Modeling Soil Test Phosphorus and Potassium Calibration Data

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SERA-6, MASTPAWG, and NRSP11

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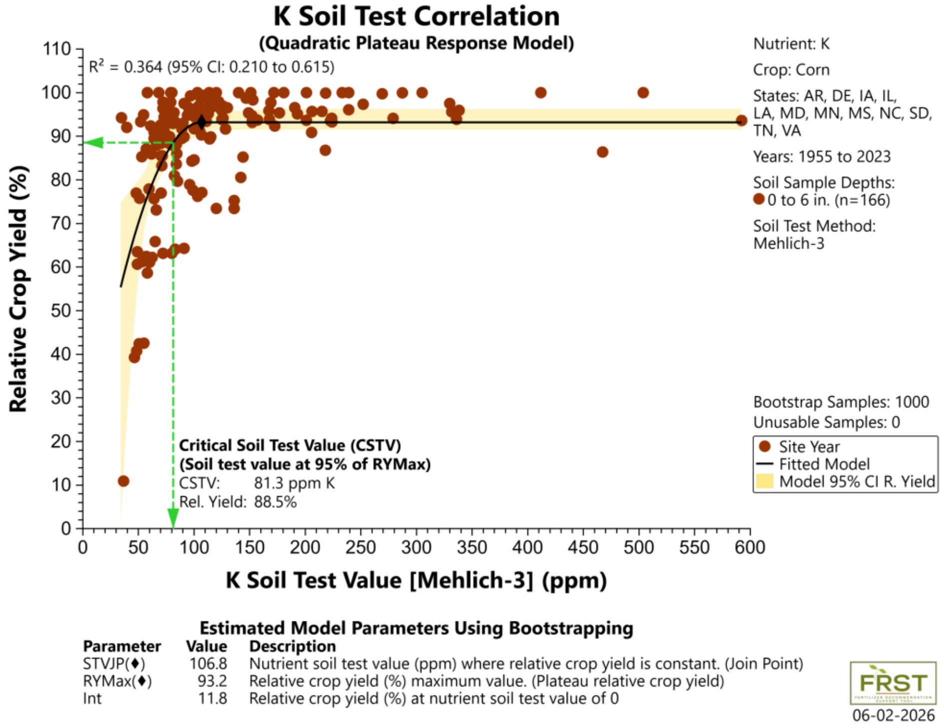
Phosphorus and potassium fertilizer recommendations are based on:

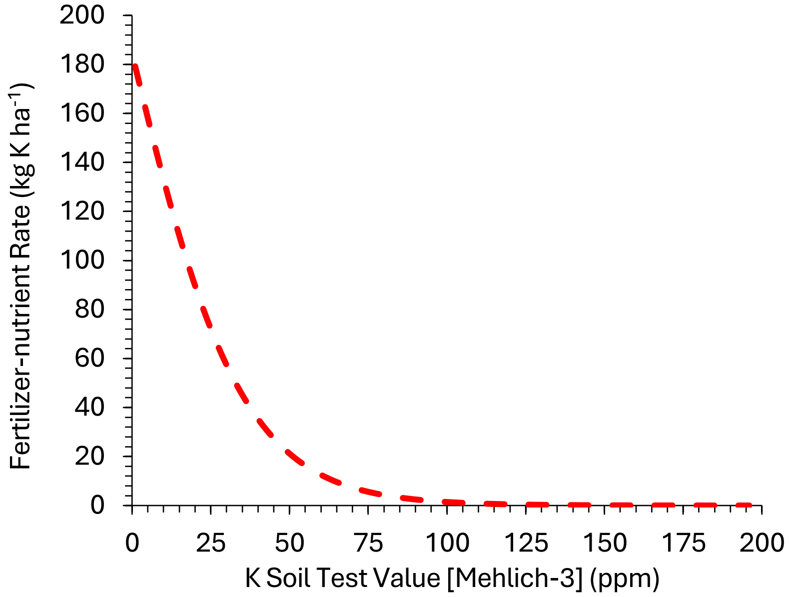
Soil test correlation

Identify the critical soil test value (CSTV)



Soil test calibration

Estimate the fertilizer-nutrient rate required to achieve optimal yield across soil test values (STVs)



Why test soil test calibration frameworks?

- **Relatively few soil test calibration frameworks for estimating fertilizer-nutrient requirements have been published**

- **The strengths and limitations of calibration frameworks have rarely been evaluated**

- **Calibration frameworks present some methodological challenges:**
  - Multicollinearity among predictor variables in regression-based approaches
  - Discontinuous recommendation functions in class-based methods
  - Limited flexibility for incorporating uncertainty and risk preferences

- **The lack of a standardized calibration framework creates challenges for improving soil test–based fertilizer recommendations**

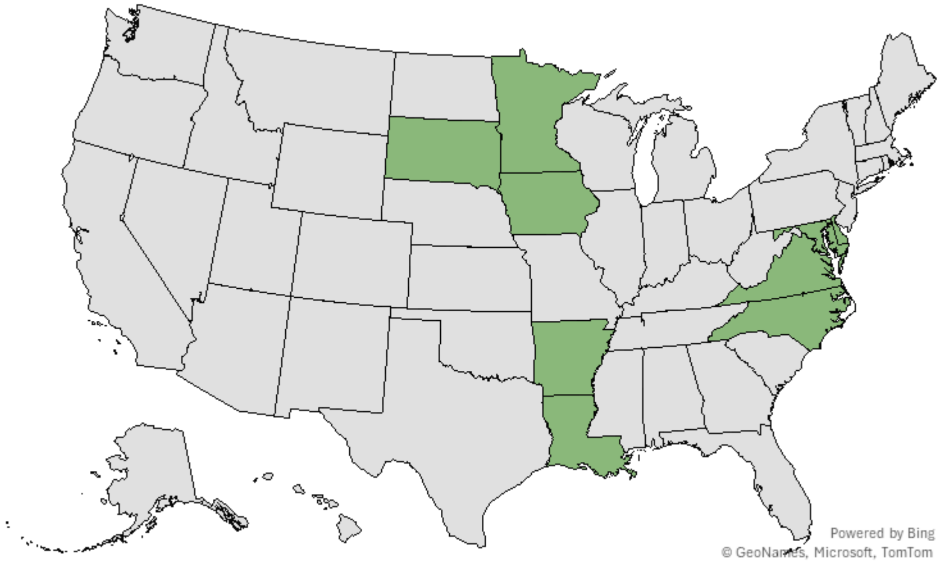
Objectives

(i) Evaluate how soil test calibration frameworks influence estimated fertilizer-P and -K rate recommendations

(ii) Identify a calibration framework suitable for implementation in the FRST decision-support tool

Dataset selection for modeling fertilizer-nutrient rate

Representation across geographic regions (nine U.S. states), crops (corn and soybean), nutrients (P and K), and soil test extractants (Mehlich-1 and -3, Olsen, and Bray-1)



Dataset	# site-years	STV range (mg kg^{-1})	CSTV (mg kg^{-1})
1 Mehlich-3 K soybean	45	46–353	94
2 Mehlich-1 K soybean	41	16–196	46
3 Olsen P corn	35	3–31	5.0
4 Bray-1 P corn	25	2–59	11
5 Mehlich-3 K corn	134	37–592	70

Fertilizer-P and -K application rates ranged from 0 to 75 kg P ha^{-1} and 0 to 224 kg K ha^{-1}

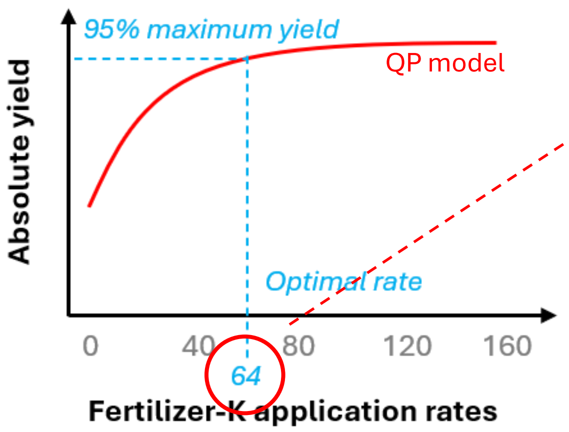
Source: Bourns et al., 2025; Lyons et al., 2021; Mallarino & Blackmer, 1992; Mallarino et al., 2009; Parvej et al., 2018; Popp et al., 2020; Williams et al., 2018

Dataset preparation

Input trial data

Trial's mean STK (mg kg^{-1})	Fertilizer-K application rates (kg K ha^{-1})	Absolute crop yield (kg ha^{-1})	RY (%)
72	0	2892	77
	40	3195	86
	80	3652	98
	120	3685	99
	160	3733	100

Determine the optimal fertilizer-nutrient rate



Two-step calibration framework

Trial's mean STK (mg kg^{-1})	Optimal fertilizer-K rate (kg K ha^{-1})
72	64

Single-step calibration framework

Trial's mean STK (mg kg^{-1})	Fertilizer-K application rates (kg K ha^{-1})	RY (%)
72	0	77
	40	86
	80	98
	120	99
	160	100

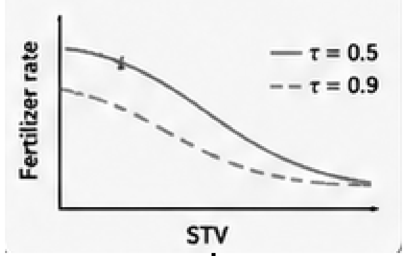
Modeling approaches for fertilizer-nutrient rate estimation

Two-step calibration framework

Quantile regression
Declining sigmoidal quantile regression

Process

- **Fit declining sigmoidal model**
- **Estimate fertilizer-nutrient requirement at**
  τ = 0.5 (median)
  τ = 0.9 (upper-bound)



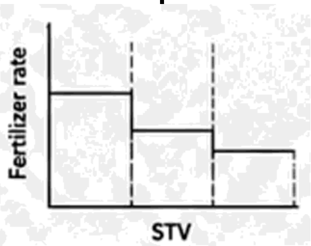
Output

Continuous fertilizer recommendation curve

STCI
Soil test class-interval

Process

- **Define STV class intervals**
- **Calculate the median fertilizer-nutrient rate in each interval**



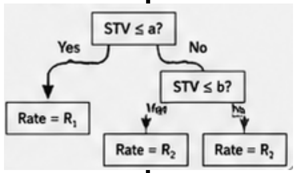
Output

Stepwise fertilizer recommendation by class interval

CART
Classification and Regression Tree

Process

- **Build a regression tree using recursive partitioning**
- **Identify STV thresholds that best explain fertilizer-nutrient rate variation**
- **Calculate the median fertilizer-nutrient rate within each STV threshold**



Output

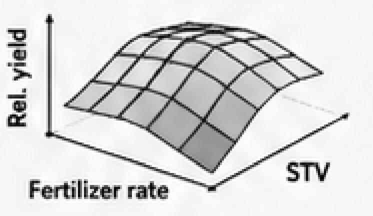
Stepwise fertilizer recommendation by STV threshold

Single-step calibration framework

ENET
Elastic Net Regression

Process

- **Model relative yield as a function of STV and fertilizer-nutrient application rates**
- **Predict fertilizer-nutrient rate for target relative yield (e.g., 95%)**



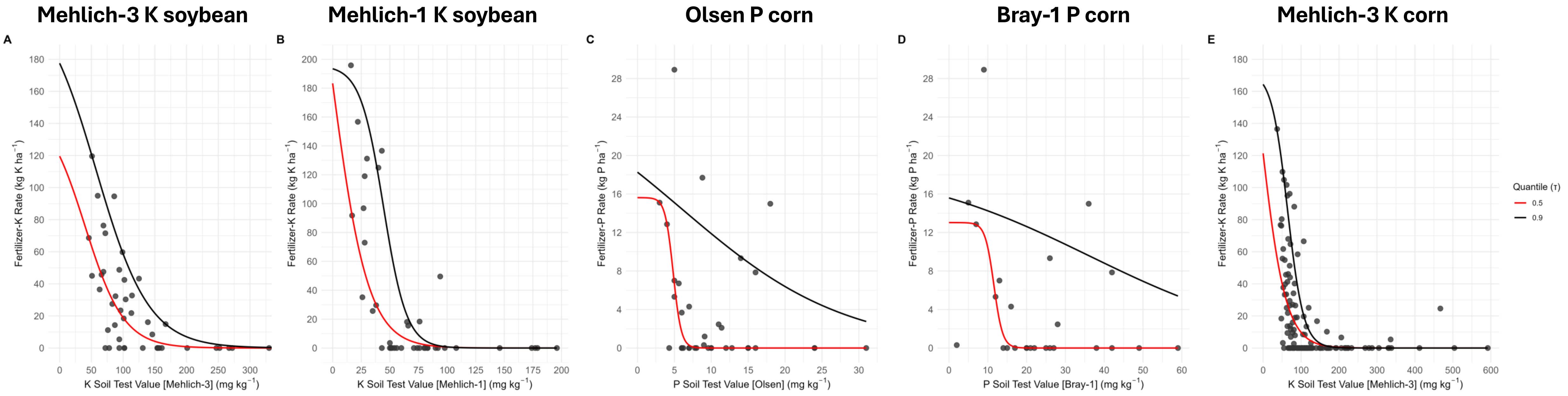
Output

Predicted fertilizer recommendation surface

Results

Overall, all frameworks predicted declining fertilizer-nutrient requirements with increasing STV; however, the magnitude and pattern of decline varied among approaches and datasets

Quantile regression (nonlinear declining sigmoidal quantile regression)



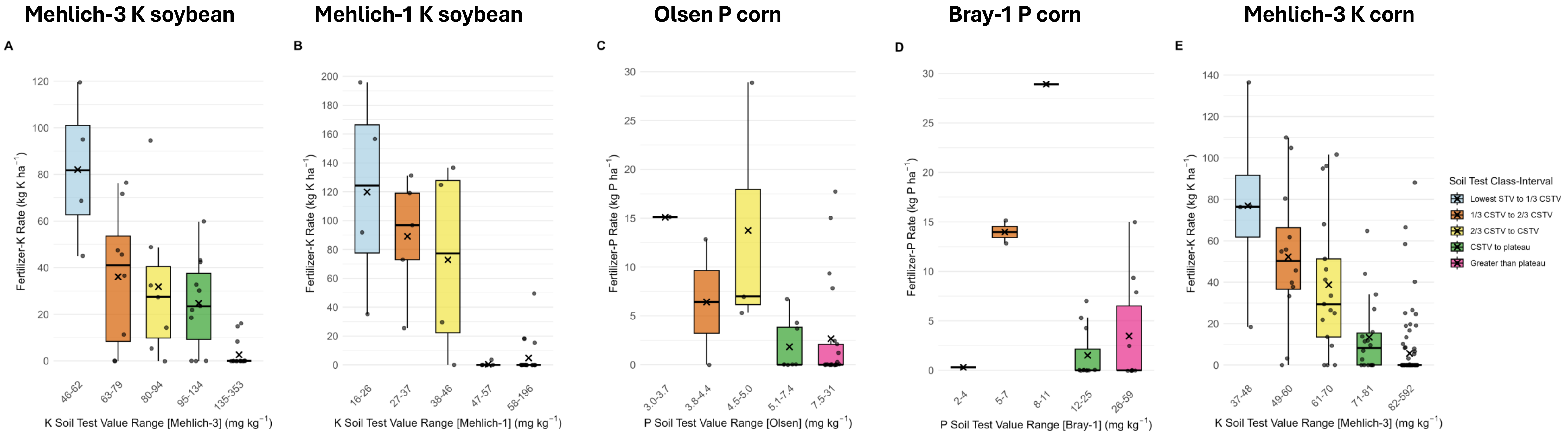
Advantages

- The 0.5 and 0.9 quantiles represent the median and upper bound of the fertilizer-nutrient requirement
- Provides a continuous function to estimate fertilizer-nutrient rate across STVs
- Provides a range of fertilizer-nutrient rates at the same STV

Limitations

- The model's performance depends on the dataset structure
- Data processing to determine the optimal fertilizer-nutrient rate

STCI (Soil Test Class-Interval)



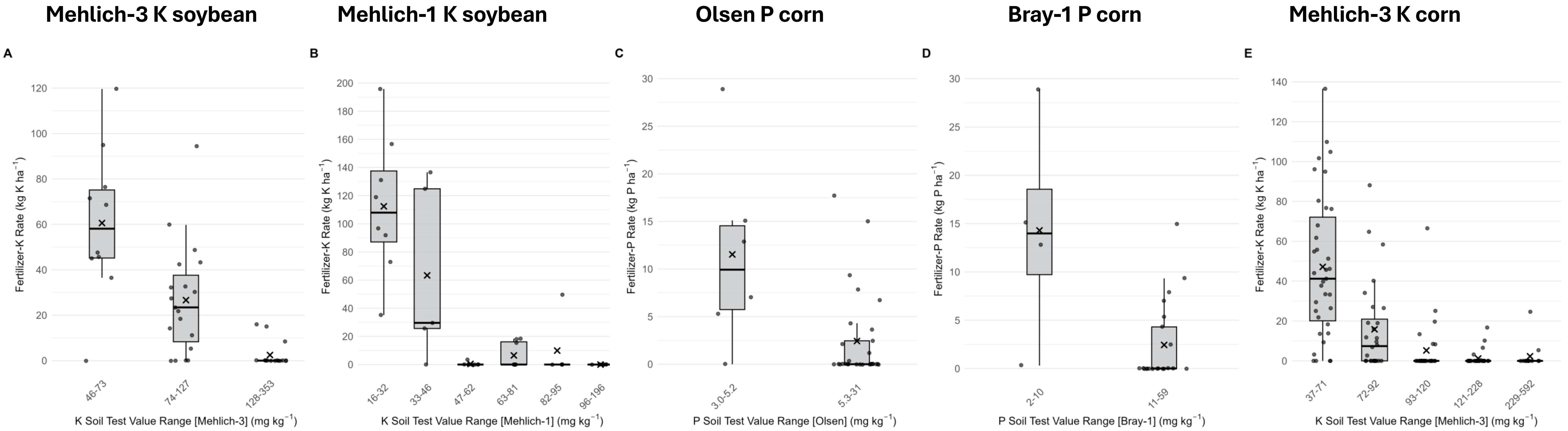
Advantages

- Transparent and assumption-free summary of data
- Computationally simple and easy to communicate with end users
- Can reduce the influence of scatter observations (e.g., Olsen P corn)

Limitations

- Requires predefined soil test class boundaries
- Stepwise behavior (sensitive to the number and distribution of the observations)
- Data processing to determine the optimal fertilizer-nutrient rate

CART (Classification and Regression Tree)



Advantages

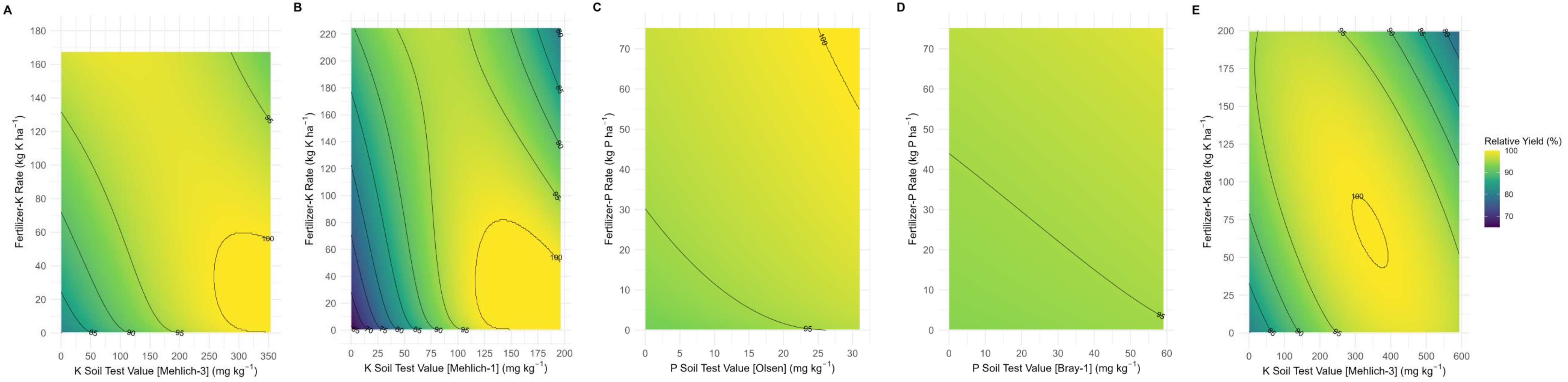
- Effective at capturing changes in fertilizer-nutrient requirements
- Easy to communicate with end users

Limitations

- Stepwise behavior may oversimplify nutrient response patterns
- Data processing to determine the optimal fertilizer-nutrient rate

ENET (Elastic Net Regression)

Mehlich-3 K soybean | **Mehlich-1 K soybean** | **Olsen P corn** | **Bray-1 P corn** | **Mehlich-3 K corn**



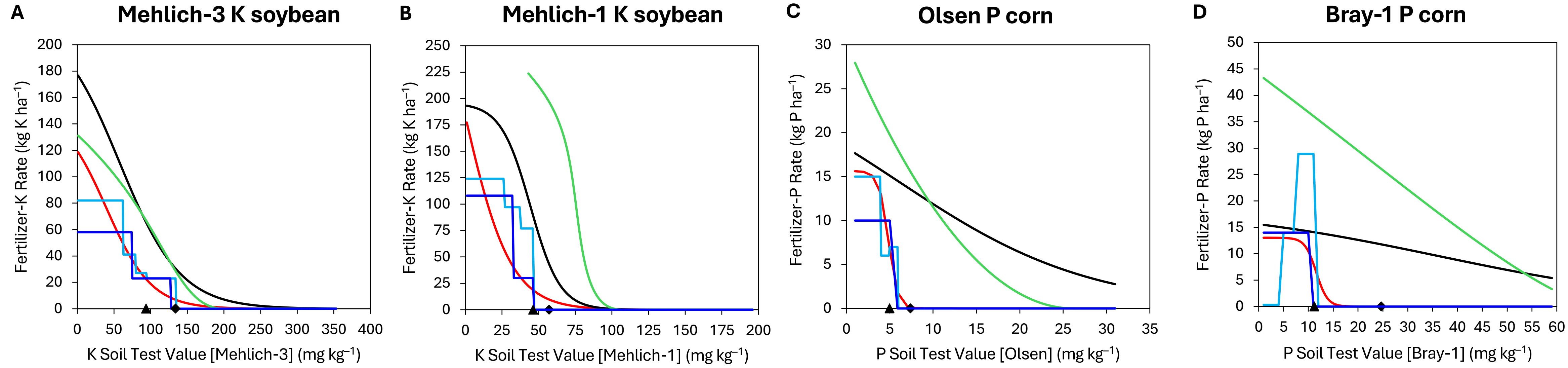
Advantages

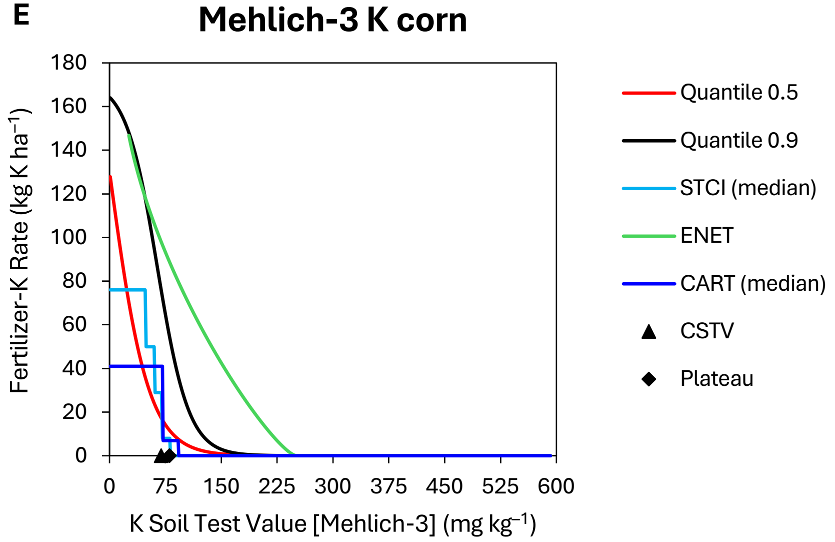
- Use of the full experimental dataset without requiring prior estimation of an optimal fertilizer-nutrient rate

Limitations

- Limiting applicability in datasets lacking observations at low STVs
- Dual solutions for achieving a target RY
- Training the end-users to interpret the response surface

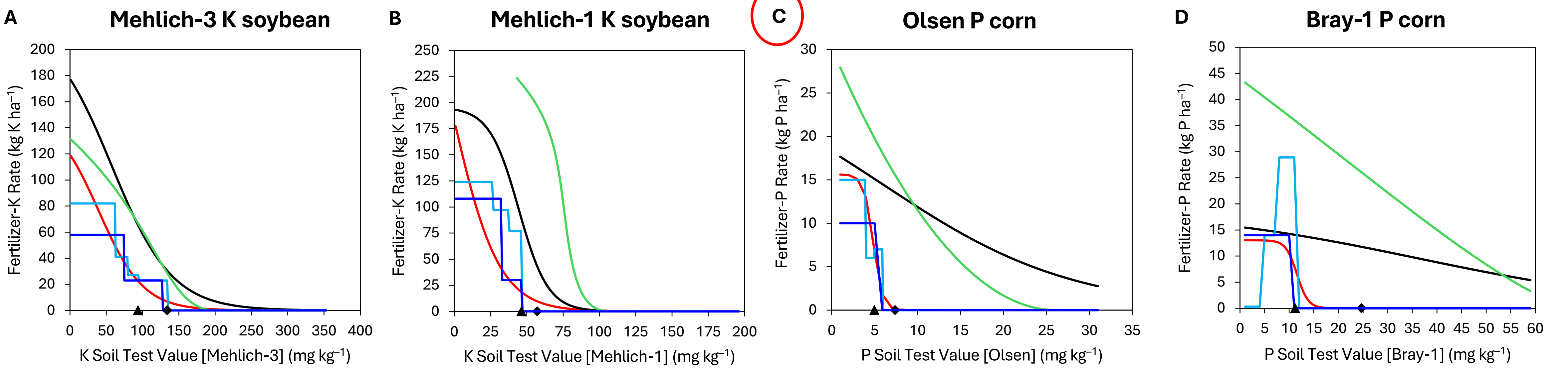
At agronomically relevant STVs, how different are the recommendations?

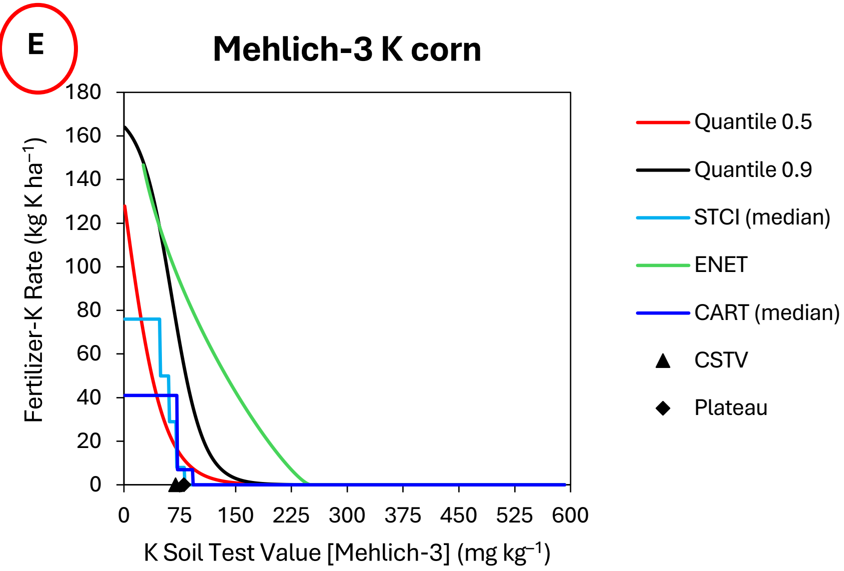




- **Continuous vs. stepwise behavior**
- **Overestimation tendencies**
- **Plateau behavior**
- **Divergence among frameworks**

At agronomically relevant STVs, how different are the recommendations?

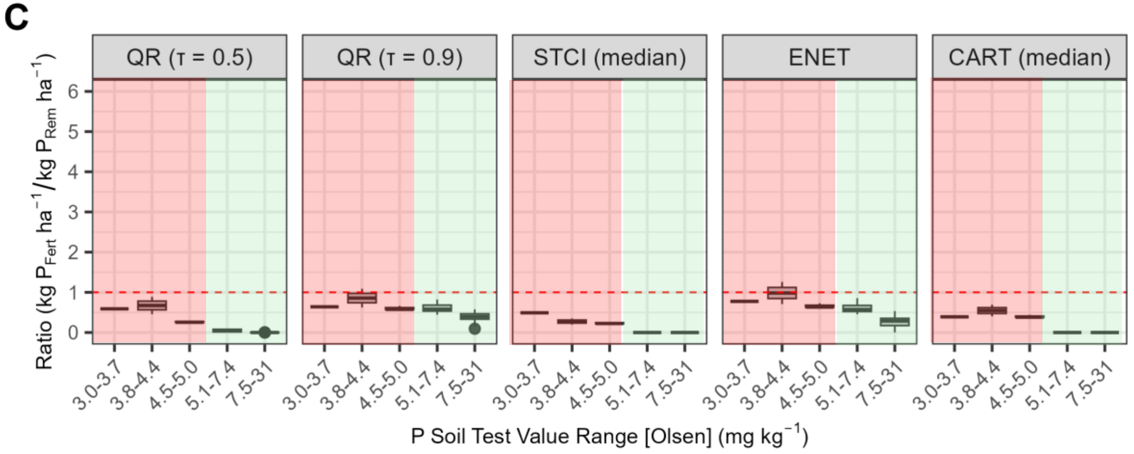




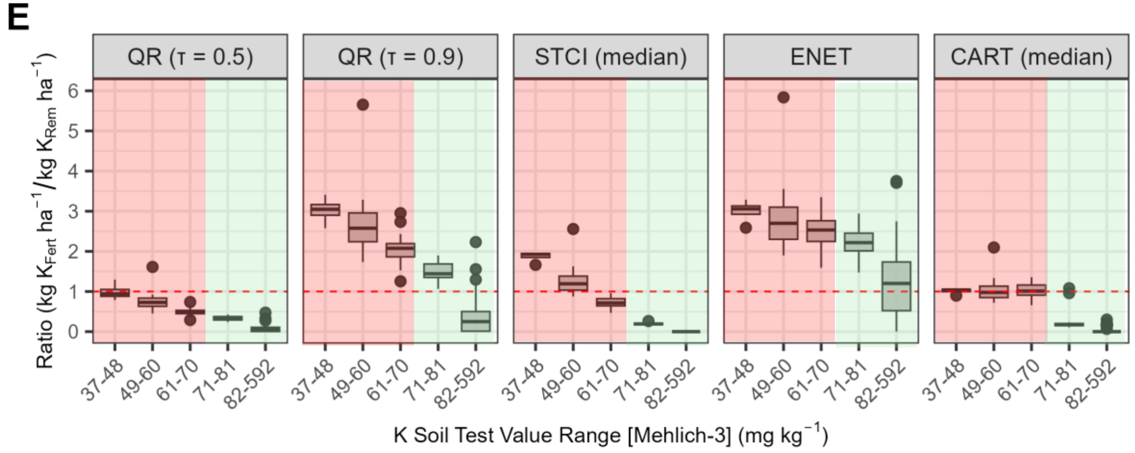
Dataset	STV	Quantile (τ = 0.5)	Quantile (τ = 0.9)	STCI (median)	ENET	CART (median)
	mg kg^{-1}	Estimated fertilizer-P or -K rate (kg ha^{-1})				
Olsen P corn	**4**	13	16	6	22	10
	5	7	15	7	20	10
Mehlich-3 K corn	**48**	36	118	76	118	41
	70	17	75	29	98	41

Ratio between the estimated fertilizer-nutrient rates and the estimated amount of nutrient removed by grain

Olsen P corn



Mehlich-3 K corn



- **Ratio = 1.0 (red line): fertilizer input equals nutrient removal**
- **Suboptimal STV (below CSTV): fertilizer requirements exceed crop nutrient removal**
- **Above CSTV: fertilizer requirements approach or fall below crop nutrient removal**

Conclusions

- **Calibration framework selection is a major source of variability in fertilizer recommendations**

- **All frameworks have strengths and limitations that may support or constrain their application for soil test calibration**

- **Quantile regression produced the most consistent and agronomically interpretable recommendations.**
  - Continuous recommendation curve
  - Agronomically realistic fertilizer-nutrient recommendations
  - Flexible recommendations for different risk preferences ($\tau = 0.5$ and $\tau = 0.9$)
  - Potential application for variable-rate nutrient management

- **FRST implementation:**

- Quantile regression as the primary calibration framework
- Soil Test Class-Interval (STCI) as a complementary framework

Future efforts to address

- Economic optimization
- Multi-year trial integration
- Additional crop response functions
- Probability-of-response metrics

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