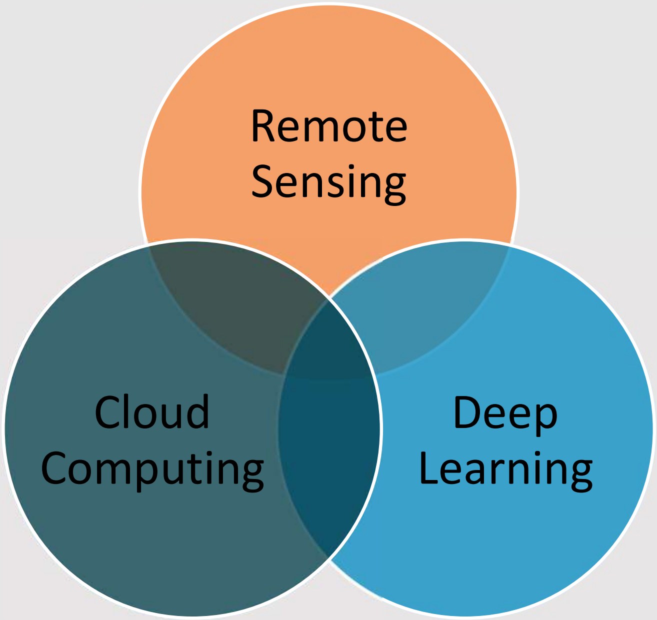
Deep Learning in the Chesapeake

Dr. Michael Evans, Sr. Data Scientist

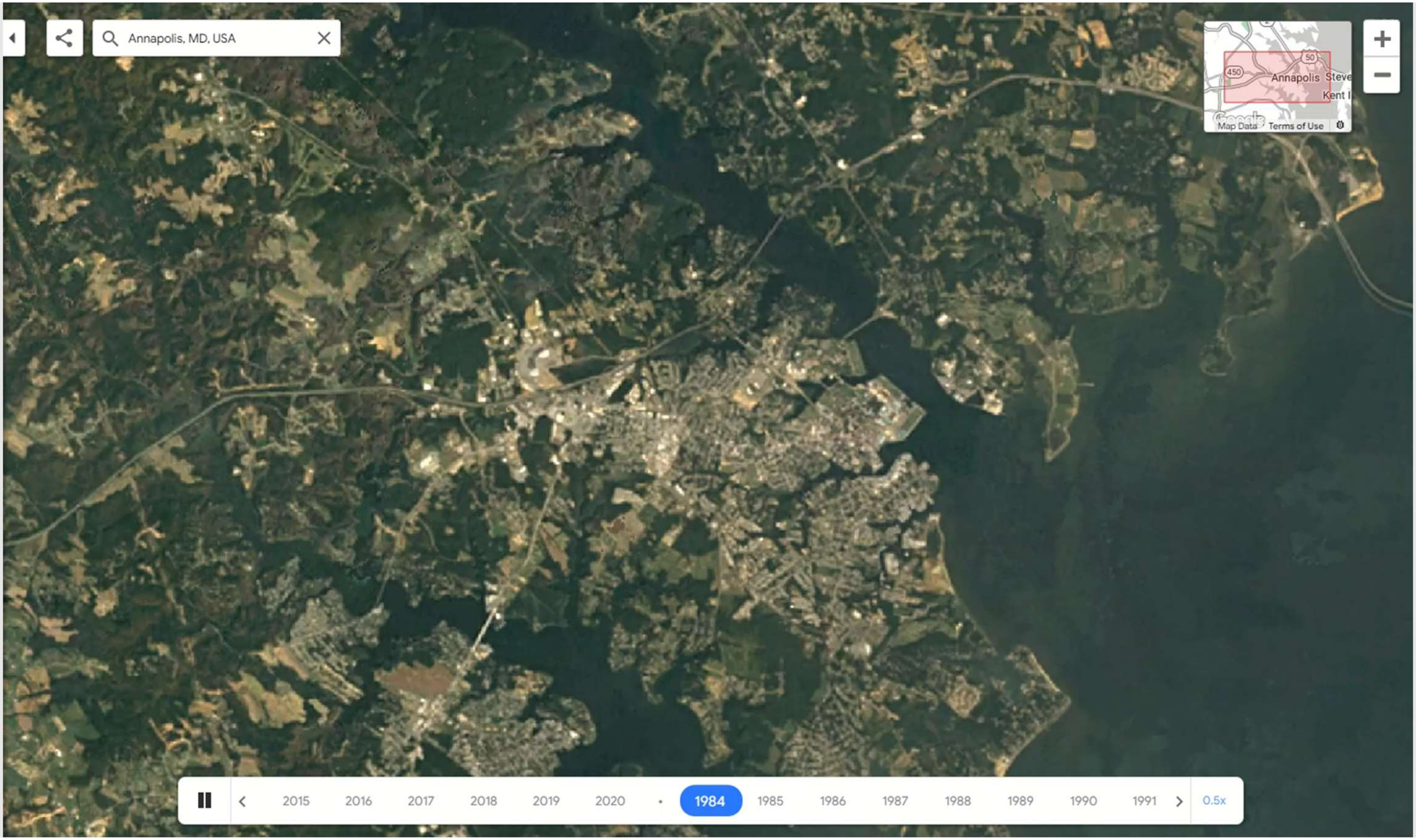
Where are the things we care about?

Why are they where they are?

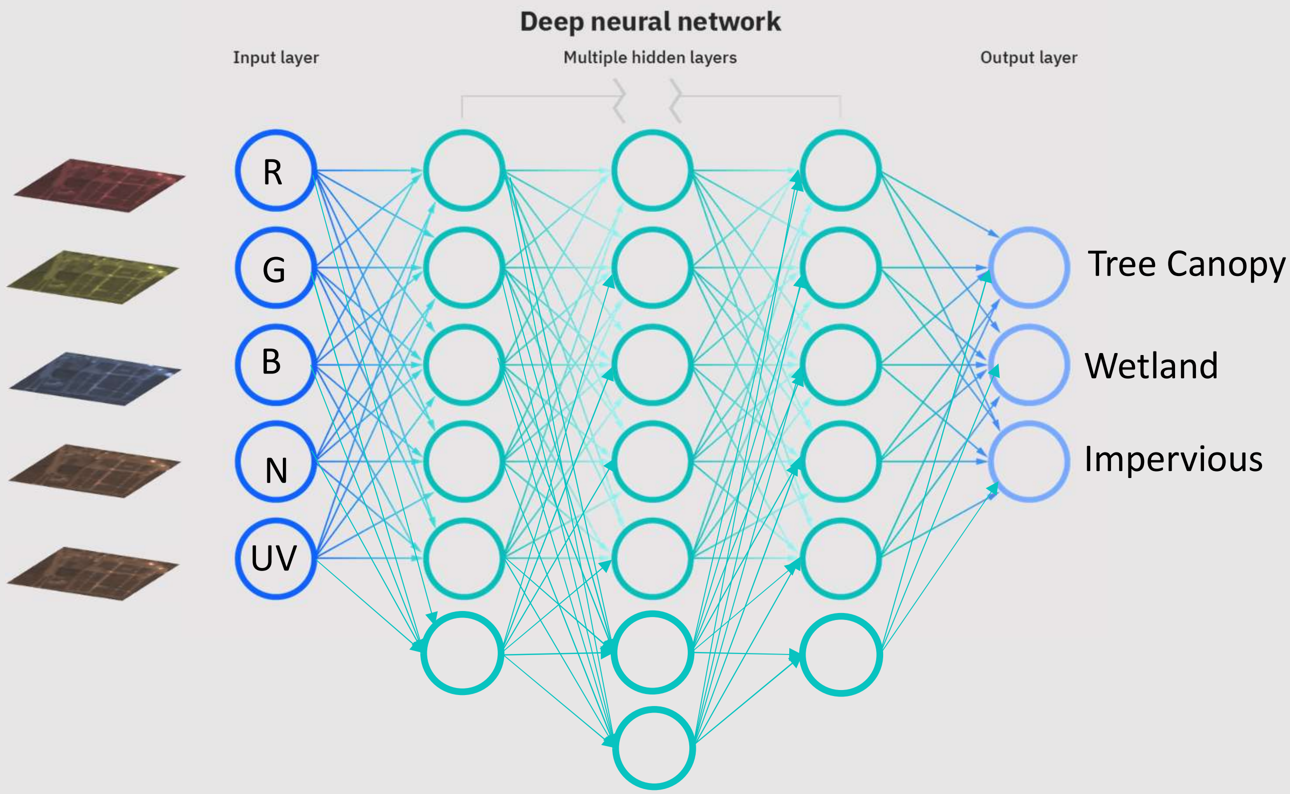


Remote Sensing

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.)

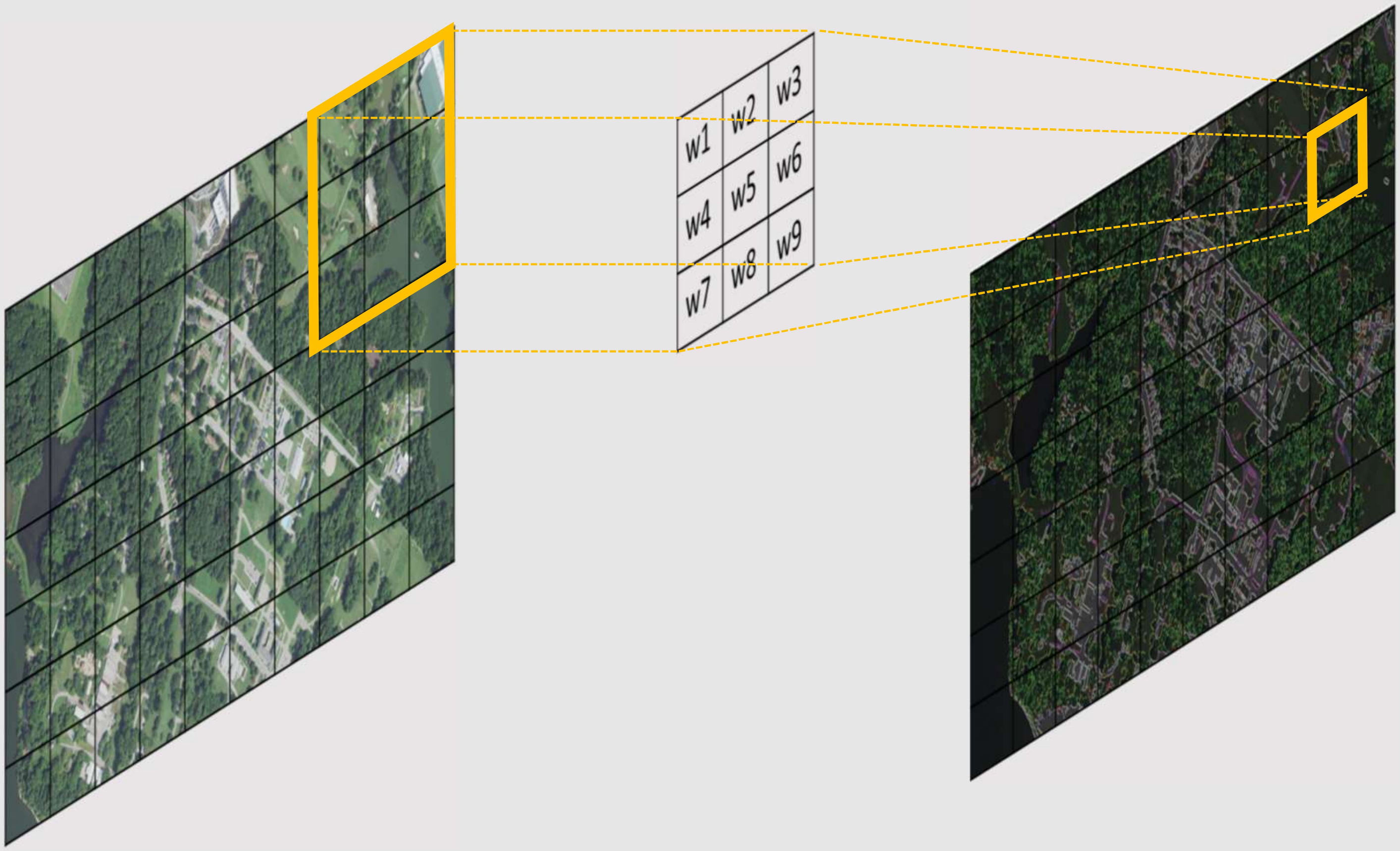

Annapolis, MD, USA
Annapolis
Steve
Kent I
450
50
Map Data
Terms of Use
2015
2016
2017
2018
2019
2020
1984
1985
1986
1987
1988
1989
1990
1991
0.5x

Deep Learning (AI)



Good at learning non-linearities, conditionality, complex interactions

Convolution – Spatial Patterns



Convolution - Spatial Patterns

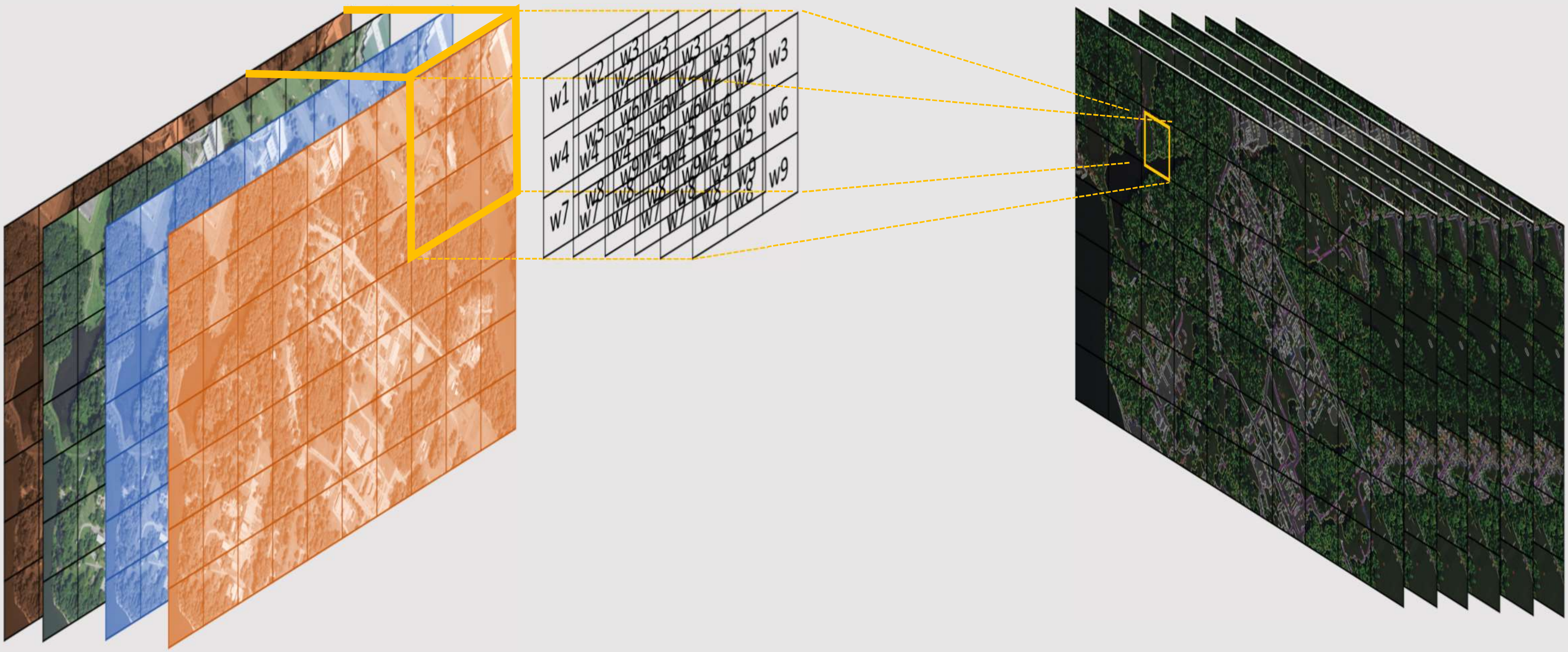
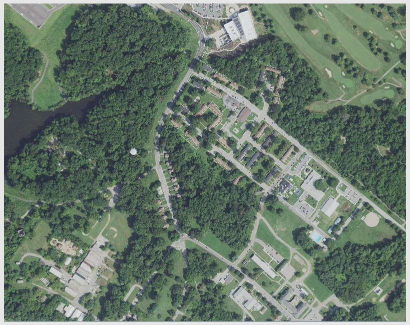


Image Segmentation (U-Net)



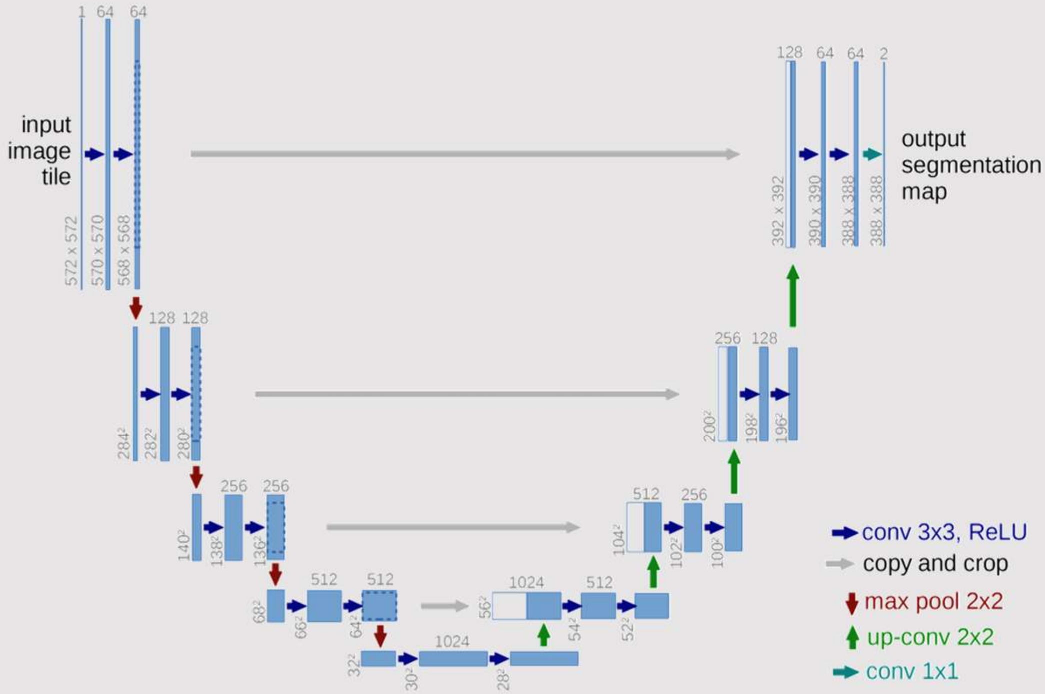
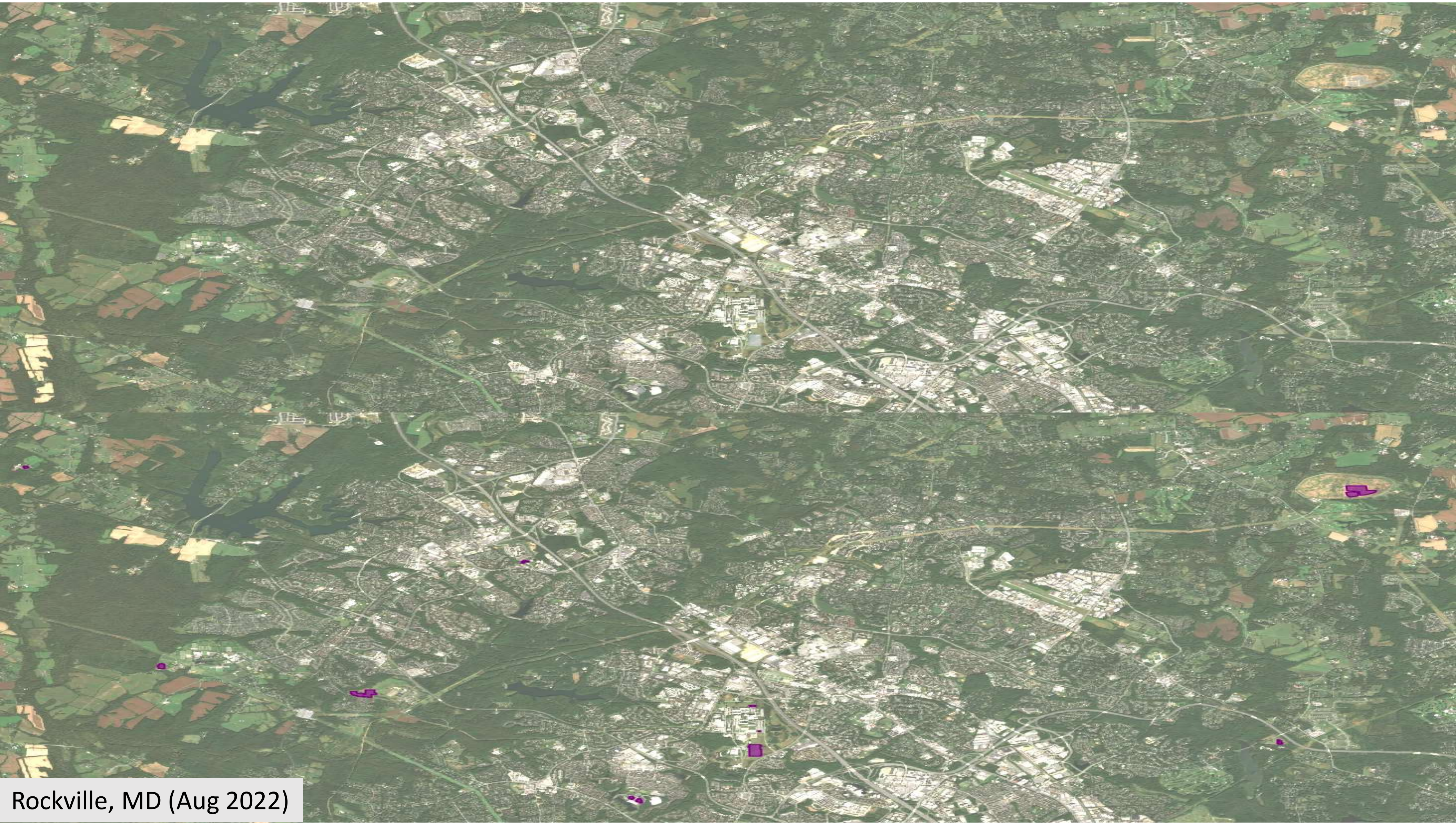


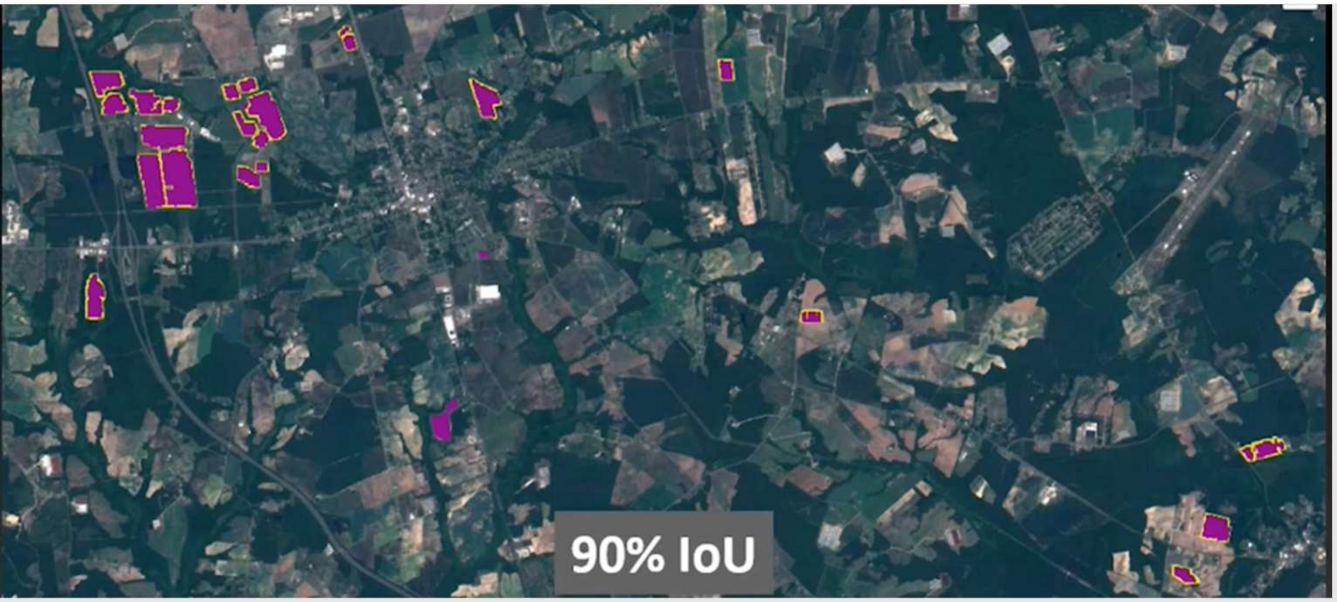
Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

Ronneberger et al. 2015

Solar array mapping

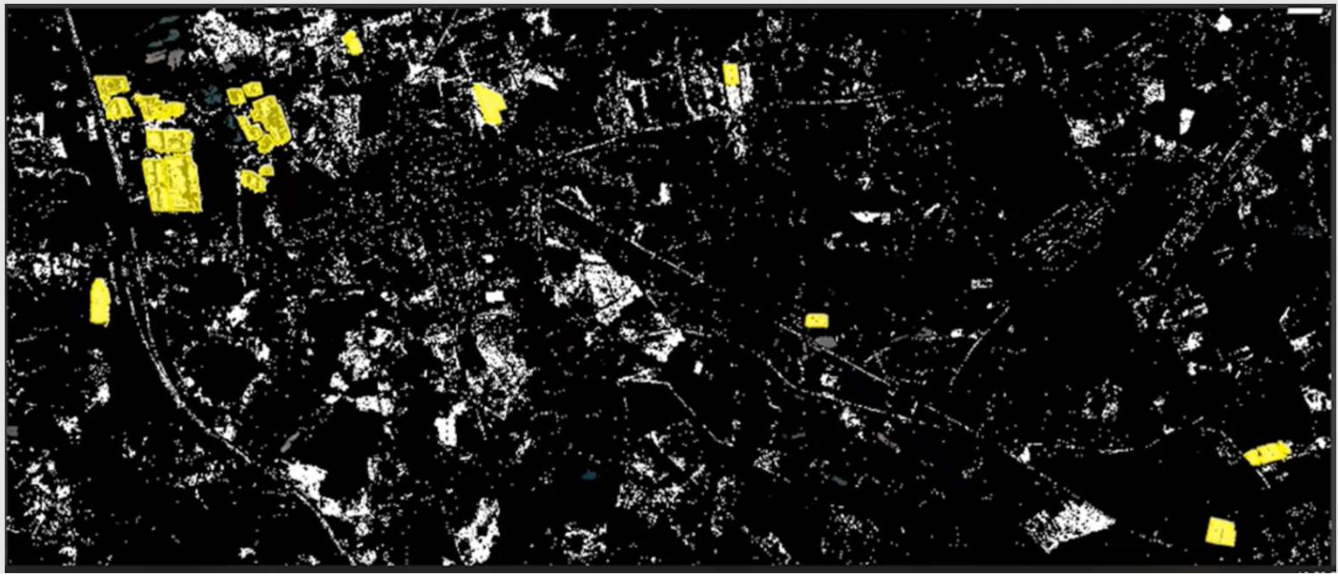
1. Map solar arrays with AI
2. Quantify land use transitions
3. Predict future trends


Rockville, MD (Aug 2022)

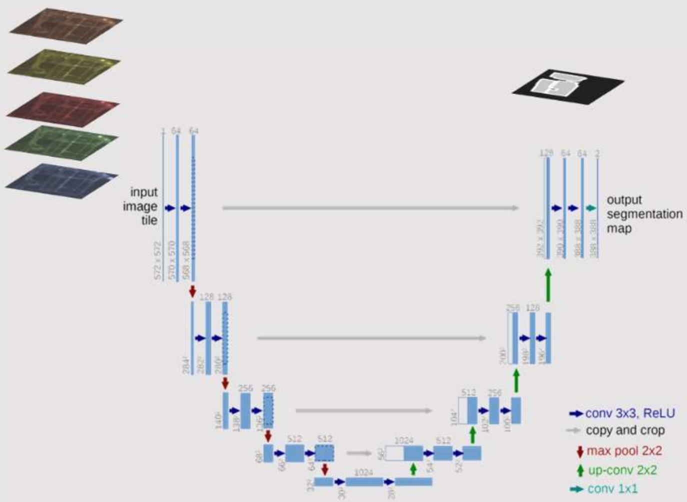


Convolution – learn the shape and context of objects in images

Traditional ML – evaluates pixels independently



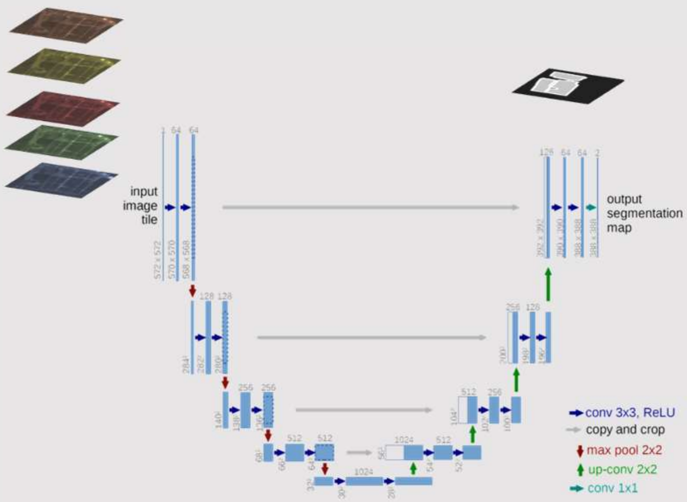
AI Solar Mapping



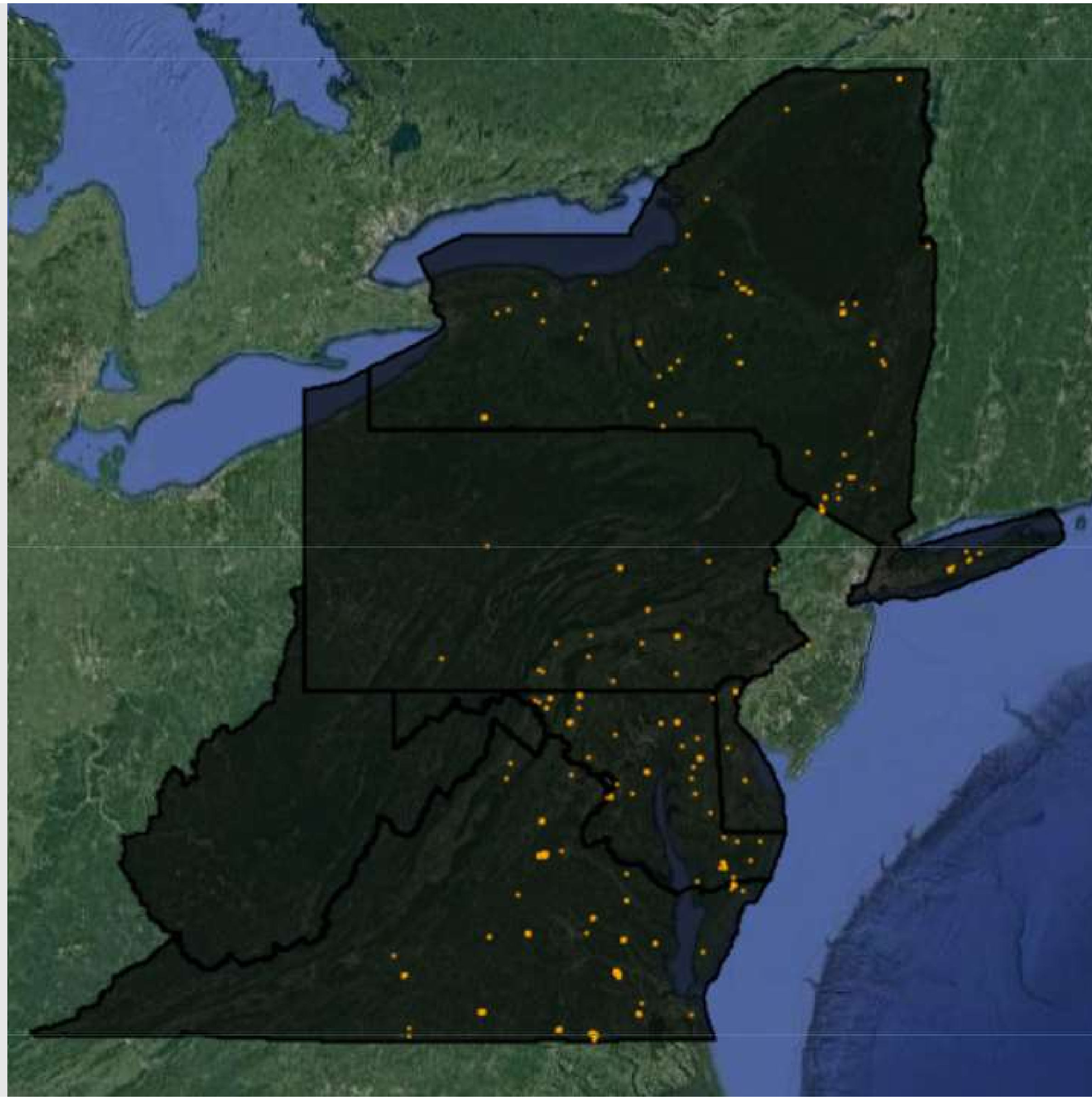
Map all solar arrays in DC, DE, MD, PA, NY, VA, WV

Each year from 2017 - 2021

AI Solar Mapping



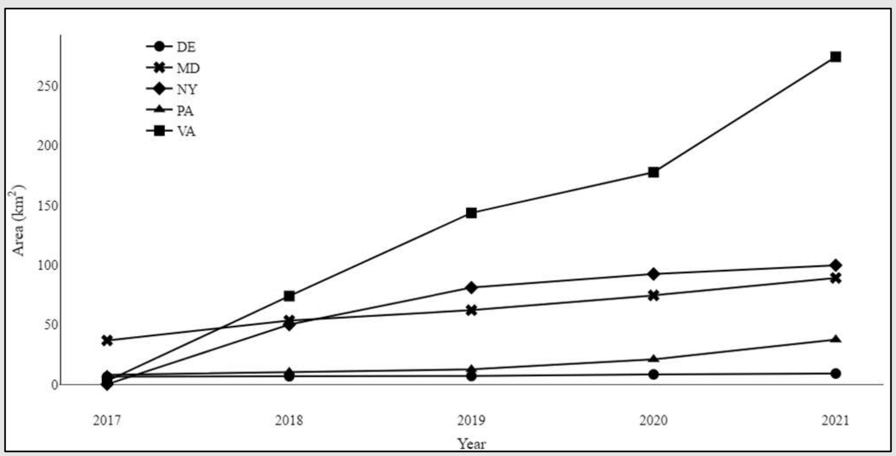
Recall: 90.2%
Precision: 90.1%
IoU: 85.6%



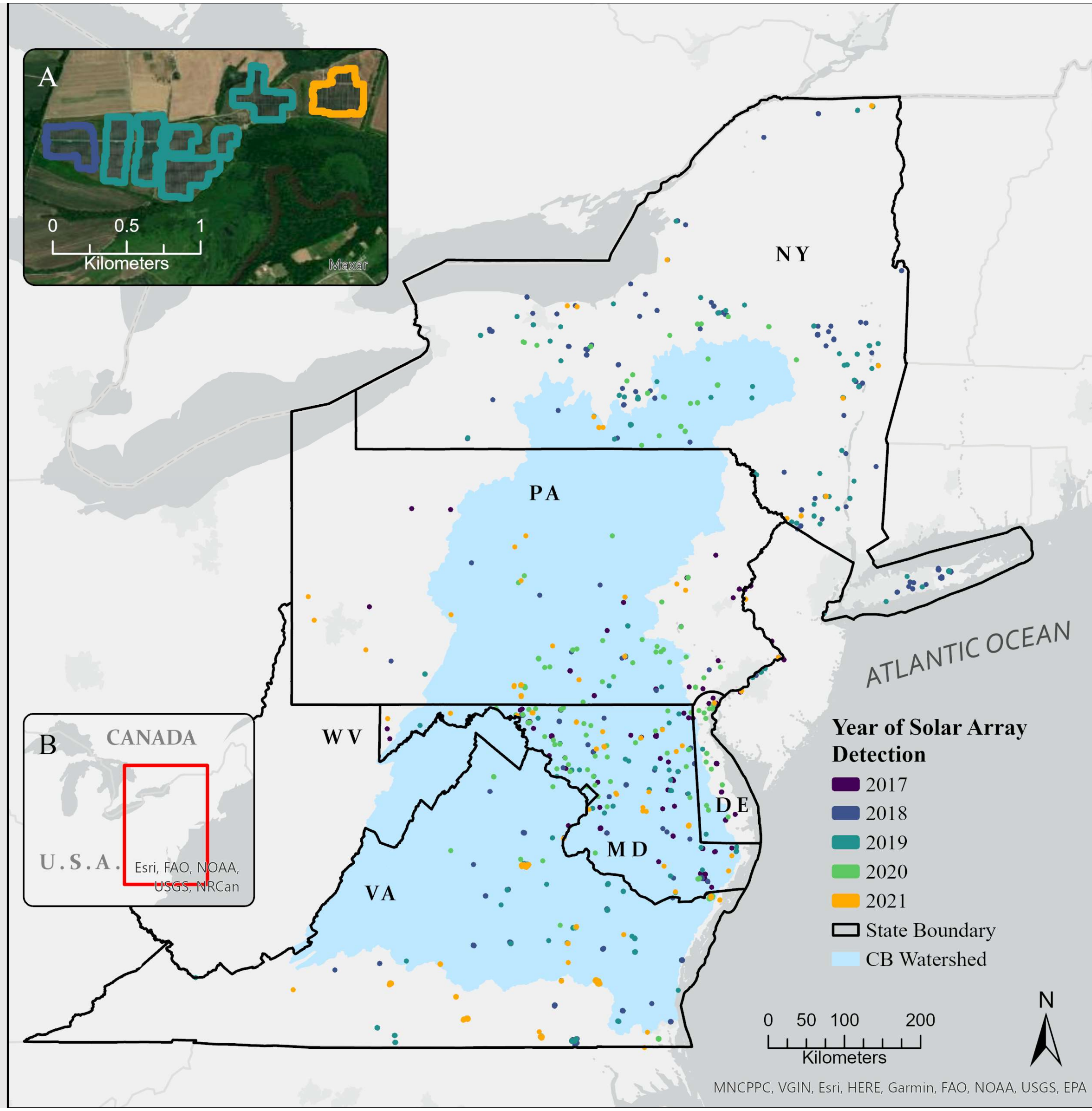
Solar mapping

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**



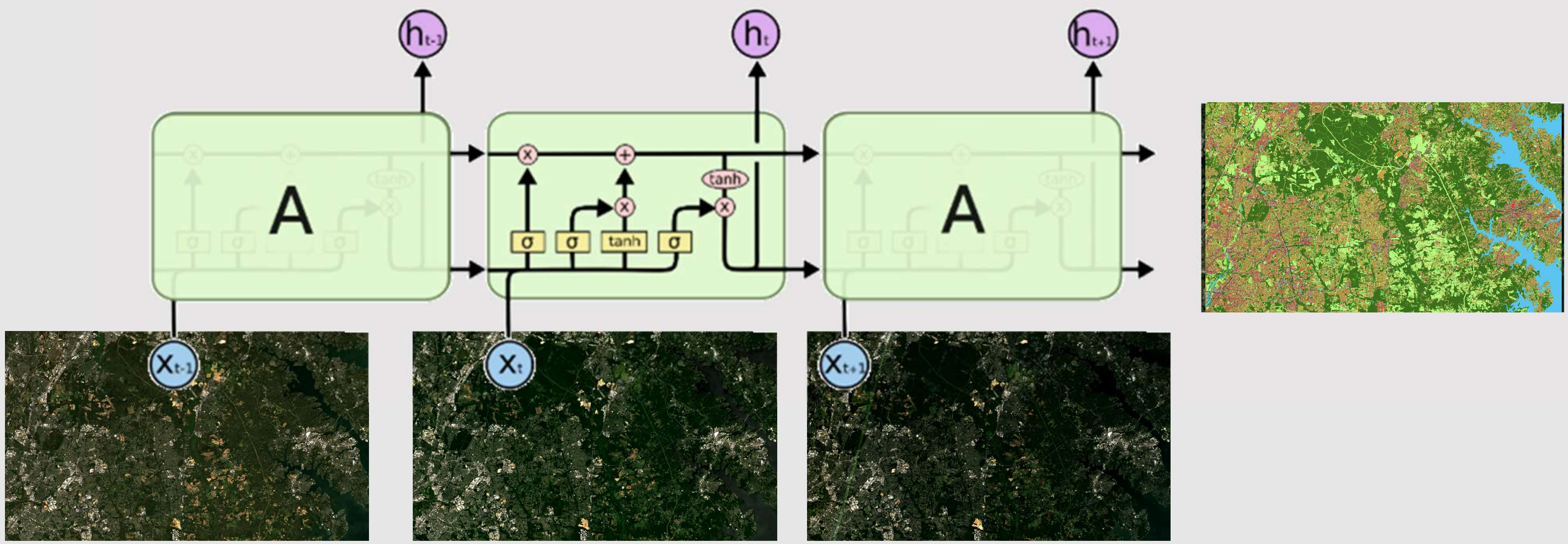
Evans et al. (2023) *Biological Conservation*



Wetland Mapping

1. Deep learning to capture variability across space and through time
2. Pilot methods in 4 county-sized areas
3. Update maps across Chesapeake watershed

LSTM - Temporal Signals



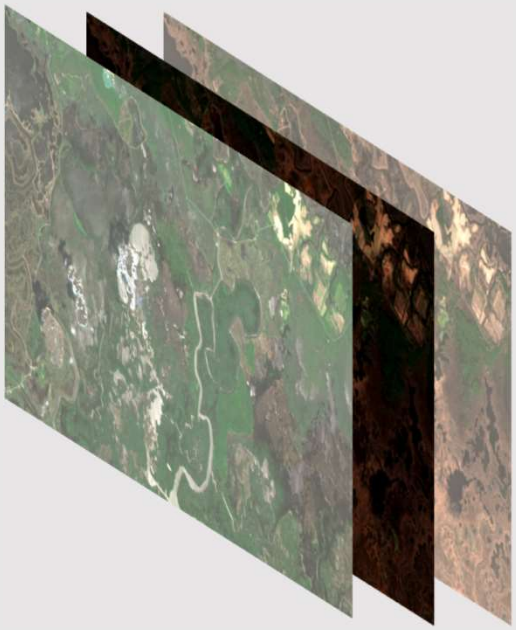
April/May

June/July

Aug/Sep

Input data experiments

Sentinel-2

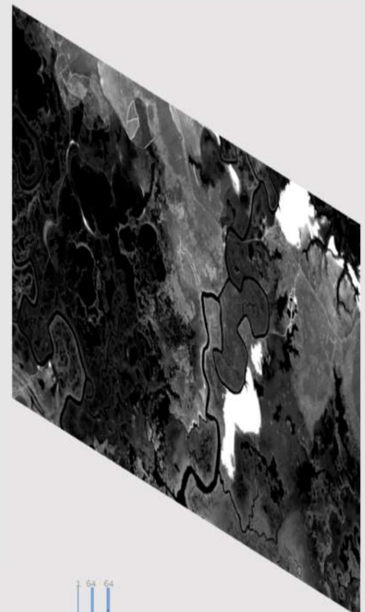


\+

NAIP

\+

LiDAR



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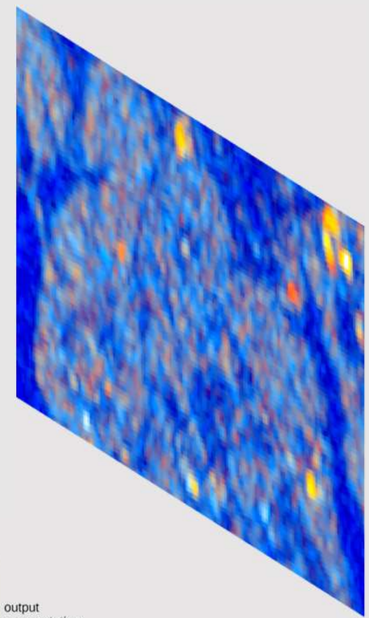
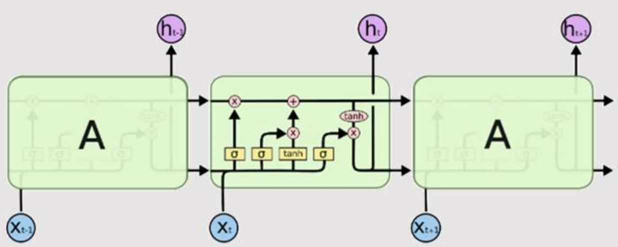
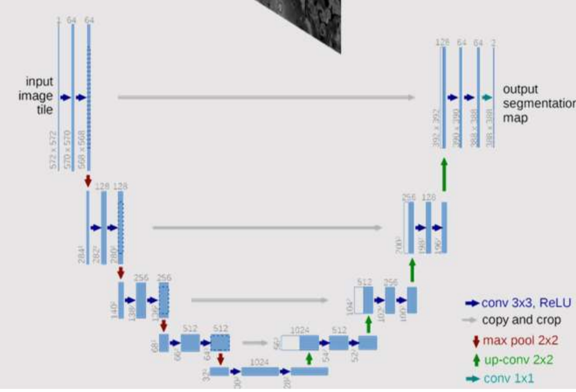
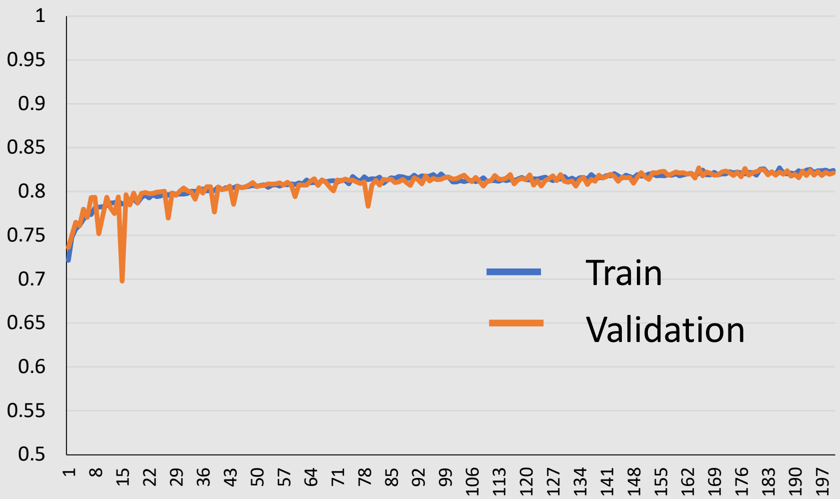
Geomorphons





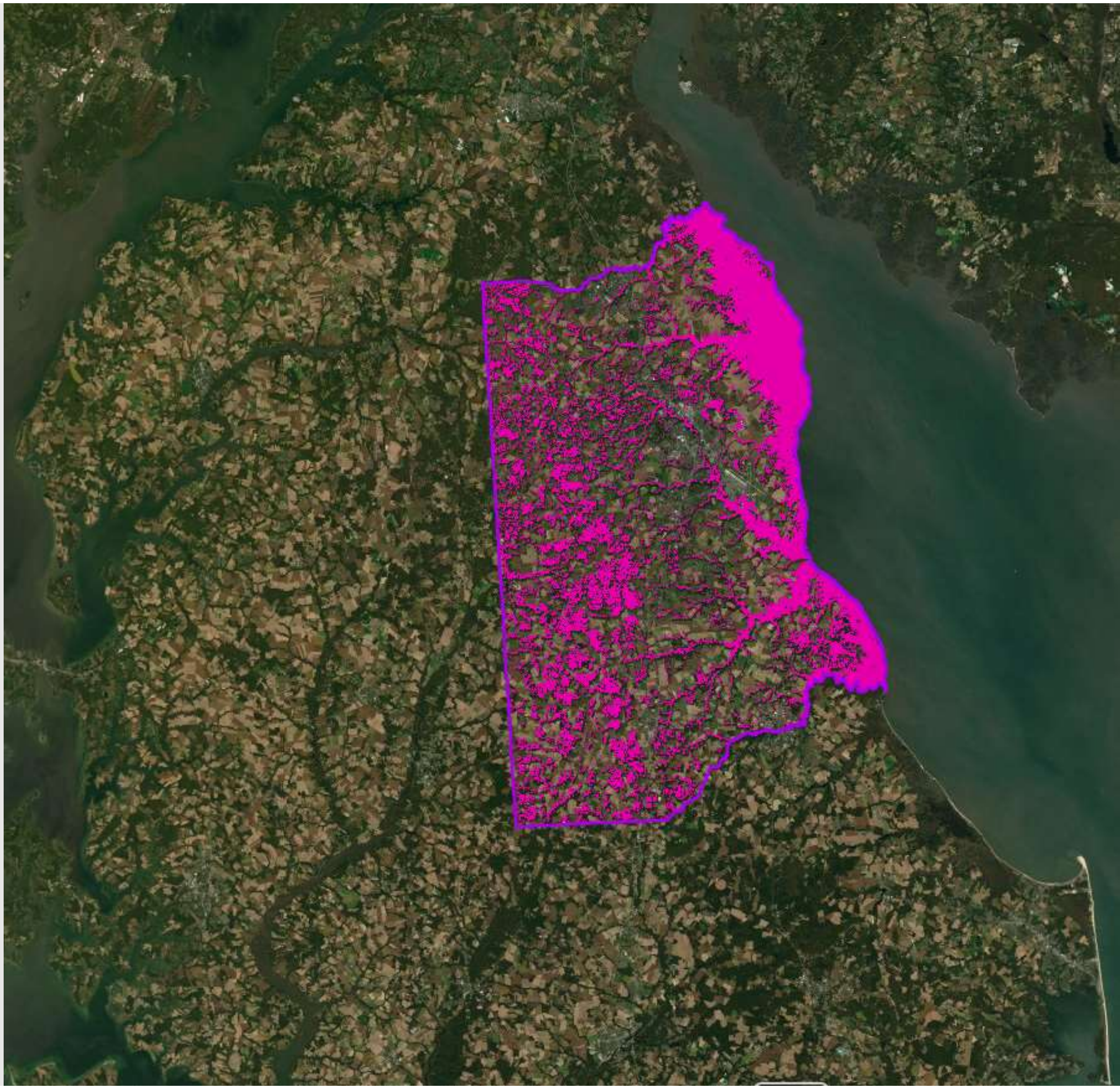


Improving wetland mapping



Recall: 90.2%
Precision: 96.5%
IoU: 87.3%

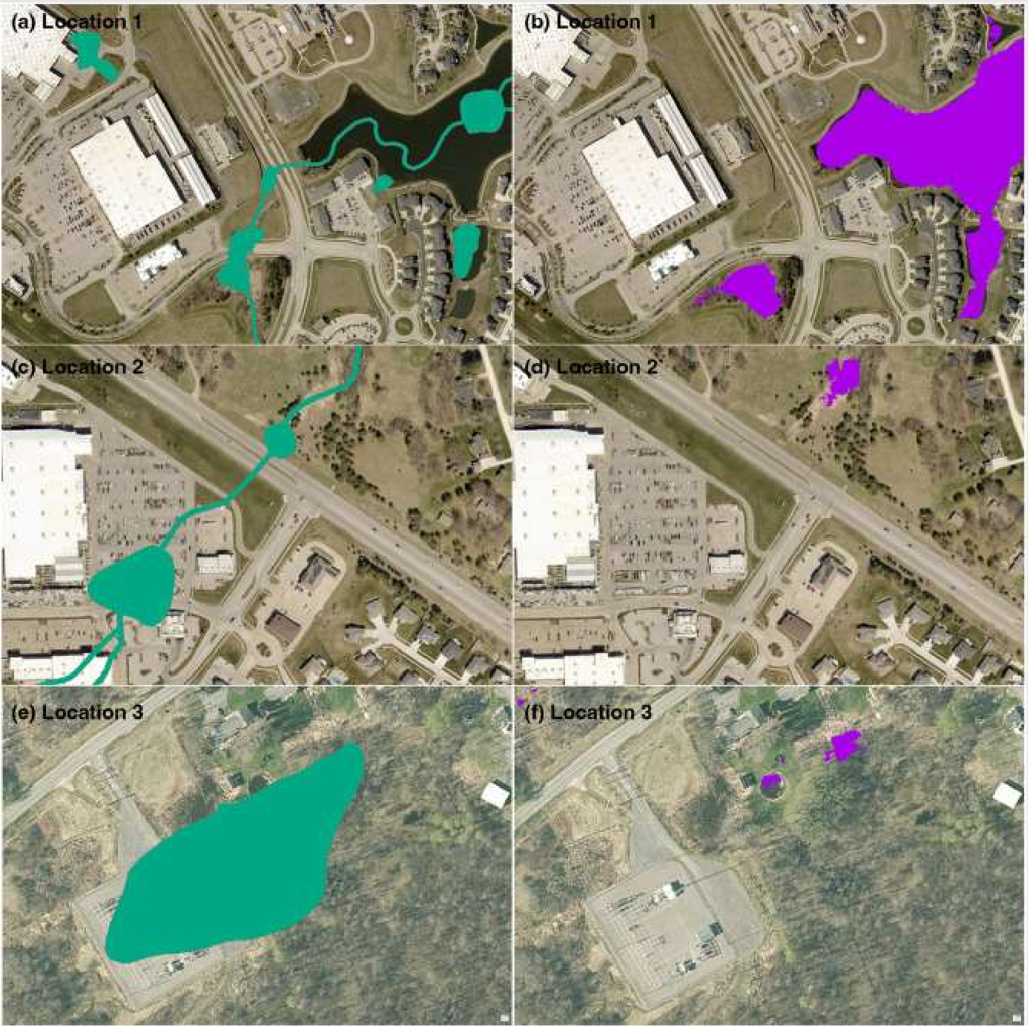
Mainali & Evans (2023) *Science of the Total Environment*

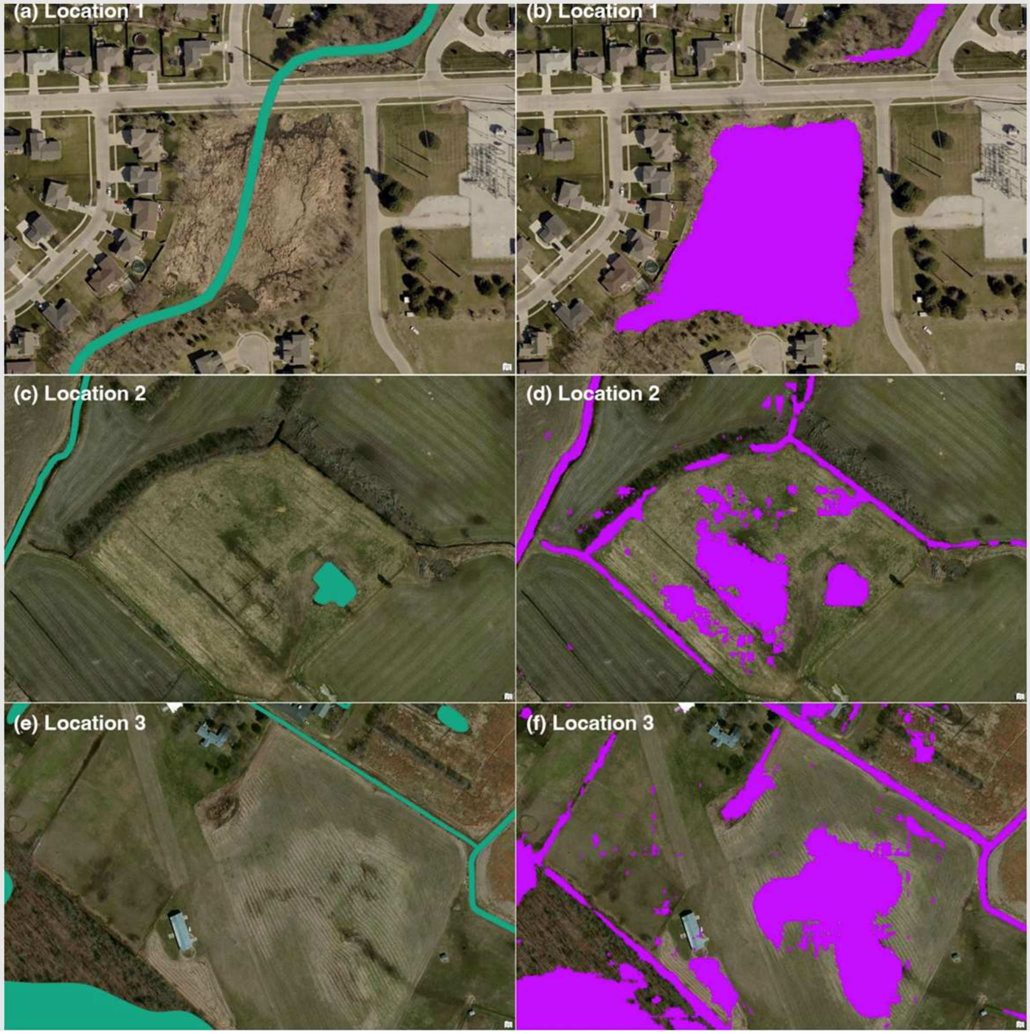


Improving wetland maps

NWI labels

Model predictions





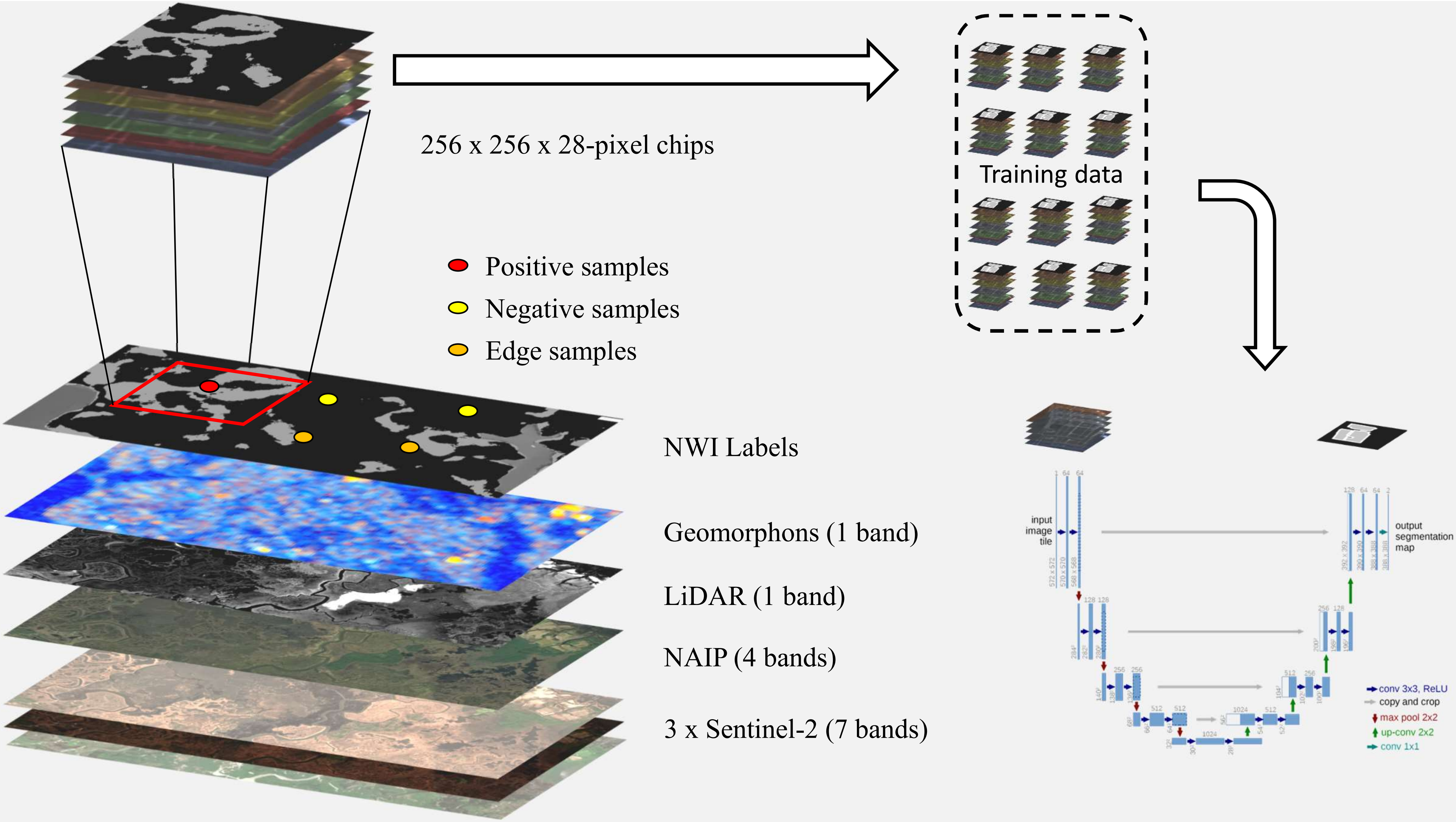
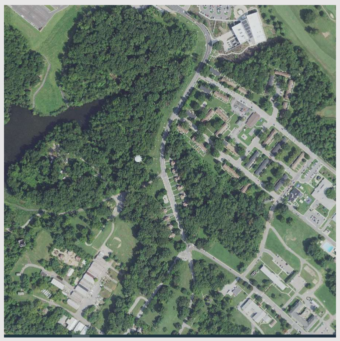
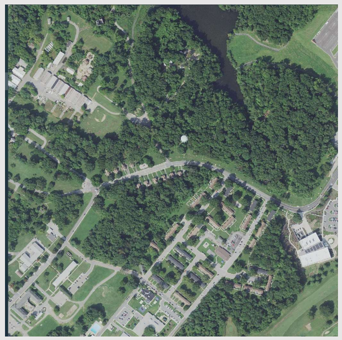

256 x 256 x 28-pixel chips
Training data
Positive samples
Negative samples
Edge samples
NWI Labels
Geomorphons (1 band)
LiDAR (1 band)
NAIP (4 bands)
3 x Sentinel-2 (7 bands)
input
image
tile
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

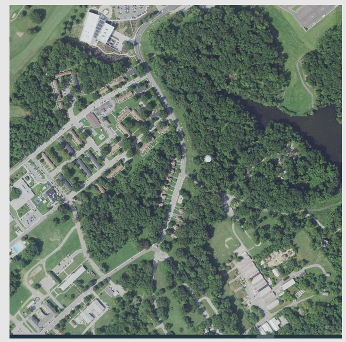
Image Augmentation



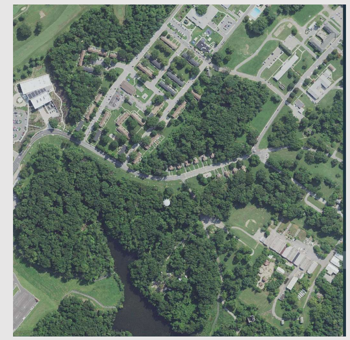
Original



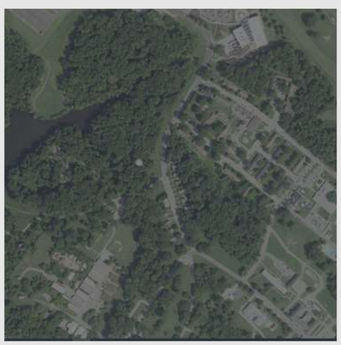
Rotate 90°



Rotate 180°

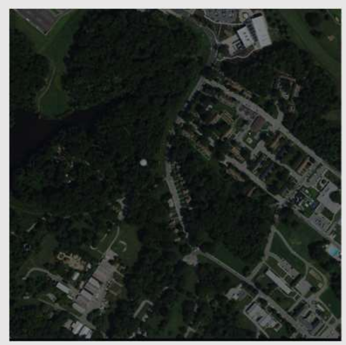


Rotate 270°

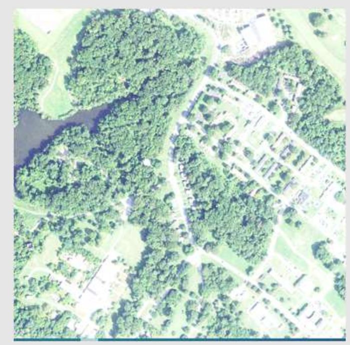


Brightness -5%
Contrast -5%

Brightness +5%
Contrast -5%

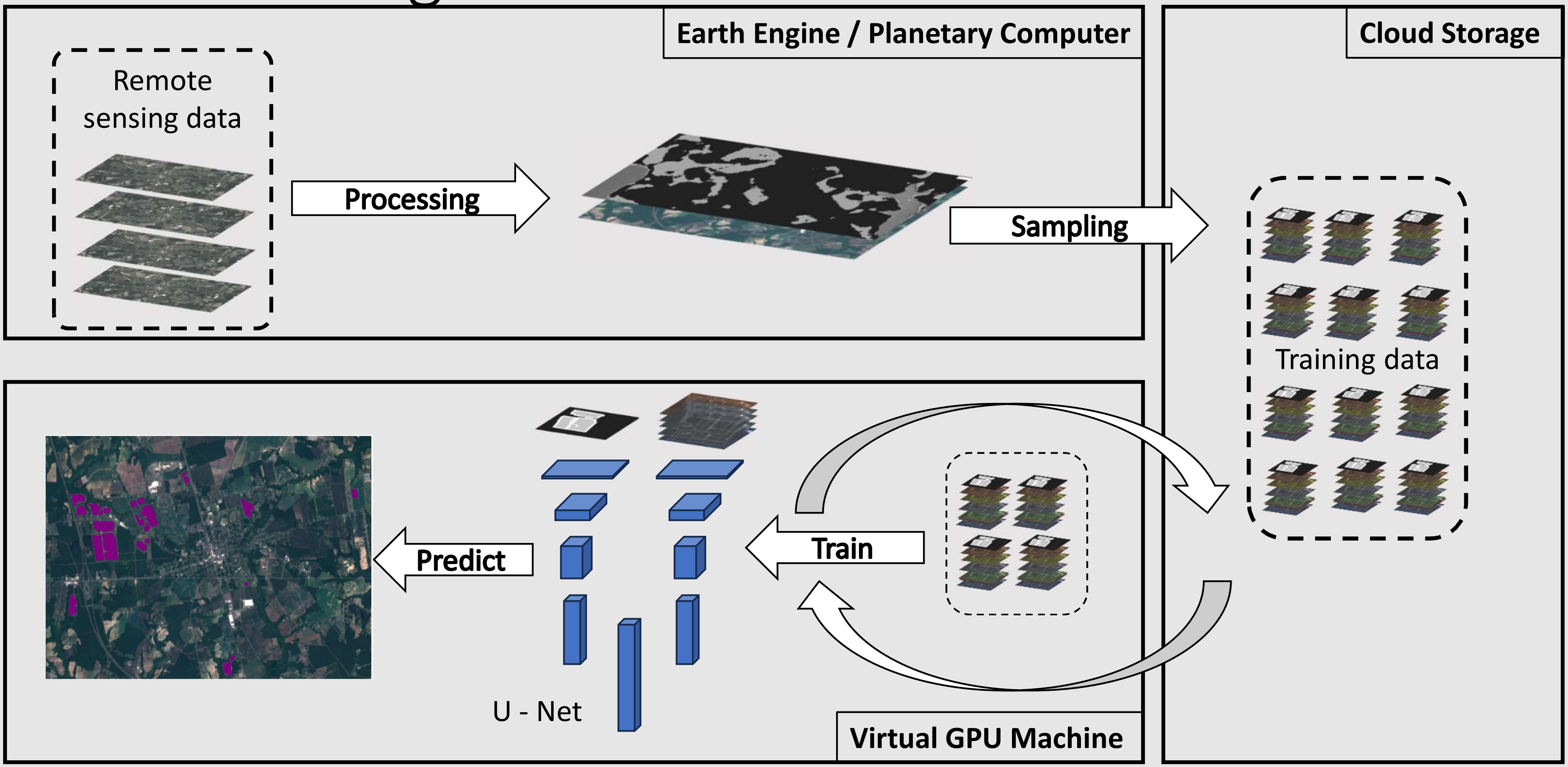


Brightness -5%
Contrast +5%



Brightness +5%
Contrast +5%

Model Training Workflow



Questions?

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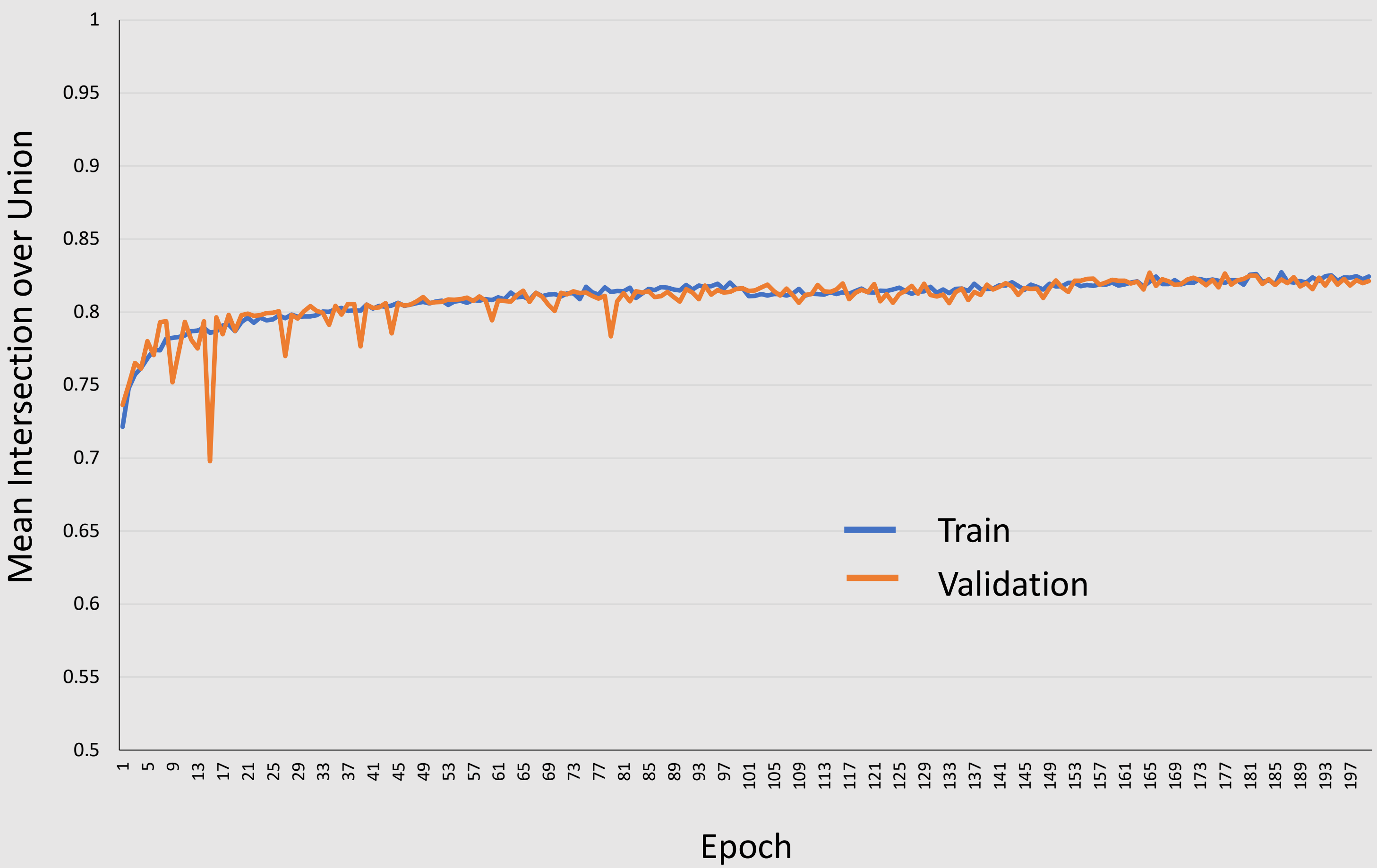
Chesapeake Conservancy

EXPLORE. CONSERVE. INNOVATE.

CONSERVATION INNOVATION CENTER

CHESAPEAKE CONSERVANCY

Wetland Model Performace



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