Estimation and Mapping of Vertisols Soil Nutrients by Geostatistics and Remote Sensing Approach

Thesis

Submitted in partial fulfillment of the requirement for the degree

of

DOCTOR OF PHILOSOPHY

By

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(148011CV14F18)

DEPARTMENT OF CIVIL ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA
SURATHKAL - 575 025
DECEMBER- 2021

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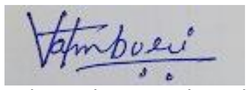
D E C L A R A T I O N

I hereby *declare* that the Research Thesis entitled **"Estimation and Mapping of Vertisols Soil Nutrients by Geostatistics and Remote Sensing Approach"** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfilment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Civil Engineering Department** is a *bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.



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Place: NITK-Surathkal

Date: 15/12/2021

CERTIFICATE

This is to *certify* that the Research Thesis entitled **"Estimation and Mapping of Vertisols Soil Nutrients by Geostatistics and Remote Sensing Approach"** submitted by **VINOD TAMBURI** (Register Number: **148011CV14F18**) as the record of the research work carried out by him, is *accepted as the Research Thesis submission* in partial fulfilment of the requirements for the award of degree of **Doctor of Philosophy**.

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VINOD TAMBURI

Dedication

To my parents for all their love and support and putting me through the best education as possible,

To all my former teachers through whom the Almighty led me to the world of knowledge and wisdom,

&

To my loving wife, Mrs. Chaitra Vinod, for her constant source of encouragement and inspiration during the period of my research work.

ABSTRACT

The status of soil fertility is a concern, especially in the Deccan plateau vertisols of India. Vertisols are productive if they are managed well. Understanding the spatial variability of soil nutrients is necessary for agriculture to maintain sustainability. The objective of the present study is to characterize the status of soil nutrients, spatial variability of selected soil nutrients, and the estimation of the presence of these soil nutrients by spaceborne Hyperion data in scattered small-size fields of Gulbarga taluk, northern Karnataka, India. This region is known as the "pigeon pea vessel" of the state.

The geostatistical analysis is carried out in SpaceStat 4.0® to find the spatial variability of all the selected nutrients. The coefficient of variation monitors the variation in the nutrients of the soil. The variogram analysis has shown that all the selected nutrients are the best fit for the spherical model except nitrogen, organic carbon, and phosphorus. The nugget/sill ratio is utilized to know the spatial dependence of soil nutrients. Using the best fit model, surface maps are generated by the ordinary kriging method.

The estimation of soil nutrients from Hyperion data with statistical regression is measured as an alternative technique. The spectral information of the visible near infrared and short wave infrared range (400-2500 nm) is utilized to characterize soil nutrients. The potential of the Hyperion data has not yet been exploited completely due to noisy atmospheric components in spectral signatures especially in fields of smaller size. Sixty-eight random topsoil samples were collected from small farms, which are less than two acres in size. The systematic sampling of soil was conducted in the month (third week) of November 2016. This duration is also synchronized with the passage of the Hyperion satellite above the study area. The atmospheric (FLASSH) and geometric corrections is carried out and then the spectral reflectances are extracted. The PLS_Toolbox is used for filtering (Savitzky Golay), and the Partial Least square regression (PLSR) technique is applied for the estimation of soil nutrients by Hyperion data. The variable importance in projection (VIP) is identified, which reduces the non-significant wavelengths for the PLSR model. Two indices are used to assess the prediction accuracy, Coefficient of determination (R^2), and root mean square error (RMSE).

From analysis of soil nutrients, it is observed that the spatial variability maps exhibited a heterogeneous pattern of soil nutrients because of individual farming methods. The spatial variability maps are used as initial regulation by policymakers for site nutrient management, including fertilization in vertisols. This is essential for sustainable management of the fields, which are aimed at increasing the productivity of the crops; low productivity vertisols are to be used in cultivation on a global scale due to the current shortage of food supplies and agricultural resources land.

The utilization of Hyperion data and PLSR technique showed that it has the low to moderate potential to estimate certain vertisols nutrients such as iron (R^2=0.40), potassium (R^2=0.45), and Copper (R^2=0.41), and moderate estimation for nitrogen (R^2=0.54) even though vertisols have less reflectance values compared to other soil types.

The vertisols of India exhibit low reflectance, which are deficient in humus, nitrogen, phosphorus, and potassium due to low permeability and moisture stress throughout the drought. Hence the presence of soluble nutrients concentration is low compared to other soil. Generally, the white color contributes to higher reflectance in all wavelengths, so the grey-brown color is natural in the vertisols fields and along with less organic matter, which leads to the low reflectance. Hyperion data can be inventively utilized to estimate vertisols soil nutrients with reasonable accuracy in heterogeneous and small size fields.

Keywords: Vertisols, Soil nutrients, Geostatistics, Spatial variability, Hyperion, PLSR, and Sustainable agriculture.

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CHAPTER 1

INTRODUCTION

1.1 Background

Soil is the soul of all living beings on earth. A soil sustains, monitor, supply and provide services to cultural ecosystems, and plays an important role within the global framework for primary biogeochemical cycles and energy. Soil formation is attributed to parent material, organisms, climate, relief, and time.

Soil is one of the most vital components of agricultural production and can have a prevailing effect on crops quality and yield. For a substantial period of time, agriculturist used in-filed soil data to make decisions on crop management practices.

The highest concentrations of nutrients and microorganisms occur on topsoil (0 to 20cm) that provides the framework for most of the biological soil activity. Soil characteristics are neither static nor uniform with time and space. Topsoil is mainly used in agriculture, since plants gain most of the nutrients from it. The soil properties information at finer resolution is vital in many fields, more so in precision agriculture.

Major types of soils are mountain soils, black soils, laterite soils, red soils, alluvial soils, and desert soils. Among these, the worlds black soils (vertisols) occupy a great deal territory. Australia (70.5 m ha), India (72.9 m ha), Sudan (40 m ha), Ethiopia (10 m ha) and Chad (16.5 m ha) are major territories of vertisols and associated soils. These five nations comprise more than 80% (250 m ha) of the total vertisols area on the planet (Figure 1.1).

In India, vertisols occur mostly in the peninsular region between 8^o 45' and 26^o 0' N latitude and 66^o 0' and 83^o 41' E longitude, and approximately 0.42 million km^2 of the deccan plateau area covers the vertisols (Sharma et al., 2011).

The vertisols are derived from base-rich rocks parent material (basalt), generally alkaline. Vertisols are soils that can be easily recognized from their clayey textures and dark colours. Generally, for agricultural practices vertisols are not preferred due to stickiness and shrink – swell characteristics (Eswaran and Cook, 1987). Besides, inadequate soil moisture , poor drainage and poor fertility are the major related problems of vertisols (Blaise et al. 2005). Actually, when vertisols are well managed, their productivity is high.

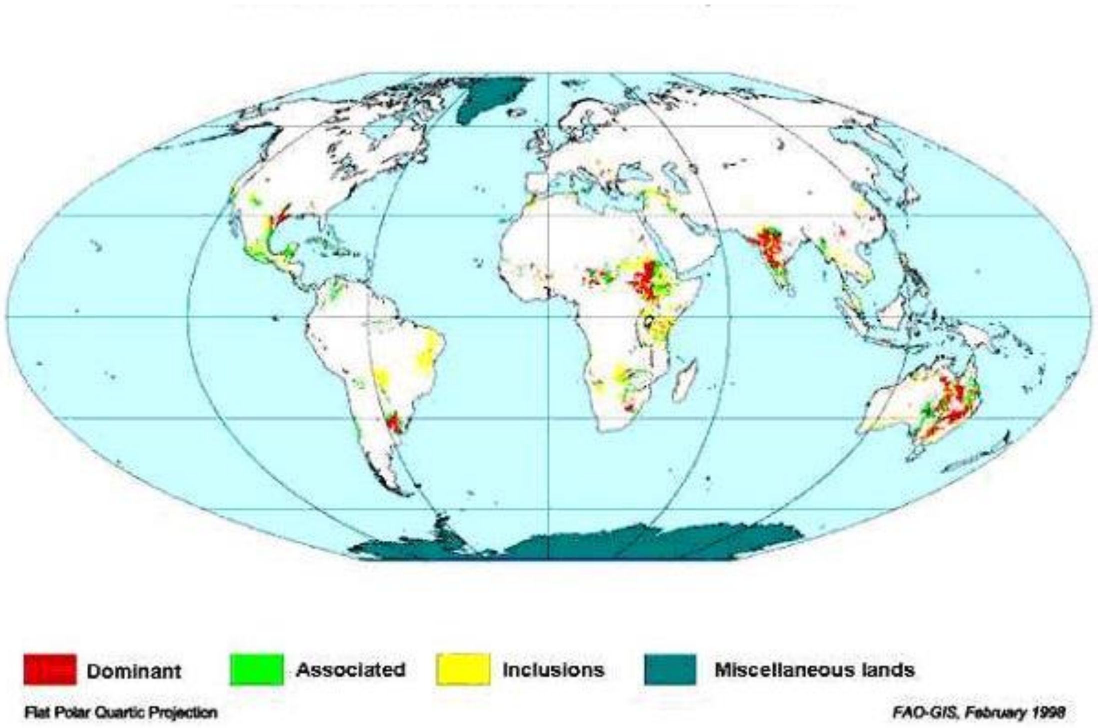


Figure 1.1 Distribution of vertisols

1.2 Sustainable farming

Around 40 % of the world's total poverty is dominant in the sub- continent’s South Asian nations. Major limitations on the improvement of livelihoods among agriculturalists in these areas are mainly due to small farms with high cropping intensity, various field monitoring practices have been implemented for different crops with generalized nutrient recommendation systems, associated with inadequate technical support, resulting in insufficient and imbalanced use of plant nutrients, resulting in low crop yields in the county (Chatterjee et al., 2015). Over the last decade, the food production has increased, which resulted in the expansion of irrigated lands (Ambast et al., 2002), in contrast the poor water management practices are disturbing the soil structures. The agricultural practices vary owing to the large difference in farmer's knowledge, applications of fertilizers, crop pattern, farm management, and use of resources available among farmers lead to the high variability of soil nutrients. The application of fertilizers to the soil will go through diverse physiochemical reactions thus making nutrients present in the soil vary from place to place (Debnath et al., 2016). In general, for sustainable development it is important to make progress in individual fields and then interlinking them for overall sustainable development (Singh et al., 2009). Similarly, in agriculture sectors, individual fields need to be addressed and interlinking the fields will lead to overall sustainable agricultural development.

The soil nutrients are essential elements for crop growth. The applications of commercial fertilizers contribute to a considerable increase in yields of crops that feed the population of the world. For enhancing the availability of nutrients, application of fertilizers are essential (Shrivas et al., 2019). However, excessive use of these fertilizers has been recognized as a source of contamination of soil and groundwater. Ideally, application rates should be adjusted based on estimations required for optimal production at each location as the spatial variability of nutrients will be high within individual agricultural fields.

Precision farming is the integrated agricultural management system integrating several technologies. In this sense, the specific management of land is one of the efficient procedures for improving the productivity of agricultural land. The soil management approach is focused on the application of GIS, GPS, and remote sensing. (Mulla and Schepers, 1997). Remote sensing is recognized to be cheaper, faster, and relatively precise compared to conventional methods (e.g., Drying combustion method for soil organic carbon concentration). Remote sensing imaging is in the process of being recognized in precision farming methods for soil property determination.

1.3 Remote sensing in soil science

When optical and radiometric instruments were in partial use almost 80 years ago, colours were the most recognizable and useful characteristics to chart variations between soils. Soil scientists have projected new methods and instruments for assessing soil spectra and more specifically linking them to soil properties and curving them for remote sensing.

The primary prerequisite in remote sensing approach is the accessibility of robust relationships between soil property of interest and its respective reflectance spectra availability (Lagacherie et al., 2008). In the 1930s, when black & white aerial photos were prepared as the base plots for soil surveys, the early attempt to use remote sensing for soil studies occurred in the US (Stoner et al., 1980).

The advent of satellite remote sensing technology and geographic systems has contributed a lot to soil studies. Earth-observing optical remote sensing satellite systems loaded with sensors that record broad bands in the visible and near-infrared spectral regions like Landsat multispectral scanner, Thematic mapper, Enhanced thematic mapper, Advanced Spaceborne Thermal Emission and Reflection Radiometer, sensors economically provide a wide range of varying spatial resolution. Of late, advancements in space-borne remote sensing have led to the introduction of hyperspectral sensors.

Hyperspectral data analyses are superior to traditional broadband analysis in spectral information. In the field of remote sensing, hyperspectral image analysis is one of the most influential and fastest-growing technologies. It can reduce methods of collecting labour-intensive soil data. It is accepted in digital soil mapping workshop that, poor soil dataset has been an issue that can rigorously limit the progress of digital soil mapping. Hence it is significant to include the soil sensors that can provide precise estimates of soil property over large areas (Bottinger et al., 2010).

1.4 Spatial variability of soil nutrients

The soil formation processes and farm management practices vary the topsoil properties temporally and spatially. The spatial variability of soil nutrients by Digital Soil Mapping (DSM) is one of the key aspects of precision agriculture (Mertens et al., 2008). The DSM constructs a spatial soil data system-utilizing field and laboratory observation techniques in combination with the method of spatial prediction. This is supported by advances in soil analysis incorporating mathematical and statistical techniques to better predict regions with a minute or no data of soil properties, highlighting the uncertainty of such predictions. The importance of soil nutrients and their main functions in crop physiology (Minasny and Hartemink, 2011) is given in table 1.1.

The aim of the soil science is to determine the reason and effect of a connection between soil nutrients. Geostatistics (Yost et al., 1982) are often used to deal with the spatial distribution of soil nutrients. The estimation and mapping of the soil property at un-sampled zones defined as interpolation is the main application of geostatistics in soil science (Goovaerts, 1997). One of the key driving factors affecting soil management practices is accurate measurement of spatial variability of soil nutrients (Zhang et al., 2014).

India is classified into fifteen Agro-climatic zones based on soil pattern, climate, physiography, and cropping patterns (Venkateswarulu et al., 1996). Small farmlands, especially in the Deccan plateau, are a prominent feature for agriculture in India. About 80% of the farmers hold approximately 2 hectares, which accounts for > 50% of agricultural production. The average size of agricultural land ownership decreased from 2.3 ha in 1970 to 1.3 ha in 2000, with 0.32 hectares per capita in 2001 (Mythili and Goedecke 2016). These small farms create severe financial pressures for farmers. Due to this stress, the use of green fertilizers or soil conservation facilities is restricted by labour, land, and capital resources (Bhattacharyya et al., 2015).

As a direct source of degradation, land scarcity, and poverty, as a whole, leads to unsustainable land management practices. The reason for two other immediate causes of soil degradation are inadequate crop rotations and unbalanced use of fertilizers (Young, 1994). The use and practices of specific site management are strongly linked to the quality of the soil, and the implementation of adequate soil management procedures and planning the land use would be useful both to bring back the physicochemical quality of the degraded soil and to ensure consistent and sustainable soil conductivity (Panday et al., 2019). The specific site management is an alternative to traditional practices and cost-effective, which reduces the input of fertilizer application (Shaddad et al., 2019).

Table 1.1 Importance of Nutrients

NUTRIENT	Importance	Units
Nitrogen (N)	Present in a wide range of compounds essential for growth and energy transfer, including chlorophyll. Deficiency may lead to chlorosis with a pale colour turning to yellow or grey in severe cases, and lead to slower growth rates.	g/Kg
Phosphorus (P)	An essential part of the process of photosynthesis, respiration, and energy transfer in plants. Deficiency may cause stunted form delayed maturity and dark green colour.	g/Kg
Potassium (K)	Involved in building starch and proteins, an activator of many enzymes essential for photosynthesis, and assists in reducing diseases. Deficiency may cause chlorosis discoloration and plant weakness due to reduced turgor pressure.	g/Kg
Iron (Fe)	Essential for the formation of chlorophyll, certain enzymes, and proteins that carry electrons during photosynthesis and respiration. Symptoms of Fe deficiency include chlorosis and necrotic lesions.	mg/Kg
Zinc (Zn)	Required in trace amounts to activate enzymes and may be required for chlorophyll formation. Deficiency may cause chlorosis and growth reduction of young foliage.	mg/Kg
Calcium (Ca)	A component of plant cell wall structure plays a vital role in the transportation and retention of other elements. Deficiency may cause low plant strength and poor plant form.	g/Kg
Magnesium (Mg)	An essential part of chlorophyll molecules and activates enzymes needed for photosynthesis and DNA formation. Deficiency is rare but may cause chlorosis.	g/Kg
Copper (Cu)	An enzyme activator thought to be involved in chlorophyll formation and protein synthesis. Deficiency may cause reduced growth rates, poor plant form, and chlorotic needle tips.	mg/Kg

(Source: Sims et al. 2013)

1.5 Statement of the problem

A host of factors in India, such as small farms (less than two hectares in size), poor machinery owing to financial constraints and a lack of scientific knowledge have lead to lack of awareness in precision agriculture. Human interventions in soil ecosystem for producing food to meet the demand are reducing the essential nutrients. In India, the continuous cropping system for greater yield eliminates significant amounts of topsoil nutrients. In addition, the topsoil losses its fertility status due to poor vertisols watershed management. Mapping the spatial variability of soil nutrients and understanding the condition of soil nutrients and estimating soil nutrients through remote sensing data will be the first step towards the practice of precision agriculture.

Vertisols are highly productive even with low-input farming when well managed. In the Deccan plateau region of India, lower crop productivity is a major concern, averaging less than 1600 kg/ha due to poor soil fertility and water scarcity (Vasu et al., 2017). Precision farming is the integrated agricultural management system integrating several technologies. In this study, an attempt will be made to predict vertisols soil nutrients integrating remote sensing, hyperspectral, GPS, and GIS. By the development of precision farming, which demand the high spatial resolution of properties in-filed soil, engineers and agricultural scientists have turned to remote sensing for characterization of soil properties.

The characterization of the spatial variability of macro and micronutrients in vertisols of the Deccan plateau of India is limited. To date, only a few studies have attempted the exploitation of existing satellite hyperspectral capabilities for retrieval of soil nutrients from vertisols. The scattered and small size fields pose challenges for extracting soil properties from satellite data.

The current chapter has introduced the predicament and an overview of geostatistics and remote sensing application in characterizing the soil nutrients. The next chapter looks at the research conducted previously in this field.

CHAPTER 2

Literature Review

2.1 General

This chapter presents a review of relevant literature to bring out the background of the study undertaken. Geostatistics and remote sensing techniques play a vital role in the estimation and mapping of soil nutrients in small sized fields of marginal farmers.

2.2 Spatial variability of macro and micro nutrients in the soil

The precise soil management is an effective technique to increase the productivity of agricultural areas in sustainable agriculture (Yasrebi et al., 2008). The management of soil also depends on knowledge of the spatial variation in soil, mainly soil nutrients (Lagacherie and McBratney, 2007; Mulla, 2015). The precise estimation of spatial variability is an essential factor influencing land management practices (Chatterjee et al., 2015).

Soil nutrients change spatially from small field scale to regional scale affected due to extrinsic and intrinsic factors such as the soil formation process, crop rotation, soil management practices. The variations of soil nutrients are gradual changes in geomorphic elements, soil management, functions of landforms, pedogenic factors, and soil-forming factors (Cambardella and Karlen 1999). The variations in the yield are affected by specific management practices and ecological environments of site. The systematic data concerning distribution and spatial variability of soil nutrients is important for farmers to increase the production of crops (Tesfahunegn et al., 2011).

The soil nutrients are categorized into macro and micronutrients, the macronutrients (N, P, K) are required in large portion in the life cycle of the crop. The macronutrients helps the crop in monitoring the metabolism by protein constituent, helps in energy transfer and in osmoregulation which is vital for movement of stomata and cell extension (Hawkesford et al., 2012). Other than N, P, K rest all the nutrients are considered as micronutrients (Fe, Cu, Zn, and Mn). These micronutrients are taken up by crops in lesser quantity for entire crop life cycle. They play prominent part in crop metabolism and its development. Though, the deficiencies of these nutrients hinder the quantity and quality of any crops will leads to the diseases in crop life cycle (Tripathi et al., 2015). The micronutrients have not for the most part been applied consistently to soil related to normal composts and preparing soils with macronutrients just is probably going to advance irregularities between these supplements of nutrients (Sillanppa ,1982).

2.2.1 Spatial variability of Macronutrients

The Spatial analysis of macronutrients is important, given the close relationship to soil productivity and the anthropogenic effects (Liu et al., 2014). It was estimated that annually about 4.17, 2.13, and 7.42 million tons of nitrogen, phosphorus, and potassium respectively are removed in agricultural systems in India, affecting the fertility of soil (Bhattacharyya et al., 2015). Hence understanding the spatial variability of soil macronutrients is necessary for agriculture to maintain sustainability.

The current agricultural practices are depleting the soil nutrients causing adverse affect on soil health. By evaluating the current practices, Uygur et al., (2010) characterized the spatial variability of macro nutrients in the amik plain soils, Turkey, through the IDW (inverse distance weighting) method. They stated spatial variability maps are used to identify the agricultural areas, which require fertilizers for better yields and even prevent environmental pollution. This type of practices is to be encouraged to increase the productivity of fields of marginal farmers and restore the soil nutrients in India.

The geostatistical approach used to describe the spatial variability of soil nutrients has been discussed by Liu et al., (2014). In their study spatial variability of macronutrients, pH, and zinc was explored. The higher nugget to sill ratios indicates that soil nutrients are strongly affected by extrinsic factors. They have also found that soil variability affects the yield of the rice in South China. Hence it becomes important to consider the external factors affecting the agricultural practices while evaluating the spatial variability.

The characterization of major soil nutrients (N, P, and K) was carried by Tagore et al. (2014) in the malwa plateau of the Indore district, India. Spatial variability was quantified by semivariogram analysis, and ordinary kriging is used for generating the spatial variability maps. They have estimated the ordinary kriging has predicted accurately than assuming the mean of observed value at non-samples locations. The geostatistical approach considers the distance between the samples, which makes better predictions of spatial variability of soil nutrients. The ordinary kriging for interpolation is best suited to provide a balanced prediction for a specific unsampled location that reduces the variance error and makes the sum of the sample weights is equal to one (Tamburi et al., 2020a).

The practical application of geostatistics can be seen in the study by Tripathi et al. (2015) where they estimated the spatial variability of soil macronutrients, pH, and EC in the salt-affected region of Odisha, India. They have developed the spatial variability maps by using the best-fit variogram model and ordinary kriging. High-risk areas affected with saltwater and nutrient deficiency are identified to provide an effective farm management plan to farmers.

Chatterjee et al. (2015) have carried out a systemic study to characterize the spatial variability of macronutrients and organic carbon in the West Bengal’s alluvial soil, India, by utilizing geostatistics techniques. The spatial variability maps simplify managing the proper regulation of soil nutrients leading to enhanced yield and also make sure the protection of the environment. The authors suggest the spatial variability maps of macronutrients are to be exploited for developing the nutrient management policies among small scale farmers.

It is important for knowing macronutrient inputs and their spatial variability for high output of bamboo and timber production in the Moso bamboo area is significant (Tang et al., 2016). Ordinary kriging is utilized for spatial interpolation. They have found that both extrinsic and intrinsic factors controlled the macronutrients stock. Different spatial patterns indicate that different sites require a different ratio of NPK fertilizers. This demonstrates the significance of generating the spatial variability maps before fertilizers are applied. Similarly, Reza et al. (2017) carried out an extensive study to explore the variability of soil macronutrients along with soil pH, organic carbon (OC), and Available Zn northeastern part of Bihar, India using geostatistical approach. The maps of spatial variability can be utilized as the primary guidance for specific region farm management.

The kriging is the optimum method, for the interpolating to know the unsampled values, conversely its application should involve a precise determination via variogram construction and best model fit (Dey et al., 2017). In the Katni district of Madhya Pradesh, India, they have investigated the spatial variation of macronutrients along with pH, EC, OC, and zinc by random sampling technique. Ordinary kriging is used for developing the spatial variability of soil nutrients. They propose constant monitoring of soil nutrients spatial distribution is must, which helps in regulating the rate of fertilizers and also to monitor the soil fertility and crop yield.

The kriging is a statistical estimator that provides weight to each sample so that their linear structure is equitable and gives the marginal variance of the estimate (Denton et al., 2017). The spatial variability of soil macronutrients, pH, and OC has been investigated. They propose that ordinary kriging is ideally suited for predicting the spatial variability of soil nutrients. The spatial variability is to be a prerequisite for soil management and must be the first step moving towards sustainable agriculture.

The spatial distribution and heterogeneity of alfisol soil nutrients in the tropical landscape of Sri Lanka have been defined by Rosemary et al. (2017). To estimate the chemical properties (pH, EC, and OC), they collected 58 soil samples. Ordinary kriging is used to assess soil nutrient spatial variability, and its findings are useful for site-specific management. Similarly in Nitisols, Laekemariam et al. (2018) conducted a geostatistical investigation to establish macronutrients spatial variability maps, including other soil nutrients. The long spatial correlation ranges are demonstrated by the spatial structure being weak to solid. These results indicate that the variability of soil nutrients is affected by external and intrinsic influences. Site-specific, and according to crops, should be the rate of fertilizer applications.

It is supported by Gao et al. (2019), that the awareness of the spatial variation of soil nutrients for the protection of vulnerable ecological areas is important for soil and fertilization management. They also established the spatial variability of NPK. The nugget-to-sill ratio showed that all soil nutrients showed moderate spatial dependence. In the Sichuan Basin, China, the variability of soil nutrients is primarily differentiated due to the parent material and land use. They recommend that more attention be paid to the implementation of practical land use types.

The site-specific management is currently urgently required to maximize the use of natural resources and to incorporate sustainable agriculture in order to capitalize on soil production and minimize costs while minimizing environmental impacts which is noted by Shaddad et al. (2019). They also developed a methodology for the delineation of fields in Egypt based on geostatistics. To know the spatial variability of electrical conductivity, available potassium, available nitrogen, and organic matter, ordinary kriging has been used. They state that the guidelines are not for traditional farming practices whereas the site-specific practices should be carried out with as many benefits as possible; for example, they are efficient and economical.

Chen et al. (2020) have analysed the spatial variability soil macronutrients by comparing the surface maps of 2007 and 2017, which were developed by using the ordinary kriging technique. By long term production, the spatial variability and dependence of soil nutrients drop. The change in spatial variability is due to extrinsic factors, and soil fertility has decreased over the decade.

The table 2.1 provides the detailed summary of parameters for spatial variability of macro nutrients. The efficient technique for determining the spatial variability of nutrients in soil and their inconsistencies is carried out by geostatistics (Shukla et al., 2016). The use of geostatistics for interpolation in soil science is used to estimate the soil attributes at a nonsampled location and its mapping (Goovaerts, 1999). The use of geostatistics should be used as part of sustainable farming in developing countries such as India as it has a long record in soil science applications (Yost et al., 1982; Cambardella et al., 1994; Webster and Oliver, 2008). It is significant to recognize the spatial variability of soil nutrients in vertisols. In the deccan plateau, the uniform recommendations of fertilizers lead to excess or depletion of macronutrients. The spatial analysis of macro nutrients is important, given the close relationship to soil productivity and the anthropogenic effects (Liu et al., 2014).

Table 2.1 Summary of spatial variability of soil macronutrients

Author's	**Fields nature**	**Soil type**	**Nutrients**	**CV (%)**	**Range (m)**	**Technique**
Uygur et al. (2010)	Agricultural land. Amik Plain, Turkey	Alluvium, Clay chalk and sandstones	N	68.97	-	IDW
			P	103.90		
			K	55.11		
Tagore et al. (2014)	Soybean farm, Indore, India	Vertisols	N	20.26	706.7	OK
			P	44.43	3130	
			K	42.73	1295	
Liu et al. (2014)	Rice cropping area, South China	-	pH	17.38	711	OK
			Avl.N	36.02	1200	
			Avl.P	74.66	1200	
			Avl.K	52.09	1200	
			Avl.Zn	57.46	1200	
Tripathi et al.	salt-affected coastal parts,	Salt affected	pH	4.43	2981	OK
			EC	62.50	2998	

Author's	Fields nature	Soil type	Nutrients	CV (%)	Range (m)	Technique
(2015)	Odisha, India	soils	OC	50	2220	
			Avl.N	37	2899	
			Avl.P	25.9	4050	
Tang et al. (2016)	Moso bamboo forests, southern China	Oxisol	N	27.92	6100	OK
			P	29.10	30570	
			K	29.17	25700	
Chatterjee et al. (2016)	Paddy and vegetables, West Bengal, India	Alluvial	OC	21.2	58	OK
			Avl. N	10.1	43	
			Avl. P	47.8	283	
			Avl. K	38.6	55	
Reza et al. (2017)	Alluvial plain, Bihar, India	Fluvisols, Cambisols, Arenosols	pH	11.3	3315	OK
			OC	31.3	3101	
			Avl.N	23.6	1958	
			Avl.P	94.3	2420	
			Avl.K	50.6	2345	
Dey et al.	Katni	Alluvial	pH	14.16	95800	OK

Author's	Fields nature	Soil type	Nutrients	CV (%)	Range (m)	Technique
(2017)	district, Madhya Pradesh, India	soil	EC	73.51	92570	
			OC	25.68	95800	
			N	26.29	95800	
			P	80.74	24830	
			K	41.78	95800	
			Zn	140.19	41970	
Rosemary et al. (2017)	Tropical landscape, Sri Lanka	Alfisols	pH	18	590	OK
			EC	76	830	
			OC	37	984	
Denton et al. (2017)	Local government area, Oyo State, Nigeria	-	pH	9.83	0.0035	OK
			N	29.30	0.0022	
			P	40.19	0.0038	
			K	37.93	0.0036	
			OC	28.35	0.0022	
			pH	10	523.7	

Author's	**Fields nature**	**Soil type**	**Nutrients**	**CV (%)**	**Range (m)**	**Technique**
Laekemariam et al. (2018)	Coffee and annual crop growing fields, Ethiopia	Nitisols	OC	36	777	OK
			N	47	813.5	
			Avl.P	236	10606	
			K	69	4465.9	
			Ca	50	6313	
			Mg	45	1833	
			Cu	71	276	
			Fe	35	536	
			Mn	35	15118	
			Zn	84	301	
Gao et al. (2019)	Mountain area, woodland, paddy fields, Sichuan, China	Alluvium and Purple sand shale	N	38.75	9500	OK
			P	37.68	30900	
			K	30.56	31200	

Author's	Fields nature	Soil type	Nutrients	CV (%)	Range (m)	Technique
Chen et al. (2020)	Jianli, Central China	paddy soil, tidal soil	2007			OK
			pH	6.5	4980	
			OC	32.6	2760	
			Avl.N	31.7	3330	
			Avl.P	66.7	5400	
			Avl.K	50.9	21900	
			2017			
			pH	5.8	19560	
			OC	22	12287	
			Avl.N	12.2	44427	
			Avl.P	70.6	5940	
			Avl.K	43.2	79880	

2.2.2 Spatial variability of Micronutrients

Over time, the availability of micronutrients is declining and is required to be applied externally to maintain soil health and increase crop yield (Kumar and Babel, 2011). Micronutrients are depleted by intensive cultivation from the soil. Thus, the evaluation of soil fertility should be performed when intensive cultivation is carried out to obtain a high yield (Tamburi et al., 2020b). The evaluation of the spatial variability of micronutrients and their mapping is essential to understand soil behaviour variations (Denton et al., 2017).

There are many kriging techniques to estimate the spatial variability, among which Wang et al. (2009) have used the Block Kriging (BK) to determine the spatial variability of soil micronutrients in paddy fields of Southeast China. A grid sampling with grid intervals (20, 30, and 40m) they have collected the samples of soil as well as grains. They recommended the spatial variability of micronutrients in both rice grain and soil will ease information regarding fertilization and site-specific farm management.

The sampling density and the uniformity plays vital role in estimation of accurate spatial variability of soil nutrients. Weindorf and Zhu (2010) described how the optimum sampling density is related to the spatial variability of soil nutrients. They selected samples by forming a gridded equilateral triangle and selected three random points within the triangle. To generate the spatial variability, they have used ordinary kriging techniques. They identified that chemical parameters have strong spatial variability than physical parameters.

As discussed at beginning of this section knowing the spatial variability of micronutrients is also important. In that regard, Wani et al. (2013) conducted the spatial variability of micro soil nutrients in the region of Kashmir, India. They generated spatial variability maps by Ordinary kriging (OK) and Indicator Kriging (IK). The nugget effect (the variogram bisects at zero lag distance) and the range values are used for assessing spatial dependency. Foroughifar et al. (2013) have done sampling by grid method for determining the spatial variability of micronutrients, pH, OC, and P. They utilized the Cokriging (CK) technique for semivariogram analysis. They found the soils are heterogeneous in nature. Hence, the traditional farm practicing will not be supplying the necessary nutrients to crops.

The comparative study is also carried out by Liu et al. (2013) to know the spatial variability of soil micronutrients between semivariogram and Moran's I method.

Semivariogram investigation provided them with the sum of negative and positive autocorrelation and the distance of spatial correlation for micronutrients. The spatial dependency reflected was similar in both spatial analyses.

In South Africa, Manyevere et al. (2017) determined the spatial variability and status of soil micronutrients in the two zones of the Zanyokwe irrigation scheme in which there are maximum small scale farmers. The simple kriging (SK) is utilized for developing the spatial variability maps. They recommended the corrective measures for low spatial variability of soil micronutrients. Similarly in India, Shukla et al. (2017) characterized the spatial variability of soil micronutrients and secondary nutrients in the foothill of Himalayas. They tried to describe the potential zones. The range of spatial dependency on soil nutrients showed long ranges. The soil pH has considerably influenced the variability of soil micronutrients. The spatial variability maps produced by the OK method are used as preliminary guidance for site-specific farm management.

The knowledge of understanding the spatial variability of micronutrients is essential for the development of a site-specific nutrient recommendation through the purpose of improved agriculture and more sustainability in agricultural production. It is estimated the delineating management zones in saline soil of eastern India by using OK for generating spatial variability maps of both micro and macronutrients (Rahul et al.,2019).

The availability of current knowledge of factors affecting soil micronutrients, in the long run, is limited (Zhuo et al.,2019); hence they compared the spatial variability of soil micronutrients in 2007 and 2017 in orchids agricultural land of Beijing, China. The spatial variability of micronutrients available in soil was mainly influenced by random factors like field management, fertilizer application, and land use type, and it has been regularly strengthening from 2007 to 2017.

Paris et al. (2020) state that for agricultural production the soil fertility is the key aspect to be monitored. The geostatistical analysis is an adequate method for evaluation of the spatial variability of soil micronutrients. They analysed the spatial variability of micronutrients by ordinary kriging in the macadamia nut plant fields.

The ranges obtained varied due to fertilizer applications. Organic matter in the fields correlates micronutrients significantly, and the yield has varied on the available zinc in the fields. The table 2.2 provides the detailed summary of parameters for spatial variability of micronutrients.

Table 2.2 Summary of spatial variability of soil micronutrients

Author's	**Fields nature**	**Soil type**	**Nutrients**	**CV (%)**	**Range (m)**	**Technique**
Wang et al. (2009)	Paddy fields, Southeast China	-	pH	7.1	110	BK
			OC	31	60	
			Cu	17.7	60	
			Fe	29.2	60	
			Mn	26.8	60	
			Zn	28.6	60	
Weindorf and Zhu (2010)	Natural vegetation (Woody species, grass, and wildflowers), New Mexico	Bandera soil, and Fallsam soil	pH	8.5	507	OK
			OC	47.26	1554	
			Ca	29.77	1845	
			Mg	26.61	762	
			Zn	61.68	194	
			Cu	28.45	299	
Wani et al.	Rice and	-	Cu	38.8	140	OK and IK

Author's	Fields nature	Soil type	Nutrients	CV (%)	Range (m)		Technique
(2013)	maize crop, Kashmir, India		Fe	52	120		
			Mn	73	136		
			Zn	78	243		
Foroughifar et al. (2013)	Wheat and barley fields, Dasht-e-Tabriz, Iran	Salty soil (adjacent to saline Orumieh Lake)	Fe	138	5700		CK
			Cu	44.3	6000		
			Mn	52.5	7364		
			Zn	43.5	2200		
			pH	5	1600		
			OC	99	2270		
			P	69	2150		
Liu et al. (2013)	Agricultural development land, Shandong province, China	Halosols, Cambosols, and Luvisols	Fe	20.29	29700		-
			Mn	15.16	20900		
			Cu	30.22	61900		
			Zn	21.81	58000		
Manyevere et al.	Maize, cabbage and butternuts,	Vertisols, Nitisols, and	Zn	-	3	4	SK
			Cu	-	6	10	

Author's	Fields nature	Soil type	Nutrients	CV (%)	Range (m)		Technique
(2017)	Eastern Cape, South Africa	Fluvisols	Mn	-	10	11	
			Fe	-	20	13	
Shukla et al. (2017)	Green oak, silk cotton tree, and maize Shiwalik Himalayan tract and foothills of the great Himalayas, India	Alluvial soils	pH	13.83	132000		OK
			EC	80	65000		
			Zn	76.34	66000		
			Fe	77.56	82000		
			Cu	61.74	70000		
			Mn	66.91	80000		
			OC	38.85	59000		
Rahul et al. (2019)	Paddy fields, Mahakalpada block, Odisha, India	-	pH	7.1	5175		OK
			EC	100	4950		
			Avl.N	40.1	5004		
			Avl.K	56.7	4096		
			Avl.P	62.7	6425		

Author's	Fields nature	Soil type	Nutrients	CV (%)	Range (m)	Technique
			Zn	148.1	3966	
			Fe	38.1	9215	
			Cu	29	4096	
			Mn	160.4	7963	
Zhuo et al. (2019)	Pinggu intermountain basin, Beijing, China	-	2007			OK
			Cu	29.61	1180	
			Zn	73.10	720.4	
			Fe	57.64	3423.86	
			Mn	36.80	7333.0	
			2017			
			Cu	62.25	697.54	
			Zn	128.4	6586.5	
			Fe	92.29	503.27	
			Mn	95.09	8213.5	

Author's	Fields nature	Soil type	Nutrients	CV (%)	Range (m)	Technique
Paris et al. (2020)	Macadamia nut yield, Brazil.	Oxisol soils	Fe	48	34.4	OK
			Cu	31.9	14.6	
			Zn	35.1	55.9	
			Mn	47	64	
			OM	16.1	133.3	

In the Indian context, information on the available calcium status of soils is somewhat inadequate. About one-third of India's soil is vertisols. A recent presentation of secondary nutrients barely mentions the extent of Ca and Mg deficiencies in India (Behera and Shukla, 2015). Due to the low base saturation, especially in areas with heavy precipitation, there may be a lack of Ca in many vertisols. No mappings are made beyond the pH and macronutrients. Among the nutrients, Ca is the least explored in India. Like Ca, deficiency of Mg can be a problem in leached vertisols under high rainfall. Mg can be leached out easily as compared to Ca making acid (Behera and Shukla, 2015).Over the decades, the declining rate of micronutrients have increased, and fertilizers are applied excessively to maintain soil health and increase the yield of the crops (Kumar and Babel. 2011). Among the micronutrients, Zn is the most important for soil and plants equally. Among all the micronutrients, Zn deficiency is the most widely spreading micronutrient disorder among different soils (Sharma et al., 2013).

2.3 Estimation of soil nutrients using remote sensing and statistical techniques.

Remote sensing data provides continues spectral information that needs to be utilized for enhanced characterization and quantification of topsoil nutrients. The spectral performance of soil is a collective property that depends on its structure. The variation of the spectral signature data on absorption characteristics can indicate the existence or nonexistence of chemical chromospheres (Minu et al., 2017). The remote sensing data provides spectral signatures that are processed by standard techniques that contribute to better results in the end-user applications (Das et al., 2015).

In remote sensing, space-based hyperspectral is the future, which provides the digital images of the earth's surfaces in a narrow continuous spectral band across the electromagnetic spectrum in the form of spectral signatures. Hyperspectral data analysis is superior to conventional broadband analysis for spectral information. Hyperspectral image analysis is one of the most influential and fastest-growing technologies in the field of remote sensing. It has the potential to reduce labour-intensive methods for collecting soil data. In a workshop on digital soil mapping, it was recognized that poor soil data is a factor that can rigorously restrict the progress of digital soil mapping. It is, therefore, important to include soil sensors that can provide accurate estimates of soil properties over large areas (Boettinger et al., 2010).

The conventional method for determining the soil nutrients is more time and energy consuming than a remote sensing approach. Hyperspectral remote sensors are utilized for the estimation of soil nutrients. The literature of some of the work carried for exploring the potential benefits is presented here.

The organic matter and electrical conductivity were mapped by using DAIS-7915 hyperspectral scanner from visible to the thermal range, along with the ASD spectroradiometer in the agricultural fields of Israel. Minimum noise fraction (MNF) for reduction of noise is carried out as a preprocessing technique by Ben-Dor et al. (2002).

Gomez et al. (2008) estimated the soil organic carbon (SOC) in the cotton and pasture fields of Australia using EO1 Hyperion data. The Hyperion data were preprocessed by ATREM and 5S code, which are algorithm-based. The PLSR prediction technique showed good result. Similarly , Zheng (2008) estimated the soil nutrients such as nitrogen, phosphorus, and organic matter using EO1 Hyperion data in agricultural fields of central Indiana, USA. The FLAASH module was used for atmospheric correction. The PLSR prediction technique estimated the better R^2 values of 0.72, 0.67, and 0.74 for nitrogen, phosphorus, and organic matter, respectively.

The partial least squares regression (PLSR) and principal component regression (PCR) are the most commonly used techniques. They are useful for reducing multiple correlated spectral variables into a few factors to be used in soil variable regression (Casa et al., 2013). Zhang et al. (2009) have built a PLSR model for the estimation of the organic matter, nitrogen, phosphorus in the open fields of central Indiana, USA. The ACRON preprocessing technique is used for atmospheric correction. The predicted R^2 values for organic matter, phosphorus, and nitrogen are 0.89, 0.69, and 0.70, respectively.

Das et al. (2015) compared several studies on estimation of soil properties by hyperspectral data, and states that the PLSR technique has gained importance due to the Eigenvalue decomposition as it has the good predictive power. The PLSR model is built with both response and predictor variables.

Nowkandeh et al. (2018) made an attempt for organic matter prediction by Hyperion data with available predictive models, in that PLSR, provided adequate accuracy of the coefficient of determination (R^2= 0.66) with six latent variables. This study was carried out in the semi-arid region of Iran. They suggested models must not remain generalized for other semi-arid regions and must be verified for more other regions.

The spectral reflectance of soil is a representative of chromophores (chemical and physical factors) for electromagnetic radiation. The incident energy is observed at distinct wavelengths from chemical chromophores, whereas the entire spectrum from the physical chromophores (Das et al., 2015).The organic matter, texture, moisture content, and mineralogy are major components that have their own fundamental features in the spectral reflectance.

The soil nutrients show a significant influence on the spectra of soil. The organic matter is reflected in the VIS-NIR wavelength range (520 to 800 nm); the decrease in the reflectance spectra over this region indicates the increased content of organic matter (Stoner et al., 1980). The iron contents in the soil are correlated in the visible range (600 to 1000 nm) by the absorbance in the spectra. The high organic matter content interferes with the absorption of the spectra. The presence of lower albedo increases the iron effect in spectra by shallow and broad absorption (Galvao and Vitorello, 1998). The soil nitrogen is found at corresponding wavelengths in the NIR region 1800 to 2300 nm range (particularly absorbance at 1702,1870 and 2052 nm) are useful in determining soil nitrogen (Ehsani et al., 1999). Gopal et al. (2015) used VIP to select effective wavelengths from high spectral dimensionality data. The application of the PLSR technique established the relationship between chemical components and the reflectance spectra (Bilgili et al. 2010; Zhao et al. 2004). Minu et al. (2016) provided a detailed review to predict the soil properties by hyperspectral data and the model used for predictions.

2.3 Summary of literature review and research gap.

The comprehensive literature indicates that, like traditional techniques, soil nutrients can be reliably calculated from remote sensing data. The advantage of these techniques is that information on most soil nutrients can be produced from a single spectrum. In all approaches, there are advantages and disadvantages; for instance, remote sensing provides a piece of information in continuous bands, and a wider region is covered, but there are limitations on retrieving information of the soil under vegetation. The spectroscopic handling is costly even though it yields better predictions due to closer distance reflectance capture. It can be recapitulated from the literature that most of the studies considered regional models for the spatial variability of soil nutrients and soil reflectance retrieval by trial and error and combinations of preprocessing techniques. It indicates that there is no hard universal method/rule to be followed for characterizing the soil nutrients. It is important to choose the appropriate techniques or methods for a specific region since each region has its predominant parent material for soil formation and land management practices, which plays a crucial role under regional conditions. The spectral behaviour is also predominantly dependent on the parent materials; it becomes important to estimate which part or region of spectral reflectance influence for estimation of soil nutrients in vertisols at regional level. Therefore, understanding soil nutrients estimations by remote sensing data from a region by applying the universal rule may yield erroneous results and lead to a wrong interpretation. There is no explicit regionalized model to the best of knowledge, and specific wavelengths are identified for vertisols nutrients in deccan plateau.

The primary issue in the Deccan plateau area is lower crop productivity due to water scarcity and poor soil fertility (Vasu et al. 2017). The farmers prefer crops such as sorghum, maize, cotton, and pigeon pea, grown in India's vertisols. Similarly, in this study region, pigeon pea is the predominant crop. The commercial value of pigeon peas has increased due to its Geographical Indication tag (GI tag) for its unique taste and aroma compared to that grown elsewhere and enhancing its commercial value. Consumers are demanding superior products, and farmers are looking for different cost-effective methods and evaluate their crops compared to production systems where the pigeon pea are of special quality, which leads to a decrease in the status of soil fertility due to the consistent application of fertilizers to increase their productivity. The primary constraints are farm management practices, and farmers expect higher yields through small farm sizes for better livelihood. The traditional practices of farmers to monitor soil fertility needs to be restructured towards precision agriculture, with scientists and policy makers involvement.

While substantial progress has been made in soil science to characterize soil nutrients, a broad range of soil precursor land studies in different soil types are available to evaluate soil nutrient spatial variation and estimate soil nutrients through Hyperion data been investigated in large and homogeneous fields. Reaching this gap, the current study focuses mainly on two aspects, namely the utilization of geostatistics to characterize the spatial variability and assessment using Hyperion's data on soil nutrients in small-scale fields of vertisols.

2.6 Research Objectives

The primary objective of the research is to come up with an inexpensive and fast approach for assessment of soil nutrients using satellite data, laboratory measurements, and GIS in heterogeneous small-sized agricultural fields of deccan plateau, India.

Specifically, the evaluation of vertisols nutrients status, characterizing the spatial variability by geostatistical techniques and estimations of soil nutrients from Hyperion data in the deccan plateau of north Karnataka, India.

The following chapter discuss the materials and methodology adopted to achieve the research objective.

CHAPTER 3

Materials and Methodology

3.1 Introduction

This chapter explains the monitored approach to achieve the objectives of the study. Soil nutrients are dynamic in nature and modify ceaselessly to long and short term changes in land utilization and atmospheric conditions. Soil quality estimations from agricultural lands are regularly called 'Soil quality observing. The topsoil is losing its fertility status because of a variety of reasons. Hence, it is very important to know the status of soil nutrients. This section describes the methodology adopted to explore the spatial viability and utilization of remote sensing data, preprocessing of Hyperion data, and software techniques for the estimation of vertisols soil nutrients.

3.2 Description of the study area

The study area is situated in Kalaburagi taluk, Karnataka, India (Figure 3.1); it is recognized as the 'Turdal bowl of Karnataka, i.e., the pigeon pea vessel of Karnataka state. The commercial value of pigeon peas has increased due to its Geographical Indication tag (GI tag) for its unique taste and aroma compared to that grown elsewhere and enhancing its commercial value. The study area covers 183.8 km^2; the area consists of flat terrain with stones of deccan trap and basalt. The temperature ranges from 26^0 C to 38^0 C and 550 mm as the average annual rainfall. The vertisols are predominantly covered. The map of the soil association with soil type code (Figure 3.2) and they are characterized by their major taxonomy and coverages (Table 3.1). Vertisols are dominant with a water retention capacity of 200-300 mm and are suitable for pigeon pea cultivation. Major crops cultivated are pigeon pea, Gulbarga tur dal (received GI tag recently 2019), jowar, and sugarcane. The average size of agricultural land holding by the farmers are approximately 2 acres. It consists of scattered agricultural fields, vegetation, built-up lands, and roads.

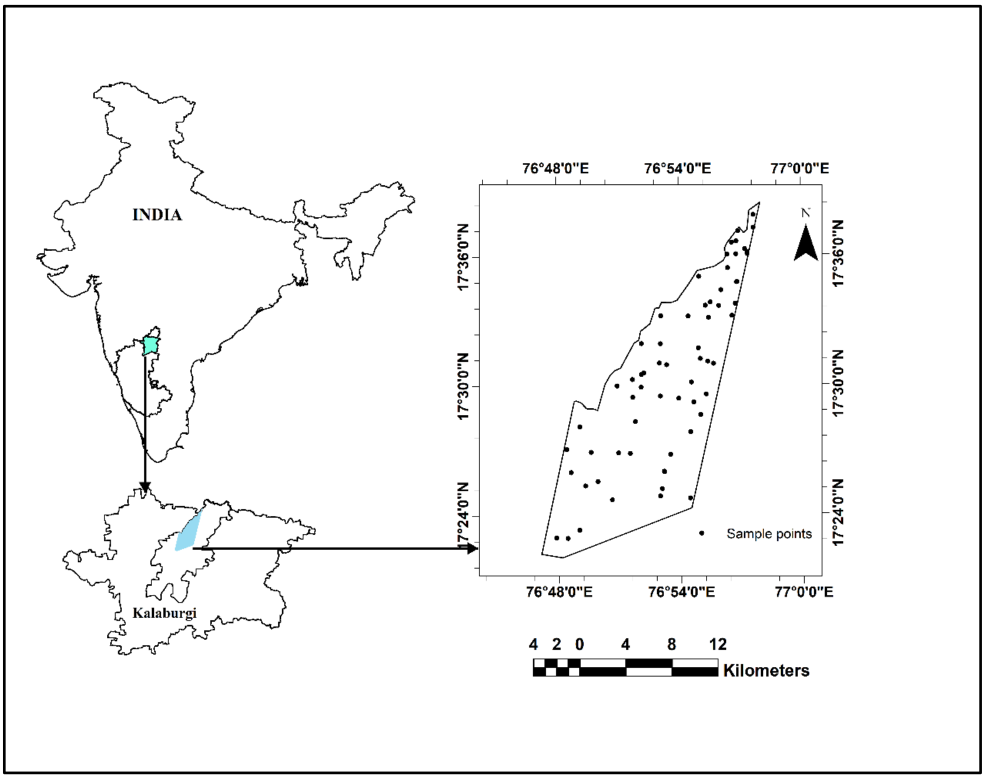


Figure 3.1 Study location with sampling points

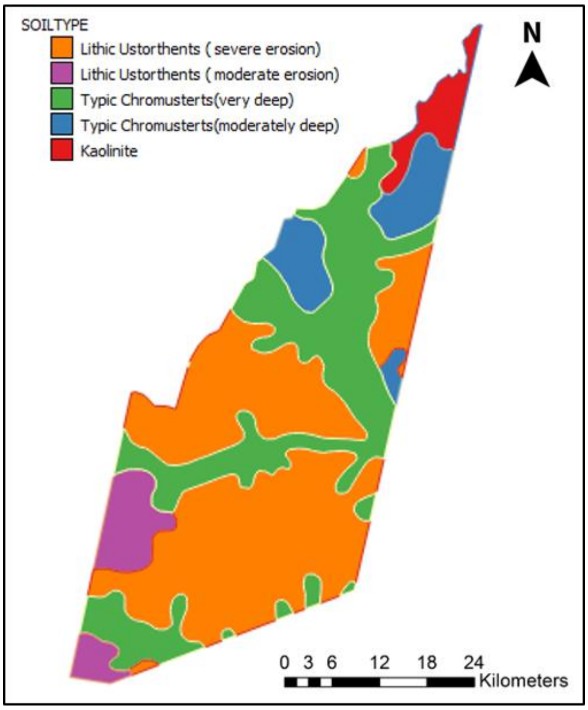


Figure 3.2 The soil map associations with soil type

Table 3.1. The soil association with corresponding major taxonomy and coverage

Soil code	Major soil Taxonomy	Coverage (%)
5	Clayey-skeletal, Kaolinite, Rhodic Paleustalfs	0.81
46	Very-fine, montmorillonite, Typic Chromusterts (Moderately deep)	16.14
47	Very-fine, montmorillonite, Typic Chromusterts (Very deep)	6.82
68	Loamy, mixed, Lithic Ustorthents (moderate erosion)	1.73
69	Loamy, mixed, Lithic Ustorthents (severe erosion)	27.42

Source: NBSSLUP Nagpur. India

3.3 Soil sample and chemical analysis

The systematic sampling of soil was conducted in the third week of November 2016. This duration is also synchronized with the passage of the Hyperion satellite above the study area. It was difficult to adopt the uniform sampling method since the fields are scattered over a small area and are at random. The topsoil (0 to 15cm) samples are collected in 68 locations covering the study region. These sampling locations are chosen from the pigeon pea harvested fields of vertisols. During sampling, it was found that some fields were waterlogged, and leftover crop residual was burnt due to early harvesting as they prepare for the next crops. Such fields are avoided. The sampling points were also avoided near to the trees and any kind of structures. The geographical coordinates of sampling locations are recorded with the Trimble Juno series GPS with an accuracy of 2m. The sample of topsoil is collected with a soil auger. Each soil sample consists of five sub-samples mixture with a radius of 5 to 10 m, which is placed in a plastic bag with a label for shipping (Figure 3.3).

Prior to analysis, the air-dried soil sample is ground to pass over the 200 μm sieve. The chemical analysis for measuring soil properties is carried out according to the standard tests recommended by the Food and Agriculture Organization of the United Nations (FAO) (Motsara and Roy, 2008). Accordingly, soil pH is measured by a pH meter; electrical conductivity is measured using an electrical conductivity meter. Available nitrogen is determined using alkaline potassium permanganate by Kjeldahl method. Available phosphorus is determined using Olsen's method in a spectrophotometer, and available potassium is estimated using a flame photometer in the laboratory. The ammonium acetate extraction method for Ca and Mg (Table 3.2).

Figure 3.3 Representative images of field sampling and chemical analysis

Soil micronutrients are also calculated according to Indian standards. DTPA extraction method for available Fe, Zn, Cu, and Mn is used. 10 g of soil sample was weighed into a polyethylene shaking bottle, and the DTPA reagent of 20 mL was added (Lindsay and Norvell 1978). Then after stirring for 120 min, samples were filtered over a Whatman #42 filter paper. Micronutrients were estimated in Microwave Plasma-atomic emission spectroscopy (MP-AES) (Vysetti et al. 2014).

3.4 Software used

In this study, the geostatistical analysis is carried out in SpaceStat 4.0, Hyperspectral analysis in ENVI 4.7, and PLS_Toolbox 4.0; and ArcGIS 10.1 for mapping.

3.4.1 ArcGIS 10.1®

Environmental Systems Research Institute (ESRI) has developed professional GIS software called ArcGIS ®; with ArcGIS, maps can be created, spatial analyses carried out, and share intelligent visualizations for superior decisions. It offers several comprehensive tools for data visualization and analysis of the processing of geodata.

The study uses ArcGIS version 10.1 for the creation of location maps and visualization of the soil sampling locations from GPS data.

Table 3.2 Soil chemical analysis methods

Test	**Method adopted**	**Instruments used**	**Reference**
Soil pH	pH meter	EUTECH pH 700 model	(Thomas, 2018)
Soil EC	Electrical conductivity meter	Equiptronics EQ-660	
Organic carbon	Walkley and black method	Titration	(Walkley and Black, 1934)
Available nitrogen	Kjeldahl method (Alkaline potassium permanganate)	Kelplus- Elite EX	(Subbiah and Asija, 1956)
Available phosphorus	Olsen's method	Systronics AU-2701	(Olsen et al., 1954)
Available potassium	Flam photometer (767 nm with red filter)	Systronics	(Black et al., 1965)
Exchangeable calcium and magnesium	EDTA Method	Titration	(Tucker and Kurtz, 1961)
Estimation of micro nutrients	Plasma-atomic emission Spectroscopy	Agilent 4200 MP-AES	Vysetti et al., 2014

3.4.2 ENVI 4.7®

Exelis Visual Information Solutions markets the "ENvironment for Visualizing Images," abbreviated as ENVI®, as an application for the analysis and processing of geographic images. ENVI® bundles a number of scientific algorithms for the image analysis and process of entirely multispectral, hyperspectral, SAR, and LiDAR data. For the preprocessing of Hyperion data and atmospheric corrections, the study used version 4.7.

3.4.3 PLS_Toolbox 4.0®

Eigenvector Technologies have developed this multivariate analysis tool that works within the MATLAB ™. It allows users to analyze their data and predict models by the Partial Least Squares regression technique (PLSR). Version 4.0 is used for the statistical analysis of our data.

3.5 Descriptive statistics and data transformation

The descriptive statistics such as mean, Coefficient of variation (CV), standard deviation (SD), skewness, kurtosis, and Pearson's correlation between soil nutrients are calculated with the SPSS® software. To determine the degree of variation in a region, the CV is used, and skewness is often used for defining the form of data scattering and flatness (Veritas, 2010).

For semivariogram analysis, the data must follow the normal distribution; otherwise, they cause fluctuations of variance, sill, and nugget. Hence the normal distribution tests for the original data must be tested (Jing et al., 2014). For the normal distribution of data, the skewness coefficient will be zero. If the data distribution differs significantly from the normal distribution, data transformation is often achieved to moderate the impact of extremely high or low values that are outliers in spatial analysis. The Kolmogorov-Smirnov test (K-S test) is carried out for validating the normal distribution of original data in SPSS® software. The logarithmic transform is applied to data that fails in a normal distribution test (Fu et al., 2010).

3.6 Geostatistical analysis

The kriging is used in Geostatistics to interpolate the values of the un-sampled location. Ordinary kriging is used to generate maps of the spatial distribution of soil nutrients. The variograms are quantified for interpolating the scattered point's data to know their spatial structure. The variogram examines the differences between paired data values and provides the spatial structure of variables (Bogunovic et al. 2014). The spatial variability in the soil is calculated from the semivariogram $\gamma(h)$, by quantifying the mean difference between the isolated values through the vector(h). The empirical variogram is evaluated according to equation 1 (Webster and Oliver 2008; Fu et al. 2010).

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(x_i) - z(x_i + h)]^2 \qquad [1]$$

In the above equation, the number of pairs of samples detached from the interval $h$is represented by n and $z\ (x_i)$is the value of the single sample under the study region in the i^{th}position. The theoretical models (Gaussian, Exponential, and Spherical) are evaluated on an experimental semivariogram for selecting the best fit model with data. The representative model of the variogram is shown in Figure 3.4.

Nugget: Theoretically, the semivariogram value at the origin (0 lag) should be zero. If it differs significantly from zero for lags close to zero, this semivariogram value is called the nugget. It also represents the measurement error and variability at a smaller distance than the sampling distance.

Sill: The sill is the total variance at which the model flattens out, which is also the sum of the nugget and the sills of each nested structure.

Range: it is a lag distance were the semivariogram reaches the sill value

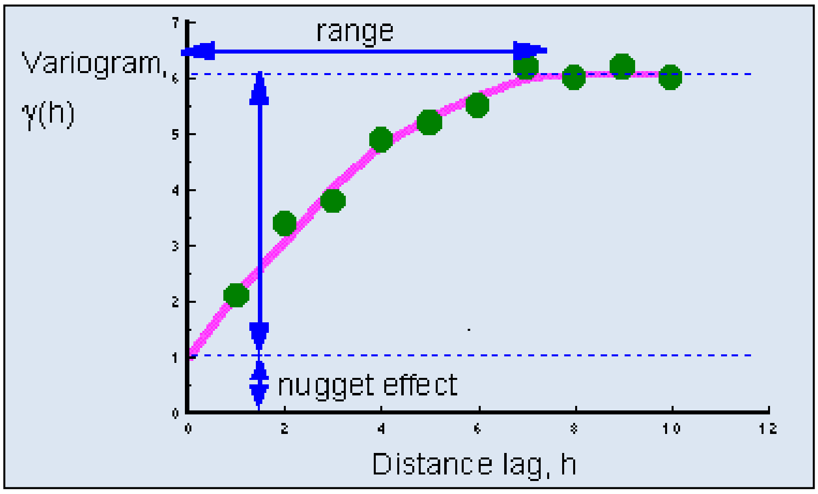


Figure 3.4 Representative figure of the variogram model

The variogram best fit is conducted, such as the model fits the experimental values closely. The model with minimal MSS error is considered as the most suitable model. Then this model is used for prediction, and results are used to compute MAE and RMSE. The differences between the mean sum of the squared values of the theoretical and experimental models are presented by MSS error, and it can be used to evaluate the effect of modifying some factors. The factors of the variogram (range, nugget, sill, and semivariance) were clearly defined for the spatial structure of soil nutrients. The ratio of the nugget to sill used to calculate the spatial dependence of soil nutrients (Bogunovic et al. 2014; Cambardella et al. 1994). The Ordinary kriging is best suited for an unbiased prediction of specific un-sampled positions that decrease the variance error (Lin and Chang 2000; Montanari et al. 2012; Tesfahunegn et al. 2011; Zhang et al. 2014).

The precision of the best fit variogram model is verified by cross-validation, which included performance indicators, the root mean square error (RMSE), and the mean absolute error (MAE). MAE (equation 2) measures the sum of the residuals (Voltz and Webster 1990).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} z(x_i) - \bar{z}\ (x_i) \qquad [2]$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[z(x_i) - \bar{z}(x_i)]^2}{n}} \qquad [3]$$

In equations, $\bar{z}(x_i)$ indicates the value predicted at the position, and a smaller MAE value indicates a smaller error. However, the MAE measured will not disclose a degree of error that could come at any point. Therefore, the RMSE (equation 3) is considered which at one point takes the square root of the variance that contributes to a magnitude of error indication. The smaller the values of RMSE, the better the predictions.

3.7 Hyperion data

The EO-1 (Earth Observing 1) spaceship was propelled on November 21, 2000, from Vandenberg Air for Base, as a component of NASA's new millennium Program. It had finished its task in March 2017 following 17 years in orbit. The Spaceship had a synchronous with sun orbit at an elevation of 705 Km. its orbital period was 98.9 minutes and 98.2 degrees of orbit tendency. It had sixteen days repeat cycle with a 6.74 Km/sec velocity of the nadir point. The Hyperion is the first of its kind of hyperspectral sensors, which provided a continuous spectral profile through the electromagnetic spectrum, which ranges from 400 nm to 2500 nm with 224 bands. The Hyperion is a push-broom imaging instrument. Each image taken in this alignment captures the spectrum of a line 30m along-track by 7.5Km wide perpendicular to the satellite motion.

Gulbarga's Hyperion image was captured on November 12, 2016, and soil samples were taken in the second week of November (Figure 3.5). There are 220 unique bands with a spectral range of 357-2576 nm at a bandwidth of 10 nm. However, there are only 198 bands calibrated (bands 8 to 57 for VNIR and 77 to 224 in the SWIR range) (Datt et al. 2003). Due to an overlap of the focal planes of VNIR and SWIR, there are only 196 distinct channels. The reason that not all 242 channels are calibrated is a weak detector. The uncalibrated bands are set to zero. Characteristics of the Hyperion images are shown in table 3.3.

The preprocessing approaches for Hyperion data are must, as the image needs to be converted from radiance to reflectance for analysis. These include removing the bands without information, destriping, and atmospheric corrections to convert the radiation into reflection. Figure 3.6 shows the steps of preprocessing.

Table 3.3 Characteristics of Hyperion image

Sensor altitude	703 Kms	**Number of rows**	256
Target path	145	**Target row**	48
Spatial resolution	30 m	**Number of columns**	3128
Radiometric resolution	16 Bits	**VNIR range**	0.45-1.35
Swath	7.2 Kms	**SWIR**	1.40-2.48

3.7.1 Bad band removal

It was found that some bands are set to zero during the processing of Level 1. The zeroed bands are 1 to 7 and 225 to 242 (EO1 User Guide, 2003). Then there are water vapour absorption bands that need to be eliminated. The list of bands that are eliminated, including the water absorption bands, is given in table 3.4. These bands selection is made by using Spectral Subsetting.

Table 3.4 Hyperion sensors unused bands

Bands	Characteristics
1 to 7	Not Illuminated
58 to 78	Overlap Region
120 to 132	Water Vapour Absorption Band
165 to 182	Water Vapour Absorption Band
185 to 187	Identified by Hyperion Bad Band List
221 to 224	Water Vapour Absorption Band
225 to 242	Not Illuminated

3.7.2 Destriping

The Hyperion datasets contain several damaged pixels and dark vertical stripes, which are due to calibration differences in the Hyperion detector array and time Fluctuations in the detector response. These vertical stripes and the damaged pixels are called abnormal pixels. The minimal digital number (DN), usually zero or low DN values compared to adjacent columns.

3.7.3 Atmospheric correction

The Hyperion data acquired from USGS is in radiance. The radiance intensity is a physical quantity that measures the amount of light that an object emits and then falls in a specific direction into a specific solid angle. It can also be considered as a quantity of light entering the remote sensing instruments.

However, both the object being observed and the atmosphere are radiated by the radiance measured by the instruments. Therefore, atmospheric correction is necessary to convert the radiation into reflectance. Reflectance is the ratio between the amount of light leaving an object and the amount of light that falls on the object.

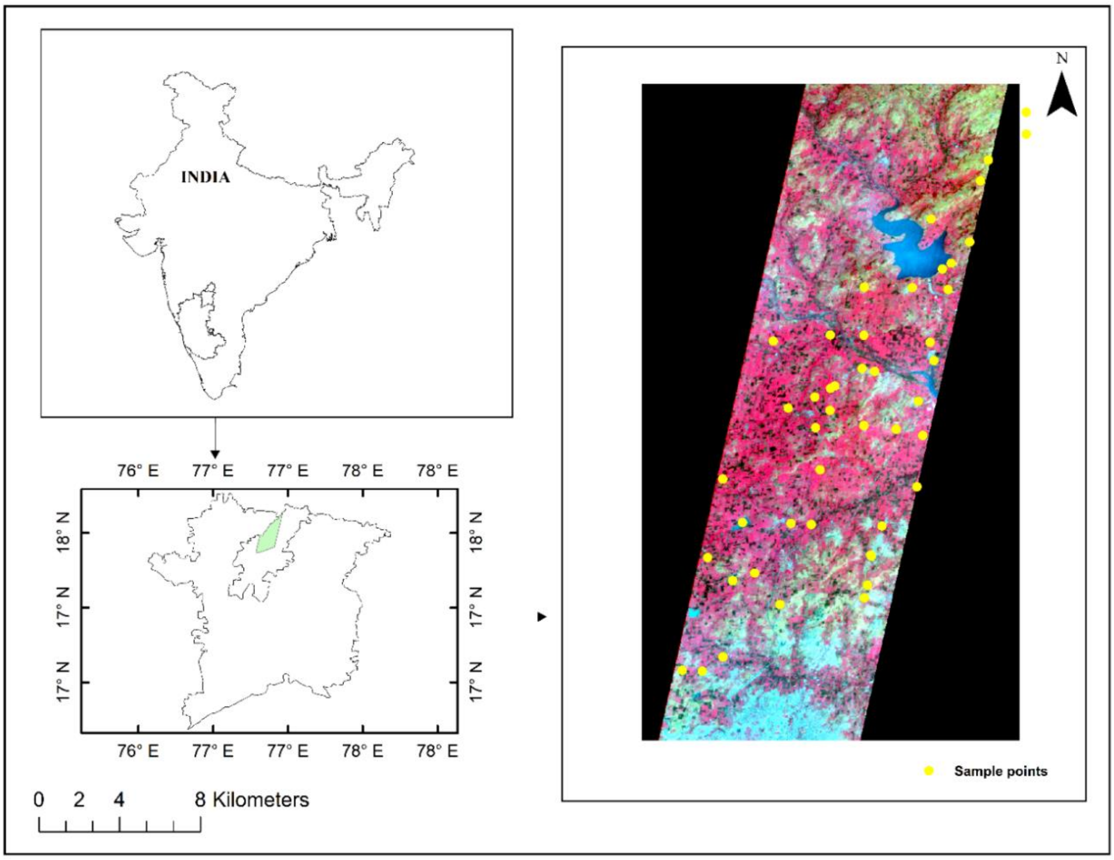


Figure 3.5 Hyperion image with sampling points

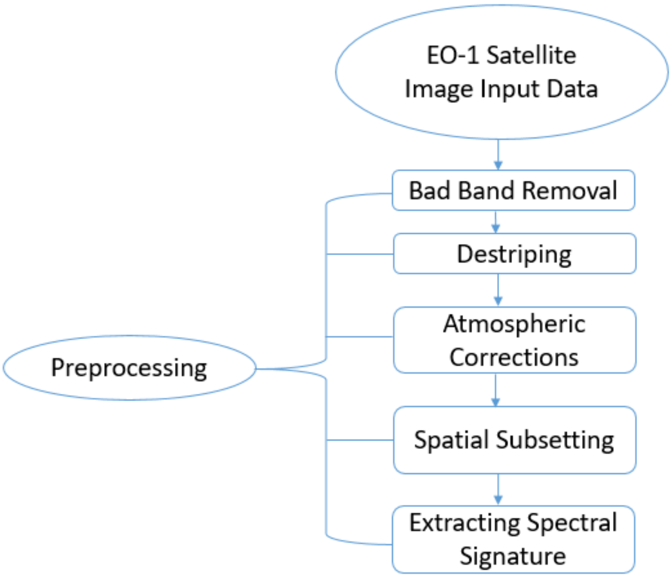


Figure 3.6 Flow chart of Hyperion preprocessing

The Hyperion images were atmospherically corrected with the ENVI FLAASH module, a calibration program used to convert the radiance into reflectance. According to the guidance of the EO-1 User Guide, the atmospheric correction was completed.

3.7.4 FLAASH- Fast line-of-sight atmospheric analysis of spectral hypercubes

FLAASH is an atmospheric correction mechanism based on physics (Golden et al., 1998). The MODTRAN4 code is used to calculate the parameters required for RT equations, giving a surface reflection in return (Minu et al., 2017). It compensates for atmospheric effects and corrects Wavelengths in visible range of the electromagnetic spectrum by NIR and SWIR region.

Every image is provided with information such as the scene centre location, sensor altitude, sensor type, ground elevation, satellite zenith, flight time, flight date, and azimuth angles were provided for each image. The rural aerosol model and tropical atmosphere are assumed in the study region.

3.7.5 Spatial subsetting

The spatial subsetting of image is typically used to extract area from the raw Hyperion image, which resizes the data. The spectral signatures were extracted using the region of interest tool (ROI tool) from the sampling locations. The mean spectral profile of the Hyperion image before and after atmospheric correction is presented in figure 3.7.

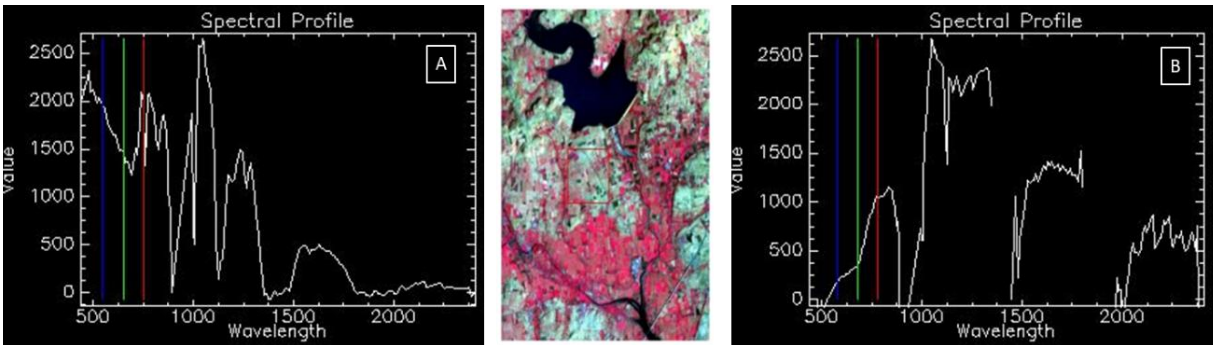


Figure 3.7 Spectral profile (A) before atmospheric correction (B) after atmospheric correction of Hyperion

The work was carried with the detail insightful of the technique based on previous literatures. The results acquired with respect to the objectives have been discussed in following chapters.

CHAPTER 4

Assessment of the vertisols nutrients status in deccan plateau of North Karnataka, India

4.1 Introduction

The data sets of soil nutrients obtained from the chemical analysis are evaluated for descriptive statistics, which investigates the real situation. This chapter deals with the descriptive statistics of data sets and nutrient index (NI) of soil properties.

4.2 Descriptive statistics of vertisols nutrients

The data sets of soil nutrients obtained from chemical analysis are evaluated for descriptive statistics like mean, standard deviation, and Coefficient of variation, skewness, and kurtosis (Table 4.1). The violin plots are plotted to know the density of samples scattered around the mean and the outliers (Figure 4.1). These plots are completely suitable even if the data is normally distributed or not.

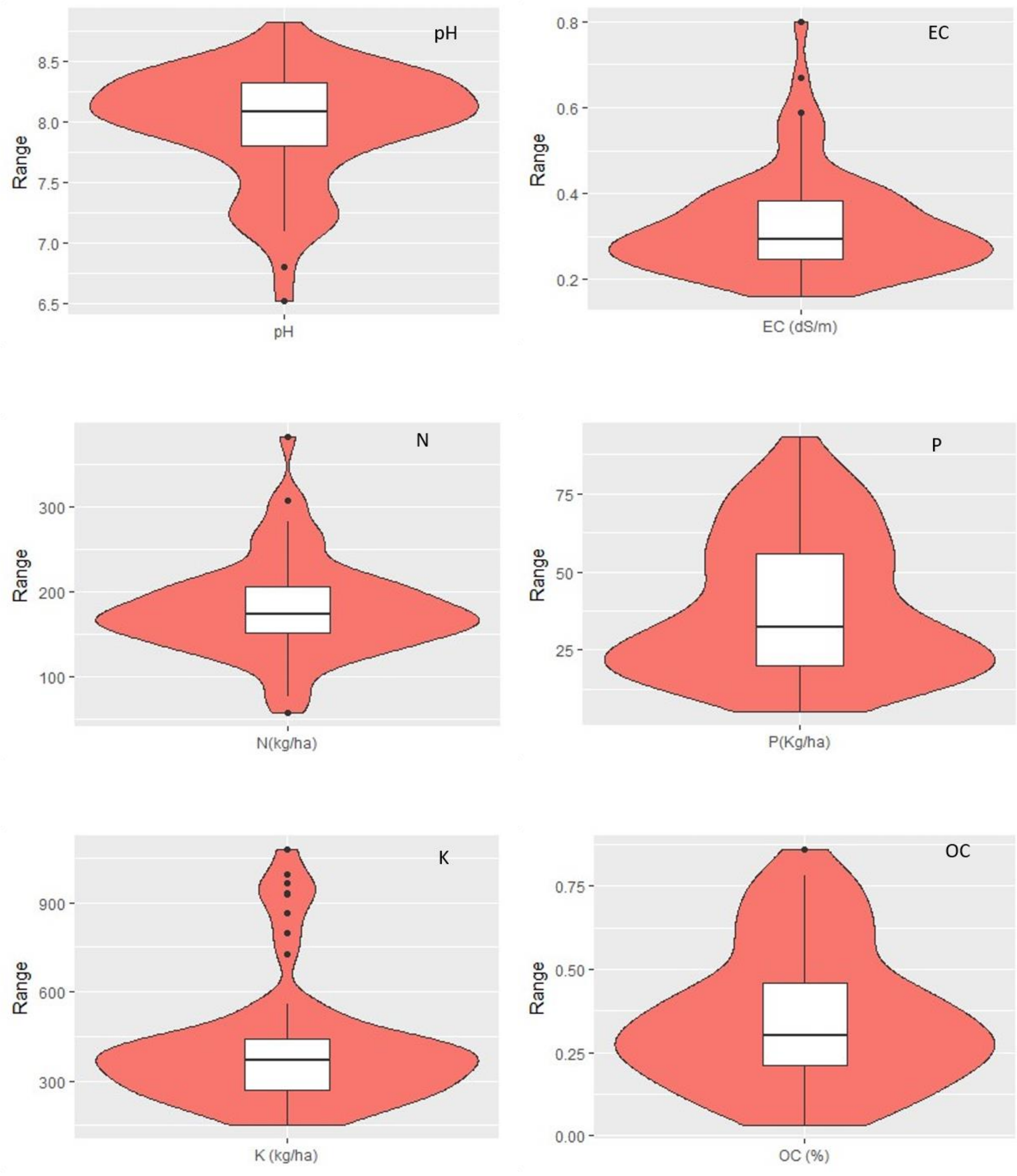
The pH and EC in the study region varied from 6.52 to 8.82 and 0.16 to 0.80 dSm^{-1}, with mean values of 7.98 and 0.33 dSm^{-1}, respectively, in the month of November 2016. The available macronutrients N, P, and K varied from 75.26- 382.59 kg ha^{-1}, 12.21-93.14 kg ha^{-1}, and 150.39 -1080.04 kg ha^{-1}, with a mean value of 180.83 kg ha^{-1}, 39.22 kg ha^{-1}, and 417.13 kg ha^{-1} respectively. The OC, Ca and Mg varied from 0.03 - 0.86 %, 18.67 – 79.09 meq 100 g^{-1}, and 5.3 – 44.19 meq 100 g^{-1} with mean values of 0.34 % , 43.82 meq 100 g^{-1} and 20.43 meq 100 g^{-1} respectively. In addition, the micronutrients Fe, Mn, Zn, and Cu varied from 0.02 – 87.0 ppm, 1.6 – 328.68 ppm, 0.22 – 11.0 ppm, and 0.54 – 24.44 ppm with a mean value of 22.47 ppm, 80.33 ppm, 1.98 ppm, and 4.95 ppm respectively.

Table.4.1 Descriptive statistics of measured soil properties

Si. No	Parameters	Min	Max	Mean	Std. Dev	CV (%)	Skewness	kurtosis	Skewness#	Kurtosis#
1	pH	6.52	8.82	7.98	0.481	6.0	-0.997	0.590	-	-
2	EC (dS/m)	0.16	0.80	0.32	0.123	37	1.527	3.037	0.504	0.190
3	OC %	0.03	0.86	0.34	0.203	58.2	0.627	-0.308	-0.888	0.787
4	N (Kg/ha)	75.26	382.59	180.83	52.91	29.2	1.060	2.749	0.309	1.492
5	P (Kg/ha)	12.21	93.14	39.22	22.42	57.1	0.647	-0.823	0.039	-1.281
6	K (Kg/ha)	150.39	1080.04	417.13	216.0	51.8	1.578	2.034	0.441	0.170
7	Ca(meq/100 g)	18.67	79.09	43.82	11.78	26.8	0.585	0.697	0.393	0.680
8	Mg(meq/100g)	5.3	44.19	20.43	9.348	45.7	0.505	-0.631	0.385	-0.295
9	Fe (ppm)	0.02	87.0	22.47	18.40	81.8	1.668	2.742	0.643*	0.466*
10	Mn (ppm)	1.6	328.68	80.33	86.00	107	1.129	0.092	0.099*	1.108*
11	Zn (ppm)	0.22	11.0	1.98	1.410	70.9	4.683	7.838	0.586*	6.255*
12	Cu (ppm)	0.54	24.44	4.95	4.819	97.2	2.261	6.802	0.076*	0.743*

* Box-Cox transformation

A fraction of the standard deviation to the mean, articulated in percent, which is a valuable indicator of the overall variability, is the coefficient variation (CV). Soil nutrient variability is rated as high (CV > 35 percent), moderate (CV 15-35 percent) and low (CV < 15 percent), according to Wilding (1985).



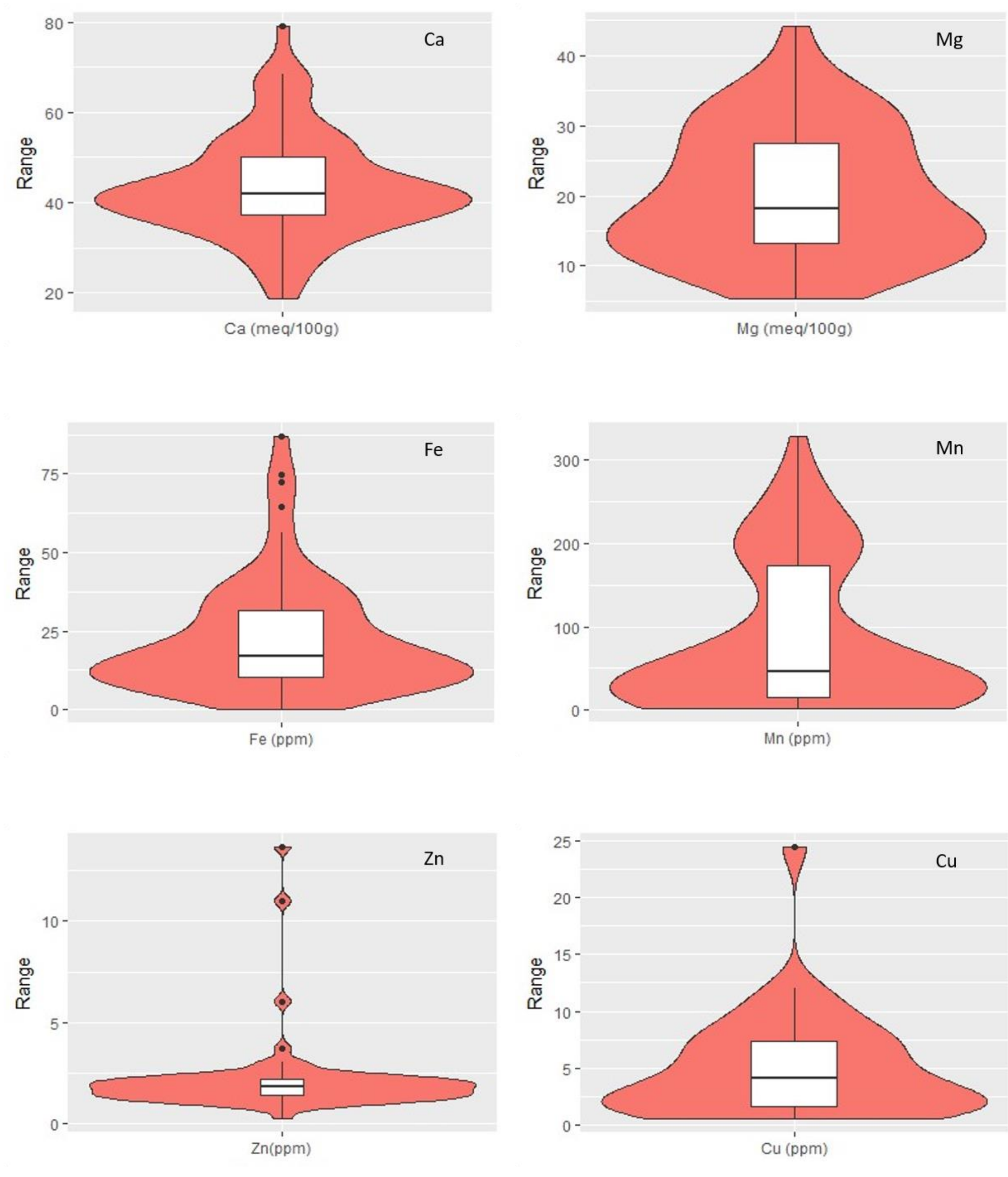


Figure 4.1 Violin plots for vertisols nutrients

In this study, as seen in Table.4.1 EC, OC, P, K, Mg, Fe, Mn, Zn, and Cu are highly variable compared to other nutrients. High variability is due to the exceptionally high values obtained in certain samples that influence the skewness of the information that can be regarded as outliers. How to deal with outliers can be debatable, even if they are not estimate errors, they have to be used if possible (Fu et al., 2010); in our study, outliers are not excluded. The N and Ca have moderate variability, whereas pH has low variability in study area. The CV value observed in the present study is similar to the results of (Virgilio et al., 2007; Fu et al., 2010). The significance of CV is to understand how the soil nutrients are varied across the fields. The variability of soil nutrients in the study region ranges from low to high, which may be due to topographic variations affected by pedogenic processes (Vasu et al., 2017). The variability can also be attributed to farming and fertilizer application methods. According to the need, farmers must lower their fertilizer application rate (Liu et al., 2014; Vasu et al., 2017).

4.3 Pearson correlation of vertisols nutrients

The Pearson linear correlation analysis is shown in Table 4.2. It can be observed that the soil pH with Ca showed a more positive relationship (r=0.43) and a more negative relationship with P (r=-0.24). The water used for agriculture will directly influence soil pH as indicated by the positive correlation of EC and soil pH (r=0.11). The soil pH correlated positively to Ca significantly (r = 0.438). An indication that the increase in pH gradually increases the Ca and vice versa, (Iticha and Takele, 2019) found a similar correlation in vertisols. The pH is negatively correlated to Mg, and Zn is not as significant. There is a negative correlation between Ca and Mg (r = -0.318); results are contradictory to other soil types. This correlation is related to soil acidity and fertilizers application rate (Behera and Shukla, 2015; Iticha and Takele, 2019).

Micronutrients are negatively correlated to soil pH, which indicates that soil pH influences the availability of micronutrients. There is no significant correlation between micronutrients except Cu and Fe, which are positively correlated (r=0.75). The positive relationship between OC and essential plant nutrients, including Mg, Fe, Zn, and Cu, are in line with the similar to other studies (Reza et al., 2017). The nutrients pairs, which are significantly negative correlated, are predictable to have spatial patterns that are mirror images (Corstanje et al., 2006).

4.4 Nutrient indexing of vertisols

Assessing the soil fertility of an area is important in the context of sustainable agriculture. Soil nutrient availability is periodically estimated due to nutrient removal through intensive cultivation. To compare soil fertility from one region to another, it is important to have an individual value for nutrients. The values of the nutrients index (NI) for available nutrients present in the vertisols are calculated using the formula suggested by Parker et al., (1951). The formula is given by equation 4.1.

$$NI = \frac{[(NL \times 1) + (NM \times 2) + (NH \times 3)}{NT} \qquad 4.1$$

Here, NL, NM, and NH represent the sample numbers falling in low, medium, and high categories of permissible limits of nutrients status and one, two, and three weightages are given respectively. The index is classified as low (<1.67), medium (1.67-2.33), and high (>2.33).

Table 4.2 Correlation of soil properties

	pH	**EC (dS/m)**	**OC%**	**N (Kg/ha)**	**P (Kg/ha)**	**K (kg/ha)**	**Ca (meq/ 100g)**	**Mg (meq/ 100g)**	**Fe (ppm)**	**Mn (ppm)**	**Zn (ppm)**	**Cu (ppm)**
pH	1											
EC (dS/m)	0.11	1										
OC%	-0.21	0.15	1									
N (Kg/ha)	0.1	0.28^{*}	-0.1	1								
P (Kg/ha)	-0.24^{*}	-0.02	-0.1	0.07	1							
K(kg/ha)	0.29^{*}	0.07	-0.4	0.22	-0.03	1						
Ca (meq/100g)	0.43^{**}	0.08	-0.4	0.13	-0.19	0.51	1					
Mg (meq/100g)	-0.12	0.07	0.06	0.01	-0.29	0.01	-0.31^{**}	1				
Fe (ppm)	-0.66	-0.14	0.25	-0.2	0.395	-0.31	-0.35	0.03	1			
Mn (ppm)	-0.07	-0.23	-0.1	-0.2	0.33	-0.19	-0.14	-0.1	0.130	1		
Zn (ppm)	-0.26	0.15	0.26	-0.1	0.048	-0.05	-0.04	0.08	-0.005	0.013	1	
Cu (ppm)	-0.38	0.16	0.39	-0.1	0.332	-0.3	-0.26	0.02	0.756^{**}	0.25^{*}	0.15	1

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

* Correlation is significant at the 0.05 level (2-tailed)

The results to index of nutrient availability (Table 4.3) indicates for N, P, K, OC, Cu, Fe, Mn and Zn 88.4 %, 1.44 %, 15.94 %, 78.26 %, 31.88 %, 2.89 %, 30.43 %, and 1.44 % found deficient in soil samples ; 11.59 %, 24.63 %, 44.92 %, 17.39 %,15.94 %, 14.49%, 14.49%, and 15.94 % soil samples were medium and 0 %, 73.91%, 39.13

%, 4.34 %, 52.17 %, 82.60% 55.07 %, and 82.60 % samples of soil fall in high respectively in the study area.

Table 4.3 Soil nutrients index of the study area

Soil Nutrients	**Samples Percent**			**NI**
	Low	Medium	High	
Nitrogen (kg/ha)	88.4	11.59	0.00	1.11
Phosphorus (kg/ha)	1.44	24.63	73.91	1.15
Potassium (kg/ha)	15.94	44.92	39.13	2.23
Organic carbon (%)	78.26	17.39	4.34	1.21
Copper (ppm)	31.88	15.94	52.17	2.20
Iron (ppm)	2.89	14.49	82.60	2.81
Manganese (ppm)	30.43	14.49	55.07	1.69
Zinc (ppm)	1.44	15.94	82.60	2.79

The NI values indicted that N, P, and OC are low with values of 1.11, 1.15, and 1.21, respectively. The K, Cu, and Mn are medium with values of 2.23, 2.20, and 1.69, respectively. The high nutrient indexes in the study area are shown by Zn and Fe with values of 2.81 and 2.79, respectively.

The status of soil nutrients are assessed in the current chapter. Further results for characterizing the spatial variability and estimation using Hyperion data of soil nutrients have been discussed in the upcoming sections.

CHAPTER 5

Characterization of spatial variability of vertisols nutrients by geostatistical techniques

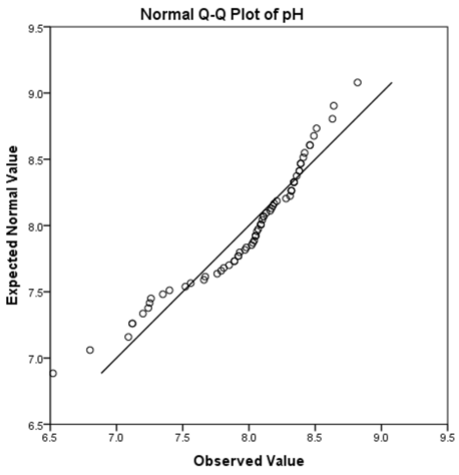
5.1 Introduction

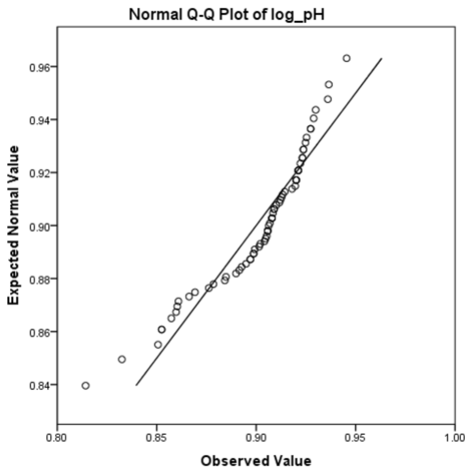
It is important to identify how these soil nutrients vary in diverse land use context; so that the best management practices options may be suggested to producers based on limited nutrients. For efficient soil nutrients management, spatial variability mapping is the important factor for sustainable agriculture (Behera et al., 2016). This chapter deals with the analysis of the normal distribution of datasets, descriptive geostatistical parameters, selection of semivariogram, range, and spatial dependency of soil nutrients in the study area. The spatial variability of soil nutrients obtained by ordinary kriging is characterized.

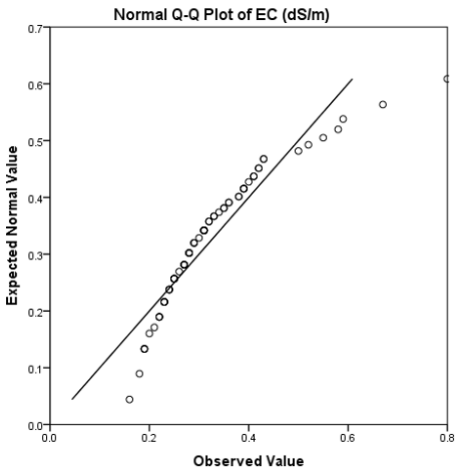
5.2 Normal distribution

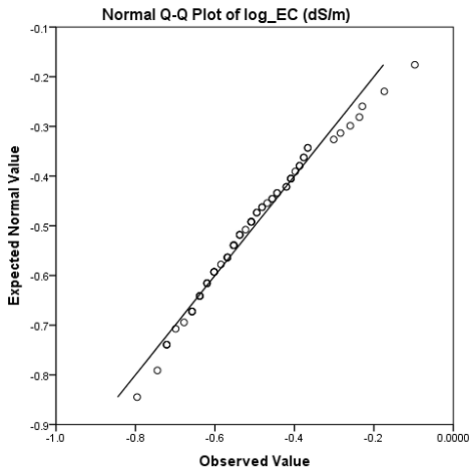
For the normal distribution of datasets, Q-Q plots for raw datasets are plotted; these plots indicate how samples are uniformly distributed across the diagonal line and even help to identify the outliers. In this study area, most of the variables are greater than zero in skewness and are positively skewed (Table 4.1). The kurtosis values are sharp indicating most of the samples grouped at a relatively higher range. Since the points are not clustered around the diagonal (Figure 5.1), the data needs to be transformed to minimize the effect of extreme values. The log transformation for N, P, K, OC, Ca, and Mg; box-cox transformation for Fe, Mn, Zn, and Cu has made data more efficient, where the skewness is reduced.

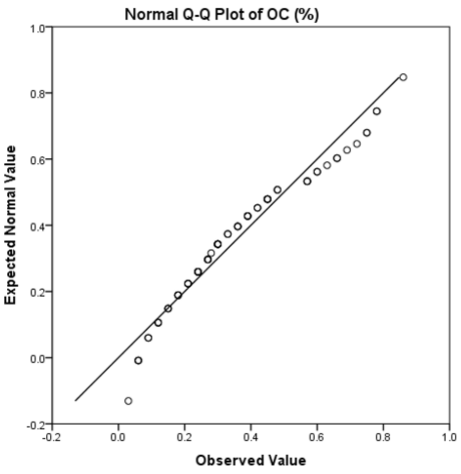
After transformation, it is observed that the soil nutrients distributed close to the diagonal line, which was not normally distributed (Figure 5.1). The reason for non-normal distribution of nutrients is the presence of very high or low concentrations of nutrients at certain sampling points, i.e., outliers, due to individual farm practices and topographic effects (Tesfahunegn et al. 2011).

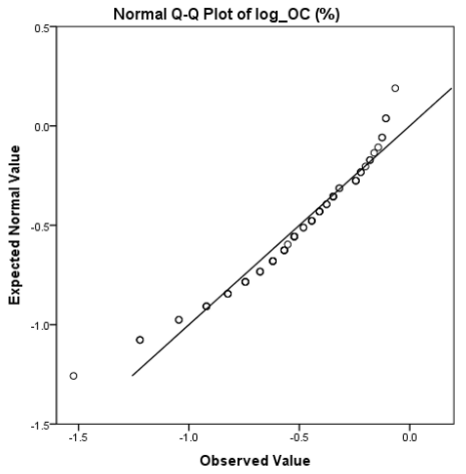

Normal Q-Q Plot of pH
Expected Normal Value
Observed Value

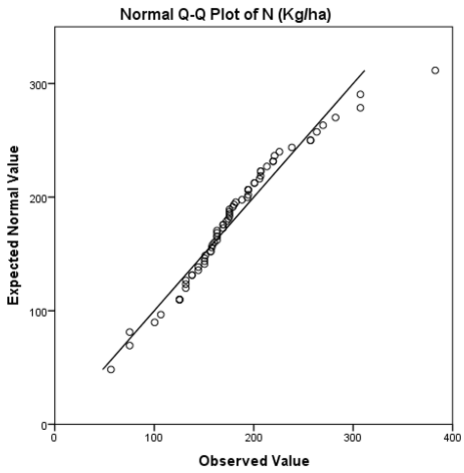

Normal Q-Q Plot of log_pH
Expected Normal Value
Observed Value

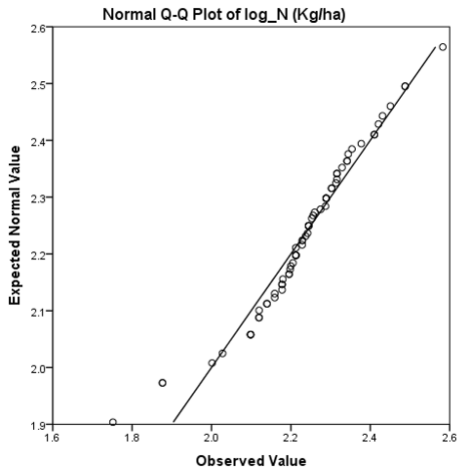

Normal Q-Q Plot of EC (dS/m)
Expected Normal Value
Observed Value

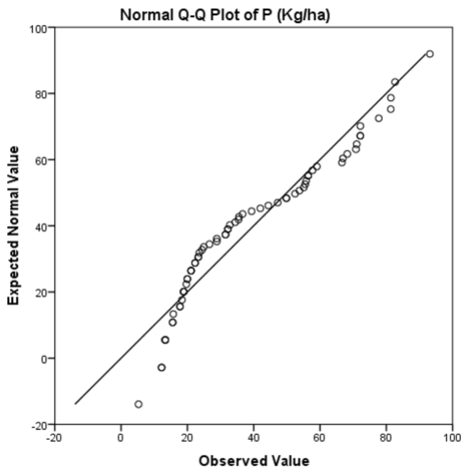

Normal Q-Q Plot of log_EC (dS/m)
Expected Normal Value
Observed Value

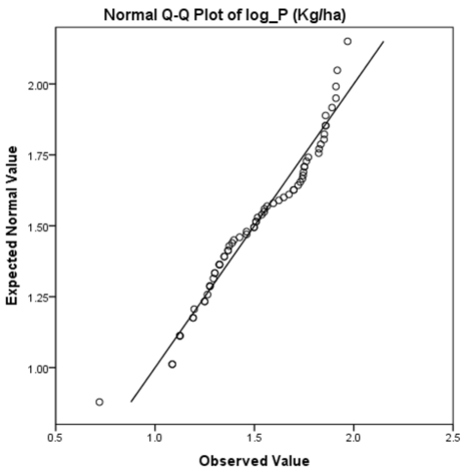

Normal Q-Q Plot of OC (%)
Expected Normal Value
Observed Value

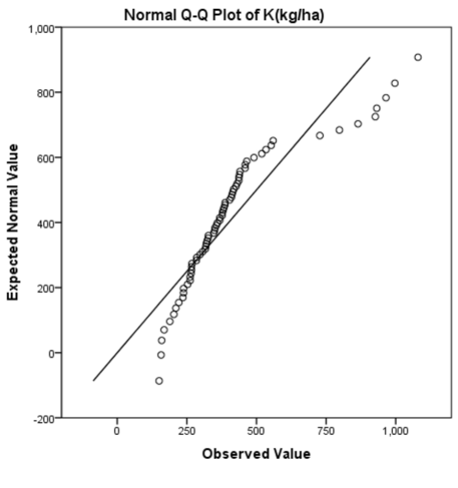

Normal Q-Q Plot of log_OC (%)
Expected Normal Value
Observed Value

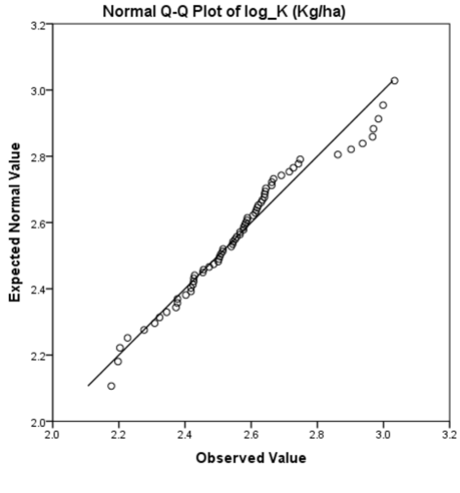

Normal Q-Q Plot of N (Kg/ha)
Expected Normal Value
Observed Value

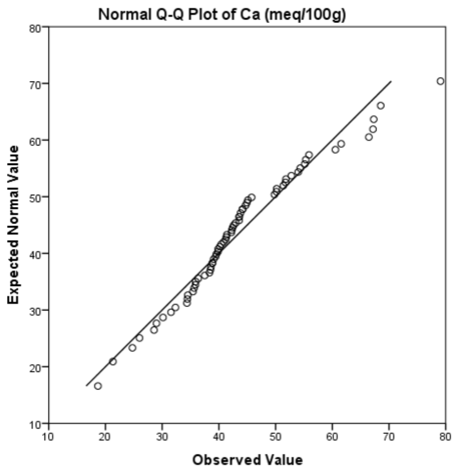

Normal Q-Q Plot of log_N (Kg/ha)
Expected Normal Value
Observed Value

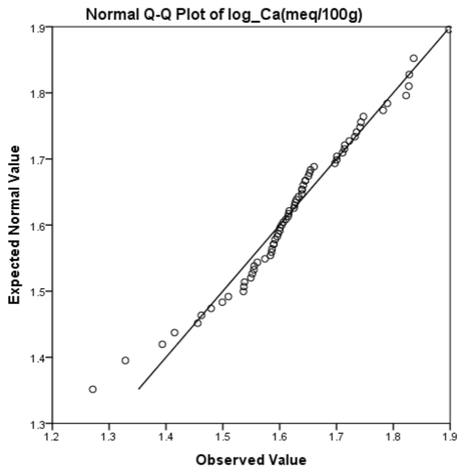

Normal Q-Q Plot of P (Kg/ha)
Expected Normal Value
Observed Value

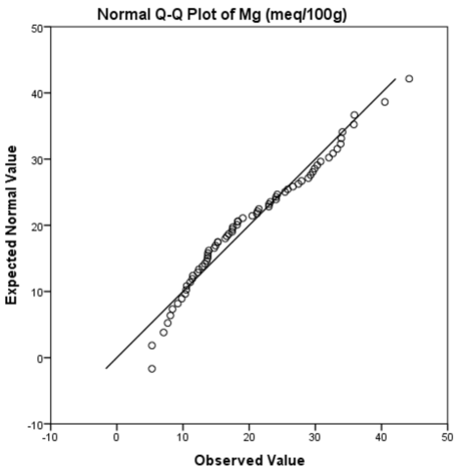

Normal Q-Q Plot of log_P (Kg/ha)
Expected Normal Value
Observed Value

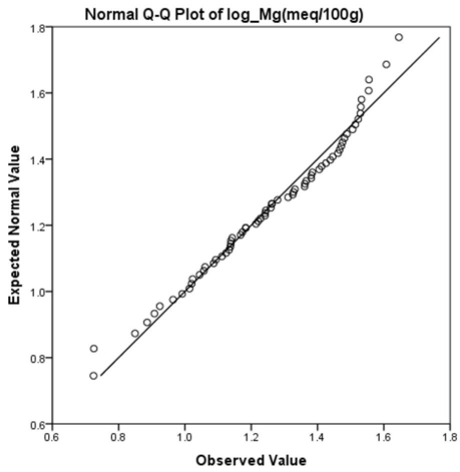

Normal Q-Q Plot of K(kg/ha)
Expected Normal Value
Observed Value

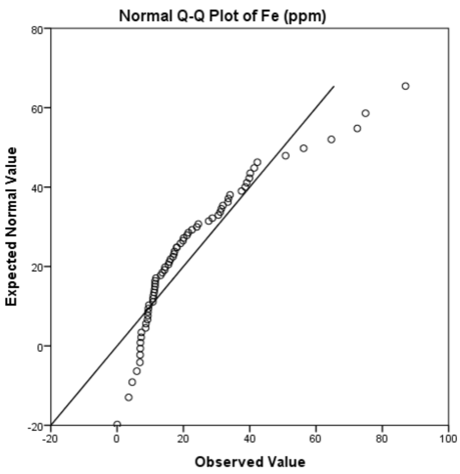

Normal Q-Q Plot of log_K (Kg/ha)
Expected Normal Value
Observed Value

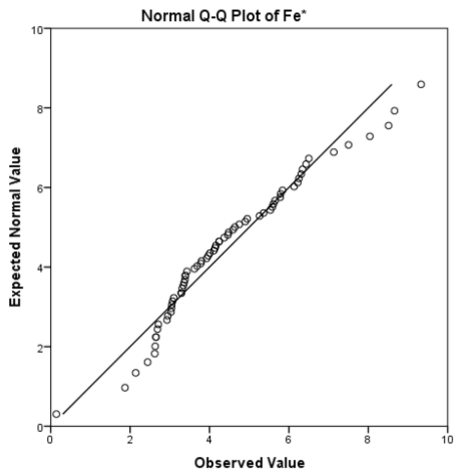

Normal Q-Q Plot of Ca (meq/100g)
Expected Normal Value
Observed Value
10
20
30
40
50
60
70
80


Normal Q-Q Plot of log_Ca(meq/100g)
Expected Normal Value
Observed Value
1.2
1.3
1.4
1.5
1.6
1.7
1.8
1.9


Normal Q-Q Plot of Mg (meq/100g)
Expected Normal Value
Observed Value
-10
0
10
20
30
40
50


Normal Q-Q Plot of log_Mg(meq/100g)
Expected Normal Value
Observed Value
0.6
0.8
1.0
1.2
1.4
1.6
1.8


Normal Q-Q Plot of Fe (ppm)
Expected Normal Value
Observed Value
-20
0
20
40
60
80
100


Normal Q-Q Plot of Fe*
Expected Normal Value
Observed Value
0
2
4
6
8
10

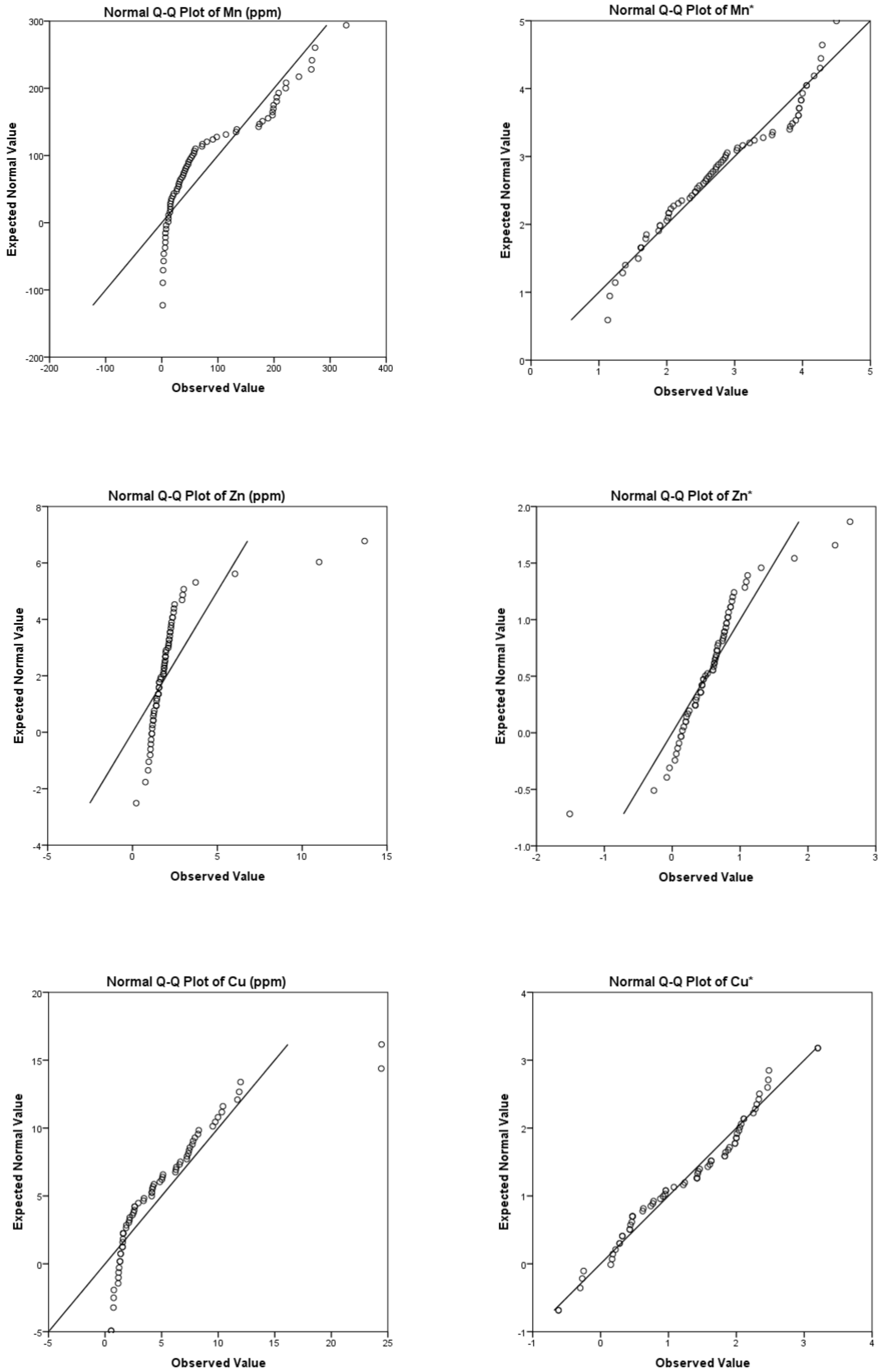


Figure 5.1 Q–Q plots for soil nutrients (*box–cox transformation)

5.3 Descriptive Geostatistical analysis

For spatial data, before the variogram touches the sill and stabilizes, semivariance increases with distances that are correlated. The dissimilarity rises until it finally touches a maximum Υ at which the variogram flattens out. The lag (h) in which the variogram extends the sill variance signifies the range of spatial correlation. It is assumed that the observations in the range are spatially correlated, while those larger than the range are considered spatially independent (Goovaerts 1997). The variance observed at a shorter range than the sampling range will be identified at zero lag distance is referred to as the nugget effect. This signifies any measurement errors (Burgos et al., 2006).

The fit of the variogram model is conducted; such the model fits the experimental values closely. The MSS error (mean sum of square error) was found to be minimal corresponding to the spherical model for all soil nutrients and exponential models for OC, N, and P; therefore, both are considered as the most suitable model. Then this model is used for estimation, and results can be used to compute MAE (mean absolute error) and RMSE (root mean squared error). In this study, the MSS error with the least value among models is considered as the best fit model as one of the parameters along with the initial flatness of the curve in SpaceStat 4.0® (BioMedware). The initial flatness in the model signifies a very strong degree of uniformity along with small distances (Goovaerts, 1997). Nugget/sill ratio is used to calculate spatial dependency (less than 0.25-strongly spatially dependent, 0.25 to 0.75-moderately spatially dependent and greater than 0.75-weakly spatially dependent) (Bogunovic et al., 2014; Cambardella et al., 1994)

The range is the maximum distance to which parameters are spatially correlated. This suggests the optimal interval of sampling for an reliable measurement of spatial variability. The spatial dependency varied between 878 m and 3723 m for selected soil nutrients in vertisols, which indicates there is spatial dependency among the soil nutrients within this range. The isotropic semivariogram for all soil parameters was calculated, and best fit models were determined by low MSS error and initial flatness of the model curve. Based on the results OC, N and P were best fitted for the exponential model, and the rest of the other parameters best fitted for the spherical model are tabulated in Table.5.1.

High spatial correlation to greater distance was shown by EC followed by pH relative to other parameters, which could be due to agricultural water; while Fe showed a high spatial correlation at small distances, compared to other parameters. The range of pH, EC, OC, N, P, K, Ca, Mg, Fe, Mn, Zn, and Cu indicates that the sampling interval can be maintained within 3347.84 m, 3723.12 m, 1051.60 m, 1069.88 m, 1898.65 m, 1787.54 m, 1002.21 m, 923.53 m, 877.90 m, 1737.60 m, 974.06 m and 974.46 m respectively for spatial sampling for these properties (Table.5.1).

Table.5.1 Model parameters for variogram of selected soil properties

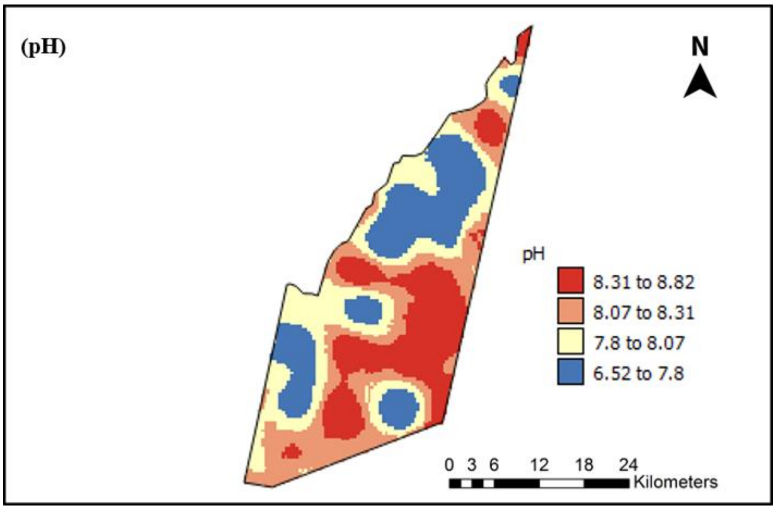
Parameters	**Variogram parameter**			**N:S Ratio**	**Spatial Dependence**	**MSS ERROR**	**Model**	**MAE**	**RMSE**
	Nugget	**Sill**	**Range(m)**						
pH	0.0895	0.1721	3347.84	0.52	moderate	0.3200	spherical	0.34	0.96
EC	0.0164	0.0254	3723.12	0.64	moderate	0.4016	spherical	0.11	1.04
OC	0.0040	0.0824	1051.60	0.04	strong	0.2692	exponential	0.24	0.83
N(Kg/ha)	0.0053	0.00561	1069.88	0.94	weak	0.4995	exponential	0.10	1.019
P (Kg/ha)	0.0403	0.0857	1898.65	0.47	moderate	0.2268	exponential	0.11	1.18
K(Kg/ha)	0.0256	0.0926	1787.54	0.27	moderate	0.3345	spherical	0.14	1.10
Ca (meq/per100 g)	0.0128	0.0104	1002.21	1.23	weak	0.3320	spherical	0.08	0.97
Mg(meq/per100g)	0.0176	0.0335	923.53	0.52	moderate	0.6299	spherical	0.17	0.98
Fe (ppm)	1.0487	2.0134	877.90	0.52	moderate	0.2650	spherical	1.305	0.874
Mn(ppm)	0.2230	0.6788	1737.60	0.382	moderate	0.3353	spherical	0.701	0.887
Zn (ppm)	0.0279	0.2896	974.06	0.096	strong	0.5967	spherical	0.341	0.961
Cu (ppm)	0.1649	0.5608	974.46	0.294	moderate	0.2176	spherical	0.647	0.840

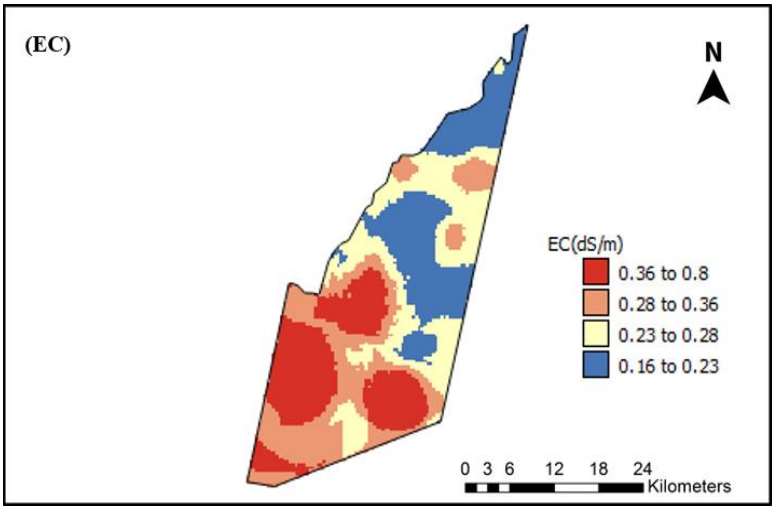
The low range of spatial dependence indicates that this continuity disappears fast. It indicates in this area, beyond this range, the soil nutrients are not spatial correlated. Generally, the greater the range indicates the more homogeneity of the soil within its scale. About variation in ranges of soil nutrients, Laekemariam et al. (2018) compared various ranges, which were attributed to sampling intensities and study area size. They reported range varies because of the combined effect of agricultural practices, environmental conditions, and parental material. In our study area, the range is varied due to agricultural practices (Tamburi et al. 2020c).

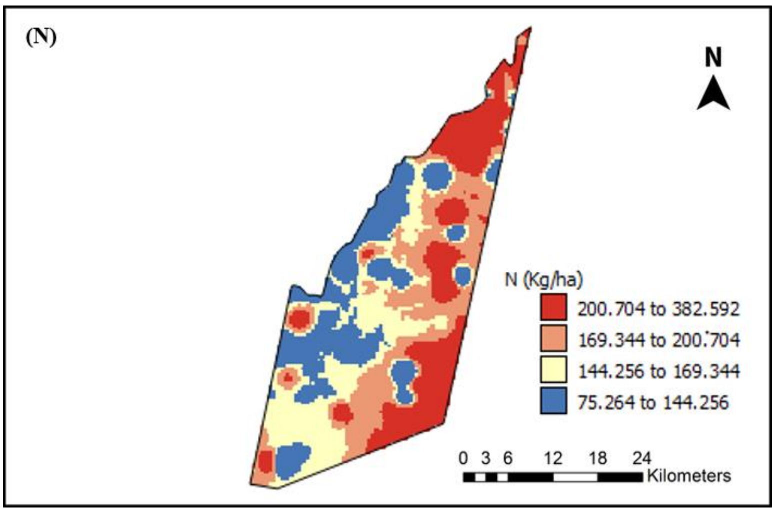
The nugget to sill ratio specifies pH, EC, P, K, Mg, Mn, Fe, Zn, and Cu are moderately dependent, whereas nitrogen and calcium showed weak dependency, and on the other side organic carbon showed strong spatial dependence. Interestingly the nitrogen showed weak spatial dependence when other macronutrients (P and K) have moderate spatial dependence; it might be due to the high intake of nitrogen by crops. The variation in dependence would be subjected to extrinsic factors, including the rate of use of fertilizers by farmers (Cambardella et al., 1994; Geypens et al., 1999; Vasu et al., 2017).

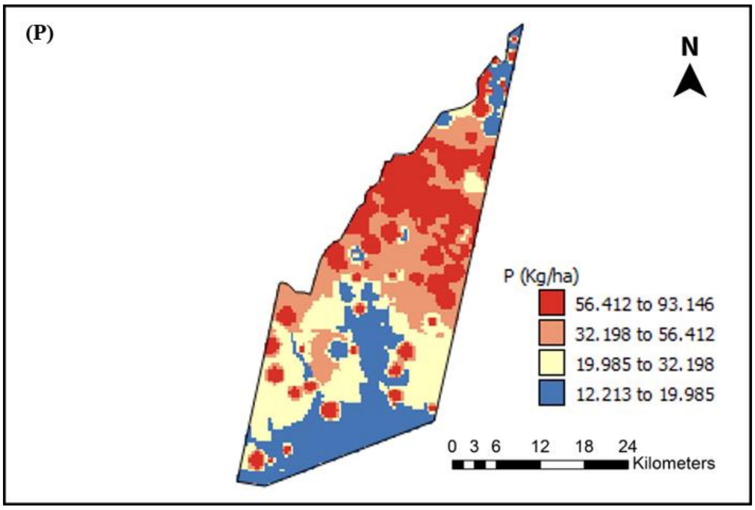
5.4 Spatial distribution of vertisols nutrients

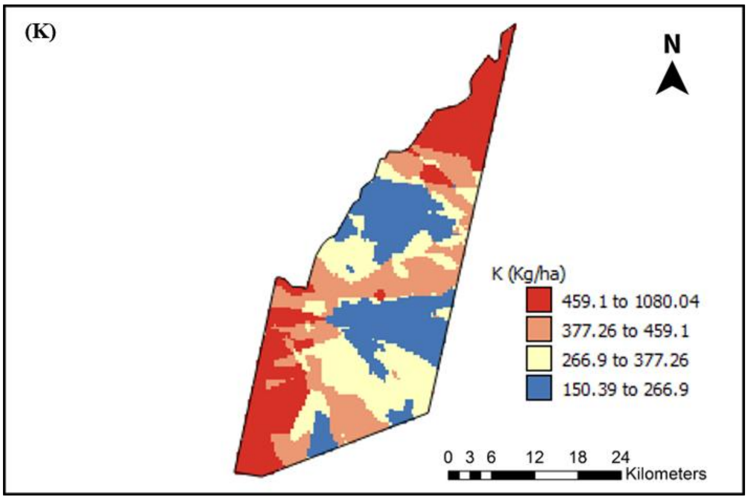
Maps of the spatial distribution of all soil nutrients prepared using ordinary kriging are shown in Figure 5.2. These surface maps provide information regarding the spatial distribution of nutrient variations in the soil and their deficiency. The spatial variability maps show that pH generally varies from neutral to alkaline in nature, the southern part of the area is mostly alkaline, which may be related to the quality of irrigation water, as well as the rich presence of calcium carbonate (Srivastava et al., 2002). The EC is high to the north, indicating normal soil with fewer amounts of dissolved salts.


(pH)
N
pH
8.31 to 8.82
8.07 to 8.31
7.8 to 8.07
6.52 to 7.8
0 3 6 12 18 24
Kilometers


(EC)
N
EC(dS/m)
0.36 to 0.8
0.28 to 0.36
0.23 to 0.28
0.16 to 0.23
0 3 6 12 18 24
Kilometers


(N)
N
N (Kg/ha)
200.704 to 382.592
169.344 to 200.704
144.256 to 169.344
75.264 to 144.256
0 3 6 12 18 24
Kilometers





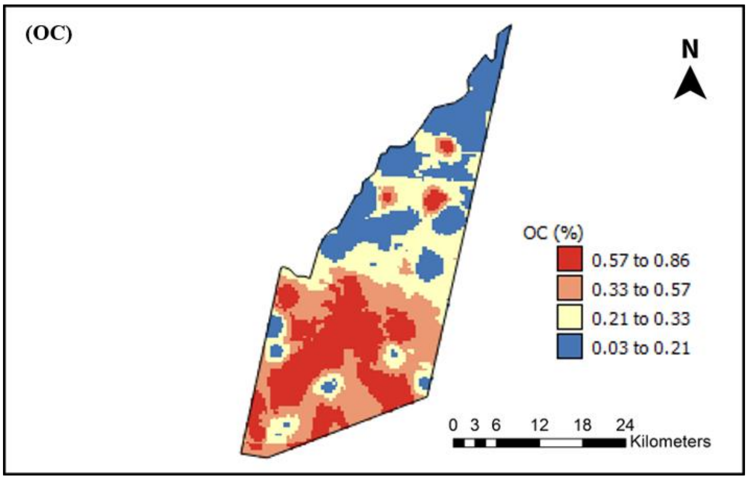


Figure 5.2 Spatial variability maps of pH, EC, OC and Macronutrients (NPK)

The nitrogen is low towards the southwestern part of the study area, while high to the northeast side. On the other hand, with a hot summer period, decomposition of organic matter occurs, which leads to a decrease in the nitrogen content (Uygur et al., 2009). The K content is high to the north of the study area, and to the south, the remaining middle portion showed a comparatively low presence of K. Phosphorus ranged from medium to high across the study area; only a small portion was low. However, due to intensive farming in this area, the soil phosphorus has greatly increased. The organic carbon was comparatively higher on the south side of the study area, and this variability may due to the use of organic manure and fertilizer application. In spatial variability maps, regions where there is more EC also showed a high range of organic carbon availability; it is due to positive correlations between EC and OC ($r = 0.15$). The Ca and Mg are negatively correlated (Table 4.2); the spatial variability maps indicate similarly as the region in which Ca is low has shown a relatively high presence of Mg (Figure 5.3). The calcium content is on higher ranges, as well as magnesium. The presence of higher ranges of calcium and magnesium in this region may be due to vertisols formation from basalt rocks along with agricultural practices (Tamburi et al. 2020a).

The spatial distribution maps of soil micronutrients are prepared from their semivariograms. The transformed dataset of the Box-Cox data set used for interpolation, and then the results are transformed again for generating the spatial variability maps (Cassie 1993; Fu et al. 2013).

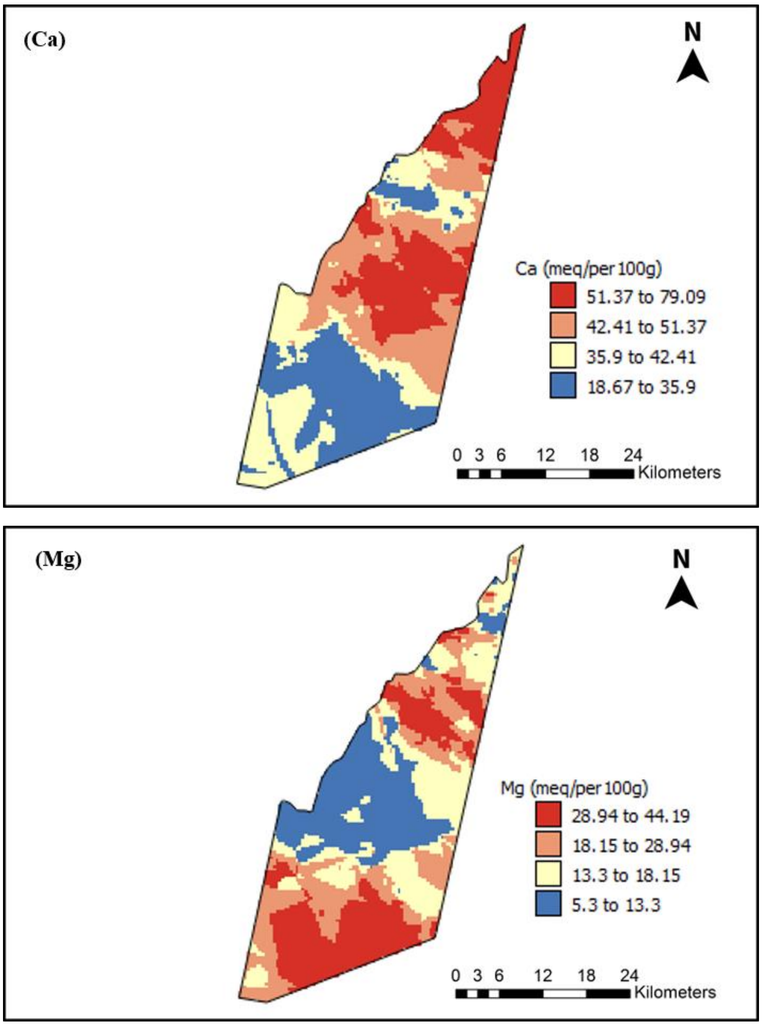
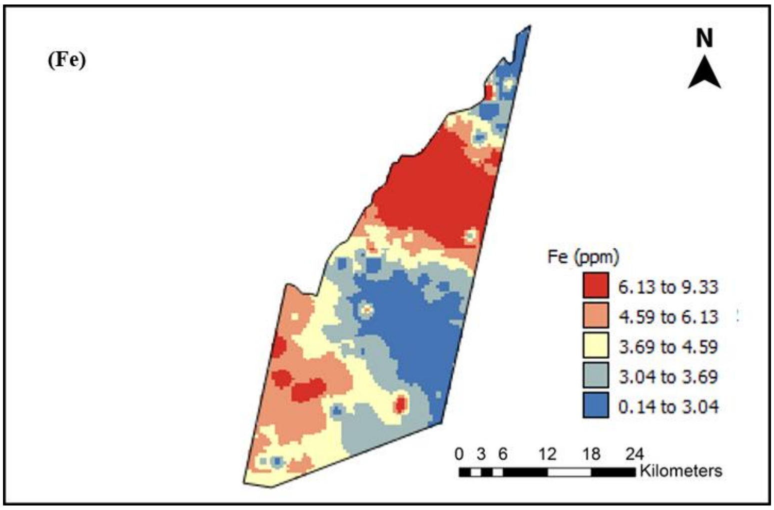
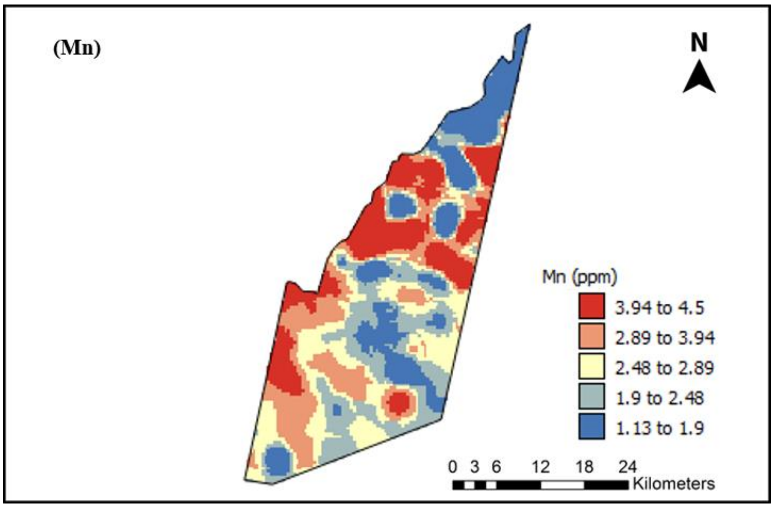


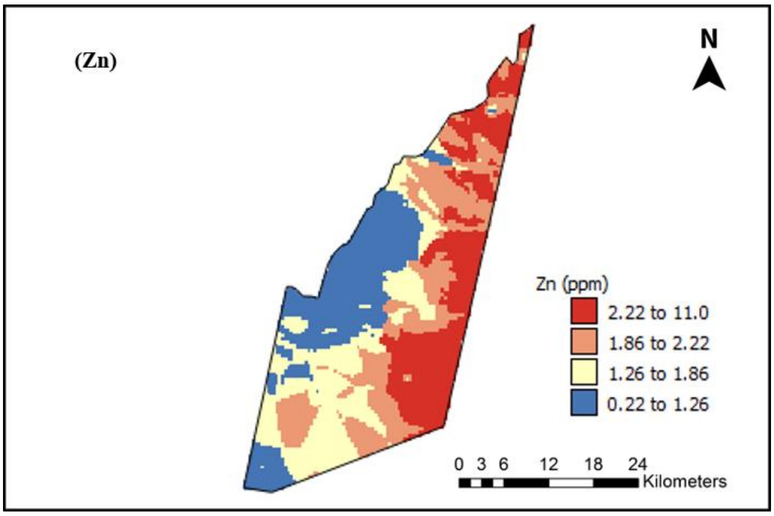
Figure 5.3 Spatial variability maps of Ca and Mg

From spatial distribution maps (Figure 5.4), Fe is distributed evenly in a few areas and highly concentrated towards the north and south-west parts of the study area. The vertisols generally contain a high amount of Fe due to high adsorption, as clay fractions are more (Jelic et al., 2011) Mn is distributed in patches across the study area and has no proper distribution. The higher values Mn are distributed across the western and eastern borders in patches (3.94-4.5 ppm). Zn is comparatively higher towards the northeast and southeast part of the study area; lower Zn content results in less productivity. Cu is uniformly distributed at specific regions; it is high in the middle part of the study area and low towards the south part. The variability of micronutrients is mostly dependent on soil pH, organic matter, and the direct application of micronutrients through fertilizers to increase soil health and productivity. Rainfall also influences the distribution of micronutrients in the site (Dimkpa and Bindraban, 2016).

The cross-validation of spatial variability maps is evaluated by MAE and RMSE indices (Table 5.1). The lower values indicate that the semivariogram parameters better prepare the value of soil property at the non-sampled position than by the assumption of the average of the observed value. The kriged maps for micronutrients indicates the distribution of micronutrients and helps to plan proper agricultural practices, including fertilization (Fu et al., 2010; Ramzan and Wani, 2018).







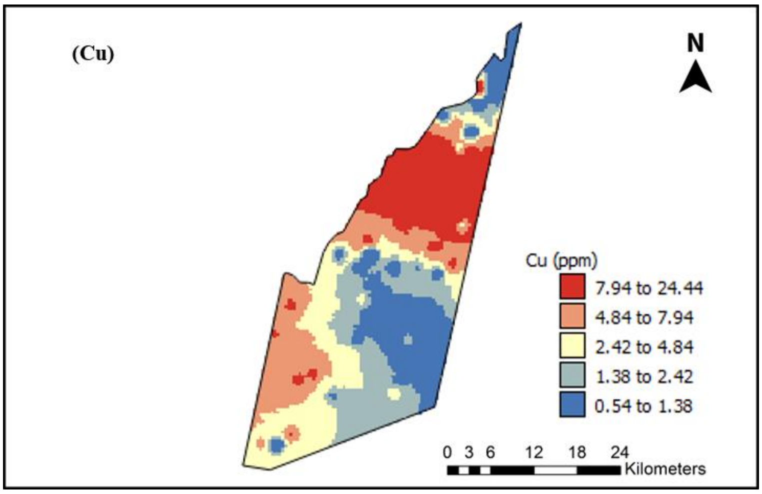


Figure 5.4 Spatial variability maps of Micronutrients (Fe, Mn, Zn and Cu)

These predictive maps provide accurate information about soil nutrients at arable depth. They may be critical to soil nutrient management at specific sites, as well as variable application rates of fertilizers. At the same time, regional maps are obtained from kriging provides quantitative information about soil nutrients on a wider scale and thus facilitate decision making or regional planning, monitoring, and environmental protection. Extension officers can communicate to small scale farmers regarding the soil health status of their fields. Hence sustainable farming is useful for site-specific fertilization for a sustainable environment.

CHAPTER 6

Hyperion data and PLSR model for estimation of vertisols nutrients.

6.1 Introduction

The measurement of soil properties by traditional techniques is time-consuming and laborious. Hence it becomes important to look for quicker and easier measurements, and the remote sensing approach is the alternative approach. Numerous studies have been carried out using hyperspectral and multispectral remote sensors. The spectral behavior of Indian soils was studied by using the Landsat Multiple Scanning systems (Landsat MSS) in the mid-eighties (Sinha, 1986). The discrete bands of multispectral sensors limited the study of soil characteristics. Later the hyperspectral remote sensing showed the ability for estimation of soil properties (Spaceborne and airborne). This chapter looks at using preprocessed Hyperion data to develop the models to estimate vertisols nutrients, split data sets for training/calibration, and test/validate to estimate the model and determine the significant wavelength estimating vertisols soil nutrients.

6.2 Partial Least Square Regression (PLSR)

The PLSR is a known chemometric technique based on bilinear regression; it extracts a minimum latent factor from large data, which is multidimensional. Then these latent factors represent linear combinations of the spectral reflectance and the soil nutrient properties (Dhawale et al., 2015).

The PLSR models are developed by correlating spectra's reflectance from the Hyperion image pixels with the soil variables measured at the sample points. It is a multivariate method that estimates a dependent variable from a large number of correlated variables (reflectance values) by extracting a limited number of uncorrelated factors (i.e., latent variables), which has the strongest relationship to the dependent variable (soil nutrients). The impact of the latent variables is verified by cross-validation (Castaldi et al., 2014).

The PLS regression analysis is made by correlating the soil chemical properties with atmospheric corrected Hyperion data. For soil parameters, lowest RMSECV (root mean square error of cross-validation, highest R^2CV (Coefficient of determination in cross-validation) and combined with lowest LV numbers (latent variables) are selected as the best model.

6.3 Methodology

The PLSR models are developed by correlating spectra's reflectance from the Hyperion image pixels with the soil variables measured at the sample points. It is a multivariate method that predicts a dependent variable from a large number of correlated variables (reflectance values) by extracting a limited number of uncorrelated factors (i.e., latent variables) that have the strongest relationship to the dependent variable (soil nutrients). The effect of the latent variables is checked by cross-validation. The models are executed in PLS_Toolbox 4.0. Figure 5.1 shows the methodology used for the PLSR model

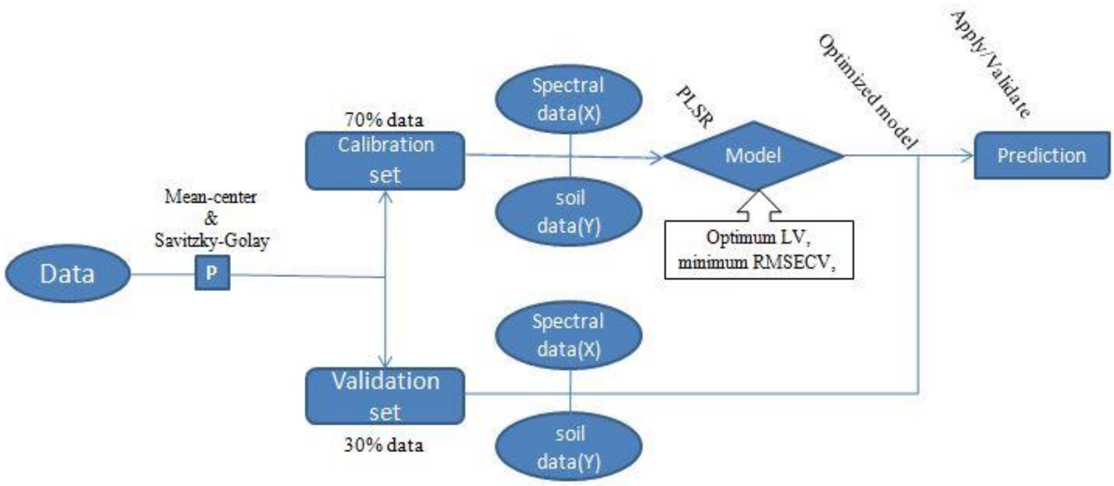


Figure 6.1 Flowchart for PLSR model

The identical method for establishing the PLSR models are observed for all soil parameters to be predicted. Initially, spectral pretreatment was carried using Savitzky-Golay derivatives (first order and second order) (Savitzky and Golay, 1964) and mean centering on optimizing the correlation between soil nutrients and spectra.

The calculation of the projection with variable importance (VIP) enables us to define each wavelength's relative importance or range in the PLSR model to estimate soil nutrients (Castaldi et al., 2014). The VIP scores estimate the importance of each variable in the projection used in the PLS model. The variable selection improves the accuracy of estimation by identifying a subset of important predictors, increasing the model interpretability with accurate representation (Farres et al., 2015). A wavelength with a VIP value of more than one can be considered significant in a PLSR model (Castaldi et al., 2014). As a result, VIP and regression coefficient statistics embedded in PLS are used to visualize a subset of independent variables controlling the variation in response in diverse disciplines, including soil nutrients and hyperspectral data.

The PLS regression analysis is made by correlating the soil chemical properties with spectral signatures of atmospheric corrected Hyperion data. For soil parameters, lowest RMSECV (root mean square error of cross-validation, highest R^2CV (Coefficient of determination in cross-validation) and combined with lowest LV numbers (latent variables) are selected as the best model. The selection of important wavelengths are used for PLSR is identified by VIP; the graphs shown are only for those soil nutrients which show good estimations.

6.3.1 Data Preprocessing and Sample Separation.

The preprocessing of the data is carried out by the mean centering and the Savitzky-Golay smoothening techniques (Savitzky and Golay, 1964); these pre-processed data are used to build the PLSR model. The mean-centred are the values that are subtracted by the mean of the response at each wavelength point on all samples by the response of spectral value. While the value of the response at each point of wavelength is subtracted by the column mean, the data in every row after averaging represents the variation between that sample and the mean sample of the original data (Han et al., 2020). The mean centering has the result that an adjustable intercept is included in multivariate models. For example, centering the mean of both the X blocks and the Y blocks in a regression model efficiently enables a non- zero regression line intersection (Wise et al., 2006), by doing this it is ensured that the interpretation of results is around the mean (Jiang et al., 2017).

The smoothing is a high-pass filter that removes high-frequency noise from samples that are in built-in PLS_Toolbox. This operation is often used for spectra and is carried out separately in each row of the data matrix and affects neighbouring variables. The Savitzky- Golay smoothness is based on the least-squares fit based on polynomials segments of data (Savitzky and Golay, 1964). It is capable of differentiation and smoothing. It maintains the shape of the original signal. It has two degrees of freedom: the window length and polynomial order (Minu et al., 2016). Smoothing presumes that the variables are close to each other in the data matrix (i.e., adjacent columns) are connected and included related information that can be averaged collectively to reduce the noise without considerable impact loss of the signal of interest. The Savitzky Golay algorithm fits characteristic polynomials to windows approximately to every point in the spectrum. The algorithm requires the selection of both the order of the polynomial and the window size (filter width) (Wise et al., 2006). The lower the polynomial order and the larger the window, the more the spectrum is smoothed. However, it appears that no hard rules are decided for preprocessing to utilize; frequently, trial and error is the only approach. The leave one out cross validation is used for determining the optimal numbers of latent variables in PLS toolbox.

To validate the model, the new data set has not been considered, and the 70% of an original dataset has been grouped as calibration set and 30% as validation set (Dhawale et al., 2015). The selection of the calibration and validation set is divided as follows. Initially, the values of the soil nutrients and their corresponding reflectance are sorted in ascending order; then, the lowest nutrient value is positioned into a validation set and the next three successive samples in the calibration set (Minu and Shetty, 2018). The process is continued to alternately place the next sample in the validation set and the next three in the calibration set. This selection process for calibration and validation sets ensures even distribution of soil nutrients value in the calibration set (Mark and Workman, 2003). The selection of important wavelengths are used for PLSR is identified by VIP; the graphs shown are only for those soil nutrients which show good estimations.

The precision of the best fit PLSR model is verified by cross-validation, which includes performance indicators, such as:

(i) Root mean square error (RMSE) for cross validation (RMSECV) and prediction (RMSEP).

(ii) Coefficient of determination for prediction (R^2)

6.4 Results of PLSR model

6.4.1 Nitrogen

The results from PLSR model indicate the capability for estimation of soil nitrogen from the spectral reflectance of the Hyperion. The medium estimation is obtained for nitrogen. The optimal number of LVs for nitrogen is five after cross validation with R^2 value of 0.547 (Figure 6.2). The low estimation was observed for nitrogen using airborne sensor (HyMap) with R^2 of 0.28 (Vohland et al. 2017) and R^2 of 0.44 for total nitrogen (Pechanec et al. 2021). While estimating better model it is important for RMSECV and RMSEP values to be similar or close (Figure 6.2). The prominent peaks observed for estimation of soil nitrogen are at wavelengths 1346, 1754, 2072, 2294, and 2335 nm (Figure 6.3).

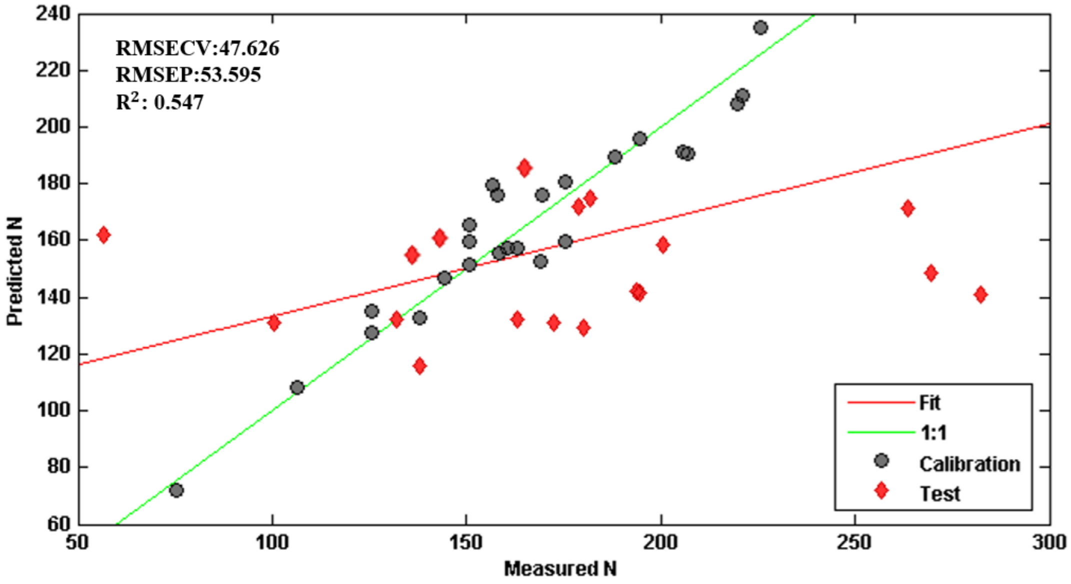


Figure 6.2: Results of PLSR model for Nitrogen.

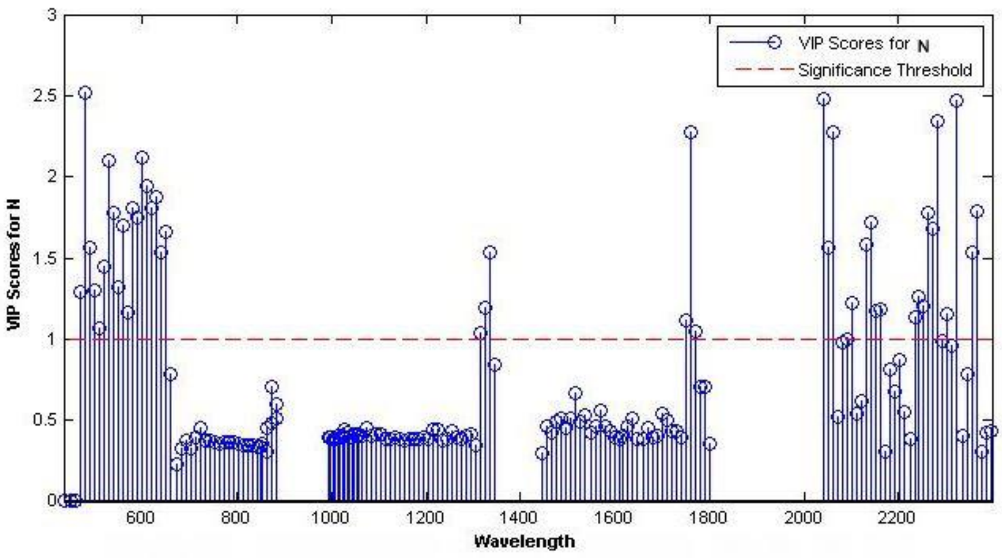


Figure 6.3: VIP for Nitrogen using PLSR

6.4.2 Potassium

The estimation accuracy for potassium is medium with R^2 value of 0.455 (Figure 6.4). The optimal number of LVs for potassium is four. The similar estimations are shown by Bajwa and Tian (2013) using hyperspectral imaging. The potassium content in the study area is minimal, and it has been estimated that it is highly soluble and nutrient leaching is limited in clay soils. Contrastingly, potassium 's high solubility in sandy soils will leach out at higher rates compared to vertisols, resulting in low concentrations (Lee et al., 2003). The prominent peaks observed for estimation of soil potassium are at wavelengths 437, 671, 882, 892, 1047, 1316, 1548, 1822 and 2335 nm (Figure 6.5). Lee et al. (2003) had obtained similar prominent peak loading for PLSR technique in Florida soils at 430, 522, 612, 1356, 1604, 1912 and 2206 nm.

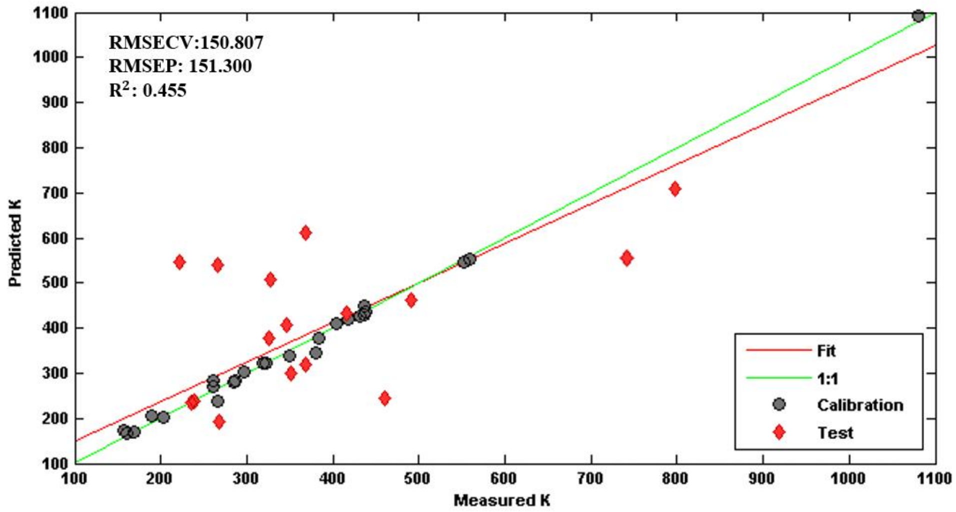


Figure 6.4: Results of PLSR model for Potassium

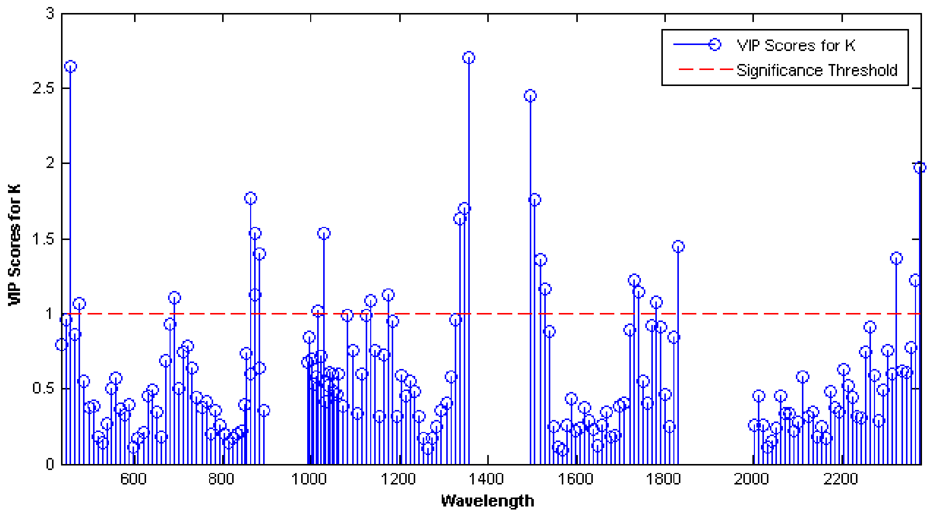


Figure 6.5: VIP for Potassium using PLSR

6.4.3 Iron

The results obtained for estimation of iron is medium. The optimal number of LVs for iron is six with R^2 value of 0.401 (Figure 6.6). The prominent peaks observed for estimation of soil iron are at wavelengths 1063, 1194, 1205, 1598, 1729, and 2183 nm (Figure 6.7). Ben-Dor et al.(2006) have also observed peaks at 990, 556, and 489 nm.

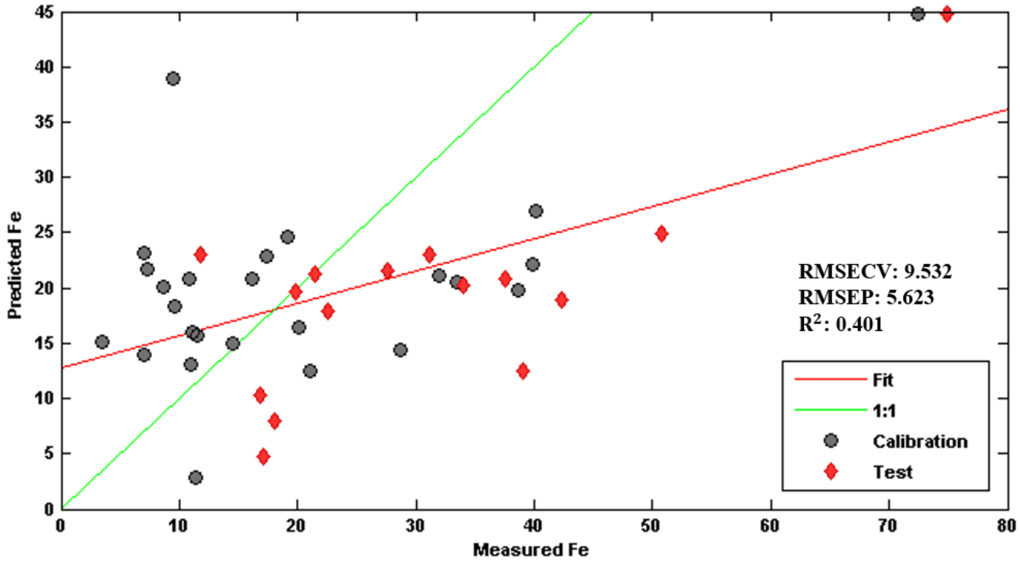


Figure 6.6: Results of PLSR model for Iron

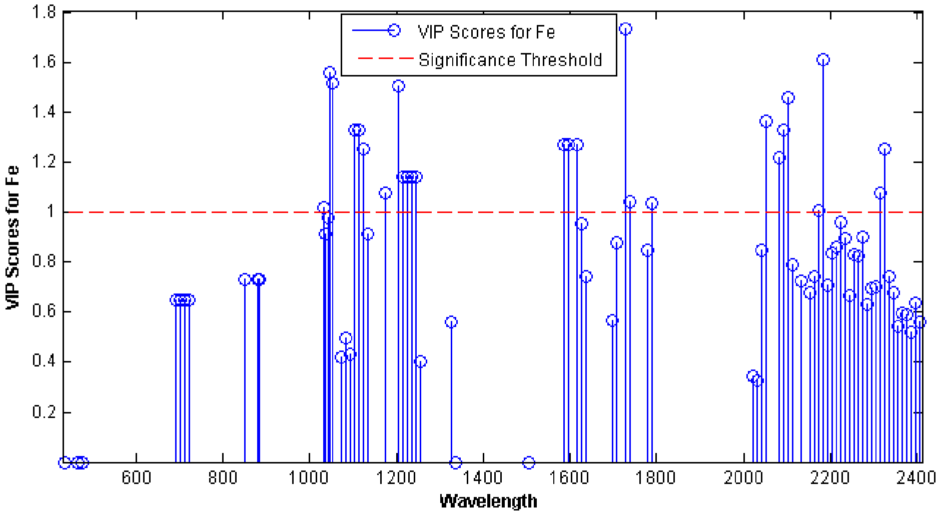


Figure 6.7: VIP for Iron using PLSR

6.4.4 Copper

The dataset analysis by PLSR for estimating the soil copper is medium from Hyperion data. The optimal number of LVs for copper is four with the estimations for validation is R^2 is 0.412 (Figure 6.8). Conversely, low estimation was shown by Kemper and Sommer (2002) with R^2 of 0.22, and Cheng et al. (2019) with R^2 of 0.26. Malley et al. (2004) has reported good estimations wit R^2 of 0.69 from spectroscopy. The prominent peaks observed are 508, 548, 559, 2092, and 2345 nm (Figure 6.9).

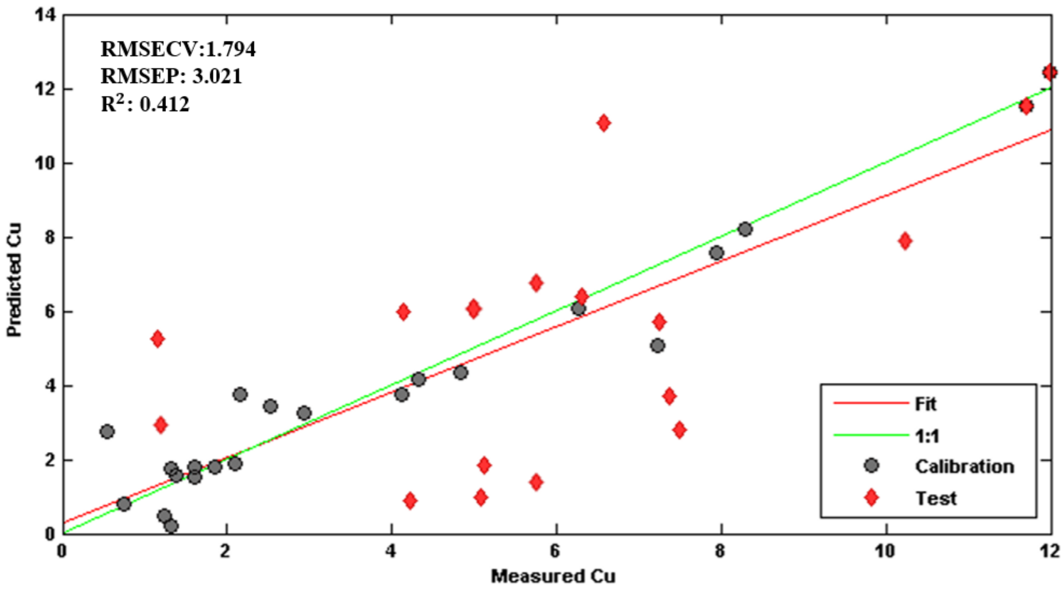


Figure 6.8: Results of PLSR model for copper

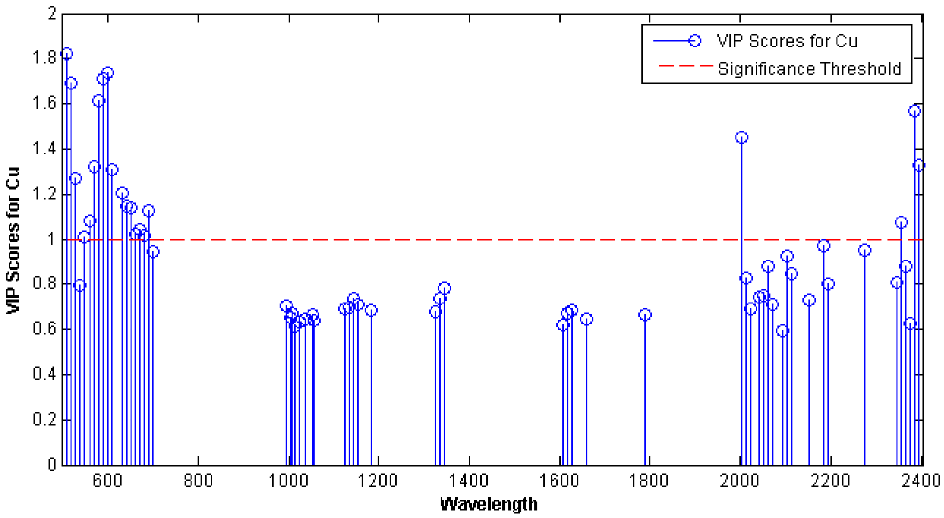


Figure 6.9: VIP for Copper using PLSR

Mapping the soil nutrients by Hyperion data

The optimal PLSR models developed from Hyperion data are incorporated for soil nutrients mapping. The bare soil pixel are identified by normalized differential vegetative index (NDVI) technique (equation 5). Then masked the pixel values more than 0.2 to avoid vegetation interference, and less than 0.1 for water bodies (Stevens et al. 2008). This technique avoids the vegetation and water interference.

$$\mathrm{NDVI} = \frac{[\mathrm{NIR} - \mathrm{RED}]}{[\mathrm{NIR} + \mathrm{RED}]} \tag{5}$$

Here reflectance at spectral bands of 833 nm and 660 nm are used for NIR and RED respectively. The only soil pixels were considered for mapping; other pixel like vegetation and water were removed, which are indicated in white pixels. The relative variations can be recognized by these maps (Fig. 14). Except iron, other soil nutrients have over predicted the values which is resultant of low prediction accuracy by PLSR technique.

India's vertisols exhibit low reflectances that are deficient in humus, nitrogen, phosphorus, and potassium due to low permeability and moisture stress throughout the drought. Hence the presence of soluble nutrients concentration is low compared to other soil. Generally, the white colour contributes to higher reflectance in all wavelengths (Sinha, 1986), so the grey-brown colour is natural in the vertisols fields and less organic matter, leading to low reflectance. In comparison, relative to airborne data, Hyperion satellite hyperspectral data is constrained by a lower spatial resolution with a nominal pixel size of 30 m, which increases, for example, the issue of different surfaces mixed in one pixel (Vohland et al., 2017).

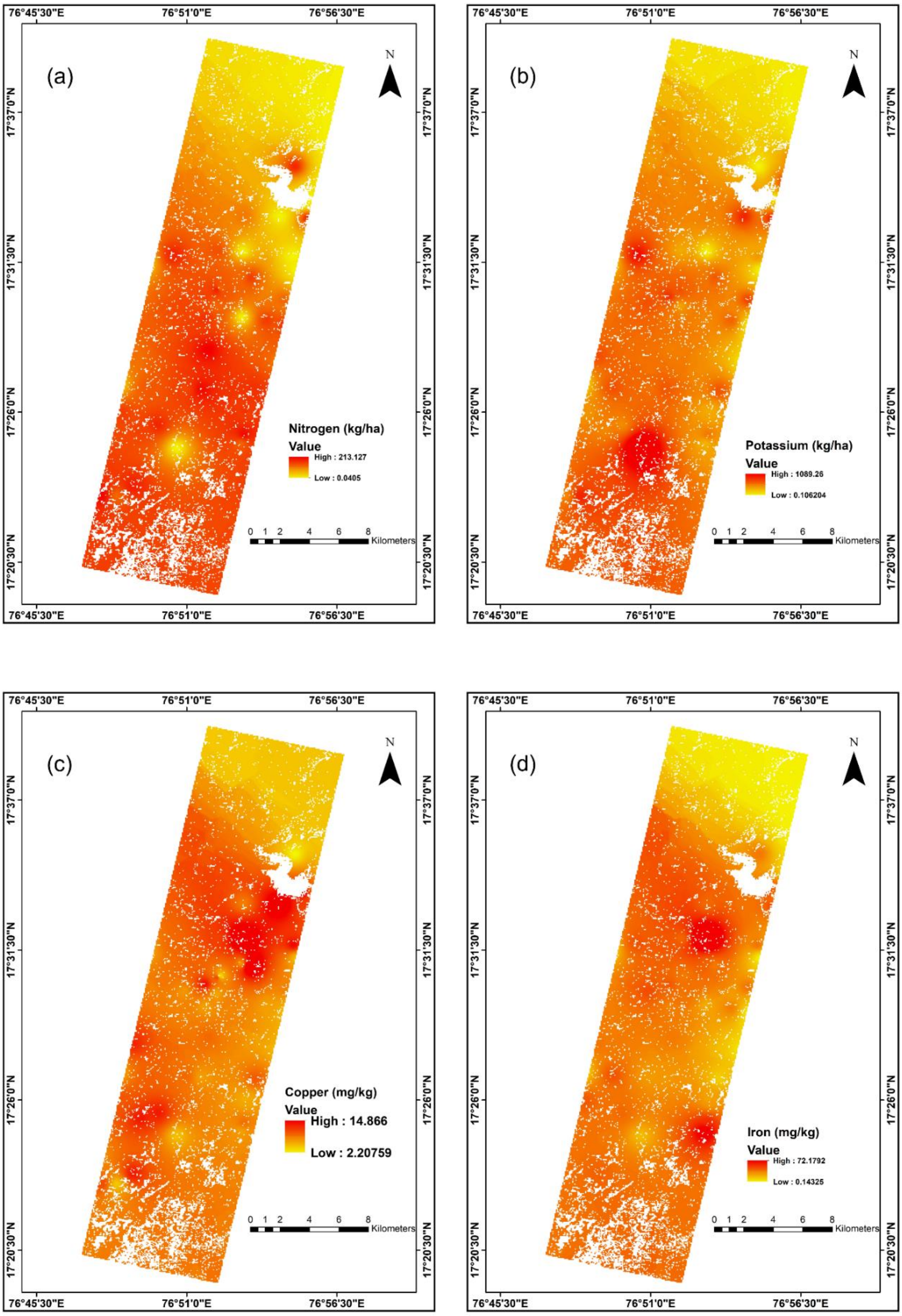


Figure 6.10: (a) Nitrogen (b) Potassium, (c) Copper and (d) Iron, mapping by using Hyperion data. The white pixel indicate vegetation and water bodies.

CHAPTER 7

Summary and Conclusions

The primary objective of the work was to characterize the spatial variability of the soil nutrients and find the quick estimation of vertisols nutrients through satellite data and laboratory measurements using the PLSR technique. The work demonstrated to which extent Hyperion data is utilized to predict the macro and micronutrients of vertisols in India. The research work was carried in a small region of north Karnataka, India. Systematic soil sampling was carried out in the month (third week) of November 2016. This duration is also synchronized with the passage of the Hyperion satellite over the study area. The uniform sampling method was difficult to adopt since the fields are scattered over a small area and are random; some fields were waterlogged, and leftover crop was burnt, as the farms were preparing for next crop. The chemical analysis was conducted according to IS Codes. The nutrient index values and spatial variability maps are generated. To obtain the reflectance spectra of Hyperion image, suitable preprocessing and filtering methods were applied. Later, the PLSR technique is applied to the estimation of vertisols soil nutrients.

In many underdeveloped and developing countries, including India, various factors, such as small agricultural land (less than two acres), failure to manage advanced technological equipment due to financial constraints, and lack of technical knowledge among farmers, are driving to a decrease in awareness of sustainable and precision agriculture. In India, the topsoil layer loses fertility attribute to poor water management and the rate of fertilizer application. Under such conditions, initial preparation is to map the spatial variability of soil nutrients for nutrients status availability, proper planning, and estimation of soil nutrients using remote sensing data is important.

Specific conclusions drawn from research work:

- The soils in the study area varied from neutral to alkaline, representing the soil's calcareous nature. The Coefficient of variation indicated the high variability of soil nutrients due to no proper specific agricultural practices over the study area. Due to individual agricultural practices, the maximum values are on the upper quartile revealing the positive skewness, especially micronutrients.
- The status of macronutrients N, P, and K are low, low, and medium with NI values of 1.11, 1.15, and 2.23, respectively. The micronutrients Cu, Fe, Mg, and Zn are medium, high, medium, and high with NI values of 2.20, 2.81, 1.69, and 2.79, respectively.
- Based on the variogram results, OC, N, and P were best fitted for the exponential model, and the rest of the other parameters best fitted for the spherical model. The spatial variability maps indicate the heterogeneous distribution of soil nutrients. The ranges of spatial dependency indicate that approximately up to one kilometre, there is a spatial correlation between samples; above this range, soil nutrients are not correlated amongst the sampling points. The spatial variability maps are used as a primary guideline to farmers for specific site nutrient management. The obtained ranges act as adequate information for future sampling in vertisols.
- The variable important projection facilitates identifying prominent wavelengths, thus decreasing the wavelengths used in PLSR.
- Estimation of soil nutrients using Hyperion data indicates it has potential. The PLSR technique, coupled with Hyperion, provides non-destructive and rapid determination of soil nutrients in small scattered vertisols fields. The estimation of N, K, Fe, and Cu are with an accuracy of 54 %, 45 %, 40%, and 41%, respectively.
- The soils exhibited low reflectances, which are deficient in humus and macronutrients due to low permeability and moisture stress. Hence the presence of nutrients concentration is low.

7.1 Limitations of the work

The ranges obtained to act as adequate information for future sampling in vertisols. However, the study has been limited by small sample size and random collection of soil. For adequate information on the spatial variability in the small-size farm, a design to increase the number of the samples and grid sampling must, therefore, be carried out. The low estimation of soil nutrients may be due to low signal to noise ratio of Hyperion. Since the work is concentrated for only acquisition of prominent spectral information for estimating the soil nutrients, it can be also concentrated to establish the spatial information of soil nutrients from Hyperion data.

7.2 Scope for the future work

- The grid sampling techniques can be used for soil collection. Only Ordinary kriging is used for generating the spatial variability maps, other kriging techniques can be used, and comparative studies can be carried.
- The estimation of soil nutrients is influenced only by FLAASH atmospheric corrections. However, it is important to use and compare other well-defined atmospheric corrections (ATCOR, QUAC, and 6S).
- Spectral reflectance can be pretreated with other pretreatment methods (only Savitzky-Golay is used). Coupled or combination of other smoothing techniques can be used for better results.
- In this research, R^2 and RMSE are used for the evaluation of model performance. The uncertainty analysis and these global indicators and uncertainty due to the choice of calibration set, georeferencing errors, and laboratory reference values could also be studied.
- The data set of estimated regression with better results is to be used for precise estimation and mapping of soil nutrients and results to be compared with maps produced by geostatistical method.

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Bio-Data

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