GIS-Based Spatial Variability Analysis of Soil Fertility in *Zea mays* L. Production Systems

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ABSTRACT
Background: The soil fertility levels in *Zea mays* L. are characterized by inherent heterogeneity, while traditional methods of applying fertilizers evenly do not consider the variability of soil properties within the fields, thus leading to under-utilization of fertilizers and unstable crop yields. The application of GIS in combination with geostatistics allows for accurate descriptions of the variability of soil properties.
Objective: The purpose of the current study was to evaluate the variability of the properties of soil along a maize crop growing area using GIS techniques and to create the areas of precise management of soil fertility for specific locations.
Methods: Soil samples were collected using the grid sampling method with the reference of GPS coordinates. The samples were tested for their pH, electrical conductivity, organic matter, nitrogen, phosphorus and potassium content as well as for the presence of micronutrients. The process of spatial interpolation was carried out with the application of ordinary kriging and inverse distance weighting methods in GIS with the use of the semivariogram modeling technique.
Result: The properties of soil have demonstrated moderate to high spatial dependence with available Phosphorous and potassium having high spatial variability. Kriging method has shown superior performance compared to IDW regarding cross-validation accuracy. The fertility map has shown the presence of different fertility regions representing low, medium, and high fertility with high prospects for variable rate fertilization.
Conclusion: GIS-based spatial variability analysis offers an effective way of assessing soil fertility and can result in location-specific nutrient management which enhances fertilizer efficiency and helps enhance sustainable maize production.

Keywords: *Zea mays*; soil fertility; Geographic Information System (GIS); geostatistics; ordinary kriging; spatial variability

1. Introduction
Zea mays L. (maize) is one of the most common types of cereal crops grown in the world, and it is an important source of food, animal feed, and raw materials. Maintenance of the sustainability of maize productivity requires balanced soil fertility, however, agriculture soils tend to display great variability in space, which is due to many factors, such as the type of the parent material, terrain features, management practices, and biological factors. Thus, one of the major problems with uniform distribution of fertilizers across heterogeneous agricultural areas is uneven supply of fertilizers and inefficient use of nutrients in the agriculture sector.
GIS makes possible the convenient collection, storage analysis, and visualization of information on soils. GIS helps convert point observations concerning soil into continuous soil maps using the interpolation of spatial data required in precision farming. One of the key aspects of the precision farming practice is digital soil mapping that combines GPS data collection with modern statistical modeling.
By using data obtained through GIS, nutrient management could be undertaken with variable rates, meaning that fertilizers could be applied according to the specific analyses of soil conditions in each area thereby minimizing wastage of nutrients. In comparison with traditional scouting and blanket applications, GIS offers tremendously better abolition resolutions and a relatively higher accuracy of interpretation.
The objective of the present study was to (i) analyze spatial variations of the most important soil macro properties in the maize field, (ii) assess various interpolation methods with regard to the ability to develop fertility maps, and (iii) prepare recommendations for effective fertility management.

2. Literature Review
GIS applications in agriculture have expanded considerably, supporting spatial data management for soil, crop, and yield monitoring [1, 2]. Spatial variability of soil fertility is well documented, with nutrient availability varying markedly even within small field units

due to microtopography and management history [3, 4]. Digital soil mapping combines field sampling with statistical models to predict soil properties across unsampled locations [5, 6].

GPS-assisted grid sampling improves spatial representativeness compared with traditional composite sampling [7, 8]. Geostatistics, particularly semivariogram analysis, quantifies spatial dependence structures in soil properties, informing interpolation method selection [9, 10]. Ordinary Kriging is frequently reported as superior to Inverse Distance Weighting (IDW) for properties exhibiting strong spatial autocorrelation, owing to its unbiased, minimum-variance estimation [11, 12].

GIS-based decision-support systems integrating fertility maps with crop models have supported variable-rate fertilizer prescriptions in maize and other cereals [13, 14]. Maize-focused studies report substantial spatial variability in available phosphorus and potassium relative to more stable properties such as pH [15, 16]. Gaps remain regarding integration of multi-nutrient interpolation with remote-sensing covariates and long-term validation of management zones across seasons [17, 18], which this study addresses through comprehensive multi-property geostatistical assessment.

3. Materials and Methods

3.1 Experimental Site

The study was conducted in a maize field at 27.9°N, 78.1°E, within a semi-arid subtropical zone with mean annual rainfall of 720 mm and mean temperature of 24.6°C. Soils were classified as Typic Ustochrepts (sandy clay loam). The field had a continuous maize–wheat cropping history, and the hybrid used was PMH-1.

3.2 Soil Sampling

A grid-based design at 20 m × 20 m spacing yielded 64 georeferenced sampling points recorded using a handheld GPS unit (±3 m accuracy). Samples were collected from 0–20 cm depth, and composite samples were prepared from three sub-samples per location, air-dried, and sieved (2 mm) before analysis.

3.3 Laboratory Analysis

Soil pH and electrical conductivity were measured in 1:2.5 soil–water suspensions. Organic carbon was determined by the Walkley–Black method. Available nitrogen was assessed by the alkaline permanganate method, available phosphorus by the Olsen method, and available potassium by ammonium acetate extraction with flame photometry. Cation exchange capacity was determined by ammonium acetate saturation, and micronutrients (Zn, Fe, Mn, Cu) were extracted using DTPA and quantified by atomic absorption spectrophotometry.

3.4 GIS and Spatial Analysis

GPS coordinates and laboratory results were compiled into a spatial database using ArcGIS 10.8, projected to the WGS 1984 UTM coordinate system. Semivariograms characterized spatial dependence for each property, followed by Ordinary Kriging and Inverse Distance Weighting interpolation. Cross-validation used leave-one-out procedures, comparing RMSE between methods. Digital fertility maps were generated, and zones delineated using natural breaks classification into low, medium, and high categories.

3.5 Statistical Analysis

Descriptive statistics and coefficient of variation (CV) were computed for all properties. Geostatistical parameters (nugget, sill, range) were derived from fitted semivariogram models. Pearson correlation examined inter property relationships, and ANOVA assessed differences among fertility zones ($P < 0.05$). Analyses were performed using R (v4.3) and ArcGIS Geostatistical Analyst.

4. Results

4.1 Soil Fertility Characteristics

Soil pH ranged from 6.4 to 8.1 (mean 7.2, CV = 6.8%), indicating low variability, whereas available phosphorus (CV = 38.4%) and potassium (CV = 33.7%) displayed high spatial variability. Organic carbon (mean 0.58%) and available nitrogen (mean 218 kg ha^{-1}) showed moderate variability (CV = 21.5% and 24.2%, respectively). Micronutrients (Zn, Fe, Mn, Cu) varied moderately, with zinc deficiency (<0.6 mg kg^{-1}) observed at 22% of sampled locations.

4.2 Geostatistical Analysis

Spherical semivariogram models fit best for most properties. Available phosphorus exhibited a nugget-to-sill ratio of 0.21 (strong spatial dependence, range = 142 m), while pH showed weaker spatial structure (ratio = 0.52, range = 96 m). Cross-validation indicated lower RMSE for Ordinary Kriging (phosphorus RMSE = 3.8 mg kg^{-1}) versus IDW (RMSE = 5.1 mg kg^{-1}), confirming Kriging as more accurate for spatially dependent properties ($P < 0.05$). For weakly structured properties such as pH, differences between methods were not significant.

4.3 GIS-Based Soil Fertility Mapping

Digital fertility maps delineated three zones: low-fertility (18% of field area), medium-fertility (47%), and high-fertility (35%), driven largely by spatial patterns in phosphorus, potassium, and organic carbon. Low-fertility zones clustered in the upper field section, coinciding with historically shallower topsoil. ANOVA confirmed significant differences in nutrient concentrations among zones ($P < 0.01$), supporting valid zone delineation for variable-rate fertilizer recommendations and targeted micronutrient correction.

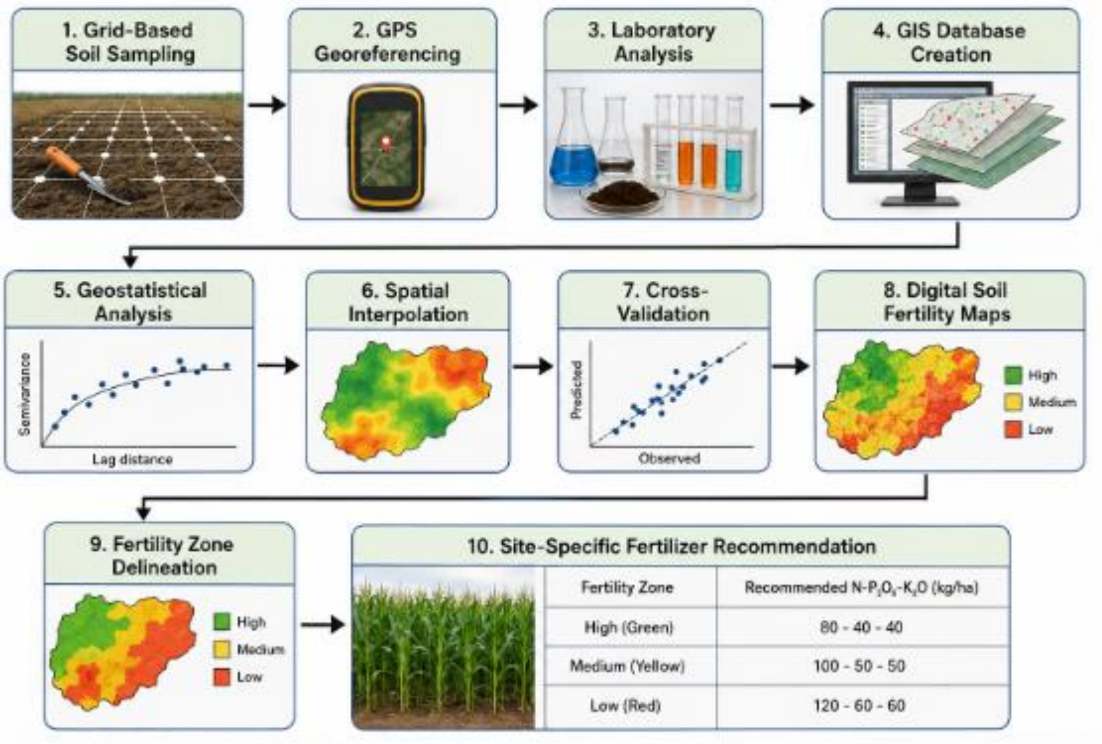

Fig 1: Workflow illustrating grid-based soil sampling, GPS data collection, laboratory analysis, GIS database creation, geostatistical analysis, spatial interpolation, and digital soil fertility mapping.

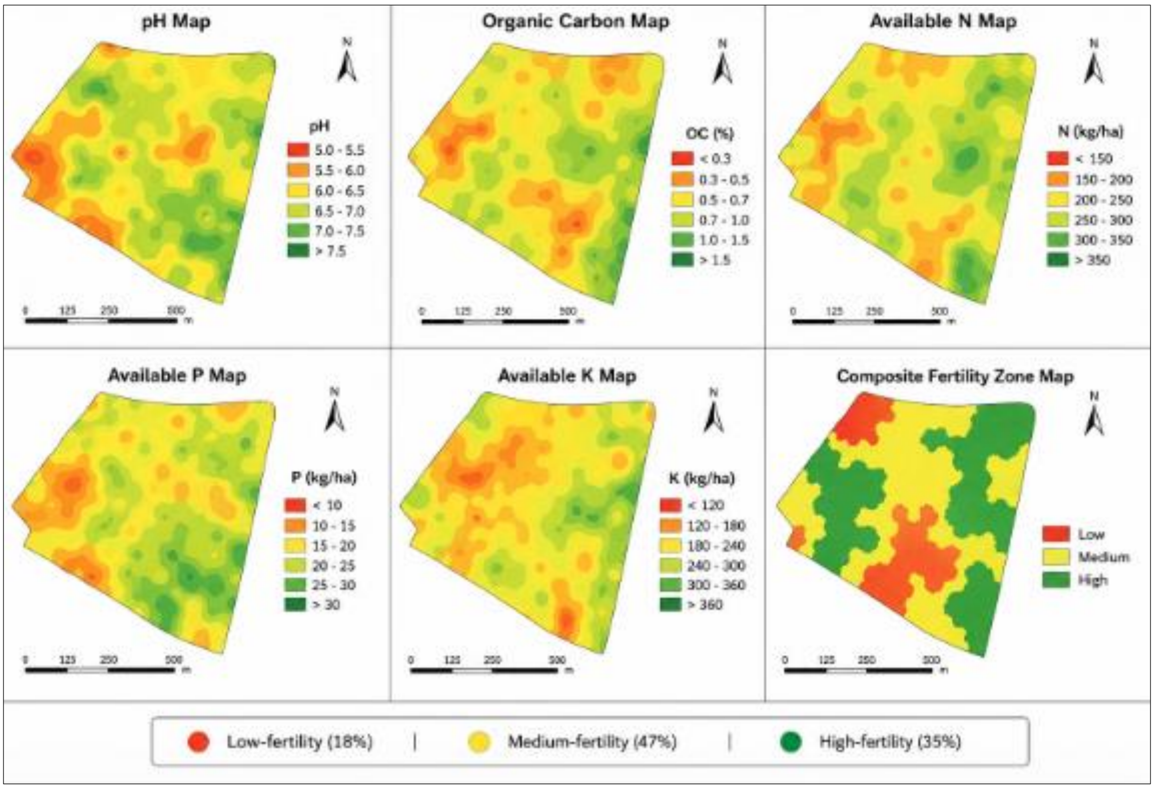

Fig 2: GIS-generated fertility maps depicting spatial distribution of soil pH, organic carbon, available N, P, K, and delineated fertility management zones (low/medium/high) across the maize field.

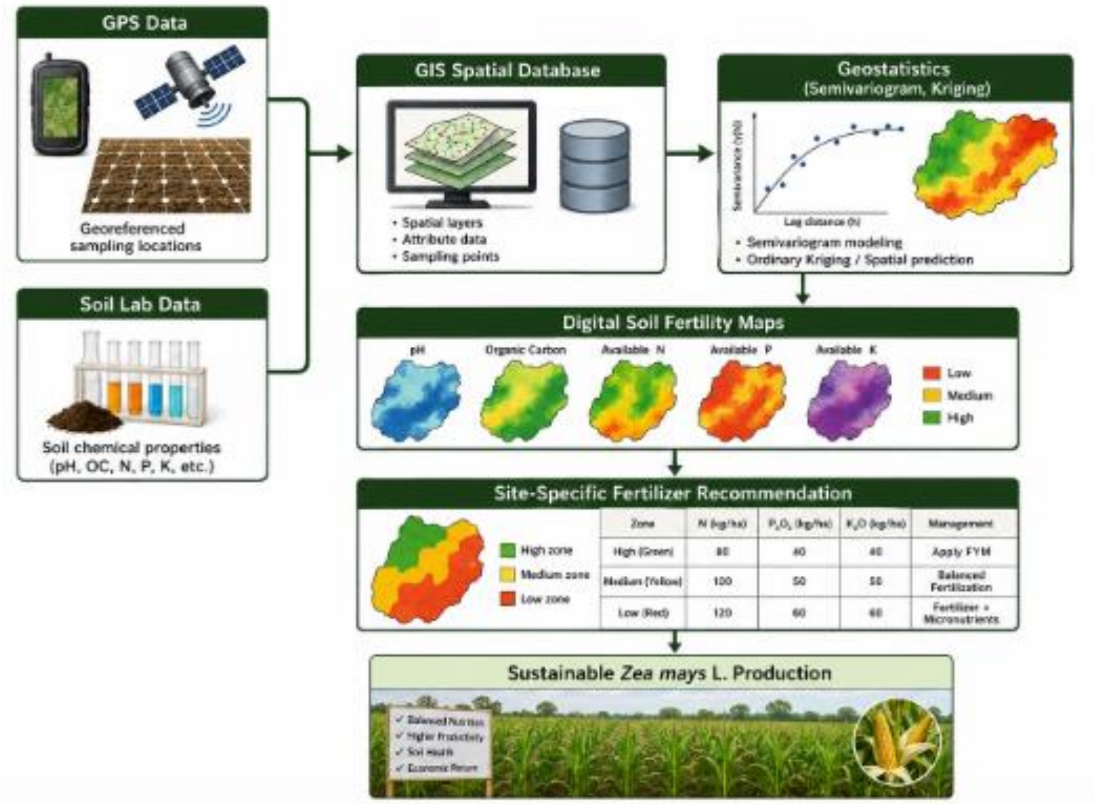

Fig 3: Conceptual framework integrating GIS, GPS, geostatistics, spatial interpolation, digital soil maps, and site-specific fertilizer recommendations for sustainable maize production.

The results confirm that GIS-based geostatistical analysis effectively characterizes spatial heterogeneity of soil fertility in maize systems, consistent with reports identifying phosphorus and potassium as the most spatially variable nutrients due to limited mobility and dependence on localized soil chemistry [3, 15]. Variability observed here likely reflects historical management, microtopographic differences in topsoil depth, and differential nutrient removal by prior crops.

Digital fertility mapping offers advantages over conventional composite sampling by revealing within-field patterns invisible to bulk analysis, enabling targeted rather than uniform fertilizer application [7, 13]. The superior performance of Ordinary Kriging for spatially structured properties supports its continued preference in precision agriculture, consistent with earlier geostatistical comparisons [11, 12]. Integrating these fertility maps with GPS-guided variable-rate applicators and GIS-based decision-support systems can operationalize precision nutrient management in the field [14].

These findings align with prior maize-focused studies reporting comparable spatial variability and zone-based delineation [16, 17], though absolute values differ due to site-specific soil and management history. Limitations include the single-season nature of the assessment and sensitivity of interpolation accuracy to sampling density and semivariogram model choice [9, 18]. Future research should incorporate multi-temporal Sentinel-2 imagery, UAV-based proximal sensing, and machine learning-based digital soil mapping to enhance accuracy and reduce reliance on dense ground sampling [19, 20].

6. Conclusion

The analysis carried out in this research indicates that analyzing spatial variability using GIS in conjunction with geostatistical interpolation allows the determination of the heterogeneity of soil fertility parameters in a maize plot, with phosphorus and potassium being defined as the most variable nutrients, while Ordinary Kriging being recognized as the most precise method for assessing properties dependent on spatial parameters. The generated maps provide the necessary information to implement a site-specific nutrient management approach that improves fertilizer application efficiency and minimizes nutrient losses in the environment. Therefore, farmers and agronomists should consider the GIS-approach to assessing soil productivity as an integral part of maize production planning. Furthermore, the recommendations for future studies include focusing on remote sensing variables, validation for several seasons, and the use of AI for predicting soil fertility.

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