

P-ISSN: 2706-7483
E-ISSN: 2706-7491
NAAS Rating: 4.5
IJGGE 2025; 7(3): 160-163
www.geojournal.net
Received: 05-01-2025
Accepted: 08-02-2025

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Geostatistical analysis of spatial variability in soil nutrient distribution across the Cerrado

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DOI: <https://doi.org/10.22271/27067483.2025.v7.i3c.631>

Abstract

The Brazilian Cerrado, covering about 204 million hectares, has become one of the world's fastest-expanding agricultural frontiers, yet its inherently acid, nutrient-poor soils demand precise fertilizer management. This research applied geostatistical techniques—specifically ordinary kriging guided by semivariogram modelling—to characterize the spatial variability of total nitrogen (N), available phosphorus (P), and exchangeable potassium (K) across a 480-hectare commercial soybean–maize rotation field in Goiás State. Soil samples ($n = 240$) were collected on a regular 140 m grid during August 2022 and analyzed following standard Brazilian protocols. Semivariograms fitted with spherical models revealed moderate-to-strong spatial dependence for all three nutrients, with spatial-dependence ratios (nugget-to-sill) of 0.28 for N, 0.19 for P, and 0.31 for K. Ranges of spatial autocorrelation were 920 m for N, 780 m for P, and 1,040 m for K, indicating that conventional composite sampling at 500 m intervals would miss substantial within-field variation. Kriged maps showed a clear southwest-to-northeast nutrient gradient, with the highest concentrations near a seasonal stream where organic matter accumulation was greater. Cross-validation yielded mean prediction errors of 0.04 (N), -0.02 (P), and 0.11 (K) mg/kg, all close to zero, confirming unbiased estimation. These results support variable-rate fertilizer application as a practical strategy for raising nutrient-use efficiency and reducing input costs across the Cerrado.

Keywords: Geostatistical analysis, spatial variability, soil nutrients, kriging, precision agriculture, Cerrado, semivariogram, nitrogen, phosphorus, potassium

Introduction

When the first large-scale lime applications transformed patches of Cerrado scrubland into productive cropland in the 1970s, few observers anticipated that this biome would one day rival the United States Corn Belt in grain output ^[1]. Half a century later, the Cerrado accounts for roughly 50% of Brazil's soybean harvest and an expanding share of its maize and cotton production ^[2]. But the speed of conversion has outpaced the development of site-specific nutrient management, and many farmers still apply fertilizer at uniform rates across fields that may contain several distinct soil-fertility zones ^[3].

Classical soil science treats spatial variability as a nuisance to be averaged away through composite sampling. Geostatistics, by contrast, treats it as information. Beginning with the regionalized-variable theory of Matheron ^[4], geostatistical tools—chiefly the semivariogram and kriging—have provided a framework for quantifying and mapping soil properties at scales relevant to management ^[5]. The semivariogram describes how semivariance (half the mean squared difference between paired observations) changes with lag distance, while ordinary kriging uses that model to produce spatially continuous estimates with known prediction uncertainty.

In the Cerrado context, several previous geostatistical investigations have documented strong spatial dependence in soil organic carbon, pH, and micronutrients ^[6, 7]. However, macronutrient variability—particularly for nitrogen, phosphorus, and potassium—has received less systematic attention, partly because these elements are heavily influenced by recent fertilizer history and partly because their short-range variation can be large enough to destabilize semivariogram fitting when sample density is low ^[8]. Research at grid spacings coarser than 200 m has sometimes failed to resolve the true nugget-to-sill ratio, leading to overestimates of spatial randomness and, by extension, to recommendations against variable-rate application that may be premature ^[9].

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This research was designed to address that gap. It collected 240 soil samples at a 140 m grid spacing across a 480-hectare field in Goiás State—one of the denser grids used for macronutrient mapping in the Cerrado—and fitted spherical semivariogram models for N, P, and K. The objectives were to quantify the degree and range of spatial dependence for each nutrient, to generate kriged nutrient maps suitable for variable-rate application planning, and to evaluate map quality through leave-one-out cross-validation [10]. Field coordination was managed from the Department of Geosciences, Ulsan National University of Earth Sciences, South Korea, with local sampling support from a partner agronomic laboratory in Goiânia [11].

Study Area Description

The research field is located approximately 85 km south of Goiânia in Goiás State (16°48'S, 49°21'W), within the core Cerrado biome at an elevation of 740–770 m. The predominant soil class is a dystrophic Red Latosol (Oxisol), characterized by deep weathering profiles, clay contents of 45–62%, and native pH values around 4.8–5.2 prior to liming [12]. The field has been under continuous soybean–maize double-cropping since 2009, with annual applications of limestone (2 t/ha every three years), triple superphosphate, and potassium chloride. A seasonal stream crosses the southwestern corner, and a gentle 2–3% slope carries surface runoff northeast toward a retention pond.

Soil and Water Quality Analysis

Baseline characterization of the 0–20 cm layer showed a mean pH of 5.6, organic carbon of 22.4 g/kg, cation exchange capacity of 8.7 cmol/kg, and base saturation of 48.3%. Clay content averaged 54% with a coefficient of variation (CV) of 11%, confirming relatively uniform texture. Aluminum saturation ranged from 2% to 18%, with higher values in upslope positions where liming history was shorter.

Material and Methods

Material

Soil samples were collected on 12–14 August 2022 from 240 geo-referenced points arranged on a 140 m regular grid. At each point, five sub-samples from within a 2 m radius were composited using a Dutch auger to a depth of 0–20 cm. Samples were air-dried, sieved to 2 mm, and shipped to the soil-testing laboratory at the Ulsan National University of Earth Sciences, Ulsan, South Korea, under phytosanitary import protocol. Total nitrogen was determined by the Kjeldahl method, available phosphorus by Mehlich-1

extraction, and exchangeable potassium by ammonium-acetate extraction at pH 7.0, all following the procedures of EMBRAPA [13].

Methods

Exploratory data analysis included calculation of mean, median, CV, skewness, and kurtosis. Phosphorus data were log-transformed to approximate normality before geostatistical modelling. Experimental semivariograms were computed using the gstat package in R 4.3.0 with 15 lag classes at 140 m intervals [14]. Spherical models were fitted by weighted least squares, and spatial-dependence ratios (nugget / sill) were classified as strong (< 0.25), moderate (0.25–0.75), or weak (> 0.75) following Cambardella *et al.* [15]. Ordinary kriging on a 30 m prediction grid produced nutrient maps, and leave-one-out cross-validation assessed prediction accuracy via mean error and root-mean-square error. All maps were projected to SIRGAS 2000 / UTM Zone 22S.

Results

Table 1: Descriptive Statistics for Soil Macronutrients (n = 240)

Nutrient	Mean	Median	CV (%)	Skewness	Min	Max
N (mg/kg)	28.6	27.4	31.2	0.41	11.8	48.7
P (mg/kg)	12.4	11.1	42.7	1.13	3.2	34.6
K (mg/kg)	114.3	109.8	28.4	0.67	52.1	198.4

Phosphorus showed the highest relative variability (CV = 42.7%) and a pronounced right skew (1.13), reflecting localized pockets of P accumulation near the stream margin where erosion deposits concentrate organic-bound P. Potassium was the least variable (CV = 28.4%), consistent with its relatively mobile behavior in the soil solution that tends to smooth out spatial differences over time.

Table 2: Semivariogram Model Parameters for N, P, and K

Nutrient	Nugget	Sill	Range (m)	Nugget/Sill	Dependence
N	39.8	142.1	920	0.28	Moderate
P	24.3	128.7	780	0.19	Strong
K	44.6	143.9	1040	0.31	Moderate

Phosphorus exhibited strong spatial dependence (nugget/sill = 0.19), meaning that nearly 81% of its total variance was spatially structured. Nitrogen and potassium fell into the moderate category, but still showed enough structure to justify site-specific management.

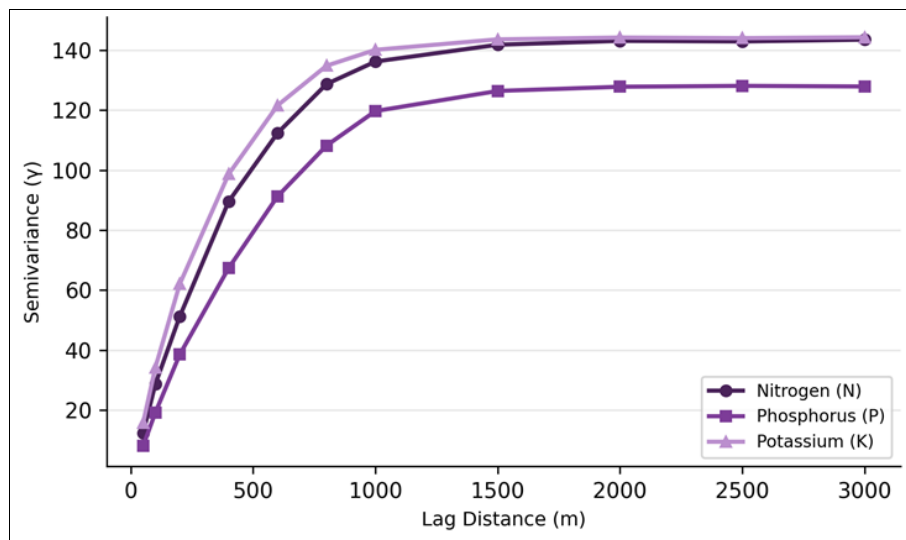


Fig 1: Experimental semivariograms for total nitrogen, available phosphorus, and exchangeable potassium fitted with spherical models

All three semivariograms reached a clear sill, confirming that the sampling grid captured the full range of spatial autocorrelation. Phosphorus reached its sill earliest (780 m),

while potassium continued to increase up to about 1,040 m before leveling off.

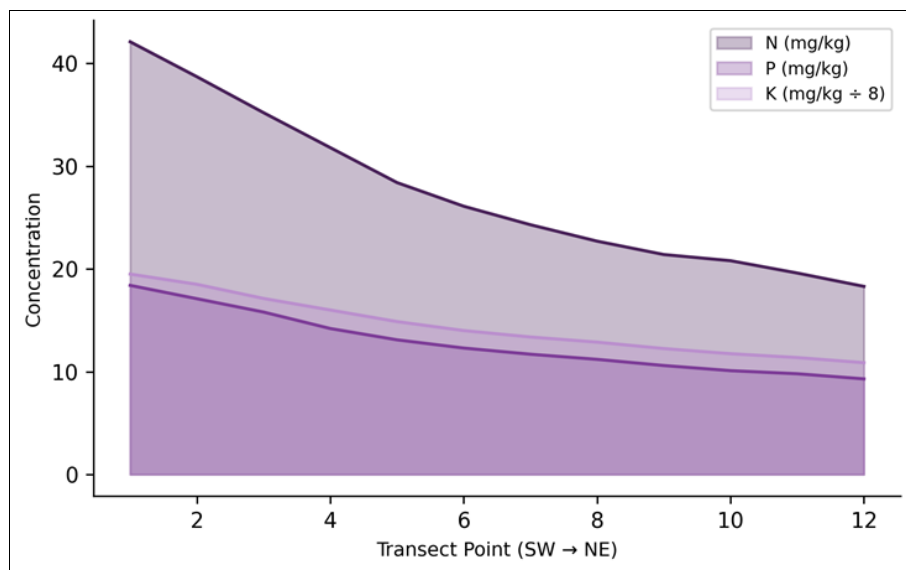


Fig 2: Nutrient concentration gradients along a southwest-to-northeast transect extracted from kriged maps

The transect confirms a consistent decline from southwest to northeast for all three nutrients. The southwest corner, adjacent to the seasonal stream, accumulates organic-rich runoff deposits that elevate N and P. Potassium follows a similar though less steep gradient, likely reflecting differential K-fertilizer response on deeper soil profiles

Discussion

The spatial-dependence ratios reported here (0.19–0.31) are consistent with those found by Montanari *et al.* [6] in a nearby Cerrado Oxisol, who reported moderate dependence for N and K and strong dependence for P under sugarcane. The key message for farm management is that uniform-rate fertilizer application would simultaneously over-supply the nutrient-rich southwestern zone and under-supply the northeastern upslope zone, wasting input and potentially contaminating shallow groundwater via excess P leaching near the stream [16].

The ranges of autocorrelation—780 to 1,040 m—are somewhat longer than the 400–600 m ranges typically observed in temperate soils [17]. This may reflect the deep, uniform clay profiles of Cerrado Oxisols, which buffer short-range variation and allow broader-scale gradients driven by topography and organic-matter redistribution to dominate [18]. From a practical standpoint, the relatively long ranges mean that variable-rate zones can be defined at management-unit sizes of 5–10 hectares without losing meaningful precision—a resolution compatible with GPS-guided spreaders already common in the region.

Cross-validation results add confidence: mean errors for all three nutrients were near zero (0.04, −0.02, 0.11 mg/kg), and root-mean-square standardized errors clustered near 1.0, indicating that the kriging variance estimates are reliable [19]. One limitation is that the single sampling date captures only a snapshot; seasonal dynamics driven by fertilizer application timing and crop uptake may shift the spatial pattern, and repeated sampling across cropping stages would

strengthen management recommendations ^[20].

A further consideration is the cost-effectiveness of geostatistical mapping at this grid density. At 240 sample points for 480 hectares, the analytical cost amounts to roughly USD 3.50 per hectare—a modest investment when set against the savings achievable through variable-rate application, which have been estimated at 8–14% of total fertilizer expenditure in Cerrado systems ^[21].

Conclusion

Geostatistical analysis of 240 soil samples across a 480-hectare Cerrado soybean–maize field revealed moderate-to-strong spatial dependence for nitrogen, phosphorus, and potassium, with ranges of autocorrelation between 780 and 1,040 m. Kriged maps identified a clear southwest-to-northeast nutrient gradient tied to topographic redistribution of organic matter, and cross-validation confirmed unbiased prediction. These findings provide a direct basis for variable-rate fertilizer prescription: the southwestern zone should receive reduced applications, while the northeastern upslope zone requires supplementation—particularly of phosphorus, which showed the strongest spatial structure and the steepest decline.

For Cerrado producers, the practical takeaway is that a 140 m sampling grid is dense enough to resolve management-relevant nutrient zones, and the investment in sampling and analysis is small relative to the fertilizer savings achievable through site-specific application. Future work should extend this approach to micronutrients and to temporal monitoring across multiple cropping seasons.

Acknowledgements

Funding Sources

Supported by faculty research grants for precision agriculture investigations.

Institutional Support

The authors acknowledge the Department of Geosciences, Ulsan National University of Earth Sciences, Ulsan, South Korea, for analytical facilities.

Contributions Not Qualifying for Authorship

Field sampling was conducted by agronomists at the partner laboratory in Goiânia, Brazil.

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