Predicting SCO and ECO Crop Insurance Payouts Using Preliminary County-Level Loss Data

Anup Paudel, Jennifer Ifft, and Micah Cameron-Harp

2026 Risk & Profit Conference

August 20, 2026

Background

Crop Insurance Basics

- Farmers buy an individual Revenue Protection (RP) policy at a coverage level ranging from (50% - 85%) selected in 5% increment (USDA RMA, 2026)
- RP pays when their own farm's revenue falls below the chosen coverage level guarantee
- Supplemental Coverage Option (SCO) and Enhanced Coverage Option (ECO) sit on top of RP, triggered based on county-average outcomes, not individual farm losses (USDA, 2026)

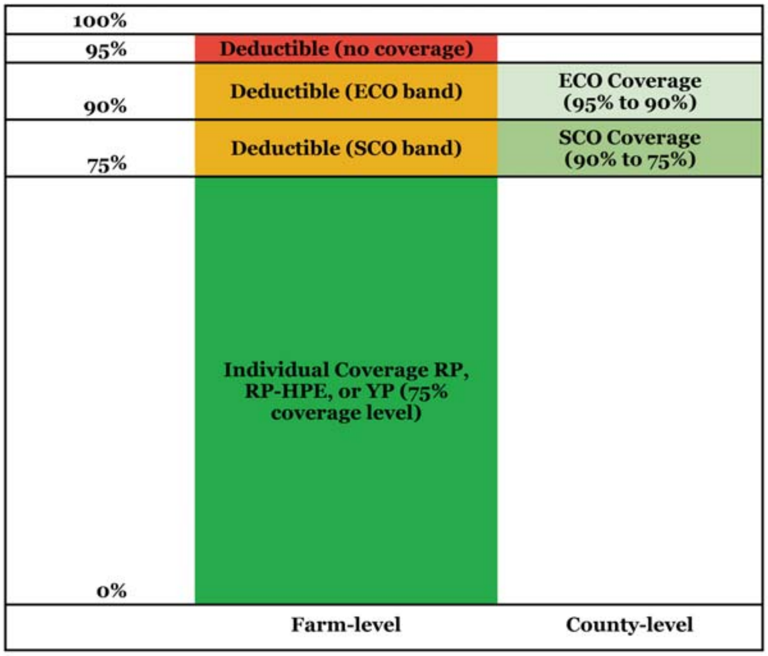
Supplemental Coverage Option(SCO)

- SCO fills the coverage gap between a farmer’s chosen RP coverage level (e.g., 70%/75%) and 86% of expected county revenue (Plastina, 2024)
- Indemnity calculation: difference between 86% and the ratio of Actual County Revenue to Expected County Revenue, scaled to the coverage band width
- Priced and paid entirely on a county basis, so that one farmer's individual loss doesn't matter for SCO

Enhanced Coverage Option (ECO)

- ECO extends coverage above SCO's 86% ceiling, up to either 90% or 95% of expected county revenue; the farmer picks one (Schnitkey et al., 2020)
- Structured "on top of" the underlying RP policy, same mechanics as SCO, but applied to a higher coverage band
- Combined with SCO and RP, a farmer can construct continuous coverage from their RP level up to 95%; effectively a 5% deductible with 95% ECO, or a 10% deductible with 90% ECO

The Coverage Bands



Policy Context: OBBBA Changes

- The One Big Beautiful Bill Act (OBBBA), passed in July 2025, raised the premium subsidy rate for SCO and ECO from 65% to 80%, effective 2026 (Schnitkey et al., 2026)
- Removes the restriction that had prevented ARC-CO participants from enrolling in SCO
- The SCO coverage trigger will rise from 86% to 90% starting with the 2027 crop year.
- These changes increase both the frequency and size of subsidized SCO/ECO enrollment and, consequently, payment activity

Research Problem

❖ **The Forecasting Gap**

- RMA finalizes official county yields and payment factors for a crop year around June of the following year (USDA RMA, 2025)
- This creates a decision-timing gap: nearly 8 months pass between harvest and official confirmation of whether a policy triggered
- Early prediction of indemnities would allow producers and lenders to improve financial planning(Goodwin & Ker, 1998)
- Predictive modeling using in-season and historical data can partially close this gap ahead of RMA's release

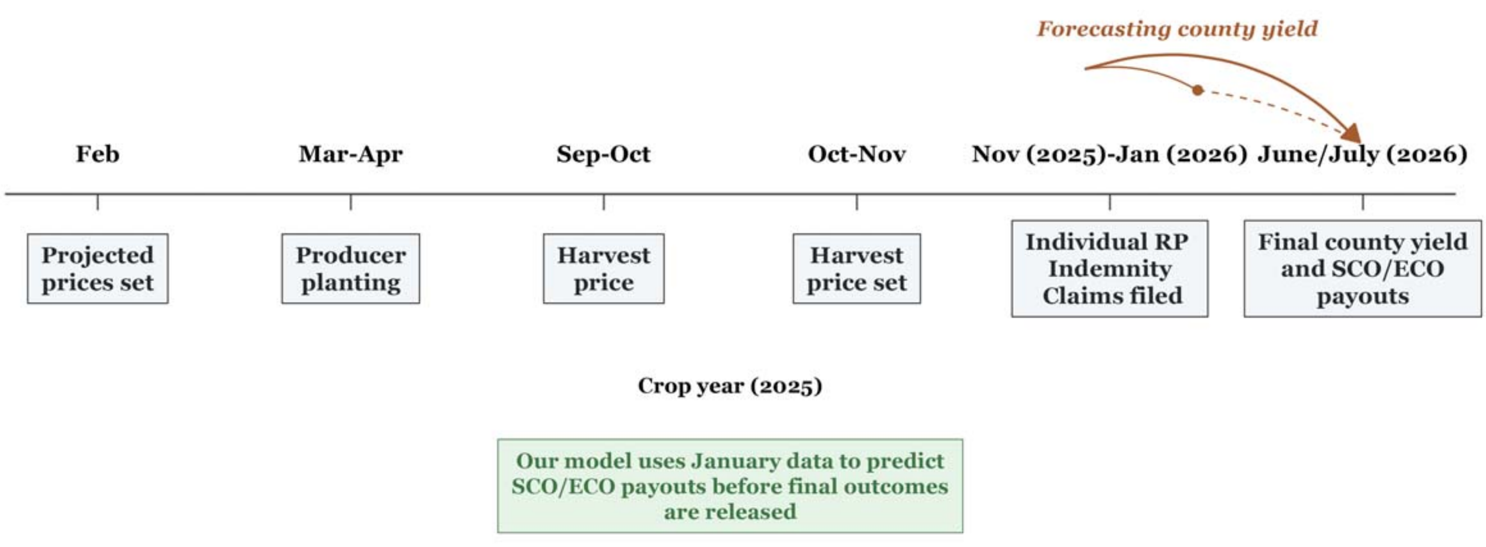
Literature Gap

- Weather-based growing parameters (temperature, precipitation, degree days) are well-established yield predictors (Kern et al., 2020; Shahhosseini et al., 2021), but most studies stop at yield accuracy without extending forecasts into real insurance payout applications
- Prior studies focus on weather-based prediction, but limited research has examined individual RP claims-filed data to predict yield.
- This study contributes to the literature by introducing individual RP claims filed data alongside weather variables, extending prior work

Research Objectives

- Predict county-level corn yield using four modeling approaches, selecting the best-performing model among them
- Evaluate model performance through rigorous out-of-sample validation
- Translate yield forecasts into actionable SCO/ECO payout predictions using the best-performing model

Crop-Year Timeline for Insurance



Note: Timeline is based on preliminary data and typical patterns; actual dates may vary.

Data

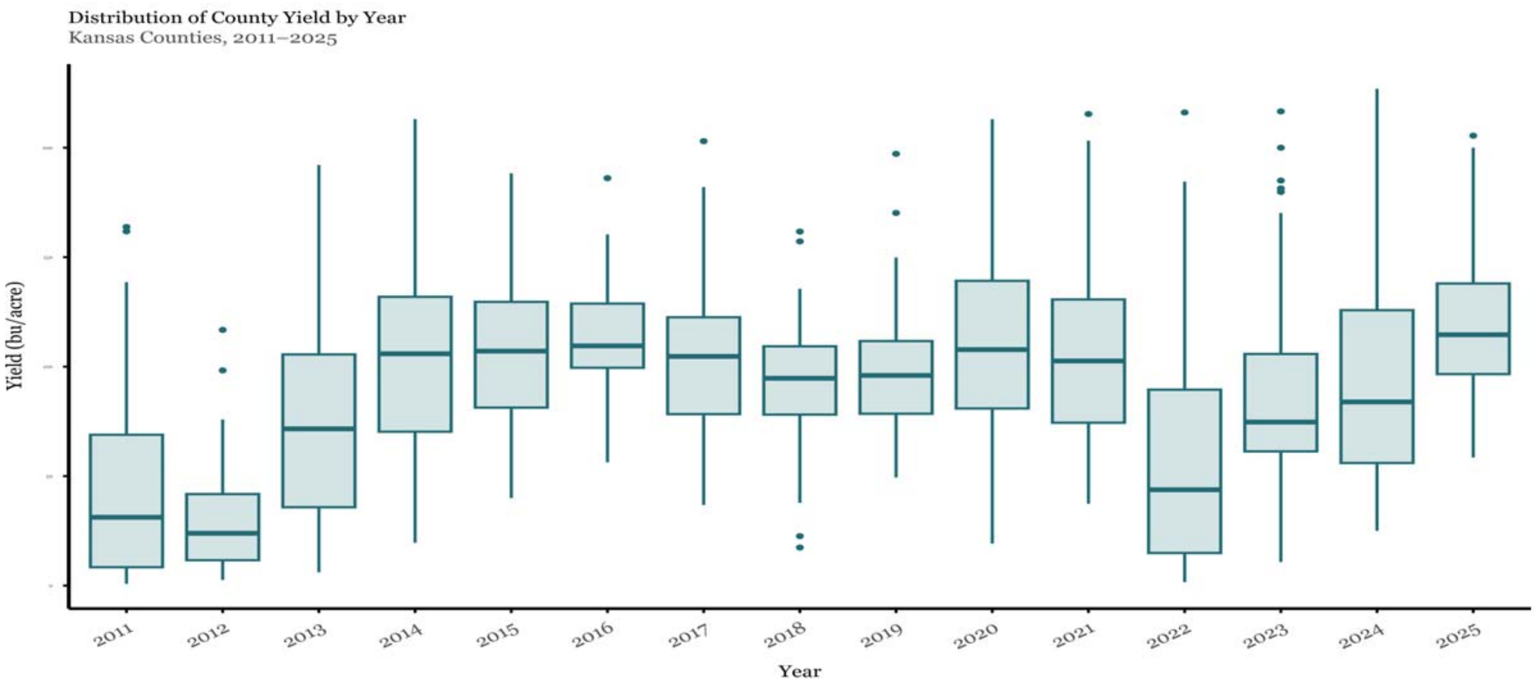
- This study uses the data from 2011 to 2025 for non-irrigated corn in Kansas

From USDA RMA	From RMA Summary of Business	From PRISM (Weather data)
Trended/Expected yield	Loss ratio	Extreme Degree Days (EDD)
Projected price	Total liability	Precipitation
Harvest Price	SCO/ECO indemnities	
Final yield	SCO/ECO liability	
	Unit structure, Coverage level	

Descriptive Statistics

Variable	N	Mean	SD	Min	Median	Max
Final Yield	1575	88.48	43.88	0.8	91	226.9
Expected Yield	1575	88.28	29.12	25	85.7	215.4
Loss Cost Ratio	1575	0.21	0.29	-0.04	0.07	1.25
Loss Ratio	1575	1.21	1.85	-0.23	0.40	14.58
Coverage Level	1575	0.74	0.02	0.5	0.7	0.85
Enterprise Unit Share	1575	0.40	0.24	0	0.41	0.98
Price ratio	1575	0.97	0.15	0.76	0.92	1.32
Precipitation	1575	589.15	210.66	131.74	569.24	1483.24
Extreme Degree Day	1575	81.37	39.29	15.74	73.99	275.91

Final County Yield



Prediction Models

For each coverage level (50% to 85%)

$$\text{Yield}_{it} = \beta_1 \text{LCR}_{it} + \beta_2 \text{EUShare}_{it} + \beta_3 \text{PriceRatio}_{it} + \beta_4 (\text{LCR} \times \text{PriceRatio})_{it} + \beta_5 \text{Precipitation}_{it} + \beta_6 \text{DD30\_inf}_{it} + \alpha_i + \varepsilon_{it}$$

Model	What it does
Linear (fixed-effects regression, feols)	Uses claims, price, and weather data in a steady, direct relationship to estimate yield
Nonlinear (fixed-effects regression with squared LCR term, feols)	Same inputs as above, but allows a squared Loss Cost Ratio term
Random Forest (ranger, 1,000 trees)	Finds similar past county-years and blends their outcomes into a prediction
XGBoost (gradient boosting, 500 rounds)	Learns from prior prediction errors and corrects for them round by round

$$Predicted\ County\ Yield_{it} = \left(\sum_{k=50\%}^{85\%} (Predicted\ County\ Yield_{ikt} \right) \times \frac{1}{8}$$

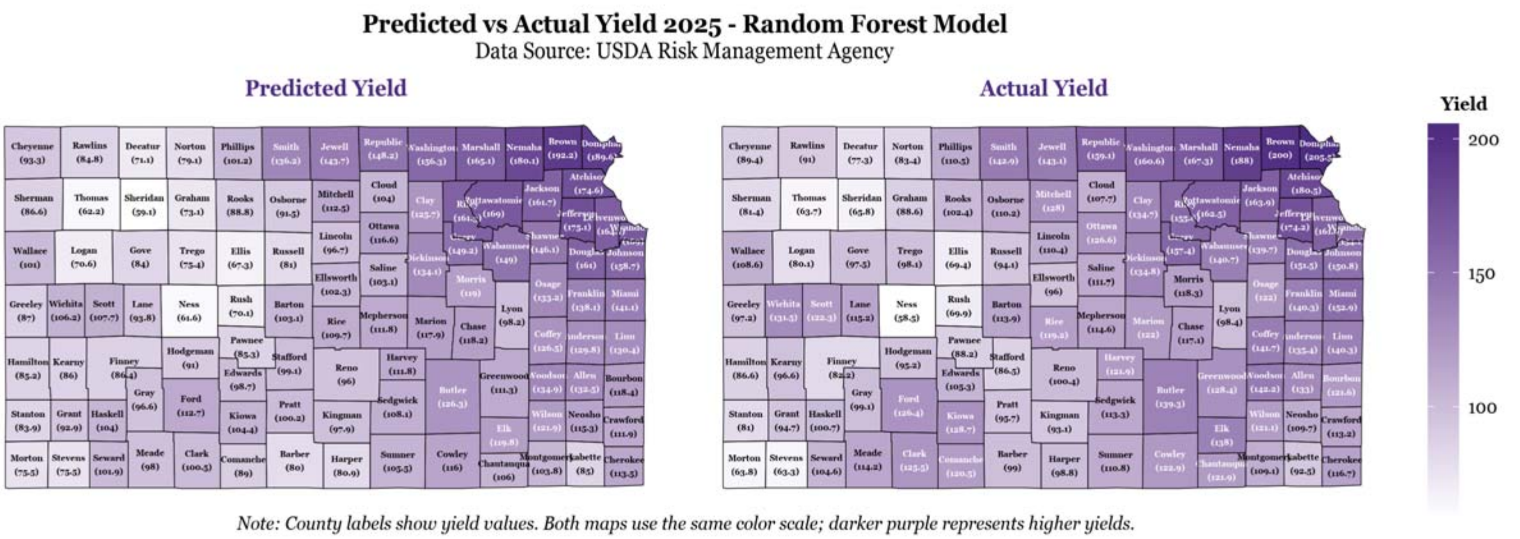
Model Performance

Rolling-based prediction from 2018 – 2024

Model	Measure of Model Performance		
	Root Mean Squared Error	Mean Absolute Error	Out of Sample R2
Linear	18.90	14.79	0.79
Nonlinear	16.00	12.42	0.85
XG Boost	15.38	11.67	0.86
Random Forest	14.24	10.83	0.88

Lower value = Better Model **Higher value = Better Model**

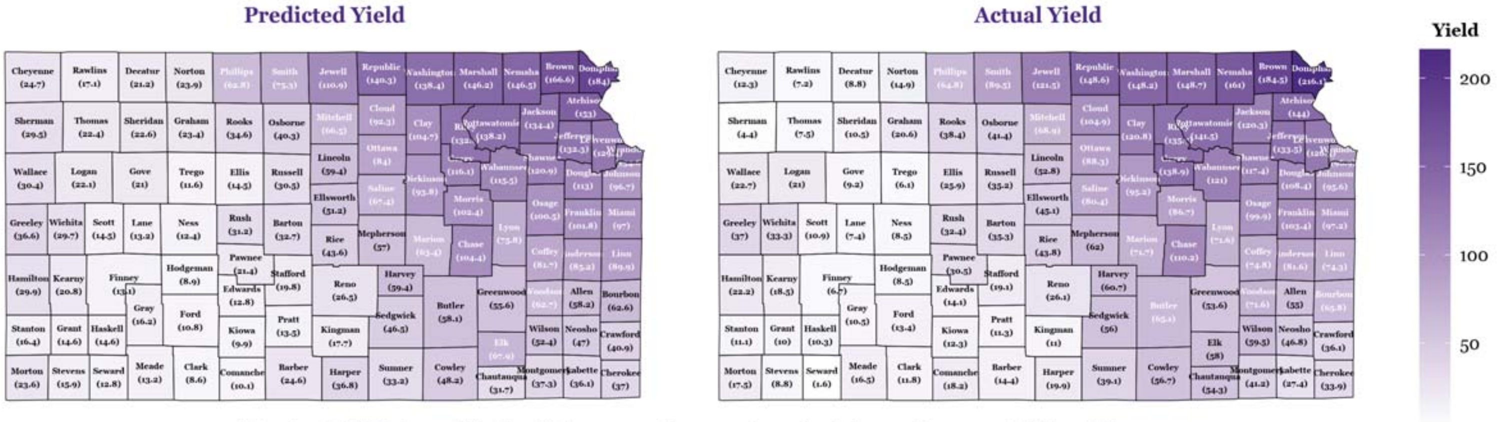
Results



Results

Predicted vs Actual Yield 2022 - Random Forest Model

Data Source: USDA Risk Management Agency

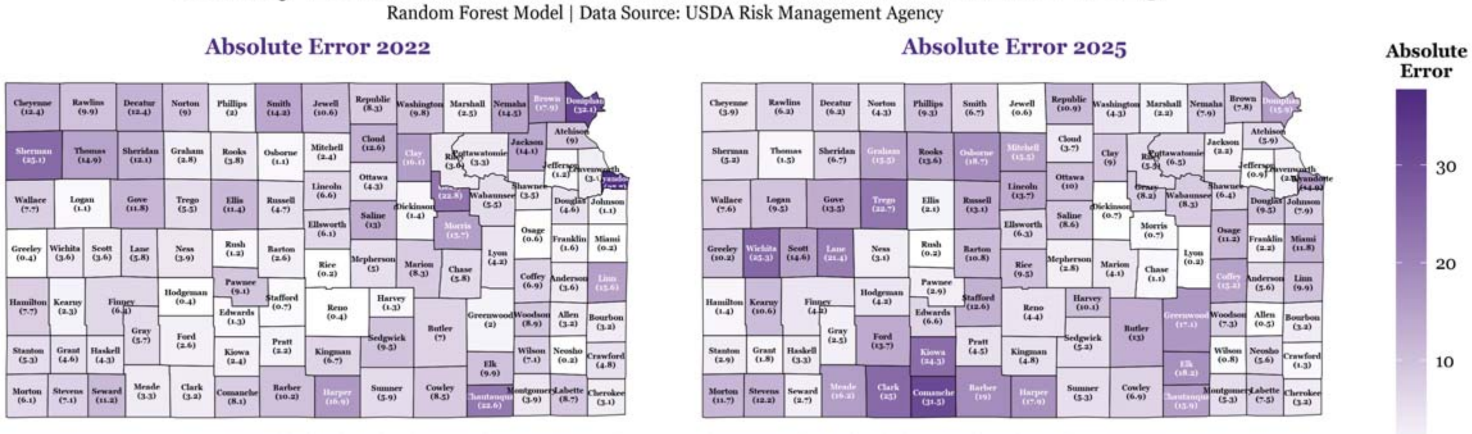


Note: County labels show yield values. Both maps use the same color scale; darker purple represents higher yields.

Results

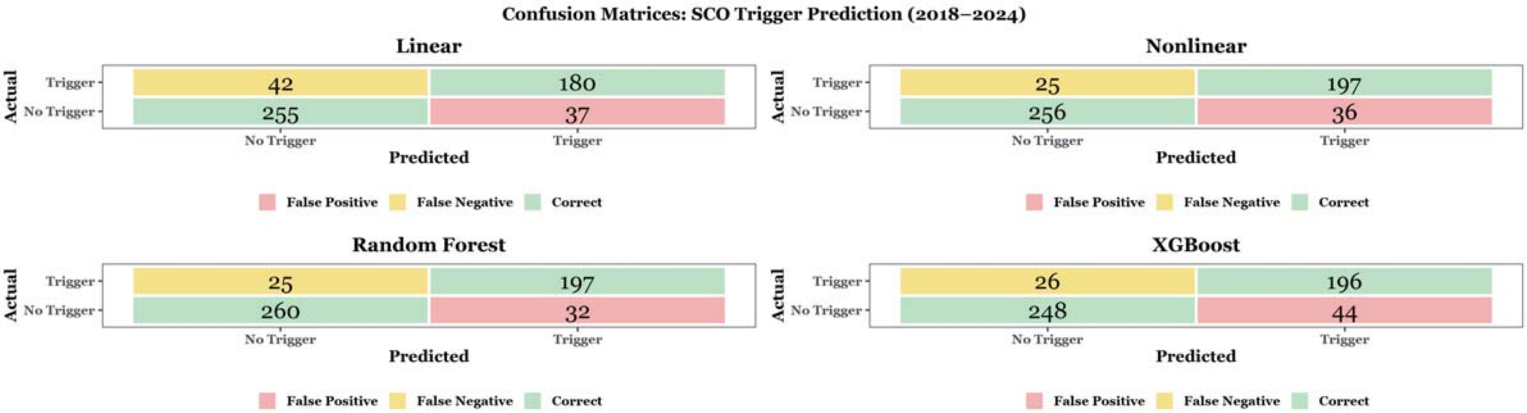
County-Level Absolute Prediction Error: 2022 vs. 2025

Random Forest Model | Data Source: USDA Risk Management Agency



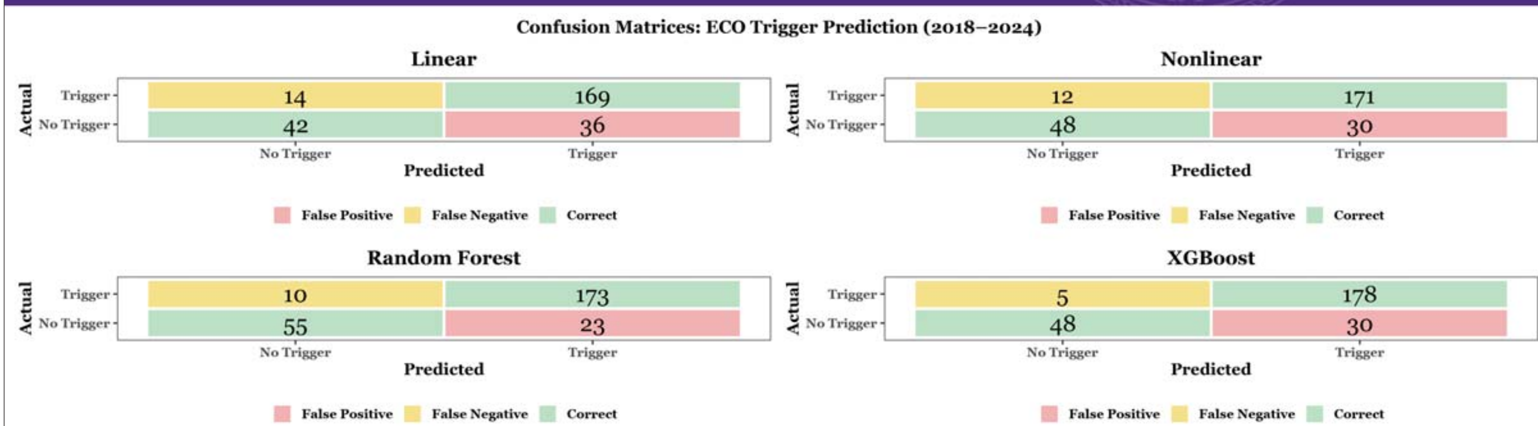
Note: County labels show absolute prediction error. Both maps use the same color scale; darker purple indicates larger error.

Results

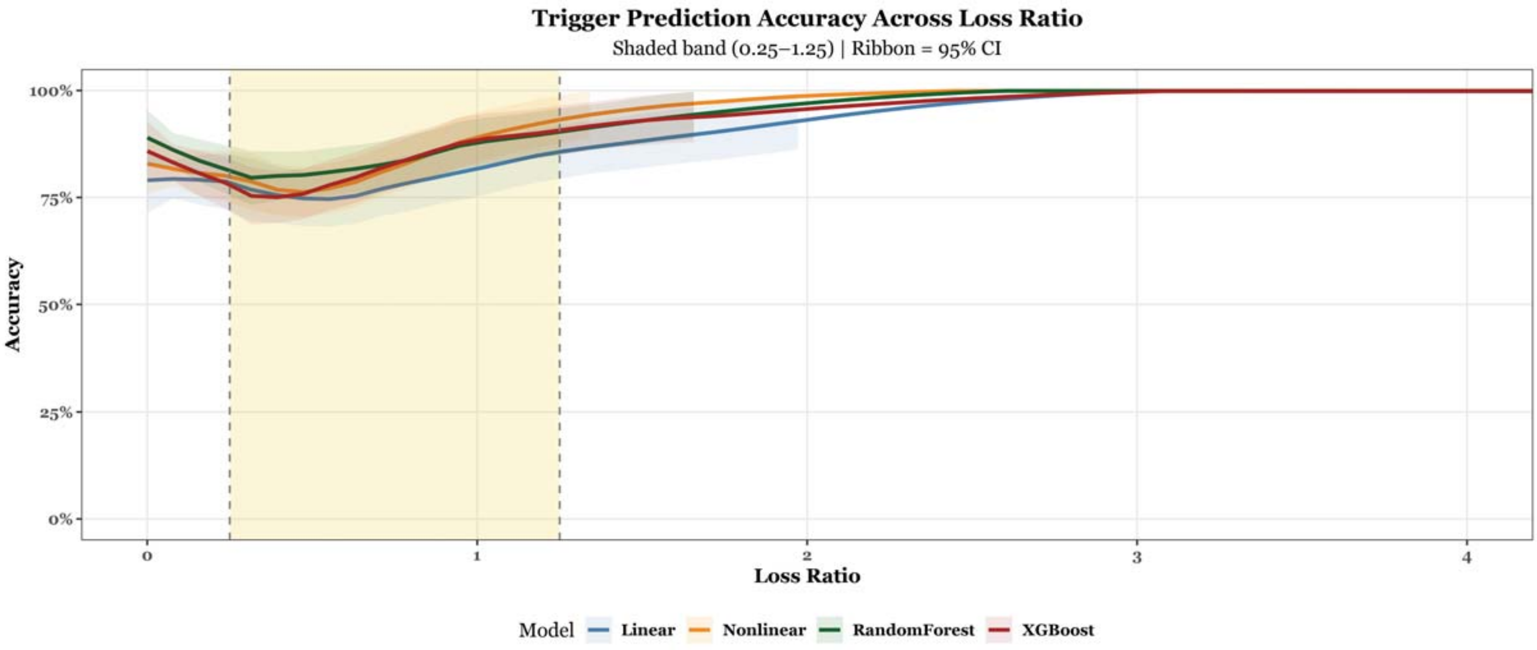


❖ False Negative: Predicted no trigger, but actually triggered
  Insurer under- reserves for real future payouts, Solvency Risk
❖ False Positive: Predicted trigger, but actually not triggered
  Farmer plans around a payout that doesn't materialize, Cash-flow risk

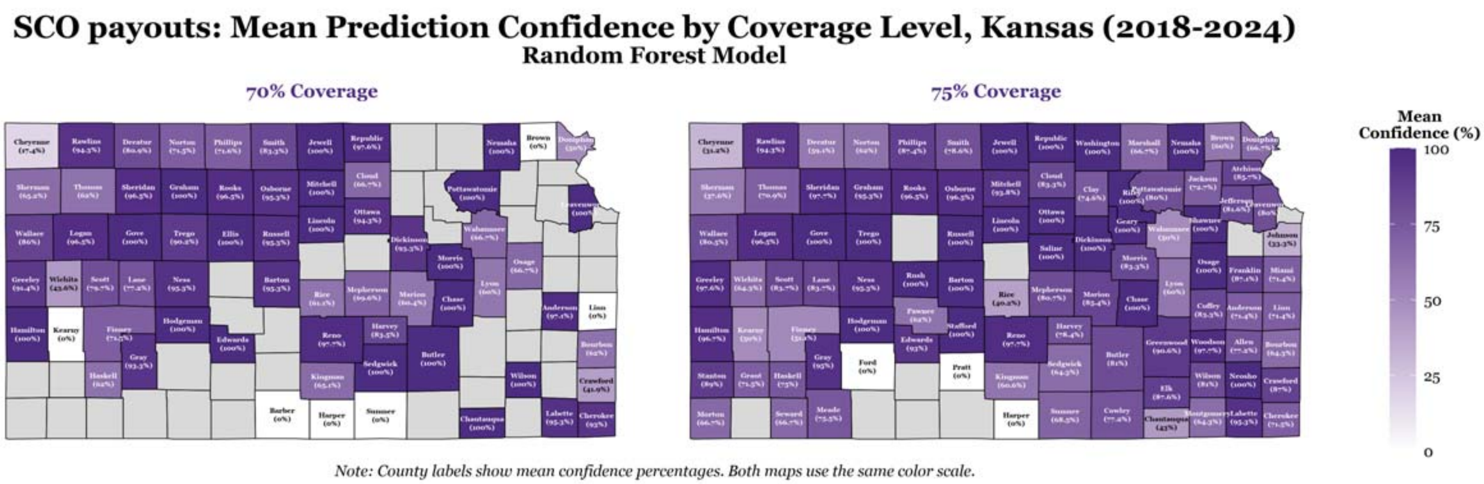
Results



Results

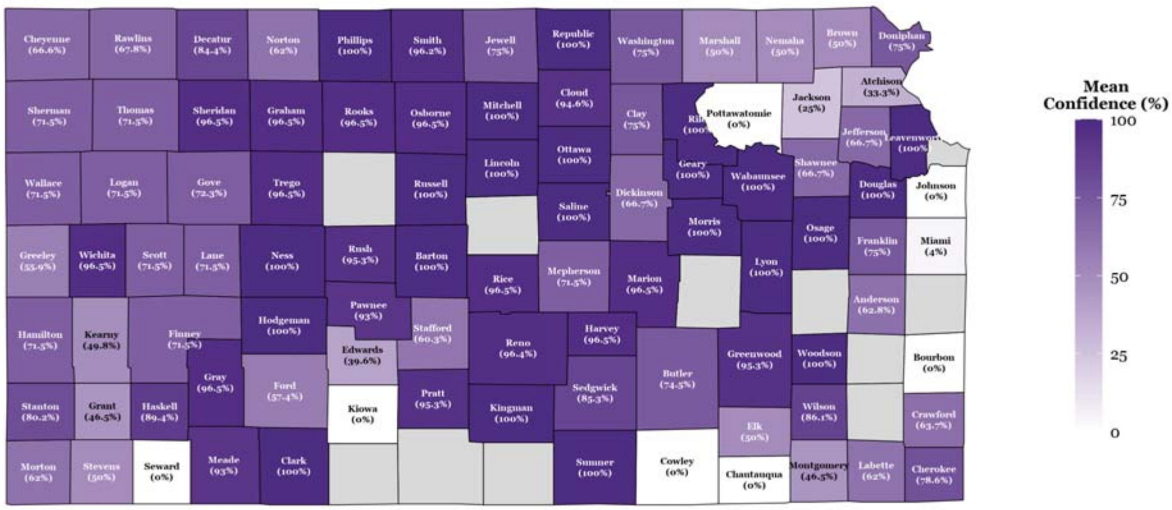


Results



Results

ECO Payouts:Mean Prediction Confidence, Kansas (2021–2024)
Random Forest Model

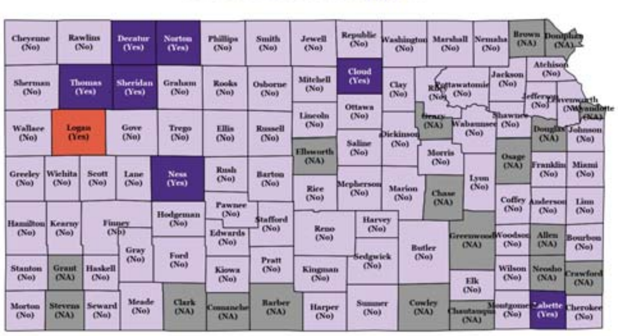


Note: County labels show mean confidence percentages.

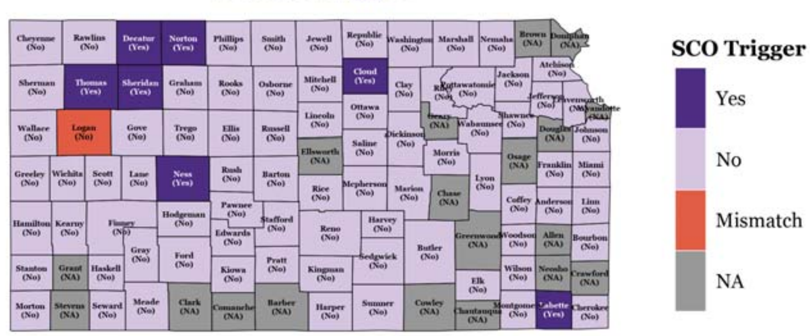
Results

Predicted and Actual SCO Trigger Status, Kansas 2025
Random Forest Model | Data Source: USDA Risk Management Agency

Predicted Trigger



Actual Trigger

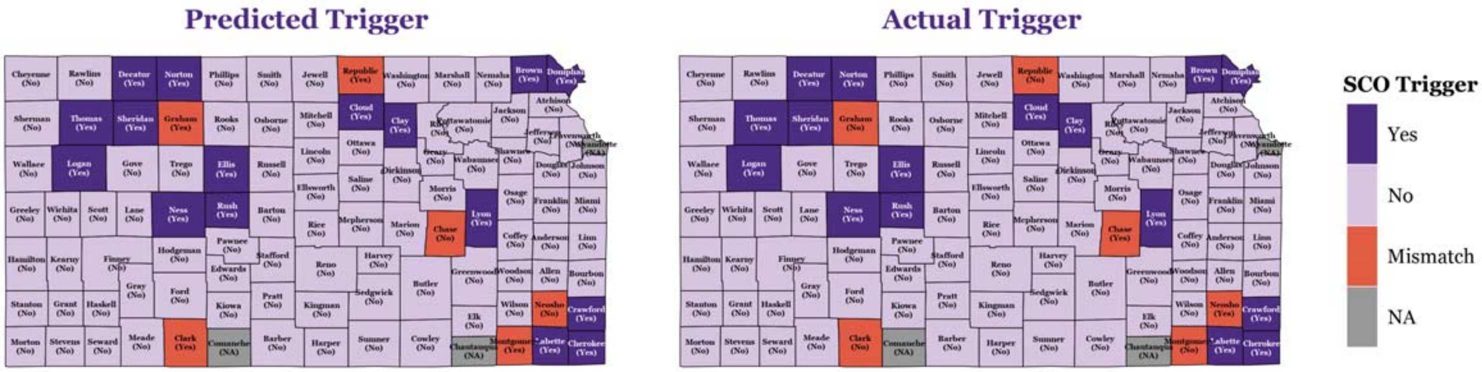


Note: False Positive: One County

Results

Predicted and Actual ECO Trigger Status, Kansas 2025

Random Forest Model | Data Source: USDA Risk Management Agency

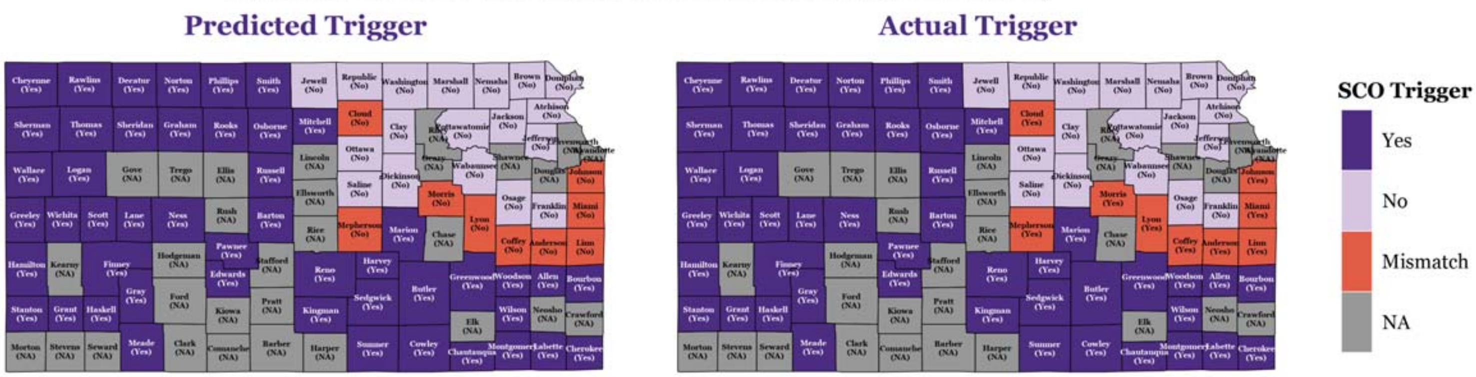


Note: False Positive: Four Counties, False Negative: Two Counties.

Results

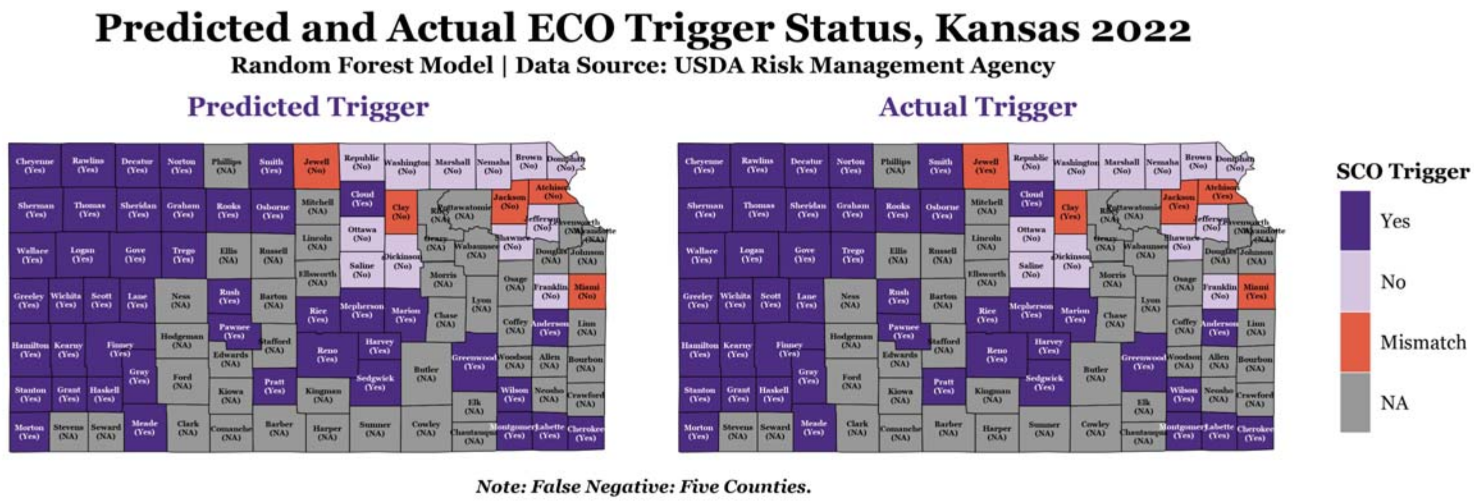
Predicted and Actual SCO Trigger Status, Kansas 2022

Random Forest Model | Data Source: USDA Risk Management Agency



Note: False Negative: Nine County

Results



Conclusion

- Out of the four models, the Random Forest model better predicts the county yield with an out-of-sample R-squared value of 0.88
- Models tested for the SCO/ECO predictions, confirming Random Forest's advantage with consistent accuracy, precision in the uncertain range of loss ratio
- Yield forecast converted into binary trigger predictions, correctly identifying roughly 89% of actual trigger events with the Random Forest model

What This Means for Stakeholder

- **Framers:** Bridging the 6-month decision gap for financial planning from early payout forecasting
- **Insurers:** Provides early visibility into which counties are likely to trigger payouts, allowing insurers to allocate reserves and capital
- **Lenders:** Gives agricultural lenders a signal of a borrower's likely risk exposure for the season, supporting informed decisions on credit terms, loan volume, and collateral requirement.

Future works

- Interpretation or the confidence for the payouts amount, to be developed
- These are the preliminary results checking the model accuracy with data for non-irrigated corn in Kansas
- This model will be further expanded to other crops and other states as well, for a robustness check
- Testing other predictors to increase the prediction accuracy
- Decision support tools for farmers for updates


Thank you
I welcome your questions
Research
Analysis
Policy
Impact