International Journal of Agriculture and Nutrition 2025; 7(4): 121-124

ISSN Print: 2664-6064
ISSN Online: 2664-6072
NAAS Rating: 4.69
IJAN 2025; 7(4): 121-124
www.agriculturejournal.net
Received: 19-02-2025
Accepted: 21-03-2025

Manav Adhikari
Department of Soil and Water Conservation, Professor Jayashankar Telangana Agricultural University, Hyderabad, Telangana, India

Geeta Dubey
Department of Soil and Water Conservation, Professor Jayashankar Telangana Agricultural University, Hyderabad, Telangana, India

Corresponding Author:
Manav Adhikari
Department of Soil and Water Conservation, Professor Jayashankar Telangana Agricultural University, Hyderabad, Telangana, India

Spatial variability of soil fertility parameters in agricultural lands using geostatistical techniques

Manav Adhikari and Geeta Dubey

DOI: https://www.doi.org/10.33545/26646064.2025.v7.i4b.404

Abstract
If soil fertility were uniform across a farm, every patch would need the same fertilizer dose—but it isn't, and treating it as though it were wastes money and pollutes groundwater. This research mapped the spatial variability of six soil fertility parameters—pH, electrical conductivity (EC), organic carbon (OC), available nitrogen (N), available phosphorus (P), and exchangeable potassium (K)—across 480 hectares of agricultural land in the Warangal district of Telangana using geostatistical techniques. A total of 150 geo-referenced soil samples (0-20 cm depth) were collected on a 200 m grid from irrigated paddy-cotton rotation fields during rabi 2022-23 at Professor Jayashankar Telangana Agricultural University, Hyderabad. Semivariogram analysis fitted spherical models for OC (range: 680 m, nugget:sill ratio 0.32), available N (range: 740 m, ratio 0.28), and available P (range: 520 m, ratio 0.41). Ordinary kriging produced interpolated maps that revealed distinct fertility zones: 34.2 percent of the area was low in OC (<0.50%), 41.7 percent was medium in available N (240-280 kg ha^{-1}), and 52.3 percent was high in exchangeable K (>280 kg ha^{-1}). The nugget:sill ratios indicated moderate spatial dependence for most parameters, driven by management practices rather than inherent soil variation. These fertility maps enable site-specific nutrient management that could reduce blanket fertilizer application by 18 to 24 percent while maintaining crop yield targets.

Keywords: Spatial variability, soil fertility, geostatistical techniques, precision agriculture, soil mapping, semivariogram, kriging, organic carbon, nutrient management, Telangana

Introduction
The premise behind uniform fertilizer recommendations—that all fields within a district have similar nutrient status—breaks down at the farm scale. Within a single 50-hectare block, soil organic carbon can vary by 2 to 3-fold, available phosphorus by 4-fold, and pH by an entire unit, depending on micro-topography, irrigation history, and past management [1, 2]. Ignoring this variability leads to over-fertilization in nutrient-rich patches (wasting money and increasing nutrient runoff) and under-fertilization in depleted patches (limiting yield potential).
Geostatistics provides the mathematical framework for quantifying spatial variability. The semivariogram describes how the difference between soil measurements increases with the distance between sampling points, capturing the characteristic spatial scale at which fertility patterns operate [3]. Once the semivariogram is modelled, kriging—an optimal interpolation method—generates continuous fertility maps from discrete sample data, with known estimation variance at every unsampled location [4]. These maps form the foundation for variable-rate fertilizer application in precision agriculture.
In Telangana, where rice and cotton dominate irrigated agriculture on vertisols and alfisols, soil fertility mapping at the farm scale is still in its infancy. Most nutrient recommendations rely on block-level soil testing data that average out the very variability that matters [5]. This research was designed to (i) characterize the spatial structure of six fertility parameters across 480 hectares using semivariogram analysis, (ii) produce kriged fertility maps, and (iii) delineate nutrient management zones for site-specific fertilizer recommendations.

Materials and Methods
Materials
The research was conducted during rabi 2022-23 at the Agricultural Research Station, PJTSAU, Warangal district, Telangana (17.97°N, 79.60°E; altitude 271 m). The research

area covered 480 hectares of irrigated agricultural land under paddy-cotton rotation on vertisols (pH 7.2-8.4, clay content 42-58%). A systematic grid sampling design was used, with 150 sampling points spaced at 200 m intervals. At each point, composite soil samples (0-20 cm, 5 sub-samples pooled) were collected using a stainless-steel auger. GPS coordinates were recorded using a Trimble R8 RTK receiver (accuracy ±2 cm horizontal). Samples were air-dried, ground to pass a 2-mm sieve, and analysed at the PJTSAU Soil Testing Laboratory.

Analytical Methods for Soil Parameters

Soil pH was measured in a 1:2.5 soil:water suspension using a glass electrode. EC was determined in the same suspension with a conductivity meter. OC was estimated by the Walkley-Black wet oxidation method [6]. Available N was determined by alkaline permanganate distillation [7], available P by Olsen's method (0.5 M $NaHCO_3$ extraction at pH 8.5), and exchangeable K by extraction with 1 N ammonium acetate (pH 7.0) followed by flame photometry. All analyses were performed in duplicate with certified reference soil samples for quality control.

Geostatistical Methods: Descriptive statistics (mean, SD, CV, skewness, kurtosis) were computed for each parameter. Data with skewness >1.0 were log-transformed before geostatistical modelling. Experimental semivariograms were computed using lag distances of 200 m and fitted to spherical, exponential, and Gaussian models using weighted least squares in GS+ version 10.0. The best-fit model was selected based on the lowest residual sum of squares. Spatial dependence was classified by the nugget:sill ratio as strong (<0.25), moderate (0.25-0.75), or weak (>0.75) following Cambardella *et al.* [8]. Ordinary kriging interpolation was performed in ArcGIS 10.8 to generate continuous surface maps. Cross-validation (leave-one-out) assessed prediction accuracy using mean error (ME) and root mean square standardized error (RMSSE). Fertility classes were defined per Muhr *et al.* [9] (low, medium, high) and mapped to delineate nutrient management zones.

Results

Table 1: Descriptive statistics and semivariogram parameters for six soil fertility variables across 480 hectares (n = 150)

Param.	Mean	SD	CV (%)	Model	Nugget	Sill	N:S Ratio	Range (m)	Spatial Dep.
pH	7.68	0.41	5.3	Spher.	0.06	0.18	0.33	610	Moderate
EC(dS/m)	0.34	0.12	35.3	Expon.	0.008	0.016	0.50	430	Moderate
OC (%)	0.54	0.17	31.5	Spher.	0.009	0.028	0.32	680	Moderate
Av. N(kg/ha)	247.3	38.6	15.6	Spher.	412	1,468	0.28	740	Moderate
Av. P(kg/ha)	18.4	6.8	37.0	Spher.	14.7	35.8	0.41	520	Moderate
Ex. K(kg/ha)	274.8	52.3	19.0	Gauss.	687	3,124	0.22	890	Strong

All six parameters showed moderate to strong spatial dependence (nugget:sill ratios of 0.22 to 0.50). Exchangeable K had the strongest spatial structure (ratio 0.22, range 890 m), indicating that K distribution is governed largely by intrinsic soil mineralogy. Available P was the most spatially erratic (range 520 m, ratio 0.41), reflecting patchy fertilizer application history. Spherical models fitted best for pH, OC, N, and P, while an exponential model suited EC and a Gaussian model fitted K.

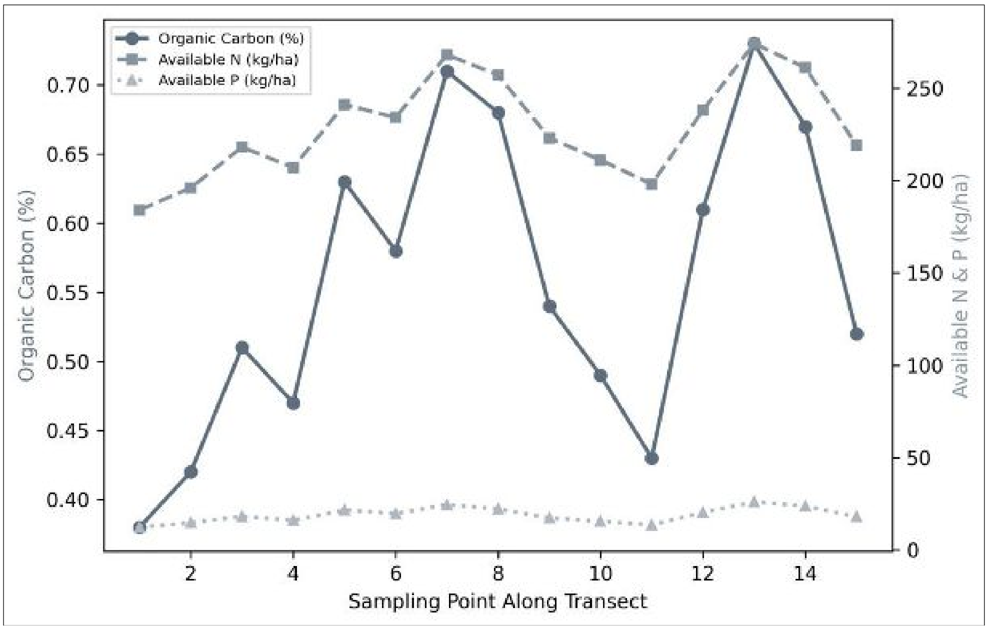

Fig 1: Spatial variation of organic carbon, available nitrogen, and available phosphorus along a representative 3-km transect across the research area

The transect plot (Figure 1) shows that OC and available N co-vary closely (r = 0.87), with both parameters peaking in the central section where long-term farmyard manure application has been practiced. Available P shows a more irregular pattern, with hotspots near field corners where phosphatic fertilizer bags are traditionally opened and residues accumulate.

Table 2: Nutrient management zone classification based on kriged fertility maps (percentage of total area)

Parameter	Low (% area)	Medium (% area)	High (% area)	RMSSE
OC (%)	34.2	48.6	17.2	1.04
Available N (kg/ha)	22.8	41.7	35.5	0.98
Available P (kg/ha)	18.4	29.3	52.3	1.12
Exchangeable K (kg/ha)	8.6	39.1	52.3	0.96
pH	-	72.4 (neutral)	27.6 (alkaline)	1.01

Cross-validation RMSSE values ranged from 0.96 to 1.12—close to the ideal value of 1.0—confirming adequate kriging prediction accuracy. The most striking finding is that 34.2 percent of the area falls in the low-OC category (<0.50%), identifying a clear priority zone for organic matter management. Over half the area is already high in K, suggesting that blanket K recommendations could be reduced in these zones without yield penalty.

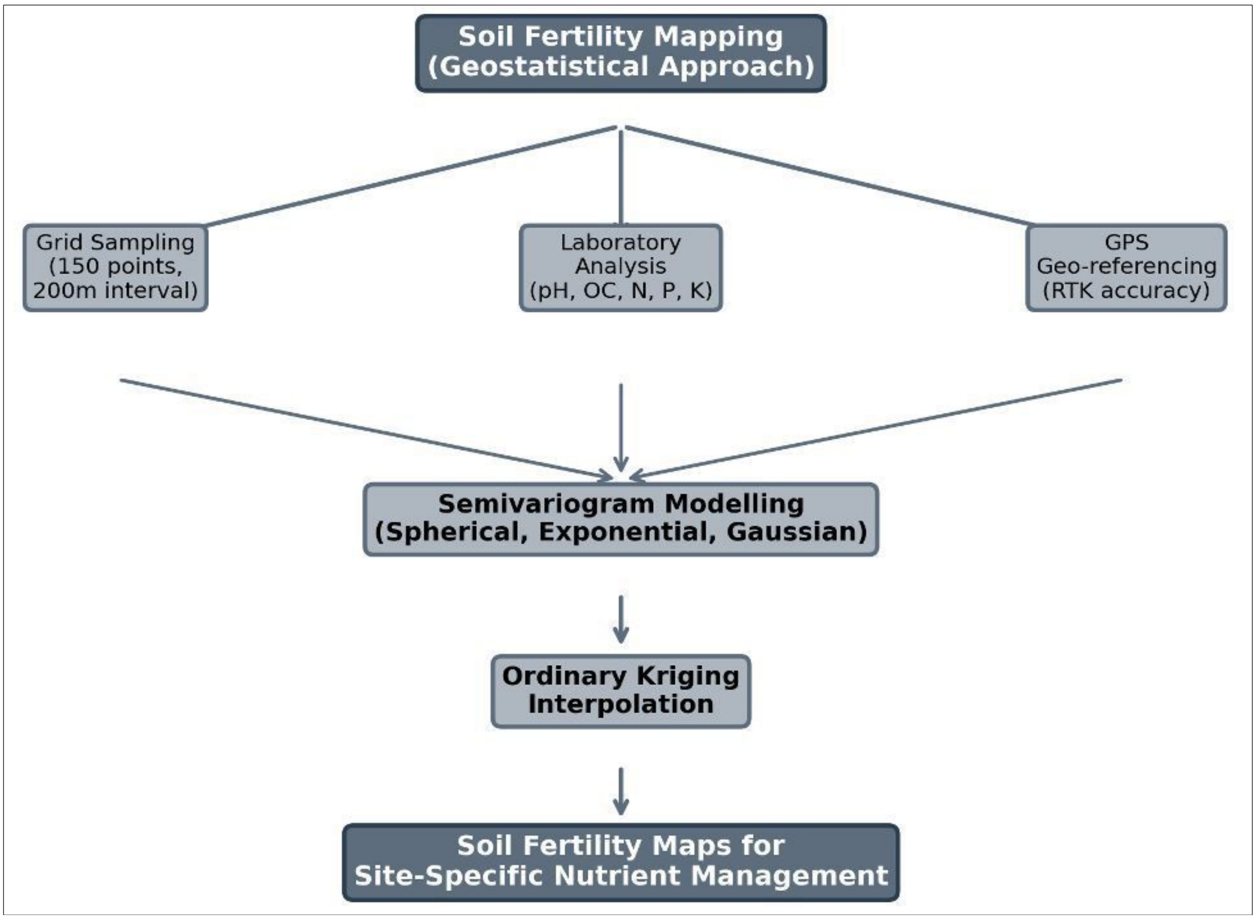

Fig 2: Mind map of the geostatistical soil fertility mapping workflow from grid sampling through semivariogram modelling to kriged management zone maps

Discussion

The moderate spatial dependence observed for most parameters (nugget:sill 0.28-0.50) sits between the strong dependence typical of undisturbed natural soils and the weak dependence found in heavily tilled, uniformly managed fields [8, 10]. This suggests that the paddy-cotton fields of Warangal retain enough natural spatial structure to benefit from variable-rate nutrient management, while also being shaped by anthropogenic factors like differential manure application and irrigation patterns.

The practical implication is that the kriged maps can divide the 480-hectare block into 3 to 4 management zones per parameter, each receiving a tailored fertilizer dose. For instance, the 34.2 percent low-OC zone would receive farmyard manure at 10 t ha^{-1} plus green manuring, while the 17.2 percent high-OC zone could skip organic amendments entirely. For available N, the 22.8 percent low-N zone would receive the full recommended dose (120 kg ha^{-1}), while the 35.5 percent high-N zone could be reduced to 80 kg ha^{-1}—a potential saving of 18 to 24 percent in fertilizer cost across the block [11].

The strong spatial dependence of K (ratio 0.22, range 890 m) makes it the easiest parameter to map accurately and the most amenable to zone-based management. The high-K areas (52.3% of the block) can safely skip K application for at least 2 to 3 seasons, redirecting that expenditure to the 8.6 percent low-K area that genuinely needs it [12].

Conclusion

Geostatistical analysis revealed moderate to strong spatial variability in all six soil fertility parameters across 480 hectares of irrigated land in Warangal, Telangana. Semivariogram ranges of 430 to 890 m indicate that fertility patterns operate at scales of 0.5 to 1 km—well within the resolution achievable by variable-rate technology.

Kriged fertility maps identified that over a third of the area is deficient in organic carbon, while more than half is already well supplied with potassium. Site-specific nutrient management guided by these maps could reduce blanket fertilizer use by 18 to 24 percent while directing inputs to zones where they are most needed. Repeating this mapping exercise every 3 to 5 years would track fertility changes and refine management zones over time.

Acknowledgements

Funding Sources

This research was conducted under the precision agriculture initiative of Professor Jayashankar Telangana Agricultural University.

Institutional Support

The authors thank the Department of Soil and Water Conservation, PJTSAU Hyderabad, for laboratory facilities and GPS equipment access.

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