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Evaluating and Mapping Soil Quality in a Limestone Mining Landscape using GIS: Insights from Ramganjmandi, Rajasthan

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ABSTRACT

The study aims to predict soil properties, including major and micronutrient levels in Ramganjmandi, India, an administrative unit significantly influenced by limestone mining. The human- environment relationship in the region is largely dictated by mining activities which expanded from 10.66 km^2 in 1990 to 50.03 km^2 in 2020. This extensive mineral extraction has led to deterioration in soil quality across mining belt. A total of 24 samples were collected using purposive random sampling. The inverse distance weightage method was applied in Arc GIS software through spatial analyst tool to interpolate the values of unsampled sites and PCA was executed using R studio. The results indicate that 95.83% of the samples are alkaline, with low organic carbon, organic matter and nitrogen content. Furthermore, 62.5% of the samples exhibit medium phosphorus and potassium levels, while 87% of the samples shows medium sulfur content,91.66% of the samples are marginally deficient in zinc, and 70.83% are deficient in iron. Notably, calcium content is exceptionally high ranging from 232 to 1088 ppm, while magnesium levels vary between 81.66 to 300 ppm. Principal component analysis revealed that PC1 and PC2 together explains 62.9% of the total variance effectively capturing the major patterns in soil chemistry. PC1 is primarily influenced by Organic content, nutrients and conductivity, while PC2 distinguishes pH and trace elements. Clear natural clusters suggest strong collinearity among variables like Organic Matter, Nitrogen and trace metals. The findings underscore the significant impact of limestone mining on soil degradation and potential implications for agricultural productivity and environmental sustainability.

Keywords Inverse distance weightage, Digital soil mapping, Interpolation, Prediction, Soil properties, Limestone mining, Principal components.

INTRODUCTION

Mining activities significantly alter soil composition and by removing topsoil, reducing organic matter and increasing heavy metal contamination (Masto *et al.* 2015). Studies indicate that mining regions often experience higher soil alkalinity and depletion of essential nutrients (Zhang *et al.* 2018). In limestone mining belt calcium accumulation can lead to soil structure degradation, further affecting fertility (Shrestha & Lal 2011). Research conducted by Singh *et al.* (2020)

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in Indian mining districts shows a direct correlation between mining expansion and declining soil health with adverse effect on agricultural productivity. Similarly Verma *et al.*(2019) reported that mining induced land degradation leads to low organic carbon and a decline in essential nutrients such as nitrogen and phosphorus. Crying sustainable future, awareness is low, all we are leaving is, legacies of contamination. 'Soil contamination' refers to chemicals or substances not in place and/or present in concentrations higher than normal, adversely affecting all non-target organisms. Soil contamination poses a serious threat to agricultural productivity, food security, human health, industrialization, warfare and mining, according to the Food and Agriculture Organization. Agricultural intensification has left a legacy of soil pollution. Soil has limited potential to deal with contamination. Soil contamination prevention should be a top priority globally. Urbanization is progressing rapidly, but pollution is the mark it leaves behind. About 80,000 sites in Australia face soil contamination. 19% of agricultural soils and 16% of classified soils in China have been declared polluted and contaminated. About 3 million sites in the European Economic Area and the Western Balkans could potentially be contaminated, and there are nearly 1,300 contaminated hotspots in the United States (Food and Agricultural Organization 2018).

The steady increase in soil contamination and degradation has led to the emergence of digital soil mapping to predict soil properties and potential levels of toxic elements in soil. In general, digital soil mapping focuses on modelling points or pattern observation points representing the relationship between soil and environment using multiple parameters such as climatic factors, geological factors, slope angle, topography, moisture index, to form a quantitative soil-environment relationship. Digital soil mapping applies models to calculate soil property values at unknown locations or unsampled sites (Agyeman *et al.* 2021). Digital soil mapping focuses on using data from sampled sites to predict values for unsampled sites. Using quantitative tools available from GIS and statistics, there are several ways to identify patterns and use those patterns to make predictions about unobserved or unsampled locations. Accurate soil data is required to produce reliable, high-resolution soil maps for hydrological analysis, conservation, agriculture, and forestry. The different information required for soil classification comes from sources with different spatial resolutions and can be easily stored in a Geographic Information System (GIS). Save and process. The quality of soil models depends entirely on the quality of the input data (Pereira *et al.* 2017). Predictive models can be accurate or inaccurate. An accurate model produces a value equal to the quantity measured at the observation point. An inaccurate model does not need to produce a surface map that matches the observer values.

The spatial heterogeneity of soil leads to obscurity in the modelling process. Gao *et al.* (2022) predicted the soil moisture of litchi orchards with the aid of meteorological information. The results indicated that the root mean square error values of the Deep-LSTM model were 0.36, 0.52, 0.32, and 0.48% in several bud stages of flowering, fruiting, autumn shoots and flower respectively. The proposed model turned out effective in predicting soil moisture in advance providing a valuable reference for the irrigation in litchi orchards. Soil organic carbon maps were prepared from the mainlands of China from the National Soil data set of 2010 on a voting based ensemble learning model with a consideration of pedoclimatic zones. A comparative model weighted ensemble learning model WELM was also run simultaneously. The whole R2 values of these two techniques ranged from 0.16 to 0.57 and declined with depth. Based on the independent validation, the R2 values varied between from 0.41 to 0.57 in the topsoil (Song *et al.* 2019). Integrating soil physical, chemical, fertility and environmental aspects is significant to achieve sustainable agricultural development.The GIS model created was based on chemical quality index, Physical Quality Index, Fertility Quality Index and Environmental Quality Index. The vector layers of these indexes were converted to raster and then subjected to raster calculator to derivate the geometric mean that represents the final quality index (Abuzaid *et al*. 2021). Soil properties of Monergala, Sri Lanka, including pH, electrical conductivity and bulk density were interpolated using inverse distance weightage method in Arc GIS using spatial analyst tool. The spatial parameters of pH, EC, and moisture content clearly do not have a significant relationship with elevation. The study was carried to predict hazard zonation of the region using based on the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) sediment delivery ratio model (SDR) (Perera *et al*. 2020). Fuzzy Logic constitutes a conceptual approach for spatial modelling. This method is generally selected when there are no occurrences or minimum occurrence of data for further statistical analysis(McBratney and Odeh 1997). Beucher *et al.* (2015) performed fuzzy logic in Arc GIS and in spatial data modeller. In their study over Sirppujoki River catchment Finland, they used an Artificial neural network known as radial basis functional link net (RBFLN). The RBFLN modelling was performed using ArcGIS 10. The study utilized more than 500 soil profiles (Abdalla 2022). In order to under the soil quality(SQ) variation in north eastern Iran, Maleki *et al.* (2022) used Random Forest model through DSM to understand the relationship between SQIs and environmental covariates. The results of the study indicated that the MDS (Minimum Data Set) model was a more reliable, fast and economical method than TDS(Total Data Set) to select the minimum effective soil properties in any study area. Schönauer *et al.* (2022) presented several methods to predict the soil moisture content (%vol) to understand soil strength and trafficability. High resolution topographic information including DTW (depth to water) and topographic wetness index were used to predict to develop linear models, a generalized additive model, Random Forest (RF) and Extreme Gradient Boosting (XGB). Predictions made with Random Forest and extreme Gradient Boosting attained the highest R2 values of 0.49 and 0.51.

Few of the soil prediction models include fuzzy methods, multiple linear regression (MLR), (enhanced) regression trees (RT), inverse distance weighting (IDW), geostatistics, regression kriging, kriging(Ordinary, Simple, Universal, Indicator, Probability) polynomial models, Bayesian methods, classification/decision trees, random forests (RF), artificial neural networks (ANN), partial least squares regression (PLSR), principal component regression (PCR), support vector machines (SVM)), multiple additive regression splines (MARS), (Agyeman.*et al.* 2021). Interpolation is the technique of reading between the rows of a table. Geostatistics engages with natural spatial & temporal data and estimates variable values (Ibrahim & Nasser 2015).

IDW method of interpolation is used for estimating unknown values based on the location of already known data points (Özkan *et al.* 2020, Vandana *et al.* 2024, Nungula *et al.* 2024, Kaing *et al.* 2024). The assumption in IDW is that the effect of a sample point over an undetermined locus is in inverse proportion to the span between them (Vandana *et al.* 2024, Manjeet *et al.* 2024). It is singularly useful when the data displays 'spatial autocorrelation' i.e. closer values are more similar and are simple as well as easy to implement (Kaing *et al.* 2024). The estimation of IDW is through:

$$R(X) = \frac{\sum_{j=1}^{m} z(X_i)\, d_{ij}^{-r}}{\sum_{j=1}^{m} d_{ij}^{-r}}$$

Where x = point of estimation, x_i = point of data, r = weight, m = weigh-determining coefficient based on a distance, and d_{ij} = distance between the data and estimated points given by

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

(Vandana *et al.* 2024, Kaing *et al.* 2024, Anh *et al.* 2025). Being an average of weighted distance, IDW the estimated values cannot exceed the extremes of input values, i.e. cannot create 'ridges and valleys' (Rana & Sharma 2020). Geostatistical methods and GIS provide improved interpolation techniques with greater accuracy and better illustration of spatial relationships (Tagore *et al.* 2014, Dutta *et al.* 2024). Soil suitability maps aid in optimizing agricultural productivity (Halder 2013, Abdel Rahman *et al.* 2016, Ausari *et al.* 2020, Sahu *et al.* 2020).

MATERIALS AND METHODS

Study area

Ramganjmandi is a tehsil (Subdivision of a district) in Kota district of Rajasthan India. The region is semi-arid and was once famous for coriander cultivation. The

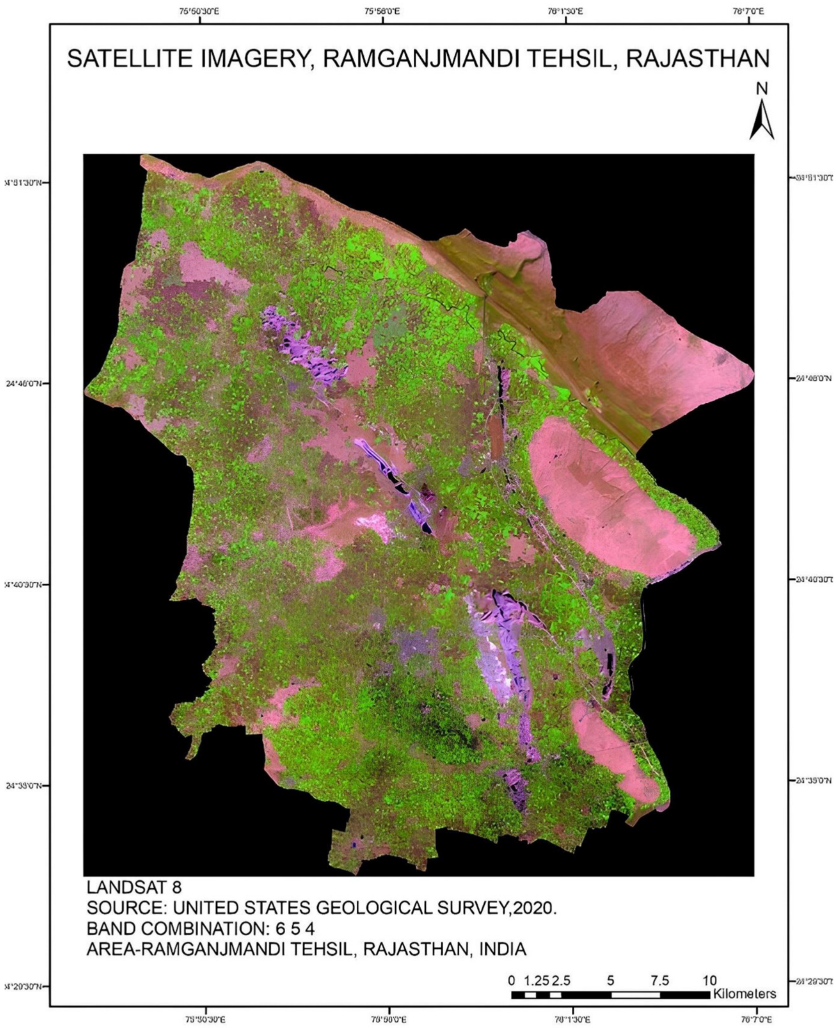

Fig. 1. Locational aspect of Ramganjmandi tehsil, Kota, Rajasthan.

latitudinal extension is 24° 08´00´´N to 24° 11´ 10´´N and the longitudinal extension is 75° 13´ 04´´ E to 76° 01´ 57´´ E (Fig.1). The average maximum temperature is 48°C and the average minimum temperature is 9°C, with an average rainfall of 85.18 cms. The soil is black with deposits of limestone. The region is undergoing massive limestone mining activity, leaving the land degrading, water air and soil polluted, and mass loss of vegetation and an emerging problem of limestone scraps disposal. It seems the region has developed a new topography, because of the mounts of kota stone or limestone scraps.

***Sampling and methods*-** Purposive random sampling is used to collect samples. The tehsil was considered as a single sampling unit, uniform in all aspects. The sampling was focused on 36 villages and 7 census towns. The sampling is also executed from the regions away from the mining activity to obtain the differential. A total of 24 soil samples have been collected from the tehsil, primarily focussing on the mining belts of Kumbhkot, Julmi, Chechat, Satalkheri using Coning and Quartering Method (Fig. 2). The soils samples were tested for pH (soil-water suspension using glass electrodes, (Richards1954), Conductivity

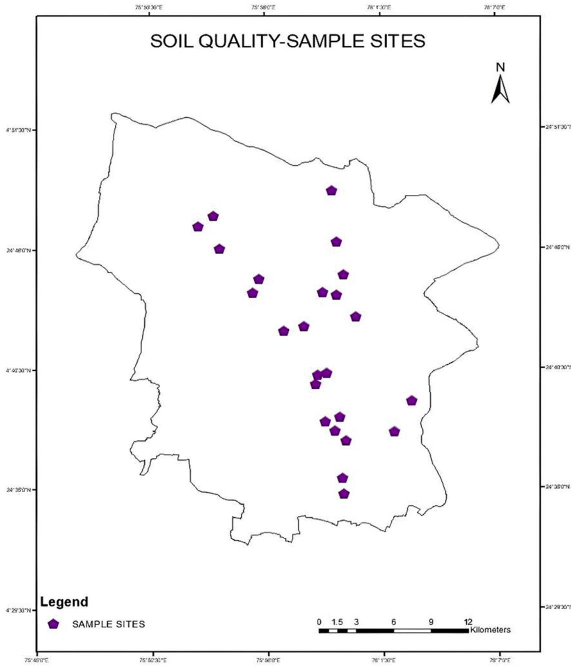

Fig. 2. Location of soil samples, Ramganjmandi, Rajasthan, India.

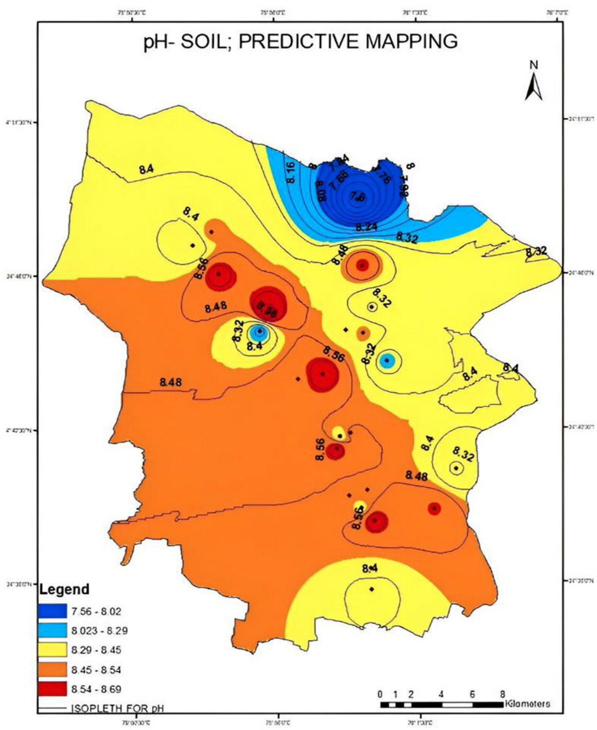

Fig. 3. pH and predictive mapping.

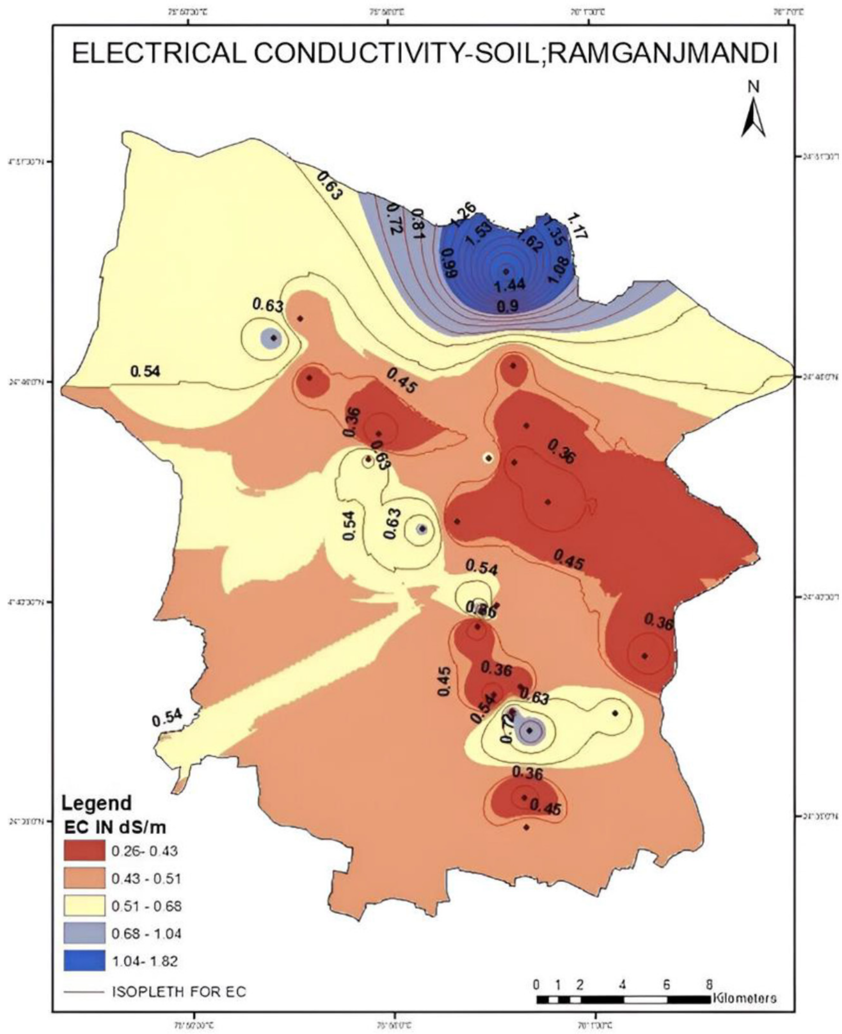

Fig. 4. Electrical conductivity and predictive mapping.

(using conductivity bridge (Richards 1954)), Organic Carbon (Walkley and Black Wet Digestion Method (Jackson 1958), Available Nitrogen (Alkaline Potassium Permanganate Method (Subbiah and Asija1956), Available Phosphorus(Olsen.*et.al.*1954), Available Potassium (K_2O) (Normal Ammonium Acetate Extraction (Richards 1954), Available Sulfur (Williams and Steinbergs 1959), Available Zinc (DTPA method of Lindsay and Norvell (1978) through Atomic Absorption Spectrophotometer), Available Iron (DTPA method of Lindsay and Norvell (1978) through Atomic Absorption Spectrophotometer), Available Manganese (DTPA method of Lindsay and Norvell (1978) through Atomic Absorption Spectrophotometer), Available Copper (DTPA method of Lindsay and Norvell (1978) through Atomic Absorption Spectrophotometer), Exchangeable Calcium and Magnesium(Versenate (EDTA) Titration Method). Inverse Distance weight age method was used for predicting values at the unsampled sites under spatial analyst tools of Arc GIS. Isopleths for each parameter is also generated under 3D analyst tool of ArcGIS.

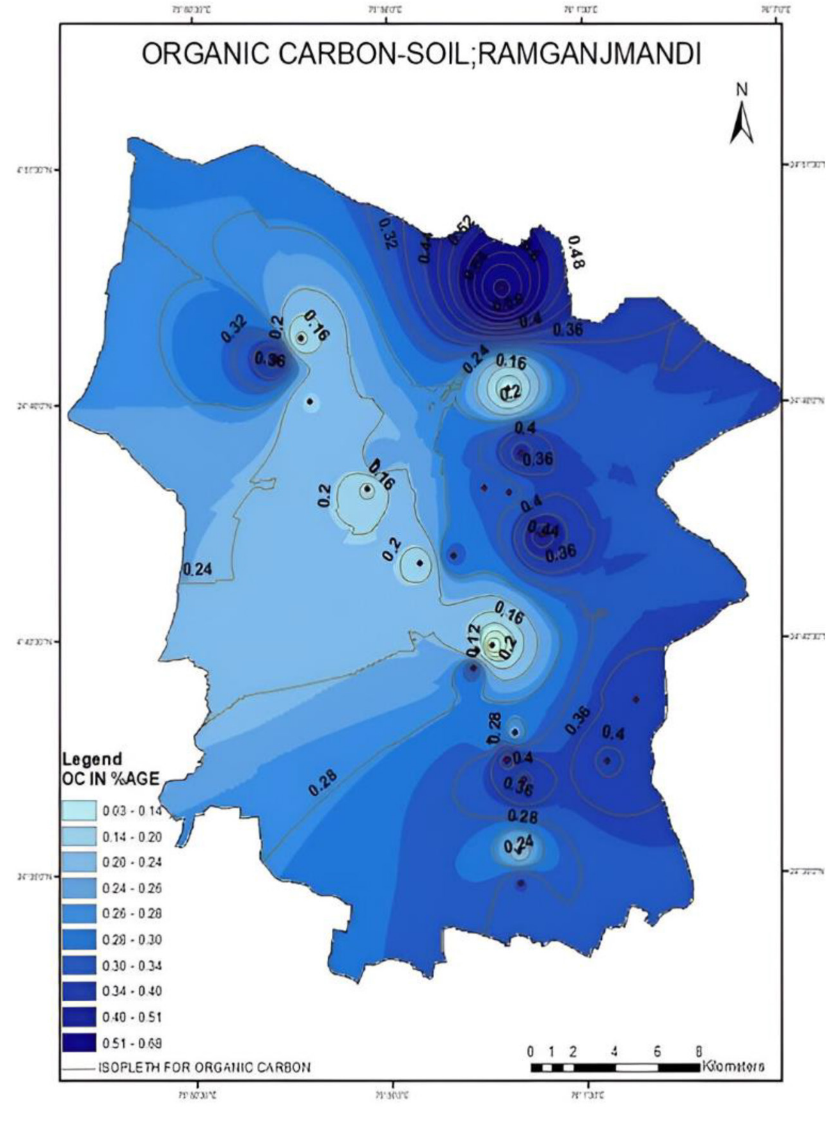

Fig. 5. Organic carbon and predictive mapping.

Static modelling- Interpolation is the estimation of a most likely estimate in given conditions. The technique of estimating a past figure is termed as interpolation. Interpolation is the art of reading between the lines of the table. Inverse distance Weightage method is used as the interpolation method. Arc GIS software is used to interpolate soil properties in the unsampled portion of the tehsil using IDW under interpolation in spatial analyst tool. The output value for a cell using inverse distance weighting (IDW) is limited to the range of the values used to interpolate. Because IDW is a weighted distance average, the average cannot be greater than the highest or less than the lowest input. Therefore, it cannot create ridges or valleys if these extremes have not already been sampled. The influence of an input point on an interpolated value is isotropic. Since the influence of an input point on an interpolated value is distance related, IDW is not "ridge preserving (Watson & Philip 1985).

RESULTS AND DISCUSSION

pH- pH of the soil is the measure of H+ ion activity in soil water system. Generally, a pH below 6 is undesirable for most plants. A low pH is often raised by adding lime to the soil. A one-unit change in pH represents 10-fold change in Hydrogen Ions. Since the study area is a limestone rich region, there is barely any sample with low pH. The pH level as per the soil samples ranges from 7.56 to 8.42(Table 1). Soil is overall of alkaline nature. 66.66% of the samples lie in the mildly alkaline category, rest 33.34% lies

Table 1. Macro nutrients and micro nutrients of soil in Ramganjmandi.

Sample No.	pH	EC(dSm-1)	Organic carbon(%)	Organic matter(%)	Available nitrogen (kg/ha)	Available phosphorus(kg/ha)	Available potassium (kg/ha)	Available sulfur (ppm)	Available zinc(ppm)	Available ion (ppm)	Available manganese (ppm)	Available copper (ppm)	Available calcium(ppm)	Available magnesium (ppm)
1	8.31	0.38	0.42	0.72	222.3	11.48	819.84	15	0.65	0.72	6.36	0.21	1088	206.4
2	8.47	0.29	0.31	0.53	196.5	13.18	255.36	10	0.68	3.78	0.96	0.57	888	216
3	8.27	0.3	0.46	0.79	232	13.2	268.8	14	0.61	0.5	2.96	0.58	1048	360
4	8.61	0.26	0.35	0.6	207.6	13.1	147.84	14	0.72	1.01	1.49	0.15	728	144
5	8.45	0.28	0.29	0.5	191	14.35	255.36	11	0.64	0.56	2.82	0.32	488	148.8
6	7.56	1.83	0.69	1.19	291	26.65	887.04	19	0.78	1.2	31.17	2.8	840	321.6
7	8.55	0.56	0.41	0.71	221.1	14.2	201.6	15	0.78	2.1	3.24	0.75	232	81.6
8	8.31	0.32	0.39	0.67	215.8	11.7	255.36	11	0.71	2.43	2.1	0.39	576	225.6
9	8.32	0.72	0.42	0.72	224.3	14.56	201.6	14	0.78	1.23	5.6	2.05	464	182.4
10	8.47	0.45	0.15	0.26	157.6	15.21	309.12	13	0.45	2.15	7.21	1.72	456	168
11	8.59	0.41	0.2	0.34	168.7	10.56	268.8	14	0.66	2.78	3.56	0.78	648	288
12	8.61	0.78	0.41	0.71	221.1	21.25	228.48	15	0.89	1.26	5.8	0.54	856	297.6
13	8.43	0.74	0.42	0.72	224.3	12.5	241.92	19	0.75	2.3	5	0.21	680	268.8
14	8.47	0.38	0.26	0.45	184.4	23.45	295.68	17	0.58	2.3	6.2	0.98	784	292.8
15	8.32	0.49	0.35	0.6	207.6	11.23	188.16	9	0.54	3.21	5.78	0.38	760	206.4
16	8.45	0.31	0.22	0.38	174.3	23.48	228.48	10	0.79	2.21	3.24	0.91	416	124.8
17	8.7	0.27	0.26	0.45	185.4	20.12	201.6	11	0.91	2.56	4.65	0.56	456	153.6
18	8.21	0.65	0.15	0.26	157.6	16.58	336	15	1.1	2.34	3.58	0.74	280	124.8
19	8.41	0.53	0.31	0.53	196.5	19.35	362.88	12	0.83	2.89	3.89	0.56	472	96
20	8.53	0.7	0.17	0.29	163.2	14.72	349.44	10	0.89	2.78	2.78	0.61	608	172.8
21	8.63	0.36	0.32	0.55	198.5	12.36	161.28	17	0.72	2.47	3.45	0.49	544	244.8
22	8.39	0.78	0.2	0.34	168.7	15.68	322.56	8	0.69	2.8	4.12	0.37	768	302.4
23	8.49	0.47	0.035	0.06	207.6	10.98	268.8	16	0.44	1.75	5.14	0.51	792	192
24	8.56	0.41	0.13	0.22	152	12.45	403.2	9	0.84	1.28	2.89	0.39	456	120
Minimum	7.56	0.26	0.035	0.06	152	10.56	147.84	8	0.44	0.5	0.96	0.15	232	81.6
Maximum	8.7	1.83	0.69	1.19	291	26.65	887.04	19	1.1	3.78	31.17	2.8	1088	360
Average	8.42	0.53	0.31	0.52	198.71	15.51	310.8	13.25	0.73	2.03	5.17	0.73	638.67	205.8

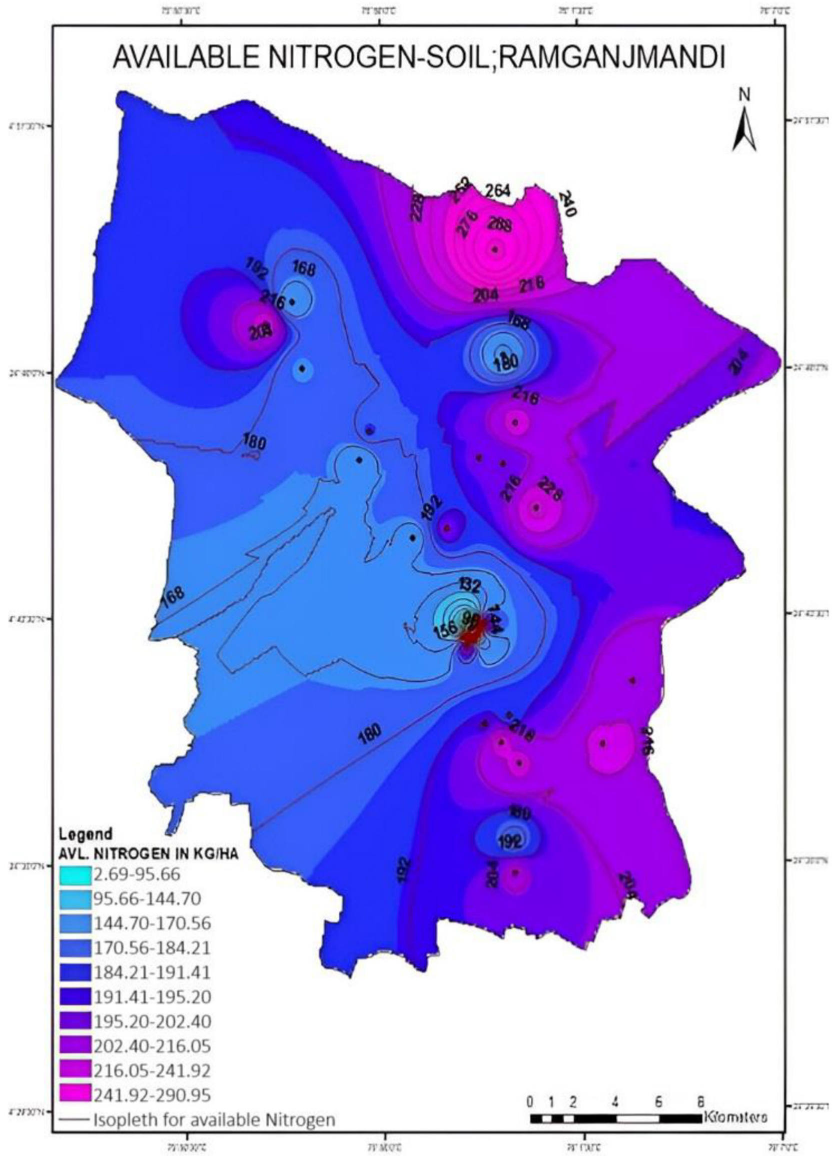

Fig. 6. Available nitrogen and predictive mapping.

in the alkaline category. A single sample of 7.56 pH lies in the sensitive zone towards the north of the tehsil which is the part of Mukundara Hills National Park (Fig.3). The predictive map shows low H values towards north of the tehsil. Isopleths from 7.6 to 8.32 category runs in this zone. Isopleth of 8.56 pH runs in the core of mining belt including Kumbhkot, Julmi, Chechat, Satalkheri regions.

Electrical conductivity- The electrical conductivity (EC) of the soil water system rises with the amount of soluble salts because ions carry electricity. At any temperature, the soil's soluble salt concentration can be causally related to the EC measurement. The electrical conductivity of the region varies from 026 to 1.83 dSm^{-1}(Table 1). 87.5% of the samples lie in the medium category and rest 12.5% lies in the marginal

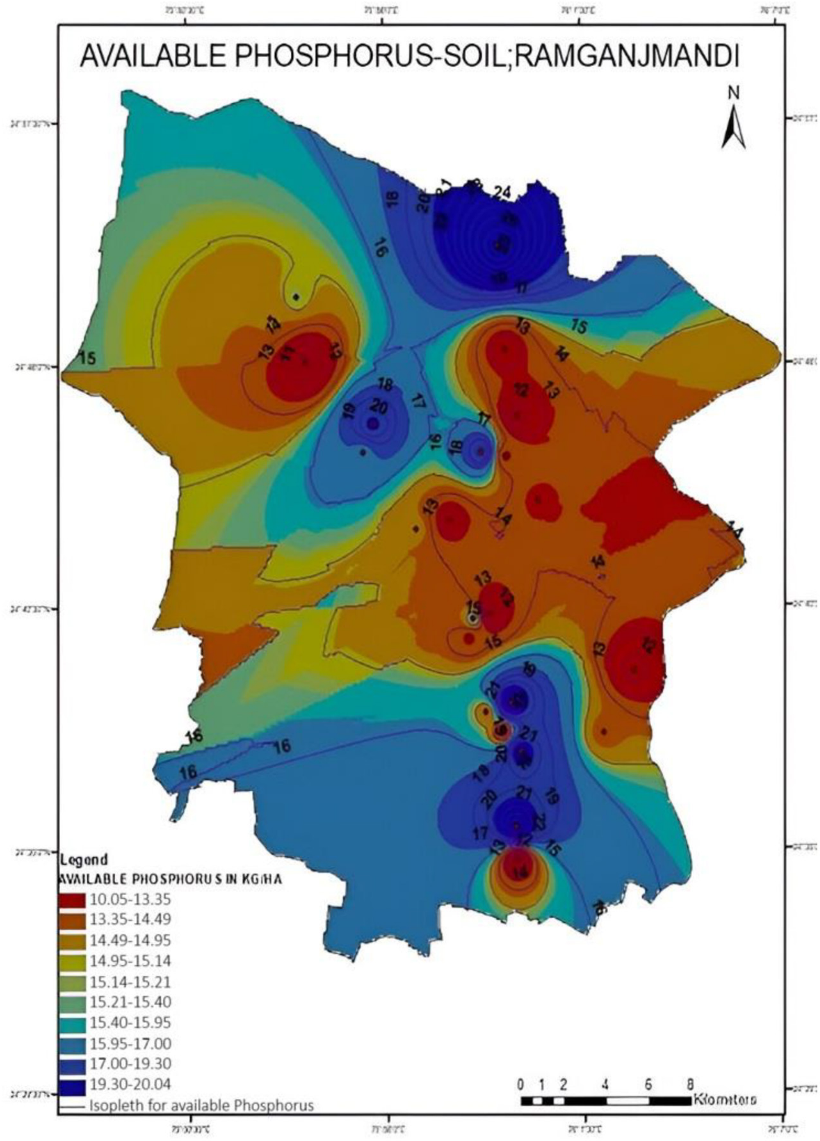

Fig. 7. Available phosphorus and predictive mapping..

category. The isopleth of 1.44 runs in the sensitive zone towards north. The isopleths of 0.36, 0.45, 0.54 and 0.63 runs in the mining belt regions of Kumbhkot, Satalkheri, Chechat, Julmi (Fig.4).

Organic carbon- Organic carbon contributes to maintain moisture and water retention in the soil. It is basically the carbon content in the soil. The value of organic carbon in the region varies from 0.035 to 0.61%. 95.83% of the samples lie in the category of low organic carbon. Only 1 sample composing 4.16% of the sample shows medium organic carbon content, which lies in the sensitive zone (Mukundara National Park) of the tehsil.The predictive mapping of organic carbon in the region, shows more organic carbon in the soil in the north of the territory. The isopleths of

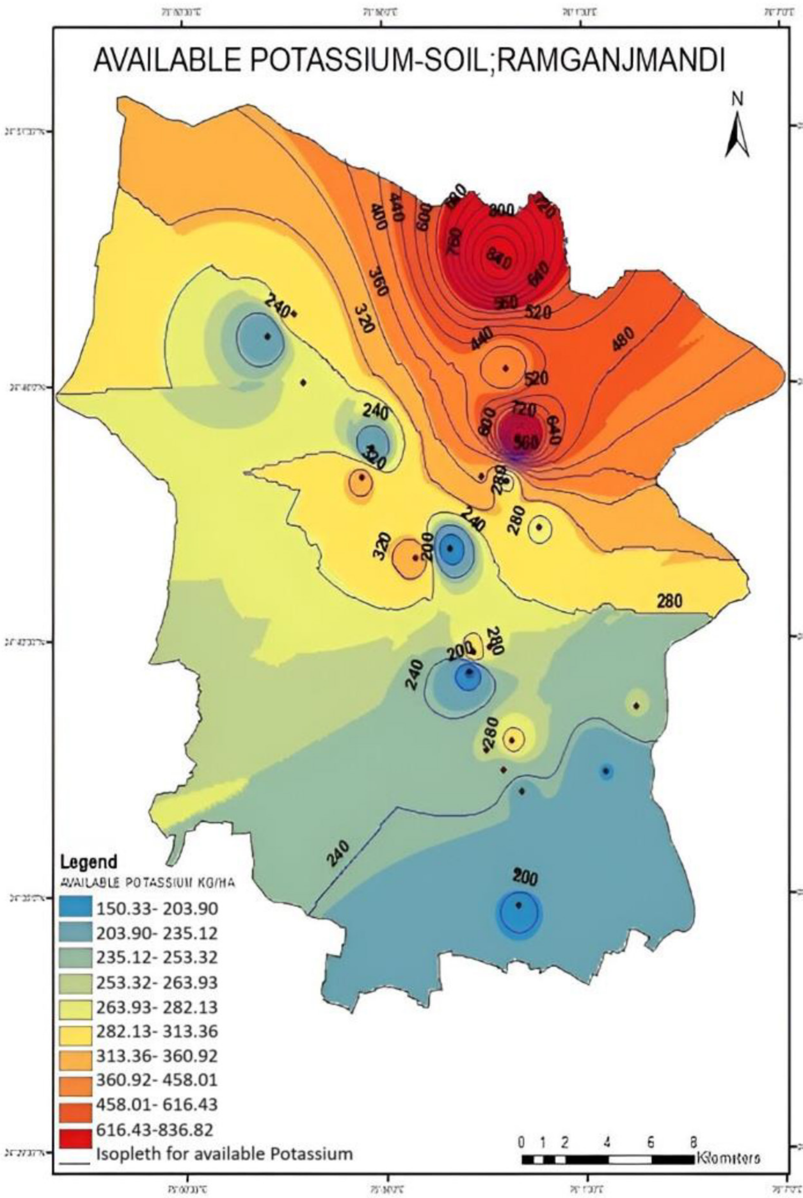

Fig. 8. Available potassium and predictive mapping.

0.56, 0.64, and 0.48% are found in the north of the region. The isopleth of 0.2, 0.16, 0.12, 0.24% encircles the mining core of the region (Fig. 5).

Organic matter- Numerous properties of the soil are influenced by organic matter, including the soil's capacity to supply N, P, S, and trace elements. water filtration and retention; amount of aggregation and overall structure of the soil; capacity for cation exchange; shade of soil. The organic matter in the region varies from 0.06 to 1.19%.

Available nitrogen- The nitrogen found in soils is easily mineralizable. Nitrogen can be found in soil

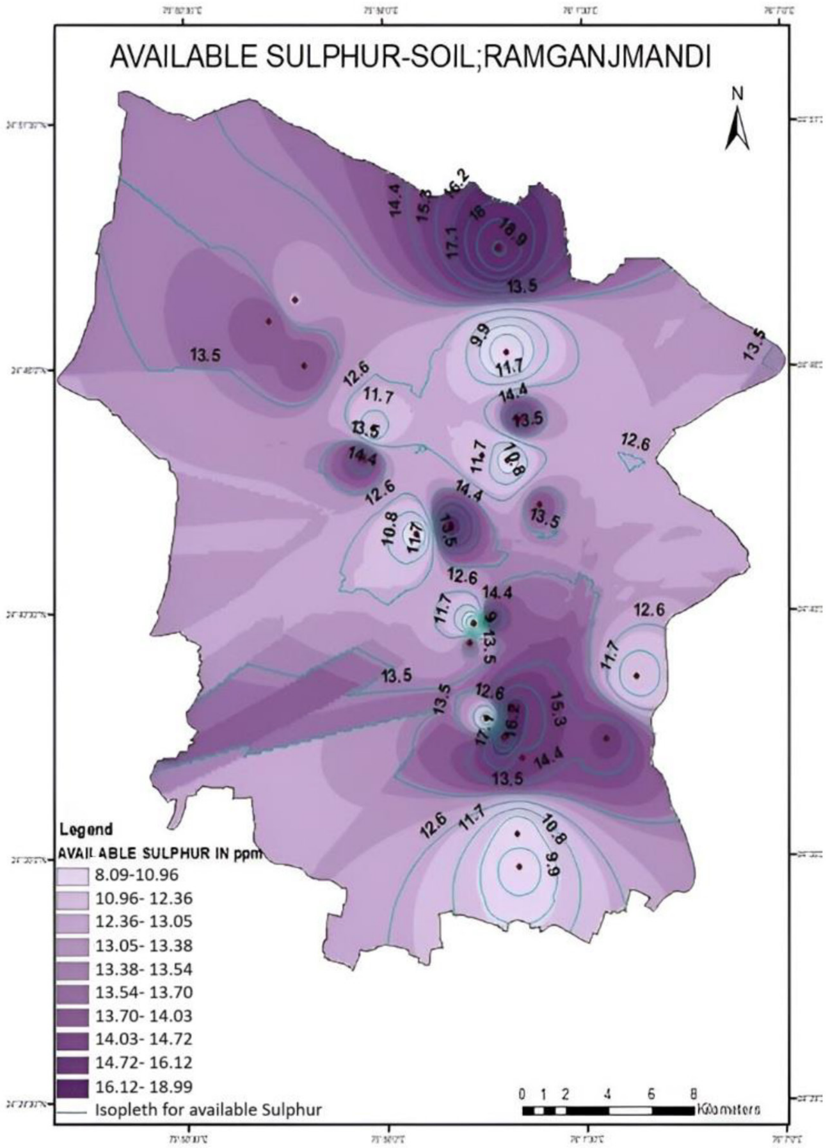

Fig. 9. Available sulfur and predictive mapping.

in a variety of forms, including organic nitrogen, ammoniacal nitrogen, nitrate nitrogen, and nitrite nitrogen. 90% or more of the nitrogen in soil is present in conjunction with organic materials. The amount of inorganic nitrogen in the soil that is accessible to plants is quite little. Estimating organic carbon is typically used to determine how much soil N is available (Maiti 2011). The available nitrogen in the region varies from 152 to 291 kg/ha (Table 1). 95.83% of the samples have low nitrogen content. Only 1 sample composing 4.16% of the sample lies in the medium category. Available nitrogen for plants lies towards Mukundara National Park, and southeast of the territory, which is also a part of reserved forest. Isopleth of available of nitrogen as high as 288, 276,252, 240 kg/ha runs in the Mukundara hills. The isopleth of

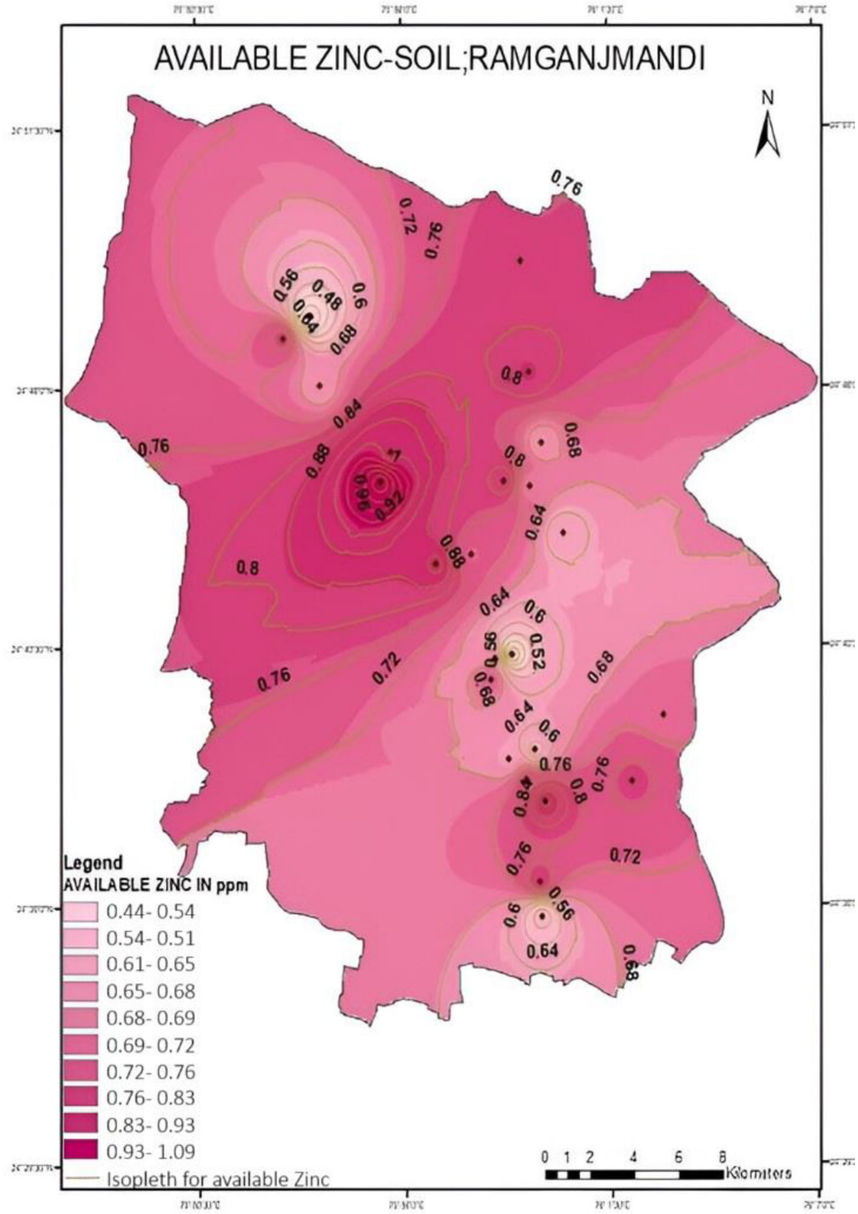

Fig. 10. Available zinc and predictive mapping.

132, 156, 144 kg/ha runs around Kumbhkot mining region (Fig. 6).

Available phosphorus- The second crucial nutrient in soil is phosphorus. The percentage of total phosphorus that is typically available to plants is less than 0.01%. Between 0.02 and 0.10% of the total phosphorus in soil is discovered by weight. The soil has two types of phosphorus: Inorganic (20–28%) and organic (20–28%) (rest of the Proportion). Orthophosphates are a

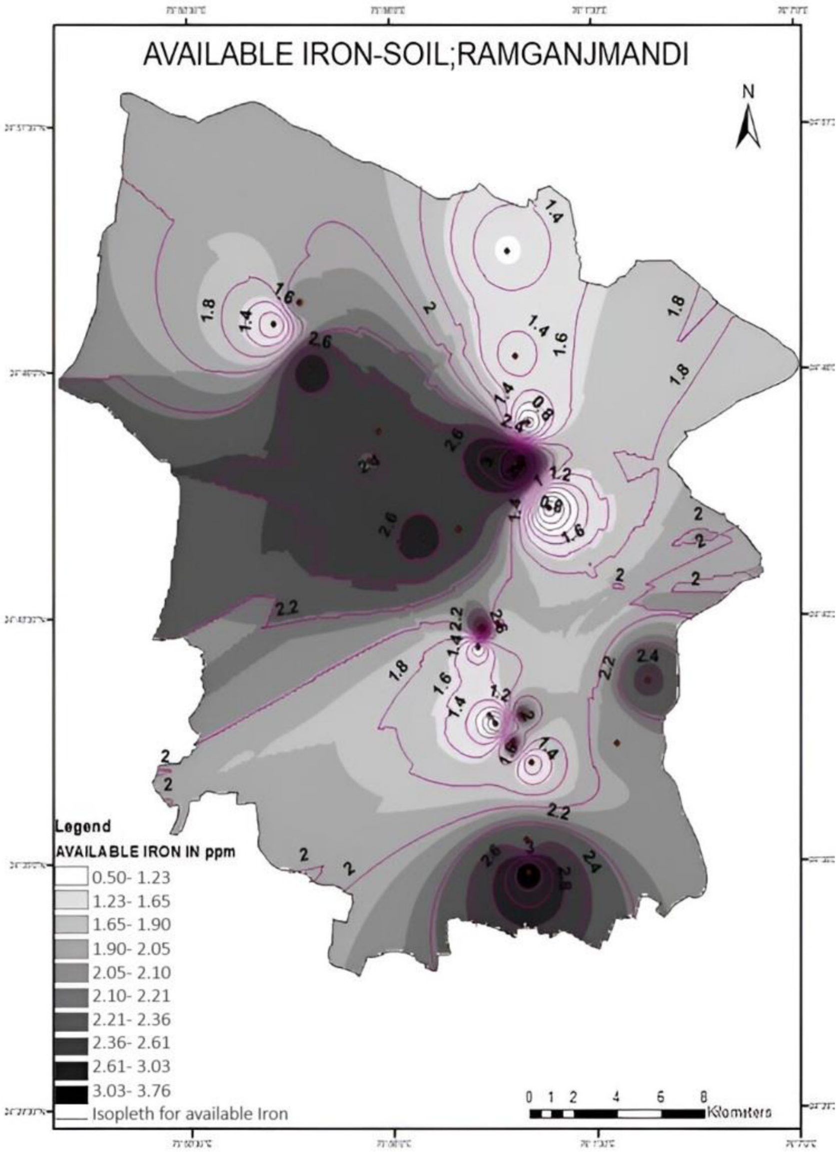

Fig. 11. Available iron and predictive mapping.

common form of inorganic phosphorus. The amount that the plants can use is extremely limited (Maiti 2011). The available phosphorus in the region ranges from 10.56 to 26.65 kg/ha (Table 1). 95.83% of the sample lies in the medium category, rest 4.16% lies in the high phosphorus category. Available phosphorus is high in the northern portion of the territory. The isopleth of 24, 26 22 kg/ha of available phosphorus is seen in the northern portion of the territory. The mining region shows less of available phosphorus of 11, 12, 13, 14 kg/ha of available phosphorus (Fig.7).

Available potassium (K_2O)- Potassium rating as per IARI manual (1983), high fertility category requires potassium more than 280 kg/ha, medium fertility potassium category has 120-280 kg/ha, low fertility soil

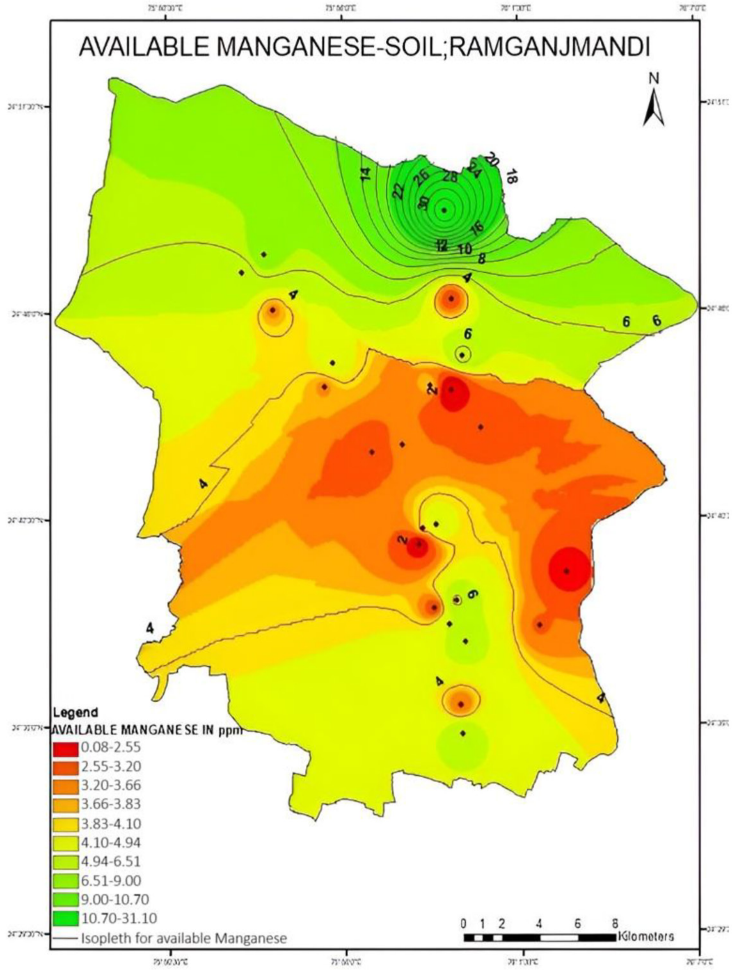

Fig. 12. Available manganese and predictive mapping.

has less than 120 kg/ha (Maiti 2011). The available K_2O varies from 147.84 to 887.04 kg/ha (Table 1). 62.5% samples lie in the medium category rest 37.5 % lie in the high category of potassium availability. The isopleths 840, 800, 760,720 lie towards the sensitive zone in the north. The mining belt has 200, 240 kg/ha isopleths running around them (Fig. 8).

Available sulfur- With an average concentration of 0.06 to 0.10%, sulfur is the 13th most prevalent element in the earth's crust. Roots take up sulfur as $SO4^{2-}$ ions. All the needs of most crops can be met in soil with 5 ppm or more $SO4^{2-}$ via mass movement. Although almost 90% of the total S in the majority of non-calcareous surface soil exists in organic form, sulfur is present in the soil both inorganically and organically (Maiti 2011). The sulfur content in the region varies from 8 to 19 ppm (Table 1). 87.5% of the samples lie in the medium category, rest 12.5 % lies in the low category. The isopleths of 18.9, 18, 17.1 ppm lie in the northern part of the territory. Low valued isopleths 9.9, 11.7, 12.6 runs around the mining belt (Fig.9).

Available zinc- The total zinc content of the lithosphere is about 80ppm, and in soil it ranges from 10 to 300 ppm. The average zinc content vary from 40 ppm in acid rocks such as granite to 100 ppm in the

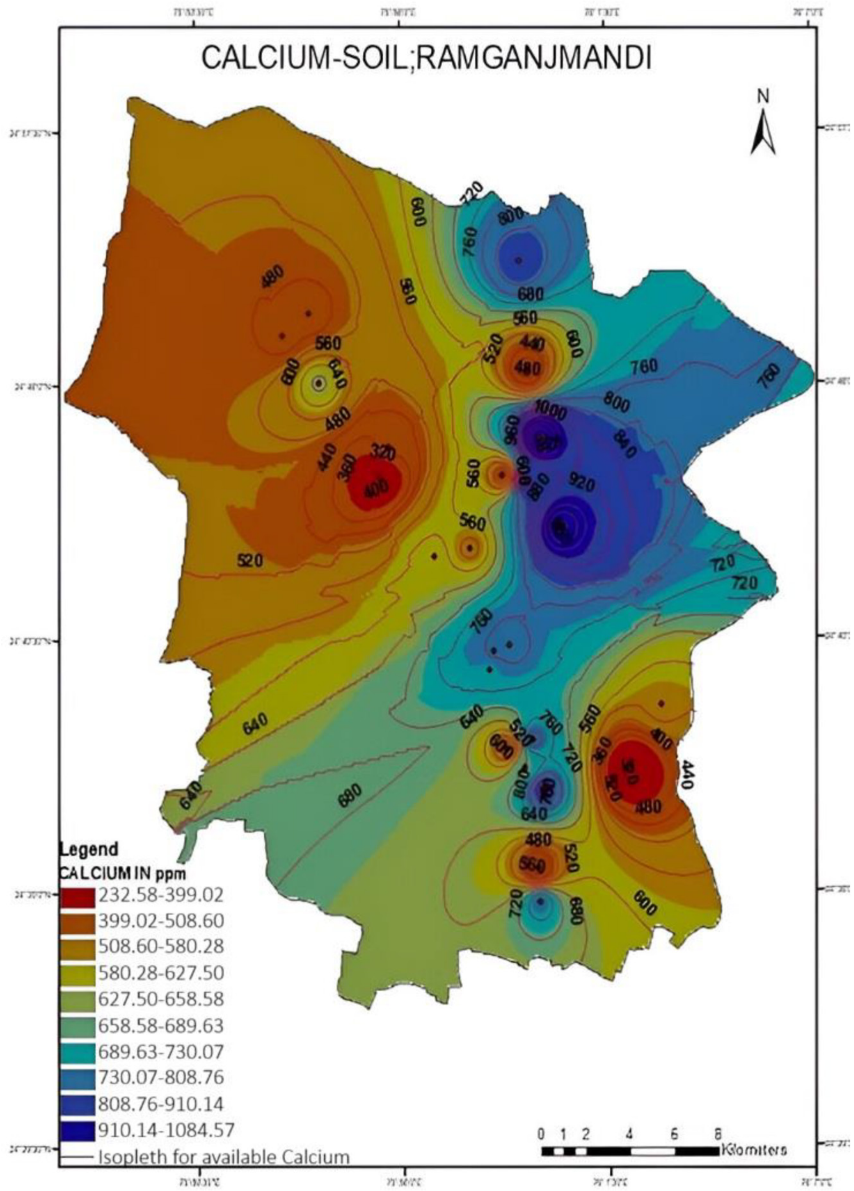

Fig. 13. Calcium and predictive Mapping.

basaltic rocks (Maiti 2011). In the study area, zinc content varies from 0.44 to 1.1 ppm (Table.1). All the soil samples lie in the deficient and marginally deficient category. 91.66% of the samples lie in the marginally deficient category, rest 8.3% lie in the deficient category. The isopleths of 0.48, 0.56, 0.6 ppm lie around Chechat region, Kumbhkot, Julmi region (Fig.10). The regions other than the mining belt has a comparatively higher amount of zinc. The low zinc content can also be attributed to the existing Geology.

Available iron- Globally, most of the arable land has iron deficiency. It is one of the central micronutrient regulating chlorophyll synthesis. Iron in the soil both exists as ferrous and ferric states. The iron availability in the region varies from 0.5 to 3.78 ppm (Table 1).

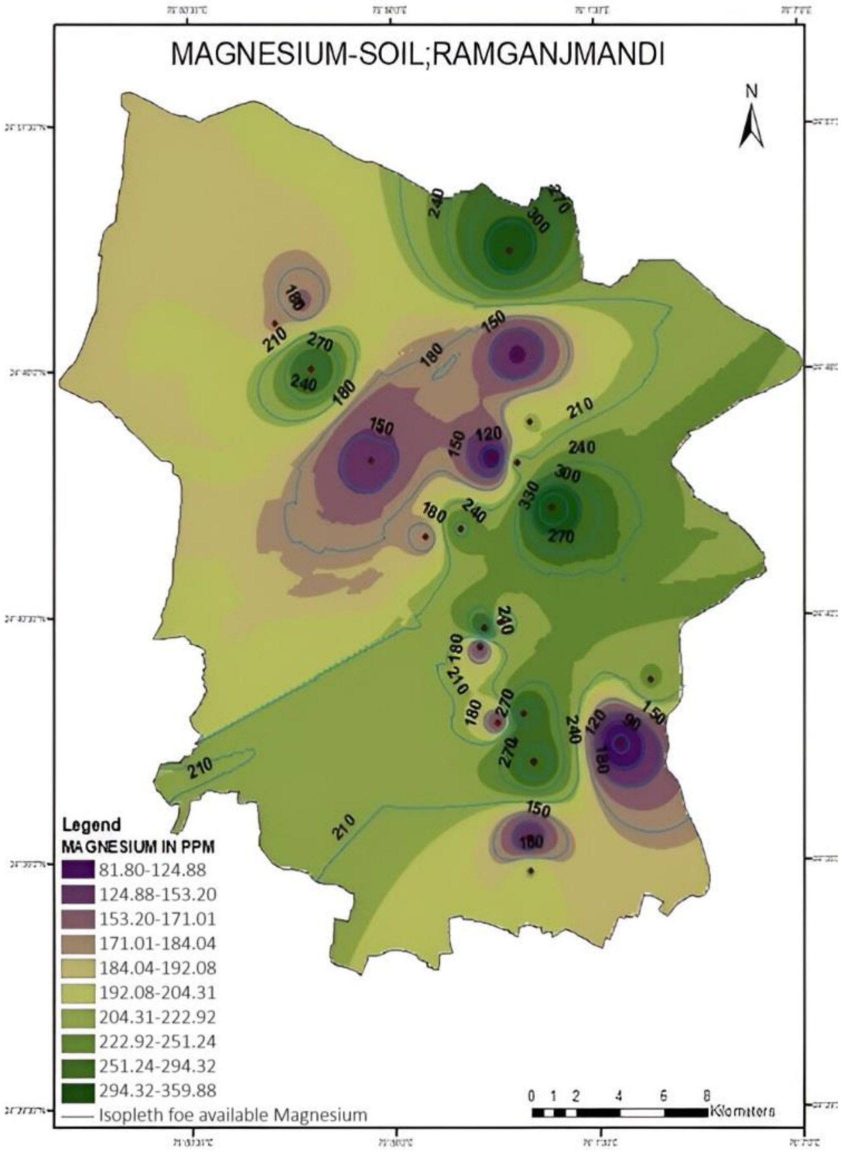

Fig. 14. Magnesium and predictive mapping.

All the samples lie in the deficient and marginally deficient category. 70.83% of the sample lies in the deficient category, rest 29.16% lies in the marginally deficient category. The isopleths of as low as 0.6, 0.8 ppm are found near Kumbhkot. 1.4 ppm and 1.6 ppm isopleth is found around Chechat region (Fig.11).

Available manganese- All Mn in the soil is derived from the parent material. The mean Mn Concentration is largely regulated by pH. The total Mn concentration in earth crust averages 1000ppm and found mostly in iron magnesium rocks. In sedimentary rocks, the concentration range in limestone is 400-600 ppm (Maiti 2011). In sandstone it is comparatively lower. Tolerance level of Mn in plants is 300 ppm. The manganese content in the sampled sites varies from

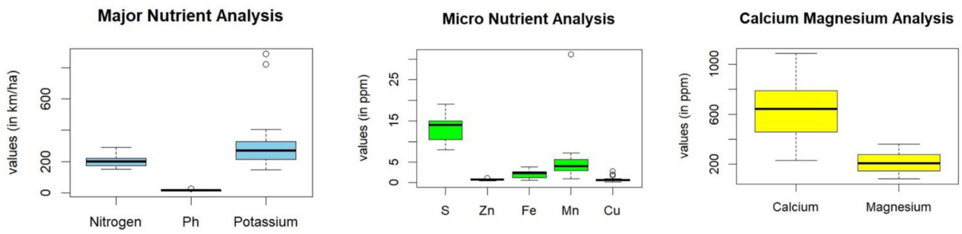

Fig. 15. Box plot representation of major nutrients and trace elements.

0.96 to 31.97 ppm (Table 1). 8.33% of the samples lie in the deficient category, 45.83% lies in the adequate category of 2-4 ppm. 41.66% of the samples lie in the adequate category of 4-10 ppm. 4.16% of the sample lies in the adequate category of 25-50 ppm which lies in the Mukundara National Park. The isopleths of 30, 28, 26, 24, 22 ppm lies in the north zone covering Mukundara hills. Isopleths of 2, 4,6 ppm revolves around the mining belt of Chechat, Kumbhkot, Julmi (Fig.12).

Available copper- Total copper concentration in lithosphere ranges between 55 to 70 ppm. Average copper range for soil is 20-30 ppm. When the soil has 25-40 ppm and the pH is below 5.5, it may be toxic. Copper concentration decreases rapidly with increasing pH. If the pH is not maintained, the availability of Cu, Mn, Zn and other elements is more a problem. The copper concentration in the region ranges from 0.15 to 2.8 ppm (Table 1). 4.16% lie in the deficient category. 33.33% of the samples lie in the marginally deficient category, rest 62.5% of the samples lie in the adequate category of 0.5 to 10 ppm of copper. The isopleths of 0.3, 0.6, 0.9 ppm is found around Chechat, Julmi, Kumbhkot region (Fig.13). The isopleths of 2.7, 1.5, 1.8 ppm of copper is found in the northern portion of the territory.

Calcium and magnesium- They both are essential nutrients to plants. These are the abundant elements of the soil. Both these elements share common chemical properties as their natural occurrence in the form of carbonate, phosphate, sulphate, or silicates. A level of 15 ppm Ca^{2+} in soil solution is adequate. The calcium content in the region is very high ranging from 232 to 1088 ppm. Magnesium ranges from 81.6 ppm to 300 ppm (Table 1). Most sandy soil has concentration of calcium more than 400-500 ppm. The isopleths of 800 760, 720 ppm of calcium runs in the northern part of the territory. 640ppm isopleth runs around Chechat region. 760ppm runs around the Kumbhkot region. 560 ppm revolves around the Satalkheri region. The isopleths of 120, 180. 240 ppm of magnesium is found in the mining region of Julmi, Kumbhkot, Satalkheri region (Figs.14–15).

PCA results

Principal components (PC)1 explains 50.4% of the total variance, and Principal Components(PC)2 adds 12.5%, so together the first two components explain 62.9% of the variance(Fig.16). The first two components are justified for PCA biplot (Fig.17). Variables like Organic matter, Organic carbon, Nitrogen, Magnesium, Calcium, Electrical conductivity are strongly aligned with PC1, zinc, iron, pH, contribute more to PC2.There are natural clusters in soil chemical properties. Dimension 1 is mainly driven by soil organic matter, nutrients and conductivity and dimension 2

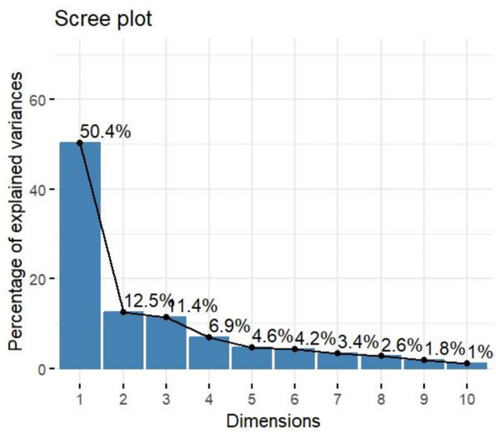

Fig. 16. Scree plot.

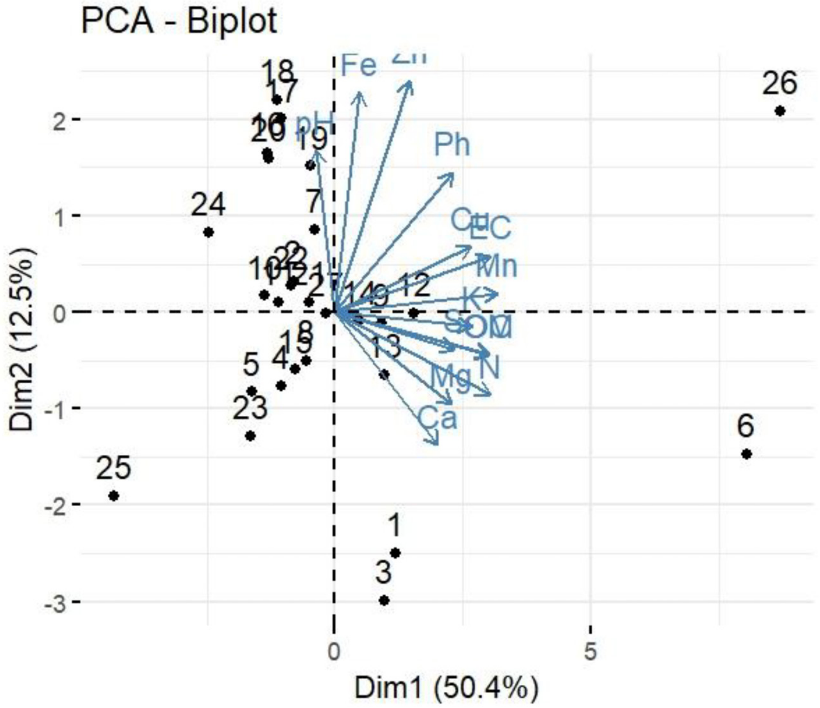

Fig. 17. PCA biplot.

separates variables related to pH and trace elements (Fe, Zn). There is a strong positive correlation between Organic carbon, Organic matter, Nitrogen, they are likely collinear. Another cluster includes Copper, Calcium, Magnesium, and Manganese showing high positive correlation (Fig.18).

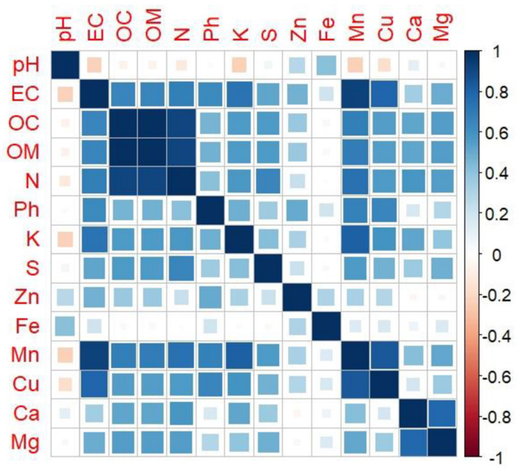

Fig. 18. Correlation matrix.

CONCLUSION

The digital soil mapping of the region shows a clear impact of mining over the soil properties. The differential is obtained by taking few samples from the protected forest region in the north of the territory. The secondary data collected from the industries report shows that the soil property is suitable for agricultural production, but the primary survey done shows some contradictory views. More than 95.83% of the samples are low in organic carbon, organic matter, nitrogen. 62.5% of the samples have medium phosphorus and potassium. 87% of the samples have medium sulfur. 91.66% of the samples have marginally deficient in zinc. 70.83% of the samples are deficient in Iron. 4.16% of the samples which were taken from the core of the mining belt is deficient in copper. Most sandy soil have concentration of calcium more than 400-500 ppm. A level of 15ppm Ca^{2+} in soil solution is adequate. The calcium content in the region is very high ranging from 232 to 1088 ppm. Magnesium ranges from 81.6 ppm to 300 ppm. In contrast to the mining belt the sensitive zone in the north has suitable levels of soil nutrients. Principal component analysis revealed that PC1 and PC2 together explains 62.9% of the total variance effectively capturing the major patterns in soil chemistry. PC1 is primarily influenced by Organic content, nutrients and conductivity, while PC2 distinguishes pH and trace elements. Clear natural clusters suggest strong collinearity among variables like Organic matter, Nitrogen and trace metals.

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