GEO-STATISTICAL MODELLING AND ASSESSMENT OF SOIL FERTILITY STATUS OF RUBBER PLANTATIONS IN A TROPICAL REGION OF KERALA

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ABSTRACT: Geo-statistical modelling of rubber growing soils of Kottayam district in Kerala was carried out to assess soil fertility status of rubber plantations in order to develop a WebGIS enabled platform for soil fertility recommendation to rubber farmers. About two thousand and eighty two soil samples were collected from rubber growing areas of the district on a fifty hectare grid basis using satellite-derived rubber distribution maps. Soil samples were analysed for soil pH, organic carbon, primary, secondary and micronutrients following standard procedures. Geo-statistical modelling was performed to interpolate soil fertility parameters using ordinary kriging algorithm in GIS platform to generate soil fertility maps. Best fit semi-variogram models were used to interpolate soil feriltilty parameters and cross-validated with standard prediction error parameters. Nugget-to-sill ratios of the semi-variogram model revealed that degree of spatial autocorrelation of most of the soil fertility parameters were moderate in the study area. Spatial variability of soil fertility parameters indicated that major portion of NR growing soils in the study area exhibited acidic status of soil pH. Available organic carbon status was high to very high whereas status of available phosphorus and potassium were low. Secondary nutrients such as available calcium, magnesium and sulphur were also exhibited low status. Micronutrients status was sufficient but available boron and zinc showed deficient in some places of the district. A WebGIS enabled application called Rubber Soil Information System (RubSIS) was developed using the soil fertility variability maps and soil depth data of the study area. It gives location-specific and need-based recommendation for use of chemical fertilisers in one holding according to the age and the extent of the rubber plantation. Results of geo-statistical modelling of soil fertility parameters used to develop RubSIS are briefly discussed in the paper.

INTRODUCTION

Para rubber is an agricultural tree crop (*Hevea brasiliensis*) and is grown on varied pedo-climatic environment in traditional rubber growing regions of Kerala and Kanyakumari district of Tamil Nadu over past eleven decades contributing ninety per cent of latex production in India (IRS 2013). Now the rubber growing tracts of Kerala is almost a third cycle of its cultivation. Thus productivity status of rubber growing soils may vary over time. Continuous cultivation of rubber resulted in a decline of soil organic carbon content and soil pH (Abraham *et al*., 2001; Ulaganathan *et al.*, 2010). Therefore proper monitoring is essential to understand soil fertility status in rubber plantations for region specific soil management practices to improve the soil productivity.

Delgado and Gomez, 2017 reported that soil's physical, chemical and biological properties are changing over timescale due to modern agricultural practices. According to Doran *et al.*, 1994 the soil productivity is more or less related to plant growth and crop yield. Thus managing soil health in a sustainable level can be achieved by conducting soil survey at regular intervals. Conventionally managing of soil productivity in rubber plantation is primarily based on surveys, analysis of soil samples. But it is usually followed by collecting samples from the fields without geographic reference. The results of such traditional survey are usually not useful for future monitoring. Recent past availability of satellite remote sensing data and development of geospatial techniques have a significant role in mapping and management of soil resources (Singh *et al.,* 2010; Wadodkar and Ravisankar, 2011; Chatterjee *et al.,* 2015). Soil fertility variability maps are one of the key inputs required for region specific soil fertility management in agricultural crops (Denton *et al.,* 2017; Sharma *et al.,* 2016; Guo *et al.,* 2015; Tagore *et al.,* 2014).

Large number of scientific studies reported the use of geostatistical modelling technique to assess soil nutrient conditions (Chabala *et al*., 2017; Mousavifard *et al*., 2013; Nourzadeh *et al*., 2012; Chen *et al*., 2011; Wang *et al*., 2009). This technique is widely used to model and study spatial variability in soil conditions (Santra *et al*., 2017; Reza *et al*., 2016; Shit *et al*., 2016; Marchetti *et al*., 2012; Panagopoulos *et al*., 2006; Dayani and Mohammadi, 2010). In agriculture tree crop like rubber, generation of soil fertility variability maps are vital to understand the soil fertility constraint areas and to manage those areas by applying correct dose of chemical fertilizers. In this aim we undertook an extensive field survey across rubber growing soils in South India in collaboration with National Bureau of Soil Survey and Land Use Planning (NBSS & LUP), Indian Council of Agriculture Research (ICAR) with an objective to bring soil test based fertilizer recommendation for entire rubber growing areas in the country using geospatial approach. Prior to this, a pilot study was undertaken in rubber growing areas of Kottayam district in Kerala (one of the major NR growing districts in India) by mapping present extent of rubber holdings and modelling of soil fertility status of rubber plantations to develop a WebGIS based application of Rubber Soil Information System (RubSIS).

MATERIALS AND METHODS

Site description

Kottayam district is located in central Kerala in South India (Figure 1). The location lies between 76°21'13.4"E to 76° 59 '54.11"East longitudes and 9°23’12.69"N to 9°52'1.92" North latitudes with an area of 2201 Sq.km consists of five Taluks, viz., Meenachil, Kanjirappally, Vaikom, Changanassery and Kottayam. About forty nine per cent of total geographical area of the study area consists of natural rubber cultivation. The soil types occurring in Kottayam district are broadly grouped in to lateritic, riverine alluvium, brown hydromorphic and forest loam. In this district, majority of rubber plantations are cultivated in less than 100 m elevation. About sixty five per cent of rubber areas occur in between slope 5-15 per cent. Study area receives plenty of rains from both South-West and North- East monsoons. The normal average annual rainfall is around 3200 mm. In addition to rubber plantations coconut, paddy, pepper, cocoa, nutmeg and various other spices and food crops are cultivated in the district. The district has an undulating topography on eastern parts, midlands and nearly level low lands in the western side and highest elevation of the district is 1158m. Rubber plantations are densely distributed all over the district except western side which is covered by Ramsar site of Vembanad Lake and backwaters.

GPS based soil sample collection

Satellite data of Resourcesat I LISS III sensor with 23.5m spatial resolution (Path and row 100-67, 3rd March 2013) was used for mapping of rubber plantations in Kottayam district (Figure 1). Exhaustive field survey was conducted across rubber growing regions in the study area to collect soil samples on a 50 ha grid basis. Extreme care was taken to collect the samples from a particular grid using satellite-derived rubber distribution maps. Global Positioning System and other ancillary maps were used as reference for soil sample collection to get maximum representation of soil samples across the rubber growing areas in Kottayam district. For this, administrative boundary, road network, important places were vectorized using Survey of India (SOI) toposheets of scale 1:50,000 scale. Random soil samples were collected on the basis of extent of rubber acreage, accessibility of terrain, road network *etc*. A comprehensive soil sample survey form was prepared to document details of the rubber holdings and farmers. Sampling was carried out during the period from December 2012 to January 2013 at 2082 randomly sampled locations from the study area (Figure 2). In order to get uniform distribution of soil samples for GIS mapping we have overlaid GPS (Garmin Dakota 20) recorded coordinates of soil samples with rubber distribution map. Composite soil samples were collected at 0-30cm depth in three different parts of a rubber holding and mixed properly. A core sample was also taken for gravel content analyses. Soil samples were subjected to air dry and seiwed using mesh size of 0.5 micro meter filter. Then the samples were analysed following standard analytical procedures for soil pH, organic carbon, primary, secondary and micronutrients in the laboratories of Rubber Research Institute of India (RRII) and NBSS & LUP, ICAR. GIS softwares such as Rolta Geomatica v 10.3.1 and ArcGIS v 10.1 were used for satellite data processing, geostatistical mapping and analyses.

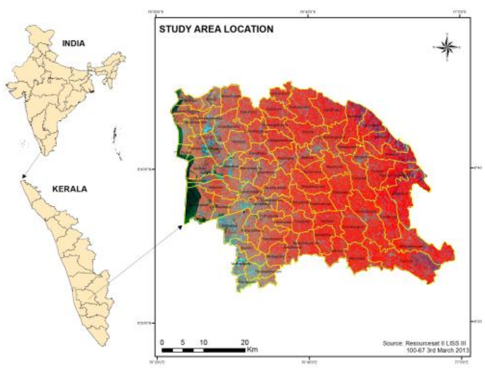


Figure 1. Study area location

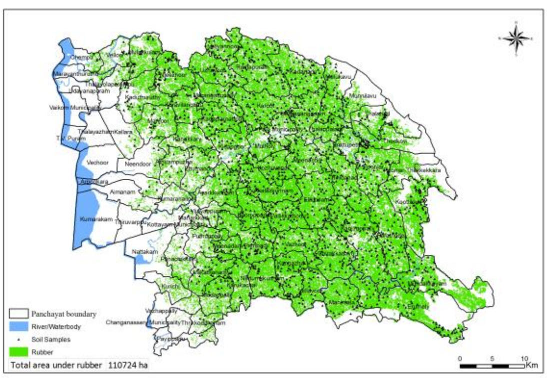


Figure 2. Soil samples collected from the study area overlaid with rubber plantation distribution

Geostatistical modelling of soil fertility parameters

Geostatistical analyst derives a surface using the values from the input samples to predict values for each location in the landscape by computing weighted average of the known values in the neighborhood of the point (Krige, 1951). Generally kriging algorithm can be expressed by the following formula (ESRI, 2003).

$$Z_{(k)} = \sum_{i=1}^{n} \lambda_i * Z_i$$

where $Z_{(k)}$ is the value of an unknown location estimated by Kriging. λ_i is the weighting coefficient for a particular location and Z_i is the known value of a particular location. Kriging is widely used in geology, hydrology, agriculture, soils, environmental monitoring and other fields to interpolate spatial data (Robinson and Metternicht, 2006; Peng *et al*., 2013; Antwi *et al*., 2016). This interpolation is built on the assumption that things that are close to one another are more alike than those farther away (known as spatial autocorrelation). This modelling involves an exploratory spatial data analysis of soil samples, calculation and modelling of the surface properties of nearby samples and surface prediction and assessment of results.

In this study commonly used ordinary kriging interpolation technique was used for prediction of soil fertility parameters (total of fourteen soil nutrients). Result of soil data was subjected to statistical analysis to understand the normal distribution pattern and transformed as appropriate for mapping of spatial variability in GIS platform. Statistical parameters were calculated for this study were the mean, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis of the soil samples. We have tested histogram and normal QQ plots of the soil samples while doing geostatistical analyses. Statistically valid prediction surface model was generated for each soil fertility parameter with cell size of 30m which equals to 0.09 ha of a rubber holding. Measure of the certainty or accuracy of the predictions of the result were validated using standard prediction error parameters such as mean error (ME), root mean square error (RMSE), root mean square standardized error (RMSSE) and average standard (ASE) error. Semi-variogram models obtained with least values of prediction error parameters were considered as measure of validity of the analysis.

Development of WebGIS enabled RubSIS

WebGIS based fertilizer recommendation for rubber growing regions in the study area was developed based on overlaying krigged variability maps of all fourteen soil fertility parameters and soil depth data following the guidelines of discriminatory fertilizer recommendation for rubber plantations. Rubber farmers can obtain soil fertility status and fertilizer recommendation of a particular rubber growing region either by search of location coordinates or by means of administrative division according to age and extent of rubber holding. This online platform of Rubber Soil Information System (RubSIS) is developed using an open source WebGIS tools in collaboration with Indian Institute of Information Technology and Management - Kerala (IIITM-K).

RESULTS AND DISCUSSION

Satellite-derived extent of rubber plantation in Kottayam district for the year 2013 was 1,10,724 ha (Figure 2). Analysis of DEM (Digital Elevation Model) and ground truth revealed that majority of rubber holdings in Kottayam district falls under the elevation class 0-100m followed by 100-300m and least in >300m elevation. Results of statistical analyses and geostatistical modelling of spatial variability of soil fertility parameters are discussed below.

Statistical analyses of soil data

The analysis of normality test of the samples is the prerequisite of kriging interpolation to calculate the valid surface prediction models (Antwi *et al*., 2016; Jemo *et al*., 2014; Robinson and Metternicht, 2006; Guo *et al*., 2015). A statistical summary of different soil fertility parameters analysed for the study is given in Table.1. In this study, statistical evaluation of the untransformed soil fertility parameters shown that variations were not normally distributed for soil properties of available P, K, Ca, Mg, S, Fe, Mn and Cu as revealed by the test of coefficient of variation (CV) and skewness values generated through statistical analyses. Thus data transformation was applied to the original values to normalise the variations before spatial interpolation. A logarithmic transformation (natural logarithm) was applied prior to prediction modelling for stabilize the variance (Guo *et al*., 2015; ESRI, 2003; Harter, 1961; Royston, 1982; Goovaerts, 1999). Results indicated Organic Carbon (OC), soil pH, exchangeable Al, gravel content, available Zn and B showed near normal distribution. The coefficient of variation (CV) is the ratio of the standard deviation to mean expressed as a percentage is a useful measure of overall variability. CV of soil pH was least variable (5.38) while available P found to be highly variable (160.3). Available OC and K concentration showed CV of 34.53 and 57.24 respectively (Table 1). Among the secondary nutrients, available S showed highly variable (CV value of 84.03) followed by available Ca (57.51) and available Mg (51.47). In the case of micro nutrients, available Fe was found least variable (29.04) whereas available B and Cu showed highly variable (71.41 and 70.83) followed by available Mn (45.75) and Zn (42.36). Statistical analyses indicated moderate to high variability of soil fertility parameters of rubber plantations in Kottayam district. The skewness coefficients are zero for normally distributed samples. If the data distributions are largely skewed from a normal distribution, data transformations are often performed in order to reduce the variability in spatial analyses (Robinson and Metternicht, 2006; Jondeau and Rockinger, 2003). Among the soil fertility parameter analysed from the study area, available P, K Ca, Mg, S and Cu were showed higher values of skewness (Table 1). After logarithmic transformation of available P, K, Ca, Mg, S, Fe, Mn and Cu followed a near normal distribution which showed soil samples were fitting for geostatistical kriging.

Table 1. Descriptive statistics of the soil samples analysed from the study area

Soil parameters	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis	CV(%)
pH	3.9	5.8	4.72	0.25	-0.17	0.31	5.38
Al	0.03	2.83	0.83	0.43	0.79	0.9	51.16
Gravel	1.41	43.66	15.4	5.67	0.88	1.96	36.83
OC	4197.46	119000	52345	18074.75	0.36	0.19	34.53
Av. P	0.77	578.82	23.87	38.27	6.1	56.21	160.31
Av. K	0	959.91	192.68	110.29	1.6	3.95	57.24
Av. Ca	10.27	1416.52	222.48	127.95	1.59	5.56	57.51
Av. Mg	7.17	217.91	48.67	25.05	1.3	2.82	51.47
Av. S	0.62	212.7	32.83	27.59	2.02	5.52	84.03
Av. Fe	3.82	156.93	55.34	16.07	0.46	1.3	29.04
Av. Mn	2.47	138.99	45.39	20.77	0.38	0.4	45.75
Av. Cu	0.4	74.37	10.11	7.16	2.12	7.18	70.83
Av. Zn	0.48	14.42	3.67	1.55	0.83	1.44	42.36
Av. B	0	6.54	1.92	1.37	0.51	-0.45	71.41

N= 2082. Av: Available

Geostatistical modelling of soil fertility parameters

Validation of the prediction modelling: Results of standard prediction error parameters and semi-variogram models used for geostatistical modelling of soil nutrients to describe the spatial autocorrelation of the soil samples are given in Table 2 & 3. The degree of spatial autocorrelation of soil fertility parameters were described by nugget-to-sill ratio, it is an important index to find the spatial dependencies of soil properties in a region (Cambardella and Karlen, 1999; Cation, 2001; Kravchenko, 2003). The parameters that were obtained from geostatistical analyses of the semi-variogram model were the nugget, sill and range. The nugget represents variability at distances smaller than the typical soil sample spacing or the value at which the semi-variogram intercepts the y value. Sill represented the amount of variation defined by the spatial autocorrelation and it is the value at which the model first levels out. The range is the lag distance at which the model first flattens out. If the nugget-to-sill ratio is less than 0.25 per cent is regarded to have strong spatial autocorrelation within sample locations (Cambardella *et al*., 1994; Liu *et al*., 2006). The spatial autocorrelation is considered moderate if the ratio is between 0.25 and 0.75 per cent and weak if it more than 0.75 per cent. The soil samples analysed for the study area showed moderate spatial autocorrelation and no strong degree of spatial association was observed. This was due to the variability of values of soil fertility parameter. The spatial dependence of soil fertility parameters revealed that nugget-to-sill ratio for soil pH, gravel and exchangeable aluminium were 0.60, 0.72 and 0.78 which gives an indication that spatial dependence was moderate to weak. The degree of spatial dependencies of available OC, P and K were moderate in the study area which shows 0.57, 0.67 and 0.52 per cent respectively (Table 2). The spatial autocorrelation of secondary nutrients of available Ca was weak (0.81) whereas available Mg and S showed moderate spatial dependence (0.67 and 0.72). All the parameters under micronutrients showed moderate spatial dependence of nugget-to-sill ratio from 0.33 to 0.61. Among these micronutrients highest spatial autocorrelation was showed by available Zn (0.33) followed by available Mn (0.38).

If a semi-variogram model satisfies a valid prediction, the cross validation parameters of mean error (ME) and mean standardized error (MSE) approaches zero, average standard error (ASE) approaches root-mean-square error (RMSE), mean standardized error (MSE) approaches zero, root mean square standardized error (RMSSE) approaches one (Granados *et al*., 2005; Nourzadeh *et al*., 2012; Chabala *et al*., 2017; ESRI, 2012). The validation of the present study was closely agreed with the values of standard error parameters which were satisfying the reliability of prediction of all soil fertility parameters. The values of ME and MSE were close to zero for all soil fertility parameters in the study area which indicated the prediction is reasonably unbiased (Table 3). The RMSE values were lower and it was close to ASE. The RMSE values were below 1 for all soil fertility parameters except gavel content (4.43), Zn (1.20) and B (1.13). The obtained RMSSE values were also close to one for all soil fertility parameters indicated none of the parameters were over estimating or under estimating the prediction. Analyses closely follow the standard values of cross validation parameters of geostatistical modelling and therefore considered prediction of soil fertility parameters were unbiased and reliable. Following results were obtained from the analyses using prediction maps.

Table 2. Parameters of semi-variogram models analysed for soil samples from the study area

Soil parameters	Nugget (C_0)	Partail sill (C_1)	Spatial dependence (C_0/C_0+C_1)	Range	Model
pH	0.037	0.024	0.60	0.0340	Stable
Al	0.122	0.033	0.78	0.0650	Stable
Gravel	15.941	5.988	0.72	0.0507	Circular
OC	0.180	0.136	0.57	0.0265	Circular
Av. P	0.490	0.237	0.67	0.0179	Circular
Av. K	0.145	0.133	0.52	0.0320	Circular
Av. Ca	0.253	0.058	0.81	0.0270	Circular
Av. Mg	0.159	0.075	0.67	0.0396	Spherical
Av. S	0.532	0.201	0.72	0.0273	Stable
Av. Fe	0.053	0.033	0.61	0.0278	Circular
Av. Mn	0.078	0.124	0.38	0.0184	Circular
Av. Cu	0.211	0.201	0.51	0.0576	Circular
Av. Zn	0.872	1.712	0.33	0.0874	Stable
Av. B	0.953	0.805	0.54	0.9530	Circular

Av: Available

Table 3. Cross-validation parameters of geostatistical modelling of soil fertility

Soil parameters	ME	RMSE	MSE	RMSSE	ASE
pH	-0.00083	0.20	-0.00371	1.005	0.20
Al	-0.00149	0.37	-0.00397	1.033	0.36
Gravel	0.00928	4.43	0.00191	1.041	4.25
OC (%)	0.00098	0.50	0.00151	1.025	0.49
P	0.00001	0.83	0.00014	1.023	0.80
K	0.00071	0.45	0.00074	1.023	0.43
Ca	0.00074	0.53	0.00159	0.980	0.54
Mg	-0.00144	0.43	-0.00271	0.990	0.43
S	-0.00101	0.76	-0.00073	0.979	0.78
Fe	0.00086	0.28	0.00283	1.068	0.26
Mn	0.00003	0.38	0.00006	1.026	0.37
Cu	-0.00025	0.51	-0.00081	1.002	0.50
Zn	-0.00208	1.20	-0.00078	0.984	1.22
B	-0.00004	1.13	-0.00023	1.016	1.11

(ME: mean error., RMSE : root-mean-square error., MSE: mean standardized error., RMSSE: root-mean-square standardized error., ASE: average standard error)

Geospatial variability of soil fertility parameters

Spatial variability maps of different soil fertility parameters for rubber growing regions in Kottayam district are shown in Figure 4 (a-n). Majority of NR growing places in the study area exhibited acidic status of soil pH ranging from of 3.5 to 5.5 (Figure 4a). Spatial interpolation map of soil pH revealed that up to 90 per cent of area under rubber cultivation in Kottayam district exhibited very strongly acidic nature of soil pH (4.5-5.0).

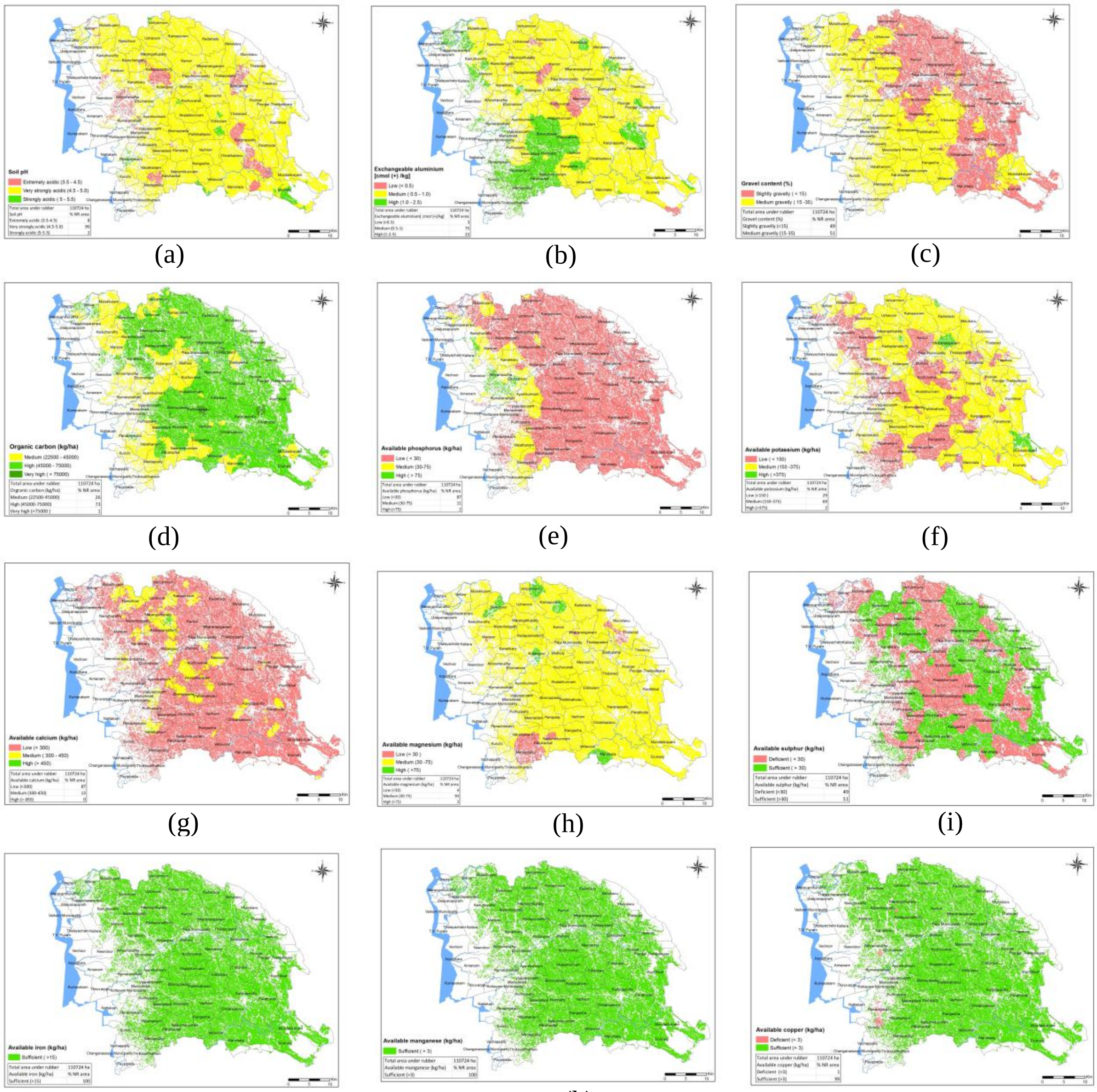
Rubber growing soils of Kottayam district has adequate available OC content ranging from high to very high (Figure 4d). Considerable spatial variability was observed in the OC content, with higher status (45000-75000 kg/ha) in the eastern and central region of Kottayam district and comparatively medium status (22500-45000kg/ha) in the western region. We found that regions where high OC content and soils deeper than one meter are not adversely affected if chemical fertilizers are not applied for a few years as evident from several field experiments conducted by us. In this district, extent of mature rubber area with high OC status and soil depth above one meter was found about 50,765 ha which will make a net saving of Rs 27.4 crore/year (estimate including expense for chemical fertilizer and labour charge). Status of available phosphorus (P) and potassium (K) were low in the study area (Figure 4e & f). For available P, 87 per cent of the rubber growing area in Kottayam district is low (<30kg/ha), 11 per cent medium (30-75 kg/ha) and 2 per cent high (>75 kg/ha). Large extent of rubber growing area in Kottayam district (69 %) is medium in available K status (150-375 kg/ha). About 29 per cent of the area is low (<150 kg/ha) and 2 per cent is high (>375 kg/ha) in available K status.

Spatial variability of secondary nutrients such as available calcium (Ca), magnesium (Mg) and sulphur (S) were also showed low status (Figure 4g-i). Of the total extent of rubber holdings in Kottayam district, 87 per cent is low in available Ca status (<300 kg/ha) and the remaining 13 per cent is medium (300-450 kg/ha). Rubber growing stretches in Kottayam district is medium in available Mg status (30-75 kg/ha) with 93 per cent area in this class. Of the total rubber area, 49 per cent is deficient (<30 kg/ha) and the remaining 51 per cent is sufficient (>30 kg/ha) in available S status. Rubber growing regions in the western, central and some parts of eastern side of the study area exhibited deficient status of available S. Micronutrients were sufficient for available iron (Fe) manganese (Mn) and copper (Cu), whereas available zinc (Zn) and born (B) revealed deficient in some locations in the study area (Figure 4j-n). About 35 per cent is deficient (<1.5 kg/ha) in available B and the remaining 65 per cent has sufficient status (>1.5 kg/ha). Deficient status of available B soils was seen in western and eastern side of the study area. Spatial variability map of available Zn showed about 73 per cent of rubber plantation extent in Kottayam district has sufficient status (>3 kg/ha) and the remaining 27 per cent exhibited low available Zn status (<3 kg/ha).

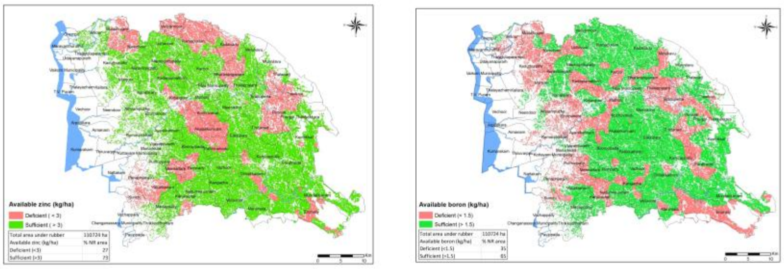
Exchangeable aluminium (Al) content of rubber growing soils in the study area showed 75 per cent is medium (0.5-1 cmol (+)/ kg), 22 per cent high (1-2.5 cmol (+)/ kg) and 3 per cent low (<0.5 cmol (+)/ kg). High exchangeable aluminium content is observed mainly in the south-western parts of the district (Figure 4b). In the case of gravel content, about 49 per cent of the rubber growing area in Kottayam district is slightly gravelly (<15%) and 51 per cent is medium gravelly (15-35%). Slightly gravelly areas were mainly observed in the eastern part of the district whereas medium gravelly areas were concentrated in western part of the study area (Figure 4c).

Rubber Soil Information System (RubSIS)

RubSIS is a free of cost online WebGIS application used for soil fertilizer recommendation of rubber growing regions in Kottayam district. The site can be accessed through http://rubsis.rubberboard.org.in. The current version of the RubSIS application is only for the study area which will be extended to entire NR growing regions in India. Application server of RubSIS is designed into home page and a customized interface meant for soil fertilizer recommendation. Home page was highlighted to give general information and technical details of soil fertilizer recommendation to rubber farmers. Platforms like RubSIS aiming rubber farmers to apply chemical fertilizer only to soil fertility constraint areas of rubber plantations. Once rubber plantation attains maturity it becomes a closed system and therefore fertility status of rubber holdings may not change much for a longer period. RubSIS is a fine example of integration of satellite-derived remote sensing data and GIS for delivering an Information and Communication Technology (ICT) tool for rubber farmers.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k) (l)



(m) (n)

Figure 4(a-n). Geospatial variability of soil fertility parameters of rubber growing regions in the study area a). Soil pH, b). Exchangeable aluminium, c). Gravel content, d). Organic carbon, e). Available phosphorus, f). Available potassium, g). Available calcium, h). Available magnesium, i). Available sulphur, j). Available iron, k). Available manganese, l). Available copper, m). Available zinc and n). Available boron

Conclusion

In rubber plantations, fertility status of soil is one of the key factors that determine its growth and performance. Thus monitoring soil health in definite interval is important to understand variability in fertility status of rubber holdings. In this study, from the traditional time consuming method of soil fertility interpretation, geospatial technology was adopted which ensure better and efficient platform for mapping soil fertility in rubber dominated landscape. In order to manage soil fertility in rubber plantations, a systematic monitoring programme may be required on a temporal basis. It is also important to use geospatial platform to demarcate soil fertility constraint areas easier and faster. Cross validation of spatial prediction of soil fertility parameters showed reliability of the prediction with reasonable accuracy. Thus, geostatistical modelling techniques are applicable to investigate spatial variability of rubber growing soils in the study area. Application like RubSIS ensures usage of chemical fertilizer only to soil fertility constraint areas of rubber plantations which can result in significant reduction in cost of rubber cultivation even as environmental pollution due to indiscriminate use of chemical fertilizers is avoided.

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