Improving Crop Type Classification for Large Geographic Areas

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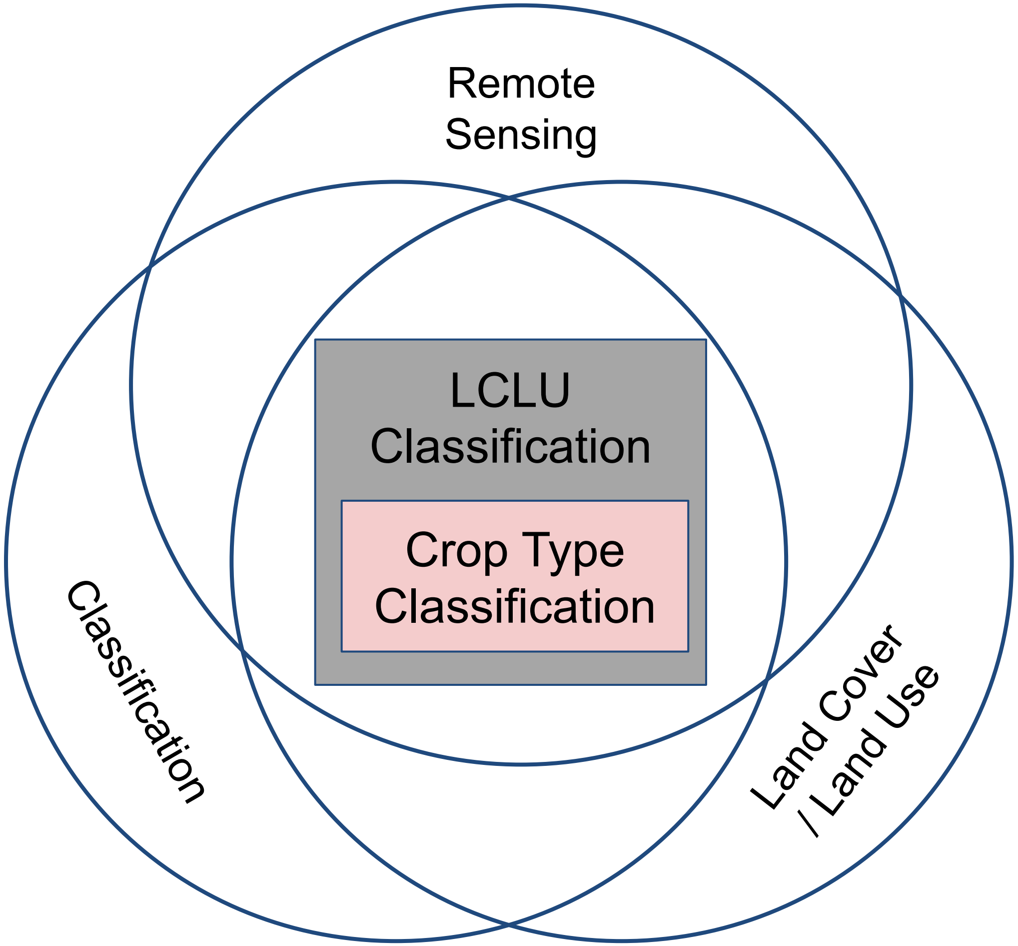
Outline

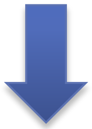
1. Introduction
2. County-level findings
3. Scale up to the State of Illinois
4. Future work

Introduction



- Applications
  - Crop insurance
  - Supply-chain logistics
  - Financial market

Field level classification



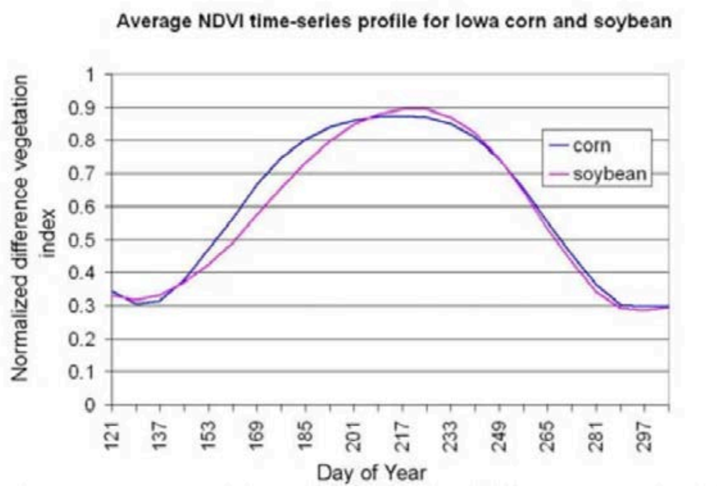
Landsat data

Accurate field-level crop type classification is very important.

Related Work

Single Spectral Information → *Spectral plus Temporal Information*

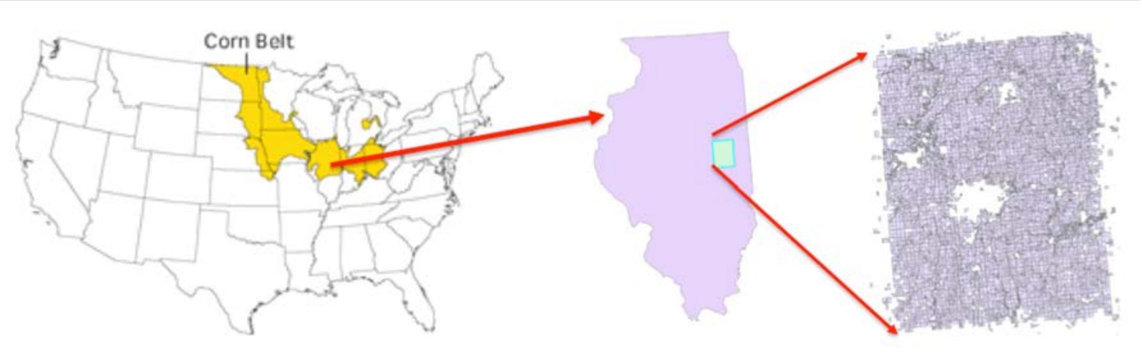
Cropland Data Layer (CDL)(*Boryan et al.*, 2011) U.S. Department of Agriculture (USDA)

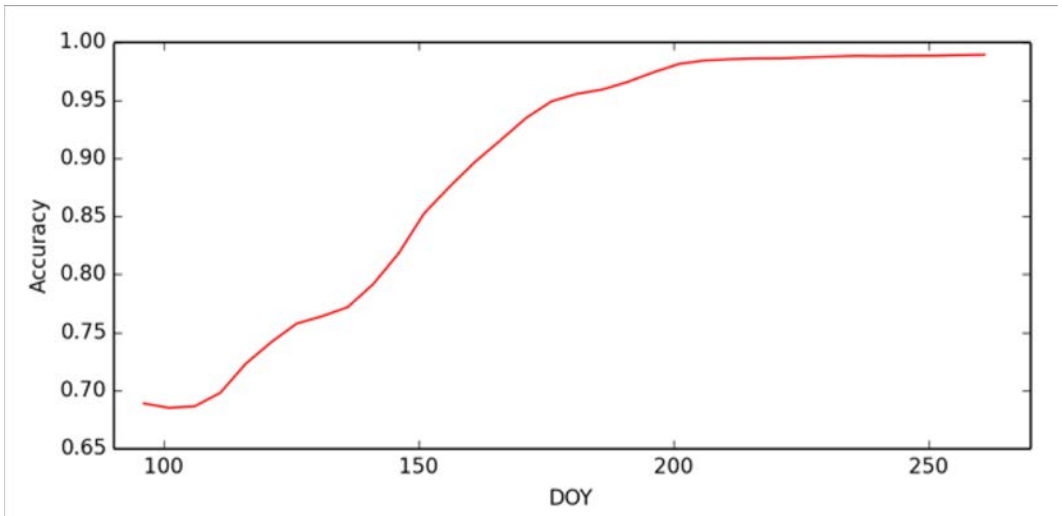


Time-series MODIS 250m Vegetation Index (VI) (Wardlow et al., 2007 & 2008)

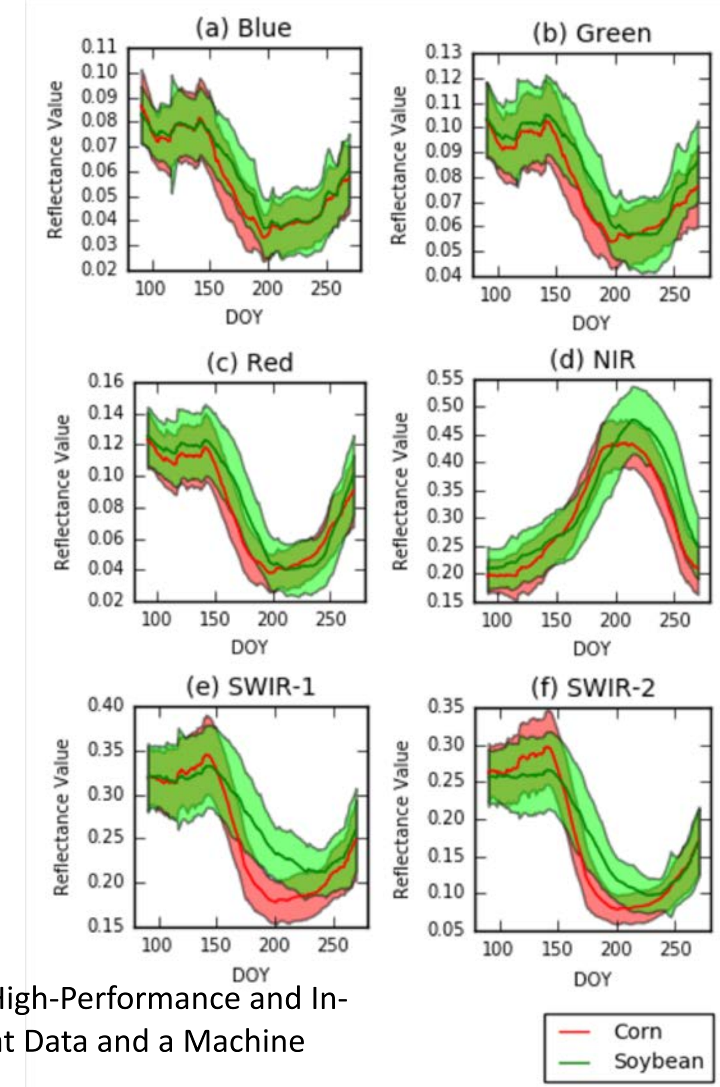
To generate in-season crop type classification is a challenge.

County-level findings



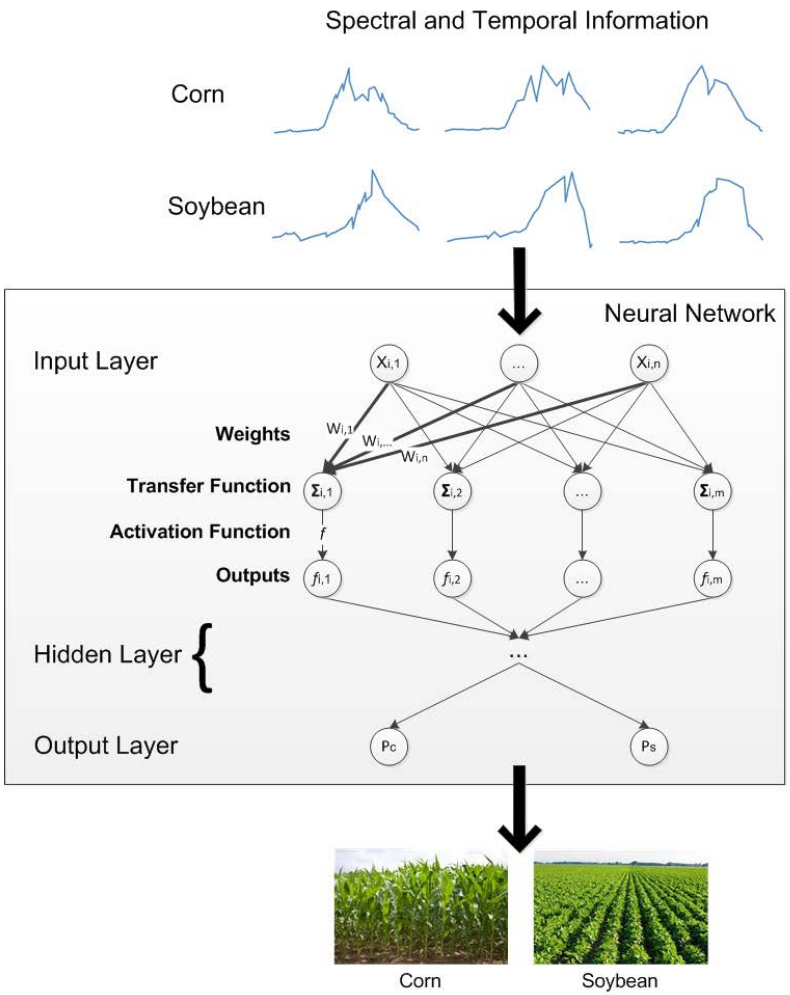


Classification performance as a function of time

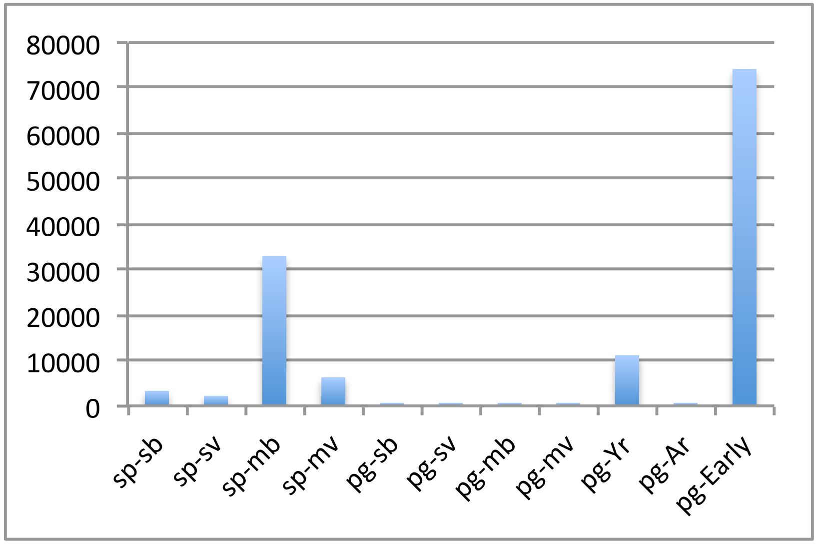


Cai, Y., Guan, K., Peng, J., Wang, S., Seifert, C., Wardlow, B., and Li, Z. (2018) "A High-Performance and In-Season Classification System of Field-Level Crop Types Using Time-Series Landsat Data and a Machine Learning Approach". *Remote Sensing of Environment.* 210: 35-47

Crop Classification Model



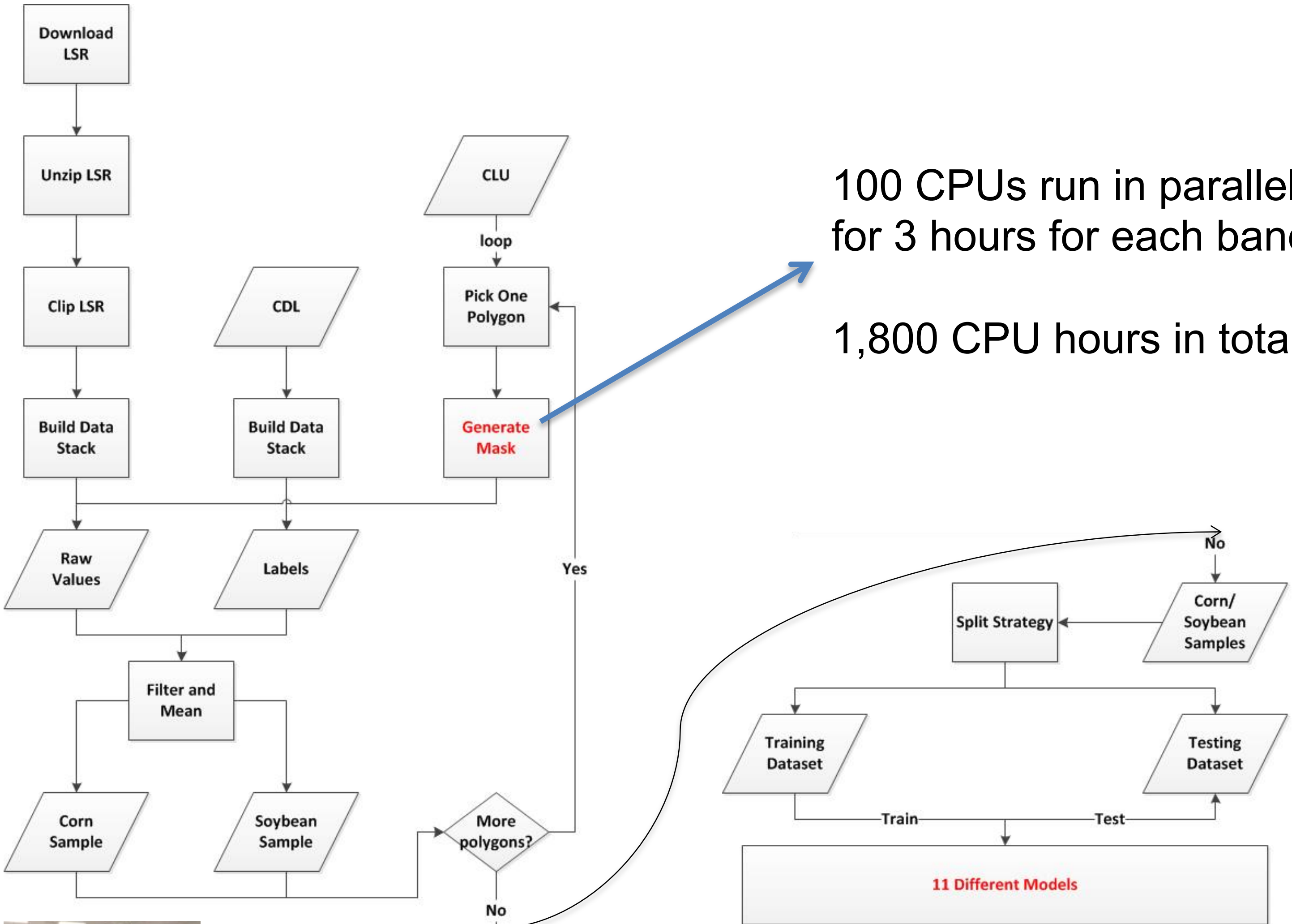
Crop Classification



131,216 CPU hours in total

Model training is computationally intensive.

High-Performance Computing Workflow



100 CPUs run in parallel for 3 hours for each band

1,800 CPU hours in total

ROGER

Blue Waters

CyberGIS Supercomputing

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INFRASTRUCTURE

home / infrastructure

Virtual ROGER

Batch system
GPU Nodes
VMware Cloud
1 Petabyte Storage

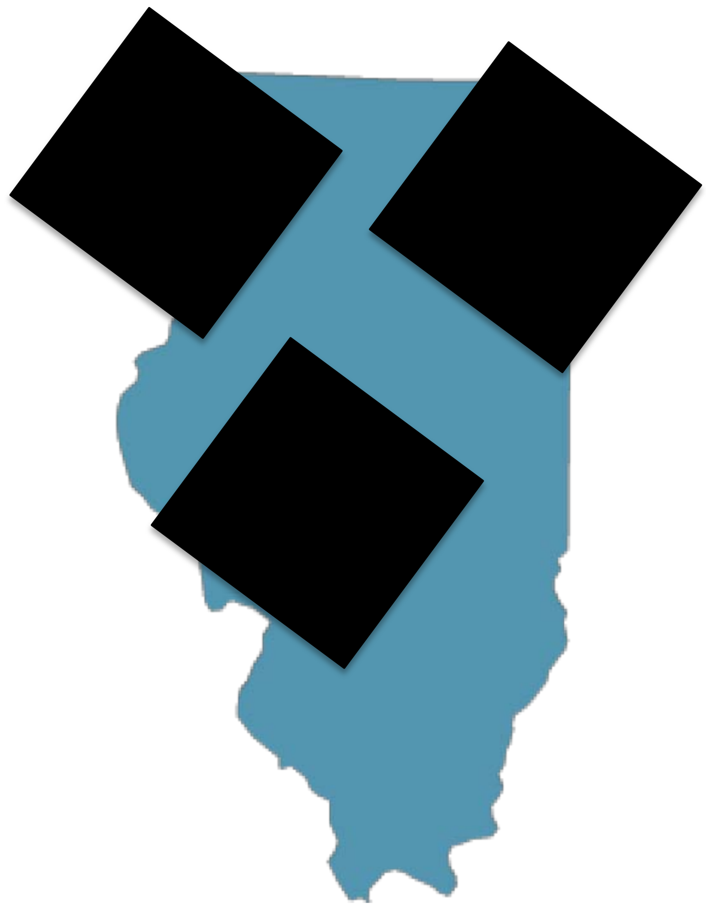
XSEDE

Scale up to IL State

Each scene can be processed in parallel

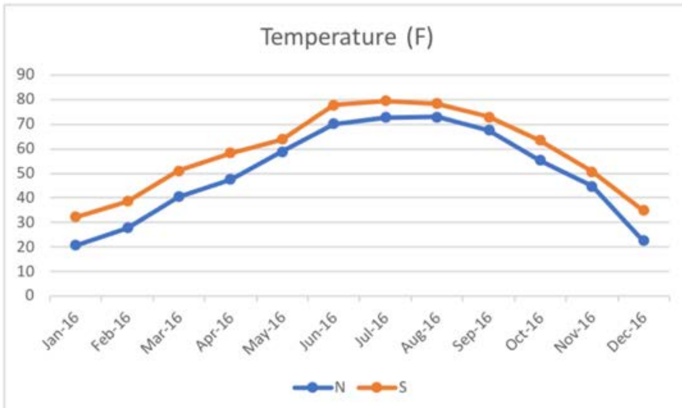
Each field can be processed in parallel

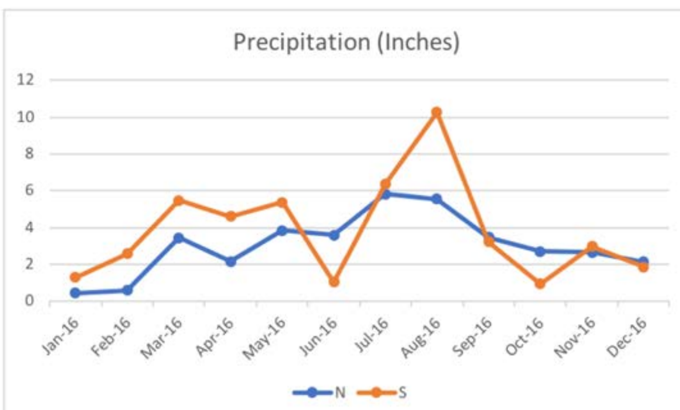
Process Each Sense in Parallel

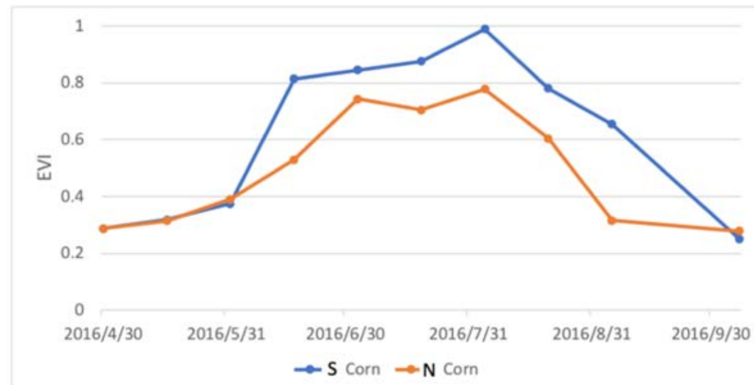


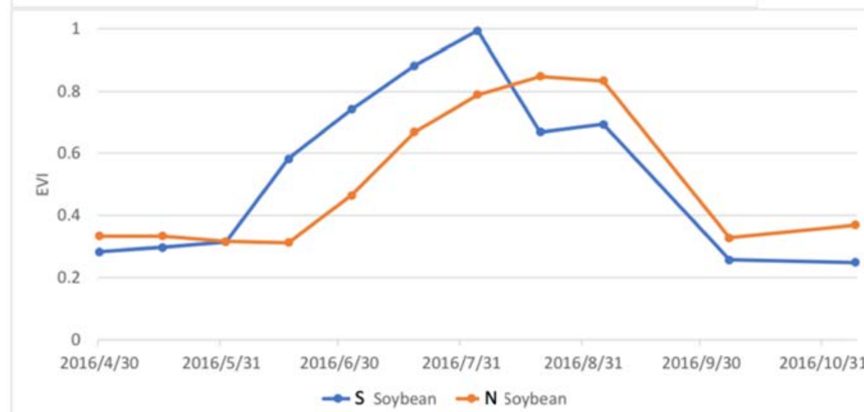
Key-Value: (FieldID+Date) – Average Reflectance

Hypothesis: Spatial Impact

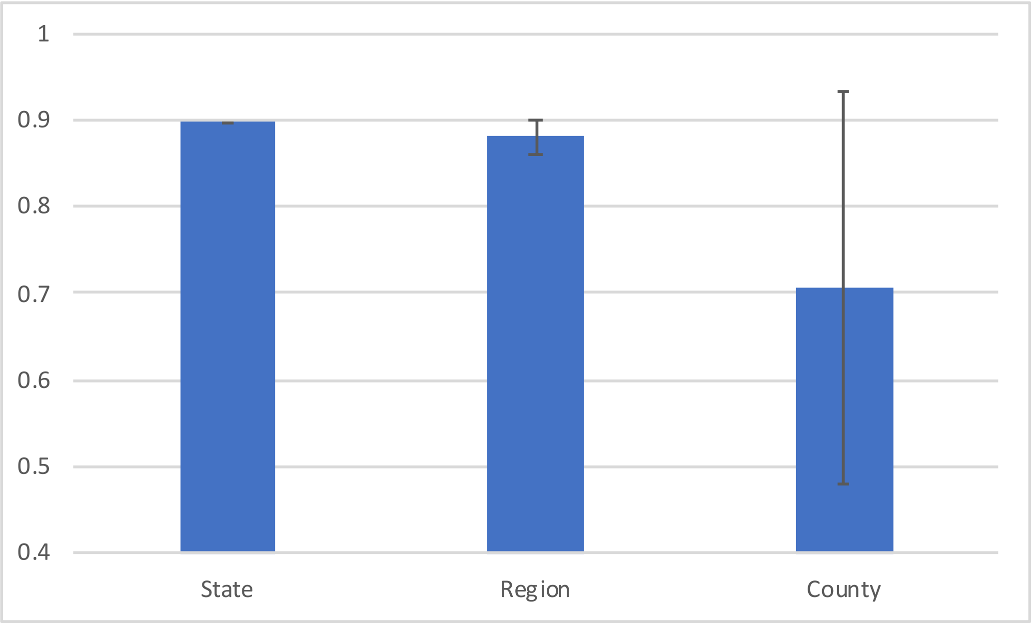


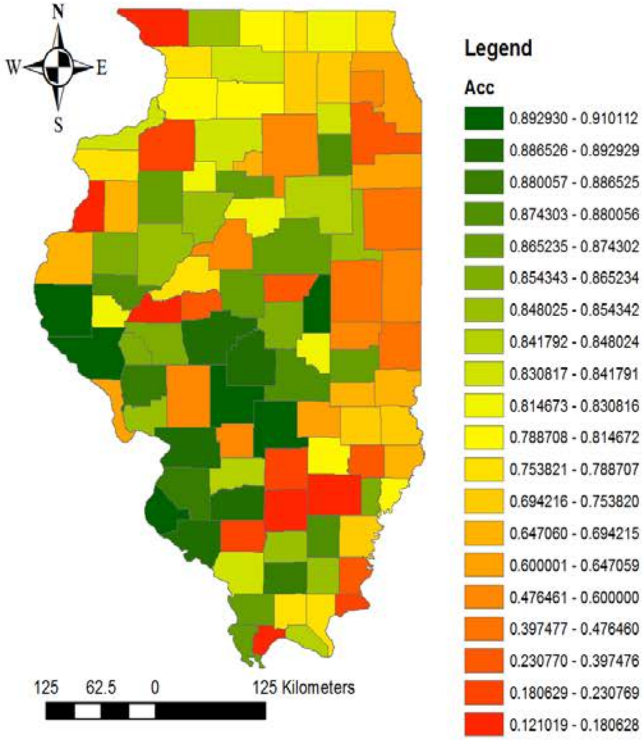




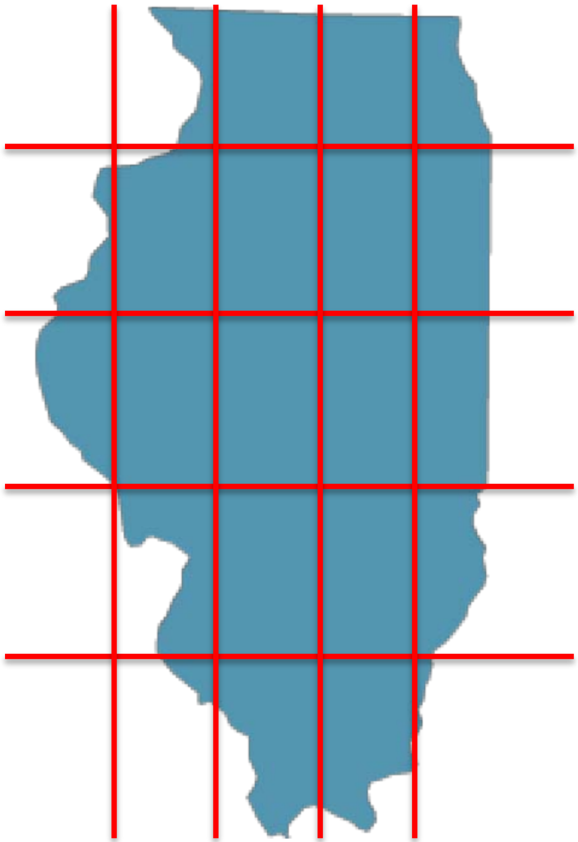


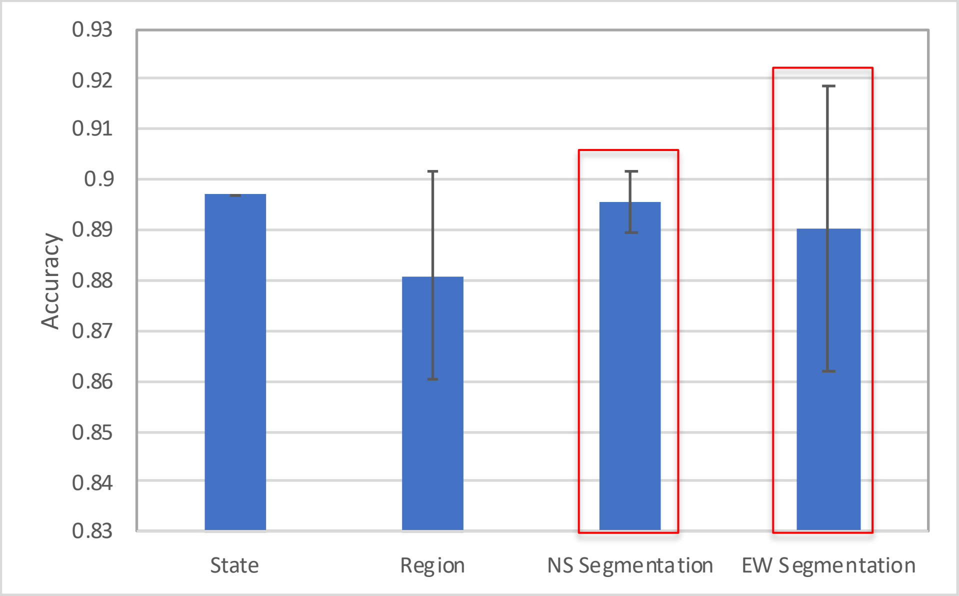
Results at Multiple Scales





Results for Different Regional Divisions





Future Work

- Improve the classification accuracy by finding the optimized spatial region division
- Extend current work to other years (currently focusing on 2016)

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Thanks !

- **Comments / Questions?**

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