Risky Business:
Using Machine Learning to Predict
Insurance Premium Rates for Specialty Crops

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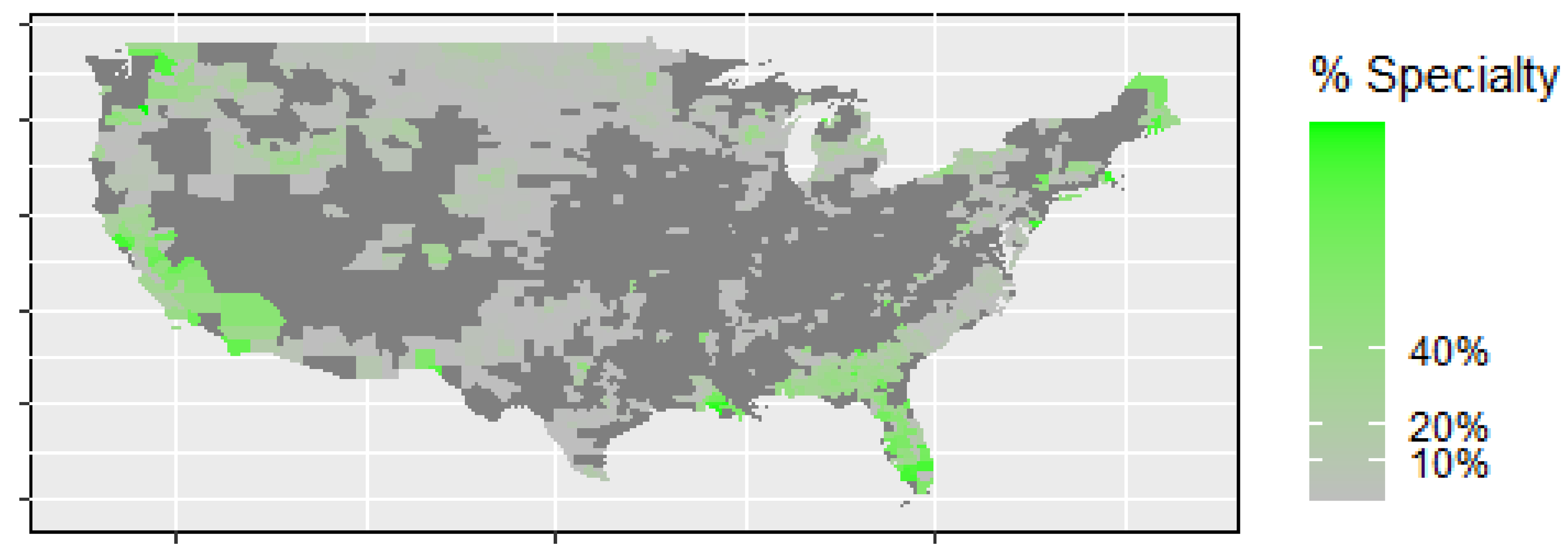
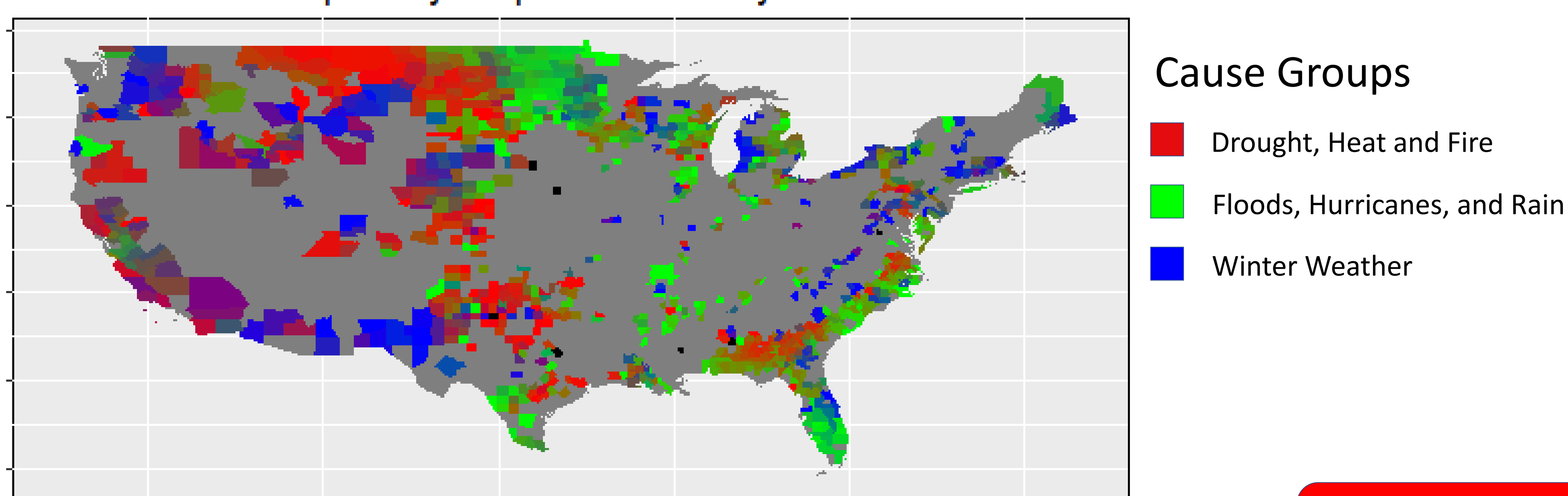
Introduction and Objectives

- Not all specialty crops are covered by the popular Federal Crop Insurance Program (FCIP)
  - Commodities with relatively low acreages and little production histories face delays getting covered by FCIP
  - Expanding the FCIP requires an intensive process to estimate the degree of risk the insurance offering would face
- The relative importance of a risk factor depends on region, commodity, and interaction effects with weather
- We use machine learning to identify key aspects of risk prediction functions without assuming simplistic functional forms *a-priori*
  - Project Base Premium Rates (BPR) for specialty crops not currently covered by FCIP or not covered in certain counties
  - Use derived functions to project future risk to illustrate heterogeneity in risk profiles for specialty crops
  - If successful, these models could serve as a baseline for estimating future USDA offerings

Specialty Crop Percentage of Insured Acres 2000-2021



Relative Share of Specialty Crop Indemnities by Cause



Data

- Create a dataset of BPR's by specialty crop policy with their associated local history of loss
  - Combining USDA data on recorded FCIP indemnities with actuarial records
  - Data is specific to specialty crop 'buckets', such as Citrus Fruit or Root Vegetables
- Describe loss by the frequency and average severity losses over the past decade
  - Use groups of causes, e.g. "Drought" or "Pests/Disease"

Machine Learning: Reducing Dimensionality

- Utilize a LASSO regression algorithm to eliminate unnecessary variables from the many created above
- Lambda, the punishment parameter eliminates irrelevant variables, determined by 10-fold cross validation
- After removing the variables whose coefficients are forced to zero, we have a more parsimonious regression function predicting aggregate risk from local history with risk factors

Types of Specialty Crops
Citrus
Berries
Root Vegetables
…

Actuarial Data
Base Premium Rate
Coverage Level
Location
…

Loss Frequency	Loss Severity	Climate Variables
# of Droughts	% Acres Lost to Drought	Rainfall
# of Freezes	% Acres Lost to Freeze	Temperature
…	…	…
Interactions		

LASSO

$$\sum_{i=1}^{n}\Big(y_i - \sum_{j} x_{ij}\beta_j\Big)^2 + \lambda\sum_{j=1}^{p}|\beta_j|$$

Tibshirani R. 1996. Regression shrinkage and selection via the lasso. J. R. Stat. Soc. B 58:267–88

Preserved Drivers of Base Premium Rates

Citrus BPR	# of Hurricanes	% Acres Lost to Wind	…

Berries BPR	% Lost to Pests	# of Pests Outbreaks	…

Root Vegetable BPR	% Acres Lost to Winter Weather	% Acres Lost to Flood	…

Next Steps:

- Evaluate model fit
  - Can training sets precisely estimate BPR out of sample?
    - Across crops, across space, or both
- Model Extensions
  - Include PRISM weather data, FEMA disaster declarations, etc.
  - Expand to additional loss causes and explore grouping
- Contrast the accuracy and precision of our LASSO regression functions against simple, 'rule of thumb' methods