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TECHNICAL REPORT

Environmental Models, Modules, and Datasets

Relationships between soil test phosphorus and county-level agricultural surplus phosphorus

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Abstract

National nutrient inventories provide surplus phosphorus (P) estimates derived from county-scale mass balance calculations using P inputs from manure and fertilizer sales and P outputs from crop yield data. Although bioavailable P and surplus P are often correlated at the field scale, few studies have investigated the relationship between measured soil P concentrations of large-scale soil testing programs and inventory-based surplus P estimates. In this study, we assessed the relationship between national surplus P data from the NuGIS dataset and laboratory-measured soil test phosphorus (STP) at the county scale for Arkansas, North Carolina, and Oklahoma. For optimal periods of surplus P aggregation, surplus P was positively correlated with STP based on both Pearson (Arkansas: $r = 0.65$, North Carolina: $r = 0.45$, Oklahoma: $r = 0.52$) and Spearman correlation coefficients (Arkansas: $\rho = 0.57$, North Carolina: $\rho = 0.28$, and Oklahoma: $\rho = 0.66$). Based on Pearson correlations, the optimal surplus P aggregation periods were 10, 30, and 4 years for AR, NC, and OK, respectively. On average, STP was more strongly correlated with surplus P than with individual P inventory components (fertilizer, manure, and crop removal), except in North Carolina. In Arkansas and North Carolina, manure P was positively correlated with STP, and fertilizer P was negatively correlated

Abbreviations: AAPFCO, Association of American Plant Food Control Officials; PC, principal component; PCA, principal component analysis; STP, soil test phosphorus.

with STP. Altogether, results suggest that surplus P moderately correlates with STP concentrations, but aggregation period and location-specific factors influence the strength of the relationship.

1 | INTRODUCTION

Understanding soil phosphorus (P) concentration and availability at large spatial scales is important for guiding best management practices (Hamilton, 2012; Jarvie et al., 2013; Meals et al., 2010; A. Sharpley et al., 2013). Typically, 70%–80% of P applied to agricultural fields remains after the first year (Jarvie et al., 2013; A. Sharpley et al., 2013), which may result in surplus P accumulation over time when applied P exceeds that removed by crops. Having accurate estimates of surplus P is important for making nutrient application decisions, and for clearly communicating and defining expectations for protecting surface water from excess nutrient inputs (Hamilton, 2012). Mass balance estimates of surplus P, based on outputs (i.e., crop removals) subtracted from inputs (i.e., fertilizer and manure), have been used to study P in soils across large spatial scales (Fixen et al., 2012; Metson et al., 2017; Sabo et al., 2021). Agricultural P surpluses are expected to be the primary driver of the "residual P" content of soils, though other factors like hydrologic losses also play a role (Zhou & Margenot, 2023).

Although mass balance-based estimates of surplus P provide insights on where P imbalances may be occurring, surplus P is generally of less direct relevance to agronomic decision-making than soil test phosphorus (STP). STP, commonly measured through chemical extractions (such as the Mehlich-3, Bray-1, and Olsen methods; Westerman, 1991), provides an estimate of the soil P that is available to plants (A. N. Sharpley, 1993), and its concentrations are commonly used to make fertilizer application recommendations. Bioavailable P is typically a small fraction of applied P, depending on the composition of the nutrient amendment (e.g., organic manures/residues vs. inorganic fertilizer) and properties of the soil (e.g., mineralogy, organic carbon content, texture, and pH) (Barrow, 1980; Dodd & Sharpley, 2015; Roberts & Johnston, 2015; Zhu et al., 2018). For example, additions of organic P may contribute to soil organic P but also be mineralized to produce inorganic P. Also, inorganic P introduced through fertilization or mineralization may become sequestered in mineral phases by sorption or precipitation rather than remaining bioavailable (Doydora et al., 2020).

Although there are several factors mediating the relationship between STP and surplus P, we largely expect a positive correlation between these variables, as demonstrated in field experiments in soils with a range of different edaphic properties (e.g., Chen et al., 2021; Khan et al., 2023; Lu et al., 2020; Sucunza et al., 2018), because greater P additions will generally result in greater available and dissolved P. Accordingly, fields accumulating surplus P over long time periods (e.g., multiple years or decades) may also have higher STP. For example, in a field experiment where high fertilizer-P rates (400-132-332 kg ha^{-1} as N-P-K) were applied for 6 years, sufficient STP had accumulated to sustain crops of corn (*Zea mays* L.) for 28 years without additional P inputs (T. Q. Zhang et al., 2004). We note, however, that diverse soils may have large P fixation capacities (Harris & Warren, 1962; Sanchez & Uehara, 1980), which may result in weakly positive or no relationship between STP and surplus P given that practically none of the surplus P would be bioavailable in such soils. In agricultural systems with consistently efficient management, STP should be high while surplus P is low (i.e., have an inverse or negative relationship), but an inverse relationship is unlikely to be observed in fields receiving excess P fertilization.

Our understanding of the relationships between STP and surplus P is largely based on studies performed at relatively local scales with repeated experiments over multiple years (e.g., Aulakh et al., 2007; Battisti et al., 2021). Few have studied how STP is associated with surplus P calculated over large scales on the order of tens to thousands of square kilometers (e.g., counties, watersheds), as is available in existing national-scale P inventories. Three published and readily accessible national P inventories are available: NuGIS (Fixen et al., 2012), and those included in Metson et al. (2017) and Sabo et al. (2021). These inventories were developed to synthesize national data on nutrient sources and sinks, identify areas with nutrient surpluses, and evaluate how surpluses change over time. Across the three inventories, surplus P is calculated through mass balances. The inputs include livestock manures and inorganic fertilizers, whereas the outputs include harvested crops. A key advantage of surplus P inventories is that they are available throughout the contiguous United States and over multiple years, but surplus P estimated over large spatial scales may eventually be transported outside of agricultural soils such as through hydrologic losses (Stackpoole et al., 2019), meaning these estimates may not reflect the P available in agricultural fields. In contrast, STP data are only available from discrete soil sampling that captures field conditions at specific points in time, but few STP datasets with extensive spatial coverage are publicly available (McDowell et al., 2023). Surplus P data may be useful for filling gaps in coarse STP records, but research is needed to understand whether existing surplus P datasets provide a useful proxy for STP, and on the amount of time over which surplus P dynamics should be considered in relation to STP. For example, Reid and Schneider (2019) successfully used cumulative surplus P estimates to predict changes in STP across Canadian provinces, but research is needed to determine whether STP's relationship with cumulative surplus P varies depending on the time period over which cumulative surplus P is aggregated (e.g., 1 year vs. 30 years).

Our goal was to determine if surplus P estimates from a national inventory covaried with discrete STP measurements summarized at the county scale, and whether the strength of the surplus P–STP relationship was affected by the duration of time over which surplus P was aggregated. Identifying key mediators of the surplus P–STP relationship would allow national P inventory users to know the most suitable areas where surplus P estimates can proxy for bioavailable P. We specifically examined the relationship between surplus P from the NuGIS inventory and agricultural STP at the county scale for three US states with diverse agricultural production systems: Arkansas (AR), North Carolina (NC), and Oklahoma (OK). We note that, although all three states produce large quantities of field crops, AR and NC produce far more livestock than OK (USDA National Agricultural Statistics Service, 2017a), and thus also have considerably high organic P applications. Our objectives were to evaluate relationships between national inventory surplus P estimates and STP: (1) within and between states; (2) as a function of aggregation period, which refers to the duration of time over which surplus P is summed; and (3) relative to correlations between STP and other P inventory components, including P in fertilizer, manure, and harvested crop biomass. We hypothesized that surplus P was positively correlated with STP and would more strongly correlate with STP when aggregated over longer periods.

Core Ideas

- The county-scale relationship between surplus P and soil test phosphorus (STP) was examined for three US states.
- Optimal aggregation periods for surplus P, in relation to STP, ranged from 4 to 30 years.
- The maximum state-level correlation coefficients for STP and surplus P ranged from 0.45 to 0.65.
- STP is more strongly correlated to the P in recoverable manure than in sold fertilizer.

2 | MATERIALS AND METHODS

2.1 | Study area

Relationships between county-scale surplus P and STP data were explored for AR, NC, and OK. We selected these states because of the availability of comprehensive county-level STP datasets, for which it was possible to isolate cropland samples (the focus of this study) from samples representing other land use types (e.g., urban and garden). These three states have notable differences in agricultural production. The greatest livestock densities (estimated based on sales data; USDA National Agricultural Statistics Service, 2017a) were in NC (approximately 832 million broilers, 35.8 million hogs, and 377,000 cattle and calves) and AR (approximately >1 billion broilers, 1.2 million hogs, and 937,000 cattle and calves), followed by OK (approximately 197,000 broilers, 9 million hogs, and 3.6 million cattle and calves). NC has greater annual average amounts of commercial fertilizer (as P_2O_5) purchased compared to AR and OK (i.e., in 2017, NC, OK, and AR purchased 136,355, 53,034, and 72,861 kilotonnes of fertilizer P_2O_5, respectively; Association of American Plant Food Control Officials for The Fertilizer Institute, 2022). On top of the nutrient management differences, dominant land uses also vary among the three states (Bigelow & Borchers, 2017). The predominant land use type for AR and NC is forest (56% and 58%, respectively), and pastureland for OK (45%). Cropland is 25%, 14%, and 26% of the total state area in AR, NC, and OK, respectively.

Agricultural soils in the three states had different geospatial patterns, which also corresponded to spatial trends in agricultural production system types. For AR, most field crops are grown in the eastern part of the state, where productive Mississippi River alluvial soils are located. Western AR is largely forested, and agriculture is more focused on cattle and poultry production (USDA National Agricultural Statistics Service, 2017b). For NC, although agriculture is present across the state, both row crop and animal production are mostly concentrated in the eastern part of the state, except for broiler production (Kulesza et al., 2024; USDA National Agricultural Statistics Service, 2017b). Animal production in NC is dominated by poultry (broilers and turkeys) and swine (USDA National Agricultural Statistics Service). For OK, the majority of cropland lies in the central and western regions, which are composed of soils of variable texture where winter wheat (*Triticum aestivum* L.) dominates cultivated acreage along with beef cattle production. To a lesser extent, grain sorghum (*Sorghum bicolor*), cotton (*Gossypium hirsutum* L.), and alfalfa (*Medicago sativa* L.) are also grown (USDA National Agricultural Statistics Service, 2017b).

2.2 | Soil test phosphorus and phosphorus surplus data

For our study, we considered the NuGIS surplus P inventory (Fixen et al., 2012), which has the highest temporal resolution of the three inventories summarized in the introduction, and annual P surplus estimates from 1987 to 2016. The NuGIS dataset calculates surplus P as P_2O_5 at the county scale, where fertilizer and animal manures are taken as inputs and crop removal as outputs, with the difference divided by the county's total cropland area. Fertilizer input into the system is estimated using a combination of Association of American Plant Food Control Officials (AAPFCO) fertilizer sales data, reported expenditures on fertilizer and lime products by the USDA Census of Agriculture, and methods by Ruddy et al. (2006) to predict farm use fertilizer sales for areas with unreliable data (Fixen et al., 2012). Manure was calculated based on livestock species, head counts, and nutrient contents for each county, as provided by the USDA Census of Agriculture. Specifically, NuGIS considered P from recoverable manure, which was calculated by subtracting field loss and other processes (such as storage and transportation loss) from total excreted manure. Crop removal was calculated from harvested biomass estimates from the USDA National Annual Agricultural Statistics Summary dataset. In addition to the surplus P estimates, we also used these NuGIS estimates of fertilizer P, manure P, and harvested P in our analysis (in units of kg P_2O_5 ha^{-1}). NuGIS estimates were available beginning in 1987 for NC and OK and in 1990 for AR.

Agricultural STP data were analyzed for AR (DeLong et al., 2019), NC (Agronomic Division, North Carolina Department of Agriculture and Consumer Services, 2017 data), and OK (Oklahoma State University Extension Services Soil, Water and Forage Analytical Laboratory). STP data from 2017 for AR, OK, and NC were obtained from public soil testing programs at the University of AR Division of Agriculture, Oklahoma State University, and the NC Department of Agriculture and Consumer Services, respectively. All three laboratories oven-dry soil samples, grind soil to pass through a 2-mm sieve, use the Mehlich-3 extraction procedure described by H. Zhang et al. (2014), and determine extracted P concentrations with inductively coupled plasma-optical emission spectroscopy. Samples were submitted to these labs by end-users seeking soil test information and crop fertilization recommendations, and were not collected as part of a systematic monitoring program or research study. Because the NuGIS surplus P estimates only consider croplands, we only used STP measurements from samples collected in agricultural lands associated with row crops and forage managed for hay production (Table S1), excluding STP measurements from samples associated with other agricultural classes, such as pastureland or gardens. The types of crops grown in fields where the STP samples were collected were self-reported by sample submitters.

2.3 | Data cleaning and statistical analysis

Before analysis, potential outliers were screened in the STP and surplus P data for the three states. We removed New Hanover County in NC and Cleveland County in AR due to unrealistically high surplus P values (464.8 and 257.4 kg ha^{-1} year^{-1}, respectively) as compared to other counties (Table S2). These removals were confirmed by statistical tests (Tietjen & Moore, 1972; Table S3). Counties with missing records for either NuGIS or STP were also omitted. After removing these data, the average number of STP samples per county within each state was 2391 for NC, 340 for AR, and 123 for OK. For each county, we determined a single median STP value based on all samples available for that county.

Correlations were calculated between county STP medians and county-scale surplus P and P inventory components from NuGIS (fertilizer P, manure P, fertilizer P + manure P, and harvested P). So that the mediating effect of the historical agricultural context (i.e., surplus P accumulation, fertilizer sales, recoverable manure, and harvested biomass) on the strength of the STP–surplus P relationship could be analyzed, we aggregated the NuGIS surplus P and P inventory components over periods spanning 1 year (2016) to the entire length of the dataset (1987–2016 for NC and OK, and 1990–2016 for AR). Each aggregation period differed by 1 year. For example, the first aggregation period only included 2016, the second included 2015–2016, the third included 2014–2016, and so on. We began the aggregation periods with 2016, instead of 2017 (i.e., the year for which we have STP data), to ensure the NuGIS data were fully antecedent to the dates of STP data collection.

To assess correlations, we used two indices—the parametric Pearson correlation coefficient (r) and nonparametric Spearman correlation coefficient (ρ). Both indices measure the strength of bivariate correlations. The Pearson correlation coefficient assesses the strength of linearity, whereas the Spearman correlation coefficient assesses the strength of monotonicity (Myers et al., 2013).

Once the optimal aggregation periods were identified from the correlation analysis (i.e., "optimal" refers to the aggregation period corresponding to the highest correlation indices between surplus P and STP), linear regression models were created to relate STP to surplus P for each of the three study states. Linear regression models allowed for assessment of the significance and strength of the rate of change in STP relative to surplus P.

Additionally, to further understand multivariate relationships across our dataset, principal component analysis (PCA) was applied to STP and P inventory components (Abdi & Williams, 2010), and a Mann–Kendall trend test was performed to assess whether the P inventory components significantly changed over time (Hipel & McLeod, 1994). These analyses were applied in support of our third objective of evaluating relationships between national inventory surplus P estimates and STP relative to correlations between STP and other P inventory components.

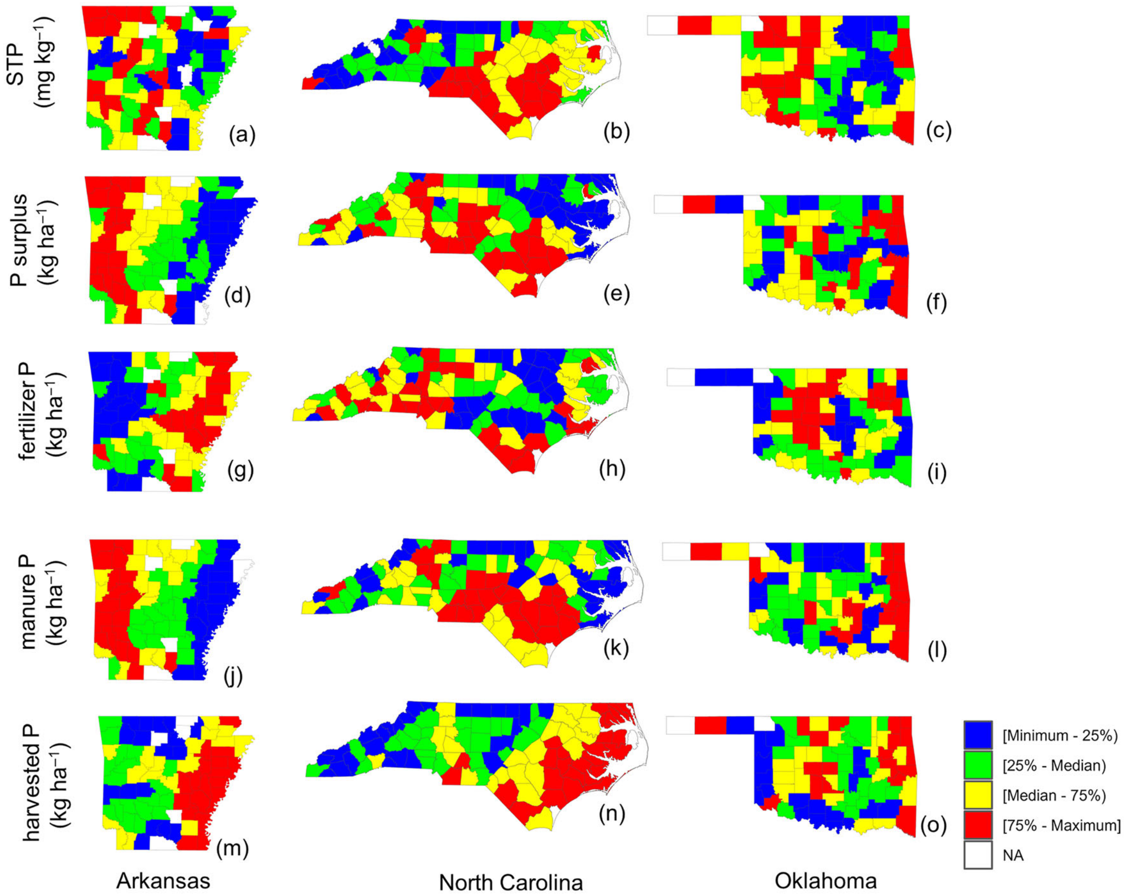

FIGURE 1 Spatial patterns in median soil test phosphorus (STP) (a–c) and inventory-based surplus P (d–f), fertilizer P (g–i), manure P (j–l), and harvested P (m–o) for AR (left column), North Carolina (center column), and Oklahoma (right column). The surplus P and P inventory components are summarized over 1987–2016 for NC and OK, and 1990–2016 for AR. Each variable is mapped at the county scale. Colors correspond to quartiles calculated for each state; see Table S2 for quartile ranges. STP is reported as elemental P (mg P kg^{-1}). For surplus P and its components (fertilizer P, manure P, and harvested P), the units are kg P_2O_5 ha^{-1}.

3 | RESULTS

3.1 | Spatial variability in STP, surplus P, and P inventory components

Agricultural STP concentrations varied among states, with NC having the highest county STP (mean ± std., 89.7 ± 47.4 mg kg^{-1}, in P), followed by AR (48.6 ± 29.6 mg kg^{-1}, in P) and OK (17.4 ± 9.3 mg kg^{-1}, in P). Furthermore, NC also had the highest surplus P (48.7 ± 39.1 kg P_2O_5 ha^{-1} year^{-1}), followed by AR (17.1 ± 35.6 kg P_2O_5 ha^{-1} year^{-1}) and OK (2.7 ± 7.8 kg P_2O_5 ha^{-1} year^{-1}); reported means and standard deviations are of the county-scale median STP values. Within each state, spatial trends in STP and surplus P were also evident. For AR, STP, surplus P, and manure P were highest in the western part of the state (Figure 1a,d,j), where the poultry industry is predominantly located, whereas fertilizer P and harvested P were highest in the state's eastern counties (Figure 1g,m). NC generally showed higher STP concentrations and P inputs in southern counties with extensive poultry and swine production (Figure 1b,h,k), whereas P removed by crops was highest in the east (Figure 1n). Spatial gradients were less evident in the OK data, although manure P was greater along the state's eastern boundary adjacent to western AR (Figure 1l), corresponding to the presence of poultry farms.

3.2 | Interannual variability in surplus P, P inventory components, and cropland area

The time series of surplus P, inputs, and outputs suggests considerable temporal consistency as well as a few long-term trends (Figure 2). Of the three study states, NC consistently had the greatest P surpluses, whereas OK consistently had the least (Figure 2a). For AR and NC, the combination of fertilizer P and manure P consistently exceeded harvested P across the 30-year study period. For OK, negative P surpluses were common after 2005.

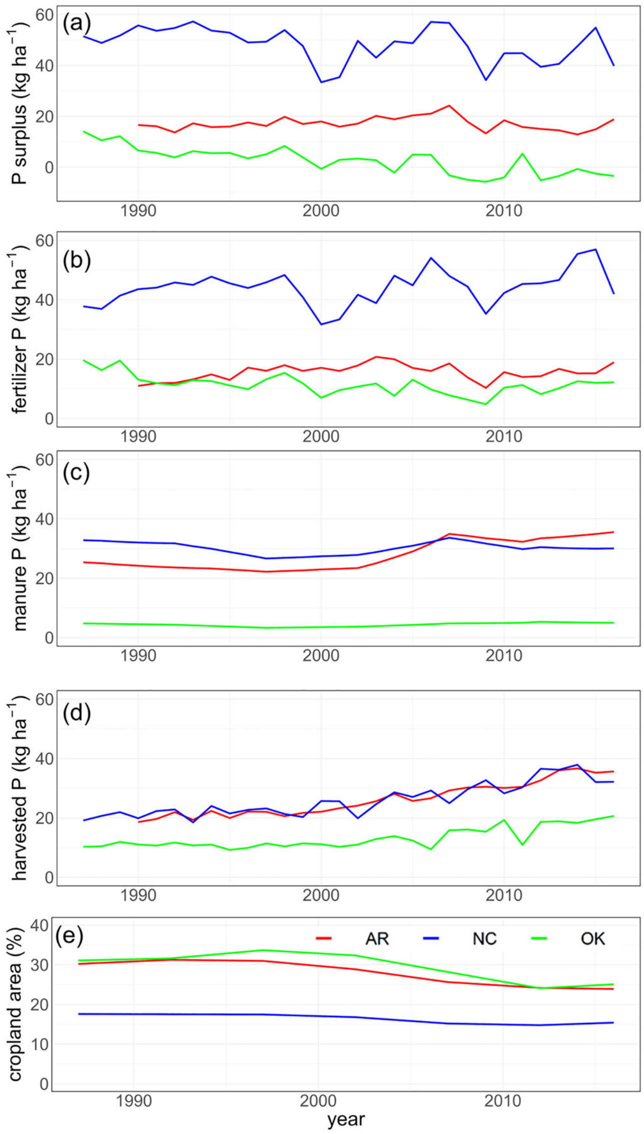

FIGURE 2 Time series plots of state-average annual P components in Arkansas, North Carolina, and Oklahoma. For panels (a–d), units are in kg P_2O_5 ha^{-1} year^{-1}, and for panel (e), the units are percentages of total land area.

For AR, the surplus P (Figure 2a) and fertilizer P (Figure 2b) were relatively stable over time (p values of Mann–Kendall trend analysis: 0.934 and 0.182, respectively; Table 1). Manure P (Figure 2c) substantially increased from 2002 to 2007, and harvested P (i.e., crop yield) generally increased over the 27-year study (Figure 2d, Mann–Kendall $p < 0.001$; Table 1). It is worth noting that across the study period, manure P was greater than fertilizer P, especially after 2005 (Figure 2b,c).

Compared to AR, NC had greater annual variability in fertilizer P inputs over time (Figure 2b), and the annual magnitude of fertilizer P was consistently larger than that of manure P (Figure 2c). Similar to AR, harvested P increased through the 30-year study period (Mann–Kendall $p < 0.001$; Table 1). Annual cropland area percentages for NC decreased over the study period (Figure 2e, Mann–Kendall $p < 0.001$).

In OK, the magnitudes of fertilizer P and manure P were generally less than for AR and NC (Figure 2b,c). Harvested P rates for OK were also relatively low but increased over the study period (Figure 2d, Mann–Kendall $p < 0.001$). Among the three states, OK had the greatest cropland area percentage, likely due to forage production in northeastern and eastern OK, with a decrease in cropland area occurring over the approximately last 15 years of the study period (Figure 2e). The increase in harvested P concurrent with the reduction in cropland area indicates yield efficiency improved during the study period.

3.3 | Relationships between STP and surplus, fertilizer, manure, and harvested P

We determined correlations between STP and P inventory components for varying inventory aggregation periods. Pearson r and Spearman ρ showed similar trends across all states and P components (Figure 3). For all three states, surplus P was positively correlated with STP based on both Pearson correlation coefficients (AR: $r = 0.65$, NC: $r = 0.45$, and OK: $r = 0.52$) and Spearman correlation coefficients (AR: $\rho = 0.57$, NC: $\rho = 0.28$, OK: $\rho = 0.66$). Notably, NC had lower Spearman correlation coefficients compared to AR and OK (Figure 3b). On average, r values were comparable to ρ values, indicating these findings are fairly robust to different measures of correlation (i.e., linearity vs. monotonicity). These correlations are based on optimal periods of surplus P aggregation (Table 2), in which optimal periods are defined as those corresponding to the highest correlation indices between surplus P and STP. For AR and OK, the optimal periods ranged from 4 to 13 years (max r at 10 and 4 years and max ρ at 13

TABLE 1 Tau values from the Mann–Kendall trend analysis for Arkansas (AR), North Carolina (NC), and Oklahoma's (OK) P inventory components.

State	P surplus	Fertilizer	Manure	Harvested P	Crop area percentage
AR	0.014 (0.934)	0.18 (0.182)	0.60 (<0.001)	0.85 (<0.001)	−0.80 (<0.001)
NC	−0.34 (0.008)	0.25 (0.054)	−0.04 (0.748)	0.70 (<0.001)	−0.82 (<0.001)
OK	−0.64 (<0.001)	−0.37 (0.005)	0.39 (0.002)	0.53 (<0.001)	−0.49 (<0.001)

Note: p-values are shown in parentheses.

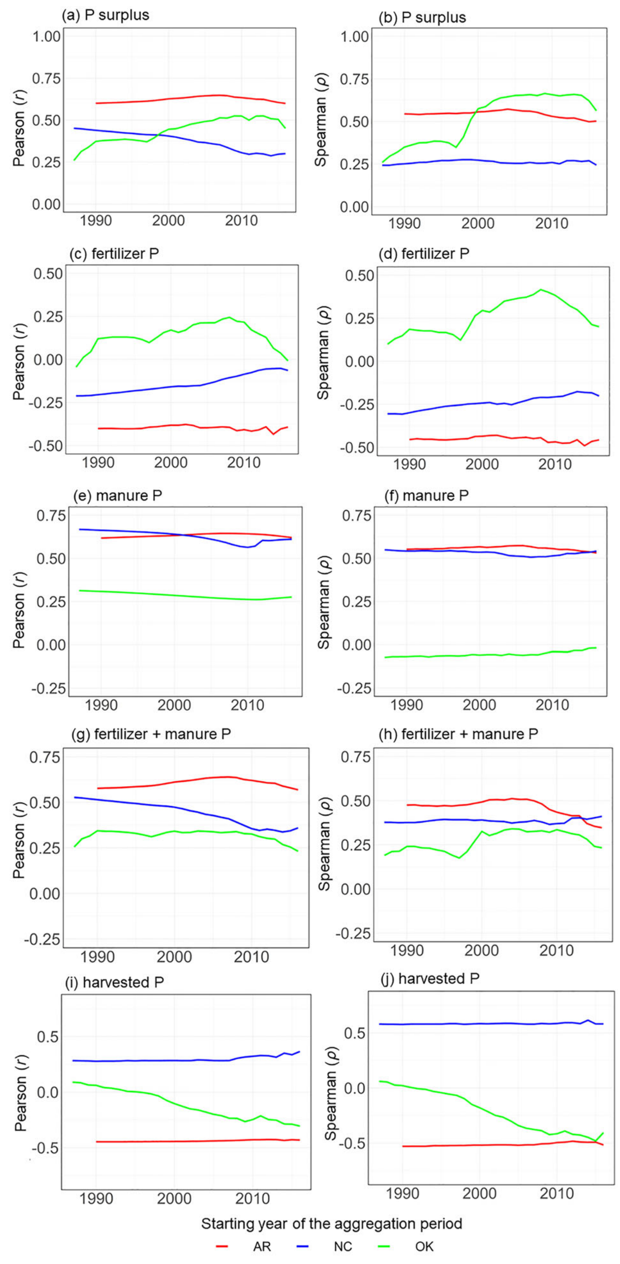

FIGURE 3 Time-based correlation plot of Pearson r and Spearman ρ. Panels (a) and (b) are the correlation between surplus P and soil test phosphorus (STP), (c) and (d) are the correlation between fertilizer P and STP, (e) and (f) are the correlation between manure P and STP, (g) and (h) are the correlation between fertilizer + manure P and STP, and (i) and (j) are the correlation between harvested P and STP. The first year to calculate the aggregation period is shown on the x-axis. For example, "1990" corresponds to the aggregation period of 1990–2016; "2000" corresponds to an aggregation period of 2000–2016.

and 8 years for AR and OK, respectively), whereas for NC, the optimal periods were 30 years for Pearson r and 19 years for Spearman ρ.

Linear regression models were constructed for each state to explain county-scale STP as a function of surplus P aggregated over the optimal period (Figure 4; Table S4). Surplus P explained the greatest variance in STP in AR (adjusted $R^2 = 0.41$) and similar variance in NC and OK (adjusted $R^2 = 0.20$ and 0.27, respectively). While AR had the largest Pearson r for the STP–surplus P relationship (0.65), it had the lowest slope in the regression models. Nonetheless, slopes were fairly consistent across the three states (0.47, 0.55, and 0.52 for AR, NC, and OK, respectively; p values < 0.001), demonstrating consistency in the STP–surplus P relationship across the three states.

Fertilizer P correlations with STP were lower than those of surplus P with STP. For AR, the r and ρ values for fertilizer–STP relationships were consistently negative ($r = -0.38$, $\rho = -0.43$). Correlation indices were also negative for NC, but the relationship was weak ($r = -0.05$, $\rho = -0.18$). For OK, maximum r and ρ values for fertilizer–STP relationships were positive ($r = 0.24$, $\rho = 0.42$) but smaller than those for surplus P–STP relationships ($r = 0.52$, $\rho = 0.66$). For manure–STP relationships, the largest r and ρ values were positive for AR ($r = 0.65$, $\rho = 0.57$) and NC ($r = 0.67$, $\rho = 0.55$). For OK, the r value was positive (0.31) whereas the ρ value was negative (-0.02).

STP was equally or more strongly correlated with manure P than surplus P in AR ($r = 0.67$, $\rho = 0.57$) and NC ($r = 0.67$, $\rho = 0.55$), but was more weakly correlated with manure P than surplus P in OK ($r = 0.31$, $\rho = -0.02$). The manure–STP relationship was more stable over a range of aggregation periods as compared to the fertilizer–STP relationship (Figure 3c–f). However, the manure–STP relationship was more sensitive to the choice of correlation coefficient, especially for OK. The influence of manure P on STP is also evident in the linear regression plots (Figure 4), where the highest county-scale STP medians were largely associated with manure being the primary P input.

For AR and OK, the maximum r and ρ values of surplus P–STP relationships were greater than those of both input P–STP relationships and harvest P–STP relationships. For NC, harvested P–STP had greater ρ but lesser r values compared to surplus P–STP. All correlations for input P–STP relationships and harvested P–STP relationships were positive, except for AR harvested P–STP relationships.

PCA was applied to illustrate multivariate relationships among the key variables used in this study (Figure 5). The first two principal component (PC) axes account for about 70% of the total variance in the data for NC and OK, and 84% of the variance for AR. Across all three states, PC1 (accounting for 44%–70% of total variance) is heavily loaded by surplus and manure P (Table 3), and it can thus be interpreted as a thematic "manure + surplus" axis, suggesting that surplus P is largely driven by excess manure applications. PC2 (14%–26% of total variance) consistently received a large loading from fertilizer P alone, and it can thus be interpreted as the "fertilizer" thematic axis. STP aligns moderately and positively with the manure + surplus axis, but its loadings are both positive (AR) and negative (NC and OK) on the fertilizer axis

TABLE 2 Maximum values of *r* and *ρ* between soil test phosphorus (STP) and P inventory components, considering different aggregation period lengths (number of aggregation years in parentheses).

P inventory component	AR *r*	AR *ρ*	NC *r*	NC *ρ*	OK *r*	OK *ρ*
Surplus P (inputs – outputs)	0.65 (10)	0.57 (13)	0.45 (30)	0.28 (19)	0.52 (4)	0.66 (8)
Fertilizer P	−0.38 (15)	−0.43 (15)	−0.05 (2)	−0.18 (4)	0.24 (9)	0.42 (9)
Manure P	0.65(10)	0.57 (11)	0.67(30)	0.55 (30)	0.31 (30)	−0.02 (1)
Fertilizer + Manure P (inputs)	0.64 (10)	0.51 (13)	0.53 (30)	0.41 (1)	0.34 (27)	0.34 (13)
Harvested P (outputs)	−0.43 (5)	−0.48 (5)	0.36 (1)	0.62(3)	0.09 (30)	0.06 (30)

Abbreviations: AR, Arkansas; NC, North Carolina; OK, Oklahoma.

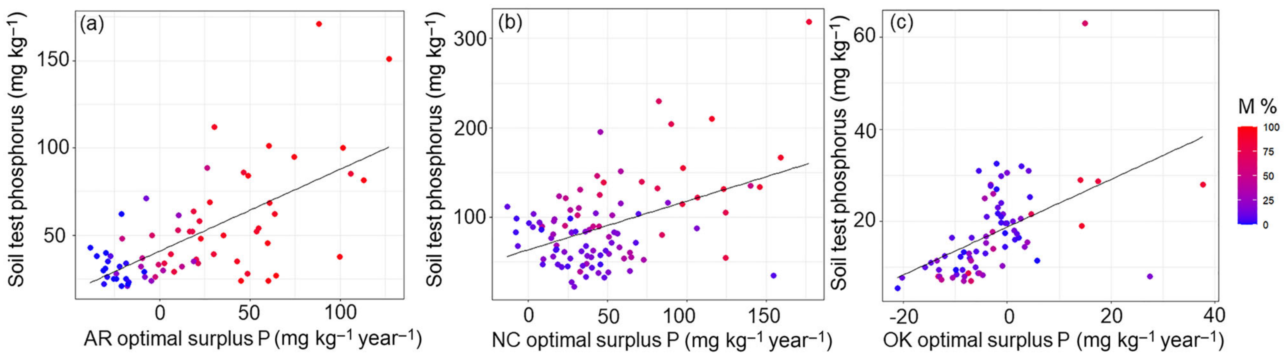

FIGURE 4 Linear regression models estimating soil test phosphorus (STP) as a function of surplus P for AR (a), NC (b), and OK (c). Surplus P was calculated for the optimal aggregation periods based on Pearson correlation coefficients (2007–2016 for AR, 1987–2016 for NC, and 2013–2016 for OK), and divided by the length of the optimal aggregation periods (10 years for AR, 30 years for NC, and 4 years for OK). The individual points, representing different counties, were color-coded based on the percentage of total P inputs (manure plus fertilizer P) corresponding to manure P (M%). Regression model statistics are summarized in Table S4.

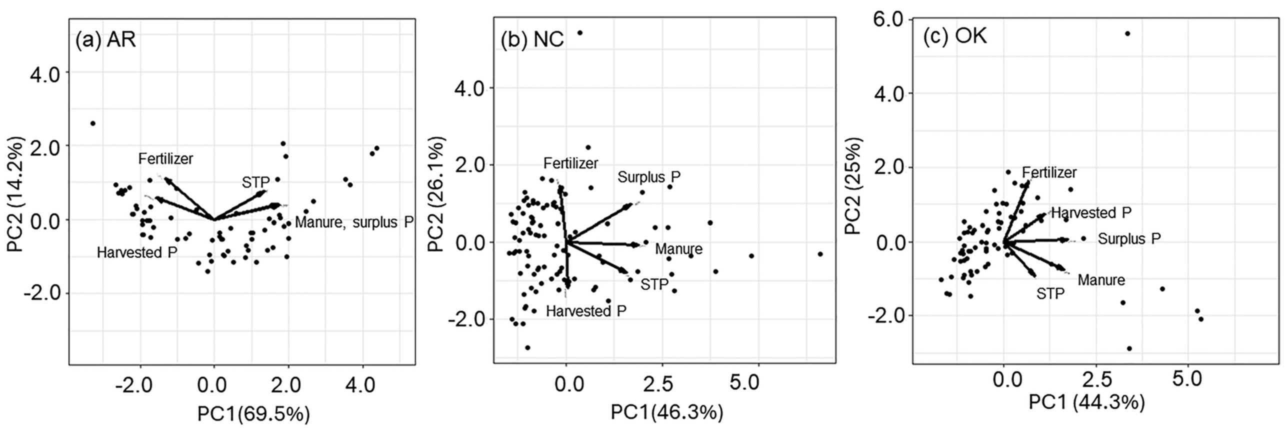

FIGURE 5 Principal component analysis (PCA) plots showing key variables (soil test phosphorus [STP], manure P, fertilizer P, harvested P, and surplus P) as vectors relative to the first two principal component axes. Axis labels show the percentage of the total variance explained by each axis (in parentheses). Panels are for (a) Arkansas, (b) North Carolina, and (c) Oklahoma. PC, principal component.

(Table 3). Considering both axes, there is a decoupling of fertilizer and STP (Figure 5). Finally, harvested P has the most variable axes loadings, suggesting inconsistent relationships with both P inputs and STP. Harvested P appears positively related to both manure and fertilizer in OK, with fertilizer in AR, and with neither in NC.

4 | DISCUSSION

Our hypothesis—that surplus P estimates from NuGIS are positively correlated with agricultural STP, and that surplus P more strongly correlates with STP when aggregated over longer periods—was partially supported by our

TABLE 3 Principal component analysis (PCA) loadings of key variables on the first two principal component (PC) axes for each state.

	AR		NC		OK	
	PC1	PC2	PC1	PC2	PC1	PC2
STP	0.39	0.48	0.53	−0.35	0.30	−0.43
Surplus P	0.50	0.25	0.56	0.44	0.61	0.03
Fertilizer P	−0.38	0.71	−0.05	0.64	0.24	0.76
Manure P	0.49	0.26	0.63	−0.03	0.57	−0.35
Harvested P	−0.45	0.37	0.02	−0.52	0.39	0.34

Abbreviations: AR, Arkansas; NC, North Carolina; OK, Oklahoma; STP, soil test phosphorus.

findings. Although the relationship between surplus P and STP was positive (Table 2), the correlations did not consistently increase with longer aggregation periods (Figure 3a,b). Across AR, NC, and OK, the maximum Pearson correlation coefficient calculated between county-scale surplus P estimates and median agricultural STP measurements was 0.65, 0.45, and 0.52, respectively (Table 2). These results demonstrate that surplus P estimates do not proxy for agricultural STP but can explain approximately 20%–40% of the county-scale variance in STP (based on the adjusted R^2 of linear regression model; Table S4), and that multi-year increases in surplus P are associated with high STP values over large spatial scales.

The maximum Pearson correlation coefficients between STP and surplus P corresponded to aggregation periods of 10, 30, and 4 years for AR, NC, and OK, respectively (Table 2). The variation in optimal aggregation period (10, 30, and 4 years) demonstrates there is not a consistent time period over which surplus P data should be summed to increase the strength of the relationship with STP (Figure 3). However, the gain in correlation coefficient when summing over multiple years is not dramatic as compared to only considering a single year or the full time period (30 years). Thus, when using surplus P inventories to assess large-scale trends in bioavailable P, summing multiple years is justified and may produce stronger relationships with STP. However, results may not be sensitive to moderate variations in the aggregation period, especially when there have not been large changes in inventory estimates over time, as is the case here.

Several factors may contribute to the variation in the optimal aggregation period across the three study states. For AR and OK, the optimal aggregation periods of 10 and 4 years, respectively, suggested that anthropogenic P inputs and outputs were most influential on STP on multi-year/decadal time scales, which may correspond to the period at which agricultural soils reached their capacity to fix excessive P after long periods of fertilization. In NC, because of the importance of swine production, the accumulation of P in swine lagoons could help explain why the optimal aggregation period for surplus P was multidecadal (i.e., 30 years). P in swine manure lagoons often remains within the sludge, whereas the liquid effluent is land-applied (Bicudo et al., 1999; Owusu-Twum & Sharara, 2020). As a result, P in swine manure may remain in storage (i.e., lagoons) over long time periods. The NuGIS approach to estimating "recoverable manure" is not well documented, but the long-term storage of swine manure in lagoons was likely not accounted for, meaning that some of the "recoverable manure" estimated in the NuGIS inventory could be stored in lagoons on swine farms and has yet to be applied to fields. Thus, the accumulation of P in swine lagoons could help explain why the optimal aggregation period for surplus P was 30 years, since there would be a greater disconnect between surplus P estimates and STP concentrations. Future research could explore how the optimal aggregation period varies between counties with and without large livestock densities.

Additionally, variation in the aggregation periods and correlation strengths could be partly explained by variation in STP concentrations at the start of our study period. For example, the longer optimal surplus P aggregation period in NC may reflect the longer duration of time over which the state has been under intensive agricultural production relative to AR and OK, as evidenced by the historical fertilizer and manure P time series (Figure 2b,c). AR began exceeding NC in manure P in the late 2000s (Figure 2c), which is around 10 years before the STP data were collected, and also the optimal aggregation period for AR (though this may be somewhat coincidental). Relatedly, the strength of the correlations reported in this study would likely increase if aggregated surplus P were to be compared to multi-year changes in STP (ΔSTP), since ΔSTP could relate to the cumulative effect of year-over-year increases in surplus P. For example, Reid and Schneider (2019) predicted 78% (R^2) of the variance in ΔSTP as a function of surplus P (referred to as "P balance" in their study) for sites across Canada, though the relationship between ΔSTP and surplus P was weaker at the provincial scale ($R^2 = 0.36–0.72$).

When evaluating which P inventory components may mediate the relationship between surplus P and STP, we found manure to be more strongly correlated with STP than fertilizer, indicating that national nutrient inventories may correspond more closely with STP values in areas with intensive animal agriculture. Correlation coefficients were greater for the manure–STP relationship for AR and NC, where there is far more broiler and hog production than OK. One likely explanation for the higher correlations of manure P and STP is that the ability to transport manure is relatively limited. High-liquid manures are considered to have a practical transport range of <10 km (Spiegal et al., 2020), whereas the transportation of dry manure such as poultry litter (<30% moisture) is not economically feasible for distances >262 km (Bosch & Napit, 1992; Slaton et al., 2004). Accordingly, manure that is generated in a county is often handled as a waste that needs to be managed locally, particularly for swine and poultry (Key et al., 2011), the most abundant livestock in NC (USDA NASS, 2023) and AR (Bosch & Napit, 1992). Manure, thus, may be applied in excess of crop needs, resulting in higher STP values and accumulation of surplus P. In particular, manure management plans are often created as a function of N, not P (Lory, 2018), leaving P relatively overlooked when assessing the risk of nutrient loading caused by manure application. However, we note that manure management is not always limited to local application, and some regions have instituted policies requiring or incentivizing the transport of manure beyond economically justifiable limits. For example, the Eucha–Spavinaw watershed agreement required that western AR counties designated as "nutrient surplus areas" export some amount of the poultry manure that was produced in the county (DeLaune et al., 2006). These policies are believed to have contributed to long-term STP declines in some soils, such as those where warm-season grasses are grown (DeLong et al., 2023). However, location-specific policies are generally not considered in national inventories, which apply methods consistently across national datasets, so we do not expect that practices driven by agreements like the Eucha–Spavinaw are considered in NuGIS.

In contrast to animal manure, fertilizer is purchased by producers, and the cost incentivizes its efficient use. Although overapplication of fertilizer is widely reported (Bouchard et al., 1992; Hallberg, 1987; Sheriff, 2005; Yadav et al., 1997), likely due to risk management by farmers in regard to crop yield potential and price (e.g., peaks in fertilizer P use may coincide with lower fertilizer prices), the negative correlation we observed between fertilizer P and STP for AR and NC (Table 2) suggests that growers may be modifying fertilizer application rates in response to STP concentrations (i.e., when STP is high, a grower may choose to apply less fertilizer given that the soil may meet crop P demand), or that manure is displacing the use of fertilizer. In contrast, because manure is often handled as a waste product, the negative feedback between STP and fertilizer does not extend to manure. At the same time, the correlation between STP and fertilizer P is small but positive for OK, which has relatively low manure P (Figure 2), suggesting fertilizer application still tends to increase STP over time; however, the effect may be smaller than for manure.

Another factor potentially degrading correlations in surplus P and STP may be changes in the location or quantity of cropland within each state. Surplus P records from further back in time (e.g., from 1987) may correspond to different (e.g., more agricultural) land areas than more recent surplus P estimates if land use change has occurred. For example, OK had a significant decrease in cropland percentage over time (Figure 2e), while also showing some of the largest drops in surplus P–STP correlations as aggregation periods extend further back in time (Figure 3a,b).

Uncertainties inherent to the STP and surplus P datasets may limit the strength of the correlations found in this analysis. One limitation of using AAPFCO fertilizer sales data is that, for counties with intermingled land uses (e.g., cropland with urban and forested lands), cropland fertilizer use can deviate from total fertilizer sales (Fixen et al., 2012). In particular, fertilizer estimates based on sales data are subject to uncertainties, most notably that fertilizer purchased in a county may not be applied in the same county. Fertilizer sales are also driven by price (e.g., more fertilizer may be purchased and stored when fertilizer prices are low), meaning sales may not be indicative of immediate application or crop use. Moreover, the nutrient content in recoverable manure was not estimated dynamically and could vary temporally due to advances in feed formulation and animal production, and different manure products could have different management strategies. For example, broiler manure is more likely to be transported across county boundaries compared to swine and dairy manure (Keplinger & Hauck, 2006; Ribaudo et al., 2003). Additionally, different states had different STP sample sizes (per county). For counties with relatively few observations, median STP values may have more uncertainty, but results were practically insensitive to removing counties with few (<5) samples. Additionally, fields of certain crops may be sampled more frequently than other crops due to their economic importance.

Moreover, challenges associated with finding comprehensive STP data limited the spatial extent of our analysis. Including more states spanning multiple climate and agroecological regions in our study would be insightful but would require greater public access to detailed STP databases. NC and AR, two of the three states chosen in this study, have large public soil testing programs resulting from free or low-cost soil sample analysis. Farmers in other states may use private soil test labs rather than public soil test labs, which limits the number of samples analyzed at many public soil test laboratories and the amount of publicly accessible data. Among existing STP datasets (e.g., Soil Test Summary; The Fertilizer Institute [TFI], n.d.), the resolution and metadata are too coarse to apply analyses like the one presented here.

Additionally, greater access to STP data would also allow for surplus P to be compared against changes in STP over time.

5 | CONCLUSION

In summary, mass balance-based estimates of surplus P calculated over large spatial scales (i.e., county) explained approximately 20%–40% of the variability in county-scale STP measurements. Thus, while surplus P can inform estimates of STP over large spatial scales, ideally in combination with other relevant factors, it is not a reliable proxy for STP by itself. When using mass balance-based estimates of surplus P to make inferences about STP, summing surplus P over multiple years was beneficial, though the optimal aggregation period was variable, likely due to area- or region-specific agricultural practices (e.g., manure management, land use change). Surplus P and STP were more closely correlated with P in recoverable manure than P in sold fertilizer, suggesting that the utility of mass balance-based surplus P estimates for inferring agricultural STP was greater in areas with intensive animal production.

AUTHOR CONTRIBUTIONS

Qicheng Tang: Conceptualization; formal analysis; investigation; methodology; software; visualization; writing—original draft; writing—review and editing. **Owen W. Duckworth**: Conceptualization; investigation; methodology; supervision; writing—original draft; writing—review and editing. **Daniel R. Obenour**: Conceptualization; funding acquisition; investigation; methodology; project administration; supervision; writing—original draft; writing—review and editing. **Stephanie B. Kulesza**: Data curation; investigation; writing—review and editing. **Nathan A. Slaton**: Data curation; investigation; writing—review and editing. **Andrew H. Whitaker**: Data curation; investigation; writing—review and editing. **Natalie G. Nelson**: Conceptualization; investigation; methodology; supervision; writing—original draft; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

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