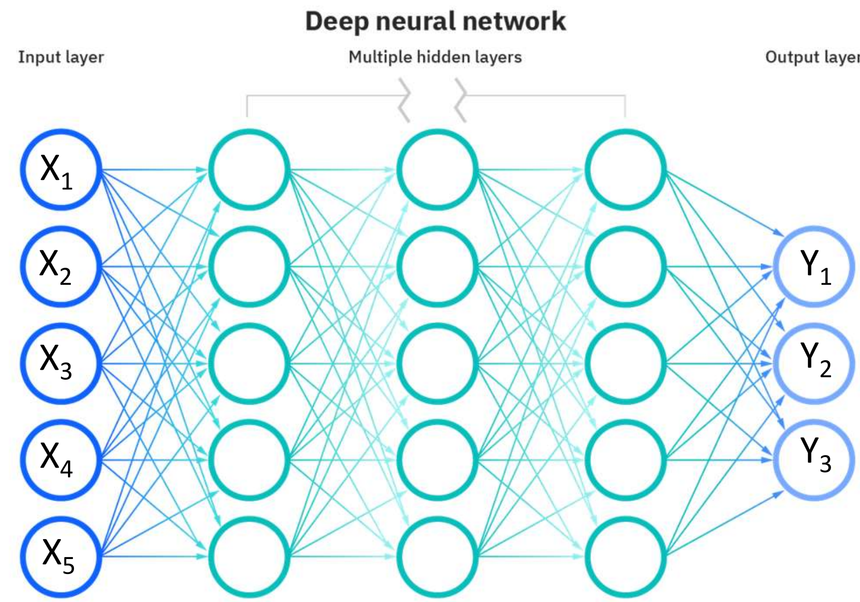
Predicting solar growth in the Chesapeake

Dr. Michael Evans
Senior Data Scientist

Solar growth in the Chesapeake

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

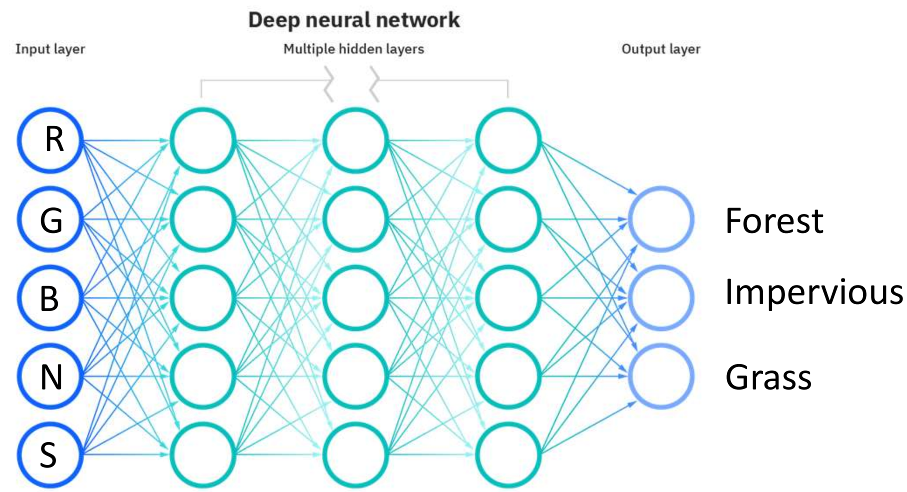
Deep Learning (AI)



Great at accommodating non-linearities, conditionality, complex interactions

Deep Learning + Remote Sensing

1. We want custom maps
2. AI interprets multiple 'bands'
3. Take advantage of 2D shape



Deep Learning + Remote Sensing

Convolution – learning spatial relations

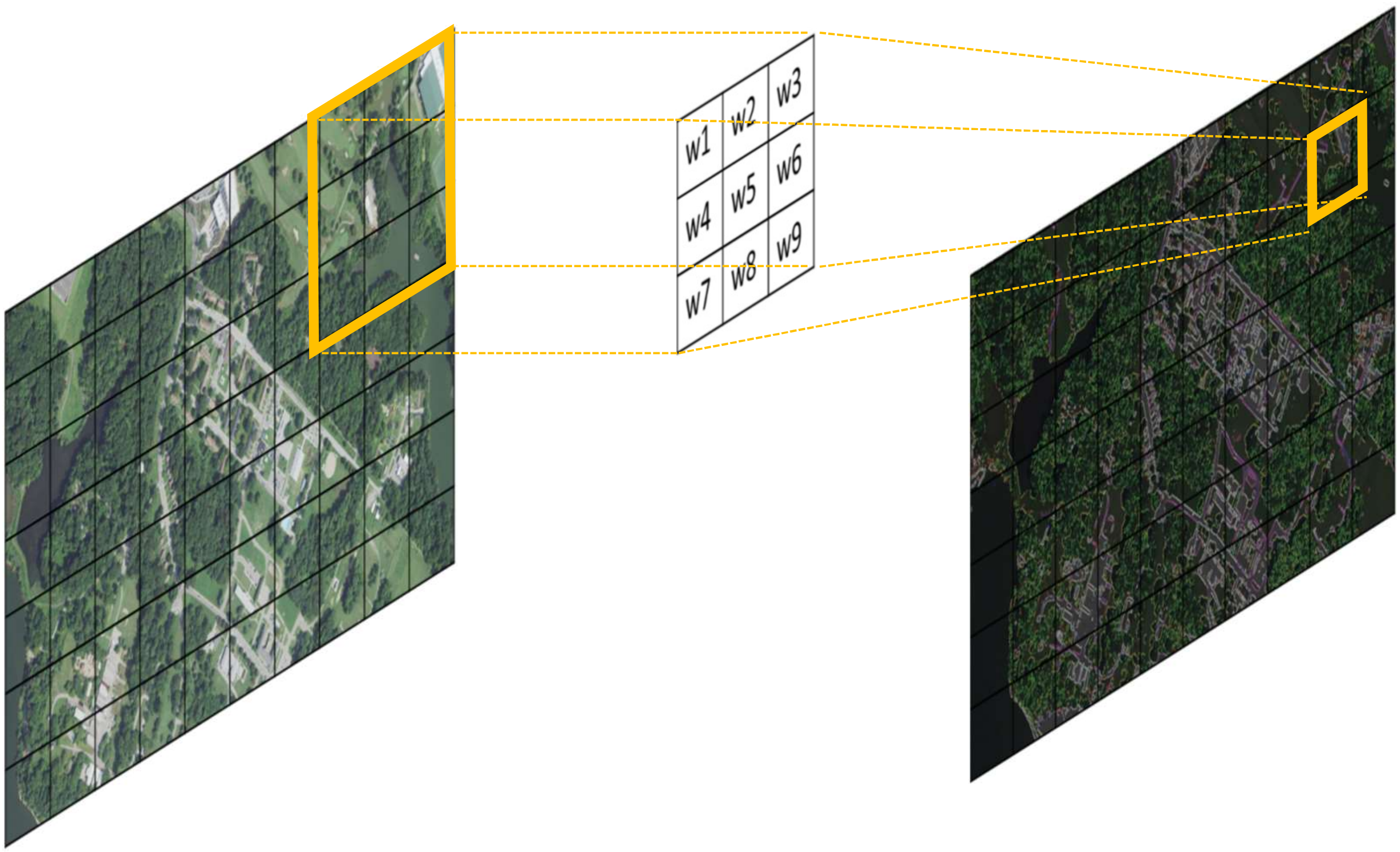
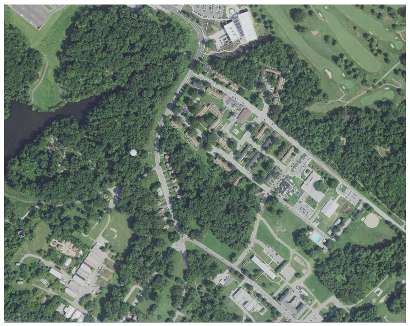


Image Segmentation with U-Net



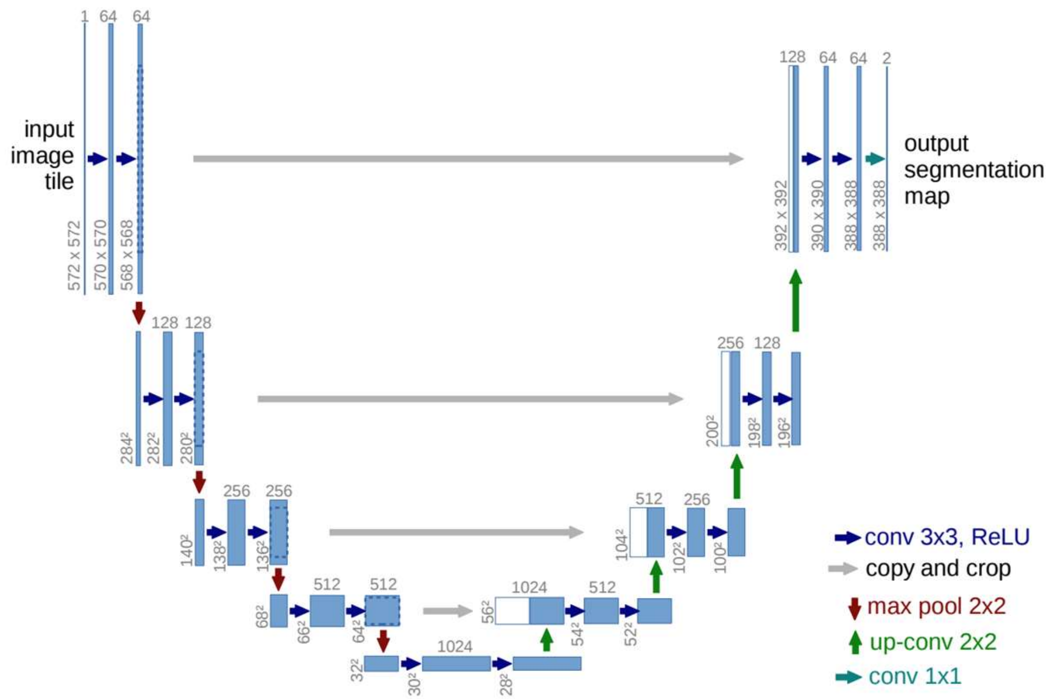
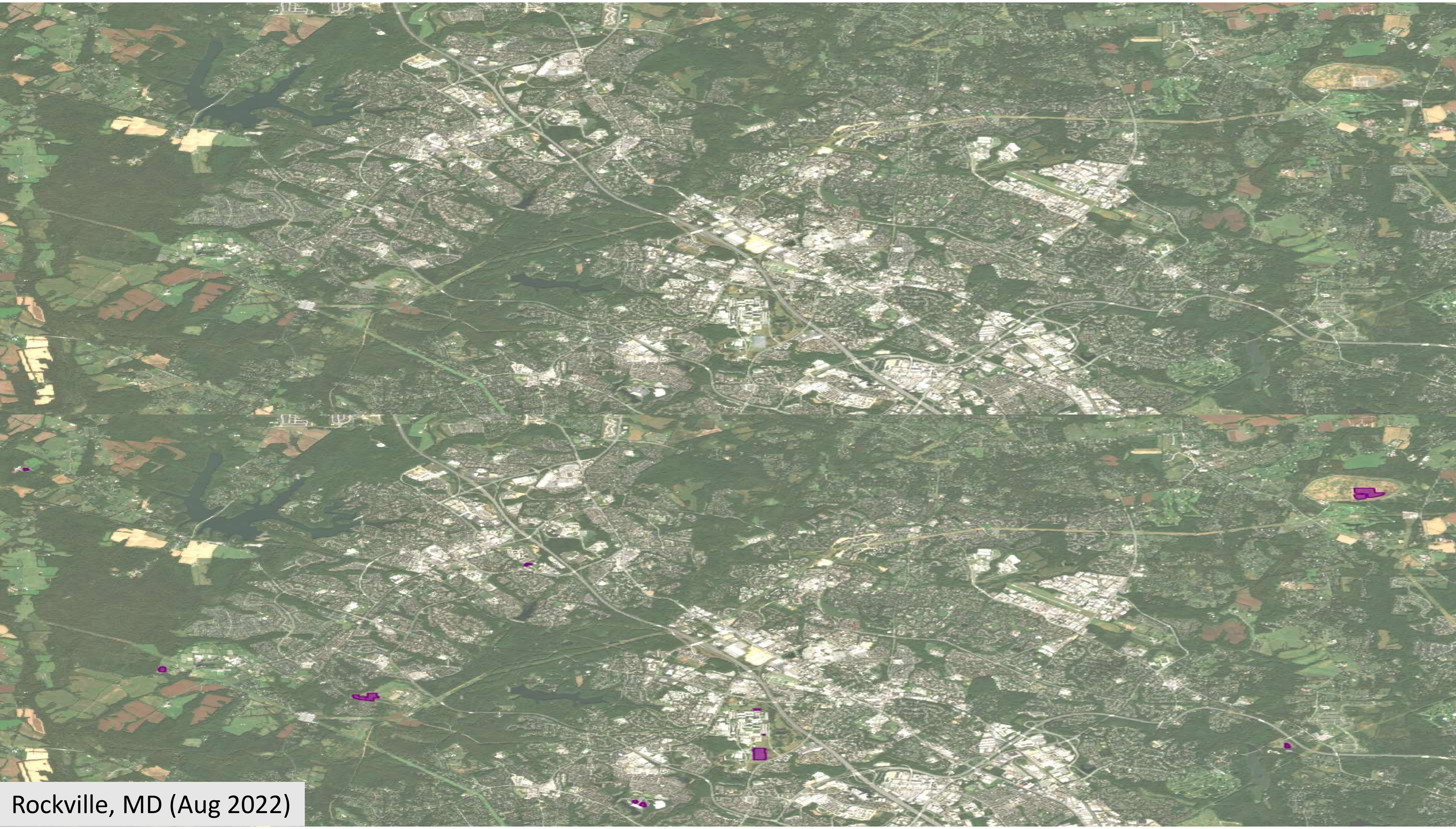


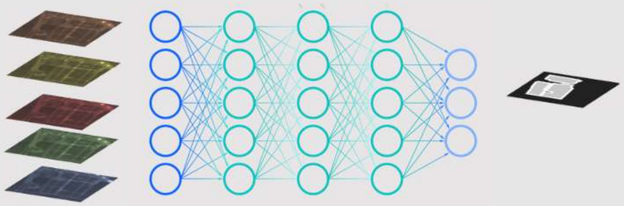
Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows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

Ronneberger et al. 2015



Rockville, MD (Aug 2022)

Solar Mapping

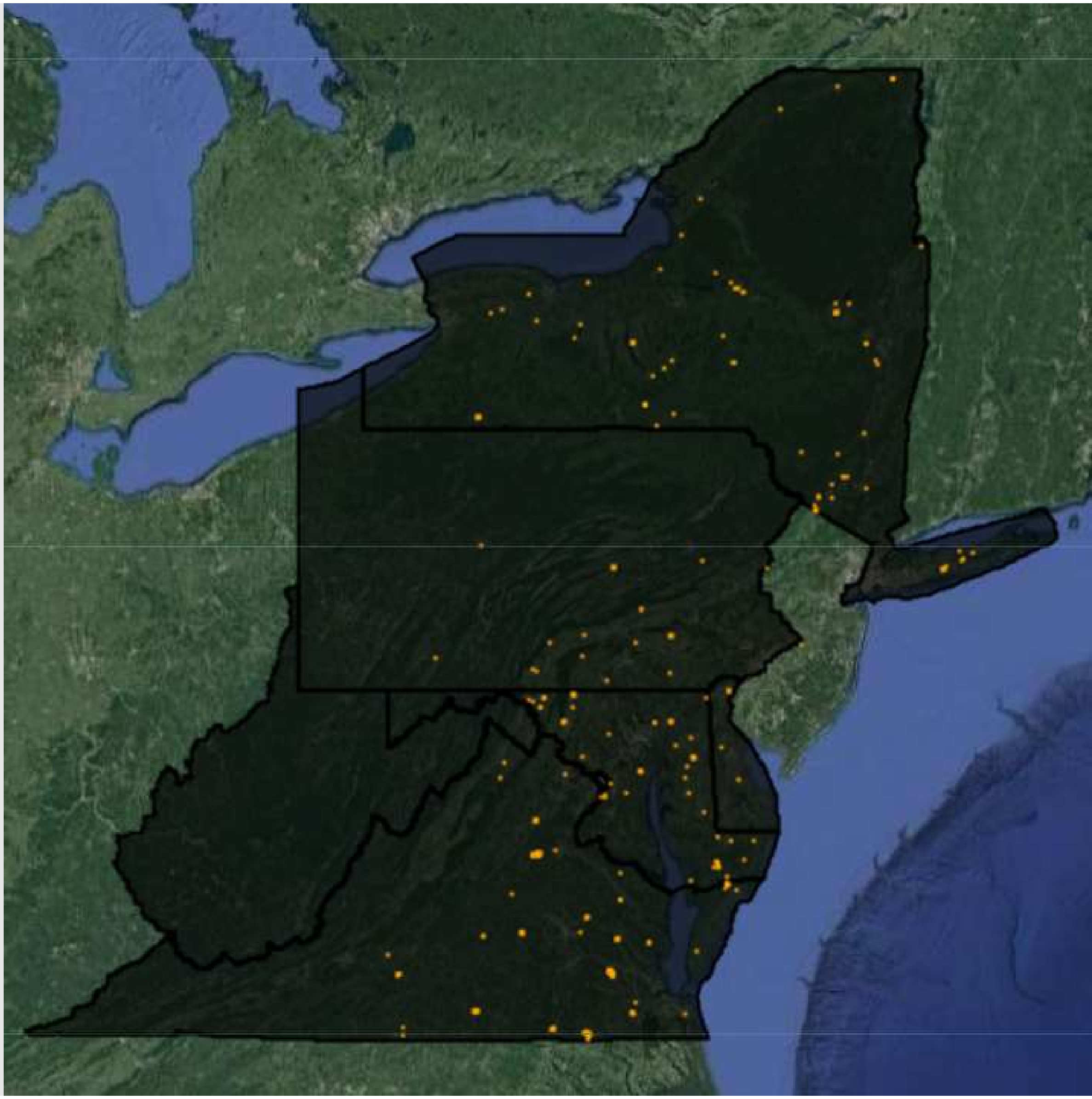


Recall: 90.2%
Precision: 90.1%
IoU: 85.6%

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

Each year from 2017 - 2021

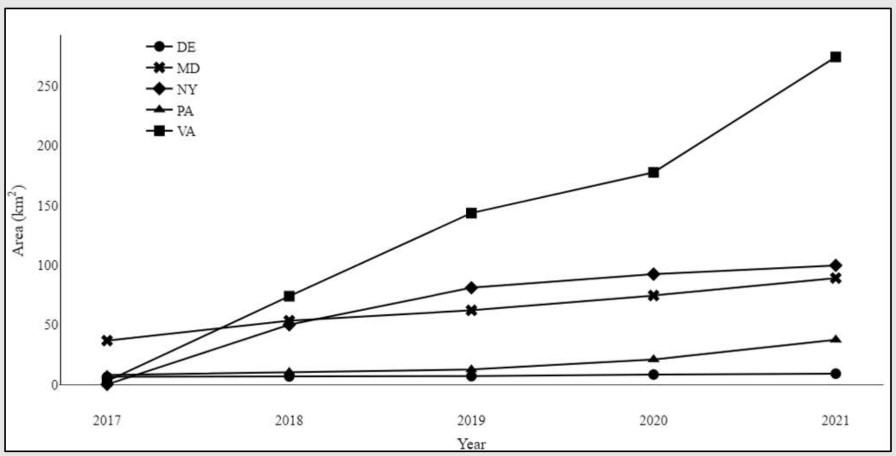
By 2021:
958 arrays detected*
523.2 km^2

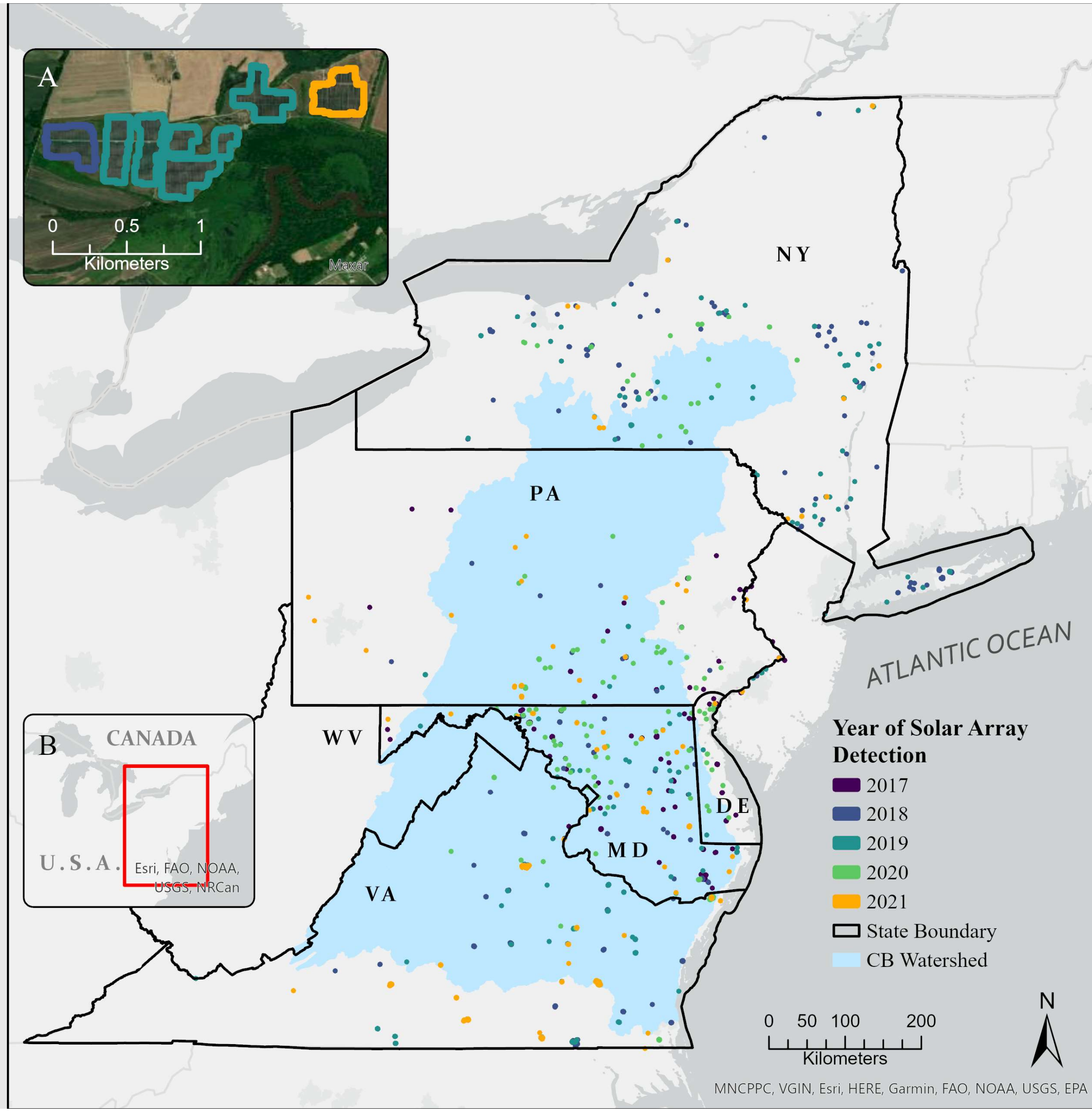


Solar mapping

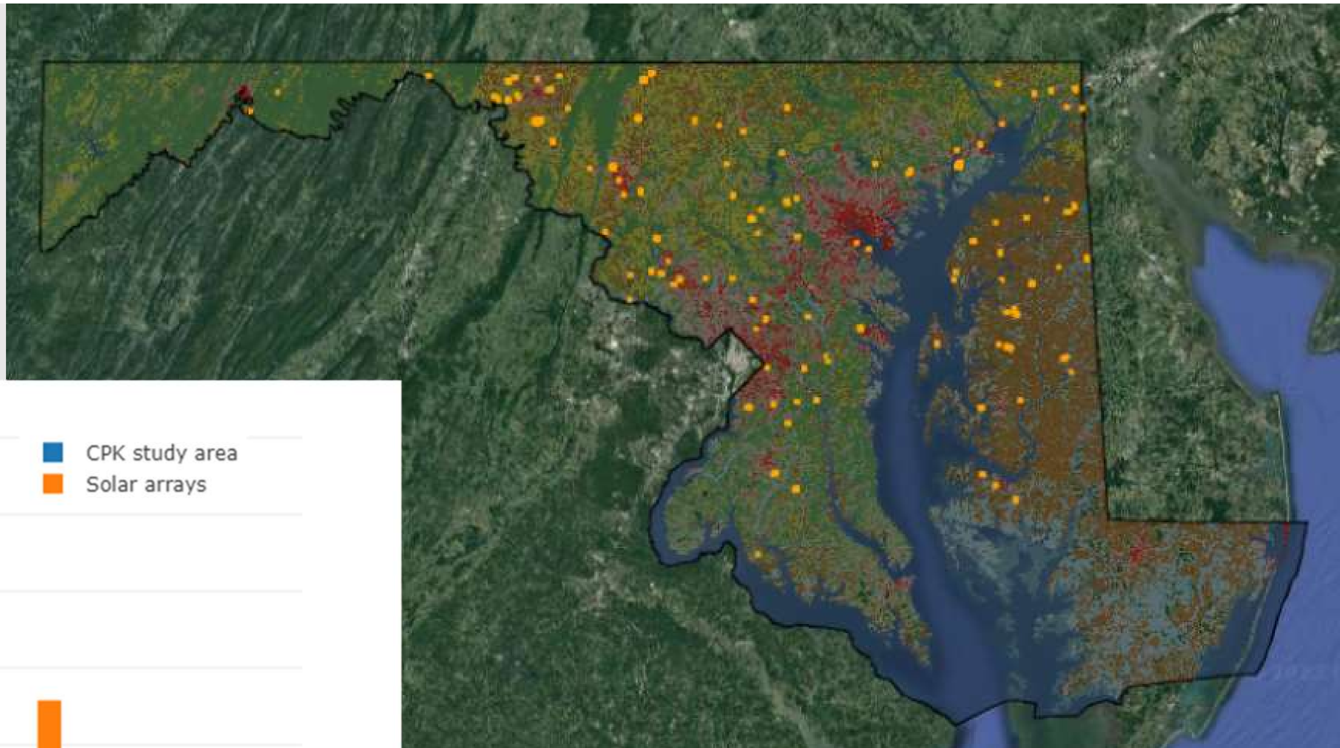
2017 - 2021

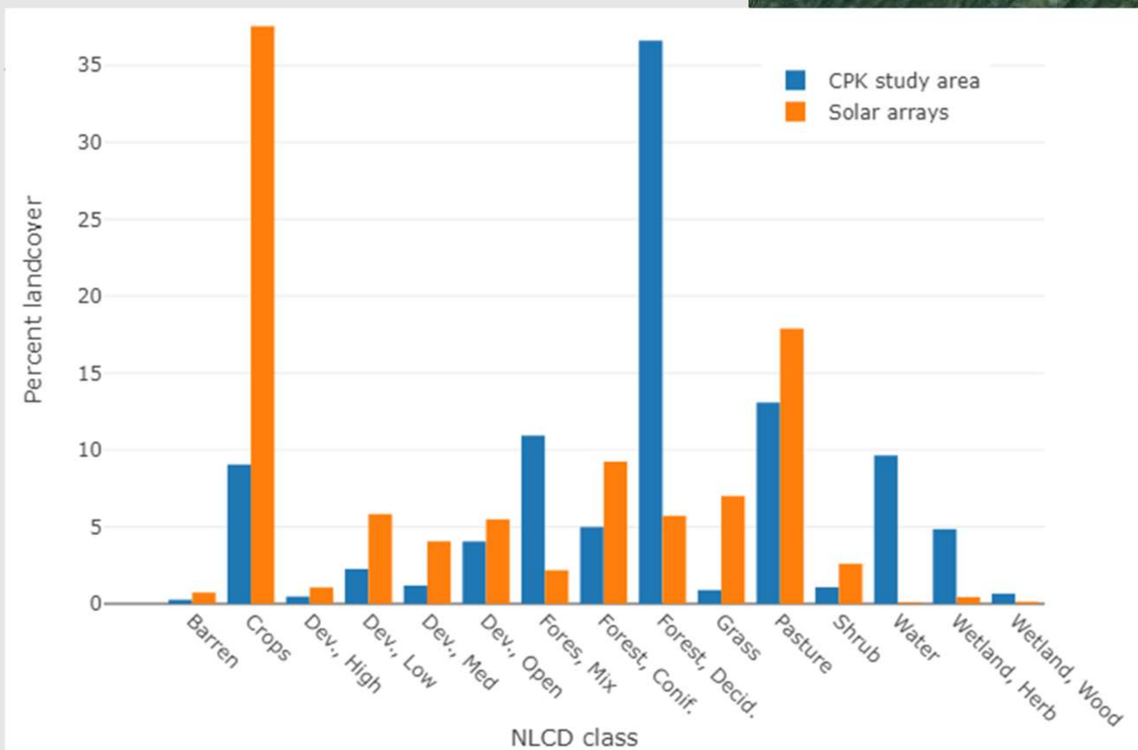
State	Area (%)	Rate of increase
DE	9.01 (1.79E-04)	1.40 ± 0.34E-03
MD	89.05 (3.54E-04)	**5.00 ± 0.34E-03**
NY	99.68 (0.82E-04)	1.33 ± 0.48E-03
PA	37.45 (0.32E-04)	0.61 ± 0.34E-03
VA	274.17 (2.69E-04)	**6.27 ± 0.34E-03**



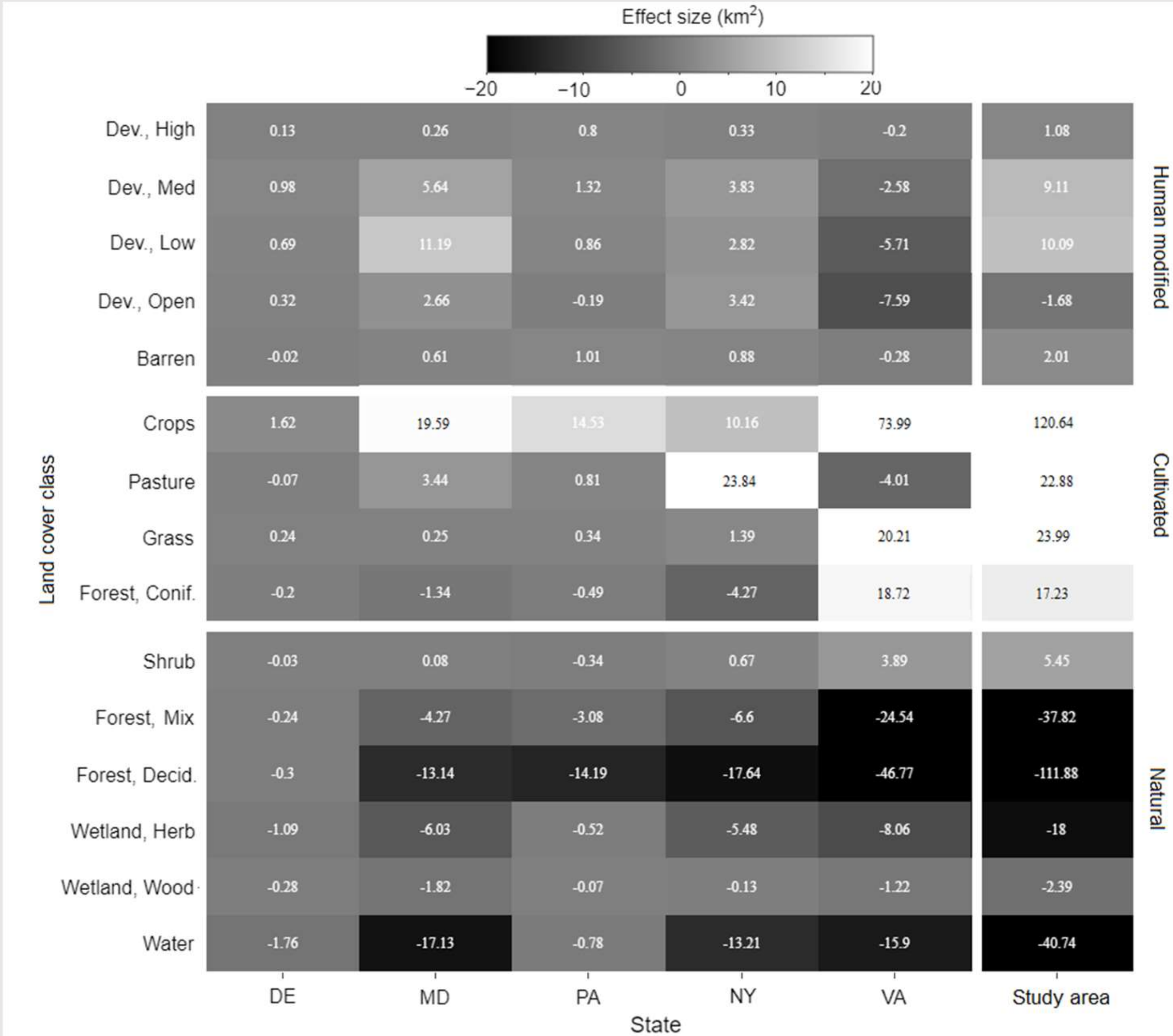


Land cover transitions





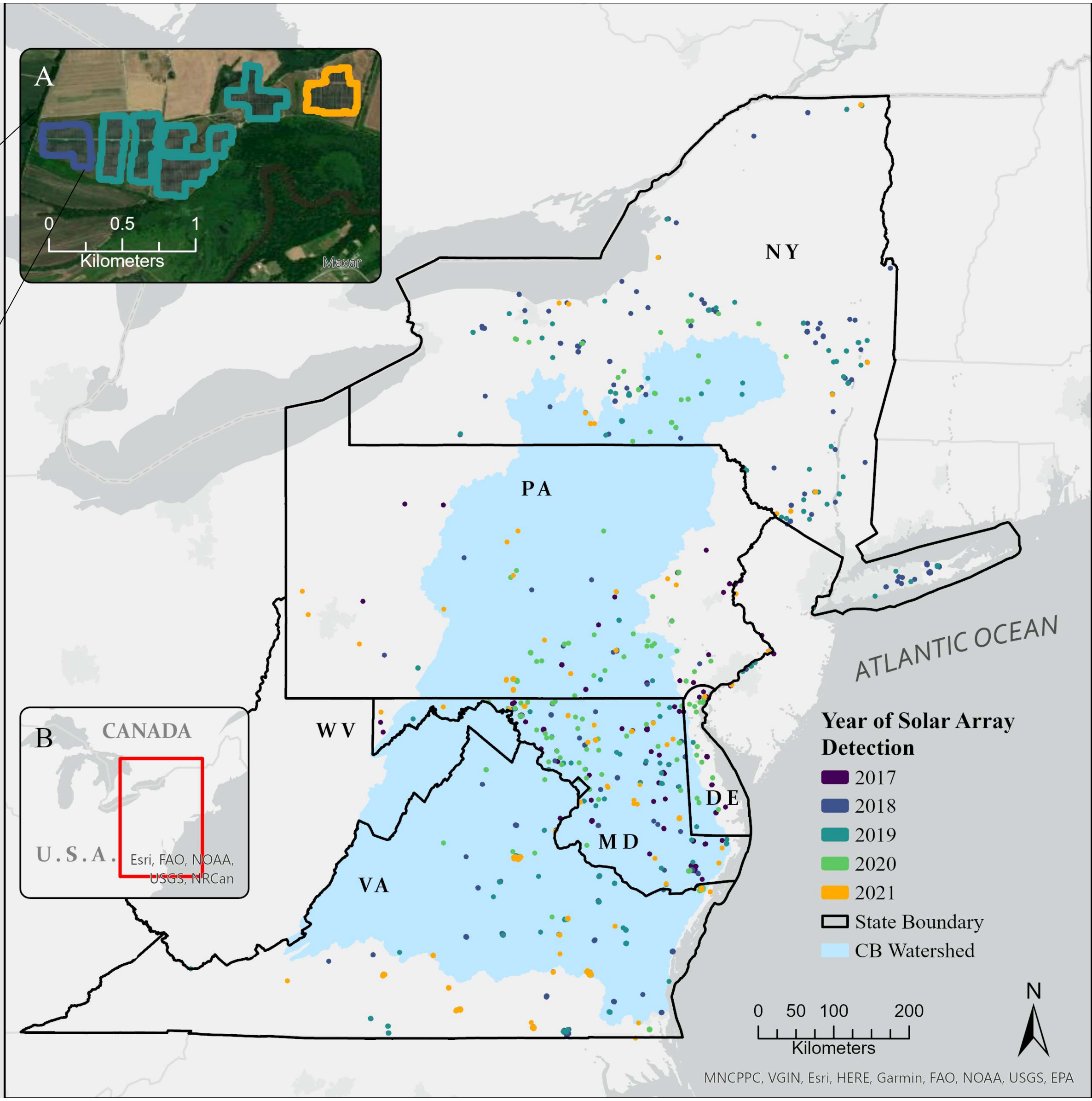
Land cover transitions



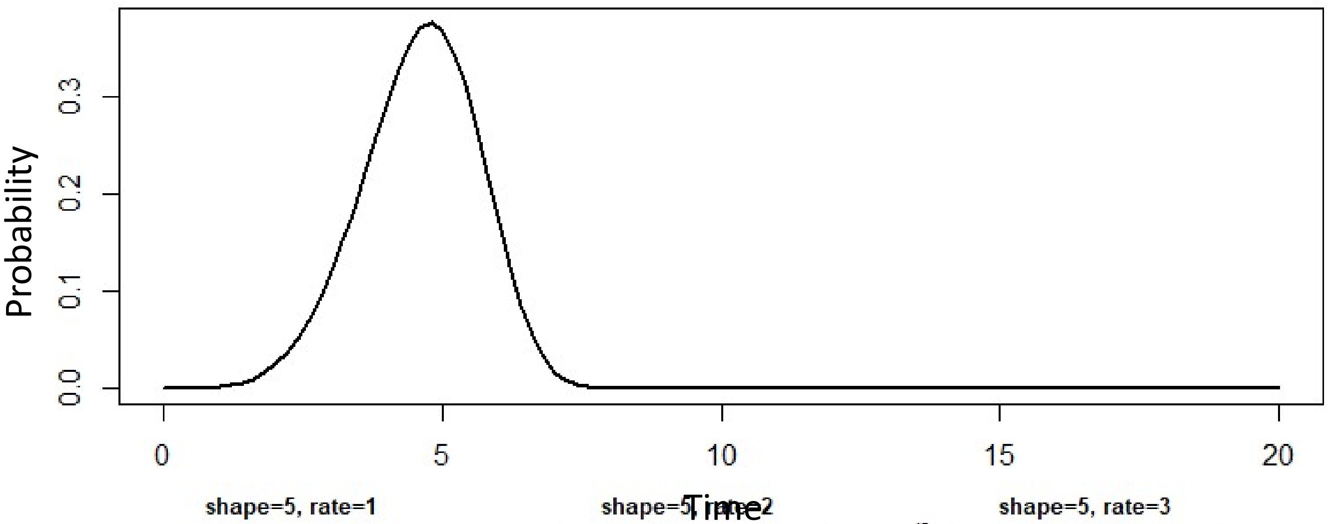
Modeling solar development

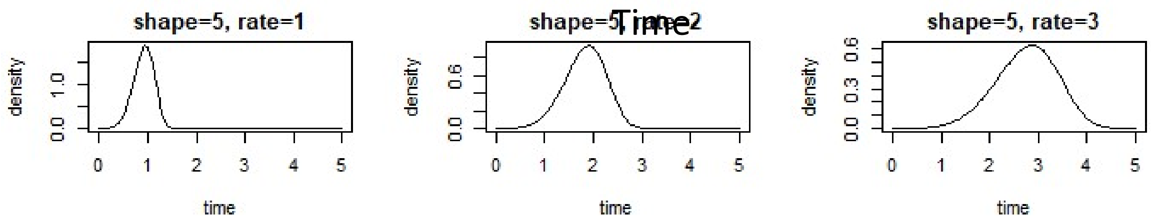
d_i = solar developed?
$y_i | d_i$ = years to development

Impervious surface
Tree cover
Open space
Cultivated
Farm Score
Distance to Transmission
Distance to Road
Population
Income
GAP Status
Slope
Latitude



Modeling solar development





(2) parameters:

1. Shape (k) - acceleration
2. Rate (λ) - probability

Weibull model for time to event data

$$y_i | d_i \sim Weibull(k_s, \lambda_i)$$

Acceleration ~ state

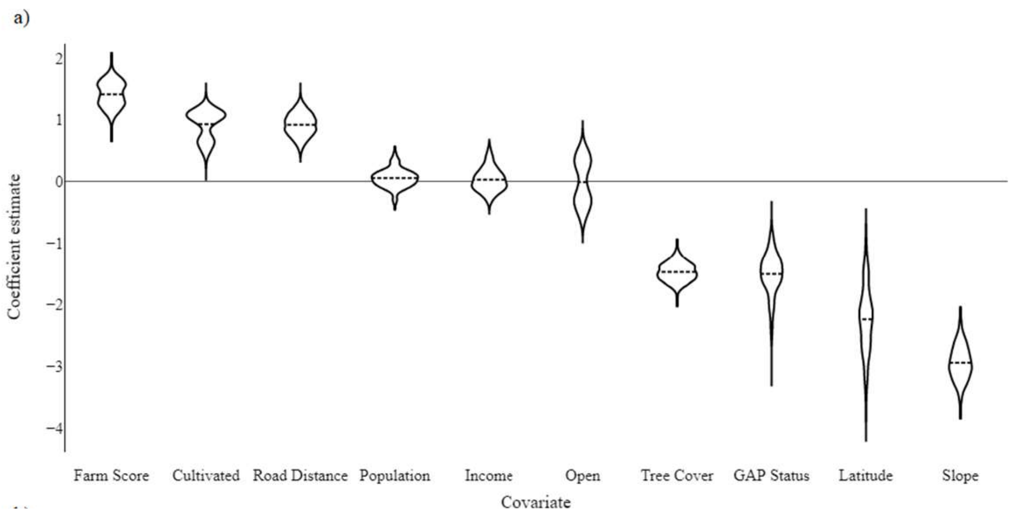
$$k_s \sim Gamma(v_k, \theta_k)$$

Rate ~ state + covariates

$$\log(\lambda_i) = \log(\alpha_{si}) + \sum_{j=1}^{J} \beta_j x_{ji}$$

Modeling solar development

$Rate\ (\lambda_i)$



$\lambda_i \uparrow$

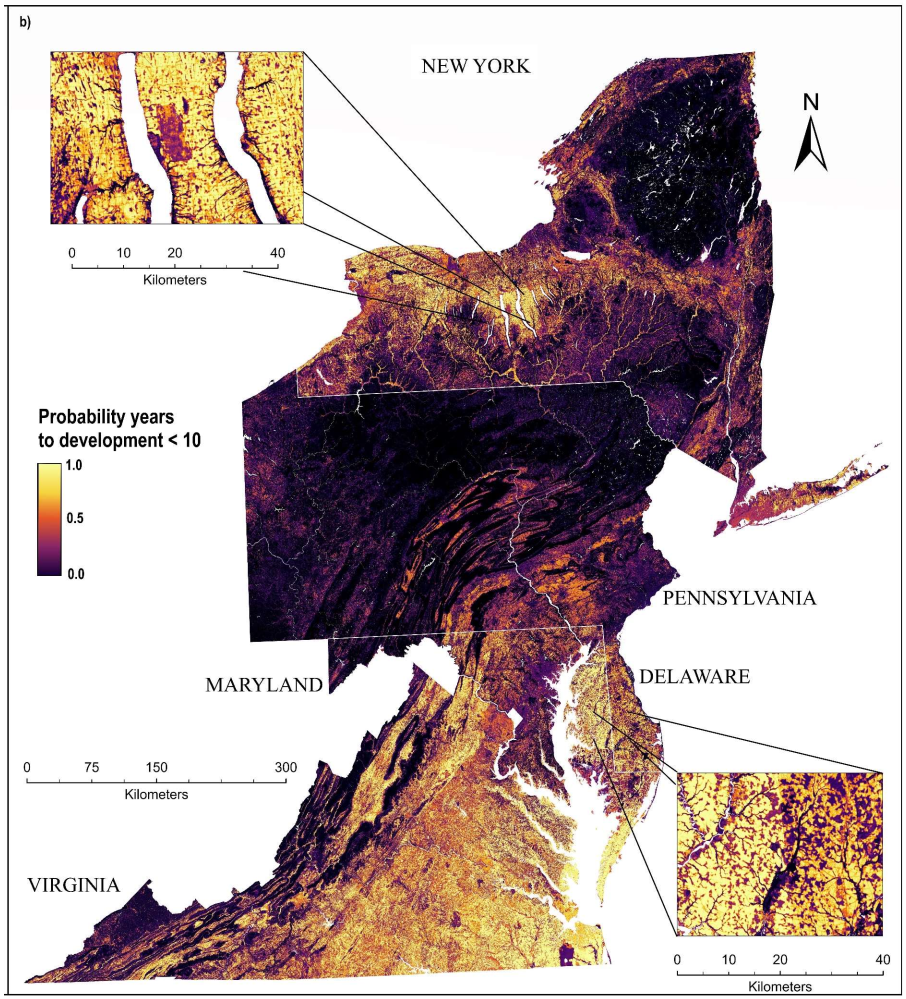
$\lambda_i \downarrow$

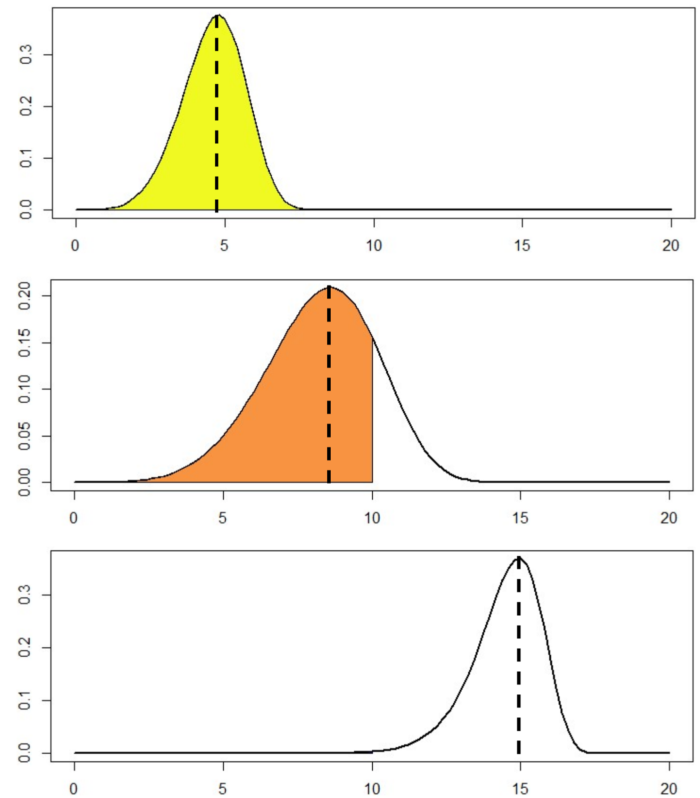
$Shape\ (k_s)$

$k_s > 1 = \ accelerating$

$k_s = 1 = constant$
$k_s < 1 = decelerating$

Future development potential





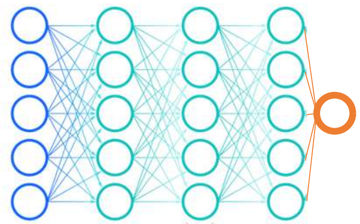
E(ttd) = 4
P(t < 10) = 0.99

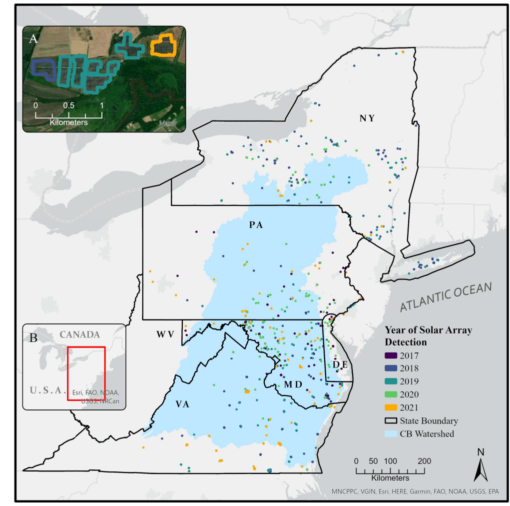
E(ttd) = 8
P(t < 10) = 0.80

E(ttd) = 15
P(t < 10) = 0.02

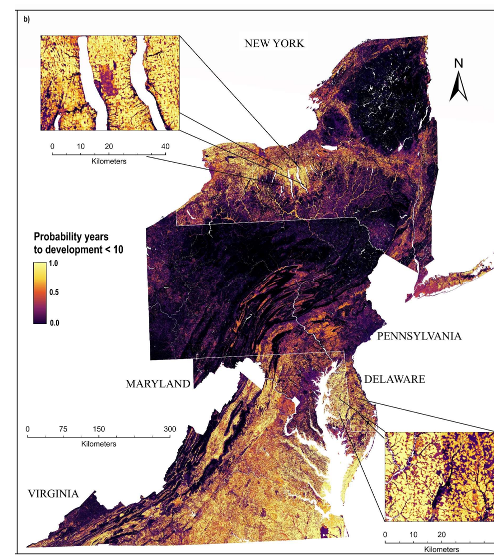
https://mevans-cic.users.earthengine.app/view/cpksolar

Conclusion





1. System for automatically producing updated maps
2. Solar arrays in the watershed have avoided ‘natural’ landcover
3. Lower-quality cultivated lands – opportunities for restoration?
4. Anticipate most and least likely places for future buildout



Questions?

Michael Evans

Senior Data Scientist

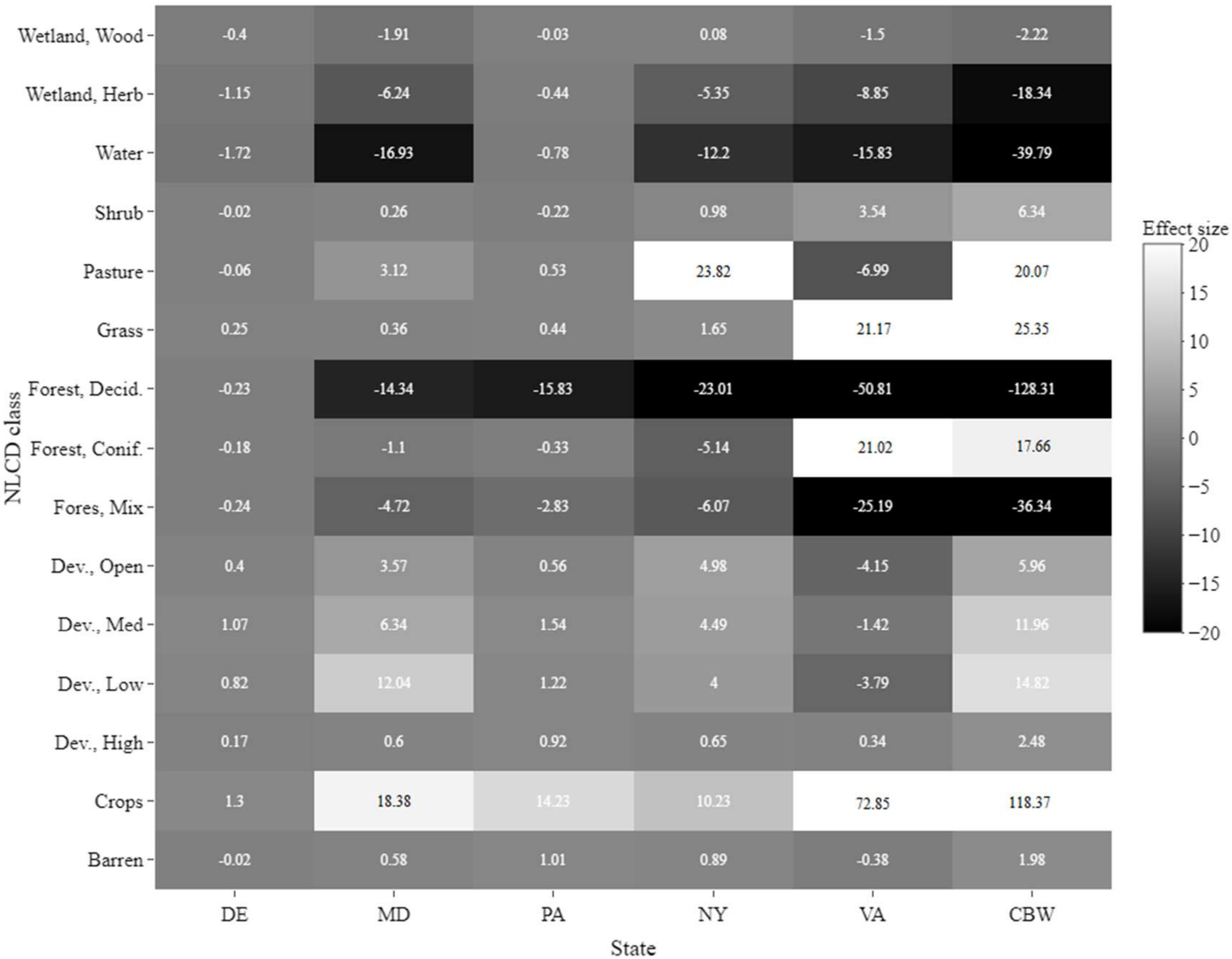
mevans@chesapeakeconservancy.org

Chesapeake Conservancy

EXPLORE. CONSERVE. INNOVATE.

CONSERVATION INNOVATION CENTER

CHESAPEAKE CONSERVANCY



Cropland:
156 km^2 (37%)

Solar covariates

Variable	Description	Format	Source	
Slope	Mean slope derived from 10 m digital elevation model	Raster	3DEP National Map (USGS, 2022)	$P(\beta_j)$ = 0.333
Year	Year of Sentinel-2 image in which array was first detected	Scalar	Authors	
Road Distance	Distance (m) to nearest local (S1400) or secondary (S1200) road	Vector	USA Roads (USCB, 2021)	$P(\beta_j)$ = 1.00
Line Distance	Distance (m) to nearest electric power transmission line	Vector	U.S. Electric Power Transmission Lines (DHS, 2022)	$P(\beta_j)$ = 0.00
Gap Status	GAP protected area status code (1 = High, 5 = Low)	Vector	USGS Protected Area Dataset of the U.S.	$P(\beta_j)$ = 1.00
Housing	2010 Housing density (km^{-2}) of the census tract	Vector	U.S. Census Bureau	$P(\beta_j)$ = 0.00
Income	2010 median household income of the census tract	Vector	U.S. Census Bureau	$P(\beta_j)$ = 0.04
Population	2010 population of census tract	Vector	U.S. Census Bureau	$P(\beta_j)$ = 0.03
Cultivated	Percentage of pixels identified as cropland in 2016	Raster	Cropland Data Layer (USDA-NASS 2021)	$P(\beta_j)$ = 1.00
Tree Cover	Percentage of pixels identified as tree canopy in 2016	Raster	National Land Cover Database (Dewitz & USGS, 2021)	$P(\beta_j)$ = 0.67
Impervious	Percentage of pixels identified as impervious surface in 2016	Raster	National Land Cover Database (Dewitz & USGS, 2021)	$P(\beta_j)$ = 0.00
Open	Percentage of pixels identified as grassland, shrub, open-developed, or low-intensity developed (i.e., lawns) in 2016	Raster	National Land Cover Database (Dewitz & USGS, 2021)	$P(\beta_j)$ = 0.191
Farm Score*	Agricultural soil suitability score (1 = High, 4 = Low)	Raster	SSURGO Farmland Class (NRCS, 2021)	$P(\beta_j)$ = 0.67
Latitude	Latitude (m) of array centroid	Scalar	Authors	$P(\beta_j)$ = 1.00

$$\log(\alpha_s) + \sum_{j=1}^{J} w_j * \beta_j * X_{ji}$$

$$w_m \sim Bernoulli(0.5)$$

$$P(\beta_j) = \frac{1}{N}\sum_{n=1}^{N} w_{j(n)}$$

What is Artificial Intelligence?

- Artificial Intelligence – machines that can solve problems or perform tasks

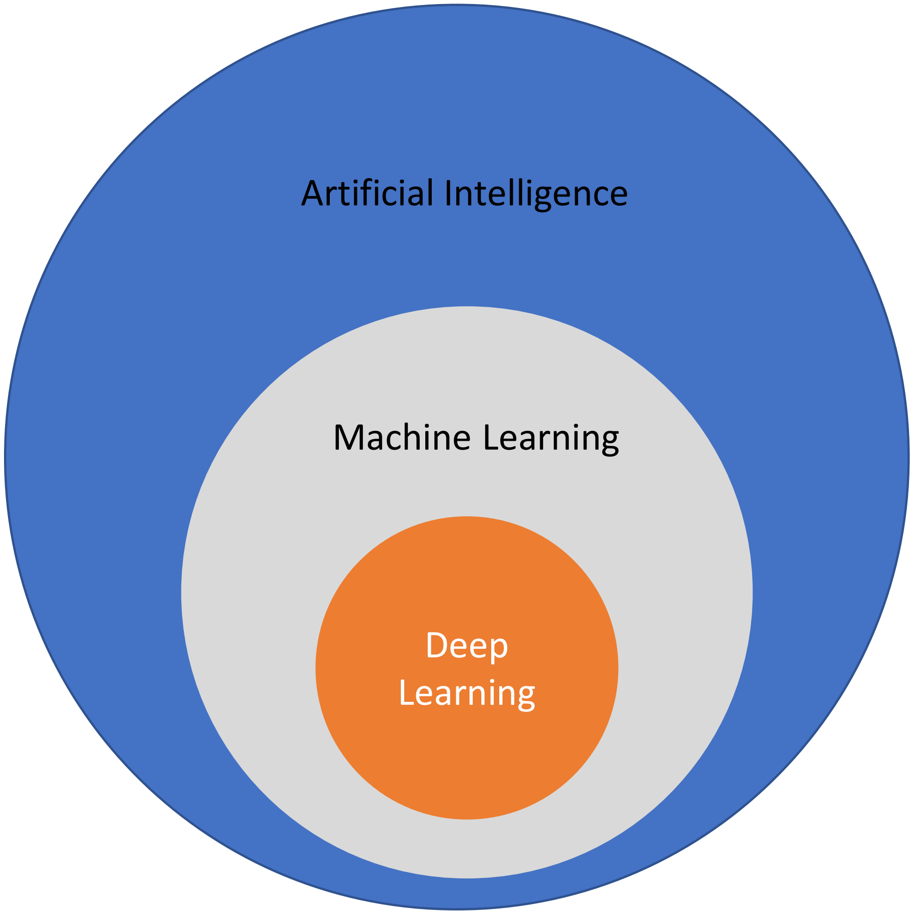
(e.g. computer chess)

- Machine Learning – machines that learn to make predictions without explicit programming

(e.g. Classification Tree)

- Deep Learning – ML algorithms that use layers of ‘neurons’

(e.g. Facial recognition)



Predictors of solar development

Coefficient	$P(w_j)$	$\bar{\beta}_j \pm \sigma$	$P(\beta_j = 0)$
Impervious	0.00	-	-
Open	0.191	0.011 ±0.375	0.479
Tree Cover	0.667	-1.48 ±0.155	0.00
Cultivated	1.00	0.925 ±0.246	0.00
Farm Score	0.667	1.41 ±0.208	0.00
√Slope	0.333	-2.95 ±0.283	0.00
log(GAP Status)	1.00	-1.51 ±0.355	0.00
log(Line Distance)	0.00	-	-
log(Road Distance)	1.00	0.919 ±0.188	0.00
log(Population)	0.035	0.054 ±0.15	0.629
Income	0.036	0.031 ±0.189	0.472
Latitude	1.00	-2.24 ±0.565	0.00

$$\log(\alpha_s) + \sum_{j=1}^{J} w_j * \beta_j * X_{ji}$$

$$w_m \sim Bernoulli(0.5)$$

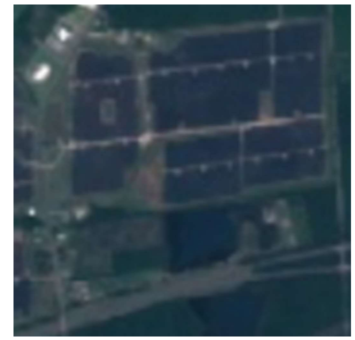
$$\mathrm{P}(\beta_j) = \frac{1}{N}\sum_{n=1}^{N} w_{j(n)}$$

Image Augmentation

Original

Rotate 90°

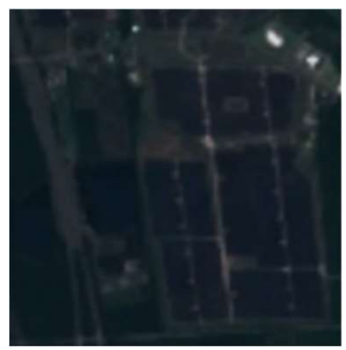
Rotate 180°



Rotate 270°

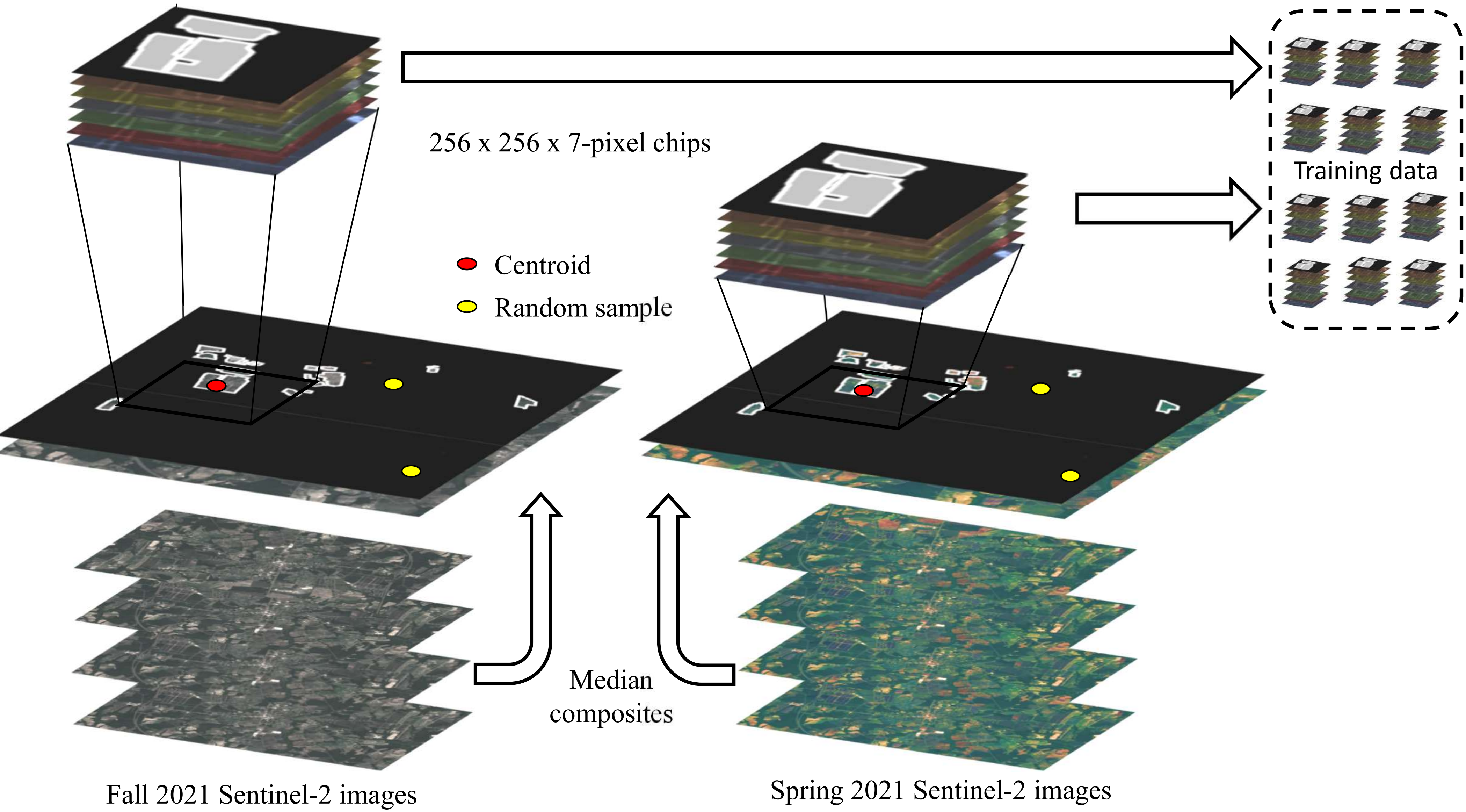
Brightness -5%
Contrast -5%

Brightness +5%
Contrast -5%



Brightness -5%
Contrast +5%

Brightness +5%
Contrast +5%


256 x 256 x 7-pixel chips
Training data
Centroid
Random sample
Median
composites
Fall 2021 Sentinel-2 images
Spring 2021 Sentinel-2 images

Model Training Workflow