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Nutrient mapping of soils of Balod district of Chhattisgarh using soil health card data

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Abstract : Soil testing and nutrient mapping are essential tools to optimize fertiliser and manure use, enabling precise, site-specific nutrient management. Detailed maps can be generated by collecting thousands of soil nutrient data points, however, scattered data requires advanced techniques for accurate mapping. This study focuses on using ordinary kriging (OK), a popular interpolation method, to map the physicochemical properties—such as soil pH, electrical conductivity (EC), organic carbon (OC) - and major soil nutrients, including available nitrogen (N), phosphorus (P), and potassium (K), in Balod district, Chhattisgarh.Using data from the National Soil Health Card program, 10,242 data points were selected from over 100,000, with 70% utilised for mapping and 30% for validation. Semivariograms were created for each parameter to understand spatial structures, with various models (spherical, exponential, Gaussian, etc.) evaluated to find the best fit. Spatial dependency ranged from weak (OC, N, P) to moderate (pH, EC, K). Validation of the generated maps yielded accuracy rates of 56% (pH), 66% (EC), 35% (OC), 31% (N), 38% (K), and 57% (P). The analysis revealed that 98% of agricultural soils in Balod were low in available N, with only 2% classified as medium. At the same time, the district exhibited medium levels of available P and high levels of available K.

Key words: *Soil testing, Nutrient mapping, Ordinary kriging, Spatial dependency, Physicochemical properties*

1.0. Introduction

India faces a critical challenge in ensuring food security for its growing population, and achieving higher agricultural production is crucial. However, a significant gap exists between current farm yields and the potential yields achievable through better nutrient management. Indian soils are largely deficient in multiple nutrients, which necessitates proper nutrient management strategies to bridge the yield gap. According to various field surveys, low soil fertility has been identified as a key factor limiting productivity (Kumar et al., 2017).

Farmers and extension workers often lack the necessary information to make informed decisions about soil health and nutrient management, limiting their ability to optimise crop yields. Soil nutrient maps can play a pivotal role in providing crop-specific fertiliser recommendations, enabling farmers to tailor their practices for better results (Sharma et al., 2020). Additionally, such maps could help manufacturers and planners in projecting fertiliser demand based on cropping patterns and intensities.The increasing availability of soil samples through government programs like the Soil Health Card Scheme provides millions of data points, which can be used to generate

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detailed maps of soil nutrients, including micronutrients. These maps are instrumental in advancing precision agriculture and improving soil health (Meena et al., 2021a).

The Soil Health Card (SHC) Program in India, launched in 2015, aims to promote sustainable agriculture by providing farmers with information on soil nutrient status and recommendations for optimal fertiliser use. The program issues individual soil health cards to farmers, containing data on 12 soil parameters, including pH, organic carbon, nitrogen (N), phosphorus (P), potassium (K), and micronutrients like zinc, iron, and boron. The goal is to encourage balanced nutrient management, improve soil fertility, and enhance crop productivity while reducing excessive chemical fertiliser use, thus promoting long-term soil sustainability.

Despite its potential benefits, the SHC program faces several major constraints. Many farmers are unaware of the program or lack the knowledge to interpret the SHC recommendations properly, limiting their adoption of nutrient management practices (Sharma et al., 2018). Soil sample collection, testing, and timely distribution of results are hindered by inadequate laboratory infrastructure, manpower, and logistical challenges (Yadav et al., 2020). Variability in data quality due to improper sampling techniques and inadequate laboratory facilities affects the reliability of SHC recommendations (Singh et al., 2019).While the program encourages balanced fertilisation, many farmers lack access to affordable organic inputs, further limiting the impact on soil health (Meena et al., 2021b). Insufficient financial incentives and technical guidance for adopting sustainable practices reduce the effectiveness of the program in achieving long-term soil health improvement (Kumar et al., 2022).

Several interpolation techniques are being used to map soil nutrients using geologically tagged point data. These techniques estimate regionalised variables at specific grid points, predicting values with minimal bias and variance. Kriging methods are widely accepted for mapping soil spatial variability on a large scale. These include ordinary kriging (OK), universal kriging (UK), indicator kriging, and co-kriging (Kumar and Sinha, 2018). OK is the most commonly used for soil nutrient assessments (Li and Heap, 2014).

The OK method involves creating an empirical semivariogram, determining the best model fit (e.g., circular, spherical, Gaussian, or exponential), and then performing kriging (Moharana et al., 2021; Sahu et al., 2020; Reza et al., 2021). Soil fertility maps have been generated using both grid-based (Ayam et al., 2019) and random sampling techniques (Banwasi, 2020). In Chhattisgarh, high-density soil health card data has been utilised to prepare soil fertility maps for districts such as Kanker (Kusro et al., 2021), Bemetara (Priyadarshini et al., 2021; 2022), and Dhamtari(Bagchi et al., 2016). This study aims to create soil fertility maps for the Balod district using high-density soil health card data and the ordinary kriging method for site-specific nutrient management.

Materials and Method

Study area

The Baloddistrict of Chhattisgarh state of India lies between 20˚24′ to 21˚03′N latitudeand 80˚47′ to 81˚31 ′Elongitude and cover satotal geographical area of 3527 km^2(Fig.1). The study area fall sunder Eastern plateau Agro-climaticzone of India and characterized by hot-humidtropical climate, with an average annual rainfall of 1027.9 mm, out of which maximum rainfall (88percent) received during rainy season (late Juneto October) and 12 percent received during winter season (December to February). The maximum temperature in summer goesto 42˚C, and it varies between 30 to 42 ˚C, whereas in winter, it is as low as 10˚C and varies between 10to25˚C. The soil moisture regime of the district is characterised by *ustic*, whereas the soil temperature regimeis *hyperthermic*.

The soils of the district have been categorized into 4 tax on omic orders, i.e., Entisols, Inceptisols, Alfisolsand Vertisol soccupying the upland, midland, plain, and low land, respectively (Kumar, *et al.*, 2019). Variation sin most of the soil properties in the district are closely related to the irposition on the land scape. The southern peripher yundulating to pographyo flow hills characterises the Balod District physiographically. The district's general lope is north-east, which is the direction in which the district's primary streamsrun. The total forest area of this district is 878$_4$ 0 ha. Out of this, the protected forest area is 1129$_4$ ha, unprotected for estis 63507 ha and unclassi fied is 11$_4$ 91ha. The agriculture in the district is rice - based, which is followed by fallow / wheat/chickpea / lathyrus (Kumaretal., 2020).

Generation of spatial data base of soil nutrient

The village-wise soil health card data downloaded from the soil health card portal (https://soilhealth.dac.gov.in/) was cleaned and converted to a geo-database. The cleaning process included removing unwanted rows and columns, rows with missing information, and unacceptable values from the tabular data. After the conversion of tabular data to a geo-database, it was again cleaned for spatial accuracies and data duplications. Finally, the geo-database was reprojected from a geographical coordinate system to a projected system. The data were also split in to calibration and validation set sina 70:30 ratios.

Statistical Analysis

Descriptive statistics such as mean, median, mode, range, variance, standard deviation, standard error, skewness, and kurtosis of soil physic-chemical properties and soil nutrient variables were analysed in R. To study their relationships, the correlation coefficient among the variables was also estimated. Various packages in R were used.

Nutrient Mapping

The ordinary kriging approach was used form aping the soil properties (pH,EC, organic carbon, N,P, and K). The steps include the generation of an empirical semivariogram, fitting of various models, and interpolation by kriging. Semivariograms were used tore presentspatial variability, implying homogeneity among equivalent lag stoillustrate the me and eviation between observations differentiated byh. The values of the semivariogram at each lag separation (h) were measured:

Where,

$$\gamma(h) = 1/2(h)\sum_{i=1}^{N(h)}[z(xi) - z(xi+h)]^2$$

$\gamma(h) = Samplesemi\,\mathrm{var}\,iance$

$N(h)$ = Numeric data combinations at a particular distance and direction class

$Z(x_i) = Value\ of\ \mathrm{var}\,iable\,at\,x_i\ po\,\mathrm{int}$

$Z(x_i + h) = Value\ of\ \mathrm{var}\,iable\ at\ disance\ of\ h\ from\ the\ po\,\mathrm{int}\,x_i$

Each soil attribute was fitted with one off our semivariogram models : Circular, Spherical, Gaussian, and Exponential. The model with the lowest sum of squarederror (SSE) was selected as the best-fit model, and its parameters (nugget, sillandrange) were calculated (Webster and Oliver,2001). Nugget (C_0) defines the micro- scale variability measurement error for there spective soil variable, sill(C) indicates the lag distance between measurement sat which one value for avariable does not influence neighbouring values and range (A) is the distance at which values of one variable become spatially independent of another. Arc GIS Desktopver. 10.2 was used for the geostatistical analyses.

Validation of kriged thematic maps

The kriged maps were validated with the validation set to assess the certainty of soil maps. The performance of each spatial interpolation method was evaluated using standard methods like R^2, Lin's concordance correlation coefficient (LCCC), root mean square error (RMSE) and bias.

Results and Discussion

Descriptive Statistics

The descriptive statistics of the soil properties in the district are shown in Table 1. The soils were slightly acidic to alkaline in reaction (5.31 to 8.5), with a mean of 6.97. EC of the soils ranged from 0.01 to 1.55 dSm^{-1} with a mean of 0.51 $dSm^{-1,}$ indicating non-salinity in the soils of the district. The OC content in the soils was low to high, ranging from 0.02-1.35% with a mean of 0.59 %. The concentration of major available nutrients N, P, and K ranged from 100 to 404.8 kg/ha (mean 222.4 ±55.28), 5 to 40.61 kg/ha (mean 15.63±7), and 3 to 760 kg/ha (mean 373±155), respectively. The skewness and kurtosis values were well within the range of -1 to +1 (except for P), indicating normal distribution and no substantial skewness in the data. The variability of soil variables was interpreted as per Wilding (1985) using the CV (coefficient of variation) classes as highly variable (CV > 35%), moderately variable (CV 15 to 35%) and low variable (CV < 15%). Accordingly, low variability was found in soil pH and moderate in the case of N; the other parameters were found to be highly variable.

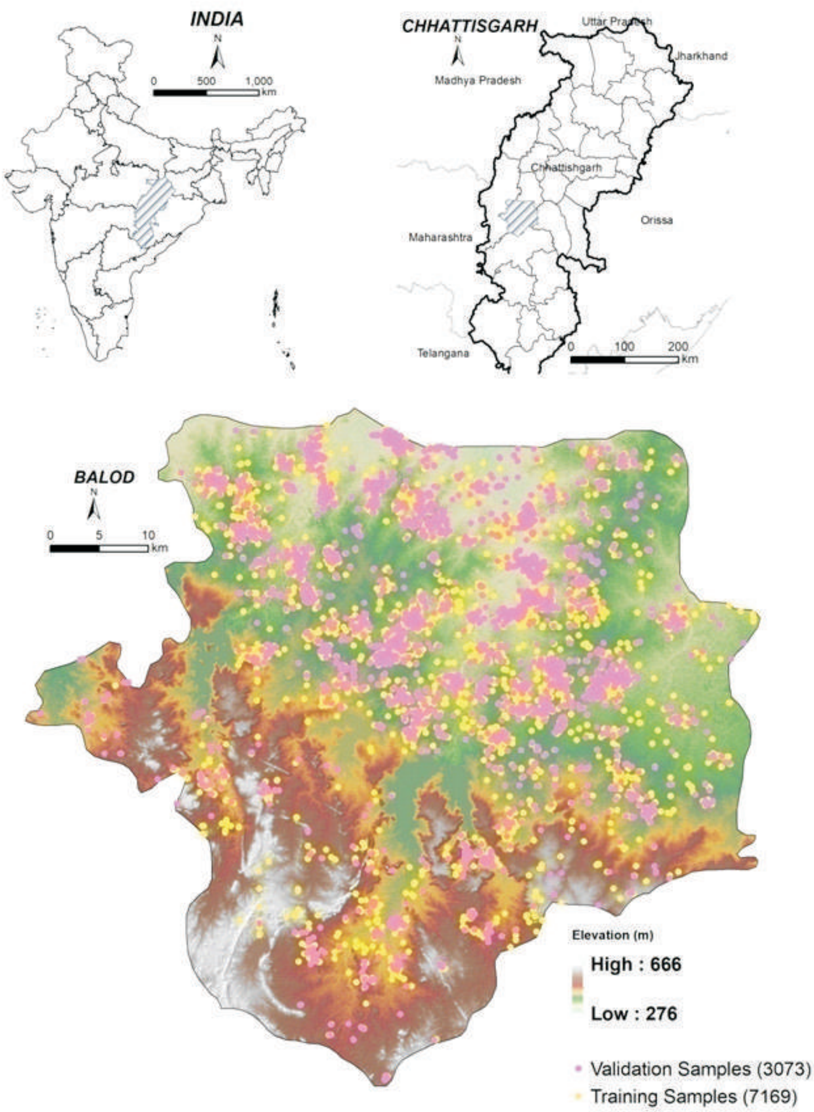

Fig.1. Studyareaandsamplelocations

Table 1 : DescriptiveStatisticsofsoilproperties

Variable	Min	Max	Mean	Median	SD	SE	Kurt	Skew	CV	Ci
pH	5.31	8.50	6.97	7.00	0.57	0.01	-0.26	-0.25	8.12	0.01
EC	0.01	1.55	0.51	0.46	0.29	0.00	-0.32	0.54	56.70	0.01
OC	0.02	1.35	0.59	0.58	0.24	0.00	-0.07	0.30	41.52	0.00
N	100.00	404.80	222.41	213.20	55.28	0.55	-0.27	0.36	24.85	1.07
P	5.00	40.61	15.63	13.44	6.98	0.07	2.07	1.44	44.67	0.14
K	3.00	760.40	373.35	387.90	154.87	1.53	-0.20	0.06	41.48	3.00

Min: Minimum, Max: Maximum, SD: Standard Deviation, SE: Standard Error, Kurt: Kurtosis, Skew: Skewness, CV: Coefficient of Variation, Ci: Conformity Index

Correlationamong Soil Nutrients:

Figure 2 depicts the correlations between soil nutrients, pH, and EC. The correlation matrix indicates a highly significant, strong, and positive connection between OC and available N. The OC also shows a significant positive correlation with available P. Soil pH is found to be non-correlated with all nutrients, with EC being positively correlated.

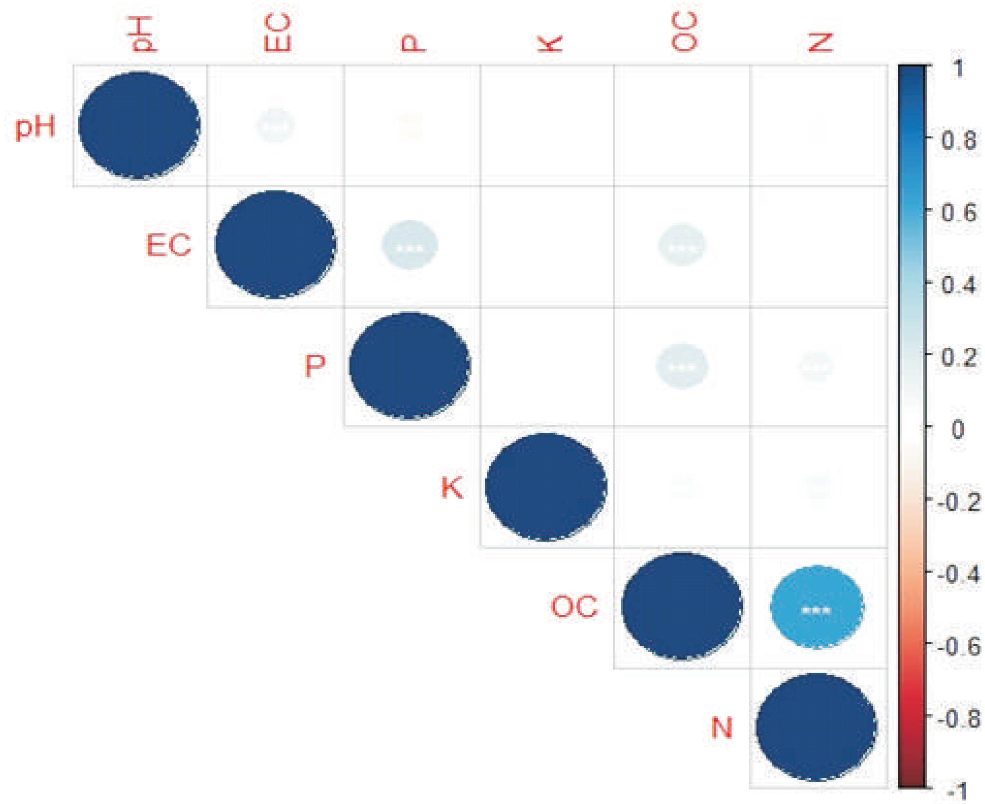

Fig. 2. Correlation matrixes of soil nutrient parameters

Soil fertility status of the district:

Fig. 3 illustrates the fertility groupings based on the number of samples classified as low, medium, or high for nitrogen (N), phosphorus (P), and potassium (K), along with their co-occurrence frequencies. The soils in the district were predominantly low in N, medium in P, and high in K, with 47% of samples (4808) falling into this category. Additionally, 11% of samples (1177) were low in N and medium in both P and K. Of the 10,242 samples, 8680 were low in N, while 7493 were high in K and 7329 were medium in P.

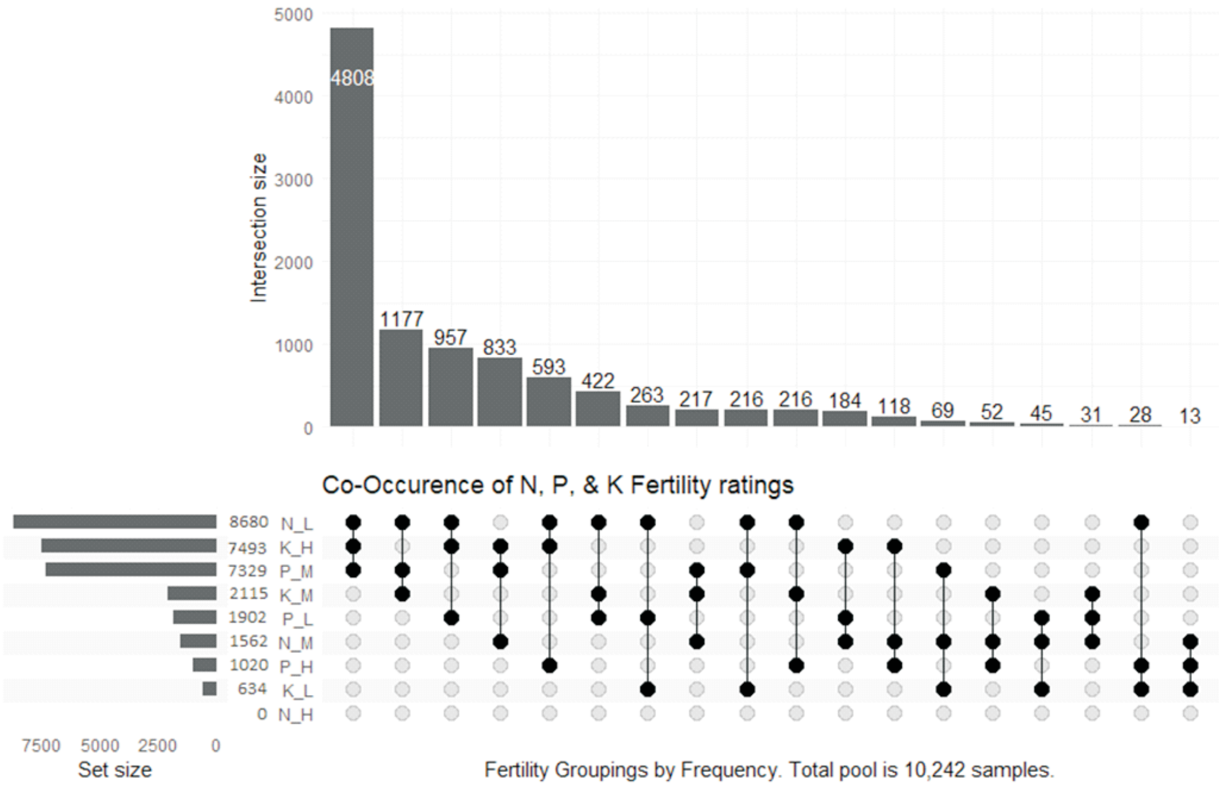

Fig. 3. Waffle plot showing fertility groupings in terms of number of samples falling under low, medium and high categories of N, P, and K and their co-occurrence frequencies

Variogram Modeling

To determine the various spatial structures of distinct soil qualities, semi variograms were created for each parameters (Fig.4). For each semi variogram, the best-fit model was determined based on the RMSE. The range, stated in meters, may be regarded as the diameter of the zone of effect, which indicates the average maximum distance between two samples′ soil properties. With the decreasing distance between the two sites, observed attributes of the two samples became comparable at distances smaller than the range. As a result, the range produced an estimate of similarity areas. Nugget (Co) denotes the degree of variation that is described by the "spatial correlation structure", where as partial sill (C) indicates the micro- scale variability and measurement error for the specific soil parameter (Kumar, 2013; Kumarand Sinha,2018). The models- exponential for pH, circular for EC, Gaussian for OC, and spherical of N,P, and K- were found to be performed satisfactorily. The nugget to sillratio (spatial dependency) was moderate for pH,EC, and K and week for OC,N, and P, according to Cambardella *et al.* (1994) (Table 2). A lower nugget/ sillratioin dicates that the structural factorse.g. factors of soil genesis play significant role inspatial variability (Shitetal., 2016).

Table 2 : Best fit model for the empirical semivariograms and their statistics

	Nugget	Partial Sill	Range	Sill	Nugget/ Sill	Model	Spatial dependency
pH	0.1	0.3	2084.0	0.4	0.28	Exponential	Moderate
EC	1.7	4.8	433.0	0.1	0.39	Circular	Moderate
OC	3.6	6.1	1740.0	0.1	0.58	Gaussian	Week
N	2208.0	785.0	5925.0	2993.0	0.74	Spherical	Week
P	34.4	18.3	17182.0	52.6	0.65	Spherical	Week
K	6331.0	8099.0	556.0	14430.0	0.44	Spherical	Moderate

Kriging

After the semivariogram model fitting, the entire district was interpolated with kriging for each soil variable. A 30 m empty grid was prepared for the entire district, and the model was transferred to it. The maps generated are shown in the Fig. 5.

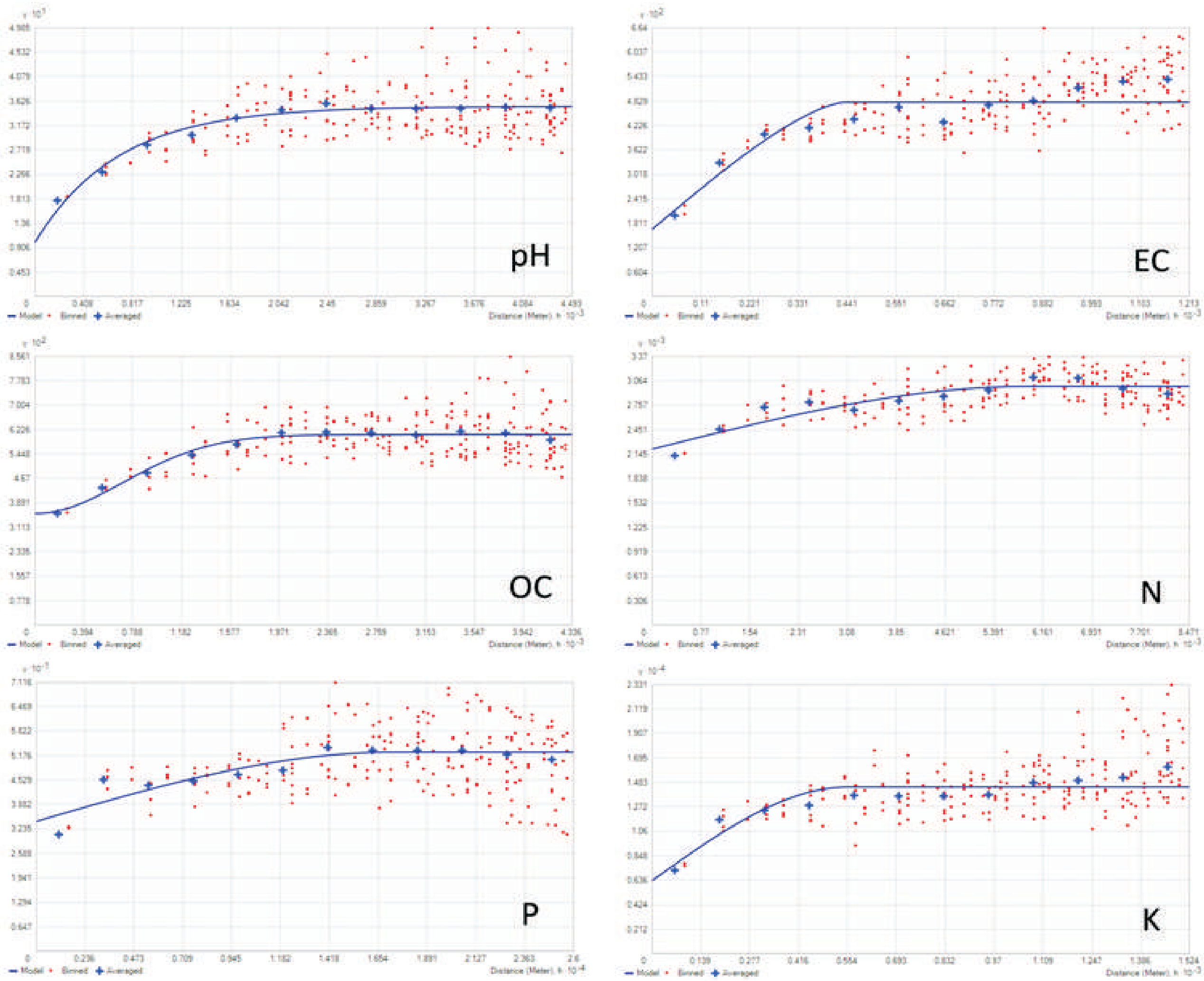

Fig. 4. Semivariogram model for the soil parameters

The inter polatedmaps show edthat the soils were slightly acidic to slightly alkaline inreaction, with a pH range of 5.3 to 8.5. The soils were mostly neutral, covering 89.6% of the total agricultural area (TAA) of the district. In nearly 2% of the area in the plains, soils are slightly alkaline, and slightly acidic soils (8.4 %) mostly occurin the foot hills (Fig.6). All of the samples had an average EC of 0.69 dS m^{-1}, with values ranging from 0.03 to 1.5 dSm^{-1}. Thus, the entire district′s soils were non-saline. The soils were mostly medium ins oil OC (63.7% of TAA) with some distinct patches of low organic carbon soils (28.4 % of TAA) in the eastern parts of the district. This may bedueto intensive agriculture in the searea sand lighter soils. The soils of these parts, of the district are clayloamands and yloam (Kumaretal., 2017).

Validation and accuracyassessment

Spatial distribution maps of soil properties were valid at edusingcross-validation and independent validation with a validation set of 3073 sample points. Evaluation indices of the predicted pH, EC, OC, N, P, and K through the OK approach are shown in Table 3. The indices for different properties follow patterns of spatial dependency. Higher cross-validation and independent validation accuracies were observed for pH, EC, and K, which showed moderate spatial dependency while the semivariogram model was fitting.

Table 3: Various validation indices of the models

Variable	Validation	R^2	Concordance	MSE	RMSE	bias
pH	Crossvalidation	0.82	0.89	0.06	0.24	0.00
	Independentvalidation	0.56	0.71	0.14	0.38	0.00
EC	Crossvalidation	0.89	0.93	0.01	0.10	0.00
	Independentvalidation	0.66	0.79	0.03	0.17	0.00
OC	Crossvalidation	0.52	0.65	0.03	0.17	0.00
	Independentvalidation	0.35	0.53	0.04	0.19	0.00
N	Crossvalidation	0.41	0.53	1755.41	41.90	-0.10
	Independentvalidation	0.31	0.45	2089.74	45.71	0.60
P	Crossvalidation	0.48	0.61	25.93	5.09	0.00
	Independentvalidation	0.38	0.54	30.78	5.55	0.09
K	Crossvalidation	0.83	0.90	3981.46	63.10	0.35
	Independentvalidation	0.57	0.72	10469.50	102.32	1.50

The agricultural regions in the district were distinctly low in N, and, in some patches, covering only 2 per cent of the total agricultural area (TAA), soils had a medium category of N. The district was found to be medium in phosphorous and high in potassium. Similar fertility status in the district has been reported by Kumar et al. (2019).

The validation indices followed the same pattern as the semivariogram models′ spatial dependencies. The pH, EC, and K were well predicted with independent validation R^2 of 0.56, 0.66, and 0.57, respectively. The spatial dependencies of their semivariogram models were also moderate. The LCCC values ranged from 0.45 to 0.79 for different soil properties in the study area, showing moderate to good correlations. An LCCC value equal to 1 indicates perfect positive agreement between observed and predicted values, whereas -1 indicates perfect negative agreement.

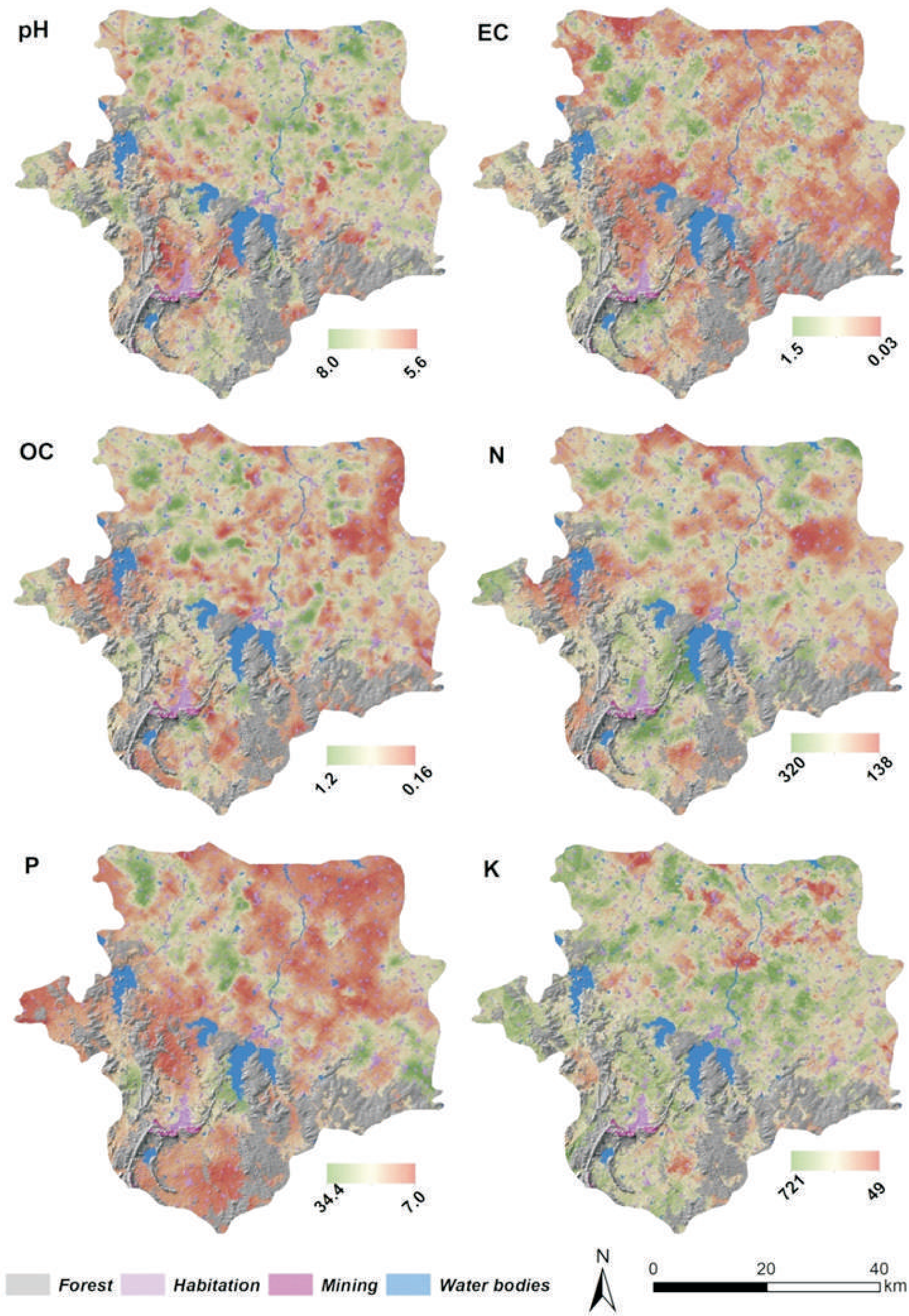

Fig. 5. Soil properties′ maps developed using ordinary Kriging

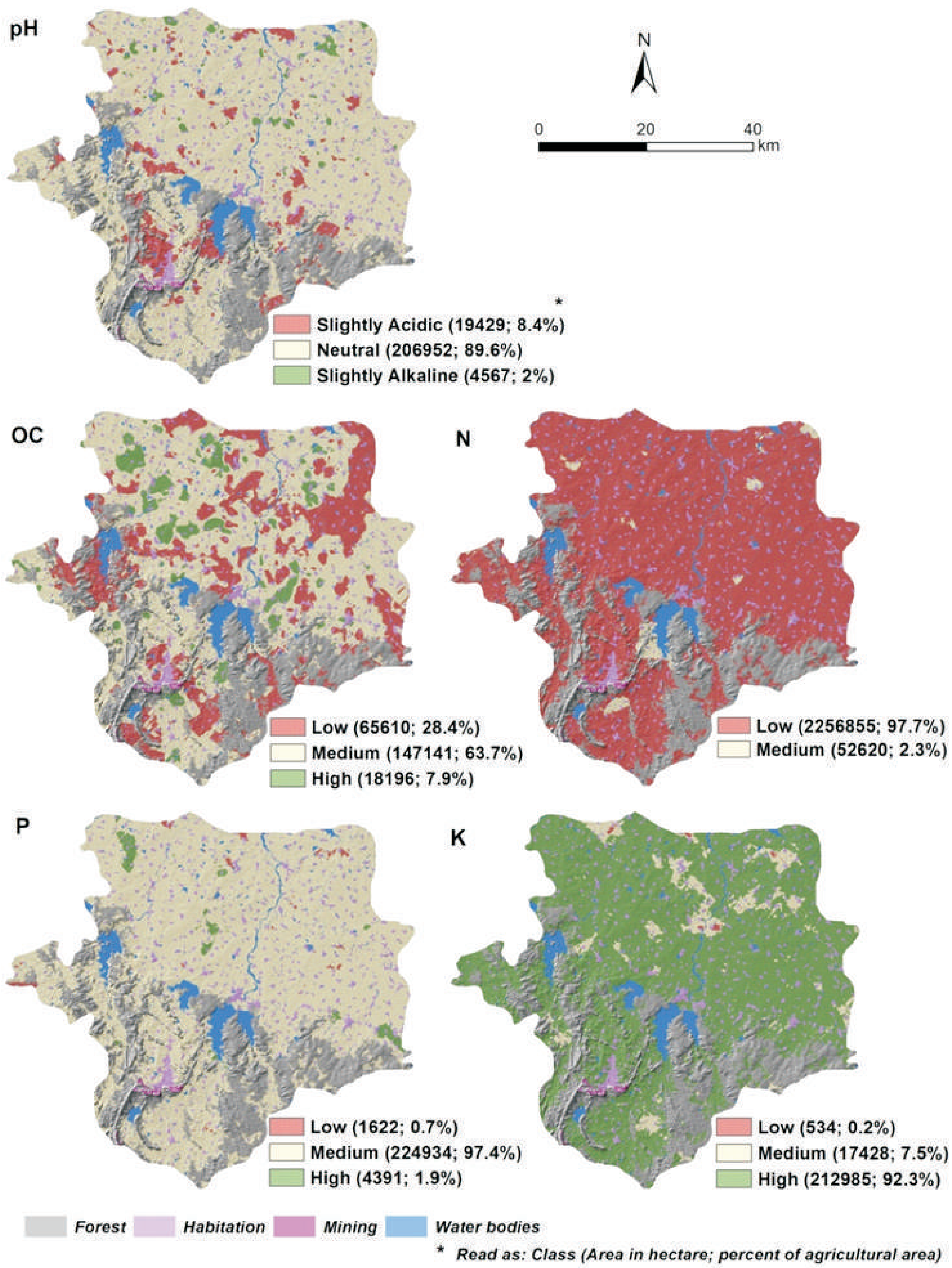

Fig. 6. Spatial distribution of soil properties in various categories

Conclusion

In the present study, ordinary kriging (OK) was successfully applied to map the spatial variability of key soil properties and nutrients in the Balod district of Chhattisgarh, utilising data from the National Soil Health Card program. The analysis provided valuable insights into the soil fertility status, revealing that 98% of agricultural soils in the district were deficient in available nitrogen. At the same time, phosphorus levels were mostly medium, and potassium levels were predominantly high. The semivariograms demonstrated varying spatial dependencies, with weak correlations for organic carbon, nitrogen, and phosphorus and moderate correlations for pH, electrical conductivity, and potassium. Validation of the nutrient maps showed accuracy rates ranging from 31% to 66%, confirming the effectiveness of OK for spatial nutrient analysis. These findings emphasise the importance of targeted nutrient management to address soil fertility gaps and optimisefertiliser application, ultimately improving agricultural productivity in the region.

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