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RESEARCH ARTICLE

Assessing of soil quality index of Holihosur sub-watershed using principal component analysis and geo-statistical techniques

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Abstract

Soil quality is defined as the capacity of soil to function effectively within an ecosystem to sustain plant productivity, maintain or enhance water and air quality and support human health and habitation. This study assessed soil quality and its spatial heterogeneity in the Holihosur sub-watershed, Belagavi district, Karnataka, using 490 surface soil samples. These samples were analyzed through principal component analysis (PCA) and geospatial methods. PCA identified 5 components with eigenvalues greater than one, collectively explaining 60.76 % of the total variance in soil properties. From 12 evaluated parameters, a minimum data set revealed key soil quality indicators: pH, available potassium, organic carbon, available nitrogen, iron and boron. Geostatistical analysis selected the circular semi-variogram model as optimal based on minimal root mean square error, enabling ordinary kriging interpolation. The spatial autocorrelation range of 608.96 m, with a 320 m grid sampling interval, provided sufficient resolution for capturing spatial dependence patterns. This facilitated the creation of detailed thematic maps to support targeted soil management. The moderate nugget-to-sill ratio (0.65) indicated that spatial heterogeneity arose from both systematic pedogenic processes and random environmental influences (climate and management of crops). Spatial distribution results showed that approximately 16% of the watershed had moderate soil quality (SQI: 0.35-0.55), while the majority (76.35 %) exhibited higher soil quality (SQI: 0.55-0.75), indicating generally favorable conditions for agriculture.

Keywords: eigen values; minimum data set; ordinary kriging; semi-variogram modelling; thematic mapping

Introduction

Soil quality is a critical determinant of agricultural sustainability, alongside other factors (management of crop, fertilizer usage, climate etc.) influencing crop productivity. In the context of agriculture, soil quality refers to the soil's ability to sustain productivity over time. It is not a single component to explain about state of soil, it is complex of parameters that influence the state and function. Soil quality indicators can be classified into physical, chemical and biological attributes. The interactions among these components create a complex functional state, underscoring the need to define soil functions in relation to each attribute. It serves as a dynamic and sensitive indicator of soil health, reflecting both its current condition and its response to natural and management practices utilized by farmers. Given its complexity as a functional concept, soil quality cannot be measured directly; instead, it must be inferred from a combination of physical, chemical and biological soil properties (1). As defined earlier, soil quality is the capacity of a specific soil to function within natural or managed ecosystems to sustain plant and animal productivity, enhance or maintain air and water quality and support human well-being (1). Soil productivity is often used as a proxy for soil quality in agricultural research, as both are interrelated. However, soil quality is also closely linked to various forms of degradation: physical (e.g. compaction, excessive tillage), chemical (e.g. nutrient depletion, contamination) and biological (e.g. organic matter loss, decline in microbial activity). The major limitation found in the study area related to soil quality is nutrient deficiency (available nitrogen). To assess the extent of soil degradation and monitor the impact of different land uses and smallholder management practices, such as fertilizer usage and management of crop, a systematic evaluation of soil quality is essential. One of the most widely used tools for this purpose is the soil quality index (SQI), which provides a composite measure of soil function and health (2). Soil quality indices serve as instruments for dynamic soil resource management, enabling agricultural practitioners and extension specialists to monitor soil health patterns and identify when modifications in management practices may be required (3). The SQI is particularly useful for detecting changes in soil condition across different agroecosystems due to its flexibility and integrative nature.

Recent developments in geospatial analytical frameworks, particularly geographic information systems (GIS) and advanced geostatistical methodologies, have revolutionized the spatial characterization and modeling of SQI distributions across heterogeneous landscapes. Geostatistical modeling techniques, including semi-variogram analysis and kriging-based interpolation methods, provide robust mathematical frameworks for understanding spatial autocorrelation structures and estimating soil properties at non-sampled locations with quantified uncertainty levels. Semi-variogram modeling characterizes the spatial dependence structure by analyzing the variance-covariance relationships between sampling points as a function of separation distance, identifying critical parameters such as nugget effect, sill variance and correlation range that govern spatial continuity patterns (4). In this context, the present study was undertaken to evaluate the soil quality status and to map its spatial variability using remote sensing and geostatistical tools in the Holihosur sub-watershed located in the northern transition zone of Karnataka. The findings aim to support land use planning and sustainable soil management in the region.

Materials and Methods

Field description of study area

The study was conducted in Holihosur sub-watershed (watershed code: 4D5B8q), which situated within the administrative boundaries of Bailhongal taluk in Belagavi district, Karnataka state, India. This sub-watershed unit is positioned within the northern transitional agro-ecological zone of Karnataka, representing a critical transition zone between the Western Ghats and the Deccan Plateau physiographic regions. The study area is located at coordinates 15° 44' 1.8" N latitude and 74° 44' 50.5" E longitude, encompassing a total drainage area of 5493.37 ha. The sub-watershed experiences a tropical monsoon climate, transitioning between semi-arid and sub-humid conditions and receives an average rainfall of 859 mm. The thermal regime exhibits pronounced seasonal variations, with maximum temperatures fluctuating between 28 °C and 38 °C during peak summer months (March-May), while minimum temperatures range from 16 °C to 23 °C during winter periods (December-February). The pedological landscape of the Holihosur sub-watershed is dominated by *Vertisols, Inceptisols* and *Entisols.* Agriculture represents the predominant land utilization pattern, covering approximately 70 %-80 % of the total sub-watershed area, with the remaining area distributed among settlements, water bodies and natural vegetation. The cropping systems are primarily monsoon-dependent, with the *Kharif* season (June-September) serving as the principal growing period, coinciding with southwest monsoon precipitation. The principal crops cultivated include maize, sugarcane, jowar, pulses, groundnut, cotton, wheat, soybean and various vegetables such as chilli and tomato.

Soil sampling and laboratory analysis

A topographic map of the Holihosur sub-watershed, at a scale of 1:7920, was digitized and geo-referenced to a standard coordinate system to facilitate spatial data generation and integration within a GIS environment. Soil sampling was conducted during the summer season (February-March) using a grid-based approach, with grid intervals at 320 × 320 m. A total of 490 composite soil samples (0-30 cm depth) were systematically collected across the sub-watershed to ensure comprehensive spatial coverage. Samples were properly labeled, air-dried and sieved through a 2 mm mesh prior to laboratory analysis. Soil pH and electrical conductivity (EC) were determined in a 1:2.5 soil-to-water suspension, following the standard procedure (5). Organic carbon (OC) content was analyzed using the wet oxidation method (6). Available nitrogen ($KMnO_4$-N) was estimated using the alkaline permanganate method described previously (7). Available phosphorus was extracted with 0.5 M sodium bicarbonate (Olsen's reagent) and analyzed according to previously described method (8). Potassium availability (NH_4OAc-K) was measured through flame photometry, following procedure explained by previous researchers (9). Available sulphur was extracted with a 0.15 % calcium chloride solution and its concentration was quantified by turbidometry using a spectrophotometer (Spectronic 20-D) at 420 nm, as per the method described earlier (10). Micronutrients including available zinc (Zn), copper (Cu), iron (Fe) and manganese (Mn) were extracted with diethylenetriaminepentaacetic acid (DTPA) and analyzed using an atomic absorption spectrophotometer (AAS, PerkinElmer) (11). Available boron (B) was determined using the hot water extraction method (12).

Soil quality assessment

The SQI was developed using the minimum data set (MDS) approach to identify a representative set of soil indicators that can effectively describe overall soil quality without the need to measure every possible soil property. To identify the MDS, a sequence of data reduction procedures was carried out, primarily utilizing PCA, using SPSS software (version 26.0) (2). Principal components (PCs) with eigenvalues equal to or greater than one were retained and variables exhibiting high factor loadings within these PCs were selected as representative indicators of key soil attributes. Within each PC, only highly weighted factors were considered for the MDS. The 'highly weighted' variables were defined as the highest weighted variable under a certain PC and absolute factor loading value within 10 % of the highest values under the same PC (13). If there were more than one variable under each PC, correlation was performed between the variables (14). If the variables were significantly correlated, then the one with the highest factor loading and absolute factor loading within 10 % of the highest value were retained and the remaining were eliminated in order to avoid redundancy. If the parameters are non-correlated, then they are considered equally important and were retained in the PC. Each selected indicator was then normalized using a linear scoring technique, with the direction of scoring based on its influence on soil function (15). For indicators where higher values were beneficial ("more is better"), the score for each observation was calculated by dividing it by the highest observed value, assigning a score of one to the maximum. Conversely, for "less is better" indicators, the lowest observed value was divided by each observation. Following normalization, MDS indicators were weighted based on the proportion of total variance explained by their respective PCs. Specifically, the percentage of variance explained by a given PC was divided by the cumulative variance explained by all PCs with eigenvalues greater than one. This resulting proportion was used as the weight for the corresponding indicator. Finally, the SQI for each observation was computed by summing the products of the PCA -derived weights and the normalized scores of the selected indicators, using the Eqn. 1:

SQI = ∑ (PC weight × Individual indicator score) (Eqn. 1)

Spatial variability mapping

The spatial variability of SQI was assessed using the ordinary kriging interpolation technique. For this purpose, SQI values derived from all sampling locations were imported into a GIS as geo-referenced point data via attribute table management. GIS-based analysis was conducted using ArcGIS version 10.4. During the kriging interpolation process, the selection of an appropriate semi-variogram model plays a vital role in determining the weights assigned to spatial predictions (16). These weights are based on the degree of spatial dependence, which is quantified using semi-variance as described in Eqn. 2 (17).

$$\gamma(h) = \frac{1}{2N(h)} = \int_{i=1}^{N(h)} [Z(x_i) - Z(x_{i+h})]^2 \qquad \text{(Eqn. 2)}$$

Where, $Z(X_i)$ = magnitude of the variable Z at location X_i, h = lag distance and N (h) = number of paired sample points segregated by h.

The nugget-to-sill ratio is a fundamental metric for evaluating the extent of spatial dependence in soil characteristics. Based on the earlier classification, strong spatial dependence is indicated when the ratio is below 0.25 (18). A ratio ranging from 0.25 - 0.75 signifies moderate spatial dependence, whereas values exceeding 0.75 suggest weak spatial dependence. The SQI data were processed and categorized into distinct homogenous classes based on defined thresholds: low soil quality (<0.35), medium soil quality (0.35-0.55) and high soil quality (>0.55) (19).

Cross validation

Cross validation was employed to evaluate the performance of various semi-variogram models. The model yielding the lowest root mean square error (RMSE) was chosen to develop the empirical semi-variograms for each soil parameter analyzed. The RMSE was calculated using the formula presented in Eqn. 3.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Z(x_i) - \hat{Z}(x_i)]^2} \qquad \text{(Eqn. 3)}$$

Where, Z (X_i) = observed value at location x_i, = $\hat{Z}$ predicated value at location X_i and N = total number of sample points.

Results and Discussion

A comprehensive soil quality evaluation was conducted across the entire arable landscape of the Holihosur sub-watershed utilizing multivariate statistical analysis through PCA. This study employed a systematic sampling approach, collected and analyzed 490 surface soil samples (0–20 cm depth) to characterize the spatial variability of soil properties across the cultivable area. The PCA technique was employed to reduce the dimensionality of the multivariate dataset while preserving the maximum amount of variance in the original data structure. This approach addresses the challenge of multicollinearity among soil variables and identifies the most significant factors governing soil quality variation within the study area. The eigenvalue-based extraction criterion (Kaiser criterion) was applied, retaining components with eigenvalues exceeding unity ($\lambda > 1.0$). The analysis successfully identified 5 PCs that met this statistical threshold (Eigen values > 1 and percent of variance > 5 %), collectively accounting for 60.76 % of the total variance in the soil quality dataset (Table 1). The MDS were chosen based on the highly weighted factor loading of variables. The scree plot provides a graphical representation of eigenvalues plotted against component numbers, serving as a complementary tool for determining the optimal number of components to retain (Fig. 1).

Selection of MDS

The selection of soil parameters for each PC was systematically conducted based on the magnitude of factor loadings, with priority given to variables exhibiting higher loading values. This approach ensures that the most influential parameters contributing to soil variability are adequately represented in the final minimum data set. Under PC1, the soil parameters that demonstrated the highest factor loadings were available Fe and Mn. These micronutrients emerged as the primary variables explaining the maximum variance in the first component, indicating their significant role in characterizing soil quality within the study area. A multivariate correlation matrix was employed to assess the correlation coefficients among the selected parameters. To minimize redundancy within the MDS, when two variables within the same PC demonstrated a

Table 1. Principal components of soil quality parameters, eigenvalues and component matrix variables

Principal components	PC1	PC2	PC3	PC4	PC5
Eigen values	2.568	1.451	1.165	1.101	1.006
% variance	21.399	12.095	9.706	9.178	8.387
Cumulative %	21.399	33.494	43.2	52.378	60.765
Weightage factor	0.352	0.199	0.159	0.151	0.138
Factor loadings (Rotated component matrix)					
pH	-0.175	**0.709**	-0.111	0.028	-0.021
EC	0.028	-0.099	0.376	0.552	0.361
OC	-0.003	0.103	-0.179	**0.815**	-0.102
N	-0.123	-0.024	**0.713**	-0.265	-0.058
P_2O_5	0.040	0.586	-0.051	-0.097	0.298
K_2O	0.204	**0.634**	0.241	0.215	-0.218
S	-0.180	-0.008	-0.607	-0.126	0.033
Fe	**0.873**	-0.106	0.160	0.008	0.114
Mn	0.844	-0.121	0.117	-0.105	0.124
Cu	0.746	0.046	0.014	0.170	-0.012
Zn	0.600	0.200	-0.194	-0.048	-0.230
B	0.037	0.065	-0.084	0.006	**0.843**

Bolded ones highly weighted variables in each PC, consider for minimum data set.

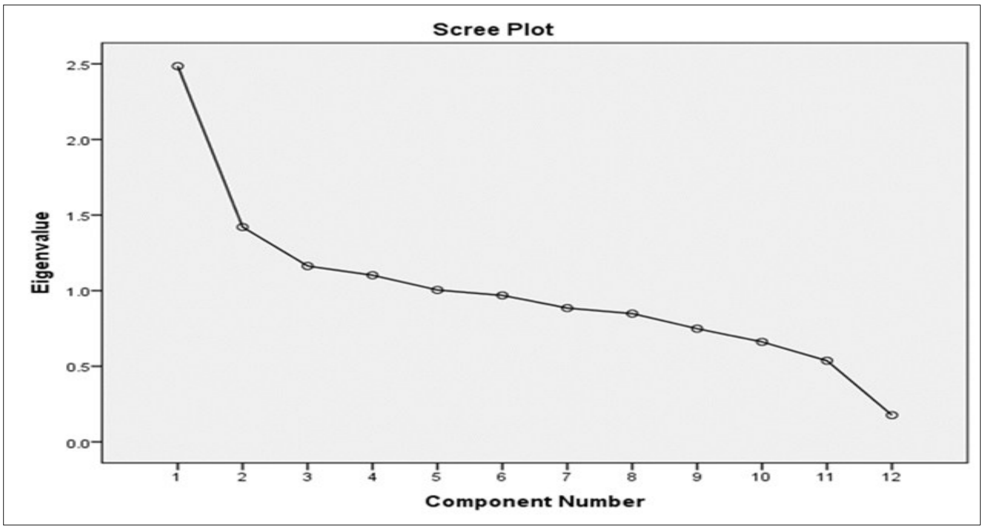

Fig. 1. Scree plot explaining the relationship of eigenvalue and principle component for 0-30 cm depth of soil.

statistically significant positive correlation ($r > 0.60$, $p < 0.05$), only the parameter with the highest factor loading was retained in the MDS. Conversely, parameters that showed non-significant correlations within the same component were considered functionally distinct and were therefore included in the MDS to maintain comprehensive soil characterization (20). Among these, highly weighted variables of PC1, Fe was selected (r = 0.809**) (Table 2). In PC2, available K_2O and pH parameters were highly weighted variables based on the 10 % factor loadings. Here, multivariate analysis showed a weak correlation between the parameters, so both parameters were retained under this PC

Table 2. Correlation between the highly weighted parameters in

	Fe	Mn
Fe	1	
Mn	0.809**	1

** Correlation is significant at the 0.01 level (2-tailed).

(Table 3). The remaining PCs yielded the following representative parameters: available N, OC and B were selected as indicators from PC3, PC4 and PC5 respectively.

Normalization and scoring of selected parameters

Following the establishment of the MDS, a systematic transformation process was implemented to convert the raw parameter values into standardized, comparable units. This normalization procedure employed non-linear scoring functions specifically designed to account for the distinct relationships between individual soil parameters and overall soil quality. The normalization process utilized 3 distinct scoring approaches as "more is better" for available K, N, B and OC. This scoring approach was applied to parameters where higher concentrations directly correlate with improved soil quality and productivity. In contrast, soil pH and available Fe were evaluated using the "optimum is better" approach, as these reflect their critical balance in nutrient availability and biological activity. The normalization process transformed all parameter values to a standardized scale ranging from 0 to 1, where 1 represents the most favorable condition for soil quality and 0 indicates the least favorable condition. These scores were integrated using a weighted additive approach to calculate the SQI for each sample (21).

Table 3. Correlation between the highly weighted parameters in PC2

	pH	K_2O
pH	1	
K_2O	0.215**	1

** Correlation is significant at the 0.01 level (2-tailed).

The final SQI was obtained by summing the weighted scores of each MDS indicator. The relative contribution of individual soil indicators to the overall SQI ranged from 0.06 (B) to 0.15 (pH). Fe exhibited the maximum coefficient of variation (CV) at 58.15 %, while pH showed the lowest CV at 6.19 %, as presented in Table 4. The calculated SQI values spanned from 0.34 to 0.87, with an average value of 0.54 (Table 4).

Soil pH, a pivotal indicator for assessing the quality of soils in the Holihosur sub-watershed, plays a fundamental role in regulating the physical, chemical and biological processes within the soil ecosystem. As a measure of the concentration of hydrogen ions (H^+) in the soil solution, pH reflects the acidity or alkalinity of the soil environment. It exerts a profound influence on soil health and plant productivity in the region. Maintaining an optimal soil pH is essential for enhancing nutrient availability, fostering the activity of beneficial microbial populations, supporting plant development, preserving soil structure and guiding effective crop selection and soil management strategies (22).

OC is a key determinant of soil health, significantly contributing to soil fertility, productivity and the overall functioning of terrestrial ecosystems (23). According to the previous study, OC is a critical component influencing soil

Table 4. Contributions of significant soil parameters to SQI

Parameters	Contribution to SQI	Minimum	Maximum	Mean	SD	CV (%)
Fe	W × optimum is better	0.010	0.344	0.124	0.072	58.15
pH	W × optimum is better	0.129	0.169	0.15	0.009	6.19
Available K_2O	W × more is better	0.023	0.199	0.066	0.030	45.11
Available N	W × more is better	0.059	0.159	0.092	0.018	19.55
OC	W × more is better	0.024	0.151	0.093	0.027	29.05
Available B	W × more is better	0.007	0.138	0.065	0.033	50.58
SQI		0.410	0.887	0.589	0.095	16.110

W= weight of the highly variable factor.

quality and the long-term sustainability of agroecosystems (24). A decline in OC levels is associated with reductions in cation exchange capacity (CEC), deterioration of soil aggregate stability and decreased crop yields. As a major source of essential nutrients, OC directly affects soil productivity and its depletion leads to impaired soil function. OC enhances plant growth by improving both nutrient supply and soil physical structure (25). Furthermore, OC plays an integral role in the global carbon cycle. The degradation of soil organic matter results in the physical deterioration of soil, making organic matter-dependent attributes reliable indicators for assessing soil quality.

Available N is a fundamental determinant of soil quality, playing a central role in regulating plant development, crop productivity and the broader ecological balance of agricultural systems. The presence of adequate available N in the soil is directly correlated with robust plant health, efficient photosynthesis and enhanced biomass accumulation. Nitrogen's influence on soil quality extends beyond plant nutrition as nitrogen availability is both a cause and consequence of healthy microbial dynamics in the soil. In the context of soil quality indexing, available N serves as a dynamic and sensitive indicator, capable of reflecting both current soil management practices and long-term soil fertility trends. Its inclusion in the MDS for SQI calculation is essential for accurately evaluating the soil's capacity to sustain crop growth and ecosystem services under varying land use and climatic conditions (26).

Potassium serves as a fundamental nutrient for maintaining soil fertility. Previous soil investigations in the Zemamra region indicated that K supplementation was necessary to enhance soil fertility status (27). The identification of K_2O as a soil quality indicator in the present study aligns with findings reported earlier (28). Elevated K concentrations in soil enhance overall soil quality, consequently improving agricultural productivity. B and Fe represent crucial micronutrients that play significant roles in soil quality assessment and plant physiological processes. Although these elements are required in trace amounts relative to primary macronutrients, their importance in supporting optimal plant biochemical and physiological functions should not be underestimated. These micronutrients are indispensable for sustaining normal plant development, preventing nutrient deficiency disorders and optimizing crop yields (29). The adequate availability of both B and Fe in soil systems directly influences plant metabolic processes and contributes to overall agricultural sustainability.

Digital SQI mapping by kriging

Spatial variability of the SQI was evaluated using ordinary kriging interpolation. Among the 4 tested semi-variogram models, the circular model demonstrated the best performance based on the lowest RMSE and was consequently selected for SQI analysis.

The geostatistical methodology involved determining spatial variation parameters, including nugget, sill and range values, from the spatial soil database through semi-variogram analysis, followed by kriging interpolation to provide unbiased estimates of soil properties at non-sampled locations. The best-fit semi-variogram model (Fig. 2), along with its associated parameters for SQI, are presented in Table 5. The range of spatial correlation for SQI was determined to be 608.96 m, surpassing the sampling grid distance and thereby validating the adequacy of the sampling design implemented in the Holihosur sub-watershed for detecting spatial relationships. The observed positive nugget effect (C_o = 0.0034) can be explained by factors including analytical errors, small-scale spatial variation, random processes and inherent soil heterogeneity, which aligns with observations reported previously (30).

The ratio of nugget to sill (N:S = 0.65) represents the extent of spatial correlation governed by both structured and random components. This moderate ratio demonstrates that spatial distribution patterns arise from the integrated influence of systematic elements (pedogenic processes, landscape features) and human-induced factors, such as nutrient management, farming operations, crop rotation systems and various land use practices.

The optimal semi-variogram model (Fig. 2) and corresponding parameters for SQI are detailed in Table 5. The spatial correlation range for SQI extended to 608.96 m, which exceeded the grid sampling interval, confirming that the sampling strategy employed in the Holihosur sub-watershed was appropriate for capturing spatial autocorrelation. The positive nugget effect (C_o = 0.0034) observed in the data can be attributed to measurement uncertainties, micro-scale variability, external factors and natural heterogeneity, consistent

Table 5. Parameters of best fitted experimental semi-variogram of SQI

Model	Range (m)	Nugget (C_o)	Partial sill (C)	Sill (C_o+C)	N:S	Spatial dependence
Spherical	608.96	0.0034	0.0018	0.0052	0.65	Moderate

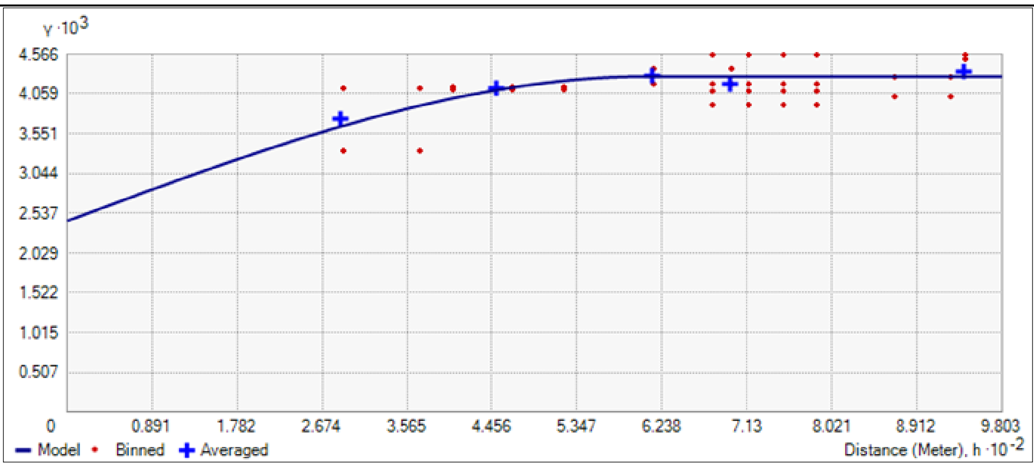

Fig. 2. Best fitted experimental semi-variogram of SQI.

with findings reported (30). The nugget-to-sill ratio (N:S = 0.65) quantifies the degree of spatial dependence influenced by both deterministic and random factors. This relatively high ratio indicates that spatial patterns result from combined effects of systematic factors (soil formation processes, topography) and anthropogenic influences including fertilizer application, agricultural practices, cropping patterns and land management activities.

Geostatistical analysis integrated with GIS enabled the development of spatial distribution maps for SQI classification. The study area was stratified into different quality classes based on index values, with area calculations performed for each category. Cadastral-level spatial variability maps provided survey-wise distribution patterns of SQI across the watershed (Fig. 3). The spatial analysis revealed that approximately 16 % of the Holihosur sub-watershed exhibited medium SQI values (0.35 -0.55), while the majority of the area (76.35 %) was characterized by high SQI values (0.55-0.75), representing the predominant soil quality condition within the study region.

Conclusion

This study underscores the importance of integrated use of PCA, MDS and geostatistics in offering precision soil management to address spatial heterogeneity in agroecosystems. By identifying key soil quality indicators, it enables site-specific interventions that enhance productivity, conserve resources and reduce environmental impacts. The synergy between these statistical methods and emerging technologies holds immense potential. In the future, coupling these approaches with advanced machine learning, remote sensing and big data analytics can support data-driven decisions in fertilizer optimization, crop and variety selection, irrigation scheduling and conservation planning. Such dynamic soil monitoring will foster sustainable agricultural intensification and resilience to changing climatic conditions.

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Authors' contributions

MV participated in drafting the original manuscript, review collection, tables and figures preparation. VBK contributed to the review collection and correction, as well as the tables and figures preparation. SSG, GRR and MVM were responsible for review correction and overall supervision. MPP participated in correction. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare that they do not have any conflict of interest.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing : During the preparation of this work the authors used QuillBot in order to improve language and readability, with caution. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

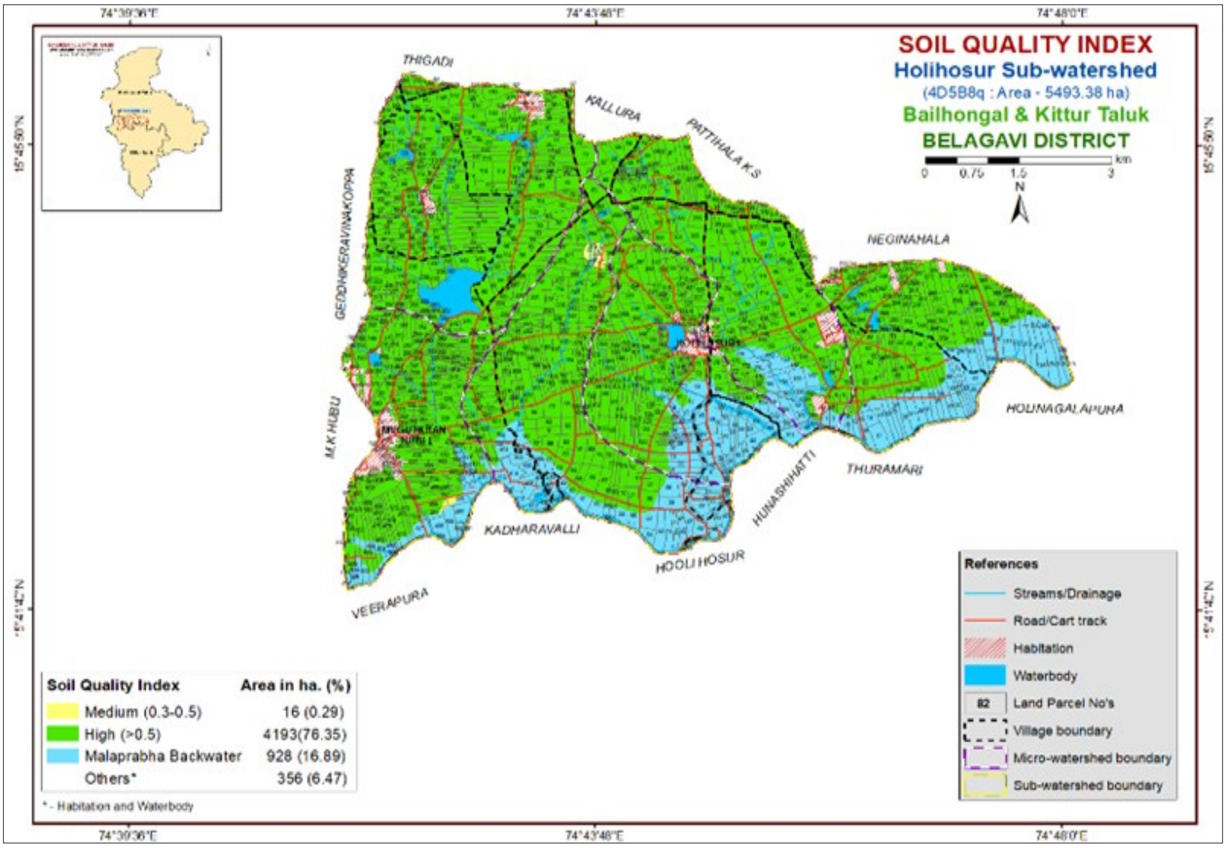

Fig. 3. Spatial variability map of SQI of Holihosur sub-watershed.

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