Climate Change Driven Crop Yield Failure

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Tackling Climate Change with Machine Learning workshop at NeurIPS 2020

Motivation

Climate variability leads to crop yield variability

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1. 1/3rd of all crop yield variability in the **world** can be explained by climate variability. [1]

2. Up to 75% of corn & soybean yield variation in **Midwest** USA can be explained by weather variations. [1]

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Understand the effect of extreme weather on crop yield

Identify weather thresholds under which yield changes

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Literature Background

- Process Based Biophysical Models
- Conventional Statistical Models
- Machine Learning

Neural Networks,
Gaussian Processes,
Bayesian Neural Networks

Dataset

NOAA, Physics Sciences Laboratory

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Weather data

US Department of Agriculture

↓

Crop Yield data

Dataset

NOAA, Physics Sciences Laboratory

↓

Weather data

US Department of Agriculture

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Crop Yield data

Data construction and design:

County-level data from Minnesota and Illinois in 2012:

Features: daily minimum temperature, daily maximum temperature, daily precipitation, geo-location information

Target: end-of-year crop yield

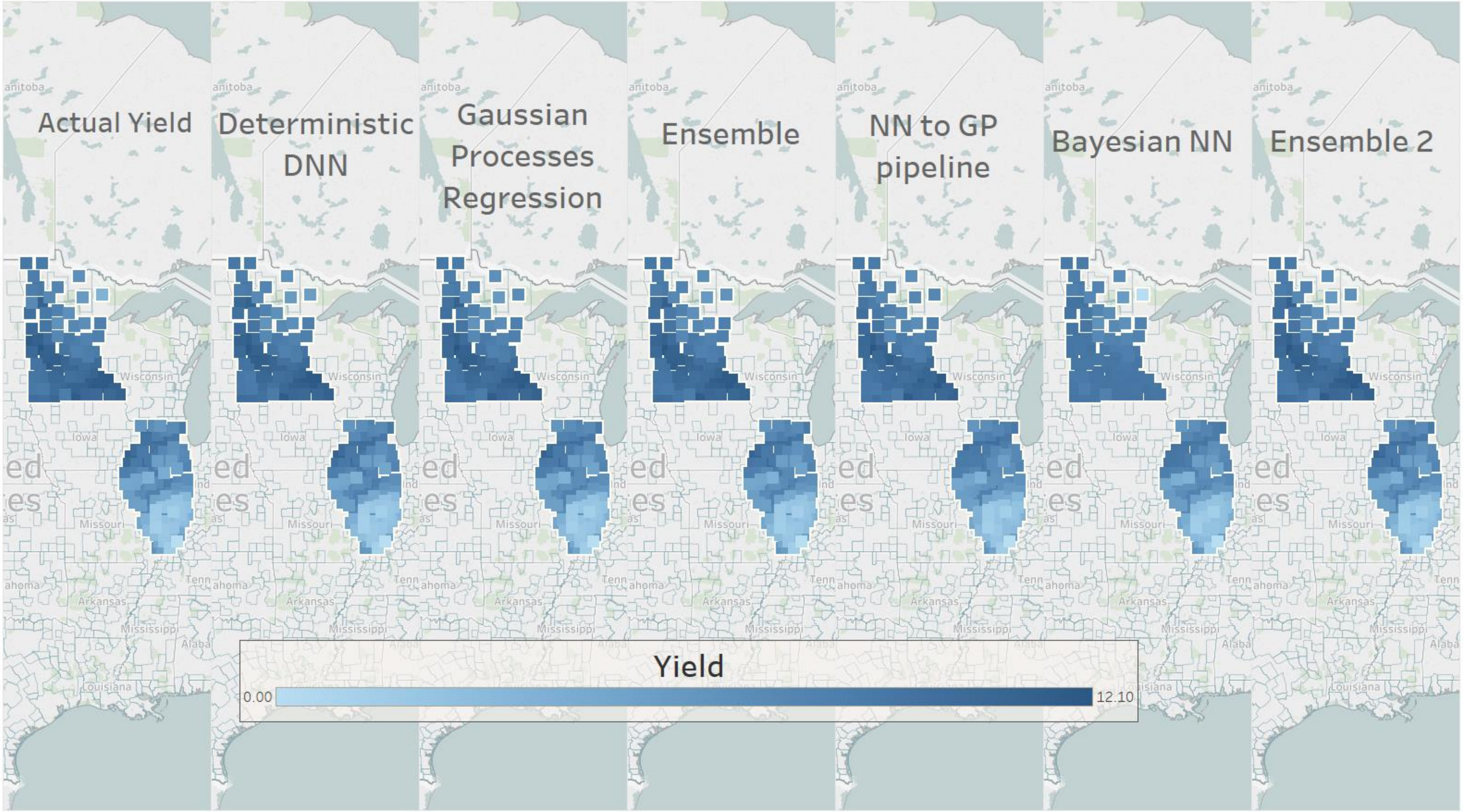
Train / test split: 70 : 30
Total number of counties: 189
Total number of samples: 189
Total number of features: 1100

Modeling Results

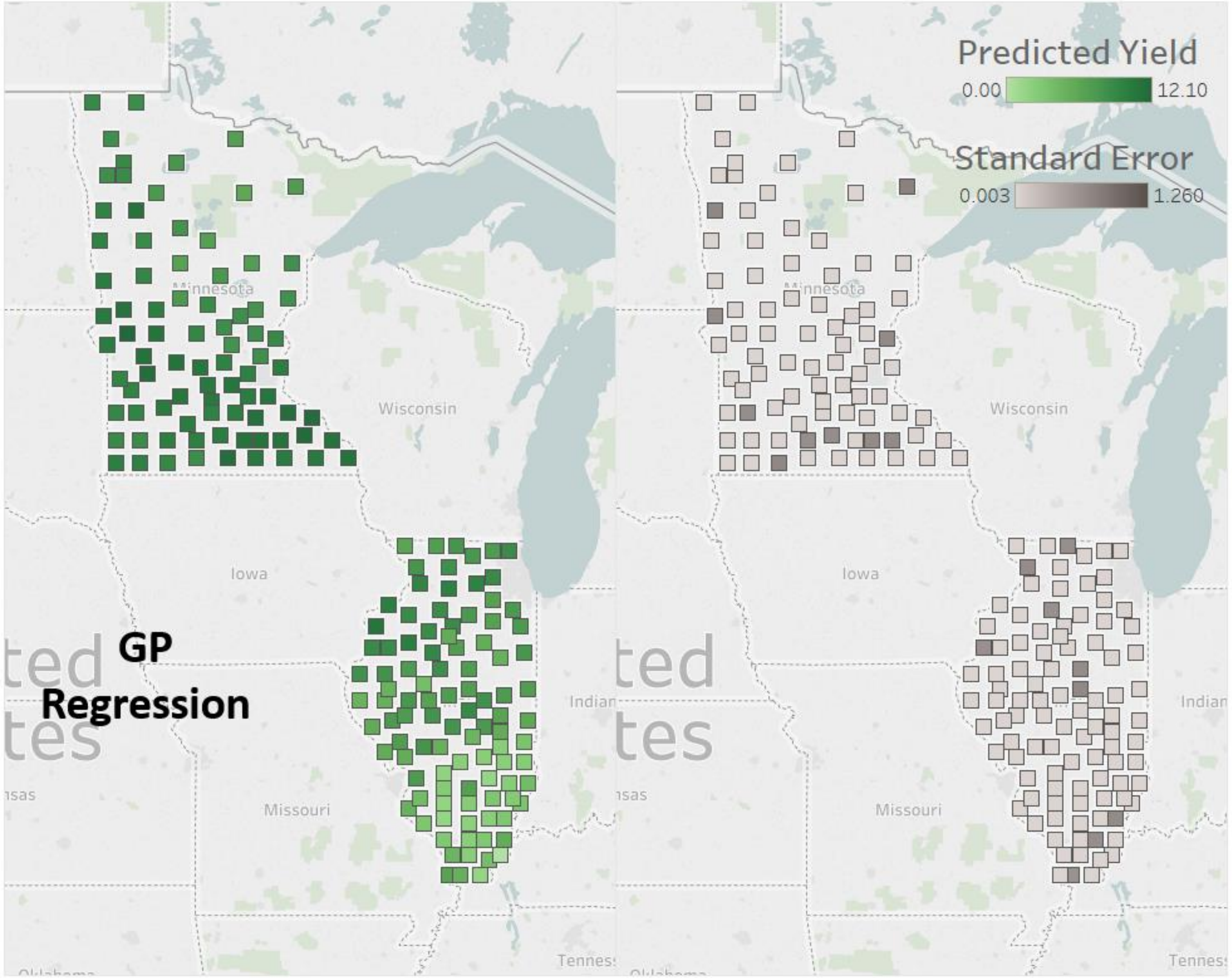
Models	MSE			R^2
	MN	IL	Overall	
Gaussian Processes	0.2693	**0.2215**	0.2432	0.9706
Deterministic DNN	0.2341	0.2942	0.2669	0.9678
Ensemble 1 (equal weights)	**0.2333**	0.2392	0.2365	0.9714
Ensemble 2 (computed weights)	0.2423	0.2296	**0.2353**	**0.9716**
GP to NN pipeline	0.4826	0.9336	0.729	0.912
Bayesian NN	1.8978	0.6833	1.2387	0.8505

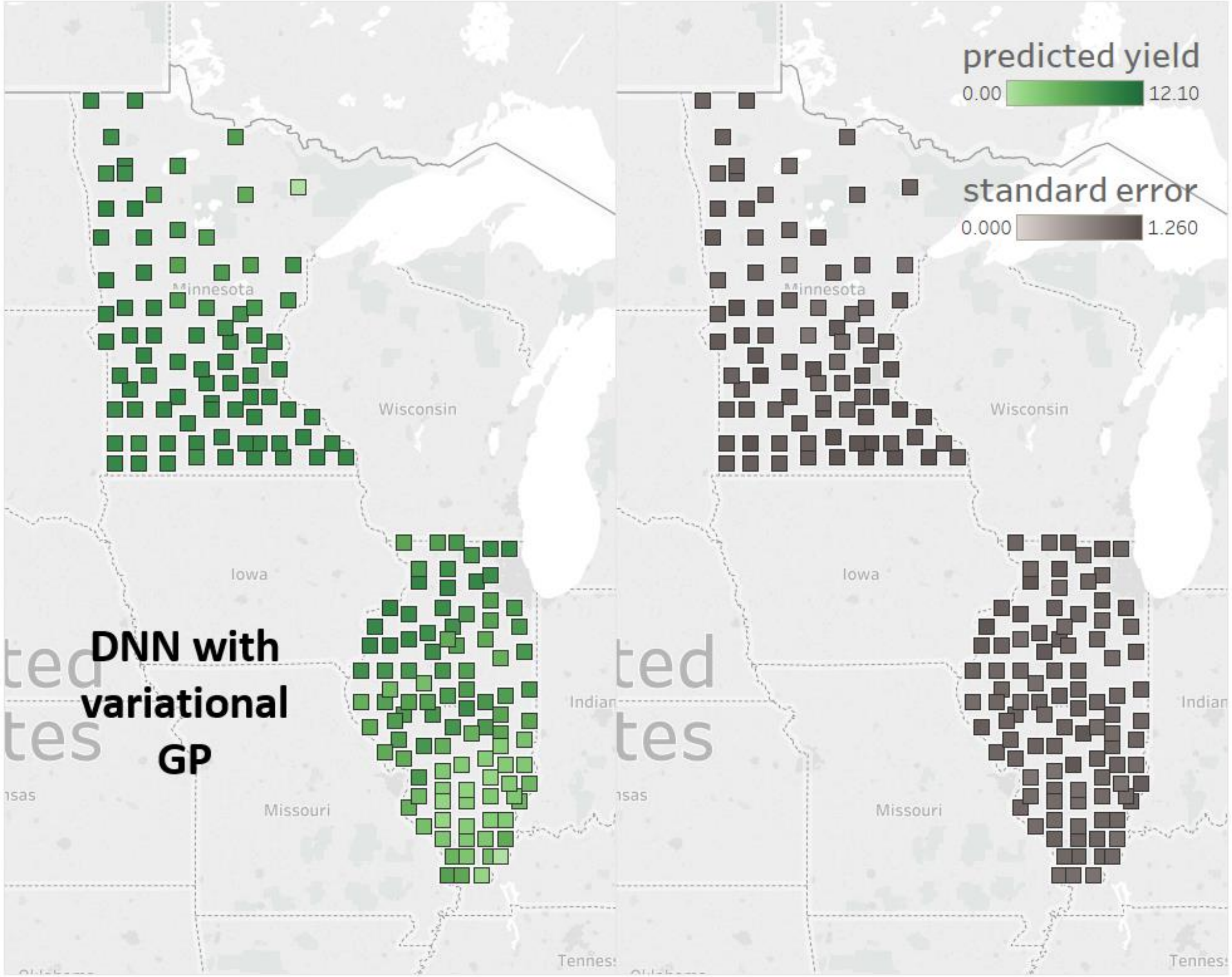
Table 1: Baseline Model Comparison

Modeling Results - Predictions

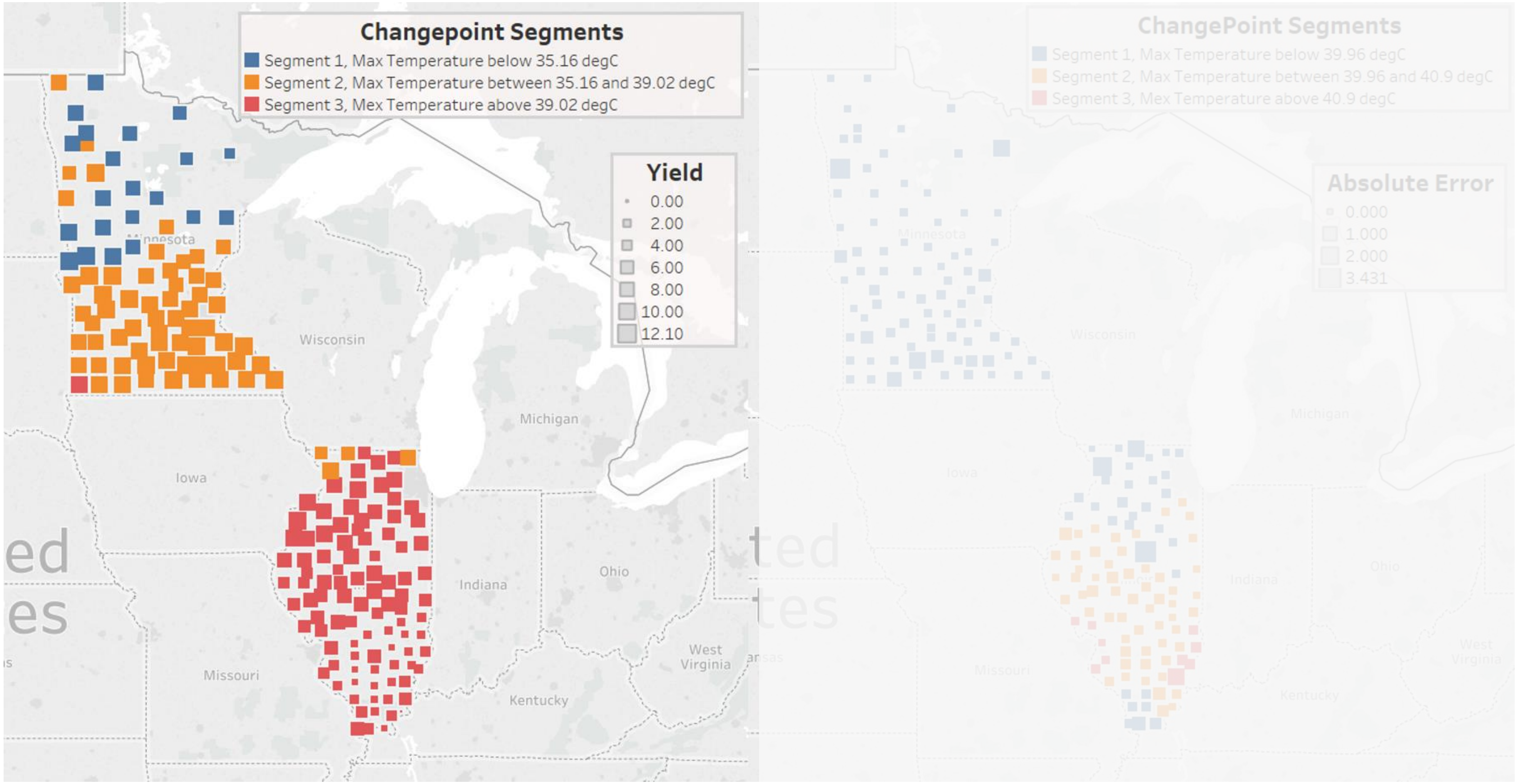


Modeling Results - Uncertainty Estimates



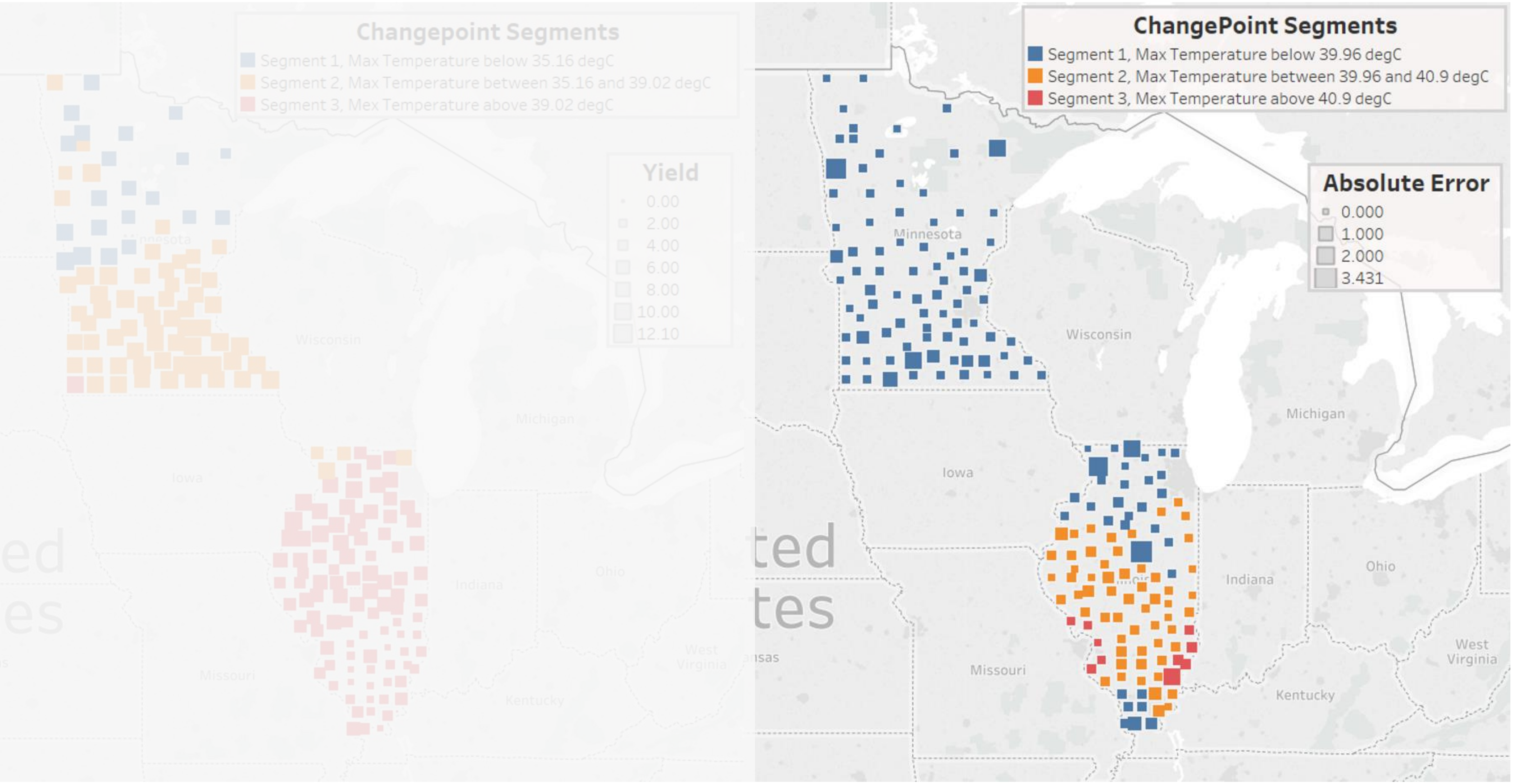


Changepoint Detection



Changepoint analysis can help with crop production planning.

Changepoint Detection



Changepoint analysis can help with crop production planning.

Thank you. Any Questions?