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Research Article

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Posted Date: November 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11519399/v1

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Additional Declarations: No competing interests reported.

Assessment of Soil Quality Using Multivariate Geospatial Techniques in an Intensively Cultivated Semiarid Region in the northwestern part of India

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Abstract

Soil quality degradation from intensive cropping and high-yielding crop varieties threatens sustainable food production in the Indo-Gangetic Plains. Accurate assessment of soil physico-chemical properties and nutrient variability is essential for targeted soil health management, yet comprehensive multivariate and geospatial studies remain limited. This study evaluates soil quality in south-western Punjab by integrating soil analysis, nutrient profiling, and a soil quality index (SQI). A total of 259 georeferenced surface soil samples were collected from six blocks for pH, electrical conductivity (EC), organic carbon (OC), available phosphorus (P), potassium (K), and DTPA-extractable micronutrients. Spatial heterogeneity was assessed using descriptive statistics, Pearson's correlation, and principal component analysis (PCA). Spatial distribution maps were generated using inverse distance weighting (IDW) interpolation, and the Nutrient Index Value (NIV) framework classified fertility at the block level. Soils were mainly neutral to moderately alkaline (pH 7.00-9.10, mean 8.20) and non-saline (EC < 0.79 dS m^{-1}). OC was low to medium (mean 0.47%), indicating a persistent deficit. Available P was generally high (8.05-231 kg ha^{-1}), reflecting accumulated phosphatic fertilizers, while available K was mostly low to medium (43.7-401.5 kg ha^{-1}; mean 138.4 kg ha^{-1}), suggesting ongoing K depletion. Among micronutrients, Fe was consistently adequate (mean 37.6 mg kg^{-1}), while Zn and Mn showed high spatial variability (CV=84.7% and 60.3%), with deficiencies in high pH and low OC regions. PCA identified three principal components explaining 79.01% of total variance, highlighting the influence of micronutrients, soil reaction, and organic-macronutrient dynamics. The SQI ranged from 0.32 to 0.62, classifying Makhu as 'good' (SQI = 0.62), Zira, Ghal Khurd, and Guru Har Sahai as 'moderate' (SQI 0.51-0.57), and Mamdot and Ferozepur as 'poor' (SQI 0.37 and 0.32). IDW maps showed clear spatial clustering of fertility attributes, and NIV analysis

identified potassium as the most deficient macronutrient across the district. These findings indicate that alkalinity, K depletion, and fertilizer imbalance shape soil quality, while micronutrient dynamics drive spatial variation. Prioritize Ferozepur and Mamdot blocks for potassium fertilization, organic matter addition, and zinc supplementation. The multivariate geospatial framework developed in this study provides a scalable approach for evidence-based soil health monitoring and precision nutrient management, particularly for K, in intensively cultivated semi-arid regions of South Asia.

Keywords: Agricultural management, Soil mapping, Micronutrient availability, Nutrient index value, Soil organic carbon, Soil quality index, Spatial variability.

Introduction

Rice (Oryza sativa L.), wheat (Triticum aestivum L.), and maize (Zea mays L.) are the primary food crops in the Indo-Gangetic Plains (IGP) of India, contributing over 75% of the nation's total food grain production (Sharma et al., 2016), the region designated as the "Green Revolution Belt." In Punjab, rice-wheat and cotton-wheat are the main cropping systems, with rice, cotton, and wheat occupying 67.0%, 11.5%, and 84.0% of the cultivable area, respectively. Despite decades of high productivity, the rice/cotton-wheat belt in Northwest India is now showing clear signs of production fatigue, with inconsistent yields and declining factor productivity (Dobermann 2004). This decline is linked to changes in soil organic matter and reduced nutrient availability, leading to nutrient imbalances from improper fertilizer use (Ladha et al., 2007). Rice and wheat are nutrient-intensive crops, and the rice-wheat system (RWS) significantly depletes soil nutrients. RWS yielding 7 t ha^{-1} of rice and 5 t ha^{-1} of wheat removes over 250 kg nitrogen (N), 50 kg phosphorus (P), and 280 kg potassium (K) per hectare (Kanwar and Mudahar 1986) alongside roughly 200 g zinc (Zn), 50 g copper (Cu), 1500 g iron (Fe), and 400 g manganese (Mn) per hectare. Critically, even when farmers follow recommended fertilizer rates and remove straw, a persistent negative balance of primary nutrients remains (Yadvinder-Singh et al., 2003), signaling that current practices are structurally insufficient to sustain the system. Agricultural soils are fundamental to terrestrial agroecosystems and provide essential ecosystem services beyond crop production. These services include regulating biogeochemical cycles, maintaining air and water quality, reducing greenhouse gas emissions, supporting biodiversity, and ensuring food safety (Aggag and Alharbi, 2022). These functions depend on

soil quality, which reflects the soil's capacity to operate within ecosystem boundaries, support biological productivity, and promote environmental health (Doran and Parkin, 1994). Soil fertility refers to the soil's ability to supply essential macro- and micronutrients such as nitrogen (N), phosphorus (P), potassium (K), zinc (Zn), copper (Cu), iron (Fe), and manganese (Mn) in bioavailable forms, sufficient quantities, and at appropriate times to support optimal crop growth, yield, and nutritional quality (Tang, 2024). Because soil fertility emerges from dynamic interactions among physical, chemical, and biological properties that govern nutrient transformation, root development, water dynamics, and microbial activity (Verma et al., 2023; Xing et al., 2025), it is inherently difficult to characterize precisely.

Spatial heterogeneity compounds this difficulty. Significant spatial variability and complex parameter interactions challenge soil fertility assessment for agricultural management, introducing uncertainty into point-based assessments (Sanad et al., 2024). This variability arises from both long-term pedogenic processes, such as weathering and leaching, and short-term anthropogenic drivers such as tillage, irrigation, fertilization, and crop rotation (Cambardella et al.,1994), so point measurements often fail to represent fertility conditions even over short distances. Reliable, landscape-scale fertility mapping therefore requires spatially distributed sampling coupled with geostatistical interpolation (Emamgholizadeh et al., 2017); conventional point-based testing, though analytically rigorous, is spatially limited and often misses within-field and landscape-level nutrient heterogeneity, undermining the accuracy of generalized fertilizer recommendations and input-use efficiency (Doneriya et al., 2013; Singh et al., 2019). Three physico-chemical properties are central to this heterogeneity in nutrient availability: organic carbon (OC), which regulates nutrient transformation, aggregate stability, water retention, and microbial diversity (Bashir et al., 2021); soil pH, which critically governs nutrient availability (Behera et al., 2025) and, in alkaline soils, drives precipitation and reduced solubility of Zn, Cu, Fe, and Mn (Dhaliwal et al., 2022); and electrical conductivity (EC), where elevated salinity induces osmotic stress and impairs plant ion uptake (Yadav et al., 2019). Compounding these dynamics, India's shrinking arable land base under population pressure demands ever-higher cropping intensity, yet excessive and imbalanced fertilizer use, groundwater over-reliance, and uneven nutrient application have already driven OC depletion, rising salinity, and widespread micronutrient deficiency (Li et al., 2019; Pahalvi et al., 2021; Ray et al., 2000).

Fertilizing without matching crop needs and baseline soil fertility deepens this imbalance and constrains productivity (Bhatt, 2013).

Addressing this problem requires field-specific fertility assessment to optimize land use and cropping decisions. Soil testing supplies the quantitative nutrient data needed for site-specific recommendations that improve productivity and input-use efficiency (Doneriya et al., 2013; Singh et al., 2019), yet as noted above point-based sampling alone cannot capture landscape-level variability (Emamgholizadeh et al., 2017). Integrating such data into sustainable management strengthens farm-level decision-making (Khadka et al., 2019), and systematic fertility assessment and mapping are increasingly recognized as essential to informed land-use planning (Rawal et al., 2018). An SQI, which consolidates multiple soil indicators into a single interpretable value, is a powerful tool for capturing spatial variation in physical and chemical properties that point-based testing misses (Aranguren and Cañón, 2023). Geospatial techniques (GIS) and geostatistical interpolation further extend this capability by generating continuous maps of soil properties (Sharma et al., 2016), enabling precise, site-specific fertilizer application (Arain et al., 2017). Because soil quality strongly shapes the plant-animal-human continuum, a spatially integrated inventory of fertility parameters is indispensable for sustaining productivity in Punjab's intensive agricultural systems. Soil fertility surveys and soil quality indices have been reported separately for parts of Punjab, but no study has integrated multivariate SQI+PCA+GIS-based interpolation within a single georeferenced framework for Ferozepur, an intensively cultivated, semi-arid district in the south-western Indo-Gangetic Plains that has received comparatively little dedicated spatial soil-fertility attention relative to central Punjab. This study addresses that gap with four objectives: (1) to determine the regional distribution of soil fertility properties; (2) to develop a GIS-based soil fertility evaluation that can refine management practices for Punjab's highly productive, irrigated, cereal-based cropping systems; (3) to analyse relationships among soil properties through correlation analysis and principal component analysis (PCA); and (4) to generate spatial distribution maps of soil attributes using inverse distance weighting (IDW) interpolation. Geo-referenced soil samples were collected and analyzed for OC, available P and K, and DTPA-extractable Zn, Cu, Fe, and Mn to promote balanced fertilization and support sustainable agricultural development with optimal profitability in the region.

2. Materials and Methods

2.1 Study Area

Punjab is located in northwestern India, between 29°32'31.563" and 32°34'39.658" N latitude and 73°53'13.453" and 76°56'40.597" E longitude. Elevation ranges from 180 to 300 meters in the plains and 300 to 700 meters elsewhere. The region has a sub-tropical, semi-arid, monsoonal climate. Summer temperatures average 29°C to 32°C, while winter averages 15°C to 17°C. During the Rabi season (November to April), the mean maximum temperature is 25°C, rising to 38°C in the Kharif season (June to October). In the southwest, temperatures may reach 44°C in May and June. The mean minimum temperature is 8°C in the Rabi season and 23°C in the Kharif season. Mean annual rainfall ranges from 400 to 1,300 mm, with over 75% occurring during the monsoon season (June to September) due to the southwest monsoon; the remainder is mainly from western disturbances. Annual rainfall variability is 25% to 35%, and monthly variability ranges from 35% to 230%. This study focuses on six blocks in Ferozepur district, southwestern Punjab: Ferozepur, Ghal Khurd, Guru Har Sahai, Mamdot, Makhu, and Zira. Together, they cover 2,190 km² at 30.9234° N, 74.6102° E, and are predominantly under intensive rice-wheat and cotton-wheat cropping systems.

2.2 Soil Sampling and Analyses

A total of 259 surface (0-15 cm) soil samples (n=40 from each block) were collected at randomly selected GPS coordinates to capture terrain variability. Samples were air-dried, crushed, and sieved to <2 mm before analysis. Soil pH and EC were measured at a 1:2 soil-to-water ratio using a glass electrode and a conductivity meter, respectively (Jackson 1967). Texture was determined using the International Pipette Technique (Piper, 2005). Organic carbon (OC) was measured by wet combustion titration (Walkley and Black 1934). Available phosphorus (P) was extracted with 0.5 M NaHCO3 (pH 8.5) (Olsen et al. 1954). Potassium (K) was extracted with 1 N NH4OAc (pH 7) and quantified by flame photometry (Merwin and Peech 1950; Richards 1954). DTPA-extractable micronutrients (Zn, Cu, Fe, Mn) were determined following Lindsay and Norvell (1978), with concentrations measured by atomic absorption spectrophotometry.

2.3 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) reduced dataset dimensionality, identified patterns in soil properties, and retained key information (Jolliffe and Cadima, 2016). Before PCA, Pearson correlation coefficients were calculated to assess linear relationships among variables, and the

resulting correlation matrix was used as input. Principal components with eigenvalues greater than 1.0 were retained for interpretation. Variables with high factor loadings on these components were identified as major contributors to soil fertility variability. Biplots, based on sample scores and variable loading vectors (Martens and Naes, 1989), visualized relationships, correlations, and sample clustering, enhancing interpretation of complex soil datasets (Gabriel, 1971).

2.4 Soil quality index (SQI)

The SQI was developed following Andrews et al. (2004). Principal component analysis (PCA), conducted in R software (version 4.5.1), reduced the nine measured soil variables (pH, EC, OC, P, K, Zn, Fe, Mn and Cu) to a minimum data set (MDS) through multivariate analysis. Variables were selected with high factor loadings on principal components with eigenvalues of at least 1 (Kaiser, 1960) as key soil quality indicators (Zhang and Castelló, 2017). After scoring these indicators, weights were assigned based on the proportion of variance each principal component explained relative to the total variance. The final SQI was calculated by integrating these weights with the normalized scores of the selected indicators.

$$SQI = Wi \times Si$$

where Wi = weight assigned to indicator i, and Si = normalized score of indicator i.

2.5 Spatial distribution maps

Spatial patterns of soil attributes in the study region were mapped in QGIS using inverse distance weighted (IDW) interpolation. This method assumes that nearby points are more similar than distant ones and estimates unsampled values as distance-weighted averages of nearby observations. The influence of sampled sites on predictions decreases as distance from the site increases. The core IDW equation is:

$$Z'(\mathrm{So}) = \sum_{i=1}^{n} \lambda Z(\mathrm{Si})$$

where:

- Z’(So) is the predicted value at location So
- Z(Si)is the measured value at a known location Si
- Λiis the weight assigned to each measured point, based on its distance from So

- The weights are determined by:

$$\lambda i = \frac{d_{io}^{-p}}{\sum_{i=1}^{n} d_{io}^{-p}}$$

where:

- d_{i0} is the distance between the known point SiS_iSi and the prediction location S0S_0S0,
- p is a power parameter that controls how quickly the weight decreases with distance-higher values of p give more importance to nearer points.

This approach allows for realistic spatial estimation by emphasizing local variability while reducing the influence of distant observations (Ouabo et al., 2020).

2.6 Nutrient Index

The nutrient index was calculated following the method of Parker et al. (1951):

$$Nutrient\ Index\ (NI) = \frac{(\mathrm{NL} \times 1) + (\mathrm{NM} \times 2) + (\mathrm{NH} \times 3)}{\mathrm{NT}}$$

where, NL, NM, and NH are the number of soil samples in the low, medium, and high categories. NT denotes the total number of soil samples.

2.7 Map preparation

The soil sampling procedure was designed to use the comprehensive information in the district soil map to prepare thematic maps (Sidhu et al. 1995). In this map, soil family associations serve as the primary mapping units, with units delineated across 220 polygons. Base maps were scanned and converted into digital format. The digitized thematic maps were georectified and transformed from computer coordinates to real-world coordinates by selecting ground control points (GCPs) for each map and minimizing the total root mean square error (RMSE) to ensure high rectification accuracy. The locations of surface soil samples collected from different soil mapping units were recorded using a GPS mapping system. This digitized layer was integrated with attribute tables and the soil-mapping-unit layer to prepare it for mapping and querying; analyses for various parameters were generated using Arc-info GIS software. In total, 240 soil samples were collected from polygons, ensuring at least one representative sample from each polygon, with larger polygons contributing two to three samples each. The sampling procedure strictly adhered to the previously verified soil mapping units.

Representative values (mean and median) for soil physical and chemical parameters using descriptive statistics. The GIS employed in this study integrates robust statistical techniques with spatial data from the base maps. All data tables were prepared in Excel worksheets and then integrated with the attribute tables of the district's GIS-based digitized maps. After integration, the data were further categorized using ArcGIS.

2.8 Statistical analysis

Descriptive statistics, including mean, range, standard deviation, standard error, and coefficient of variation, were calculated to assess data variability. Principal component analysis (PCA) identified linear combinations of variables that explain most of the variance in the dataset. Microsoft Excel was used for basic statistical summaries, and R software (version 4.5.1) was used for PCA, correlation analysis, and three-dimensional biplots.

3. Results

3.1 Descriptive statistics of soil properties across Ferozepur district

The descriptive statistics for major soil physicochemical properties and nutrient status in Ferozepur district (Table 1). Soil pH ranged from 7.00 to 9.10, with a mean of 8.20 and a median of 8.18, indicating predominantly neutral to alkaline conditions. The low coefficient of variation (CV = 5.30%) reflects uniform pH distribution, while slight negative skewness (-0.19) and platykurtic kurtosis (-0.60) indicate a near-normal distribution. Electrical conductivity ranged from 0.05 to 0.79 dS m^{-1}, with a mean of 0.26 dS m^{-1}, confirming non-saline conditions. The high CV (58.0%) indicates spatial variability in soluble salt content, though all values remained below critical limits. Positive skewness (1.44) and kurtosis (2.10) suggest most samples had lower EC values, with a few higher readings.

Organic carbon ranged from 0.05 to 0.89%, with a mean of 0.47% and a median of 0.46%, indicating low to medium OC status. The CV (35.6%) indicates moderate variability, while low skewness (-0.04) and slightly platykurtic kurtosis (-0.42) suggest a nearly symmetrical distribution. Available P ranged from 8.05 to 231.1 kg ha^{-1}, with a mean of 41.1 kg ha^{-1} and a median of 36.2 kg ha^{-1}, reflecting generally high to very high P status. The high CV (67.0%), strong positive skewness (3.35), and high kurtosis (17.8) indicate significant phosphorus accumulation in some soils, likely due to continued phosphatic fertilizer use. Available K ranged

from 43.7 to 401.5 kg ha^{-1}, with a mean of 138.4 kg ha^{-1} and a median of 123.6 kg ha^{-1}, indicating low to medium K status. The CV (44.0%) indicates moderate variability, and positive skewness (1.08) suggests more soils have lower K values.

Among micronutrients, DTPA-extractable Zn ranged from 0.18 to 12.8 mg kg^{-1}, with a mean of 2.37 mg kg^{-1} and a median of 1.83 mg kg^{-1}. The very high CV (84.7%) indicates substantial spatial variability. Positive skewness (2.29) and high kurtosis (6.99) indicate a skewed distribution, with a few soils containing very high Zn levels. DTPA-extractable Cu ranged from 0.06 to 4.39 mg kg^{-1}, with a mean of 1.41 mg kg^{-1} and a median of 1.14 mg kg^{-1}, indicating adequate Cu status in most soils. The CV (70.7%) reflects notable variability, and skewness (0.99) indicates a moderately right-skewed distribution. DTPA-extractable Fe ranged from 0.75 to 358.3 mg kg^{-1}, with a mean of 37.6 mg kg^{-1} and a median of 31.5 mg kg^{-1}, indicating predominantly high Fe availability. Very high skewness (6.22) and kurtosis (61.0) indicate extreme variability and outliers with exceptionally high Fe concentrations. DTPA-extractable Mn ranged from 0.97 to 32.0 mg kg^{-1}, with a mean of 9.50 mg kg^{-1} and a median of 8.55 mg kg^{-1}, suggesting medium to high Mn status. The CV (60.3%) indicates considerable variability, and positive skewness (1.11) suggests most soils have lower Mn values, with fewer high-Mn samples.

3.2 Block-wise range of different soil parameters and nutrient status of Ferozepur district

Soils in Ferozepur district are neutral to moderately alkaline, with pH values from 7.00 to 9.10 and mean values varying by block (Table 2). Alkaline soils predominate, with pH ranges of 7.95-9.10 in Ferozepur, 7.06-8.75 in Ghal Khurd, 8.06-8.95 in Guru Har Sahai, 7.71-8.62 in Mamdot, 7.18-7.98 in Makhu, and 7.00-8.27 in Zira. Electrical conductivity ranges from 0.05 to 0.79 dS m^{-1}, indicating non-saline conditions. By block, EC values are 0.08-0.44 dS m^{-1}in Ferozepur, 0.11-0.19 in Ghal Khurd, 0.05-0.73 in Guru Har Sahai, 0.11-0.79 in Mamdot, 0.06-0.33 in Makhu, and 0.12-0.78 in Zira.

Organic carbon content ranges from 0.05% to 0.89%, indicating low to medium organic matter. By block, OC values are 0.09-0.66% in Ferozepur, 0.05-0.80% in Ghal Khurd, 0.14-0.70% in Guru Har Sahai, 0.12-0.89% in Mamdot, 0.32-0.84% in Makhu, and 0.28-0.76% in Zira. Available phosphorus content varies widely across the district, from 8.05 to 231.1 kg ha^{-1}. By block, available P is 14.3-47.9 kg ha^{-1} in Ferozepur, 21.6-93.6 in Ghal Khurd, 8.05-149.4 in Guru Har Sahai, 14.7-231.1 in Mamdot, 29.5-93.0 in Makhu, and 21.9-98.3 in Zira.

Available potassium content ranges from 43.7 to 401.5 kg ha^{-1}, indicating low to high K status. By block, K values are 43.7-169.6 kg ha^{-1} in Ferozepur, 67.8-271.7 in Ghal Khurd, 48.0-323.9 in Guru Har Sahai, 69.9-401.5 in Mamdot, 46.4-228.2 in Makhu, and 58.9-275.9 in Zira. DTPA-extractable micronutrient concentrations also vary widely. Zinc ranges from 0.18 to 12.8 mg kg^{-1}, Cu from 0.06 to 4.39 mg kg^{-1}, and Fe from 0.75 to 358.3 mg kg^{-1}, with some locations showing very high Fe levels. Manganese ranges from 0.97 to 32.0 mg kg^{-1}, indicating broad availability.

3.3 Block-wise variation in soil properties and macro- and micronutrient status

The circular heatmaps illustrate mean block-wise variability in soil physicochemical properties and nutrient status across Ferozepur district. Soil pH was neutral to moderately alkaline in all blocks, with the highest values in Guru Har Sahai (8.66) and Ferozepur (8.59), and the lowest in Makhu (7.67) and Zira (7.86), indicating less alkaline conditions (Figures 1 and 5). Electrical conductivity remained low (0.15-0.35 dS m^{-1}), confirming non-saline soils throughout the district. Organic carbon content ranged from moderate to high, with Makhu (0.58%) highest, followed by Zira (0.48%) and Mamdot (0.47%), and Ferozepur (0.36%) lowest. Available phosphorus was high in all blocks, particularly in Mamdot (42.8 kg ha^{-1}), Zira (52.9 kg ha^{-1}), and Makhu (53.7 kg ha^{-1}), likely due to continued fertilizer use. Available potassium varied more, with higher levels in Mamdot (181.5 kg ha^{-1}) and Guru Har Sahai (146.2 kg ha^{-1}) and lower levels in Ferozepur (103.7 kg ha^{-1}) and Ghal Khurd (131.8 kg ha^{-1}).

Micronutrient distribution displayed distinct spatial patterns. Zinc ranged from adequate to high, with the highest levels in Zira (3.81 mg kg^{-1}) and Ghal Khurd (2.85 mg kg^{-1}), and the lowest in Ferozepur (1.77 mg kg^{-1}). Copper was sufficient in all blocks, with higher concentrations in Makhu (2.94 mg kg^{-1}) and Zira (2.01 mg kg^{-1}). Iron remained consistently high, particularly in Ghal Khurd (47.1 mg kg^{-1}) and Guru Har Sahai (48.0 mg kg^{-1}). Manganese varied, with higher values in Guru Har Sahai (12.9 mg kg^{-1}) and Ferozepur (11.9 mg kg^{-1}), and lower values in Ghal Khurd (5.56 mg kg^{-1}). Overall, the heatmaps reveal spatial heterogeneity in soil fertility. Makhu and Zira exhibited better OC and micronutrient status, while Ferozepur and Ghal Khurd had lower nutrient levels in some parameters. These differences reflect the combined influence of soil properties, cropping practices, and nutrient management across the district.

3.4 Principal Correlation analysis

Pearson's correlation analysis revealed significant associations among soil physico-chemical properties, macronutrients, and micronutrients (Figure 2). Soil pH was negatively correlated with available phosphorus (r = -0.93) and organic carbon (r = -0.80), indicating reduced phosphorus availability and lower organic matter in alkaline soils. In contrast, pH showed a strong positive correlation with manganese (r = 0.65), but only weak associations with EC, K, and Fe (r < 0.15). Organic carbon was strongly and positively correlated with available phosphorus (r = 0.86), underscoring the link between soil organic matter and phosphorus dynamics. Organic carbon also showed a moderate positive correlation with copper (r = 0.61). Electrical conductivity was moderately associated with K (r = 0.55) and zinc (r = 0.39), while its relationships with other nutrients were weak. Among macronutrients, available P was moderately correlated with Cu (r = 0.63) and Zn (r =0.45), whereas K generally showed weak correlations with most micronutrients. Among micronutrients, Zn was strongly positively correlated with Fe (r = 0.52), while Mn was negatively associated with P (r = -0.50) and Zn (r = -0.50). Copper was positively correlated with OC and P, but negatively associated with pH (r = -0.53). Overall, the analysis showed that soil chemical properties primarily govern nutrient relationships. Soil pH and OC were the main factors influencing macro- and micronutrient availability in the Ferozepur district.

Principal component analysis (PCA) clarified sensitivity patterns and identified correlations among soil variables based on principal component (PC) factor loadings. Components with higher eigenvalues explained the most variability among soil properties. The PCA score distribution showed well-defined block clusters with minimal overlap, indicating consistent soil characteristics within blocks and clear differentiation between them. Guru Har Sahai and Makhu blocks formed compact clusters, while Ferozepur and Ghal Khurd showed broader dispersion, reflecting greater variability in soil properties. These patterns highlight how local pedo-environmental conditions and management practices shape soil chemistry. Blocks with positive PC1 scores had higher micronutrient availability. PC1 accounted for 39.99% of the total variance and was strongly associated with micronutrients, especially Fe, Zn, Mn, and Cu, indicating a dominant micronutrient fertility gradient (Figure 3 and Table 4). PC2 explained 21.91% of the variance and was mainly influenced by soil chemical parameters (pH and electrical conductivity), distinguishing alkaline-saline soils from those with lower alkalinity. PC3 contributed 17.10% of the variance and reflected variation in organic carbon and available macronutrients (P and K), indicating differences in soil organic matter and nutrient retention.

Overall, the PCA showed that micronutrient availability, soil reaction, and organic-macronutrient dynamics shape soil variability in the Ferozepur district. The clear separation of blocks in multivariate space highlights distinct soil fertility regimes and supports site-specific soil management and nutrient optimization.

3.5 Spatial variability of soil chemical properties across blocks

Soil chemical properties varied spatially across the six blocks of Ferozepur district (Figure 4). The circular heat ring shows the percentage of samples in higher fertility categories for each soil attribute. Soil pH was predominantly alkaline in all blocks, with higher pH classes exceeding 80% in Ferozepur (83.0%), Guru Har Sahai (93.5%), Makhu (100%), and Zira (100%). Mamdot (52.8%) and Ghal Khurd (62.5%) had lower pH values. Electrical conductivity (EC) was consistently low, with all samples classified as non-saline. Organic carbon content varied substantially, with Guru Har Sahai (87.1%) and Zira (80.0%) having higher OC, and Ghal Khurd (50.0%), Makhu (50.0%), and Mamdot (54.7%) having lower proportions. Ferozepur had an intermediate OC status (62.3%). Available phosphorus (P) was generally adequate to high, with 100% of samples in higher P classes in Guru Har Sahai and Zira, followed by Ferozepur (84.6%) and Makhu (80.8%). Ghal Khurd (72.5%) and Mamdot (67.9%) had lower percentages. Available potassium (K) showed pronounced variability and generally lower fertility. Makhu had the highest proportion in higher K classes (76.9%), while Ghal Khurd (12.5%), Mamdot (28.3%), and Guru Har Sahai (32.3%) had lower values. Ferozepur (37.7%) and Zira (33.3%) had intermediate potassium status.

3.6 Soil Quality Index (SQI)

The PCA-weighted SQI revealed significant spatial variability across the study area by integrating multiple soil indicators into a single index. Indicator scores, calculated using linear scoring functions (LS) as described by Andrews et al. (2002), were classified as “more is better” or “less is better” based on their effect on soil quality. Beneficial indicators included soil organic carbon, available phosphorus, potassium, and micronutrients (Zn, Cu, Fe, Mn), while EC was considered detrimental. Soil pH was assessed using an optimal scoring function because of its non-linear relationship with soil quality. Soil quality was categorized as good (SQI > 0.60), moderate (0.40-0.60), or poor (< 0.40). Makhu exhibited good to moderate soil quality, while

Zira, Ghal Khurd, and Guru Har Sahai had moderate soil quality (Figure 6). Mamdot and Ferozepur had poor soil quality, indicating a need for improved soil management in these areas.

PCA principal components were the main drivers of SQI variation. The first principal component (PC1), accounting for 39.99% of total variance, was mainly linked to micronutrient availability (Zn, Cu, Fe, Mn). Blocks with balanced micronutrient status, such as Makhu and Zira, had higher SQI values (0.62 and 0.57, respectively), likely due to higher copper, organic carbon, and phosphorus in Makhu, and higher zinc in Zira, which had greater influence due to its PCA weight. The second principal component (PC2), explaining 21.91% of variance, reflected soil chemical properties, especially pH and EC, which influence nutrient availability and soil health. The third principal component (PC3), accounting for 17.10% of variance, was associated with soil fertility indicators such as organic carbon, available phosphorus, and potassium. Ghal Khurd (0.52) and Guru Har Sahai (0.51) also had relatively high SQI values, indicating balanced nutrients and favorable soil conditions. In contrast, Mamdot and Ferozepur had the lowest SQI values (0.37 and 0.32, respectively), reflecting poor soil quality. This was likely due to lower organic carbon, phosphorus, and potassium, along with higher soil pH, which may have limited nutrient availability. Overall, the PCA-weighted SQI effectively integrated multiple soil properties into a single index and highlighted the importance of micronutrient availability and OC in determining soil quality across the study area.

3.7 Nutrient Index value of soil parameters

The Nutrient Index Value (NIV) classified soil samples from Ferozepur district into low, medium, and high nutrient-status categories, revealing significant variation in soil fertility. NIV values ranged from 2.00 to 2.48, indicating medium to high alkalinity across the area. Mamdot (2.48) and Ghal Khurd (2.39) had higher pH values, reflecting more alkaline soils, while Makhu and Zira (2.00) showed moderate soil reactions (Table 3). Organic carbon (OC) levels were moderate in all blocks (1.55–2.00). Available P and EC were consistently high (3.00 and 2.00, respectively), indicating sufficient P and EC throughout the district. Potassium levels were generally low (1.13-1.48), except in Makhu (1.90), which was moderate, suggesting widespread K deficiency and the need for balanced fertilization. Micronutrients such as zinc (Zn), copper (Cu), iron (Fe), and manganese (Mn) mostly showed medium-to-high NIV values. Zinc ranged from medium (2.03 in Ghal Khurd) to high (2.88 in Zira). Copper was high (2.48-2.97) except at Guru Har Sahai (1.87), which was medium. Iron was consistently high (2.92-3.00), and Mn was

generally high (2.30-2.52), except at Guru Har Sahai (1.87), which was moderate. Overall, the analysis indicates adequate levels of micronutrients and P, but K is the most limiting nutrient. The moderate OC status highlights the importance of improving organic matter management to maintain soil health and productivity.

Discussion

Soil reaction (pH) proved to be the most influential single property shaping soil quality across Ferozepur district, a conclusion that follows less from the pH values (mean 8.20) than from their downstream effects on nutrient chemistry, reflected in the strong negative correlations between pH and both organic carbon (r= -0.80) and phosphorus (r= -0.93). This pattern largely reflects the region's soil mineralogy, semi-arid climate, and long-term intensive cropping. The district's soils are primarily sandy loam to loamy sand, dominated by quartz and clay minerals such as illite and chlorite that provide limited buffering capacity (Singh et al. 2016), and the acid-forming microbial activity that might otherwise counteract alkalinization is itself suppressed by low OC (Jindo et al. 2024; Khadka et al. 2019). Superimposed on this mineralogical baseline are two management-driven pressures: a semi-arid climate that accelerates residue decomposition and irrigation with calcium-, magnesium-, and sodium-rich water that drives secondary alkalinization, both likely intensified by imbalanced fertilizer use (Chander et al. 2023; Yadav et al. 2024). Electrical conductivity remained well below salinity thresholds throughout the district, a result attributable to soil permeability that allows excess salts to leach via runoff rather than accumulate (Pandit and Mookherjee 2016), whereas in other soils evaporation and shallow saline groundwater concentrate salts at the surface (Krishan et al. 2021). This buffer is not indefinite, and continued intensive fertilizer use could gradually raise salt loads if left unmanaged (Tarolli et al. 2024). Organic carbon accumulation faces a more entrenched set of the constraints such as coarse texture, high temperatures that accelerate decomposition, frequent tillage and heavy inorganic fertilizer input all work against carbon buildup (Singh et al. 2016; Rodrigues et al. 2023), in contrast to the higher OC retention seen under minimally disturbed horticultural systems in which accumulate more particulate organic matter and stable carbon fractions (Orlandini et al. 2023). This gap between what is agronomically possible and what intensive RWS currently achieve is itself the central argument for organic matter-based intervention in the district.

Potassium as the district's hidden constraint

The most consequential asymmetry in this dataset is that phosphorus and potassium, both heavily removed by RWS diverge sharply in current status. Phosphorus is generally high to very high, while K is widely deficient. This is not a contradiction but a predictable outcome of differential nutrient chemistry and fertilizer history. Phosphorus's low mobility means decades of phosphatic fertilizer application accumulate in the soil matrix largely undiminished by crop removal or leaching (Khadka et al. 2017; Pathak 2010). In contrast, potassium, historically under-prioritized relative to N and P in regional fertilizer programs, is continuously exported by crop harvest with comparatively little replacement and remains vulnerable to leaching in these alluvial soils. Where illite-bearing parent material and groundwater inputs offer some natural replenishment, potassium status holds up better (Sharma et al. 2016), which may explain the comparatively higher K status observed in Makhu block. The positive association between OC and K observed here reinforces this picture: higher OC likely improves K retention through greater cation exchange capacity and more favorable soil structure (Maini et al. 2020; Wei et al. 2014) meaning the district's parallel OC deficit and K deficiency are mechanistically linked rather than coincidental, and that organic matter management functions as a K retention strategy in its own right, not merely a soil-structure intervention.

Micronutrient status (Zn, Cu, Fe, Mn) was generally adequate to high, consistent with the combined legacy of favorable parent material, moderate OC, and long-term fertilizer use in this intensively cropped system (Dhaliwal et al. 2021; Khadka et al. 2017), though coarse texture and alkaline pH locally constrained solubility and accounted for the pockets of Zn deficiency identified in high-pH, low-carbon soils. The surface enrichment of Cu likely reflects its strong affinity for organic matter in the upper soil layers (Rajeshwar and Ariffkhan 2007), while Fe availability is sustained by primary and secondary Fe-bearing minerals in the soil matrix (Havlin et al., 2010) though the extreme Fe values noted in Results warrant verification before this pattern is generalized. Manganese status was similarly satisfactory, with approximately 67.1% of samples in the sufficiency range, comparable to reports from north-western Himalayan soils (Sharma and Chaudhary, 2007), and consistent with the broader medium-to-high fertility indices reported for Punjab Agricultural University research stations (Bhatt and Singh 2020), though block-to-block variation in that comparison data indicates such adequacy remains management-sensitive rather than guaranteed. Because micronutrients are essential to enzymatic activity and plant metabolic processes, their availability directly underpins both crop productivity and overall

soil quality. That PC1 (39.99% of total variance), the single largest source of variance in this dataset, is dominated by micronutrients (Zn, Cu, Fe, Mn) rather than macronutrients is therefore particularly notable: in a landscape where P, and now K, receive most management attention, it is micronutrient heterogeneity that most differentiates soil quality between blocks echoing the emphasis Andrews et al. (2004) and Armenise et al. (2013) place on micronutrient dynamics as an indicator of soil functional capacity under variable management. PC2 (21.91% of variance), reflecting pH and EC, offers the most direct explanation for why Ferozepur and Mamdot register the lowest SQI values in this study: elevated pH suppresses nutrient solubility across multiple elements simultaneously rather than affecting any one nutrient in isolation, consistent with Wienhold et al.'s (2004) broader observation that chemical constraints alkalinity and salinity tend to act as compounding rather than additive stressors on soil quality. This compounding effect is the practical reason these two blocks warrant prioritized intervention: a single-nutrient correction, such as K application alone, is unlikely to fully resolve their soil quality deficit if the underlying pH constraint is left unaddressed. PC3 (17.10% of variance) OC together with available P and K explains why Makhu records the highest SQI in the district: elevated OC here appears to function as a multiplier on macronutrient status rather than a standalone benefit, consistent with organic carbon's established role in improving soil structure, water retention, and microbial activity (Brar et al., 2023). This pattern has a useful precedent in Bhatt and Singh (2020) block-level comparison at Usman Seed Farm, Tarn Taran, Punjab, where OC and available N, P, and K were all at medium levels in Blocks A and B, whereas Block C had high nutrient index values for P and K but OC and N that remained only medium indicating that high macronutrient status alone does not guarantee high OC, and reinforcing that Makhu's advantage lies specifically in the co-occurrence of good OC and macronutrient status, not either alone. This reinforces the case that OC restoration should be treated as a precondition for macronutrient management gains, rather than a parallel, independent goal.

Conclusion

This study found that the region's soils are predominantly neutral to moderately alkaline, well suited to cereal and oilseed production, though spatial variability calls for site-specific rather than uniform fertilization. Organic carbon remained below the level needed to sustain long-term soil health, largely due to residue burning and limited organic inputs. Potassium was widely

deficient, resulting from decades of N- and P-focused fertilization. Phosphorus and micronutrients were generally adequate, apart from localized Zn deficiency in high-pH, low-carbon soils. Multivariate analysis identified micronutrient availability, soil reaction, and organic carbon as the principal drivers of soil quality variation, with organic carbon restoration central to stabilizing pH, improving nutrient availability, and supporting microbial activity. The Soil Quality Index highlighted Makhu and Zira as higher-performing blocks, while Ferozepur and Mamdot emerged as "soil health hotspots" needing targeted intervention. These findings support an integrated soil fertility management approach to increase organic carbon through residue recycling and manure application, balance potassium inputs to address current depletion, apply site-specific micronutrient supplementation (particularly Zn), and establish regular grid-based soil monitoring. These actions are urgently needed amid mounting pressure on soil resources under climate change to sustain productivity, food security, and soil conservation for crop production. This study's findings have practical applications for developing site-specific nutrient management strategies to optimize crop production, improve fertilizer use efficiency, reduce cultivation costs, and mitigate environmental pollution. This study has two primary limitations. First, single-point-in-time sampling restricts the ability to assess temporal trends. Second, the Soil Quality Index is based solely on nine physicochemical indicators and does not incorporate biological measures.

CRediT authorship contribution statement

Vicky Singh: Conceptualization, Resources, Methodology, Writing- original draft. **Vivek Sharma:** Methodology, Writing- original draft. **Janpriya Kaur:** Software, Writing- original draft. **Mehakpreet Kaur Randhawa:** Software, Writing- review & editing. **Chinka Batra:** Software, Writing- original draft. **Manmeet Kaur**: Writing, original draft; Writing, Review & editing. **Prabhjot Singh:** Writing-review & editing. **Manroop Singh:** Software, Writing-original draft. **S K Behera:** Writing-review & editing

Acknowledgement

The authors are grateful to the Head, Department of Soil Science, Punjab Agricultural University, Ludhiana (India), for providing the necessary research facilities during the study. The authors are also grateful to the Director of Research, Punjab Agricultural University, Ludhiana for the research support.

Declaration of competing interests

No public, private, or nonprofit funding organizations provided a specific grant for this research. The authors declare that no known competing financial interests or personal relationships have influenced the work reported in this study.

Funding Statement

Not applicable

Data Availability

Data will be made available on request.

Ethics, Consent to Participate, and Consent to Publish declarations

Not applicable

Clinical trial number

Not applicable.

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725 **Table 1: Range and mean of different soil parameters along with percent deficiency across Ferozepur district**

Soil attribute	Category	Minimum	Maximum	Mean	Median	Standard Deviation (+)	CV %	Skewness	Kurtosis
pH	<6.5 6.5-8.7 8.7-9.3 >9.3	7.00	9.10	8.20	8.18	0.43	5.30	-0.19	-0.60
EC (dS m^{-1})	<0.8 0.8-1.6 1.6-2.5 >2.5	0.05	0.79	0.26	0.21	0.15	58.0	1.44	2.10
OC (%)	Low (<0.40) Medium (0.40-0.75) High (>0.75)	0.05	0.89	0.47	0.46	0.17	35.6	-0.04	-0.42
P (kg ha^{-1})	Low (<5) Medium (5-9) High (9-20) Very high (>20)	8.05	231.1	41.1	36.2	27.6	67.0	3.35	17.8
K (kg ha^{-1})	Low (<137.5) Medium (137.5-	43.7	401.5	138.4	123.6	60.9	44.0	1.08	1.28

	270) High (>270)								
Zn (mg kg^{-1})	Low (<0.60) Medium (0.60-1.80) High (>1.80)	0.18	12.8	2.37	1.83	2.01	84.7	2.29	6.99
Cu (mg kg^{-1})	Low (<0.20) Medium (0.20-1.00) High (>1.00)	0.06	4.39	1.41	1.14	1.00	70.7	0.99	0.25
Fe (mg kg^{-1})	Low (<4.50) Medium (4.50-10.50) High (>10.50)	0.75	358.3	37.6	31.5	29.2	77.7	6.22	61.0
Mn (mg kg^{-1})	Low (<3.50) Medium (3.50-9.0) High (>9.0)	0.97	32.0	9.50	8.55	5.73	60.3	1.11	1.44

726 *Classification is based on standard critical limits for each parameter

727 **Table 2. Block-wise range of different soil parameters and nutrient status of Ferozepur district**

Soil attribute	Category	Block (Blocks)					
		Ferozepur	**Ghal Khurd**	**Guru Har Sahai**	**Mamdot**	**Makhu**	**Zira**
pH	<6.5 6.5-8.7 8.7-9.3 >9.3	7.95-9.10	7.06-8.75	8.06-8.95	7.71-8.62	7.18-7.98	7.00-8.27
EC (dS m^{-1})	<0.8 0.8-1.6 1.6-2.5 >2.5	0.08-0.44	0.11-0.19	0.05-0.73	0.11-0.79	0.06-0.33	0.12-0.78
OC (%)	Low (<0.40) Medium (0.40-0.75) High (>0.75)	0.09-0.66	0.05-0.80	0.14-0.70	0.12-0.89	0.32-0.84	0.28-0.76
P (kg ha-1)	Low (<5) Medium (5-9) High (9-20) Very high (>20)	14.3-47.9	21.6-93.6	8.05-149.4	14.7-231.1	29.5-93.0	21.9-98.3
K (kg ha-1)	Low (<137.5) Medium (137.5-270)	43.7-169.6	67.8-271.7	48.0-323.9	69.9-401.5	46.4-228.2	58.9-275.9

	High (>270)						
Zn (mg kg^{-1})	Low (<0.60) Medium (0.60-1.80) High (>1.80)	0.18-9.63	0.91-9.59	0.70-5.32	0.23-12.8	0.56-4.46	1.15-12.5
Cu (mg kg^{-1})	Low (<0.20) Medium (0.20-1.00) High (>1.00)	0.21-2.83	0.06-0.88	0.35-2.75	0.24-2.40	0.43-4.28	0.83-4.39
Fe (mg kg^{-1})	Low (<4.50) Medium (4.50-10.50) High (>10.50)	10.8-68.8	9.40-358.3	24.6-99.0	0.75-96.1	10.7-64.2	11.3-184.7
Mn (mg kg^{-1})	Low (<3.50) Medium (3.50-9.0) High (>9.0)	1.64-32.0	0.97-11.6	2.16-27.4	2.63-20.4	2.60-18.2	1.48-16.5

*values in parentheses represent the mean values

733 **Table 3. Nutrient index values of soil parameters of Ferozepur district**

Soil Parameters	Ferozepur	Ghal Khurd	Guru Har Sahai	Mamdot	Makhu	Zira
pH	2.18 (Medium)	2.39 (High)	2.06 (Medium)	2.48 (High)	2.00 (Medium)	2.00 (Medium)
OC	1.73 (Medium)	1.55 (Medium)	1.94 (Medium)	1.58 (Medium)	2.00 (Medium)	1.78 (Medium)
P	3.00 (High)	3.00 (High)	3.00 (High)	3.00 (High)	3.00 (High)	3.00 (High)
K	1.48 (Low)	1.13 (Low)	1.40 (Low)	1.48 (Low)	1.90 (Medium)	1.37 (Low)
Zn	2.48 (High)	2.03 (Medium)	2.81 (High)	2.52 (High)	2.23 (High)	2.88 (High)
Cu	2.60 (High)	2.48 (High)	1.87 (Medium)	2.50 (High)	2.97 (High)	2.95 (High)
Fe	3.00 (High)	3.00 (High)	2.96 (High)	2.92 (High)	3.00 (High)	3.00 (High)
Mn	2.33 (High)	2.39 (High)	1.87 (Medium)	2.52 (High)	2.30 (High)	2.32 (High)

734 # Range of NIV <1.67-Low, 1.67-2.33- Medium, >2.33- High

735

736

Table 4. Eigen values, explained and cumulative variance of district Ferozepur

PC	Eigenvalue	Explained Variance (%)	Cumulative Variance (%)
PC1	4.32	34.10	39.99
PC2	2.37	21.70	61.91
PC3	1.85	14.20	79.01

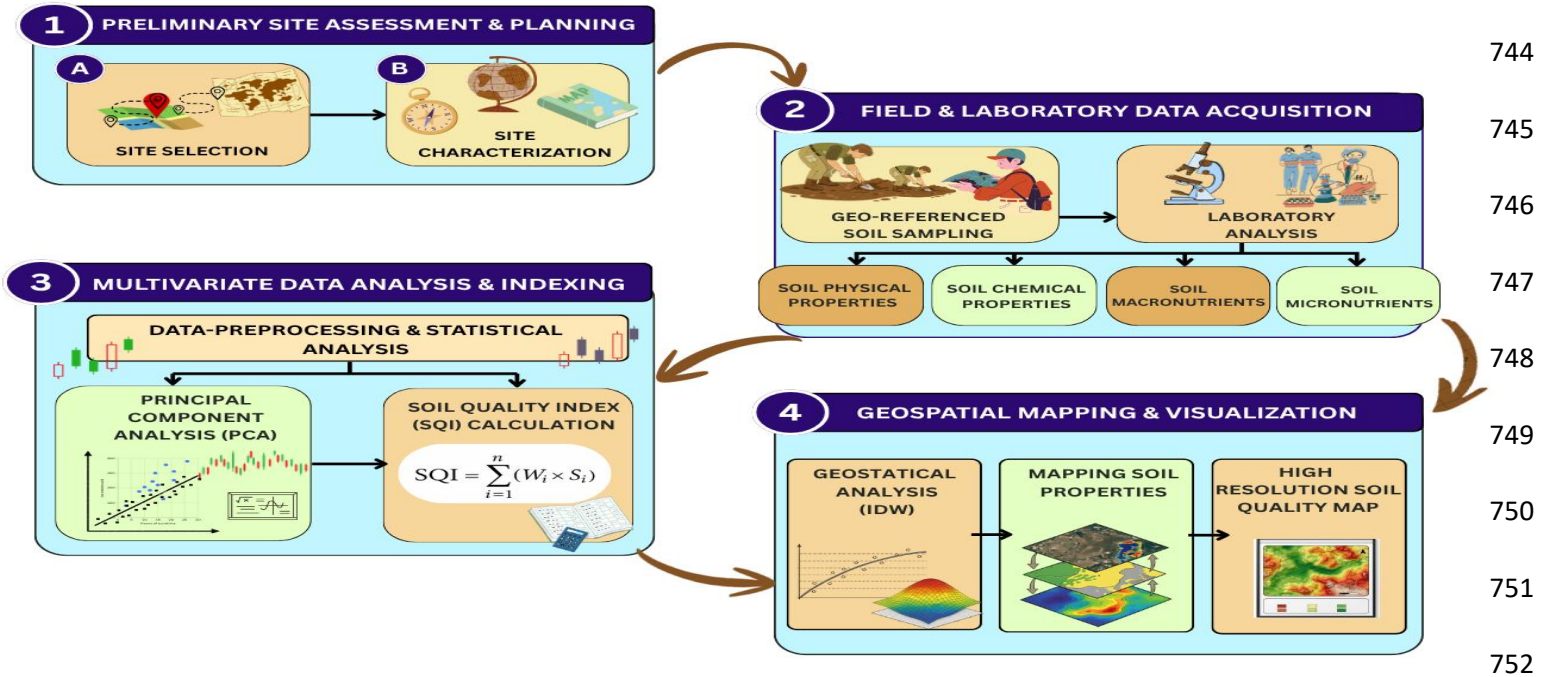


Figure: Procedure for site selection, charaterzation, soil samples collection, analysis and interpretation of Ferozepur district, Punjab

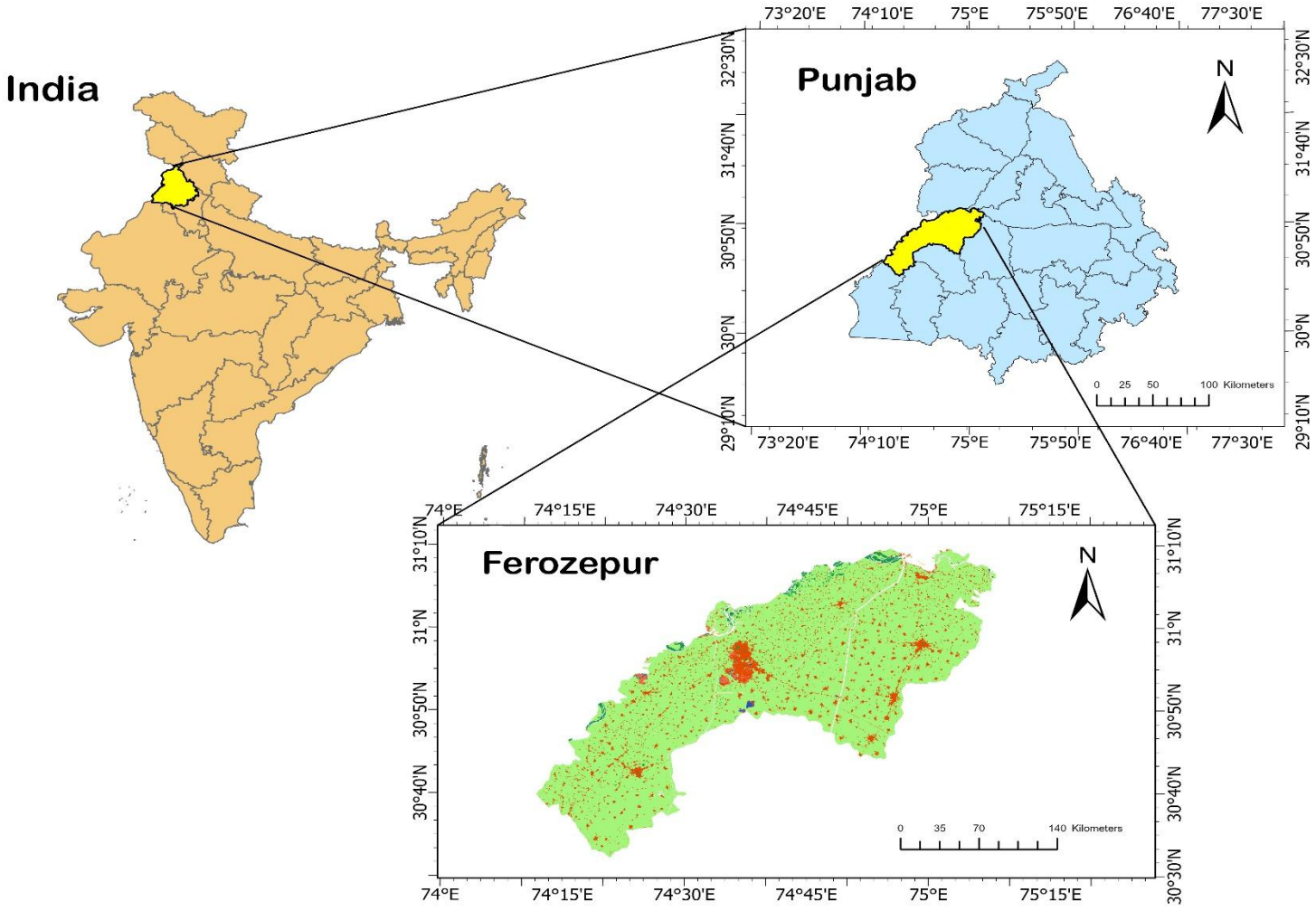


Figure: Location of study area for georeferencing soil sampling and analysis in south western part of Punjab state

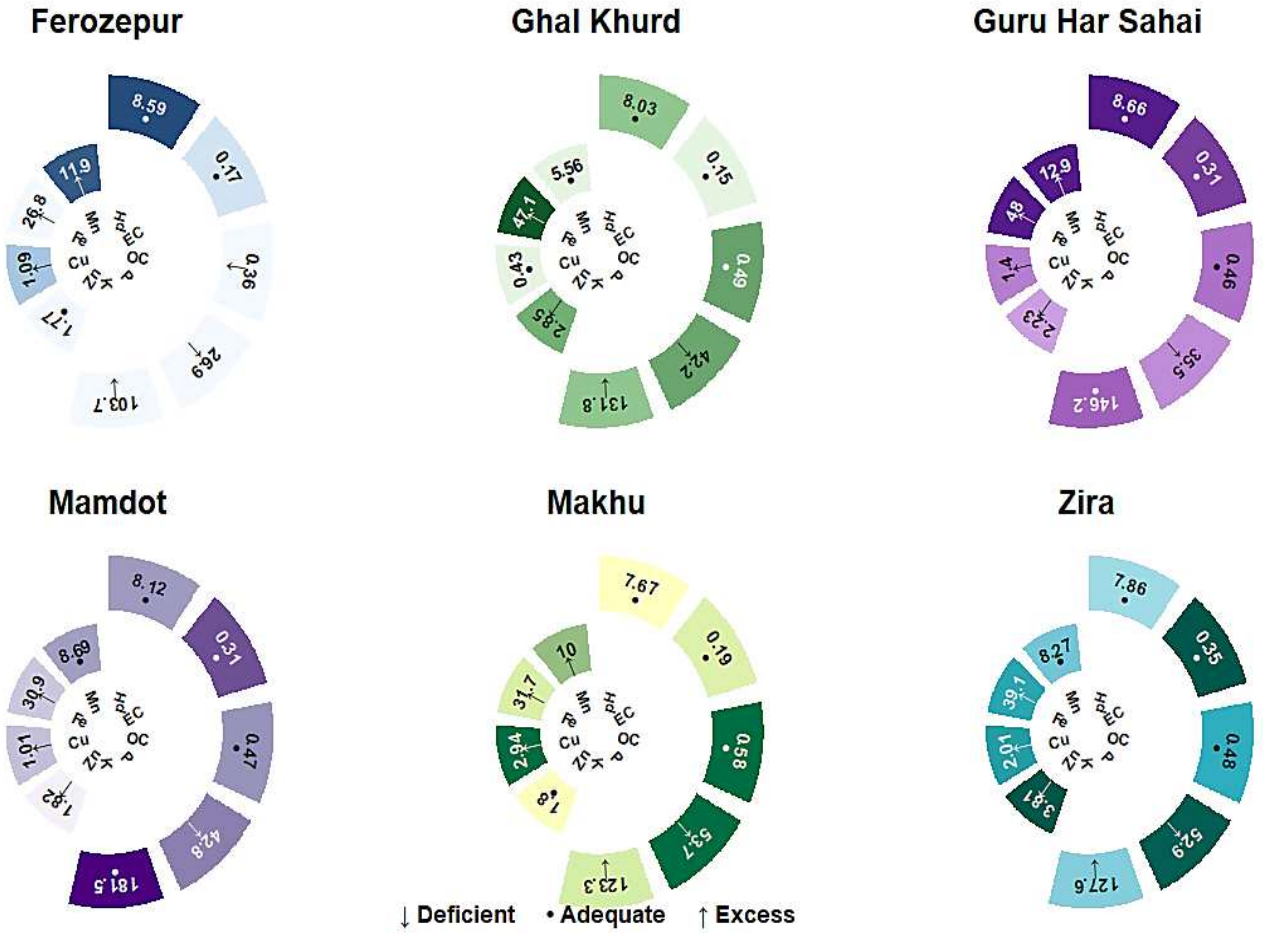


Figure 1: Synvisio-circular heatmaps depicting block-wise variation in soil physicochemical properties (pH, EC, organic carbon) and macro- (P, K) and micronutrient (Zn, Cu, Fe, Mn) status

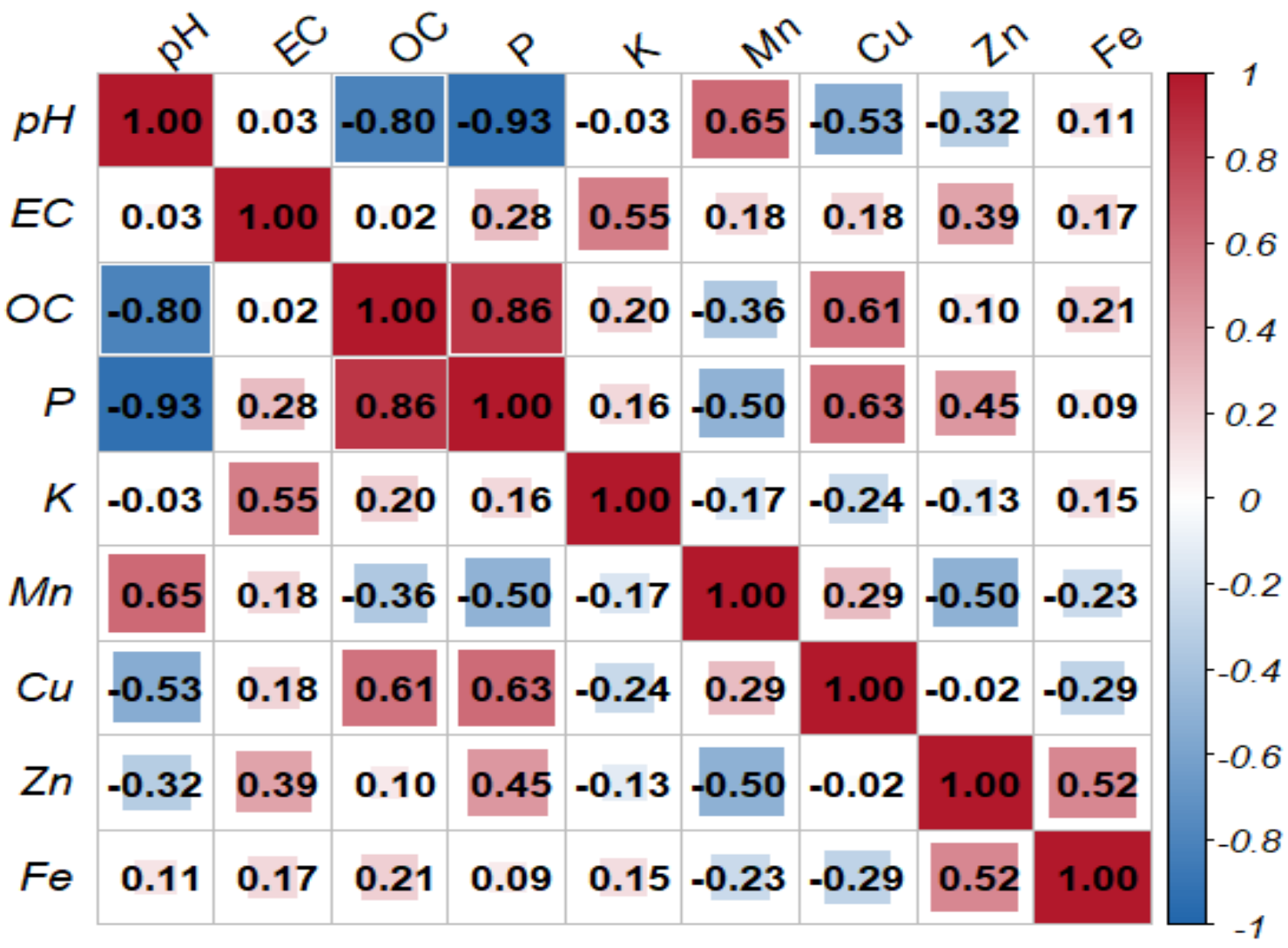

pH EC OC P K Mn Cu Zn Fe
pH 1.00 0.03 -0.80 -0.93 -0.03 0.65 -0.53 -0.32 0.11
EC 0.03 1.00 0.02 0.28 0.55 0.18 0.18 0.39 0.17
OC -0.80 0.02 1.00 0.86 0.20 -0.36 0.61 0.10 0.21
P -0.93 0.28 0.86 1.00 0.16 -0.50 0.63 0.45 0.09
K -0.03 0.55 0.20 0.16 1.00 -0.17 -0.24 -0.13 0.15
Mn 0.65 0.18 -0.36 -0.50 -0.17 1.00 0.29 -0.50 -0.23
Cu -0.53 0.18 0.61 0.63 -0.24 0.29 1.00 -0.02 -0.29
Zn -0.32 0.39 0.10 0.45 -0.13 -0.50 -0.02 1.00 0.52
Fe 0.11 0.17 0.21 0.09 0.15 -0.23 -0.29 0.52 1.00
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

Figure 2. Pearson's correlation of soil physicochemical properties, macronutrients, and micronutrients.

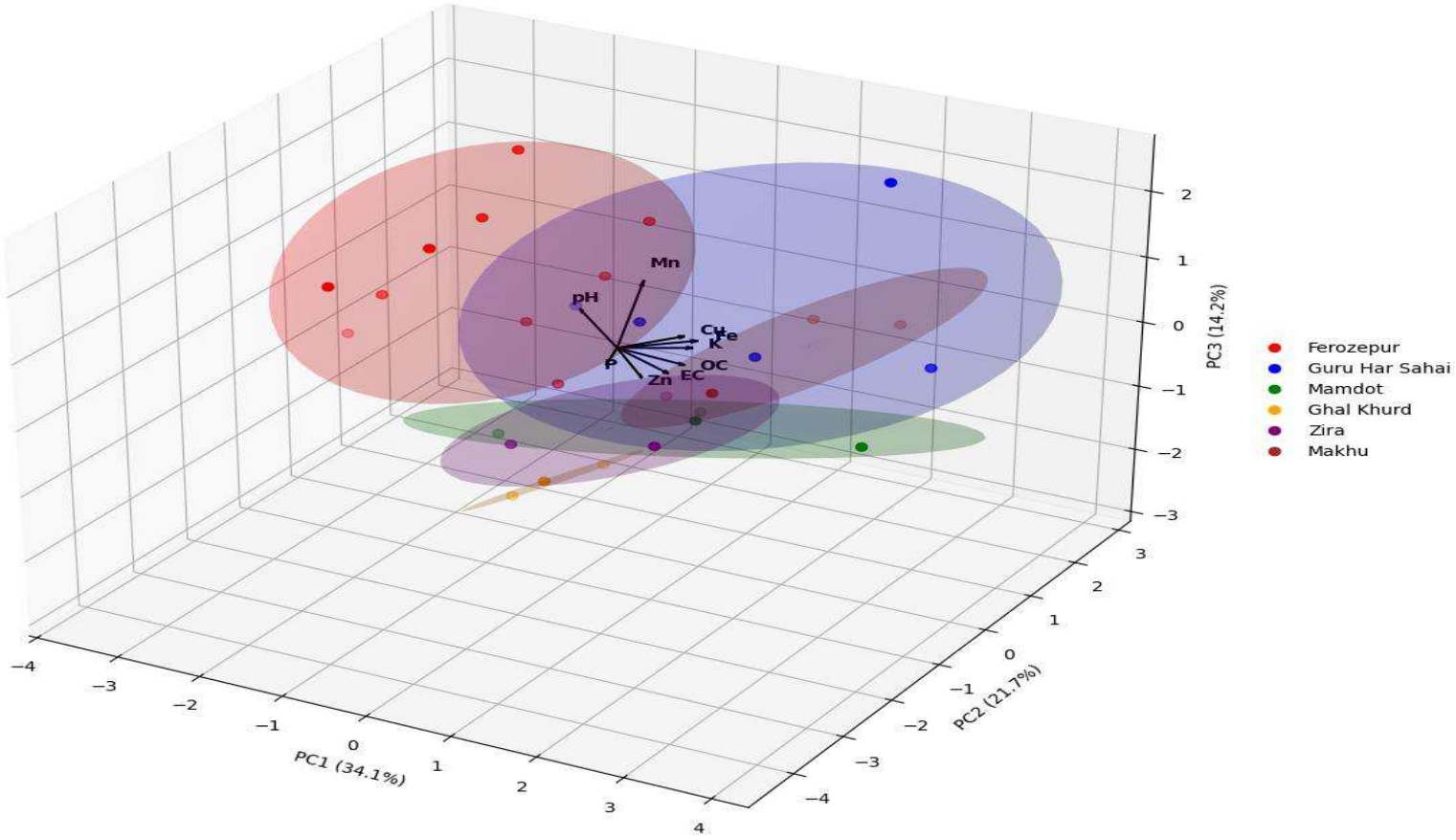
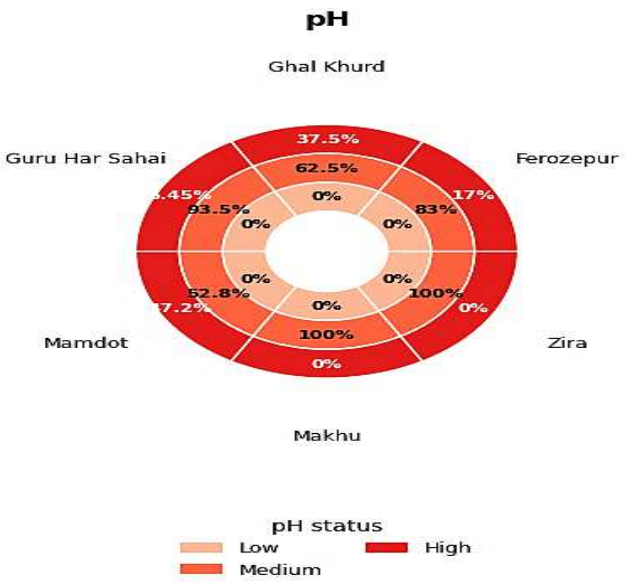
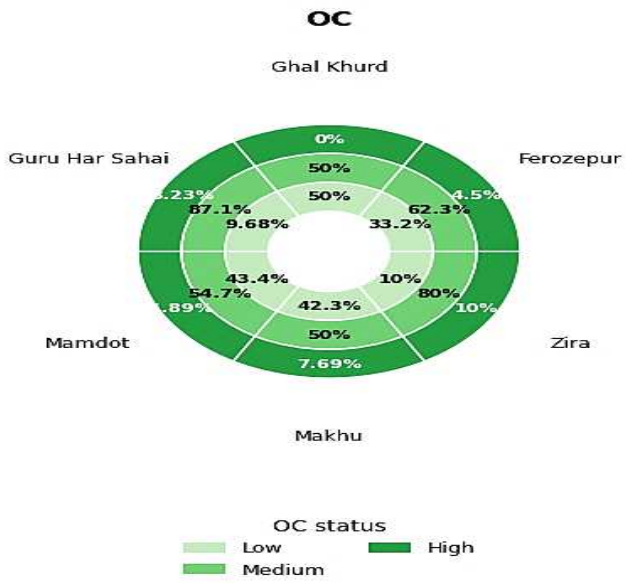
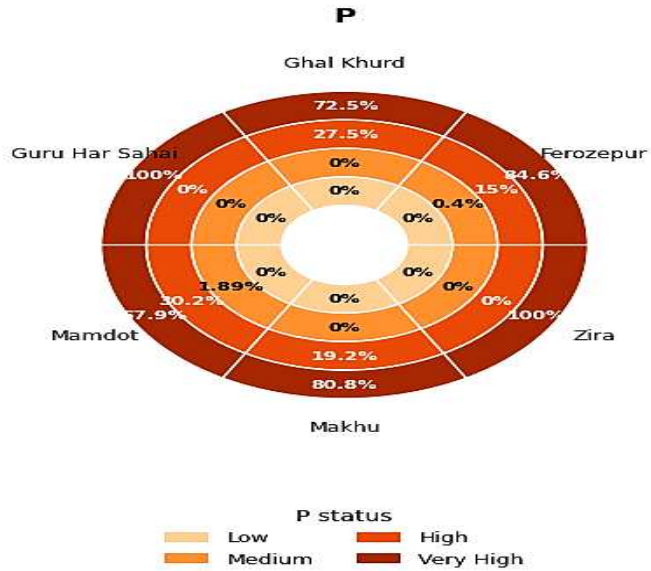
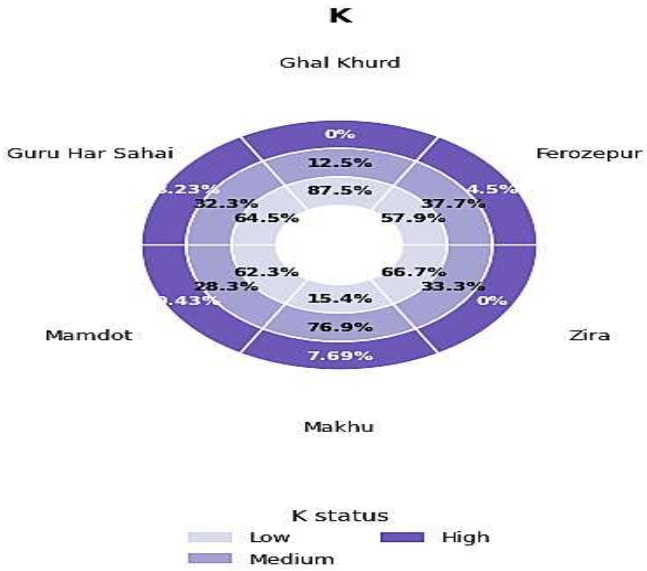


Figure 3. Three-dimensional principal component analysis (PCA) biplot of soil physicochemical properties and nutrient variables across blocks, with 95% confidence ellipsoids.


pH
Ghal Khurd
Guru Har Sahai
Ferozepur
Mamdot
Zira
Makhu
37.5%
62.5%
0%
17%
83%
93.5%
100%
62.8%
pH status
Low
High
Medium


OC
Ghal Khurd
Guru Har Sahai
Ferozepur
Mamdot
Zira
Makhu
0%
50%
4.5%
87.1%
62.3%
9.68%
33.2%
43.4%
10%
54.7%
80%
42.3%
10%
50%
7.69%
OC status
Low
High
Medium


P
Ghal Khurd
Guru Har Sahai
Ferozepur
Mamdot
Zira
Makhu
72.5%
27.5%
0%
100%
84.6%
15%
0.4%
1.89%
80.8%
19.2%
100%
P status
Low
High
Medium
Very High


K
Ghal Khurd
Guru Har Sahai
Ferozepur
Mamdot
Zira
Makhu
0%
12.5%
87.5%
4.5%
32.3%
37.7%
64.5%
57.9%
62.3%
66.7%
28.3%
33.3%
15.4%
0%
76.9%
7.69%
K status
Low
High
Medium

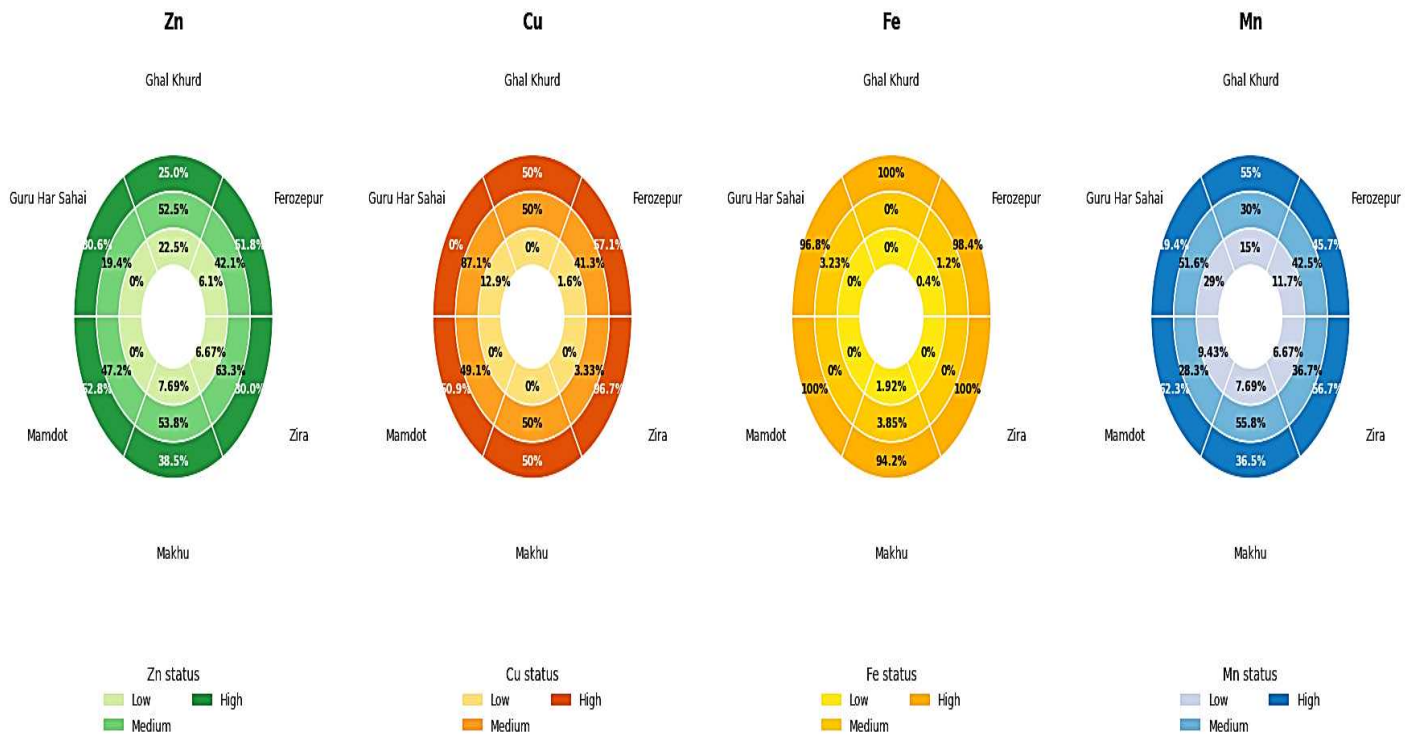
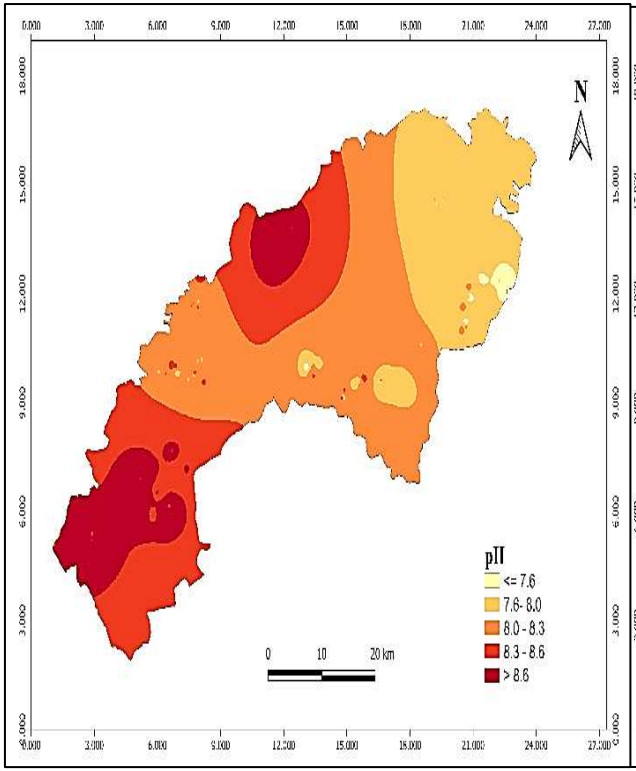
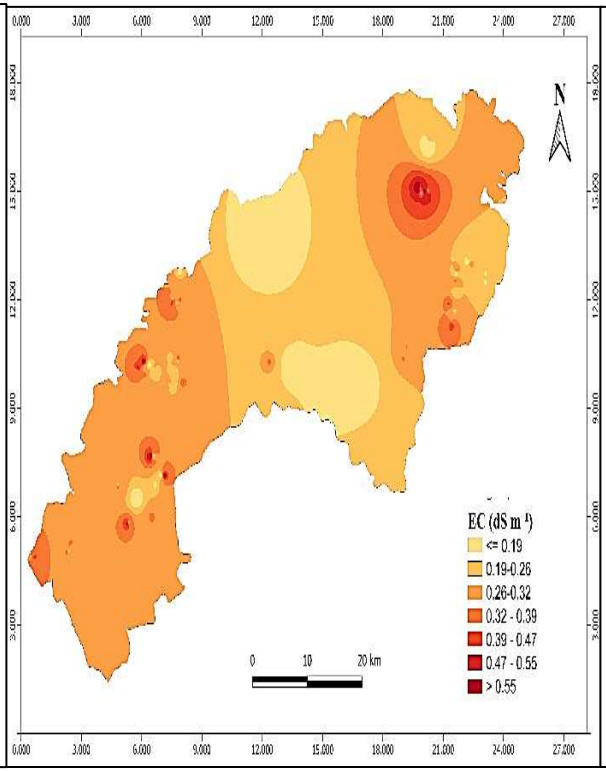
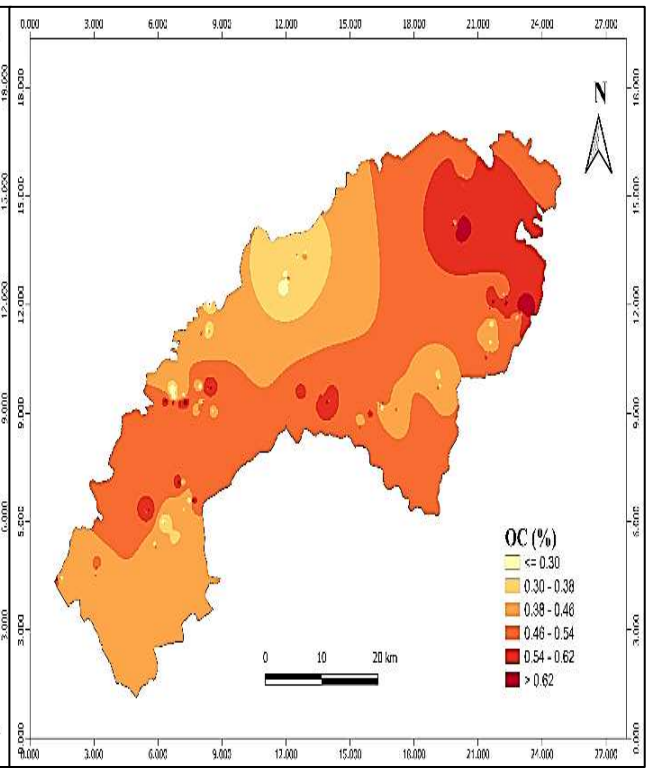


Figure 4. Circular heatmap of soil fertility status across blocks of Ferozepur district. Rings represent soil parameters and segment colours indicate block-wise percentage of soil samples under low, medium, high and very high fertility classes.







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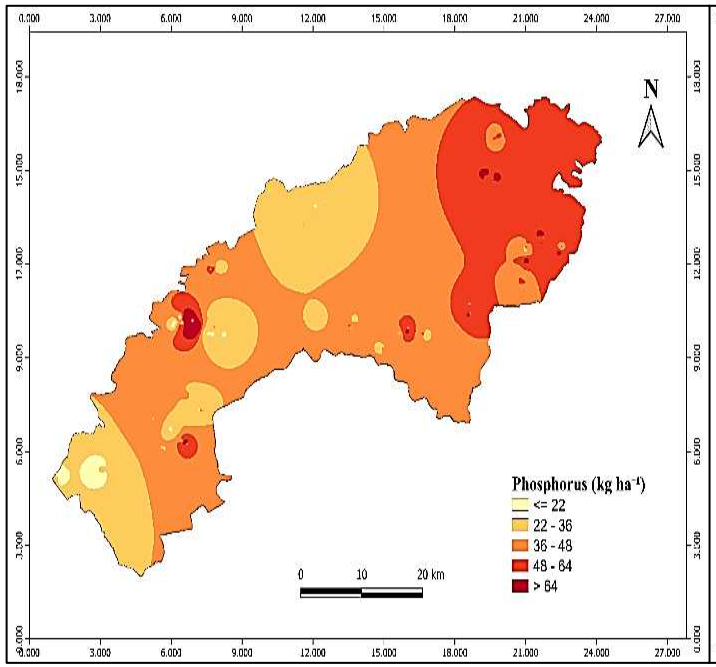
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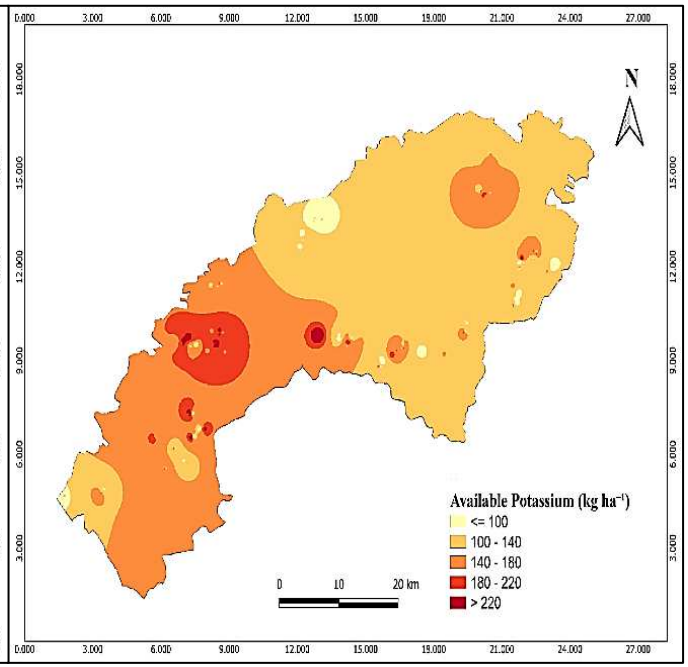
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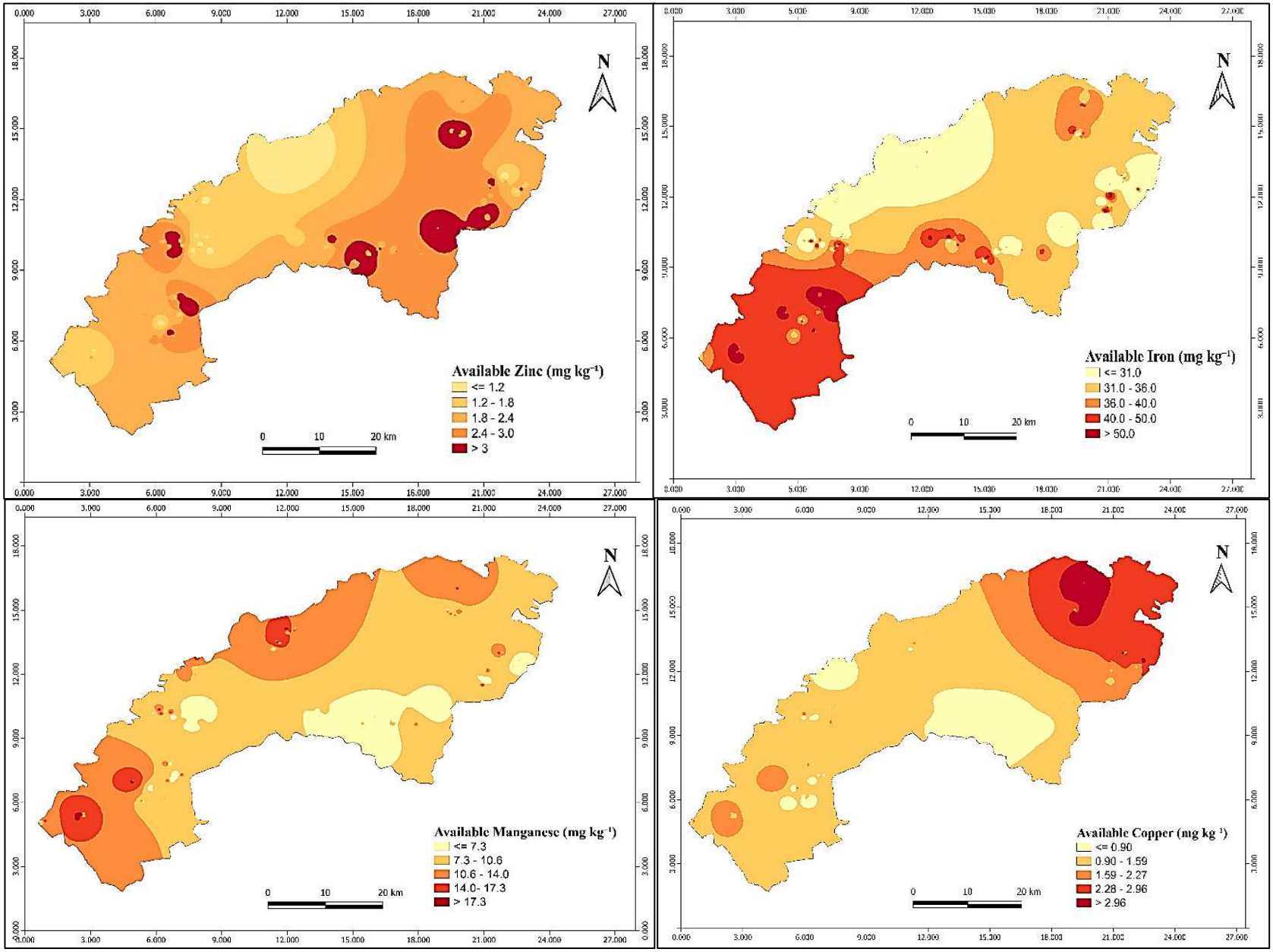


Figure 5. Interpolation maps of soil macro- and micro-nutrients in south-western part of Punjab in northern IGP of India

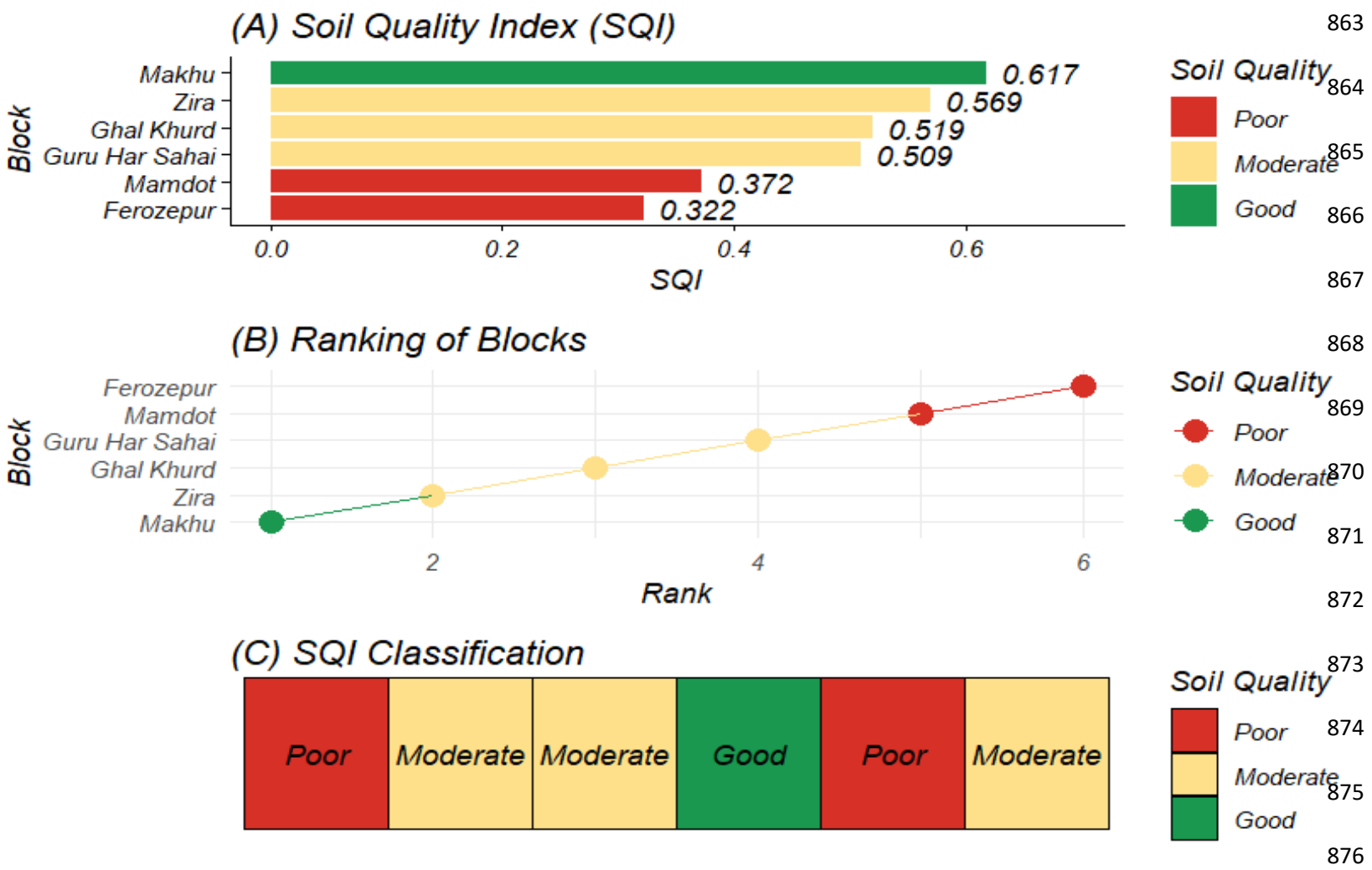


Figure 6. Soil Quality Index (SQI), ranking and classification of blocks using PCA-derived weights