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ORIGINAL ARTICLE

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Soil test phosphorus predicts field-level but not subfield-level corn yield response

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Abstract

Soil test-based fertilizer recommendations traditionally serve to predict average nutrient needs across fields, but their effectiveness for precision agriculture remains uncertain. Our objectives were to evaluate whether soil phosphorus (P) concentrations predicted corn (*Zea mays*,r L.) yield response to P at the sub-field level, and to determine if soil test critical levels varied within field boundaries. We conducted research over seven growing seasons at two Kentucky sites collecting spatially dense yield response data from over 150 paired plots per field. Mehlich 3 extractable phosphorus (M3P) soil ranged from 0.8 to 63 mg kg^{-1}, with 96% of sample points falling below the University of Kentucky's fertilizer cutoff of 30 mg kg^{-1} M3P for corn. Each plot (10^{-2} ha) received 0 or 29.5 kg ha^{-1} P. While M3P effectively predicted average field-level response, with yield increases in five of seven site-years, it failed to predict subfield responses, where only 51% of plots showed positive yield response to P application. Linear plateau models revealed that conventional statistical treatments of soil test correlation data mask important subfield variability. The poor relationship between soil test P and yield response at the subfield scale suggests that variable rate P management requires incorporating additional factors beyond soil P concentration or moving away from such deterministic models toward probabilistic models. Our findings demonstrate that while current soil test recommendations provide accurate field-scale guidance, they lack the precision required for variable rate application.

1 | INTRODUCTION

Current fertilizer prices and environmental concerns dictate that we increase fertilizer use efficiency. Precision nutrient management seeks to increase nutrient efficiency by matching nutrient inputs to spatially and temporally variable crop nutrient needs. Individual plants rely on soil nutrient supply, as a function of amount and intensity, and external fertilizer inputs to meet their internal nutrient requirement. Soil testing provides the basis for conventional phosphorus (P) fertilizer management. Soil test correlation estimates soil nutrient supply by relating extractable soil P concentration to relative crop response to P application. These correlation procedures establish critical soil test concentrations or ranges, above which we do not expect a crop response to added phosphorus. Soil test calibration predicts the fertilizer rate needed to deliver the balance of the plant's nutrient need and reach the maximum obtainable yield at a given soil P concentration (Pearce et al., 2022).

Recent studies have shown that current soil test nutrient recommendations are generally accurate; however, recommendations need more work to improve their precision by reflecting modern practices, higher yields, improved crop genetics, and spatially variable growing environments (Hopkins & Hansen, 2019; Reed et al., 2021). Often, current fertilizer recommendation systems in the United States rely on correlation and calibration data generated in the mid-20th century (Lyons et al., 2021). These studies provided average critical soil test concentrations or ranges at state or regional scales (median state area of 14.4×10^6 ha) (USDA-NASS, 2024) using soil test extractants appropriate for their regions, such as the Mehlich 3, Lancaster, Olsen, or Bray tests, (Dari et al., 2019; Sikora & Moore, 2014) to support conventional flat-rate nutrient recommendations. Our ability to develop more spatially precise recommendations from historic trial data are limited because scientists often did not include complete plot-level data in their publications (Slaton et al., 2022).

The spatial variability of nutrient supply complicates generation of precise nutrient recommendations. Studies have shown that nutrient concentrations can vary across space both vertically (Hansel et al., 2017; Howard et al., 1999; Souza, 2020) and horizontally (Solie et al., 1999). In addition, soil properties, chemical, physical, and biological, that influence nutrient availability, such as soil texture, density, pH and organic matter, also vary at the field scale (Mzuku et al., 2005). Although clear data on the prevalence of variable rate fertilizer application do not exist, it has clearly expanded in conventional grain production (Pierpaoli et al., 2013). A need exists to develop nutrient recommendations that precisely and accurately meet spatially variable crop nutrient needs.

Core Ideas

- Soil test phosphorus effectively predicts field-level but not subfield-level corn yield response.
- Variable rate phosphorus management requires models beyond traditional soil test correlation.
- High-density, paired response plots revealed spatial variability in phosphorus response not captured by current methods.

This study proposes a novel soil test correlation field study, designed to support variable rate fertilizer applications. Our study aimed to evaluate the effectiveness of soil test P in predicting crop nutrient response at sub-field levels and to examine spatial variability in soil test critical levels within fields. We hypothesized that existing soil test P critical levels for Kentucky, designed for broad-scale accuracy, would not reliably predict P response within field boundaries due to a lack of site-specific precision.

2 | MATERIALS AND METHODS

2.1 | Experimental design, crop management, and site description

We established this study in 2016 at two sites, one located near Princeton, KY (37.112, −87.267) in Caldwell County, and the other near Quicksand, KY (37.535, −83.346) in Breathitt County (Figure 1). Two grass waterways divided the Princeton field into three sections (Figure 2), which totaled 4.854 ha, and contained a Zanesville silt loam (fine-silty, mixed, active, and mesic Oxyaquic Fragiudalfs). The Quicksand field consisted of 2.55 ha (Figure 3) and contained a Chagrin–Grigsby Complex (fine-loamy mixed, active, mesic Dystric Fluventic Eutrudepts and coarse-loamy, mixed, active, and mesic Dystric Fluventic Eutrudepts). Prior to study initiation, University of Kentucky (UKY) managed both sites in no-till systems, producing continuous corn (*Zea mays*, L.) at Quicksand, and a corn, winter wheat (*Triticum aestivum*, L.), and soybean [*Glycine max*, (L.), Merr.] rotation at Princeton for >10 years. Precise fertilizer records were not available for either site prior to 2016. In general, the Quicksand site had a history of only urea fertilizer application without liming, and the Princeton site had routine N fertilizer application, and sporadic K, P, and lime applications. Prior to this study, UKY managed these fields for commercial grain production, not research, and applied nutrients uniformly across the fields.

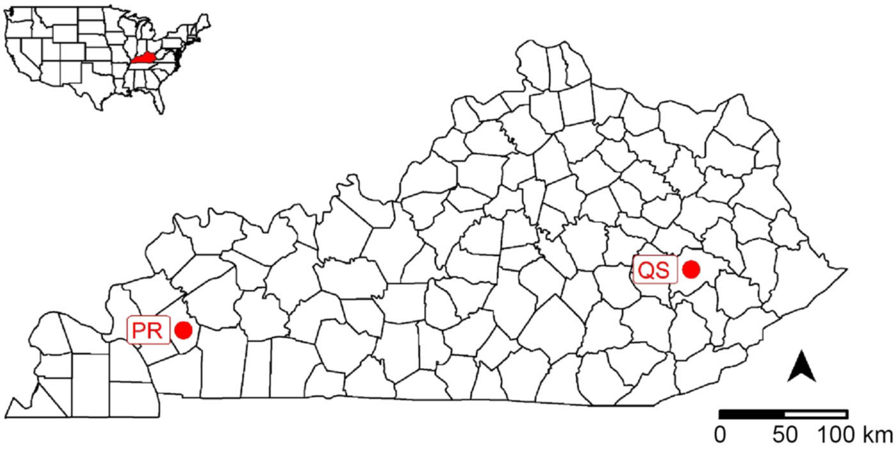

FIGURE 1 Map Depicting the two sites from this study. The "PR" label and point depicts the Princeton site, and the "QS" label and point depicts the Quicksand site. Inset shows the site of Kentucky inside the contiguous United States.

FIGURE 2 Map Depicting main plots across the Princeton site in Princeton, KY. Plots established in 2016 were 9 × 9 m, and data were collected in 2016, 2018, and 2020. Plots established in 2018 were 12.2 × 12.2 m, and data were collected in 2018 and 2020.

During the study (2016–2021), both fields followed a corn-soybean crop rotation, except for wheat-double crop soybeans at Princeton-2017 and corn after corn at Quicksand 2020–2021 (Table 1). Researchers applied lime to the Quicksand site in 2019 prior to soybean planting to address declining soil pH. This manuscript only contains data collected from the corn portions of the crop rotation.

Before trial establishment in 2016, we overlaid each field with a 9-m grid using GIS software, and randomly selected 123 and 101 grid cells as main plots at Quicksand and Princeton, respectively (Figures 2 and 3). We then divided each main plot into three subplots, measuring 3 m by 9 m (Figure 4A). We planted corn and soybean in rows 76 cm apart, and wheat was drilled in rows 19 cm apart. We assigned the control treatment (0 kg ha^{-1} P) to each edge subplot, and the P treatment (29.5 kg ha^{-1} P) to the center subplot. In 2018, we added 54 and 55 main plots to the Quicksand and Princeton sites, respectively. Due to space limitations, the main plots added to Quicksand followed the same three-subplot scheme as the 2016 season. However, because Princeton had more free space available, the new main plots in a 12.2 m grid included four subplots (Figure 4B), which allowed randomization of the

FIGURE 3 Map Depicting main plots across the Quicksand site in Quicksand, KY. Each main plot was 9 × 9 m.

TABLE 1 Cropping system employed at each site across all years. For Princeton 2017, the winter wheat crop was planted after corn harvest in 2016, and harvested in June 2017, followed by establishment of soybean crop.

Year	Quicksand (crop)	Princeton (crop)
2016	Corn	Corn
2017	Soybean	Winter wheat/double crop soybean
2018	Corn	Corn
2019	Soybean	Soybean
2020	Corn	Corn
2021	Corn	Soybean

control and P treatment with two replicates of each within the main plot.

During corn planting, we applied liquid fertilizer in a band approximately 5 cm beside and 5 cm below the seed (colloquially referred to as 2 × 2). The control treatment received urea-ammonium nitrate (UAN, 32-0-0) at a rate of 133 L ha^{-1} to provide 56 kg ha^{-1} N. The P treatment received 86 L ha^{-1} of UAN and 142 L ha^{-1} of ammonium polyphosphate (APP, 10-34-0) to provide 56 kg ha^{-1} N and 29.5 kg ha^{-1} P. A group of soil fertility experts from industry, academics, and government discussed the best way to apply fertilizer for this trial. These conversations occurred informally and formally as part of the Mule Barn meetings (Osmond et al., 2024). The size of the fields and number of plots required automated, mechanical fertilizer application instead of hand application. Mechanical application dictated that we use liquid fertilizer to allow precise rate changes over the shortest distance possible. Through expert consensus, we decided that subsurface band application offered the highest probability of seeing a corn yield response to P under no-till management. We planted corn and applied the starter P and N treatments with a four-row (76.2 cm row) not-till planter (John Deere MaxEmerge Plus 1750) outfitted with two electric variable rate pumps (SureFire Ag Systems Tower Fertilizer System for Field-IQ-PWM Control), one for APP and one for UAN. TeeJet solenoid nozzles (TeeJet, 12 V e-ChemSaver) applied the fertilizer behind Yetter fertilizer coulters. We achieved precise rate control using Geographic Position System (GPS) with Real Time Kinetic (RTK) correction (Trimble, FmX Fm 1000 internal receiver), a Trimble FmX display, and a Trimble FieldIQ controller.

We dribbled 396 L ha^{-1} UAN in between corn rows at V6 growth stage to provide an additional 168 kg ha^{-1} N, for a total season rate of 224 kg ha^{-1} N. The UKY guidelines (Ritchey & McGrath, 2021) recommend 15-98 kg ha^{-1} P for soils testing less than or equal to the critical concentration of 30 mg kg^{-1} M3P (where M3P is Mehlich 3 extractable phosphorus). Both Princeton and Quicksand had low average M3P concentrations that would receive a recommendation of up to 39 kg ha^{-1} P for surface broadcast P fertilizer. Therefore, we anticipated that banded 29.5 kg ha^{-1} P would provide more than adequate P to generate a positive yield response where M3P was <30 mg kg^{-1} (Ritchey & McGrath, 2021). This experimental design sought to map P response, rather than attain maximum yield response to P or to build soil P concentrations.

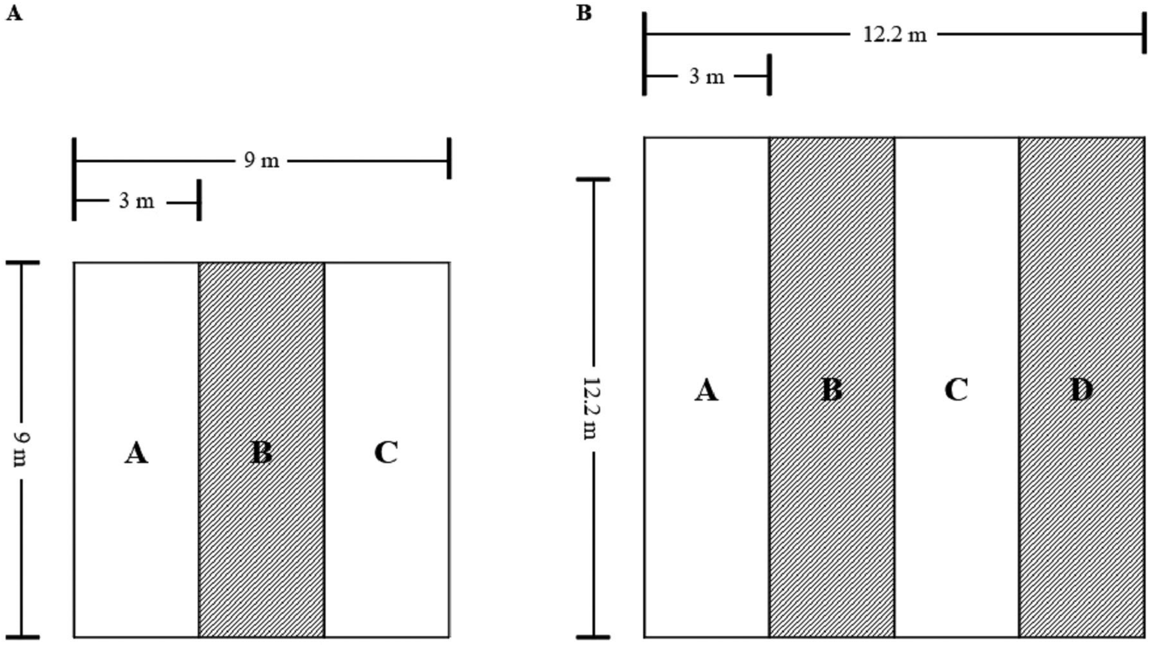

FIGURE 4 The plot design incorporated two subplots at both sites in 2016 (A), with the center plot (B) receiving phosphorus fertilizer and the two edge plots (A and C) receiving no phosphorus. In 2018, plots added at Quicksand used the original design (A). Plots added at the Princeton site used a four-subplot design (B) with two subplots randomly selected as controls and the other two receiving phosphorus fertilizer.

Based on our experiences, the banded P rate would generate a significant P response on average across soils within the range of concentrations seen at both sites.

2.2 | Soil and crop data

We used a Wintex 1000 automated soil probe (Wintex Agro) to collect soil samples (0- to 10-cm depth, 18-mm diameter) from each subplot prior to crop establishment in the 2016, 2018, and 2021 growing seasons at both sites. Each sample consisted of 10 individual soil cores collected randomly throughout the subplot and thoroughly mixed to form a composite sample. Soil samples were dried at 38°C for 24 h, ground to pass a 2-mm sieve, and submitted to the UKY Soil Testing Laboratory (UKSTL). The UKSTL determined soil pH (1 M KCl with glass electrode), Sikora Buffer pH, M3P, and Mehlich 3 extractable potassium using Inductively Coupled Plasma (ICP) methods from established soil testing protocols (Sikora & Moore, 2014). Although we sampled each subplot individually, this manuscript correlates the average of the soil test results from the control plots against relativized yield (RY). Therefore, we do not report changes in soil test P over time in the fertilized subplots. To calculate average pH for the control subplots, we first transformed subplot pH values to hydrogen concentration [H^+], averaged the concentrations, and then transformed that value to pH by taking the inverse logarithm of the [H+].

We harvested the center two rows (total area of 13.5 m^2 for 9 × 9 m main plots, 18.3 m^2 for 12.2 × 12.2 m main plots) of every four-row planter pass using a Kincaid 8-XP plot combine (Kincaid Equipment Manufacturing) with a two-row corn head. Yield was estimated from impulse and moisture measurements taken by an AgLeader sensor plate and moisture model (AgLeader Technology), which were then logged to an AgLeader Insight display, along with position and speed, determined by RTK-corrected GPS. Grain yield was adjusted to reflect industry standard 15.5% moisture content.

We calculated RY for each main plot by dividing the control treatment (average of the subplots without P fertilizer) by the P treatment (or average of P treatment subplots where replicated). Publications reporting linear plateau datasets may sometimes choose to cap relative yield values at 1.0 (Pearce et al., 2022). Relative yield can exceed 1.0 in plots where the control plots will yield greater than the plots with fertilizer application. In this study, we investigated the correlation using both constrained and unconstrained relative yield values. The discrepancy with these values can directly impact the models used to depict yield response. We conducted soil test correlation by regressing the constrained or unconstrained relative yields for each main plot against the mean M3P concentration of the unfertilized subplots in that main plot to determine the critical soil test concentration above which no further yield response was likely. Since we did not collect soil samples in 2020, we used results from 2021 soil sampling for the correlation procedures.

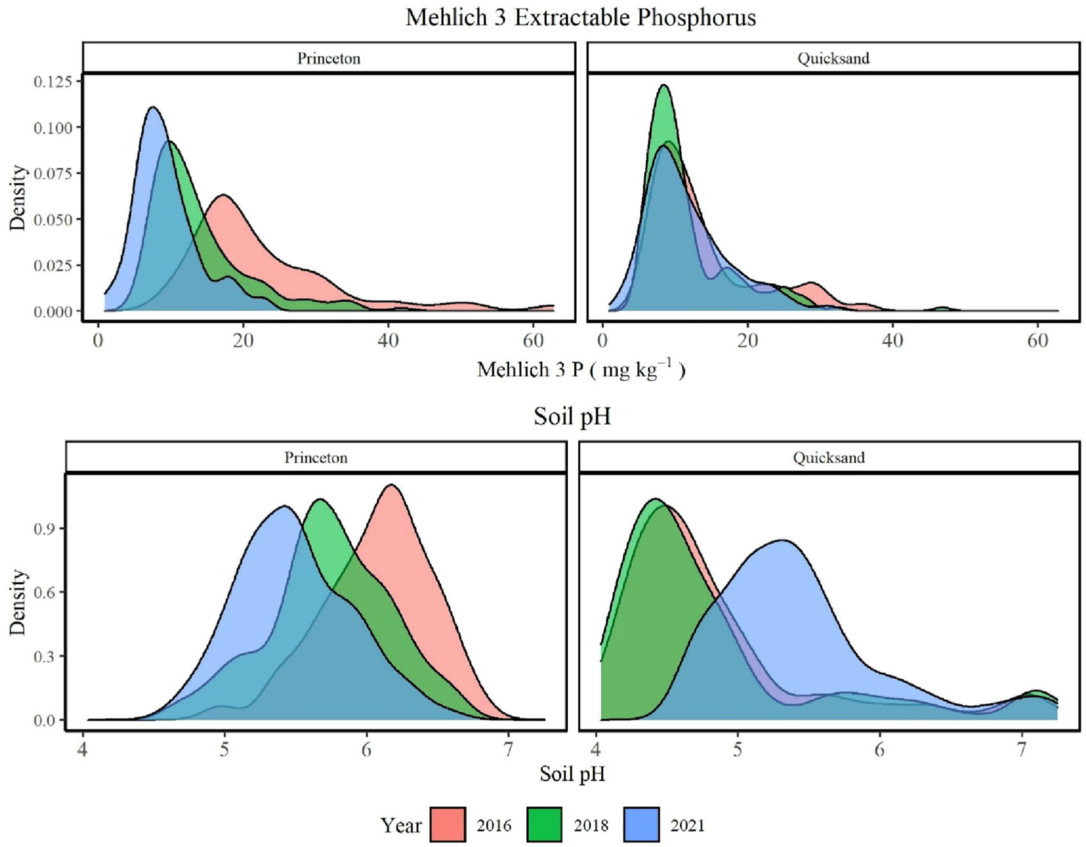

FIGURE 5 Density plots of Mehlich 3 extractable phosphorus (P) and soil pH of main plots (average of control treatment subplots) across both sites and years.

Our objective was to understand the spatial variability in nutrient response across site years. Therefore, the original plot design allowed estimation of the yield response to P fertilizer at the main plot scale. As described previously, the original design did not replicate the P fertilized treatment within main plots, and therefore, did not allow error estimation for response at the main plot level. We determined that a main plot was responsive to P if the relative yield value was <0.95.

2.3 | Statistical procedures

All regression and analysis of variance (ANOVA) were performed using R software, Version 4.2.1 (R Core Team, 2022). Datapoints from grain yield were determined to be outliers and removed if they were >50% outside the interquartile range (IQR) or 1.5 × IQR of the population from that site-year. We conducted an ANOVA ($\alpha = 0.10$) for grain yield across all site-years using grain yield as the dependent variable, and M3P as the independent variable, and included site-year and main plot as random variables to determine if M3P was a predictor of yield. If there was a significant interaction, we sliced by site-year to determine site-year-specific relationships. To determine if M3P was a predictor of nutrient response, we conducted a generalized linear model for binomial response (yes or no) and regressed against M3P concentration similar to the previous procedure.

We performed non-linear modeling with SAS software, Version 9.4, using PROC NLIN (SAS Institute). Non-linear analysis was conducted across both sites and by site, with constrained and unconstrained relative yield values. Differences between non-linear models were determined by computing the F-statistic from the difference of the sum of squares of the site specific and all sites, divided by the mean square values of all sites, with an alpha value of 0.10.

3 | RESULTS

3.1 | Soil phosphorus and pH

For this study, we selected field sites with average M3P concentrations below 30 mg kg^{-1} (Figure 5; Table 2), the M3P concentration below which UKY recommends P fertilizer for corn (Ritchey & McGrath, 2021). Across all years, main plot M3P averaged 14 and 12 mg kg^{-1} and ranged from 1 to

TABLE 2 Summary Statistics for Mehlich 3 extractable phosphorus (M3P) and soil pH.

	Mean	Standard error	Median	Median absolute deviation
	Princeton			
2016				
M3P (mg kg^{-1})	19	0.7	19	7.4
Soil pH	5.9	0.02	6.2	0.42
2018				
M3P (mg kg^{-1})	14	0.4	12	4.5
Soil pH	5.5	0.02	5.8	0.42
2021				
M3P (mg kg^{-1})	9	0.3	8	3.7
Soil pH	5.3	0.02	5.5	0.44
	Quicksand			
2016				
M3P (mg kg^{-1})	13	0.4	11	4.5
Soil pH	4.6	0.04	4.6	0.39
2018				
M3P (mg kg^{-1})	12	0.3	10	3.7
Soil pH	4.5	0.04	4.60	0.40
2021				
M3P (mg kg^{-1})	12	0.3	10	4.45
Soil pH	5.2	0.03	5.40	0.56

63 mg kg^{-1} and 3 to 47 mg kg^{-1} at Princeton and Quicksand, respectively. Approximately 94% and 98% of plots at Princeton and Quicksand, respectively, had M3P below the 30 mg kg^{-1} threshold. Moreover, the M3P data had a strong positive skew, with most samples falling below 14 mg kg^{-1}, the upper limit of UKY's "Low" interpretative category. Across all site years, 96% of the plots had M3P below 30 mg kg^{-1}, where UKY recommends P fertilizer application.

Soil pH impacts soil P availability and potential crop response (Penn & Camberato, 2019). The Quicksand site had an average soil pH of 4.6, ranging from 4.0 to 7.3 in 2016 and 2018. This site was limed in the spring of 2019, which increased the average soil pH to 5.2 (range 4.6–7.2) in 2021. The pH at Quicksand had a positive skew and a small, consistent cluster of plots with pH around 7.0. The high pH cluster was adjacent to a road with gravel shoulders and a limestone ($CaCO_3$) gravel aggregate surface at one time. We suspect this caused the cluster of high pH plots in that area. The pH at Princeton was less skewed than at Quicksand and decreased over time, starting with an average value of 5.9 in 2016 and ending at 5.3 in 2021. We attribute this change in pH to the continuous application of N during this study (Schroder et al., 2011).

3.2 | Average phosphorus response

Phosphorus fertilizer significantly impacted mean yield across all observations; however, there was a significant interaction by both site and year (data not shown). Therefore, we sliced the data by both site and year to determine site- and year-specific trends. Phosphorus fertilizer significantly ($p < 0.0001$) increased mean corn yields in 2016 at Princeton and all years at Quicksand (Table 3). Corn yield at Princeton was not consistently responsive to P fertilizer, with the only significant ($p = 0.0789$) response coming from 2016, where P fertilizer increased yield 0.46 ± 0.09 Mg ha^{-1}. On average, Princeton yielded 7.11 ± 0.09 and 3.70 ± 0.07 Mg ha^{-1} regardless of treatment (data not shown) in 2018 and 2020, respectively. Low yields in 2020 were due to poor crop establishment, and hot and dry summer, and the crop was never able to fully recover. On average, P fertilizer increased Quicksand corn yield by 0.52 ± 0.10, 0.84 ± 0.11, 0.73 ± 0.224, and 0.82 ± 0.16 Mg ha^{-1} in 2016, 2018, 2020, and 2021, respectively. Across all years, this represents an average yield increase of 6%.

3.3 | Modeling phosphorus response

Mehlich 3 P was a significant predictor of mean yield response across all data ($p < 0.0001$, Table 5). However, with yield there was a significant interaction with site and year ($p = 0.0077$); therefore, the data were sliced by site-year. At Princeton, yield responded to P fertilizer in 44%, 31%, and 50% of main plots in 2016, 2018, and 2020, respectively (Table 5). The M3P was below 30 mg kg^{-1} in 93% of the responsive plots yet was only a significant predictor of yield response in 2020 ($p = 0.0045$). At Quicksand, yield responded to P fertilizer in 51%, 53%, 70%, and 56% of main plots in 2016, 2018, 2020, and 2021, respectively. The concentration of M3P was <30 mg kg^{-1} in 99% of the responsive plots yet was only a significant predictor of nutrient responsiveness in 2016 ($p = 0.0038$).

Linear plateau models, where significant, were fitted by site and across sites, with constrained and unconstrained relative yield values (Table 4; Figure 6). Data were not robust enough to provide significant models by year, so all years were compiled to provide site-specific models. At Princeton, the linear plateau model was not significant when relative yield was unconstrained ($p = 0.3770$) but was significant when relative yield was constrained at 1.0 ($p = 0.0005$) with a joint point of 16.5 mg kg^{-1} and a pseudo-r^2 value of 0.02. At Quicksand, the linear plateau was significant when relative yield was unconstrained ($p = 0.0028$) and constrained ($p < 0.0001$), with a joint at 10.2 mg kg^{-1} and 10.0 mg kg^{-1}, respectively, and pseudo-r^2 value of 0.02 and 0.05, respectively. Across both sites, the linear plateau models were

TABLE 3 Yield and standard error (SE) for corn yield each year (Mg ha^{-1}), the *p*-value of the model with phosphorus (P) fertilizer treatment as a dependent variable, and yield as the independent variable.

	P treatment		Control		
	Mean (Mg ha^{-1})	SE (Mg ha^{-1})	Mean (Mg ha^{-1})	SE (Mg ha^{-1})	*p*-value
	Princeton				
2016	10.07	0.16	9.76	0.13	0.0789
2018	7.16	0.11	7.06	0.08	0.7280
2020	3.78	0.11	3.61	0.07	0.1850
	Quicksand				
2016	11.65	0.10	11.13	0.09	<0.0001
2018	15.49	0.13	14.69	0.11	<0.0001
2020	10.46	0.23	9.94	0.19	0.0001
2021	8.75	0.18	7.97	0.10	<0.0001

Note: Response was significant at $\alpha = 0.10$.

TABLE 4 Linear Plateau model parameters for unconstrained and constrained relative yield values across both sites, and with both sites combined.

	Slope	Intercept	Joint	Plateau	R^2	*p*-value
Unconstrained relative yield						
Princeton	–	–	–	–	–	0.3770
Quicksand	0.0128	0.83	10.2	0.96	0.02	0.0028
Combined	0.0075	0.88	12.8	0.98	0.02	0.0006
Constrained relative yield (≤1.00)						
Princeton	0.0045	0.88	16.5	0.95	0.04	0.0005
Quicksand	0.0124	0.80	10.0	0.92	0.05	<0.0001
Combined	0.0076	0.84	12.7	0.94	0.05	<0.0001

Note: Relative yield was calculated by dividing the yield of the control treatment by the yield of the Phosphorus treatment. Relative yield was either left as calculated (unconstrained) or constrained at 1.00.

significant for unconstrained ($p = 0.0006$) and constrained ($p < 0.0001$) relative yield, with joints at 12.8 mg kg^{-1} and 12.7 mg kg^{-1}, respectively, and pseudo-r^2 of 0.02 and 0.05, respectively.

We compared the linear models to determine if the site-specific models (by site) were more representative of their sites compared to models of both sites combined (across sites). Neither the unconstrained ($p = 0.3896$) or constrained ($p = 0.3413$) combined model was different from the site-specific models (data not shown).

4 | DISCUSSION

Our objective was to evaluate soil test P effectiveness for variable rate P management within fields and to understand if soil test critical levels hold at the subfield level. Our results indicated that within fields, crop response was uncorrelated to soil test P at M3P below critical concentrations for Kentucky. While 96% of our plots had soil test P below the 30 mg kg^{-1} critical nutrient threshold where UKY recommends fertilizer P (Ritchey & McGrath, 2021), only 51% responded to P fertilizer (Table 5), with significant prediction of nutrient response in just two site-years (Princeton in 2020 and Quicksand in 2016).

At the field scale, the UKY critical level of 30 mg kg^{-1} effectively identified average P need. We observed average yield increases in five of seven site-years (Table 3), supporting UKY's recommendation for P fertilizer application when M3P values are below 30 mg kg^{-1}. However, site-specific responses varied, with Princeton showing significant yield response to P in only 1 year (2016), while Quicksand showed positive yield response in all years. We attributed the lack of positive response at Princeton to poor crop stands and adverse growing conditions in 2018 and 2022, where yields lagged state averages. In contrast, Quicksand provided yields comparable to state averages throughout the study period (USDA-NASS, 2024). While only 4% of our main plots had

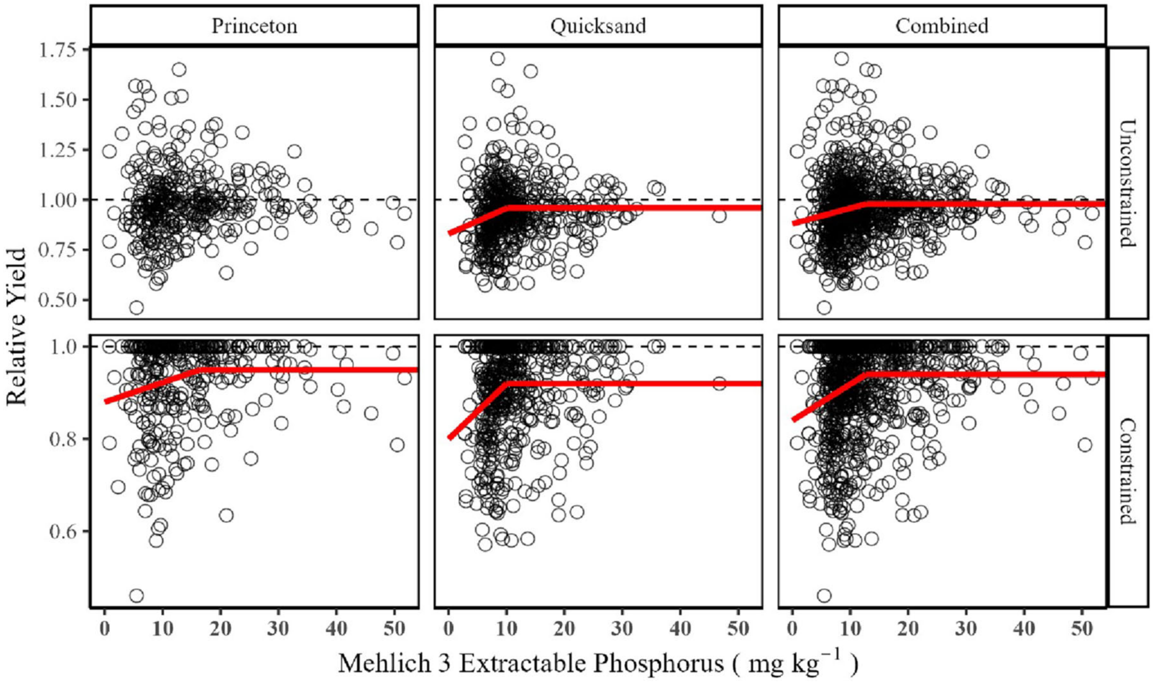

FIGURE 6 Linear plateau models for unconstrained and constrained relative yield values by and across sites. Relative yield was calculated by dividing the yield of the control treatment by the yield of the phosphorus treatment. Relative yield was either left as calculated (unconstrained) or constrained at 1.0.

TABLE 5 Summary Statistics of main plot Mehlich 3 extractable phosphorus (M3P) content of both plots that had a response and those that did not respond to the addition of phosphorus containing fertilizer across both sites and all years.

	No response				Response				
	n	Min M3P (mg kg^{-1})	Max M3P (mg kg^{-1})	Mean M3P (mg kg^{-1})	*n*	Min M3P (mg kg^{-1})	Max M3P (mg kg^{-1})	Mean M3P (mg kg^{-1})	*p*-value
Princeton									
2016	49	11	50	22	39	10	52	23	0.4290
2018	100	6	42	14	45	6	35	13	0.1740
2020	67	1	23	10	66	1	21	8	0.0045
Quicksand									
2016	58	7	36	15	61	6	31	12	0.0038
2018	77	6	33	12	88	6	47	11	0.4130
2020	38	4	26	11	87	3	31	10	0.2469
2021	60	3	20	10	76	3	31	12	0.1410
Combined									<0.0001

Note: We determined that a main plot was responsive to P if the yield of the P treatment exceeded the mean yield plus one standard deviation of the unfertilized control subplots. For main plots where standard deviation was not available due to missing data, we used the standard deviation of the control treatments at that site-year in place of the individual plot unfertilized standard deviation. Generalized linear model was used to determine if M3P was a predictor of yield response (yes/no). Response was significant at an $\alpha = 0.10$.

M3P >30 mg kg^{-1}, with an average RY of 0.96 they created a definitive plateau. This aligns with the fertilizer recommendation support tool project, which reported a plateau RY of 92% at a Mehlich 3 P of 43 mg kg^{-1} based on 177 corn response trials across 17 states using a 15 cm soil sample (Buol et al., 2024). This variable response pattern at the field level has been documented in other corn and soybean studies (Fulford & Culman, 2018; Reed et al., 2022).

Linear plateau models revealed important insights about spatial variability in P response (Figure 6). There were no significant differences between site-specific and combined-site models, with joint points ranging from 10.0 to 16.5 mg kg^{-1}

(Table 4). The poor pseudo-r^2 values (0.02–0.05) indicated minimal differences in model fits across datasets. While Dodd and Mallarino (2005) noted different joint points between sites, our spatially dense dataset specifically examined P response within fields, revealing limitations in traditional approaches. Though we focused on linear plateau models, which provide the basis for UKY recommendations, other modeling approaches (Slaton et al., 2024) would not alter our fundamental finding: yield response to P exhibits substantial spatial and temporal variability that soil test correlation alone cannot precisely predict.

Our data reveal that conventional experimental designs and statistical treatment of soil test correlation data, used to make state-level recommendations (Lyons et al., 2021), mask subfield variability that should be accounted for in variable rate fertilizer management. Notably, our study showed RY values commonly above 1.0, suggesting negative responses to P fertilizer. While negative impacts from P fertilizer application are presumed rare in the literature, this observation raises important questions about whether constraining RY values in models might mask actual spatial variability of nutrient response. As noted previously, the magnitude of positive response at low soil test P ranges outweighed the negative responses, so that the mean effect of P application was positive. Overall, the probability and magnitude of P response decreased as soil test increased, aligning with the traditional understanding of soil test correlation.

Traditional variable rate P management assumed that soil test correlation could be applied at the subfield level with high-density sampling. However, effective representation of soil nutrient variability requires prohibitively expensive sampling grids <30 m (Lauzon et al., 2005). Our findings, supported by recent research (Culman et al., 2023; Reed et al., 2021, 2022), suggest that even high-density soil P mapping cannot overcome the inherent variability in subfield response. Future research should explore incorporating mechanistic factors such as soil texture, climate zones, and crop production history (Beneduzzi et al., 2022; Jordan-Meille et al., 2012; Peltovuori, 1999; Ramamurthy et al., 2009) or develop econometric approaches using probabilistic models to account for stochastic variation and hedge against economic loss. These strategies could better support precision fertilizer management while acknowledging inherent response variability, potentially improving both economic and environmental outcomes (Zhang et al., 2024).

5 | CONCLUSION

This study demonstrated that soil test P, while effective at predicting average field-level nutrient responses, lacks the precision required for sub-field, variable rate fertilizer management. Although 96% of plots in this study fell below the critical P threshold recommended for fertilizer application, only 51% responded to P inputs, underscoring the limitations of relying solely on soil test P for precision agriculture. The inability of soil test P alone to accurately predict yield response highlights the complexity of P dynamics within fields and the influence of other contributing factors. Future precision agriculture models require innovative experimental designs to capture the spatial variability of yield response to P as a function of additional soil properties, crop characteristics, and environmental conditions. Our novel approach of collecting spatially dense yield response data correlated against soil P concentrations provides a framework for developing more precise fertilizer recommendations that optimize crop yields while minimizing environmental impacts.

AUTHOR CONTRIBUTIONS

Vaughn Reed: Formal analysis; validation; visualization; writing—original draft; writing—review and editing. **Jenni Fridgen**: Formal analysis; investigation; writing—review and editing. **Bronc Finch**: Investigation; writing—review and editing. **John Spargo**: Formal analysis; methodology; writing—review and editing. **Josh McGrath**: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; supervision; validation; writing—review and editing. **James M. Bowen**: Conceptualization; data curation; investigation; methodology; writing—original draft. **Gene Hahn**: Methodology; supervision. **Douglas Smith**: Funding acquisition; investigation; supervision. **Edwin Ritchey**: Resources; supervision.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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