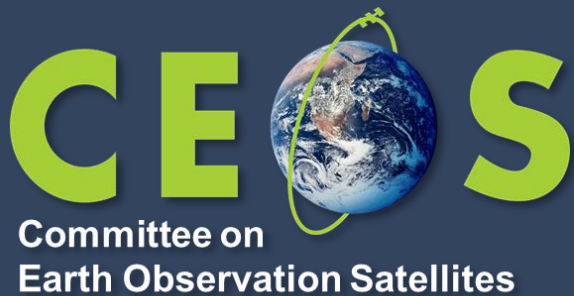


# USGS AI/ML Use Cases



Tom Sohre, USGS EROS  
Agenda ID: 2022.10.06\_12.00  
WGISS-54  
Tokyo, Japan (JAXA)  
3-7 October 2022

## ❖ USGS EROS AI/ML workflows generally make use of similar tools and data for informing our understanding of Earth surface and subsurface conditions, changes, and drivers.

- Software libraries:
  - STAC, DASK, Xarray, GDAL, Pytorch, & Tensorflow
- Compute platforms:
  - Amazon Web Services, Microsoft Azure, Google Cloud Platform, & High-performance computers (HPCs)
- Data:
  - Active and passive remote sensing imagery (e.g., Landsat Collection 2, Harmonized Landsat & Sentinel-2, Sentinel-1 and 3, Planet, MAXAR, IceSAT-2)

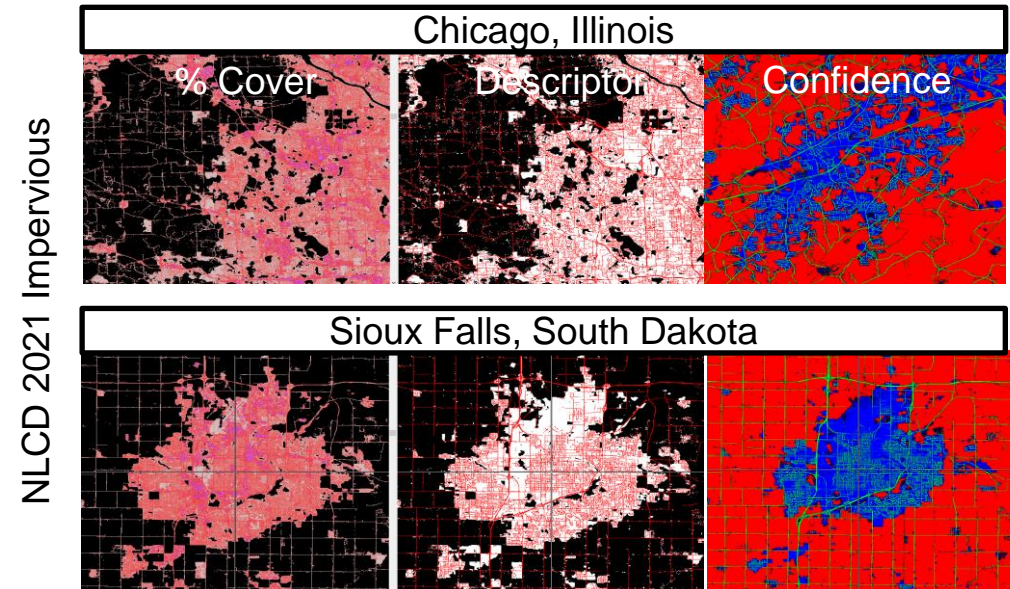
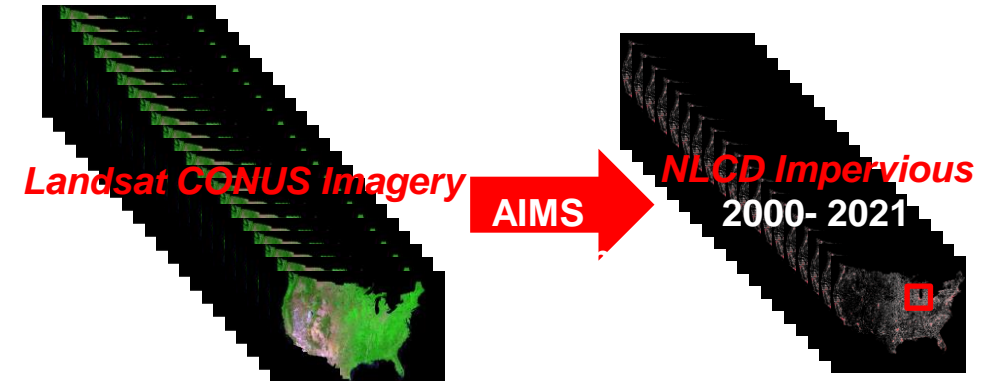
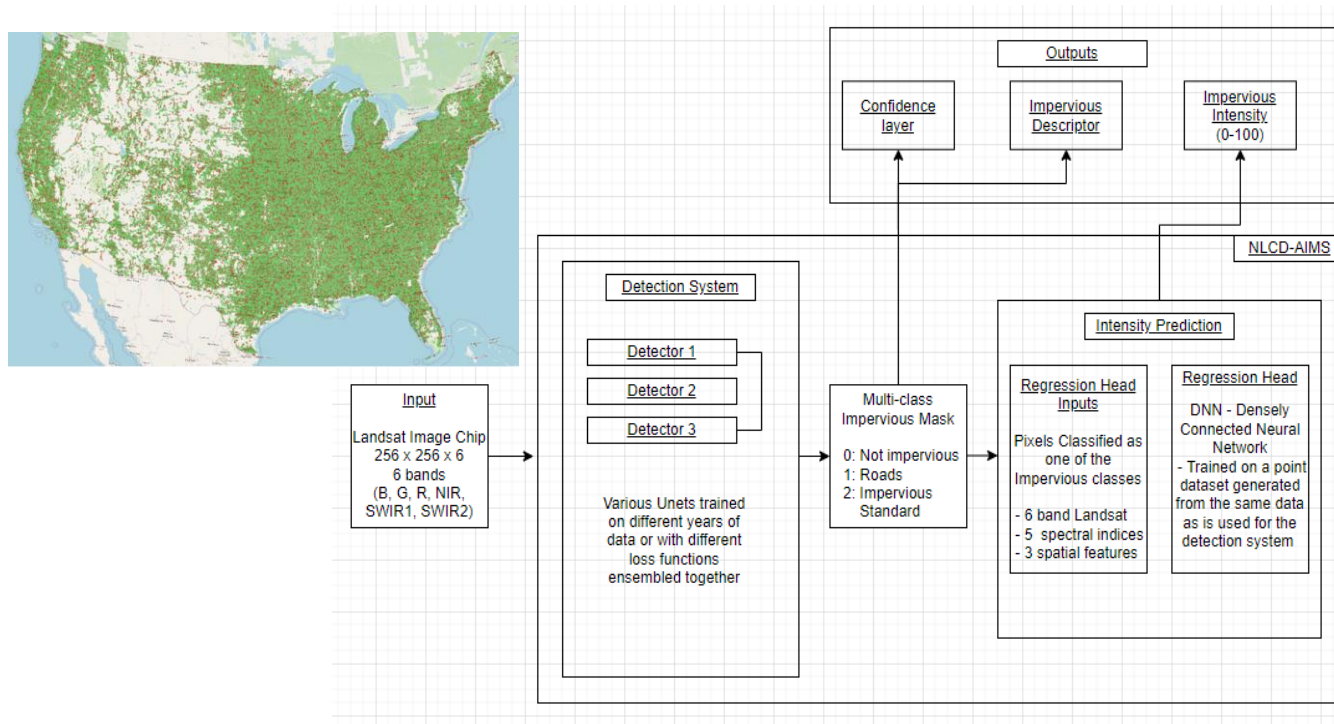
## ❖ Targets of interest:

- Land cover conditions (e.g., thematic, fractional cover), land surface phenology, species and lifeform level mapping.

# NLCD Impervious Surfaces



## Artificial Impervious Mapping System (AIMS)



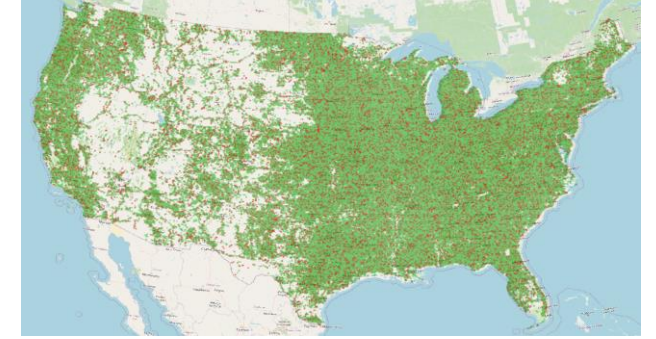
### Key methods and data:

- **Inputs:** Field and high-resolution observations of land surface conditions and remotely-sensed data (e.g., Landsat).
- **Compute:** AWS + USGS HPCs.
- **Models:** Ensemble of U-Nets + DNNs.

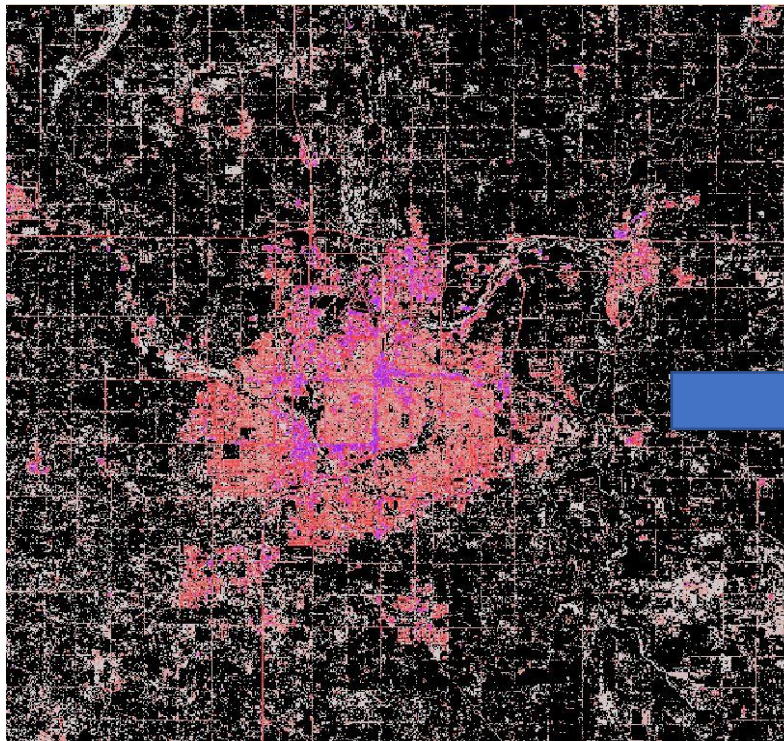


# Improvements in Impervious Surface mapping for National Land Cover DB 2021

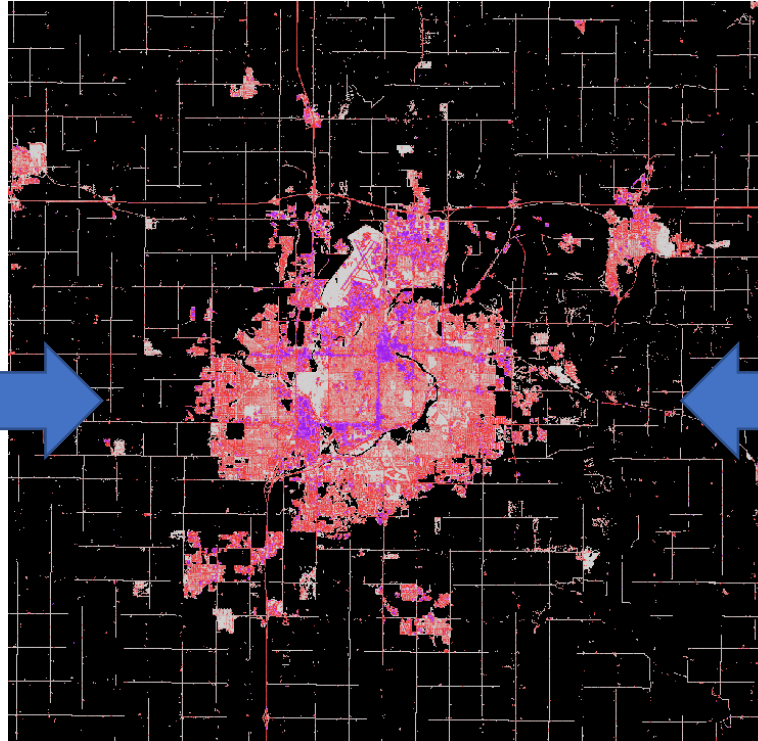
AI Approach Trained on entire CONUS



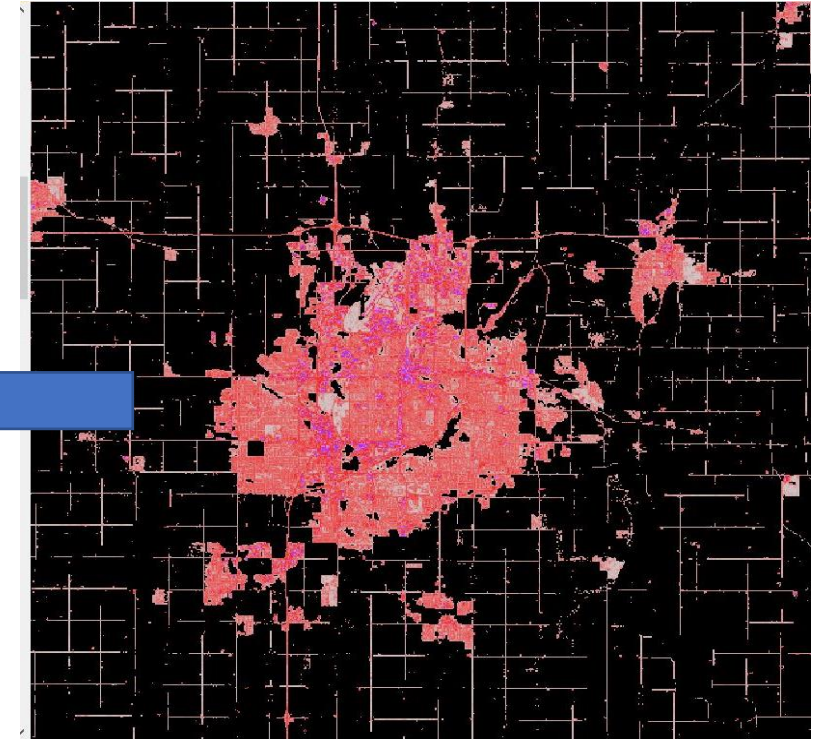
Cubist Model Outputs  
(NLCD 2019)



NLCD Final Product Hand edited  
from Cubist



Artificial Intelligence Outputs  
(NLCD 2021)





# NLCD Land Cover

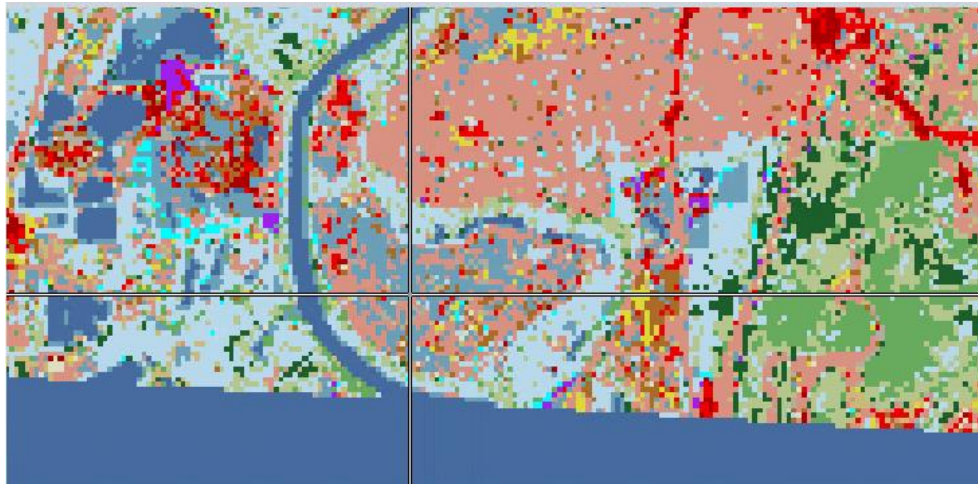


Google Earth

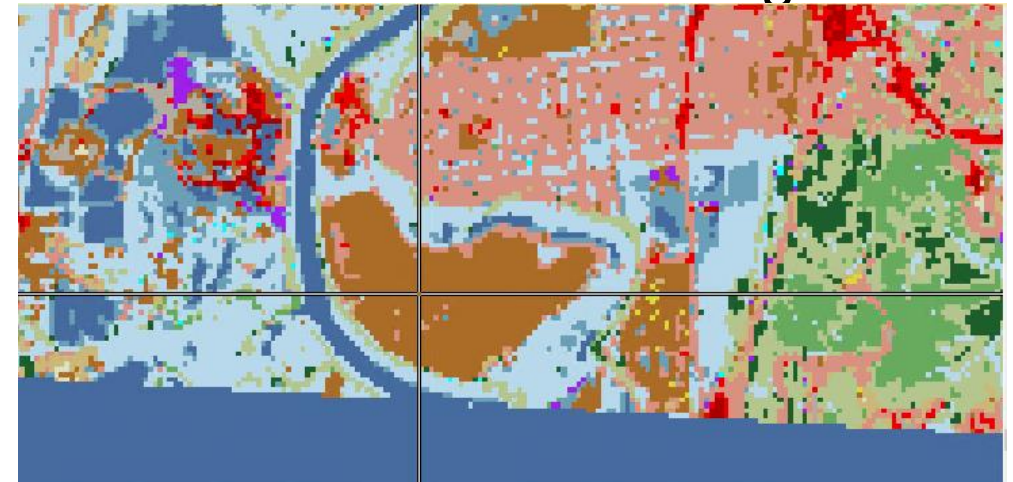


NLCD testing of AI/ML models to land cover classification

See5



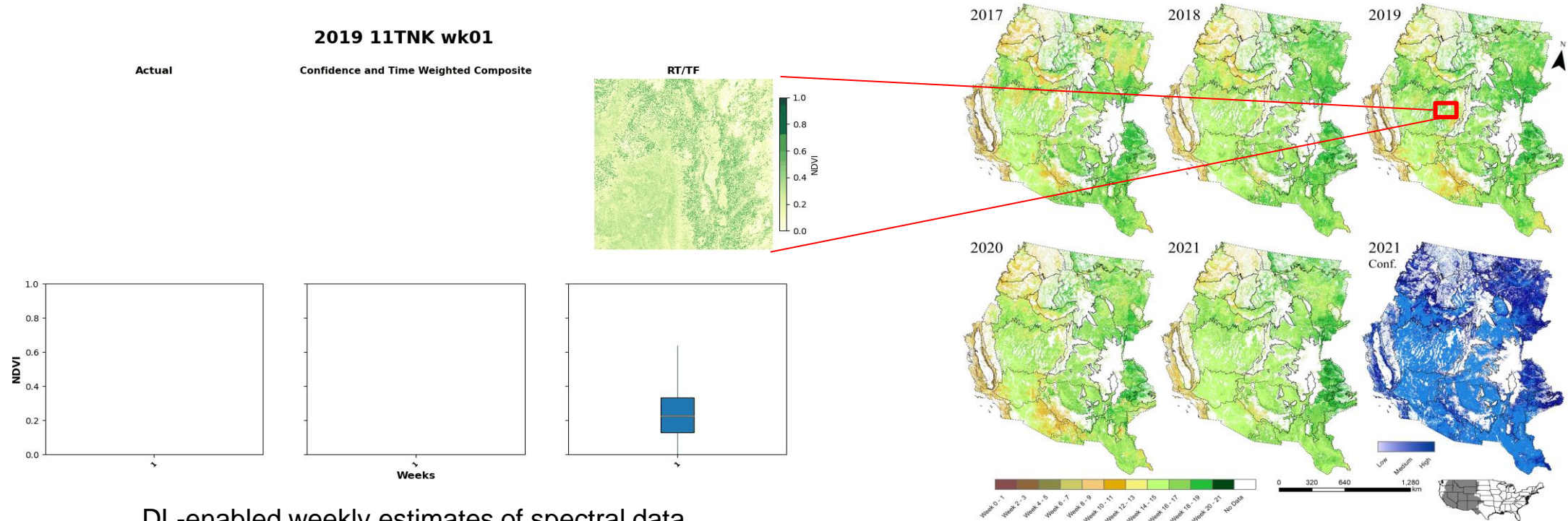
AI Regression



# Land Surface Phenology



## DL-enabled weekly estimates of spectral data and land surface phenology



DL-enabled weekly estimates of spectral data

Start of sustained growth of areas dominated by invasive annual grasses

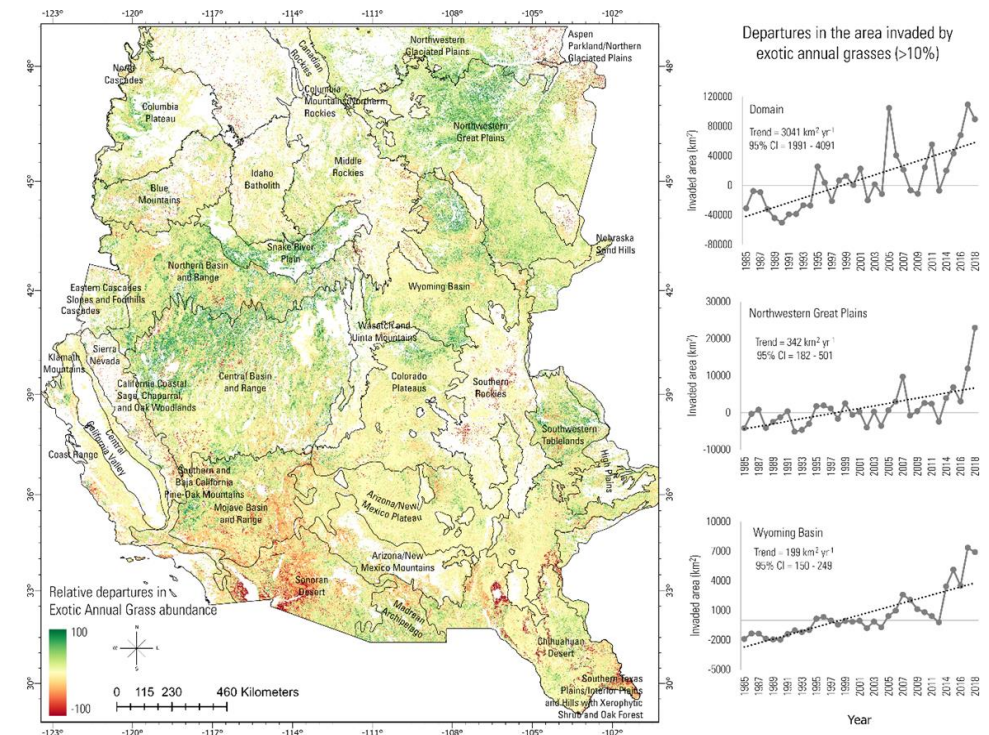
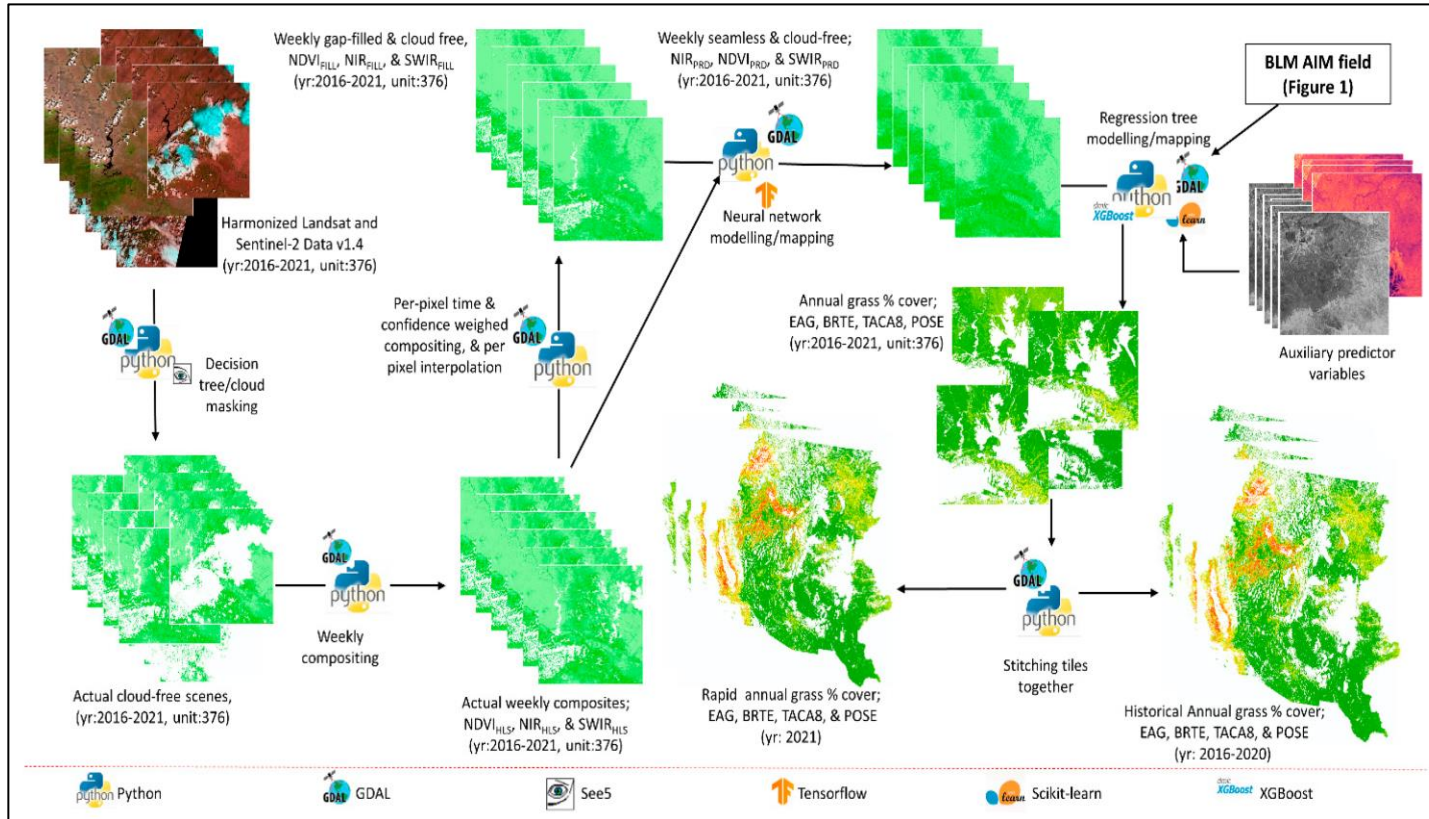
- **Inputs:** Remotely sensed observations (i.e., Harmonized Landsat and Sentinel-2, invasive annual grass cover) and interpretations of major plant life-cycle events (e.g., start of sustained growth).
- **Models:** Multi-task learning w/ deep neural networks (DNNs) & Xgboost.
- **Compute:** USGS High-Performance Computers (i.e., Denali, Tallgrass).
- **Outputs:** Seamless composites of spectral data → land surface phenology.



# Invasive Annual Grasses



## Rangeland Exotic Plant Monitoring System: Rapid & historical estimates



Departures and trends in invasive annual grass (%) cover

- **Inputs:** Field and high-resolution observations of invasive annual grass (%) cover and remotely-sensed and derived data (e.g., Harmonized Landsat and Sentinel-2, Rangeland Analysis Platform + Rangeland Condition Monitoring Assessment and Projection).
- **Compute:** USGS High-performance computers (HPCs) + Amazon Web Services (AWS) + Google Earth Engine (GEE).
- **Models:** Ensembles of XGBoost models + DNNs + LSTMs + RNNs.



# RCMAP Fractional Components



- ❖ Neural Network model used to predict the cover of several rangeland components simultaneously

- ❖ Test accuracy demonstrated a ~9% increase in accuracy moving from regression trees to neural networks

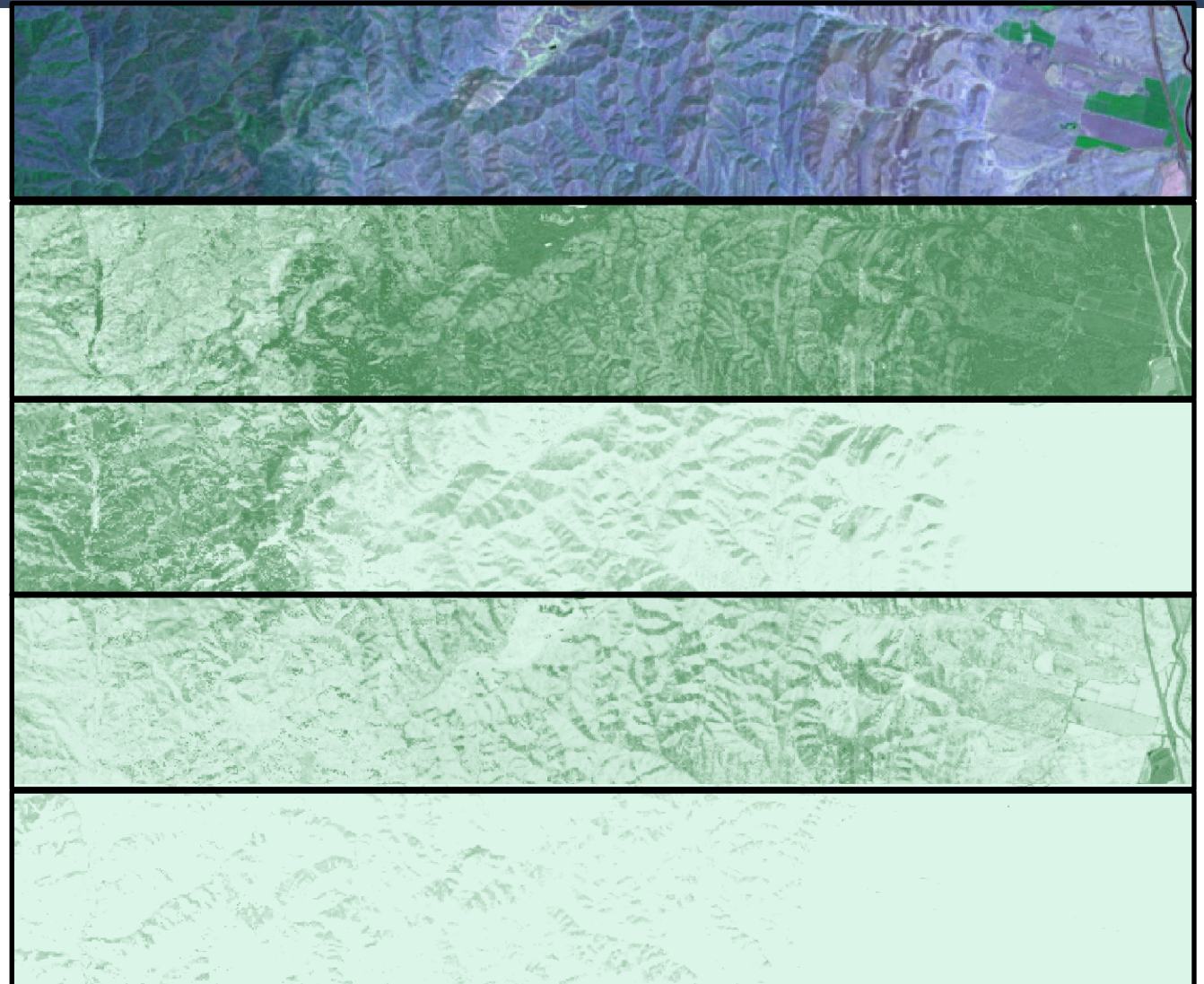
Cover %:

Herbaceous

Shrub

Bare Ground

Tree



\*RCMAP (Rangeland Condition Monitoring and Projection)

+ Sagebrush, Annual Herbaceous, and Litter

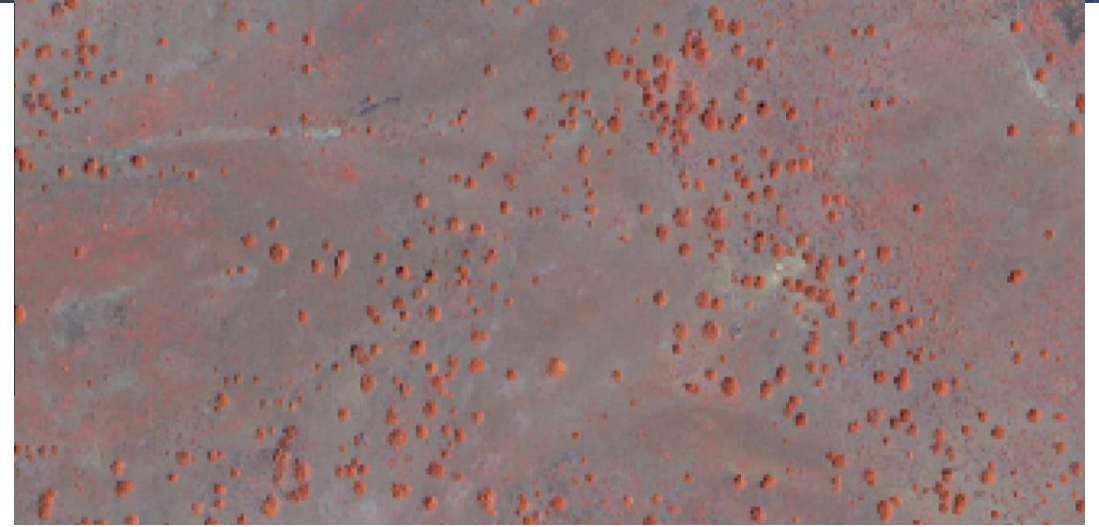
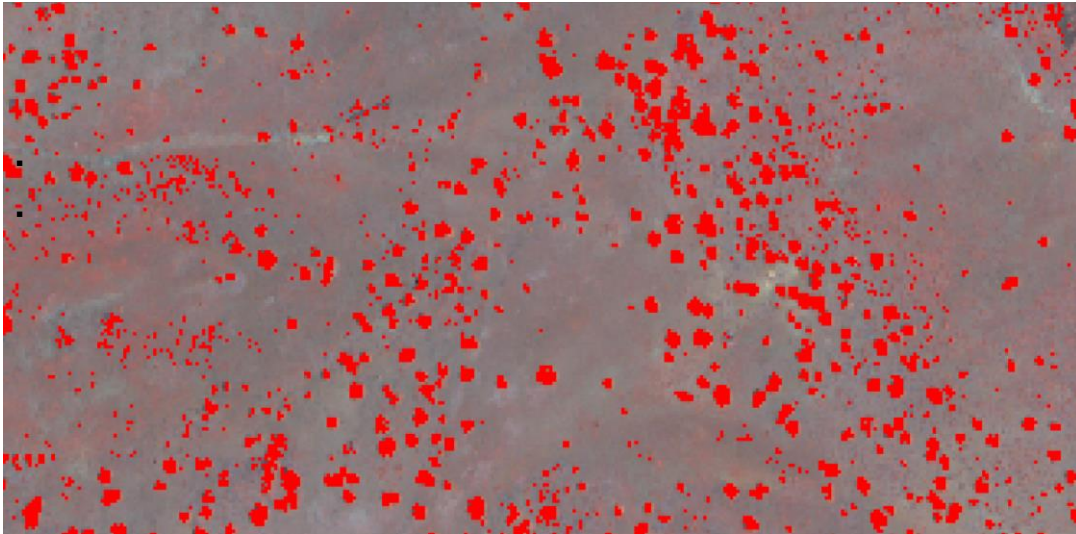


# High-Resolution UNET Tree Cover

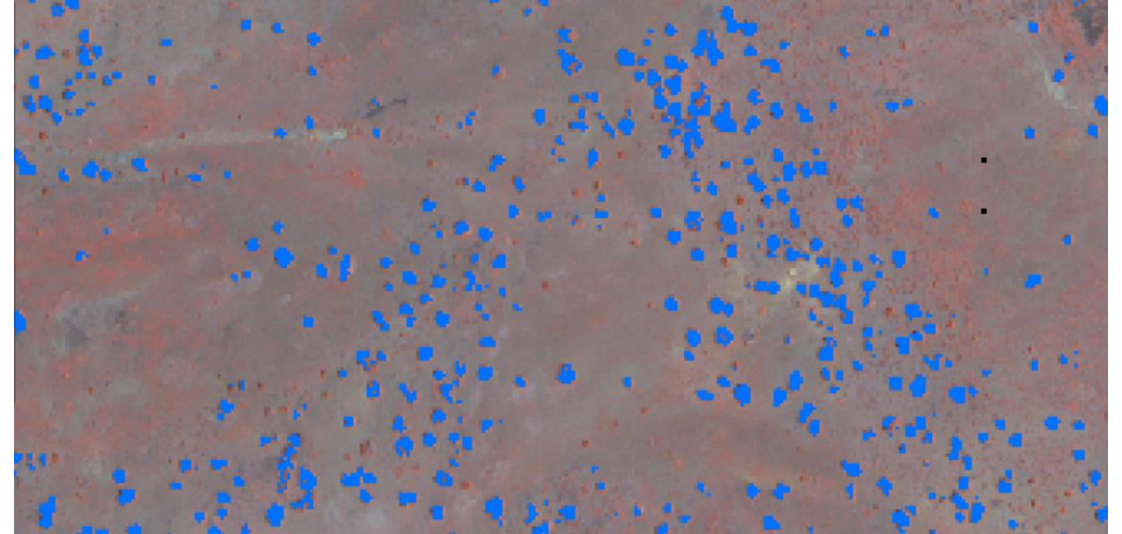


Application of Convolutional Neural Networks (UNET)  
to WorldView 2-m imagery (right) compared to  
traditional classification using unsupervised  
classification.

Unsupervised Classification



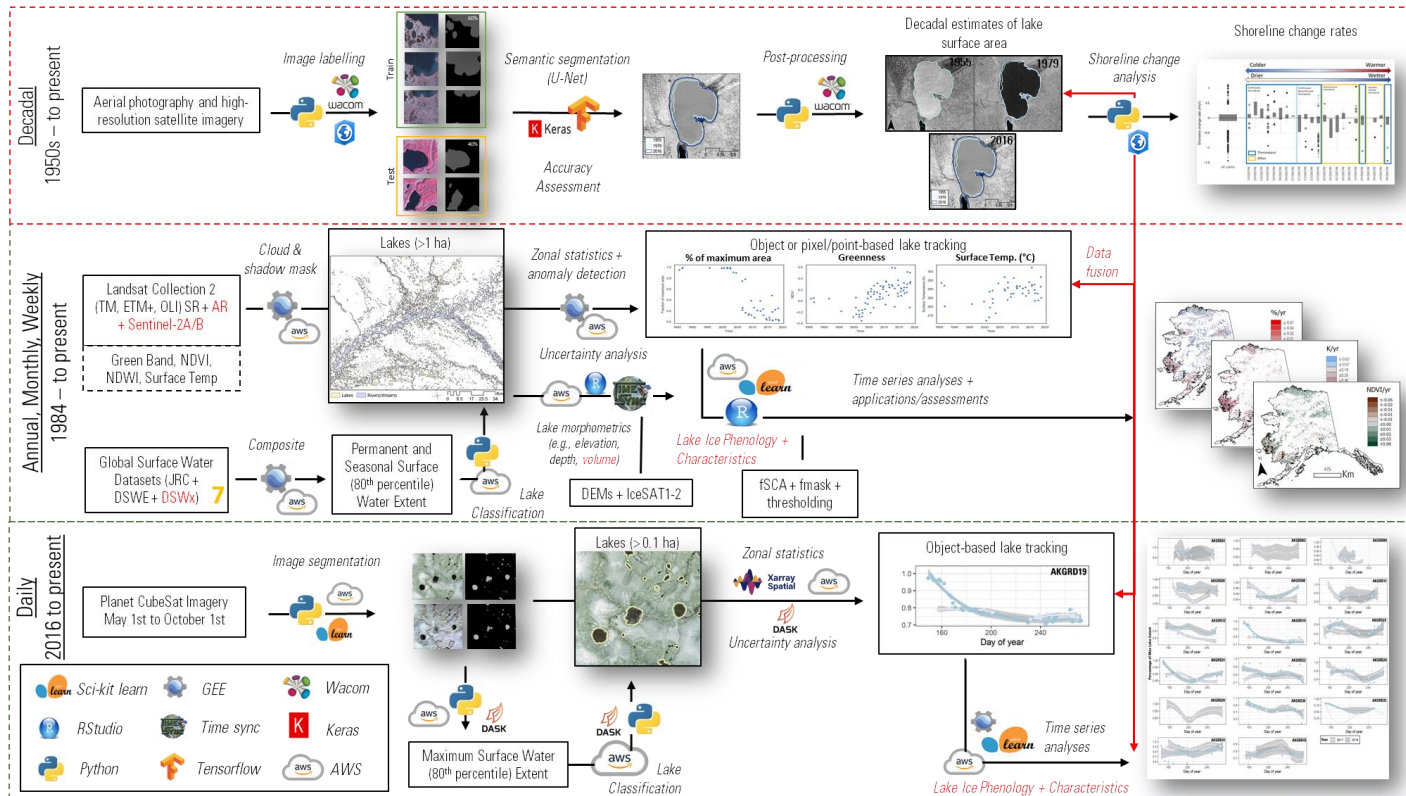
UNET



# Surface Water Conditions

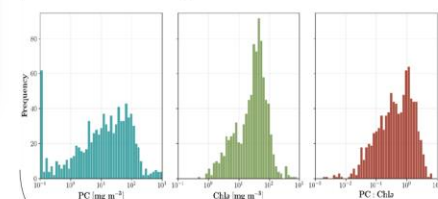


## Cloud and DL-enabled lake monitoring

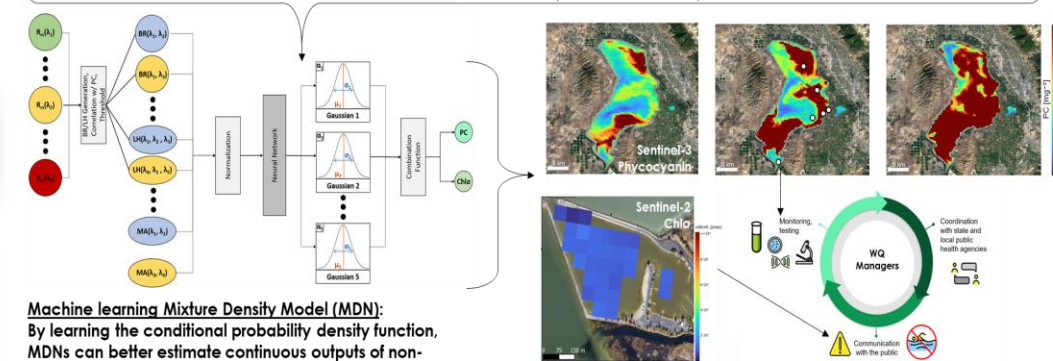
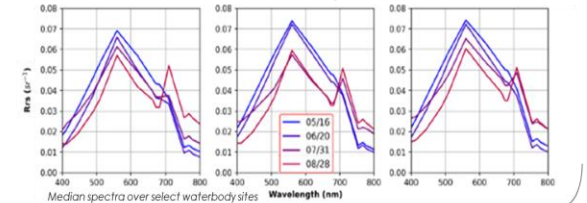


### Training in-situ data across different waterbodies

Four orders of magnitude within constituents



### Sentinel-3 and Sentinel-2 imagery processed to aquatic reflectance with ACOLITE atmospheric correction



Multimission compositing yields ability to capture spectral resolution of S3 and spatial resolution of S2 MDN outputs

Sentinel-2 and 3 chlorophyll-a (Chla) & phycocyanin (Pc) retrievals via MDNs trained on field obs.

- **Inputs:** Field and high-resolution observations of surface water conditions and remotely-sensed data (e.g., Sentinel 2-3, Landsat, Planet, Maxar, IceSAT-2).
- **Compute:** AWS + GEE + USGS HPCs
- **Models:** Autoencoders + U-Nets & Mixture Density Networks (MDNs)



## Challenges & Opportunities:

- ❖ Filling gaps between software libraries commonly used in geoscience data analysis (e.g., Xarray, Dask) and libraries commonly used for deep learning (e.g., TensorFlow, PyTorch).
- ❖ Lower barriers to entry + improve modelling tasks
  - Building catalogs/libraries of deep learning models, EO training/testing data, and reproducible workflows (e.g., Jupyter Notebooks)
- ❖ Questions: Neal Pastick ([njpastick@usgs.gov](mailto:njpastick@usgs.gov))