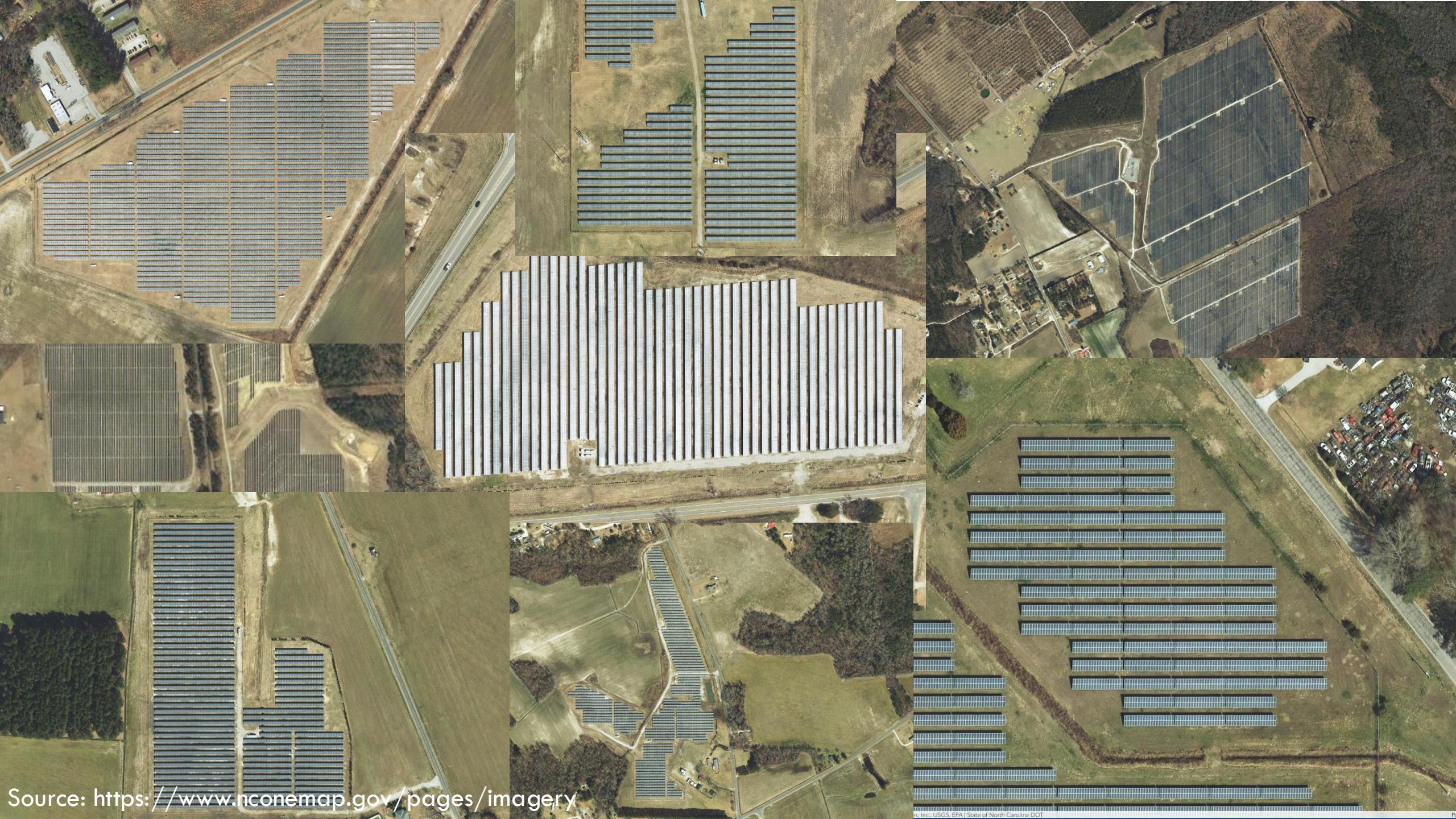


SEMANTIC SEGMENTATION OF SOLAR FARMS FROM AERIAL IMAGERY IN EASTERN NC USING U-NET

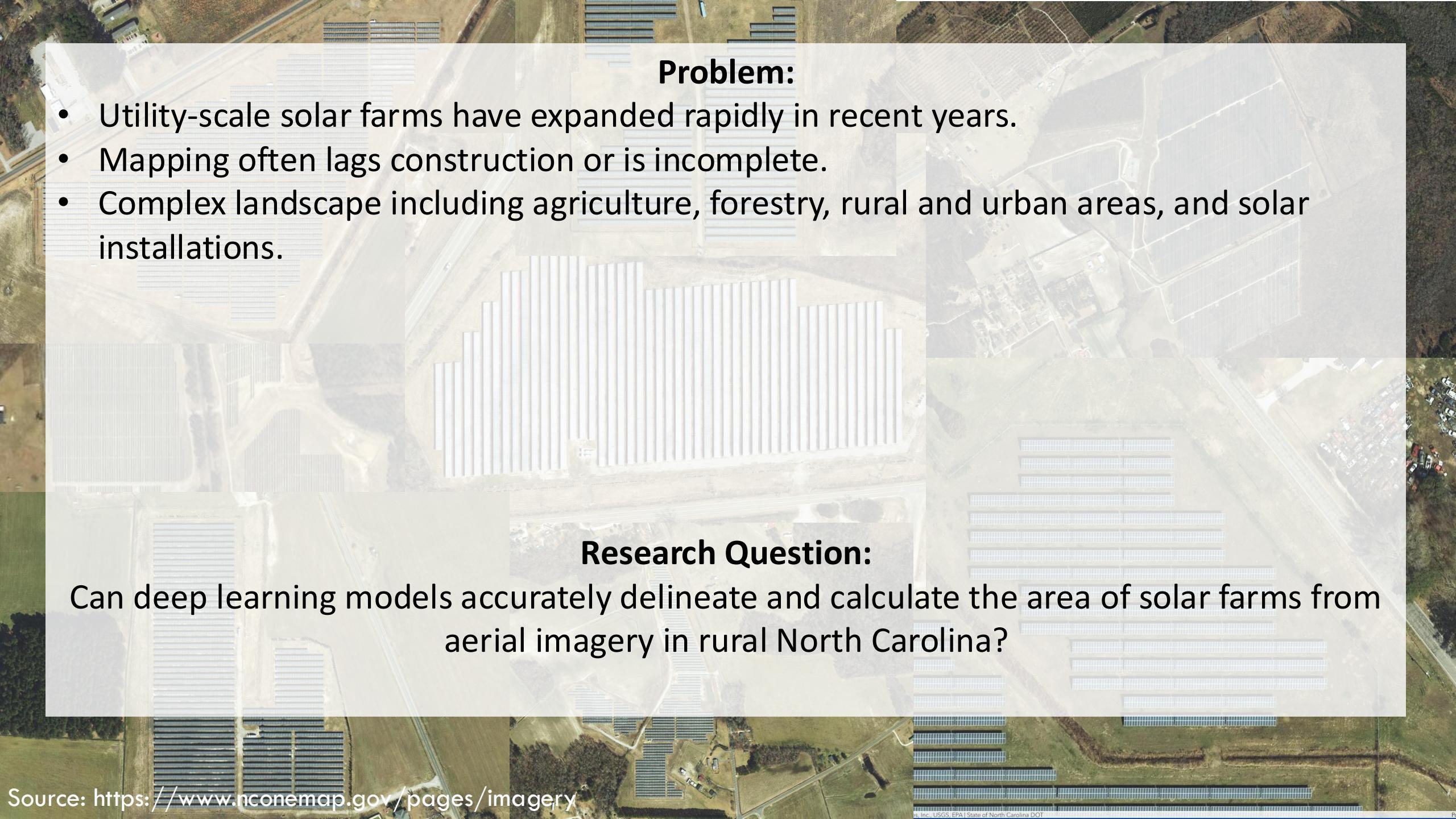
REED JOHNSON

MSDS 692: DATA SCIENCE PRACTICUM

2025 SUMMER 8 WEEK 1



Source: <https://www.hconemap.gov/pages/imagery>

The background of the slide consists of a large aerial photograph of several utility-scale solar farms in a rural setting. The solar panels are arranged in long, rectangular rows across fields. Other agricultural land, roads, and small buildings are visible in the surrounding area.

Problem:

- Utility-scale solar farms have expanded rapidly in recent years.
- Mapping often lags construction or is incomplete.
- Complex landscape including agriculture, forestry, rural and urban areas, and solar installations.

Research Question:

Can deep learning models accurately delineate and calculate the area of solar farms from aerial imagery in rural North Carolina?

OVERVIEW

Data Overview

Mask Creation

Tiling and Data Preparation

U-Net

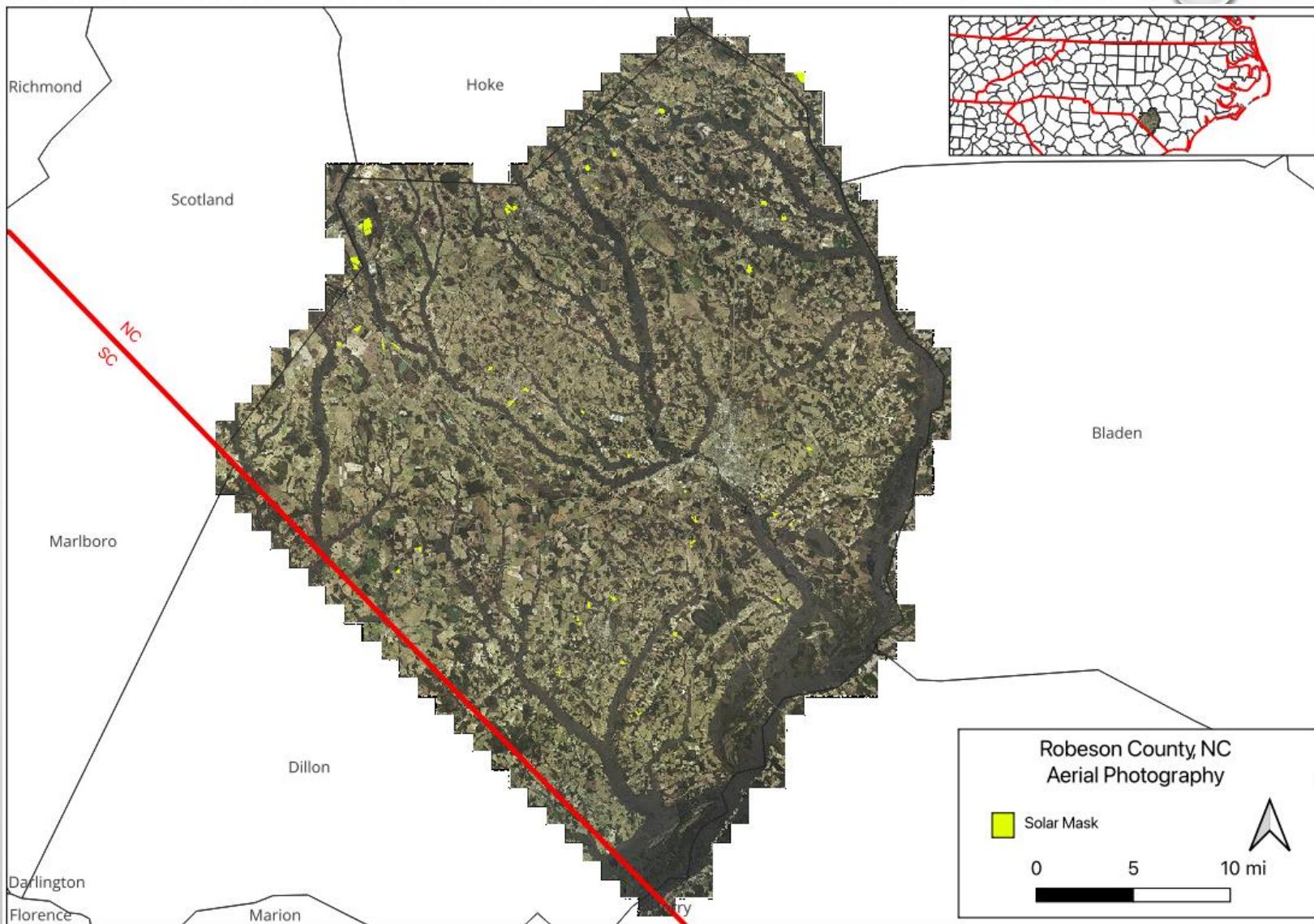
Model Results

Learnings

Next Steps and Considerations

DATA OVERVIEW – AERIAL IMAGERY

- ROBESON COUNTY, NC (946 SQMI)
- 2021 VINTAGE
- 53 SOLAR FARMS
- CONVERTED SID TO TIFF
- DOWNSAMPLED RESOLUTION
 - (0.5' TO 2')



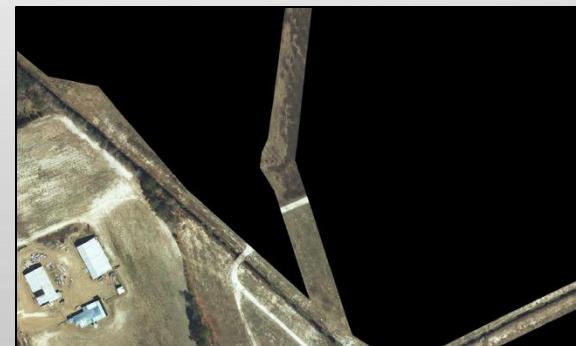
MASK CREATION

- MASKS CREATED ON SOLAR FARMS
- NUANCED AND SUBJECTIVE
- WHAT TO MASK?
 - PANELS? FENCES? ROADS? BUILDINGS?
- CONSISTENCY IS KEY
- TOOK “FENCES IN” APPROACH
- LABELING OF PIXELS:
 - 1: SOLAR FARM
 - 0: NOT SOLAR FARM

Solar Installation Boundary

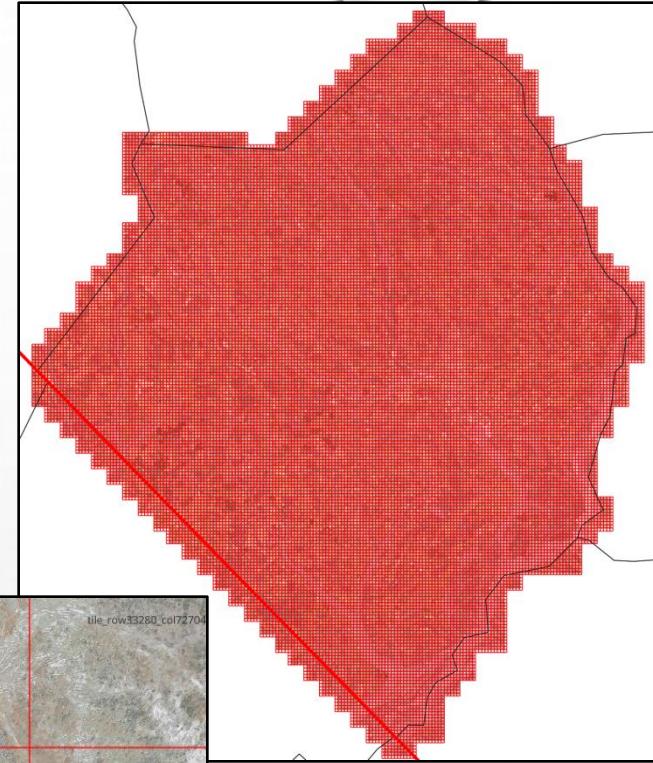


Large Solar Installation Masked



TILING AND DATA PREP

- AERIAL IMAGE AND MASK TILED
- 28,427 IMAGE TILES, 28,427 MASK TILES
 - 237 TILES POSITIVE FOR SOLAR FARMS
- TILE SIZE = 1,024' X 1,024', 512 X 512 PIXELS
- BLANK PADDING AND MOST PARTIAL EDGE TILES REMOVED
- DATA SUBSET (1:3) TO ENHANCE BALANCE
- TRAIN-TEST SPLIT (80/10/10) - STRATIFIED



SEMANTIC SEGMENTATION WITH U-NET VIA PYTORCH

Convolutional Neural Network (CNN)

UNET Useful for mapping, medical imaging, and other computer vision tasks

Encode (Filter, Downsample) > Bottleneck (distilled features) > Decode (Refine, Upsample)

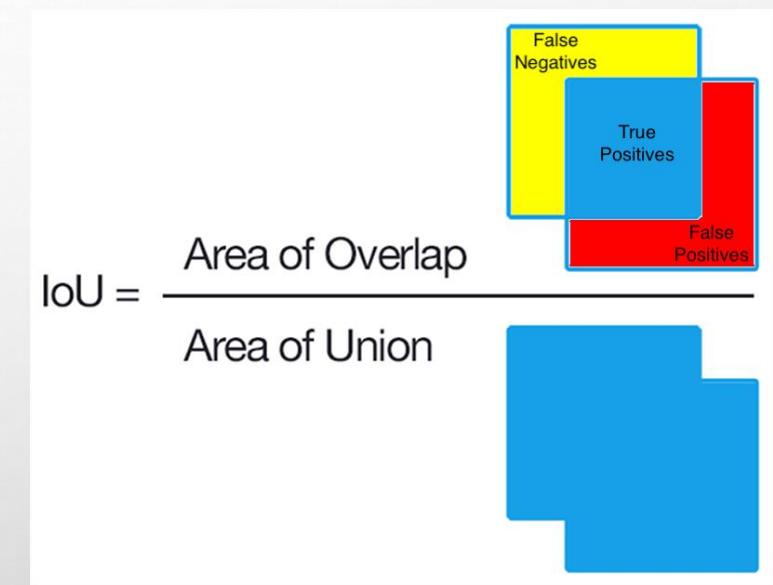
Uses skip connections between encoder and decoder to reconstruct

Trained on aerial image tiles and mask tiles

Predicts “Solar Farm” or “not Solar Farm” on a pixel-by-pixel basis

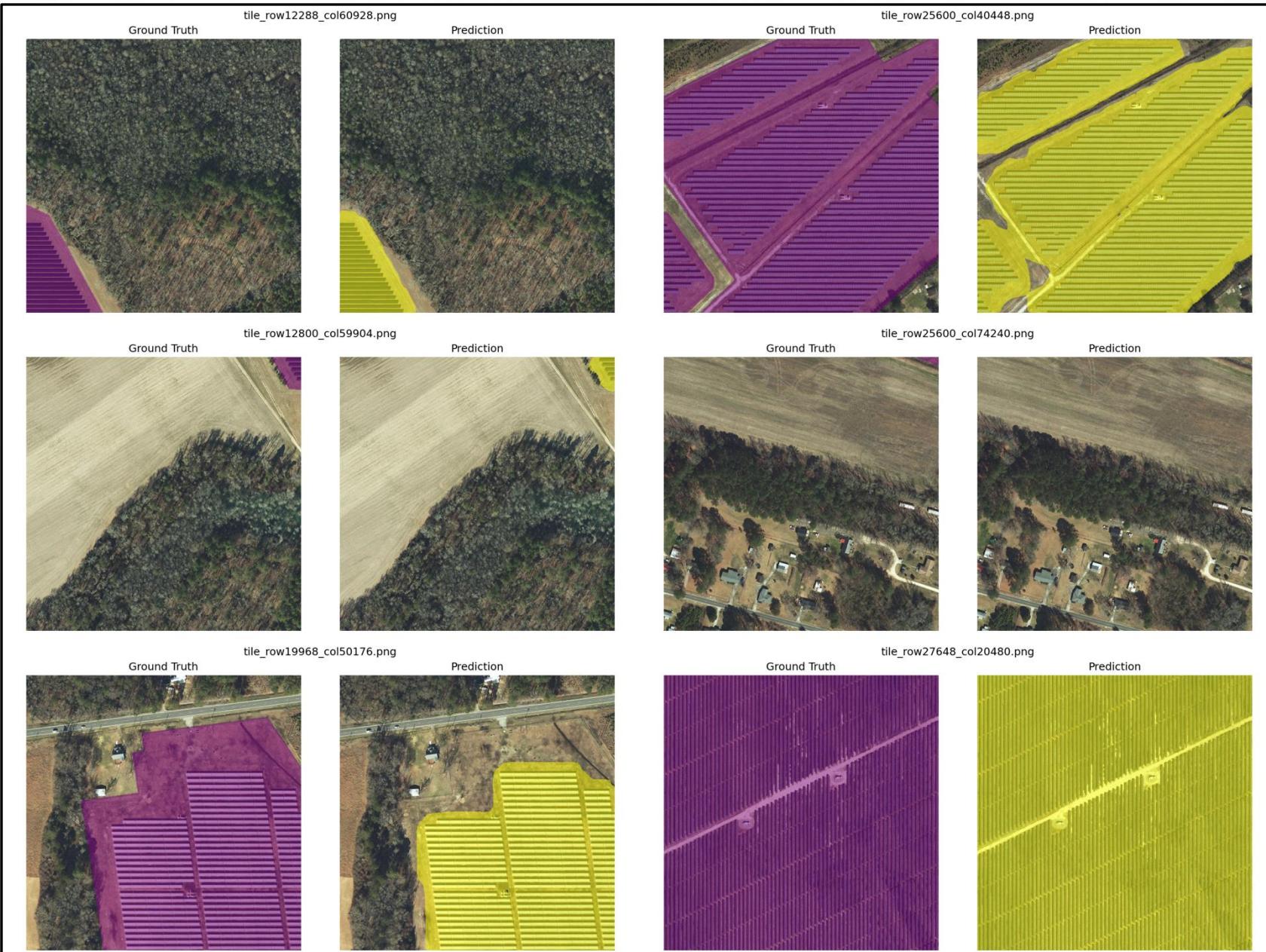
EVALUATION & RESULTS

- INTERSECTION OVER UNION (IOU): 0.93
- ACCURACY: 0.99
- DICE (F1): 0.94
- TEST MASK SOLAR FARM AREA: 161 ACRES
- TEST PREDICTED SOLAR FARM AREA: 151 ACRES



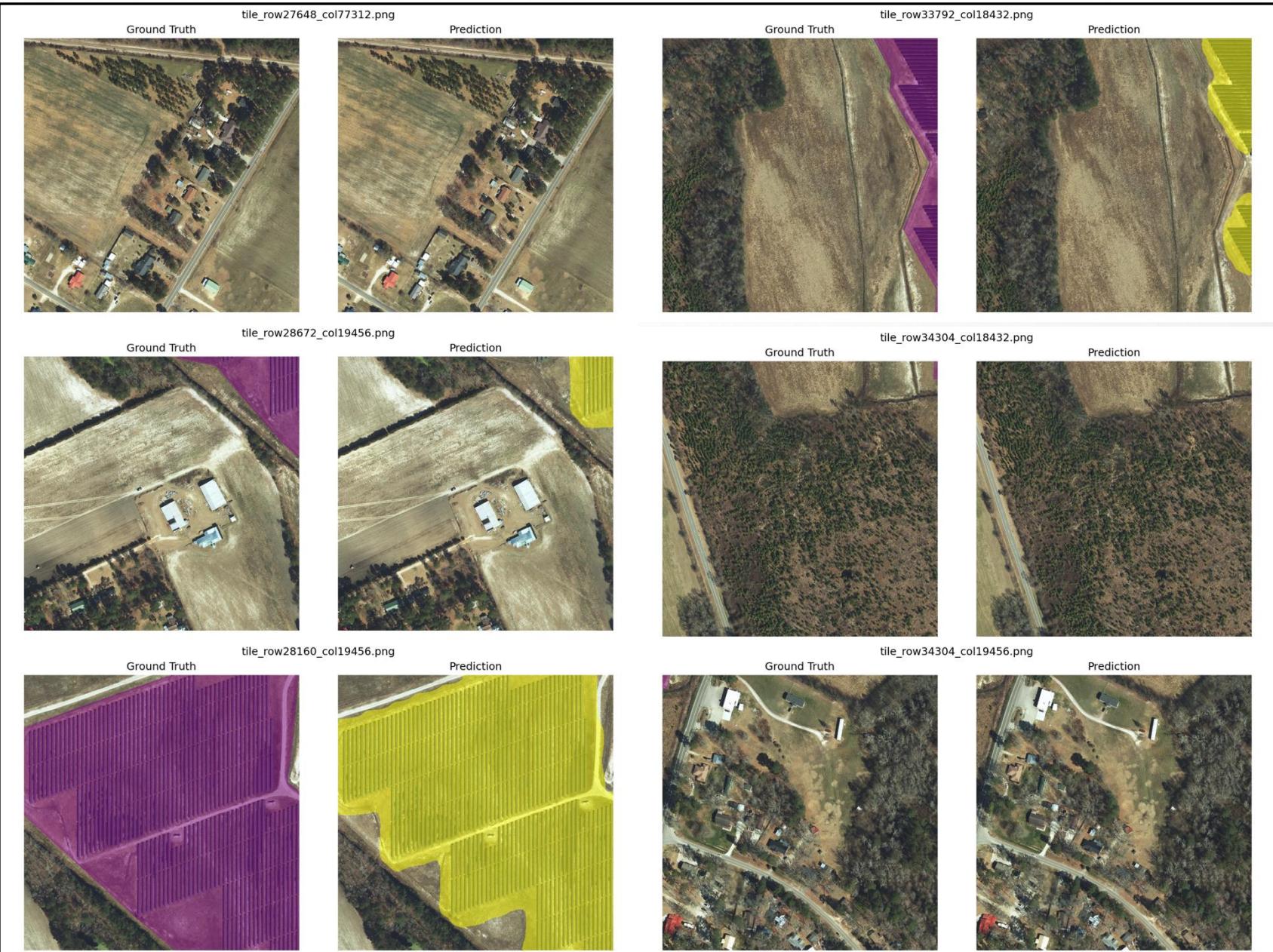
Visual Results (1 - 6)

Original Mask
Prediction



Visual Results (7 – 12)

Original Mask
Prediction



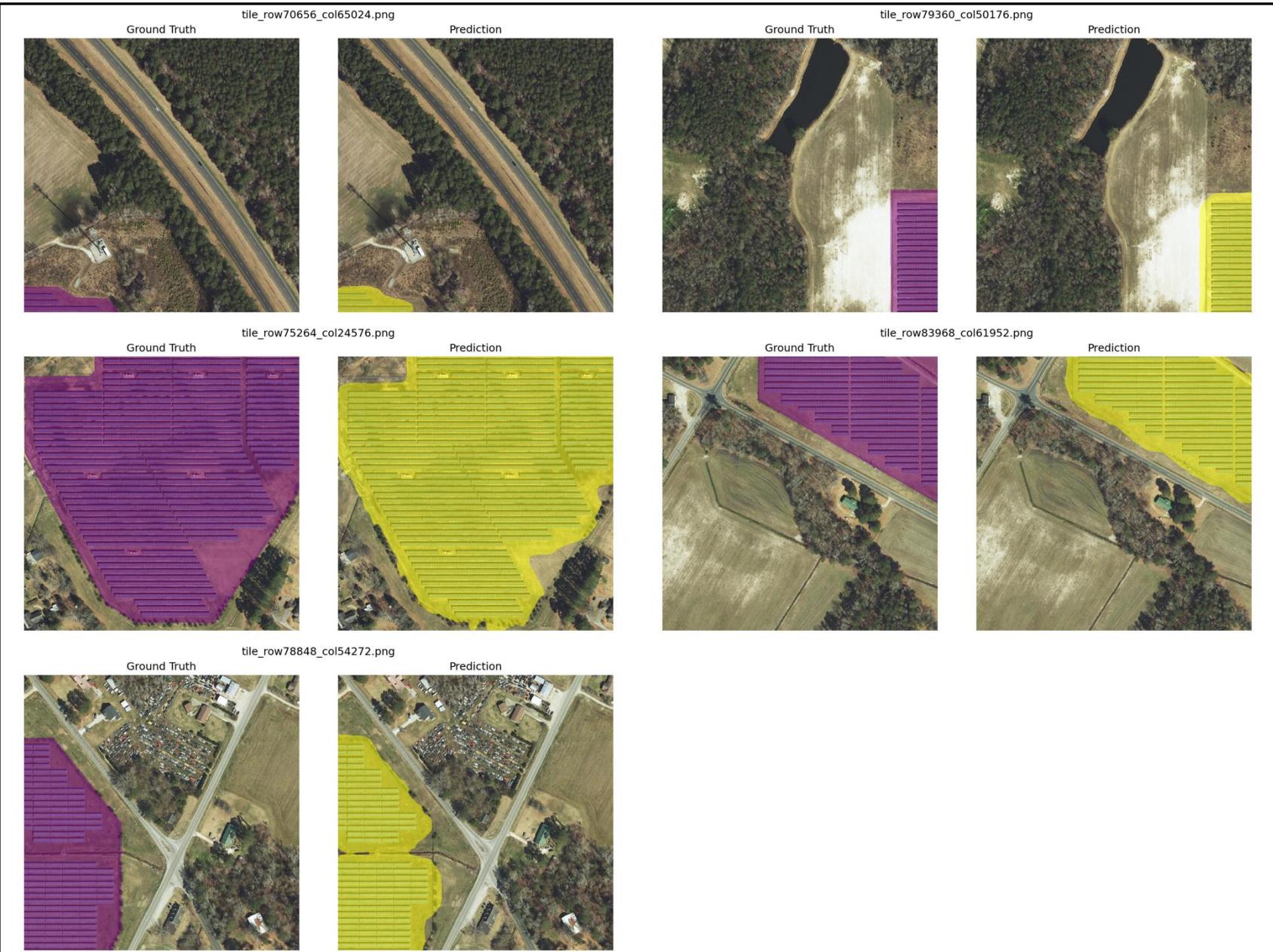
Visual Results (13 – 18)

Original Mask
Prediction



Visual Results (19 – 23)

- Original Mask
- Prediction



Visual Results – A Few Negative Examples

Original Mask

Prediction



LEARNINGS

U-Net is effective at mapping solar farms in aerial imagery

Masking strategy can significantly impact results

Data balancing and stratification are important steps

Cloud based GPU (Runpod in this case) helpful if using PyTorch/Mac

Visual inspection of results is critical

NEXT STEPS & CONSIDERATIONS

Nice IOU Score – but is data leakage an issue?

Needs to be run on outside data to gauge generalization

Some post processing to merge blobs may improve scores

Augment data to improve scores or generalization

Try other models (U-Net with attention, DeepLabv3, SegFormer) and compare results

THANK YOU!

REFERENCES

DATA SOURCES

NATURAL EARTH. (2025). 1:10M CULTURAL VECTORS.
[HTTPS://WWW.NATURALEARTHDATA.COM/](https://www.naturalearthdata.com/)

NC ONEMAP. (2019). NORTH CAROLINA DEPARTMENT OF INFORMATION TECHNOLOGY, GOVERNMENT DATA ANALYTICS CENTER, CENTER FOR GEOGRAPHIC INFORMATION AND ANALYSIS. [HTTPS://WWW.NCONEMAP.GOV/](https://www.nconemap.gov/)

OTHER

BROOKSHIRE, D., CAREY, J., & PARKER, D. (2022). NORTH CAROLINA SOLAR LAND USE AND AGRICULTURE: 2022 UPDATE. [HTTPS://ENERGYNC.ORG/WP-CONTENT/UPLOADS/2022/06/2022_Solar_AGV2.PDF](https://energync.org/wp-content/uploads/2022/06/2022_Solar_AGV2.pdf)

PRASAD, N.M., (2018). DEEP LEARNING IN MEDICAL IMAGING V, MEDIUM, DATA DRIVEN INVESTOR, [HTTPS://MEDIUM.DATADRIVENINVESTOR.COM/DEEP-LEARNING-IN-MEDICAL-IMAGING-3C1008431AAF](https://medium.datadriveninvestor.com/deep-learning-in-medical-imaging-3c1008431aae)

RUNPOD.IO. (2025). RUNPOD CLOUD PLATFORM. [HTTPS://WWW.RUNPOD.IO/](https://www.runpod.io/) (ACCESSED JUNE 25, 2025)

BACKUP SLIDES

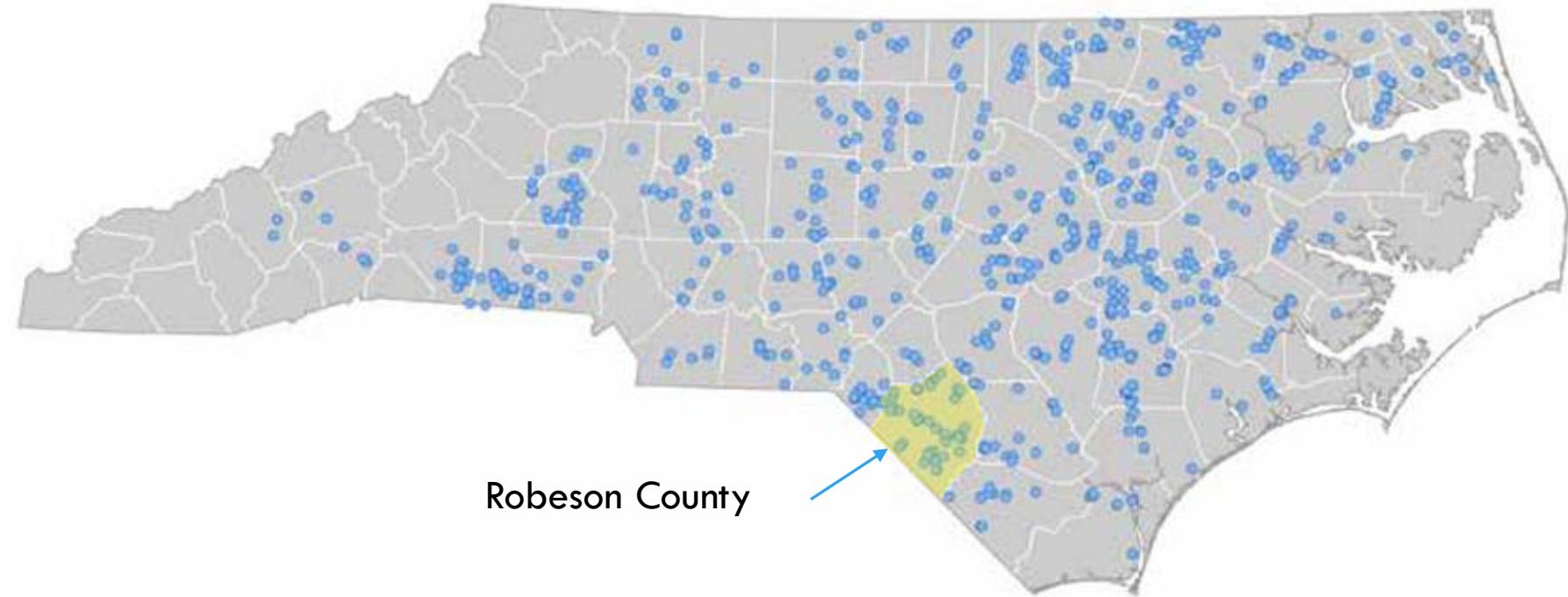


Figure 1. Locations of utility-scale solar PV systems with generating capacity of 1 MW or greater in NC

“North Carolina has more than 700 solar farms spanning nearly 35,000 acres, predominantly in rural communities” (Brookshire, et al, 2022)

TRAIN-TEST SPLIT/STRATIFICATION

- DATA SUBSET FOR BALANCE:
 - 940 TILES INCLUDING ALL POSITIVE TILES (235)
- TRAIN (80%)
 - 752 TILES (188 POSITIVE)
- VALIDATION (10%)
 - 94 TILES (24 POSITIVE)
- TEST (10%)
 - 94 TILES (23 POSITIVE)

POSSIBLE CONFUSING FEATURES



Pork/Chicken Farms in various orientations and sizes

POSSIBLE CONFUSING FEATURES



Dark wetlands in semi-regular rows



Forestry and agriculture geometric shapes and row like patterns

POSSIBLE CONFUSING FEATURES



Other infrastructure such as airports and parking lots

POSSIBLE CONFUSING FEATURES



Dark geometric wetland agriculture



Geometric forestry with rows

POSSIBLE CONFUSING FEATURES

Solar farms and confusing features together in same landscape.

