B31I-2597: Mapping center pivot agriculture with convolutional neural networks for improving estimates of land use change and water use

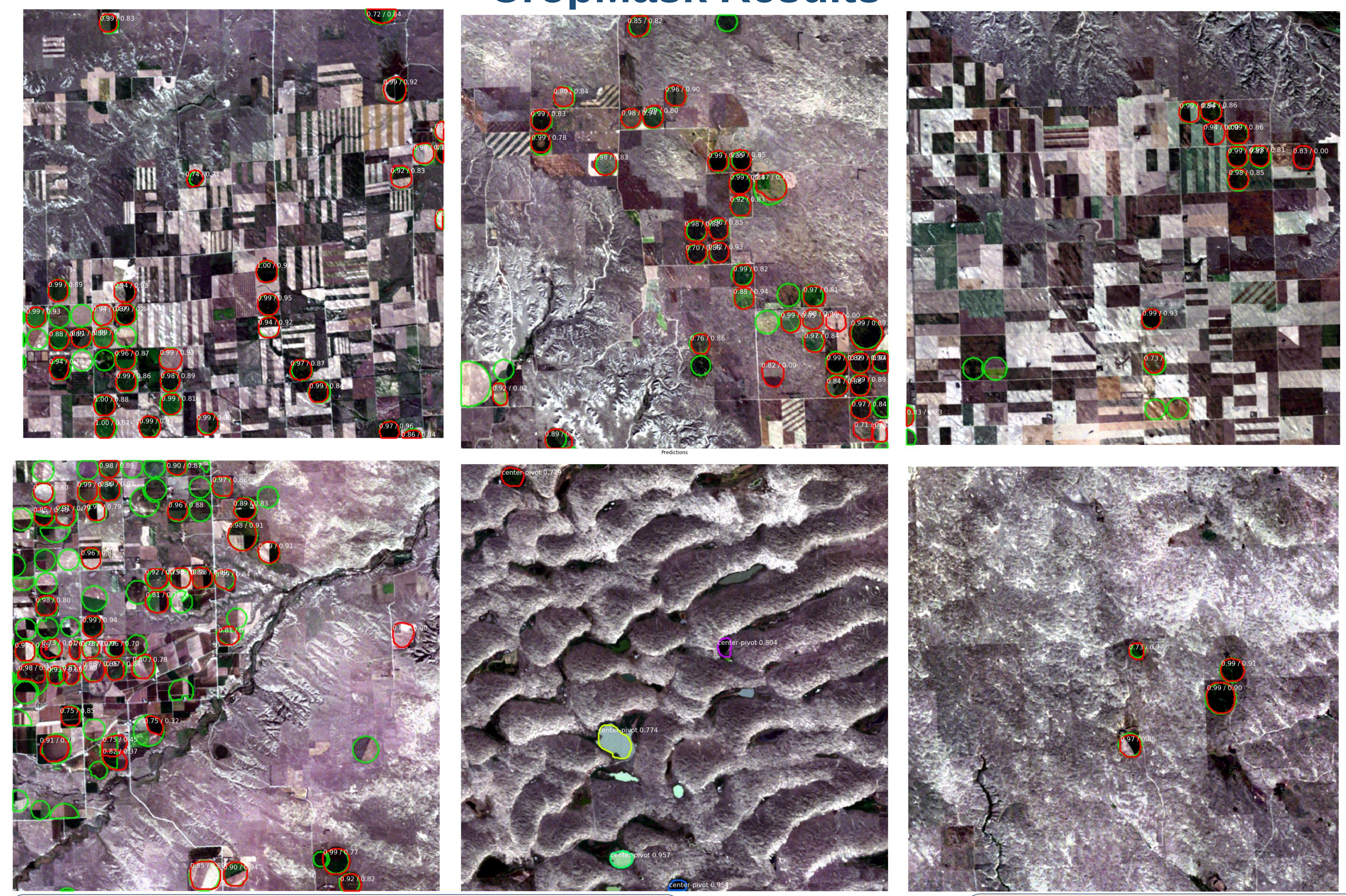
Motivations

- Agriculture accounts for up to 80% of human water use and demands grew 250% from 1960 to 2010 (Foley et al. 2005, Wada and Bierkens 2014).
- Yet we don't have a good understanding of the spatial and temporal dynamics of groundwater use.
- Many groundwater dependent regions lack datasets of center pivot fields boundaries to monitor field-scale water. This leaves gaps in our understanding of what drives water scarcity and regional water management practices.

Key Questions

- Can we segment field boundaries with high accuracy under a range of surrounding environmental conditions?
- Do models trained on a scene from have good precision and recall for a different date over the same path/row? A different path/row? How spatialy and temporally general is the model?
- Does including NIR as an input improve accuracy (separating irrigated from non-irrigated vegetation)?

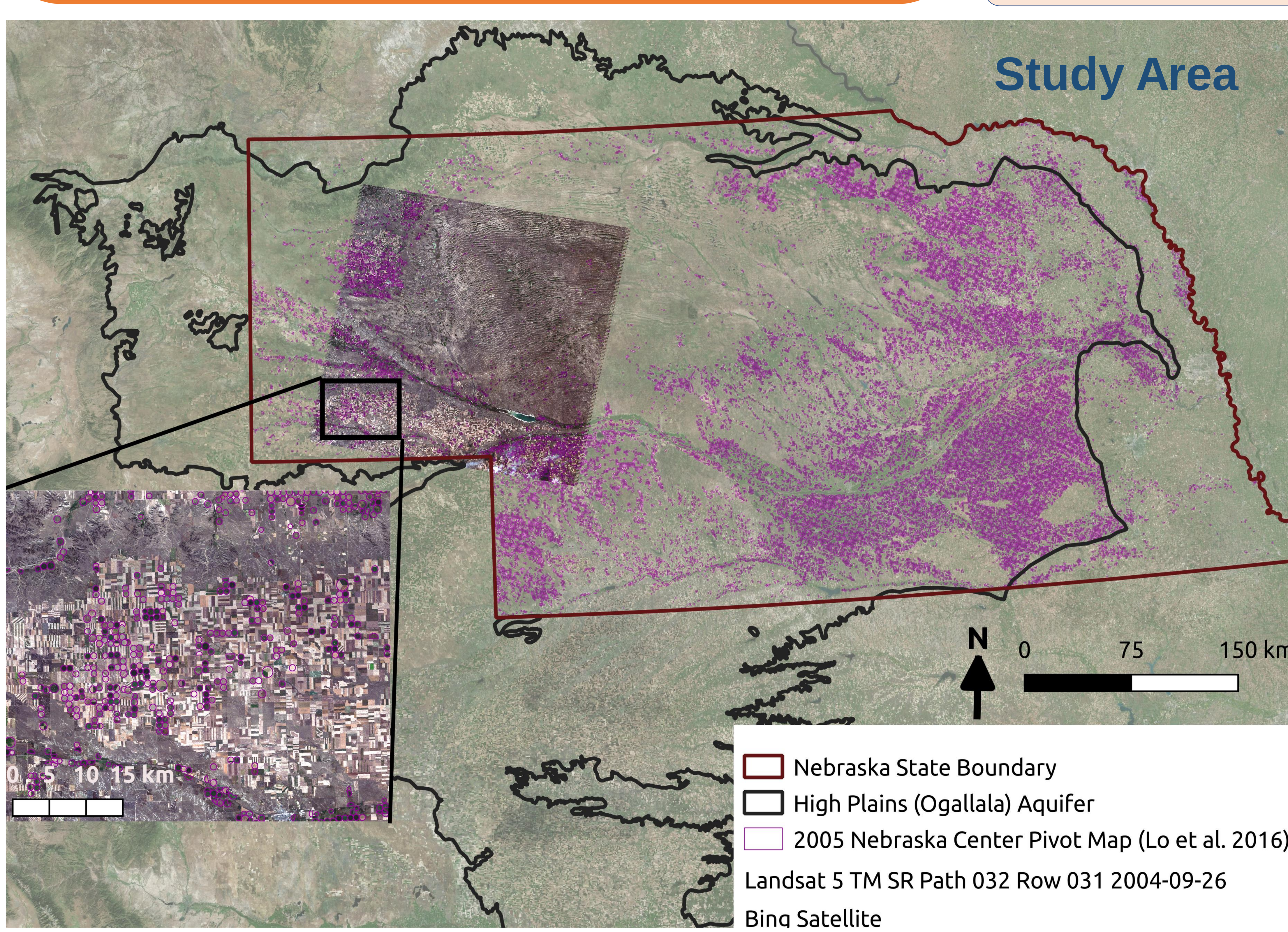
CropMask Results



Predictions (red) and groundtruth (green) for 6 of 12 512x512 tiles from the Landsat 5 TM scene

Each prediction: Probability score / Intersection over Union

Study Area

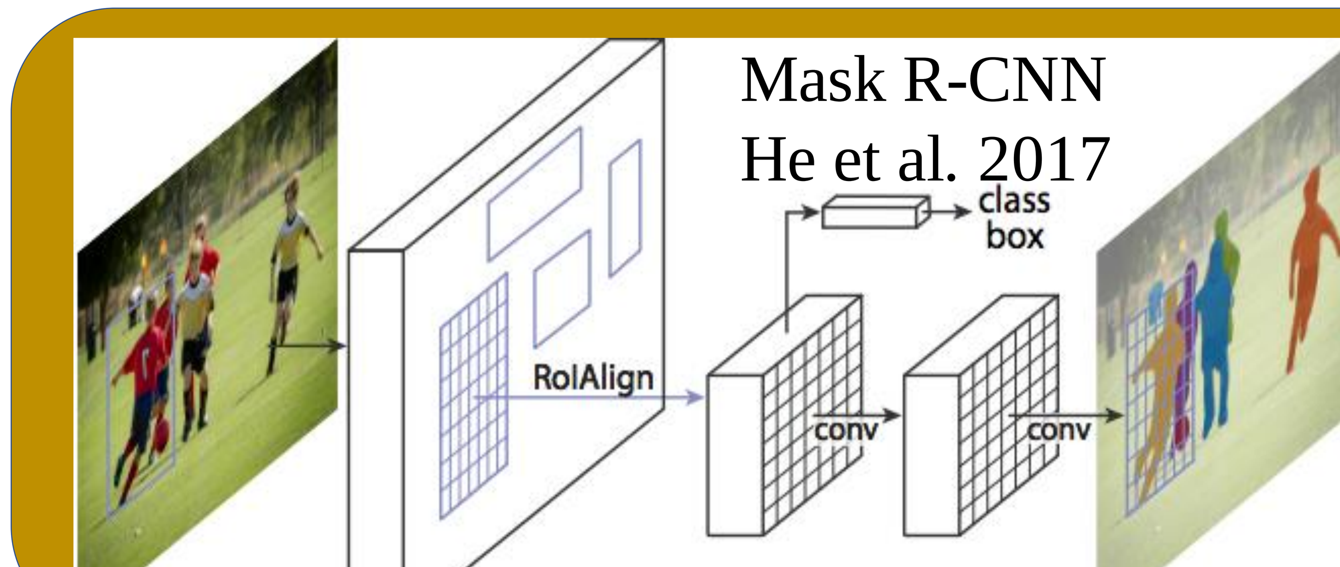


Methodology

1 Preprocess labels and tile Landsat scene to 118 512x512 pixel grids, with 90% for training and validation and 10% for testing.

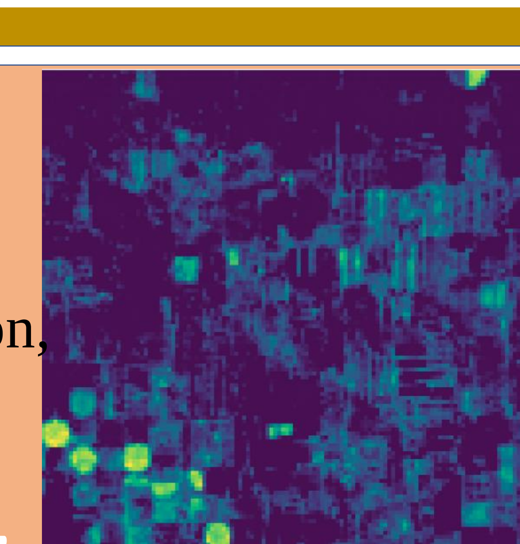
2 Transfer Learning with Resnet 50 network with COCO weights (Lin et al. 2015)

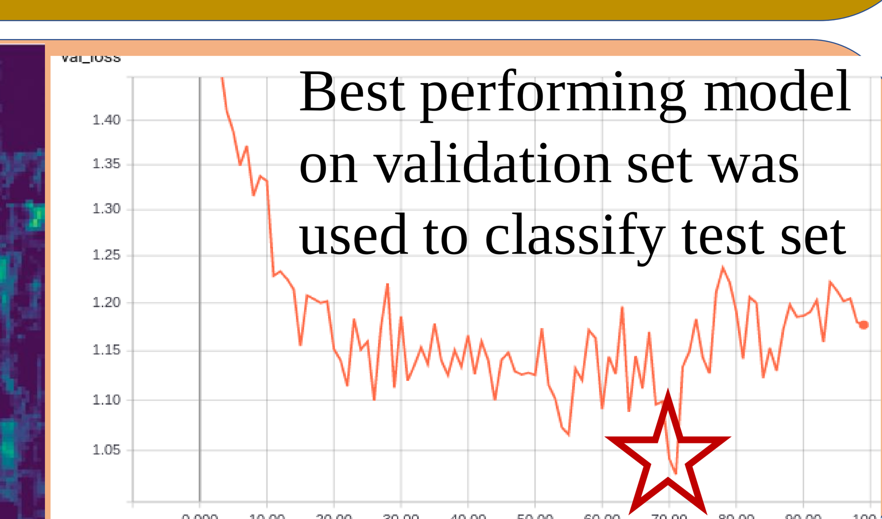
Mask R-CNN He et al. 2017



Train Mask R-CNN classifier with 90/180/270 degree rotation and L/R, up/down flip for augmentation. Tune hyperparameters. 3

Mask R-CNN learns 100s of features for pattern recognition, like bright green semi-circular features. 4





Best performing model on validation set was used to classify test set

Key Findings

- CropMask detects center pivots with great accuracy in independent tests using RGB bands. Pretraining with COCO is essential.
- False positives resulted from confusion of visibly bright, irrigated vegetation with clouds and lakes.
- False negatives resulted from date mismatch between imagery and labels and some semi-circular pivots.
- Future directions include testing the model on different path/rows, dates, and with more bands. We will pair Landsat brightness temperature with energy balance models like METRIC (Allen et al., 2007) to monitor crop water use and analyze regional differences in water management and drivers of groundwater decline.

Contributors

Co-authors: Ryan Avery, Kelly Caylor, Lyndon Estes, Marc Mayes

See detailed contributions and project code at **https://github.com/ecohydro/CropMask_RCNN**

We adapted Waleed Abdulla's Keras implementation: **https://github.com/matterport/Mask_RCNN**