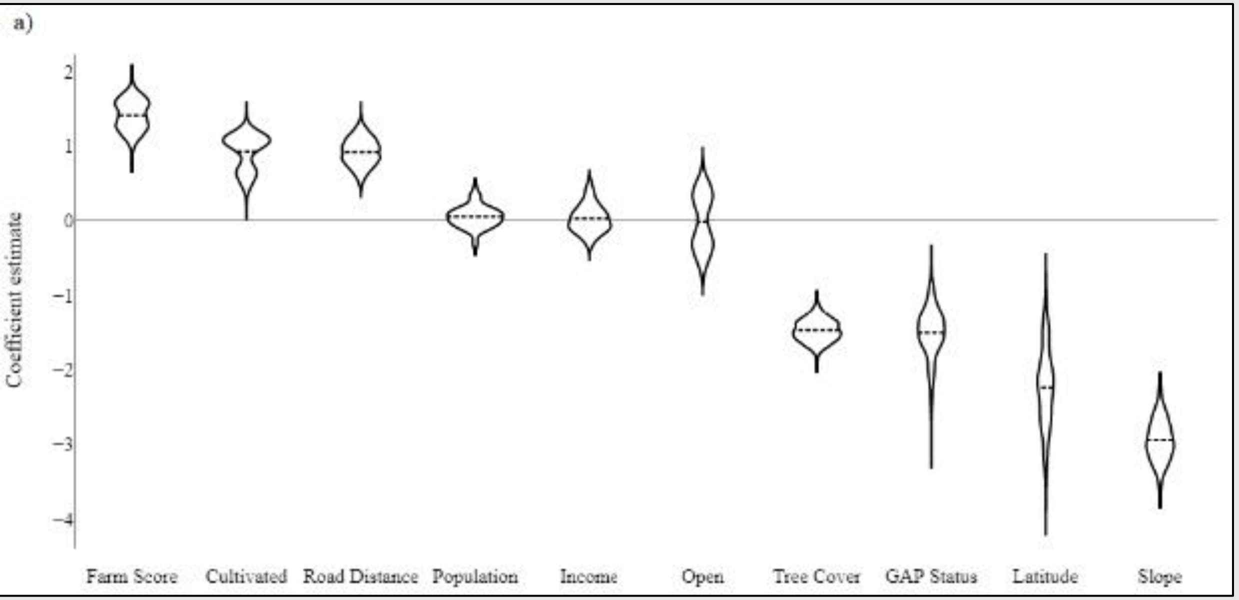
2017 - 2021

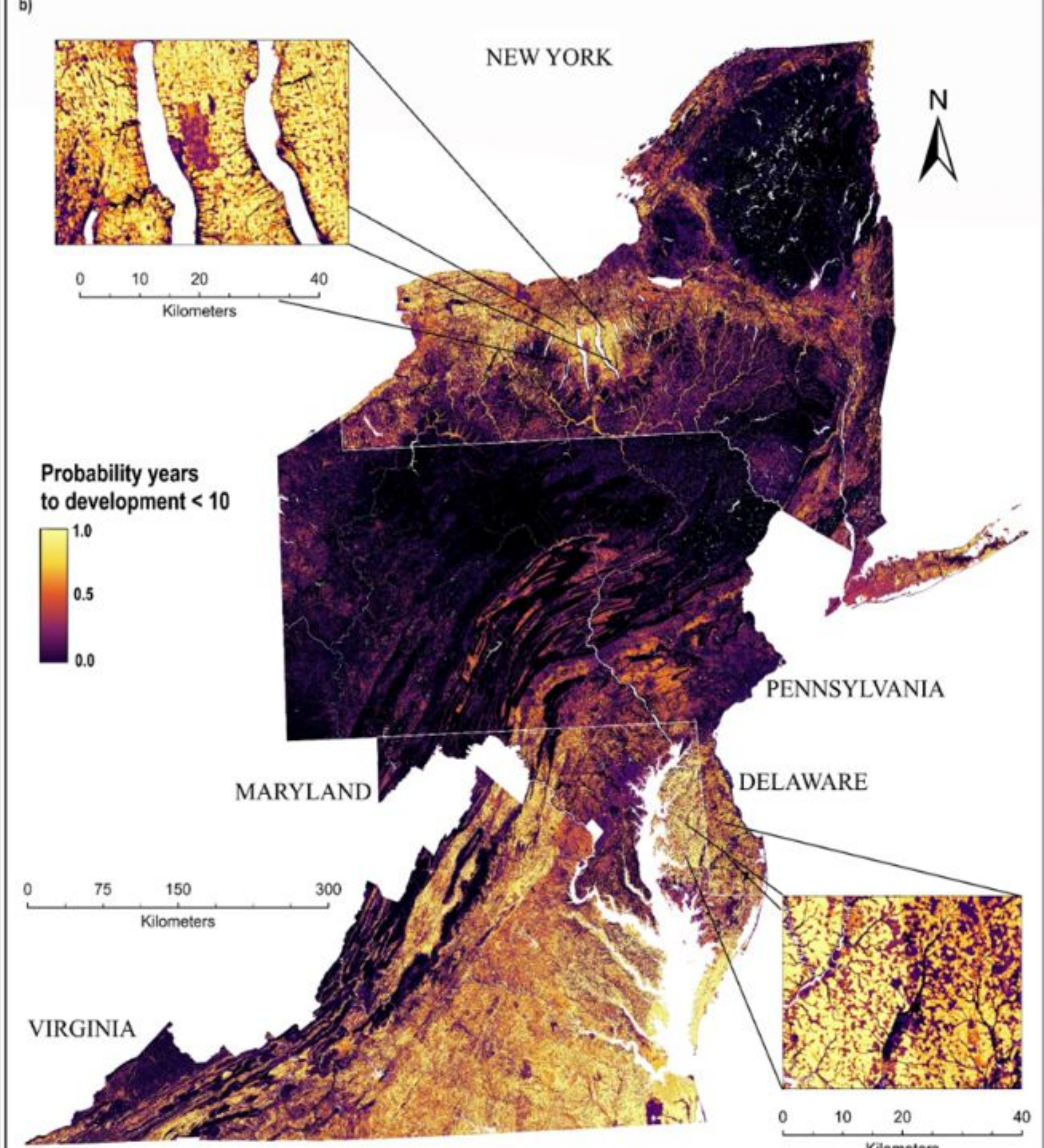
State	Area (%)	Rate of increase
DE	0.9 (1.79E-04)	1.40 ± 0.34E-03
MD	8.9 (3.54E-04)	**5.00 ± 0.34E-03**
NY	9.9 (0.82E-04)	1.33 ± 0.48E-03
PA	3.7 (0.32E-04)	0.61 ± 0.34E-03
VA	27.4 (2.69E-04)	**6.27 ± 0.34E-03**





When NOT to sue AI: Solar analysis

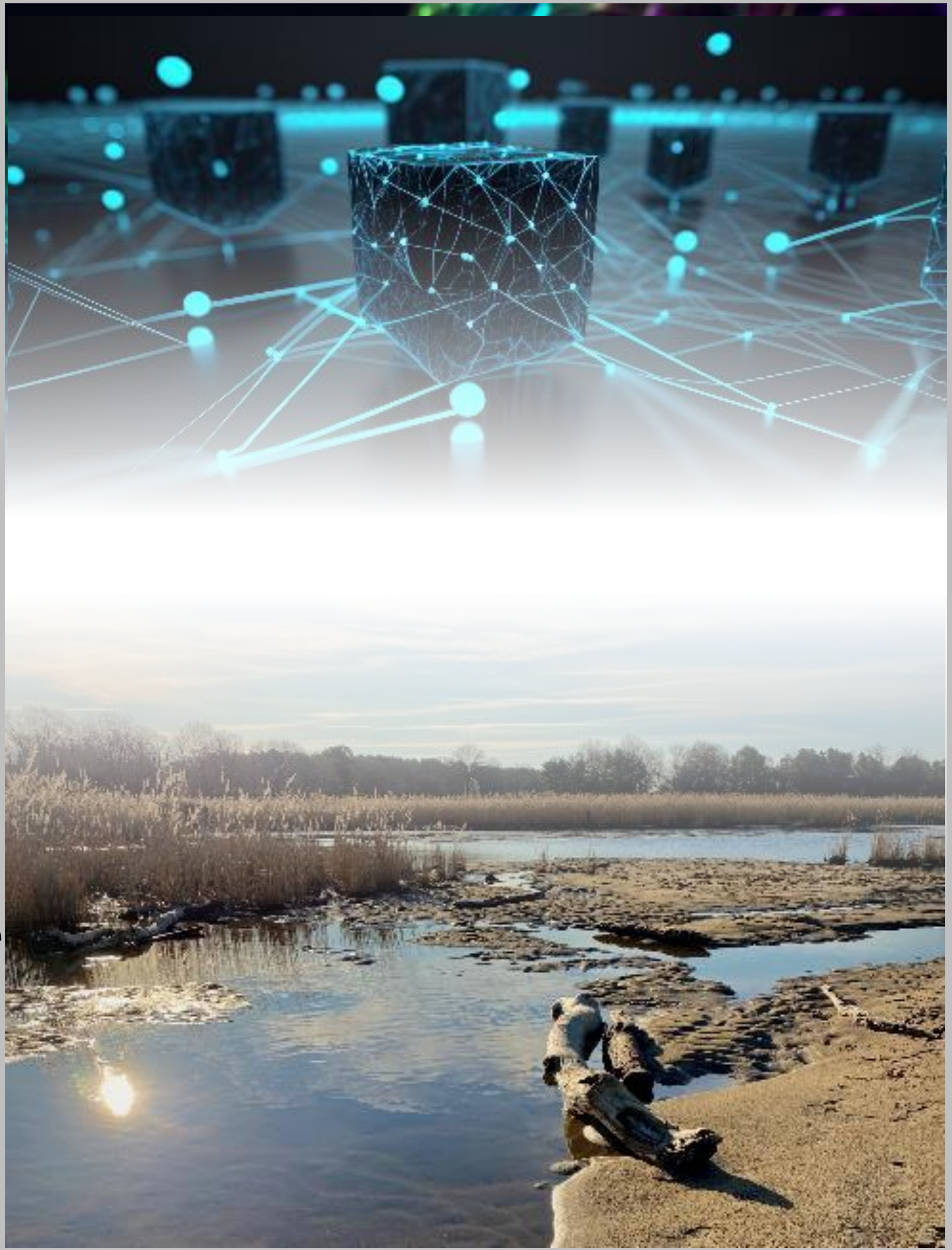




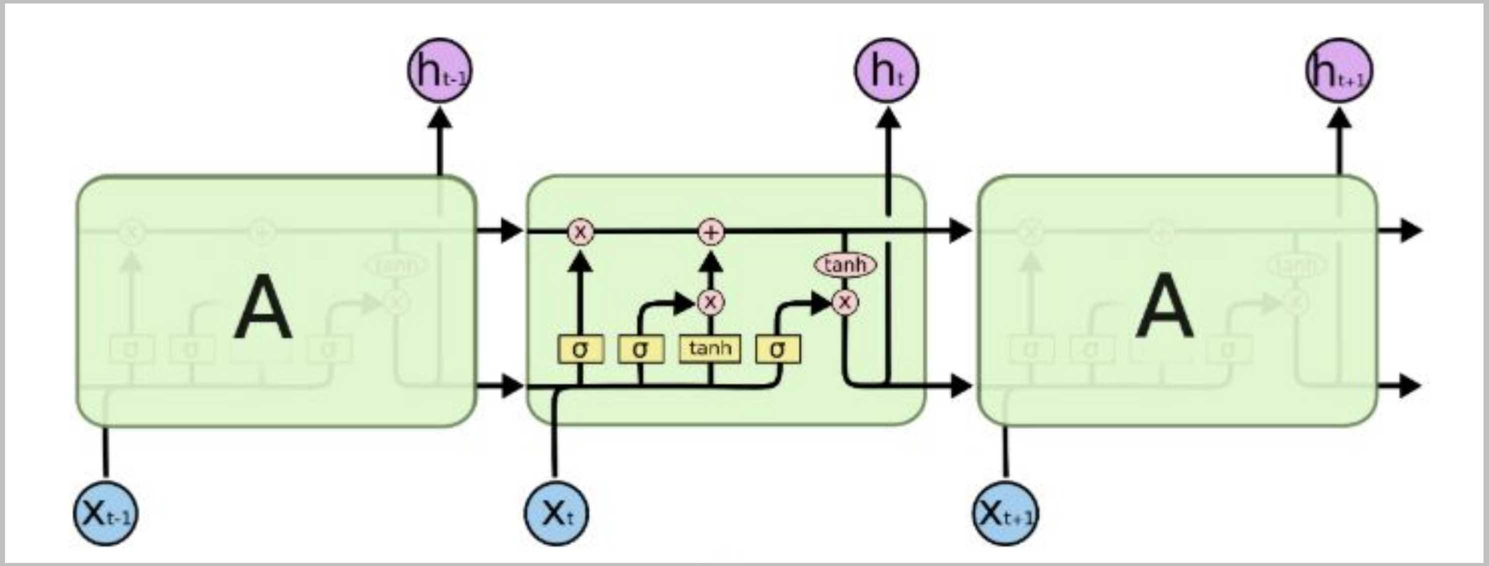
Why use AI? Solve old problems: Wetland Mapping

Goal: Develop a model that can map non-tidal wetlands across the entire Chesapeake Bay watershed

1. Accurate wetland maps needed for compliance & modeling
2. Existing wetland data inadequate
3. Wetlands are variable across space and through time



Why use AI? Big Data and Temporal Signals

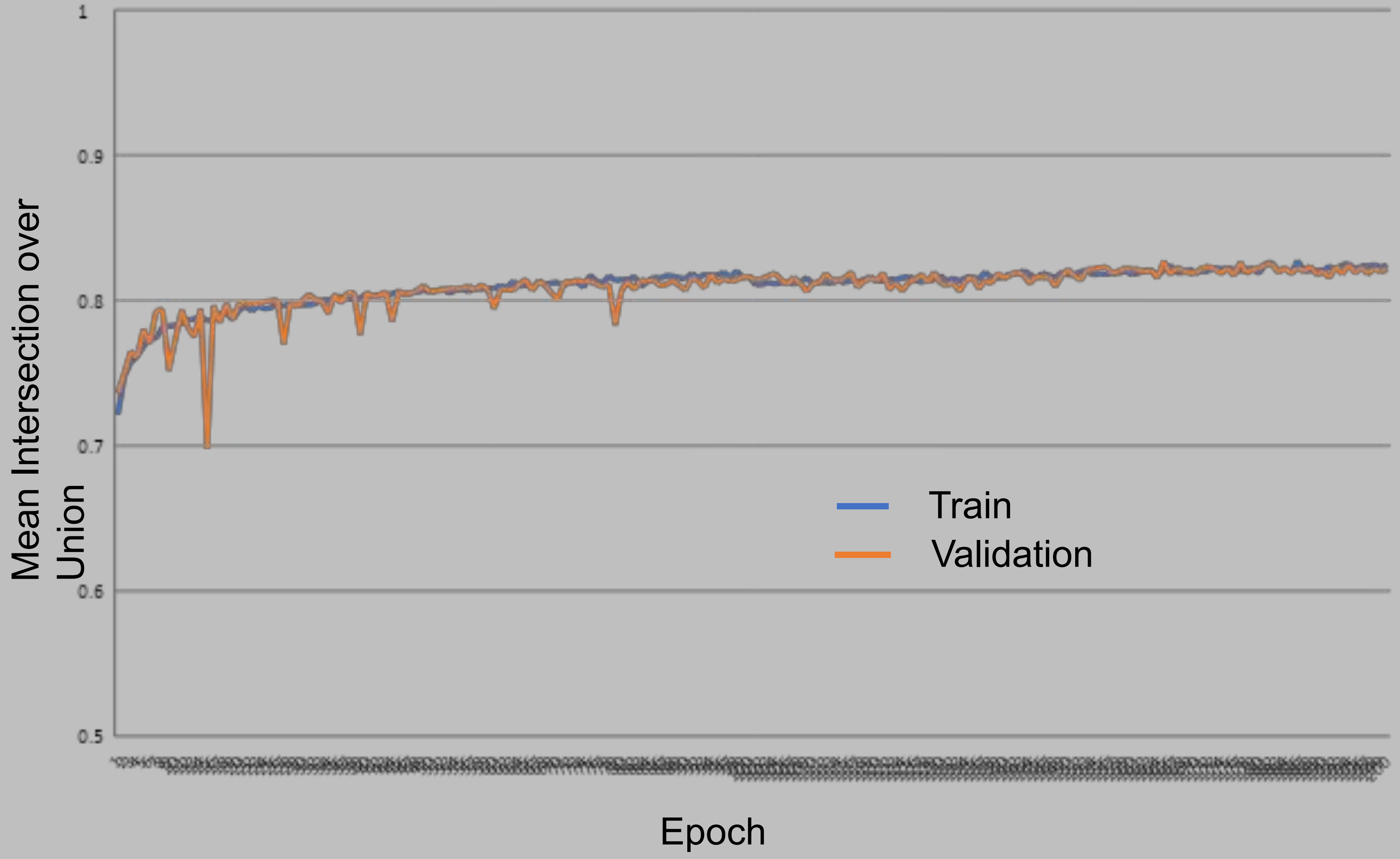


April/May

June/July

Aug/Sep

Why use AI? State of the art accuracy

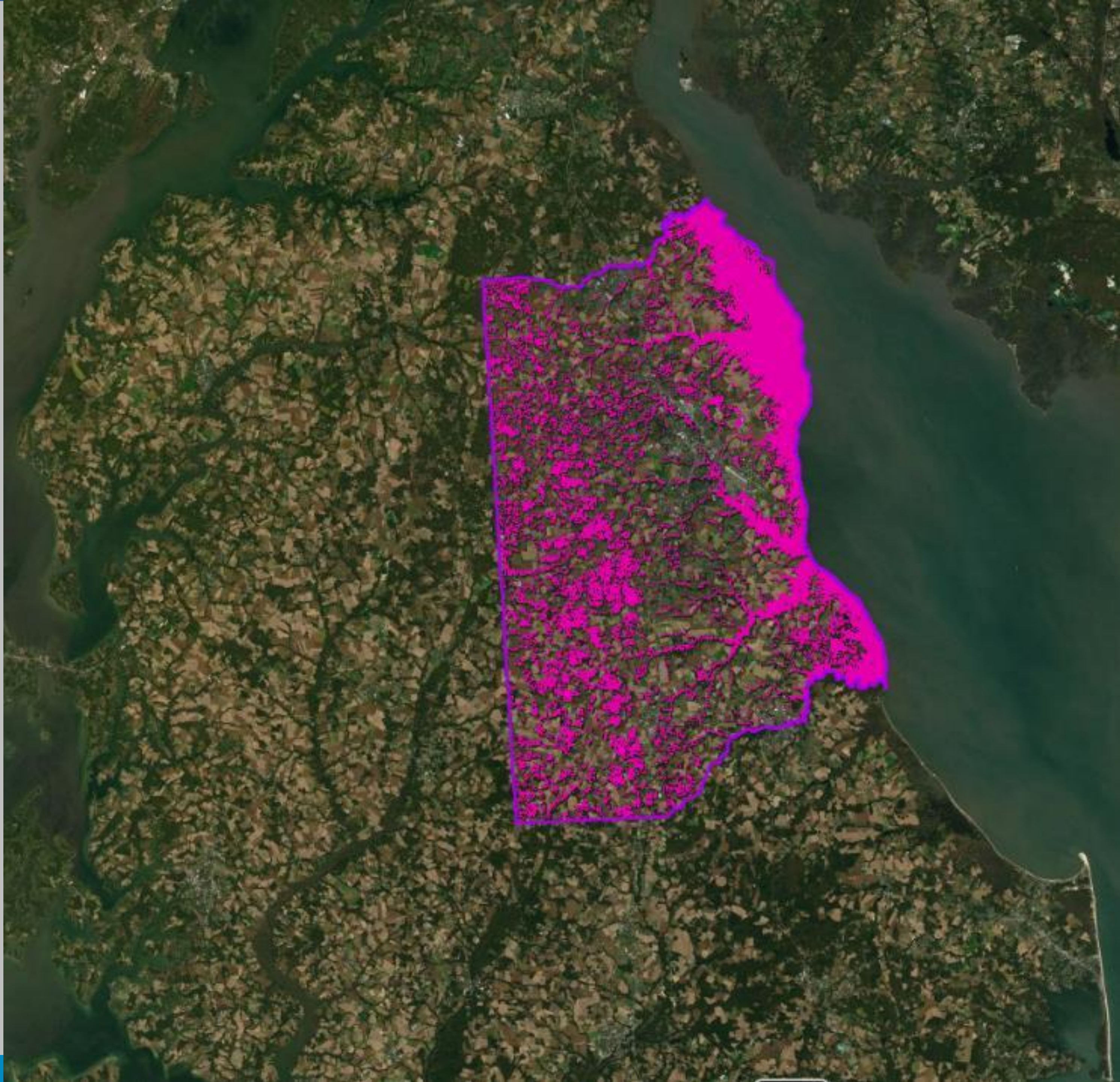


Metric	Model	
	Basic	Full
IoU	83.3%	87.3%
Accuracy	91.6%	94.0%
Precision	90.5%	96.5%
Recall	91.3%	90.2%

Why use AI? Accurate wetland maps

NWI

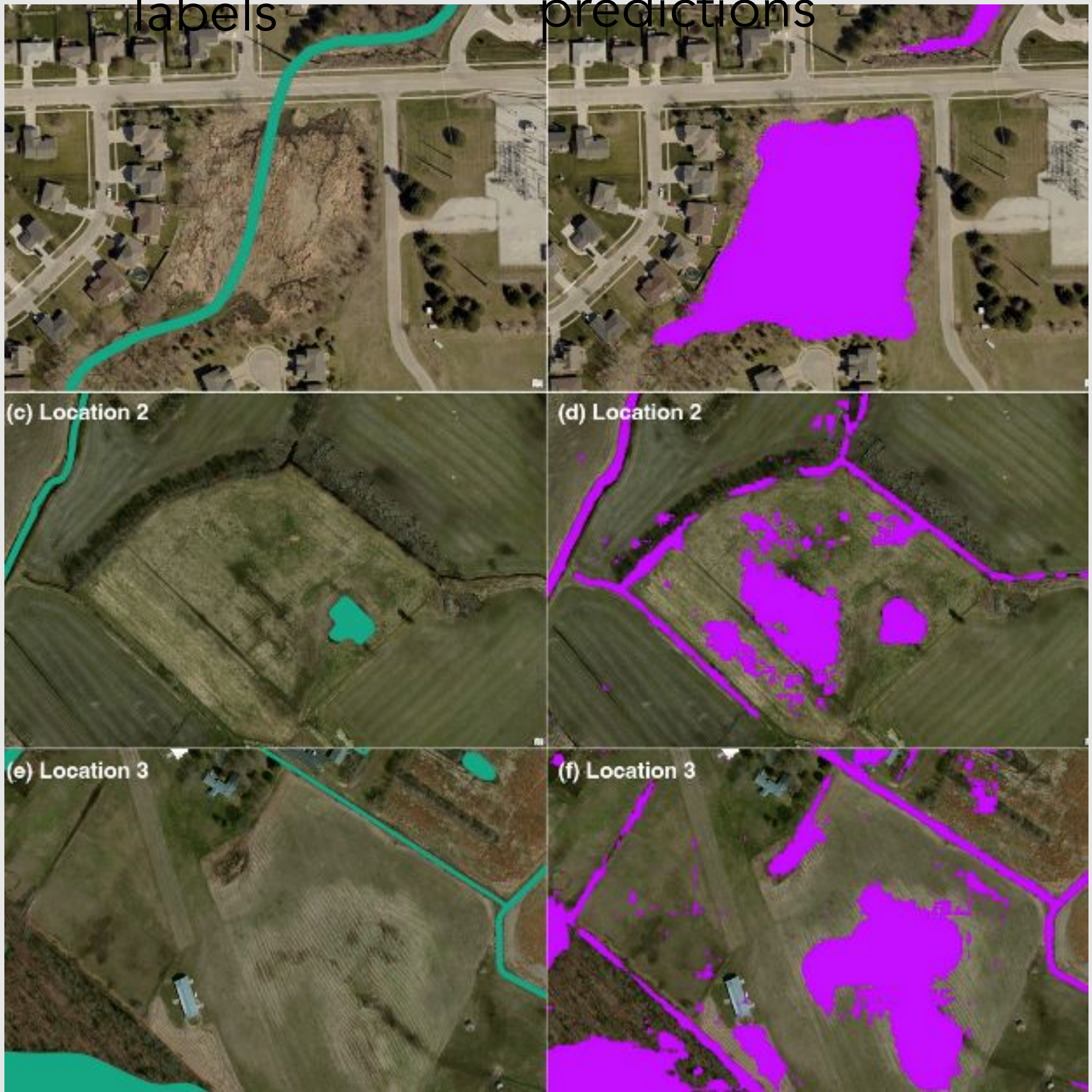
AI Outputs



Improve wetland maps

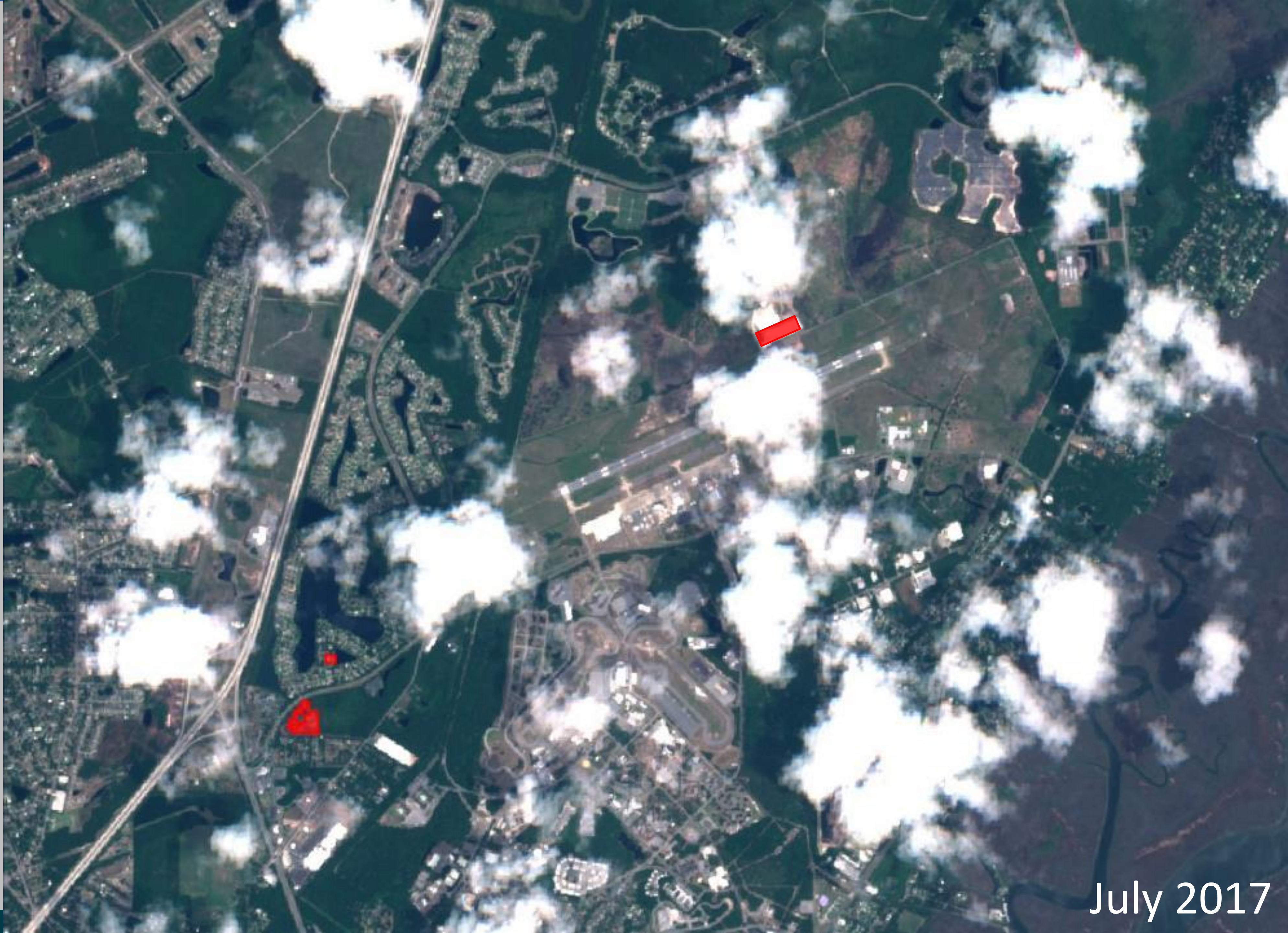
NWI labels

Model predictions



Real-time monitoring

- New images every 5 days
- Detect environmental changes in near real-time
- Better understand land cover transitions

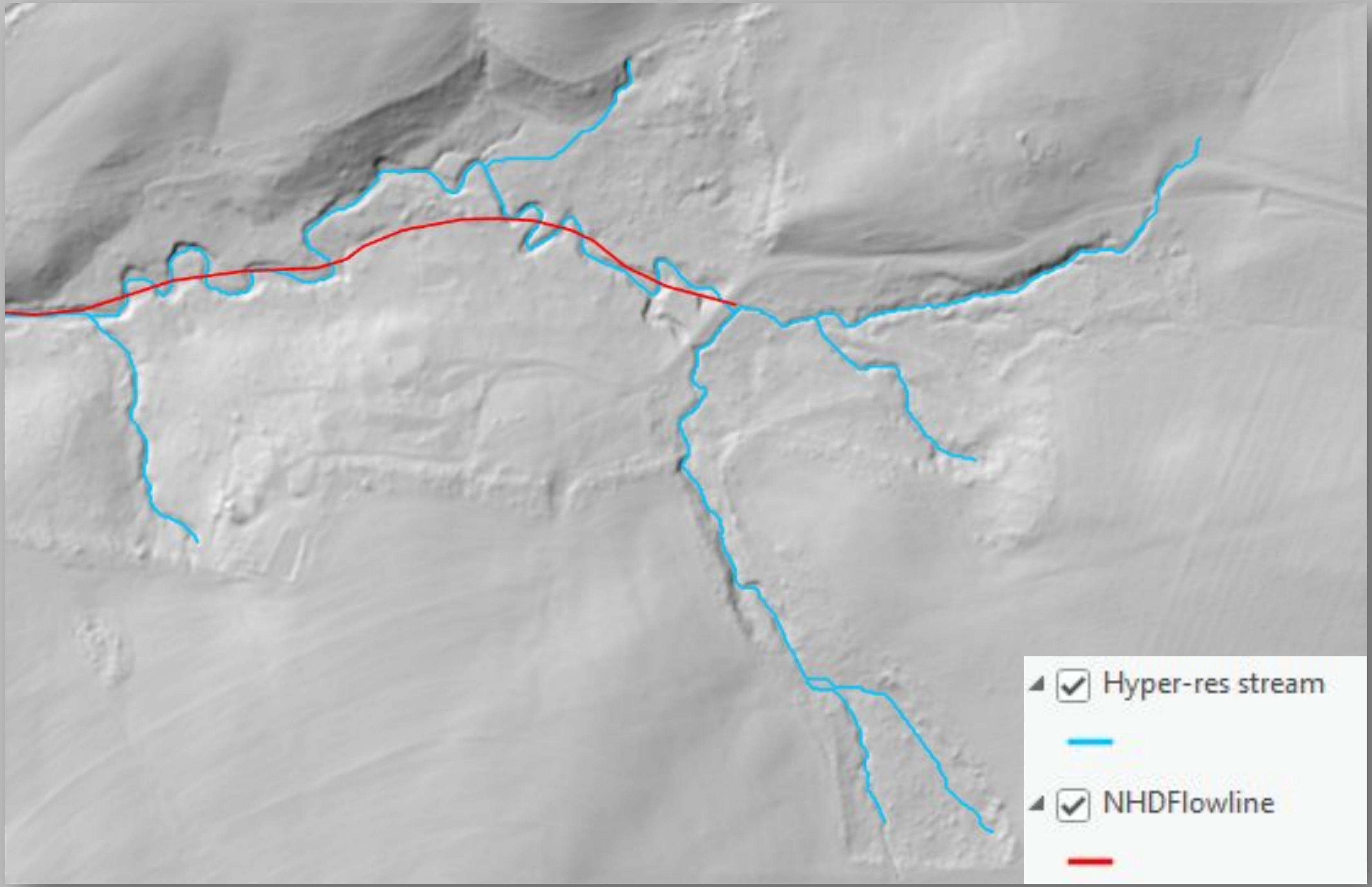


Hyper resolution hydrography

- Produced in partnership between CC, UMBC, and EPA's Chesapeake Bay Program

- Maps headward extent and lateral positioning of stream channels more precisely than NHD

UMBC

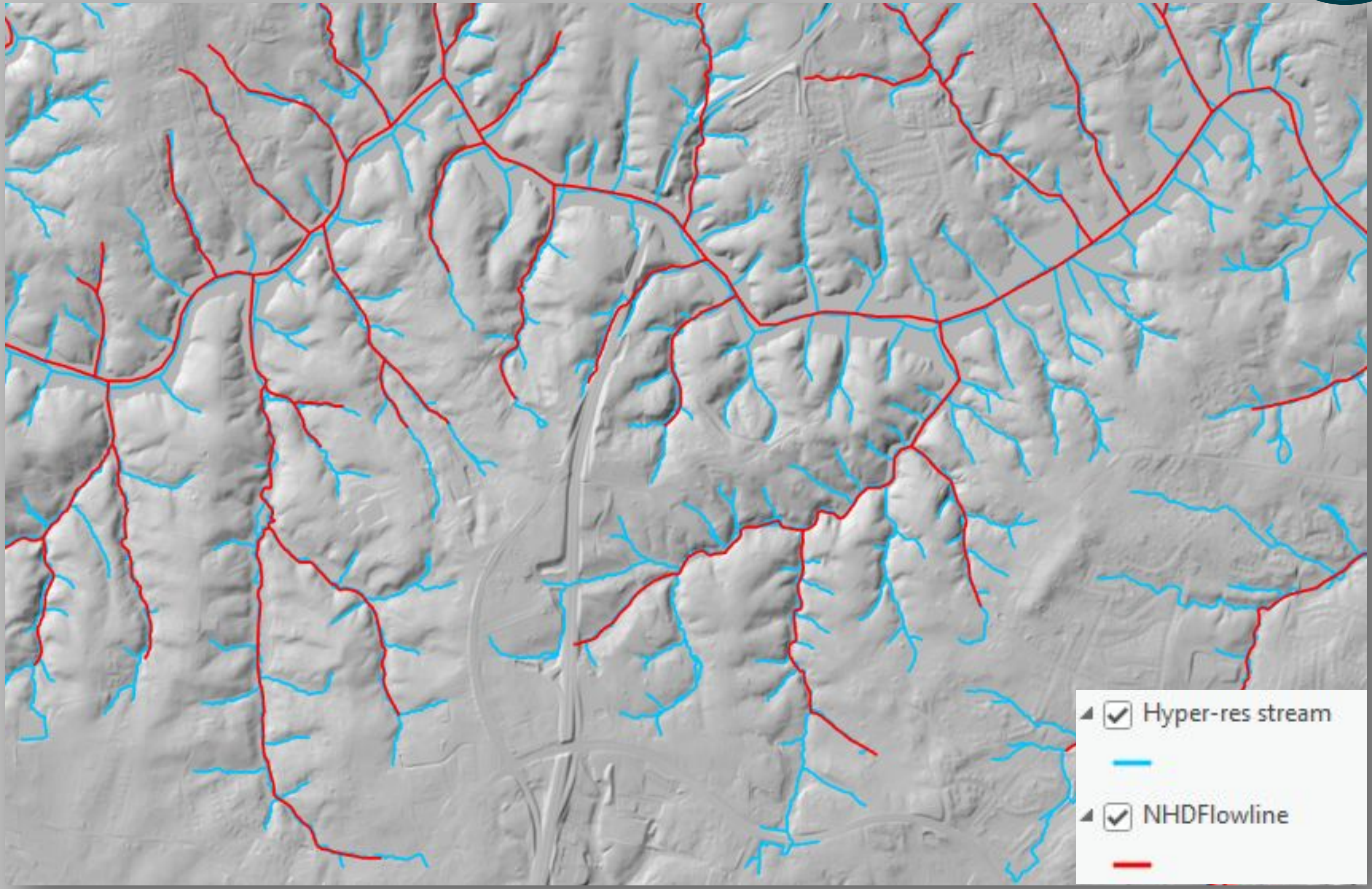


Hyper resolution hydrography

- Maps approximately 2.5x as many stream miles as 1:24,000 resolution NHD

- Covers entire Chesapeake Bay watershed

UMBC



How is it made?

- Detailed LiDAR elevation models serve as the foundation
- Geomorphic interpretation of terrain identifies visible channelized areas
- Tracing algorithm connects 2D stream polygons into 1D linear stream network

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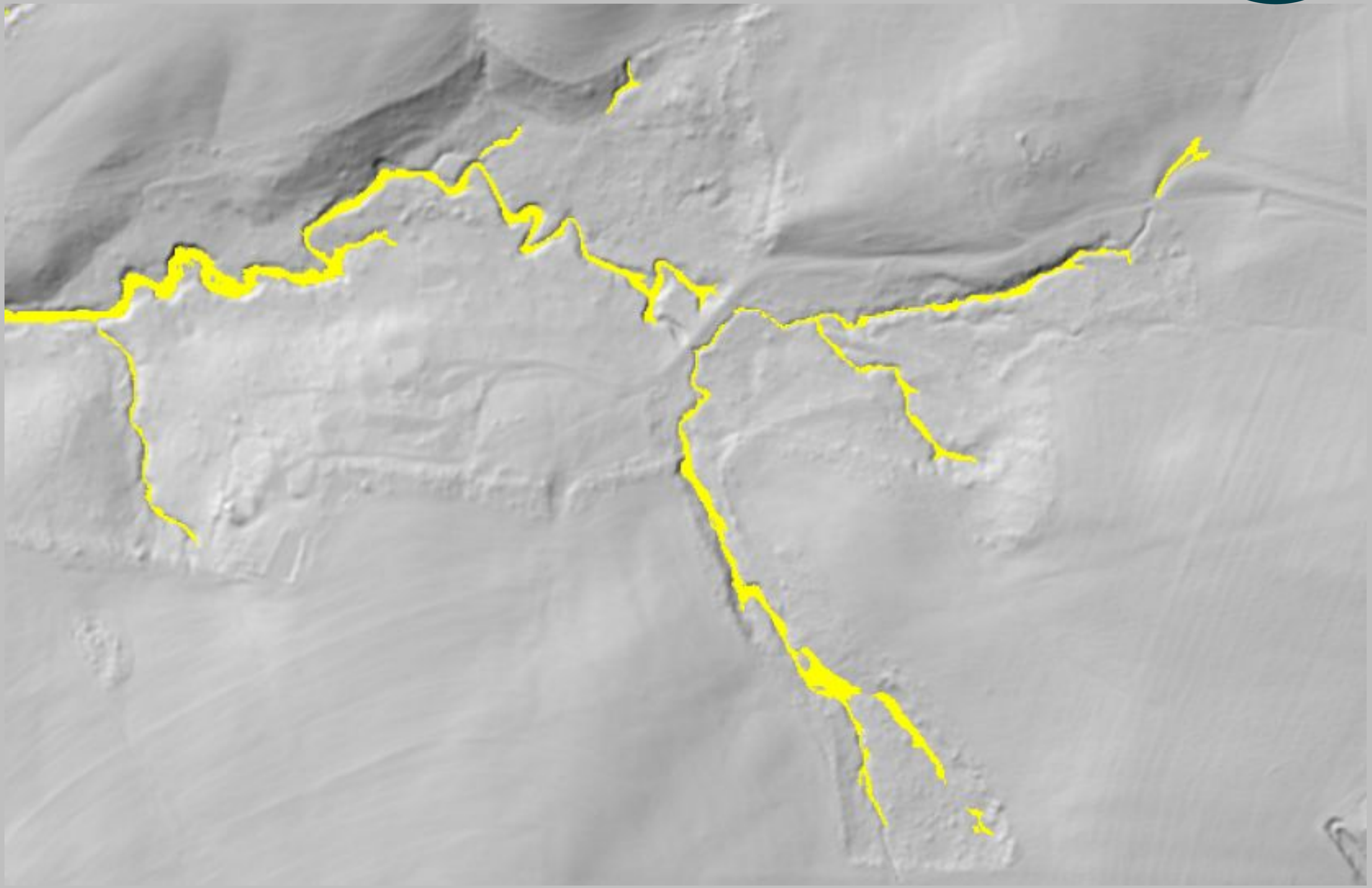

UMBC

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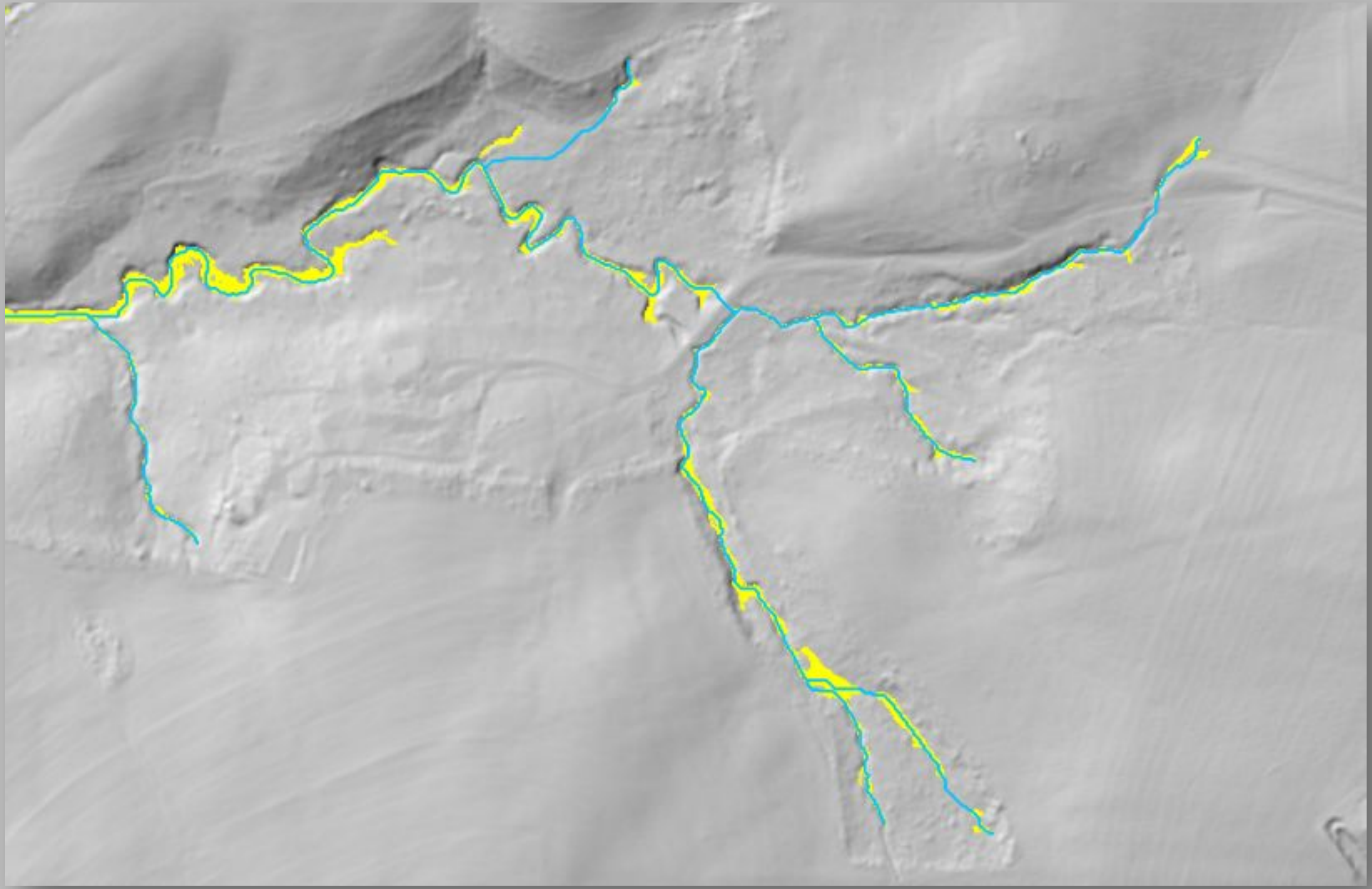
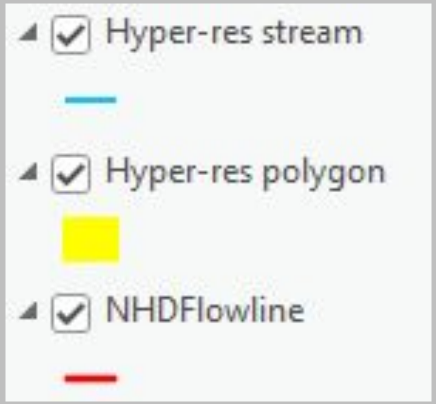


UMBC

Applications of data

Unbuffered drainage from CAFO to buffered stream

76.1811062°W
40.0054670°N



Applications of data

Unbuffered drainage from livestock pasture to buffered stream

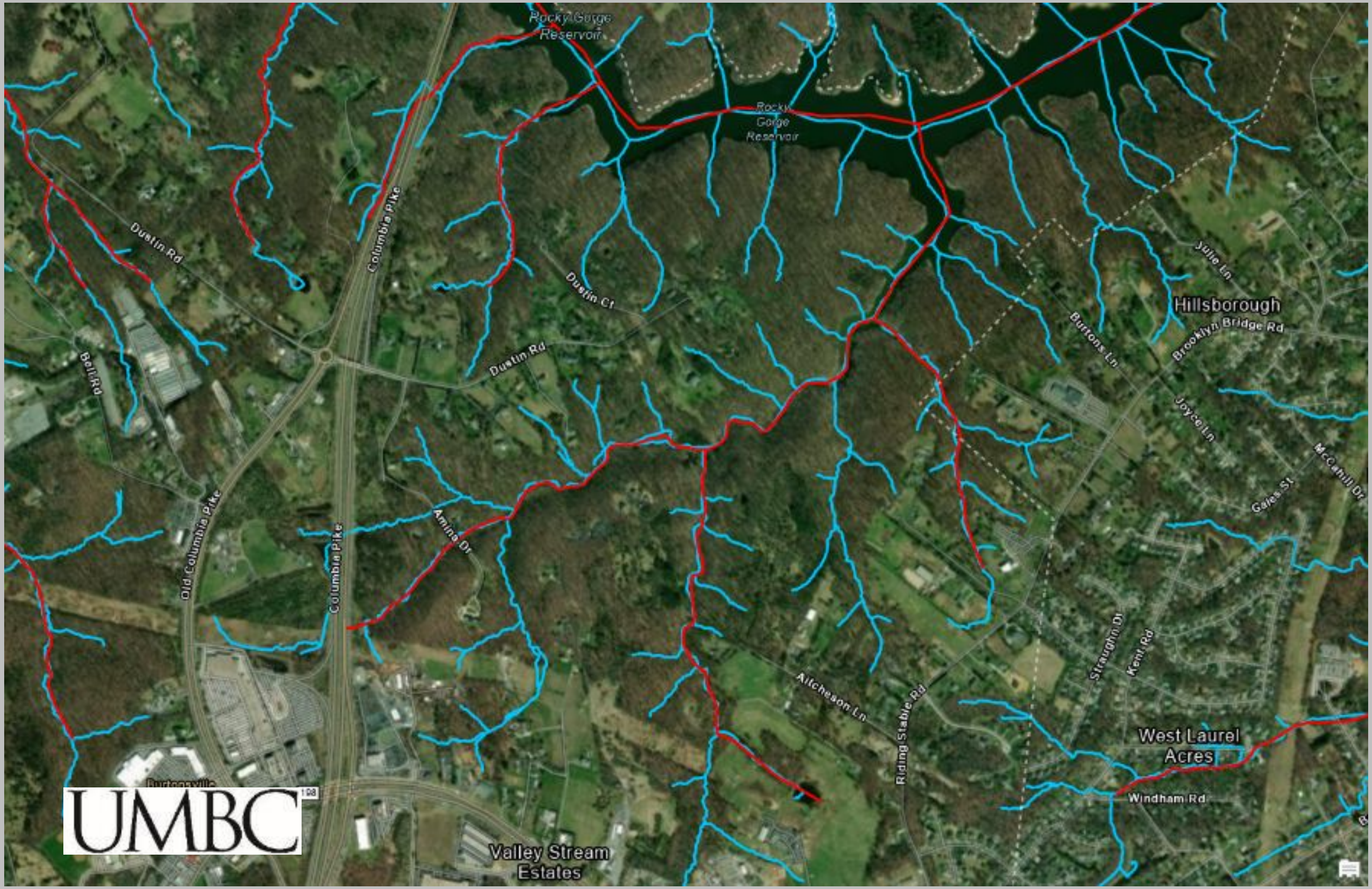
76.4115075°W
39.7265478°N

Applications of data

Identification of headcutting based on locally high bank height at transition from field drainage to forested buffer

Bank heights lessen downstream

Applications of data

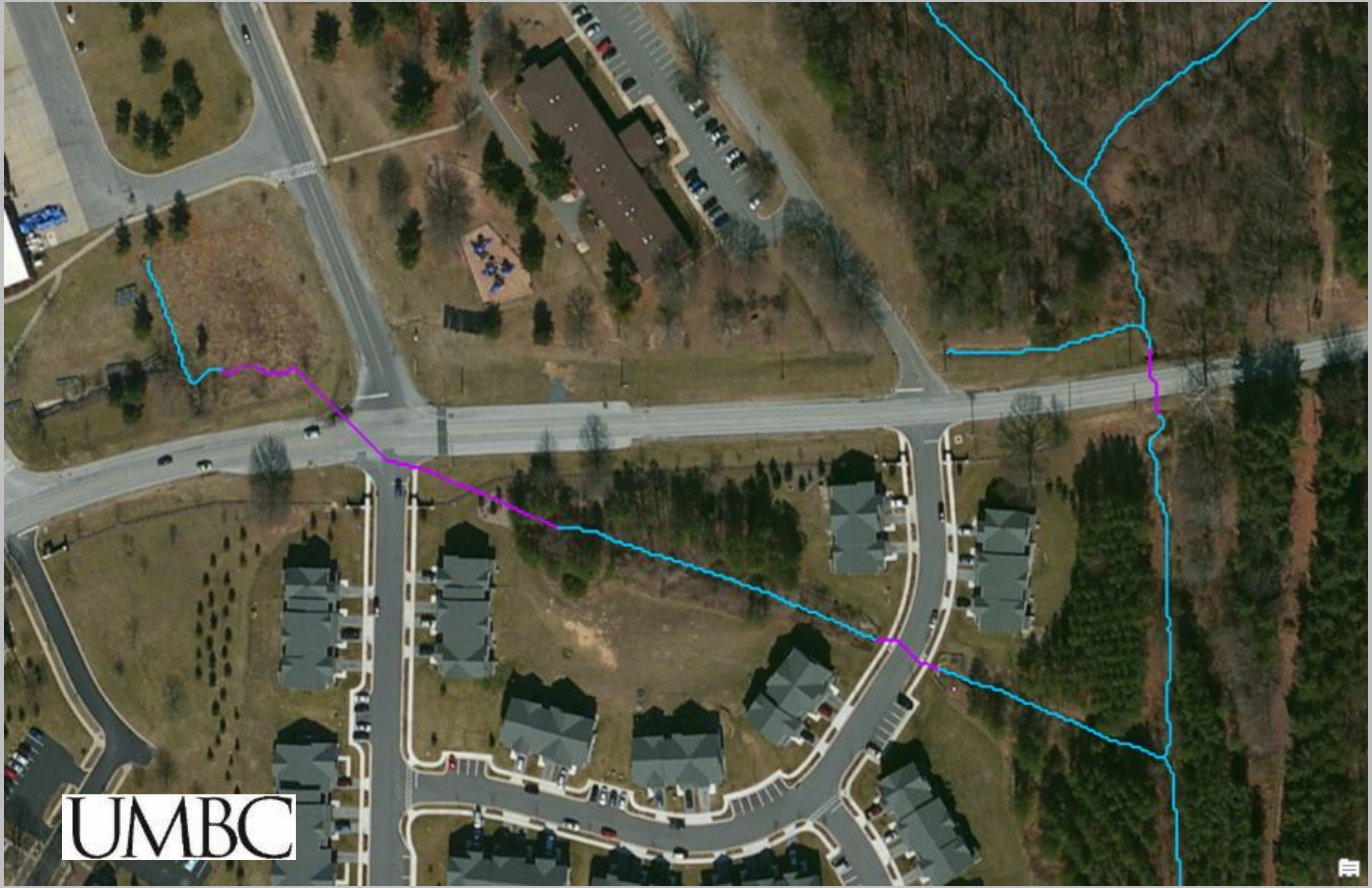


Tributaries to drinking water reservoir in Burtonsville, MD

Hyper-res stream

NHDFlowline

Applications of data



Identification of culverts and road crossings in suburban area

Hyper-res stream

Hyper-res connector

Chesapeake Conservancy

What is species distribution modeling?

- open woodland and brushy areas, particularly oak or pine woods with sandy soil
- for dispersal, degree-day at 50°F base: ~286
- caterpillar diet: legume or Fabaceae family
- adult diet: nectar from a variety of flowers including milkweed
- soil type and moisture suitable for vegetation

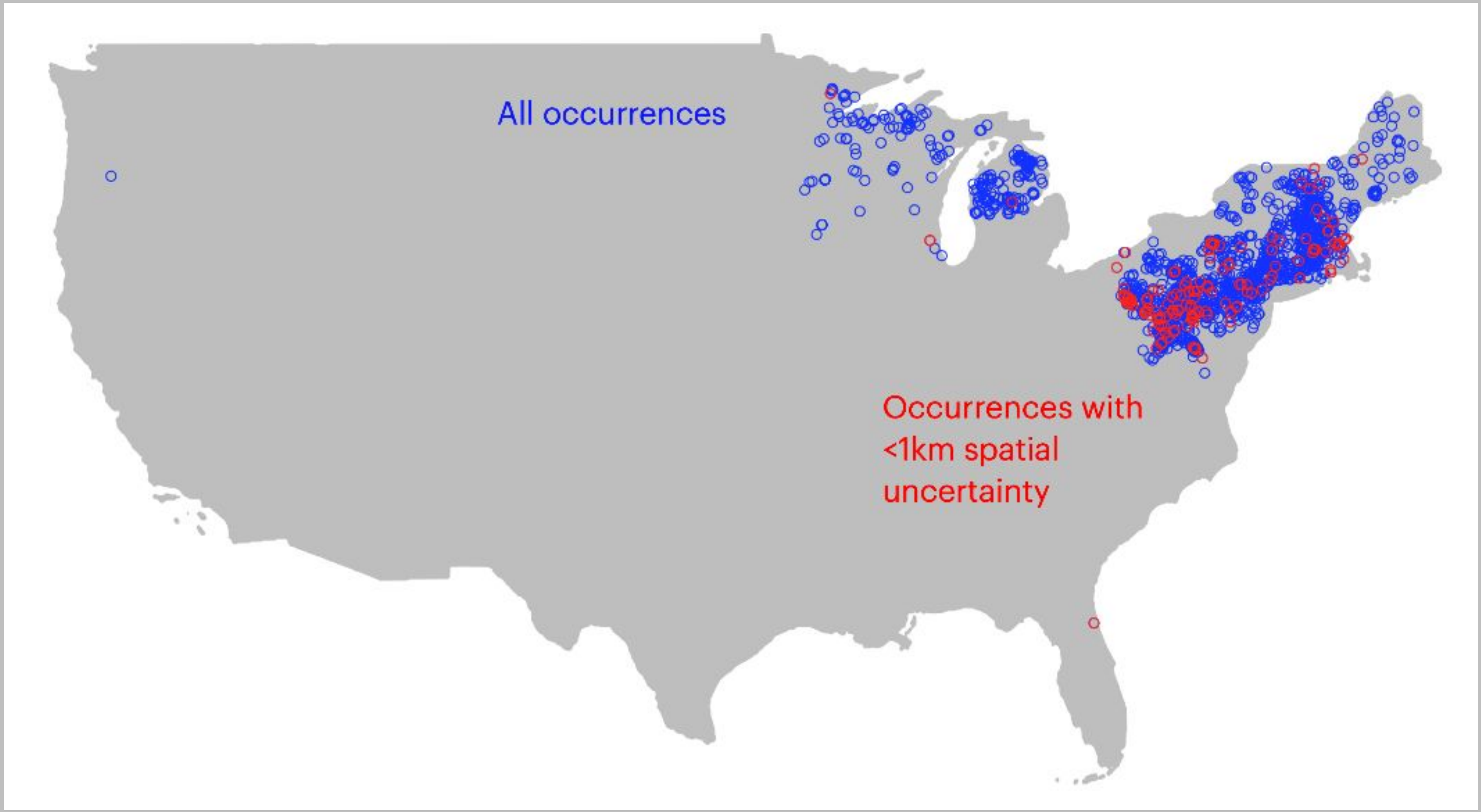
Achalarus lyciades, the hoary edge

- Ecological Niche = Conditions and Resources
- How to use machine learning to find out the ecological niche??
- Conditions and resources of the observed locations vs. other locations
- Model: in environmental space
- Project it in geographic space

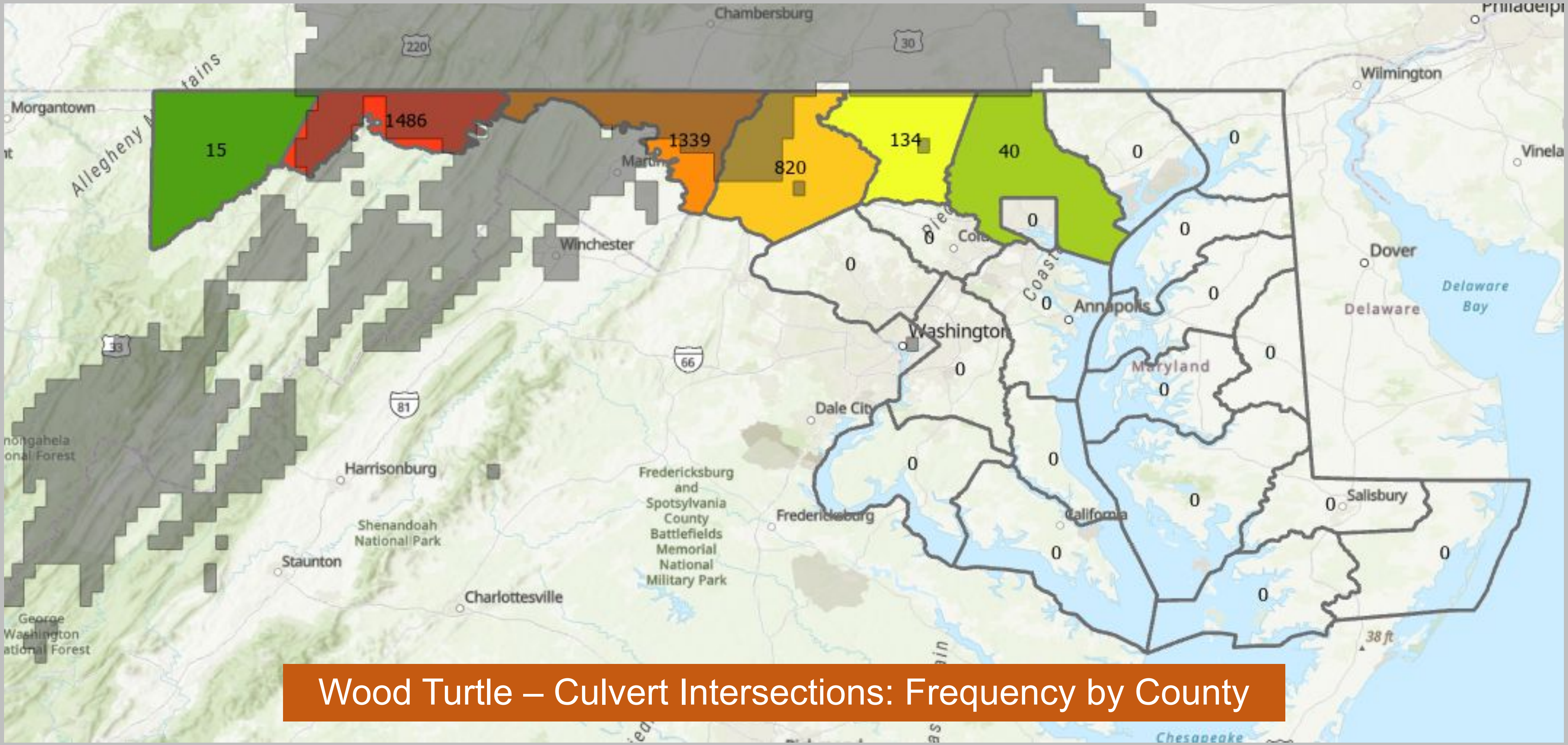
GIS Support for Assessing Culvert Impediments for Wood Turtle Movement - EXAMPLE

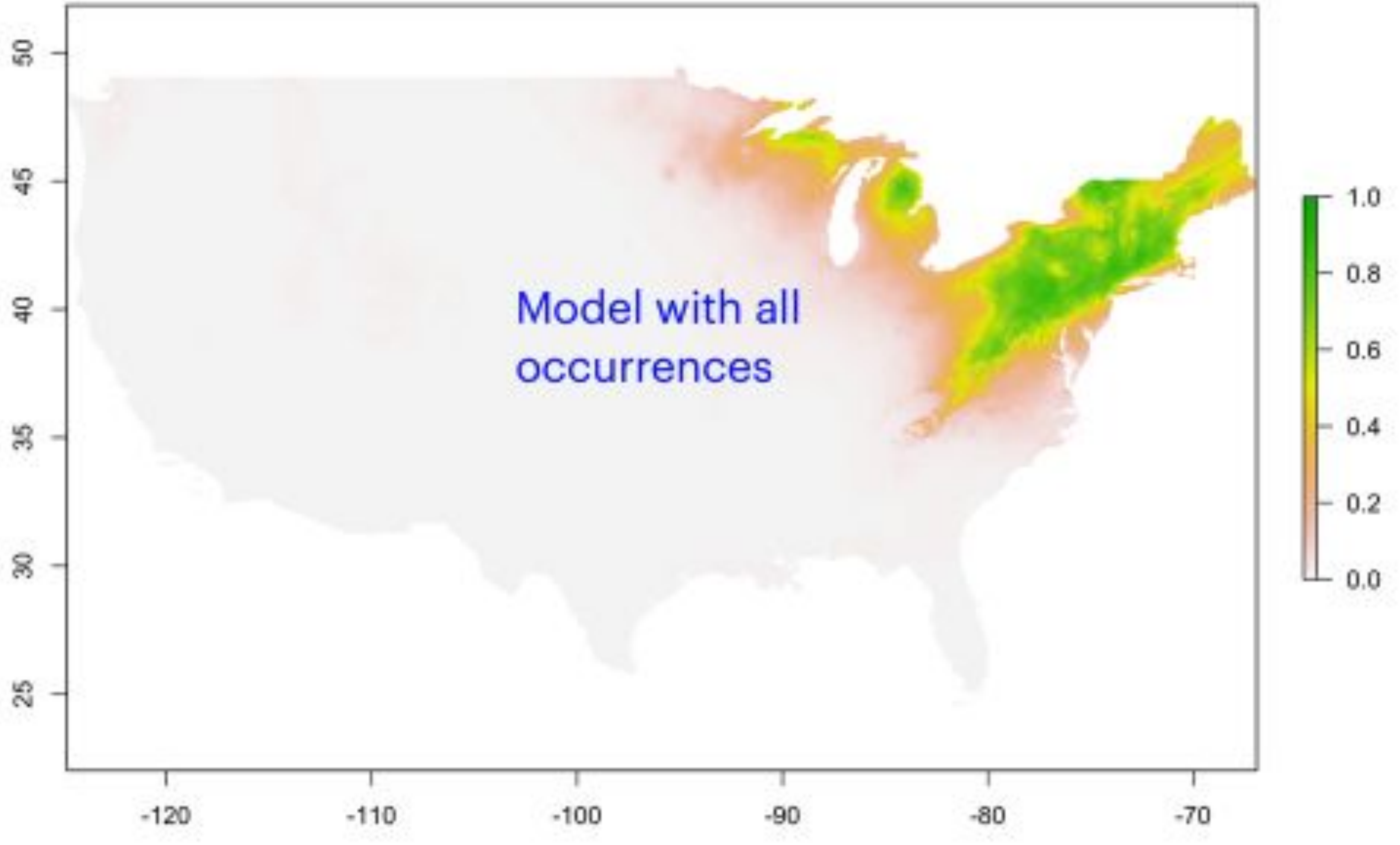
Wood Turtle (*Glyptemys insculpta*)

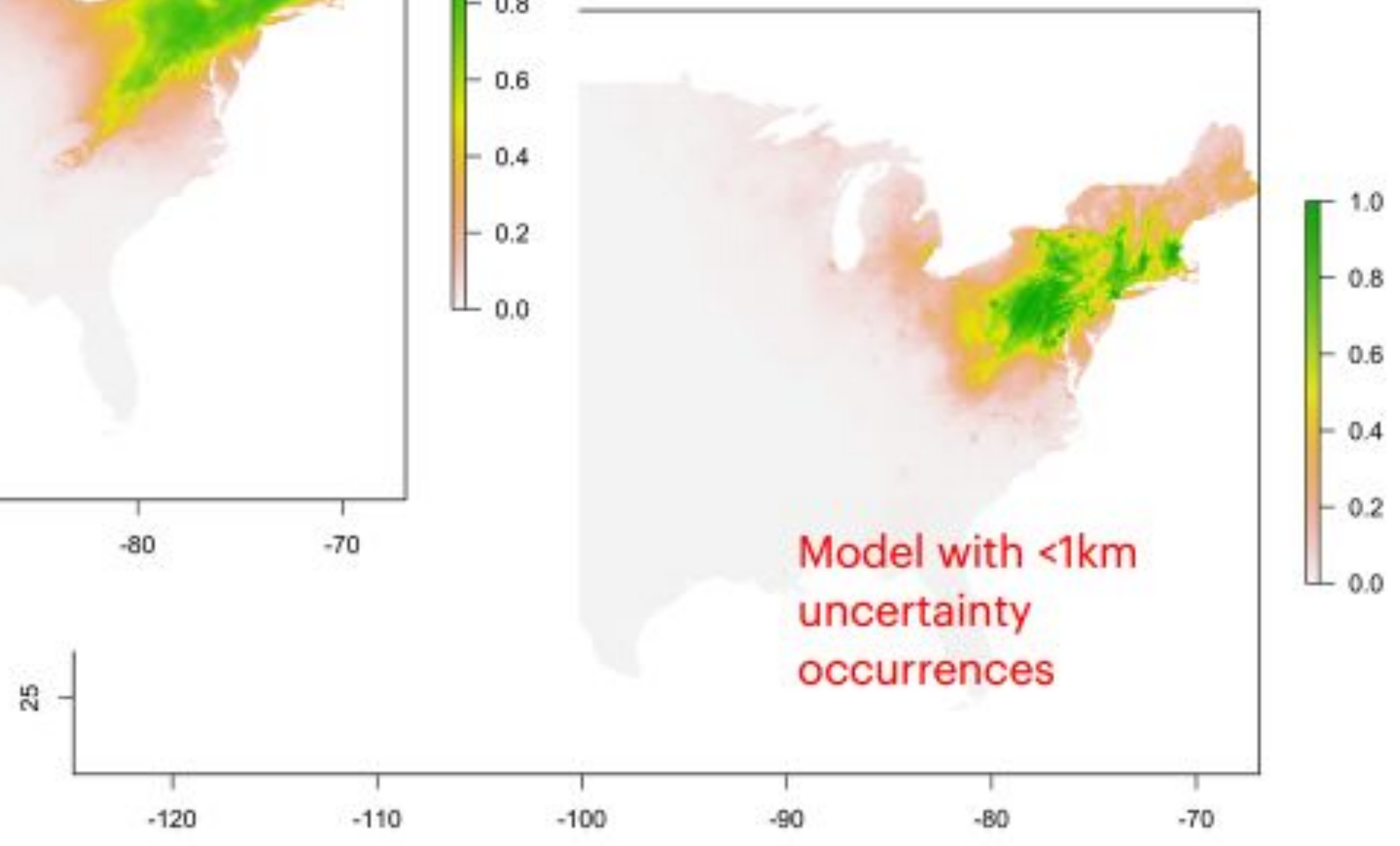
Wood Turtle Distribution - EXAMPLE



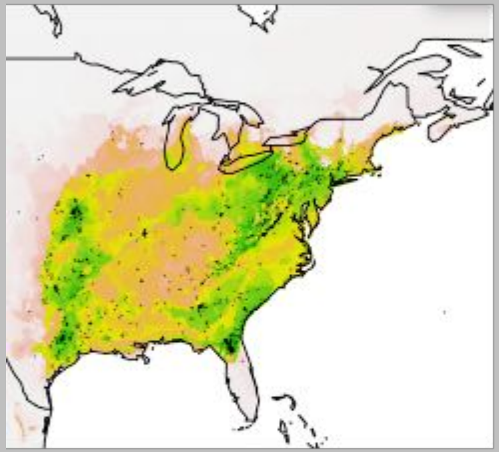
GIS Support for Assessing Culvert Impediments for Wood Turtle Movement



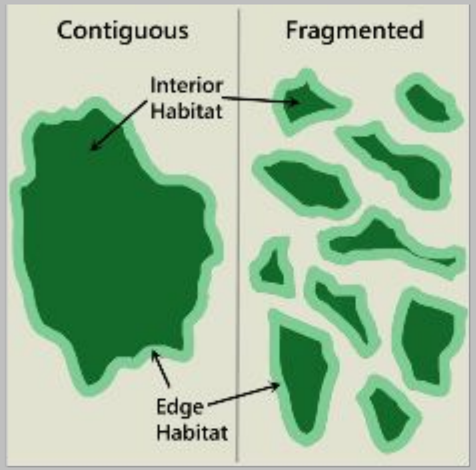

Model with all
occurrences
50
45
40
35
30
25
-120
-110
-100
-90
-80
-70
1.0
0.8
0.6
0.4
0.2
0.0


Model with <1km
uncertainty
occurrences
25
-120
-110
-100
-90
-80
-70
1.0
0.8
0.6
0.4
0.2
0.0

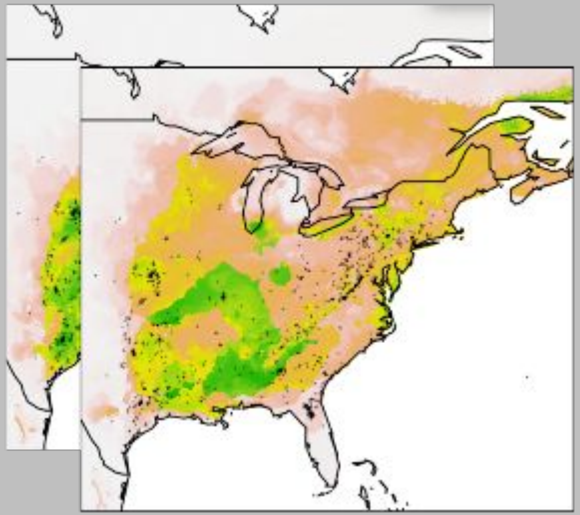
Species Distribution Modeling Objectives



High resolution mapping of species distribution under current climate



Fragmentation impact on high resolution species distribution under current climate



Moderate resolution mapping of species distribution under current and future climate

Chesapeake Conservancy in Scientific Publications

- Mainali, K. P., E. Slud, M. C. Singer, and W. F. Fagan. 2022. A better index for analysis of co-occurrence and similarity. Science Advances 8:1–9.
- Evans, M. J., K. Mainali, E. R. Soobitzky, E. Mills, and S. Minnemeyer. (n.d.). Predicting patterns of solar energy buildout to identify opportunities for biodiversity conservation. Biological Conservation 283 (2023): 110074.
- Mainali, K., M. M. Evans, D. Saavedra, E. Mills, B. Madsen, and S. Minnemeyer. 2023a. Convolutional neural network for high-resolution wetland mapping with open data: Variable selection and the challenges of a generalizable model. Science of The Total Environment 861:160622.
- Mainali, K., T. Hefley, L. Ries, and W. F. Fagan. 2020. Matching expert range maps with species distribution model predictions. Conservation Biology 34:1292–1304.
- Mainali, K. P., P. B. Singh, M. Evans, A. Adhikari, Y. Hu, and H. Hu. 2023b. A brighter shade of future climate on Himalayan musk deer Moschus leucogaster. Scientific Reports 13:12771.
- Mainali, K. P., D. L. Warren, K. Dhileepan, A. McConnachie, L. Strathie, G. Hassan, D. Karki, B. B. Shrestha, and C. Parmesan. 2015. Projecting future expansion of invasive species: comparing and improving methodologies for species distribution modeling. Global Change Biology 21:4464–4480.

Questions?

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Chesapeake Conservancy

Conservation Innovation Center