

Effect of Electrical Conductivity and Spatial Variability of Soil on Crop Productivity

A

Thesis

Submitted for the award of

The degree of

DOCTOR OF PHILOSOPHY

By

Babankumar S.Bansod



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THAPAR UNIVERSITY

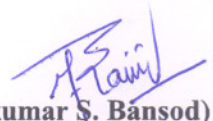
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Declaration

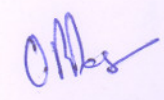
I hereby certify that the work which is presented in thesis entitled "**Effect of electrical conductivity and spatial variability of soil on crop productivity**" in the partial fulfillment of the requirement for award of the degree of DOCTOR OF PHILOSOPHY in the School of Physics and Materials Science, Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Dr. O. P. Pandey. The matter embodied in this report has not been submitted in part or full to any other university or institute for the award of any degree.


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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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O Lord, our God! And in your plans for us there is none
To equal you, should I wish to declare or tell them?
They would be too many to recount!”

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List of Publications

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- (i) **Bansod BS** and Pandey OP, An Application of Hybrid Clustering and Neural based Prediction Modelling for Delineation of Management Zones, International Journal on Computer Science and Engineering (IJCSE), Vol. 3(2), pp. 621-631, Feb 2011.
- (ii) **Bansod BS** and Pandey OP, Analysis of Spatial Soil Data Based on Apparent Electrical Conductivity in Northern India Experimental Field, International Journal of Tropical Agriculture, Vol. 29 (3-4), pp. 335-343, July-December 2011.
- (iii) **Bansod BS**, O.P. Pandey and N.L. Rajesh, Analysis and delineation of spatial variability using geo-sensed apparent electrical conductivity and clustering techniques. Int. J. Agric. Biol., Vol. 14, No. 4, pp. 481–491, 2012.
- (iv) **Bansod BS** and Pandey OP, An application of pca and fuzzy c- means to delineate management zones and variability analysis of soil. *Accepted in Eurasian Soil Science Journal, 2012.*
- (v) **Bansod BS**, O.P. Pandey, N.L. Rajesh and Dhattewal Shweta, Optimization of agricultural input application to enhance the crop quality and yield quantity in paddy under precision farming. *Accepted in Journal of Quality Assurance and Safety of Crops & Foods, 2012.*
- (vi) **Bansod BS**, O.P. Pandey, N.L. Rajesh, Analysis of Spatial Variability using Geostatistical Technique and Delineation of Management Zones using Fuzzy C-means Classification Algorithm, *Eurasian Soil Science Journal, 2012. (Under review)*
- (vii) **Bansod BS**, O.P. Pandey, Precision Farming Technologies for Sustainable Development - Global Review and Indian perspective, *Current Science Journal, 2012. (Under review)*

- (viii) **Bansod BS**, O.P. Pandey, N.L. Rajesh, A Novel Approach to aid Environmental Sustainability through Delineated Management Zone based Precision Agriculture, *Indian Journal of Agricultural Sciences*, 2012.(Under review)

2. Conferences

International

- (i) **Babankumar S. Bansod**, DHB Shashank, Ritula Thakur, **OP Pandey**, “Soil Apparent Electrical Conductivity Measurement Using Virtual Instrumentation”, 3rd International Conference on Computers and Electrical Engineering (ICCEE-2010), Chengdu, China. November 16-18, 2010.
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National

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- (ii) **Babankumar Bansod**, Shruti Trehan, **OP Pandey**, An application of hybrid clustering and neural based prediction modelling for delineation of management zones, Proceedings of National Conference on Agrionics and Food Processing Instrumentation, NCAFPI-2010, Chandigarh, 26-28 September, 2010.
- (iii) **Babankumar S Bansod**, OP Pandey, Intelligent farming- an overview across the globe, Proceedings of National Conference on Agrionics and Food Processing Instrumentation, NCAFPI-2010, Chandigarh, 26-28 September, 2010.

- (iv) **Babankumar Bansod**, Rishemjit Kaur, Ritesh Kumar, **OP Pandey**, An application of fuzzy C-means based clustering technique in smart farming, Proceedings of National Conference on Agrionics and Food Processing Instrumentation, NCAFPI-2010, Chandigarh, 26-28 September, 2010.
- (v) **Babankumar**, Ashish, Sudeshna, **OP Pandey**, Analysis of effect of apparent electrical conductivity on crop productivity through correlation analysis, Proceedings of National Conference on Agrionics and Food Processing Instrumentation, NCAFPI-2010, Chandigarh, 26-28 September, 2010.

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Preface

The emerging agricultural scenario advocates for balancing of multiple research objectives including productivity, crop quality, safety, livelihood security, protection of environment and biological diversity at affordable cost. Precision farming (PF) is one such viable technological tool which can ensure sustainable development and meet above expectations. PF is an outgrowth of technological developments. PF is the most promising sustainable agriculture (SA) approach known to date and has been hailed as one of the most influential approaches to production agriculture. It epitomizes a better balance between reliance on traditional knowledge and information and management-intensive technologies thus, safeguarding fragile environmental infrastructure. This system can be efficiently explored on the basis of emerging technological tools and sources of information such as GPS, GIS, YMs, RS, soil, plant and pest sensors, and variable-rate technologies (VRTs) for application of optimally customized inputs.

Conventionally field is managed uniformly as a whole, without reference to the agronomic variability of fertility or crop growth and development, under the assumption that the field is homogeneous. Whereas, in modern agricultural management practices (AMPs), fields are managed with respect to site-specific variability wherein these fields are delimited into smaller zones called as sub-fields and are managed separately in order to match farm specific agronomic characteristics. In such approach, variations in edaphic and anthropogenic factors including organic matter content, soil nutrient and moisture status, landscape topography of the field (slope and elevation), climatic conditions, cropping history, plant protection needs, as well as past soil management practices etc., is accounted for while developing a management strategy, in order to increase the productivity of land, improve the quality of crop, profitability of the production, reduce the risk of over or under management, conserve the natural resources, and protect the environment. There are a number of spatio-temporal variability mapping technologies including soil mapping, crop mapping and yield mapping. In case of yield monitors, they are fitted on the combine harvester but, these are not developed for all crop varieties and can't indicate what factors have resulted in bringing variability of yield productivity on a field. Similarly other mapping tools are still evolving and will take time to become fully matured technology for field usage. In contrast soil variability mapping tools are most widely used and are documented for their practical use on fields. Soil EC_a mapping is one such most popular technique which is widely accepted for

mapping and characterizing spatial variability of soils due to its several advantages such as: ease of operation, rapid measurement, ruggedness, reliability of data, cost effective operation.

Several studies have indicated that bulk soil EC measurements can serve as a substitute for soil physical properties including OM, clay content, CEC, and can be used to measure nutrient concentrations in the field. It has also been seen that EC maps are proving useful in improving economic returns to PF. On the software tools side, performance of various spatial interpolation techniques for mapping soil properties has been evaluated by many researchers to improve site-specific crop input efficiency.

As it has been now established enough that uniform rate application is inefficient, recent research in PF has focused on use of MZs as a method for variable application of inputs. MZs based farming is efficient and cost effective to yield higher quality and quantity returns in agri-production system. In MZs, homogeneous combinations of potential productivity-limiting factors which have minimal heterogeneity in a particular region are identified. This process mainly answers three questions i.e. source of information to be used for delineation of zones, procedure to be followed for delineating zones and numbers of zones that should be optimal on a given field. Often on some soils EC_a has been reported to match crop yield patterns in such zones. Similarly, EC_a in conjunction with soil and / or landscape attributes has been used to explain variability of fertility attributes as well as productivity zones and establish their patterns at different scales in addition to identify soil sampling locations.

Based on inferences drawn out of literature search, a strong need was felt to undertake PF studies on Indian fields particularly the variability of electrical conductivity and spatial distribution of soil physico-chemical properties in relation with crop productivity. As Indian land holdings are small scale, there is pressing need to establish feasibility of PFTTs on Indian fields in the local conditions where tropical weather is different and moreover a large difference in farming cultural practices exists.

Presented work deals with the studies relating to spatial variability of bulk electrical conductivity and soil physico-chemical properties and its influence on crop productivity through use of modern PF techniques and technologies. The entire work is presented in **five chapters**.

In the **first chapter**, general introduction to overall concept of PF encompassing all the concerned elements is discussed. The entire chapter is organized in different separate sections

and different titles to illustrate the present state of art in the areas of spatial variability mapping and PFTTs. Starting from origin of the first work reported in PF to latest status concerning adoption, initiatives, future directions etc. is highlighted under this chapter. Definition of PF and its different components is added in the beginning of chapter, followed by objectives, system components, mapping technologies, data analysis techniques in vogue, engineering innovations including different sensors, remote sensing technologies for soil, brief about GPS and GIS, introduction to variable-rate-technology and micro-sensors is covered. Next major section gives details of global review of PF wherein concerned issues such as worldwide adoption, developed and developing nation's perspective and PF deliberations from Indian perspective is covered. Dedicated section of Indian perspective covers present farming scenario, technological advancement and initiatives in India, and future trends and adoption strategy for India.

Chapter 2 gives a detailed account of the literature survey in context of soil spatial variability mapping technologies and geostatistical modelling techniques for studying spatial distribution of soil physico-chemical properties. The various data resources as soil information (ECa, pH, CEC, OM, Clay%, Sand%, NPK), software procedures / algorithms (FCM, HCA, SIMCA, PLS-DA), data processing approaches (PCA, PLS and MLR) and methods used by number of researchers across the globe to quantify spatial distribution of soil fertility attributes have been presented in this chapter. After reviewing all segment of literature, the need to select present work was established. The last section of this chapter presents the inferences drawn out of literature search and objectives of the work of the thesis.

Chapter 3 describes the experimental procedure and modelling approach followed in the present work. On the basis of literature survey, design of experiment was established using on-the-go bulk soil conductivity sensor; same is reported in the beginning with experimental plot description and site-specific agronomic conditions including geographic location and weather report. The sampling strategy (ESAP and CENTROID) used has been explained. The spatial variations measured using sensors followed by geo-spatial modelling of soil physico-chemical properties approach is summarized with a brief of every individual technique presented separately. Classification algorithms, FCM and PCA, for data handling, are presented with sufficient details. The brief details of statistical and geostatistical methods including univariate and multivariate spatial modelling are provided along with regression modelling details in the end.

Chapter 4 deals with results and discussion on spatial variability studies of physico-chemical properties and bulk soil conductivity in relation to crop productivity. This chapter is divided

in two major sections considering number of experimental sites (Punjab Agriculture University, PAU, Ludhiana and CSIR-CSIO, Sector-30C, Chandigarh).

Furthermore, entire analysis is presented under separate titles (exploratory analysis, geostatistical analysis (univariate and multivariate), correlation matrix between soil properties, delineation of MZs using PCA and FCM, validation of optimal zones (FPI & NCE)).

In **exploratory analysis section** number of statistical fitness parameters (Mean, Max, Min, Std.deviation, variance, skewness, kurtosis, Median) were analysed for soil properties. It explained the distribution of soil properties, convenience of delineation of zones through variance analysis, assessment about normalized distribution of data through kurtosis, skewness, mean and standard deviation, outliers if any was also analysed which otherwise could confuse model results.

In the **geostatistical section** the results obtained from krigging and or cokrigging interpolation technique for studying spatial distribution are presented and discussed. The role of different model parameters (nugget, sill, degree of spatial dependence, lag size) are also discussed in this section while optimizing the appropriate model based on least RMSE criteria. The **correlation matrix section** explains the correlation between different soil physico-chemical properties.

In **delineation of MZs and PCA analysis section**, results of PCA and FCM techniques are presented and discussed. This section explains the data processing procedures used in order to obtain best productivity potential zones. Relation between PC's and associated soil properties is shown besides representing delineated zones. In **validation of optimal zones section**, plot showing least value of FPI and NCE indices is represented indicating optimal number of MZs.

In **statistical analysis including regression modelling and PCA of soil properties section**, PCA (score plots and loading plots) for different combination of soil attributes is reported. It analyses soil EC_a , variable n-rate applied and associated crop yield behaviour. In this section, the results and discussions are provided (Inference1-Inference5) for different cases.

In **Chapter 5** the present work is summarized and concluded with future scope in the required direction. The present study showed that there exist different amount of spatial variations irrespective of landscape area. EC_a mapping of soil quantifies physico-chemical

properties and has shown spatial dependence. Utility of geospatial modelling techniques have been demonstrated to predict unknown spatial surfaces.

Future scope of the work

To avoid over application of inputs in low-producing areas and sub-optimal application in areas with high-production potential, need for definition of more refined productivity zones that can be practically managed is felt necessary. Although presented research reported FCM based methods, there are other possibilities that can lead to define more refined, economical and profitable agronomic MUs. Furthermore, there is a need and scope to support development of automated hardware (rapid field-scale mapping of properties) and software (new algorithms) tools that can make cost effective deployment of these modern technologies on field usable basis a reality.

Thus, **this section highlights** concerns of the investigator in terms of bringing more refinement in the present approach. As such, this section details need of more Artificial Intelligence (AI) techniques to make the farming smarter, profitable and sustainable.

Abbreviations used

Precision farming:	PF
Green Revolution:	GR
Sustainable Agriculture:	SA
Food and Agriculture Organisation:	FAO
Global Positioning System:	GPS
Geographic Information Systems:	GIS
Yield Monitoring devices:	YM
Variable-Rate Technologies:	VRTs
Agricultural Management Practices:	AMPs
Precision Farming Technologies:	PFTs
Information Technologies:	ITs
Delineating Management Zones:	DMZs
directed/targeted/scientific soil sampling:	DSS/TSS/SSS
Remote Sensing:	RS
global navigation satellite system:	GNSS
Precision farming techniques and technologie:	PFTT
Highest yield varietie:	HYV
Carbon di-oxide:	CO ₂
Organic matter:	OM
Gross domestic product:	GDP
centre of excellence for precision farming:	CEPF
Precision farming development centre:	PFDC
Punjab Agricultural University:	PAU
Tractor Mounted Technologies:	TMT
Centre of excellence for farm machinery	CEFM
Advanced Sustainable Agriculture Technology Clusters:	ASATC
Sustainable Agriculture Technology Incubators:	SATI
information and communication technology:	ICT
Site-specific management	SSM
Management Zone	MZ
Principal Component Analysis:	PCA
principal component:	PC
Fuzzy c-means:	FCM
genetic algorithm-based FCM:	GAFCM
apparent electrical conductivity:	EC _a
cation exchange capacity:	CEC
Site specific management unit:	SSMU
Precision Agriculture:	PA
site-specific crop management:	SSCM
site-specific management zone:	SSMZ

ordinary kriging:	OK
electrical conductivity:	EC
cokriging:	CK
kriging with external drift:	KED
Ground penetrating radar:	GPR
electromagnetic induction:	EMI
correlation coefficient:	CC
regression kriging:	RK
management unit:	MU
grid soil sampling:	GSS
fuzzy performance index:	FPI
normalized classification entropy:	NCE
nugget:	C0
partial sill:	C1
sill:	C0+C1
degree of spatial dependence:	C0/C0+C1
Krigging:	K
universal krigging:	UK
agronomic management unit:	AMU
response surface sample design:	RSSD
soft independent modelling of class analogy:	SIMCA
partial least square discriminant analysis:	PLSDA
partial least square:	PLS
multiple linear regression:	MLR
hierarchical classification:	HCA
univariate:	UVR
multi-variate regression:	MVR
coefficient of variance:	CV
In-Situ Pogo Sensor:	I.P.S.
Hanna Sensor:	H.S
Lab Analysed:	L.A
1 feet depth:	1f
2 feet depth:	2f
Temperature:	Temp
Moisture:	Moist
Real Dielectric:	RD
Potassium:	K
Phosphorus:	P

Chapter 1

INTRODUCTION

Overview

In this chapter, various issues relevant to the work undertaken have been discussed in addition to presenting origin and evolution of Precision farming (PF). Besides highlighting current food production system scenario and status of ecological infrastructure, chapter begins with the definition of PF and its history, followed by different aspects concerning PF, which include: adoption of PF and its current status at global and National level, economic and environmental relevance of PF to farmers, brief overview of PF technologies underlying present studies.

Finally, scope of work has been deliberated considering local cultural practices, soil and crop conditions in fields especially from Indian farming perspective.

1.1 Introduction

Global agriculture has made tremendous progress in expanding the world's supply of food over the past thirty years. Even though the world population has doubled over this time period, food production has risen even faster with per capita food supplies increasing from less than 2000 calories per day in 1962 to more than 2500 calories in 1995 (world resources institute, 1998). This has been credited to better seeds, expanded irrigation, and higher fertilizer and pesticides use, commonly referred to as the Green Revolution (GR).

In an effort to feed the increasing population, detrimental impacts are growing due to loss of natural habitat, the use and misuse of pesticides and fertilizers, and soil water resource degradation. Poor agricultural practices had contributed 38% degradation out of the 1.5 billion ha of crop land worldwide and since 1990 the losses have continued at a rate of 5-6 million ha annually. Although total yield continue to rise on a global basis, there is a disturbing decline in yield growth with some major crops such as wheat and maize reaching a "yield plateau" (World Resources Institute, 1998). The world population has crossed seven billion mark and is expected to reach nine billion by 2050. The prospect of feeding a projected additional 2 billion people over the next 30-40 years poses more challenges than encountered in the past 30-40 years. One billion people in the world (one-third of which are in India) go to bed hungry. The reason behind the rising number of hungry people is pattern of access to and distribution of food. Add to this, huge chunks of arable land going out of production for industrialization, infrastructure development and real estate development. In India, two million hectare land has gone out of production in the past ten years. Concerns over burgeoning population's impact on the environment have led to apprehensions that the world may not be able to feed its inhabitants in future. The UN believes that part of the reason for food shortages is a lack of investment in agriculture. For those countries in protracted crises, the Food and Agriculture Organisation (FAO) report says that only 3-4 percent of funds for development and humanitarian assistance go towards agriculture. In the longer term, the obstacles to meet expected food demand become more formidable, though not insurmountable.

Feeding the ever-increasing world population will require a Sustainable Agriculture (SA) system that can keep pace with population growth. SA needs to optimize crop productivity, use of natural resources and profitability while minimizing degradation of soil and natural resources. It

is viewed as the most viable means of meeting the food demands of ever growing world's population in today's context [1]. The emerging agricultural scenarios advocate balancing of multiple research objectives including productivity, crop quality and safety, livelihood security, protection of environment and biological diversity at affordable cost. PF is one such viable technology which can ensure sustainable development and meet above expectations. PF is an outgrowth of technological developments. PF is the most promising SA approach known to date and has been hailed as one of the most influential approaches to production agriculture, as it epitomizes a better balance between reliance on traditional knowledge, information and management-intensive technologies thus, safeguarding fragile environmental infrastructure [2].

1.2 Precision farming

1.2.1 Definition

Precision Farming is a systematic approach towards farming production system that promotes variable management practices within a field, according to site conditions. At its basic level, it involves data collection, data processing, data analysis, information development and implementation of customized farm management practices. This system can be based on new tools and sources of information provided by modern engineering emerging technologies such as Global Positioning System (GPS), Geographic Information Systems (GIS), Yield Monitoring devices (YM), soil, plant and pest sensors, Remote Sensing, and Variable-Rate Technologies (VRTs) for application of optimally customized inputs (In developing countries these technologies can be replaced by other approaches).

1.2.2 Objectives of precision farming

The objectives of PF are to increase crop production, profitability, sustainability and reduce environmental impacts of agricultural chemicals by optimally adjusting agricultural inputs (fertilizer, seeds and pesticides) such that available agronomic resources match supply and demand on a site-specific manner [3]. This new thinking was mainly derived from the emergence and convergence of several technologies including GPS, GIS, miniaturized computer components, automatic control, in-field and remote based sensing, mobile computing, advanced information processing, and telecommunications [4]. In traditional agricultural practices, field was managed uniformly as a whole, without reference to the agronomic variability of fertility or

crop growth and development, under the assumption that the field is homogeneous. This conventional farming approach ignored within field site specific variability of real world [5]. Whereas, in modern Agricultural Management Practices (AMPs), fields are managed with respect to site-specific variability wherein these fields are delimited into smaller zones called as sub-fields and are managed separately in order to match farm specific agronomic characteristics in terms of exact crop demand. In such approach, variations in edaphic and anthropogenic factors including: organic matter content, soil nutrient and moisture status, landscape topography of the field (slope and elevation), climatic conditions, cropping history, plant protection needs, as well as past soil management practices etc., is accounted for while developing a management strategy. This enables to increase the productivity of land, improve the quality of crop, profitability of the production, reduce the risk of over or under management, conserve the natural resources, and protect the environment. Thus, how well PF can be practiced depends upon the availability of spatio-temporal variability information and anthropogenic knowledge pertaining to the production site [6]. Site-specific Agricultural Management using Precision Farming Technologies (PFTs) can help farmers to improve fertilizer efficiency that results in several benefits including environmental safety, protection and conservation. Furthermore, different Information Technologies (ITs), as well as farm and farmer characteristics, could affect fertilizer decisions differently. Knowing these differences could assist targeting of specific groups of farmers for the adoption of various site-specific ITs to improve fertilizer efficiency and reduce negative environmental impacts. Technological advancements such as yield monitoring (YM), Delineating Management Zones (DMZs), and practicing directed/targeted/scientific soil sampling (DSS/TSS/SSS), and on-the-go field-scale soil property measurement has increased farmers' perceptions of the importance of PF in improving fertilizer and farming efficiency as well as productivity and sustainability. Thus, uses of PFTs make it possible for farmers to map and record yield throughout their fields and adjust chemical application rates accordingly in real time to achieve intended production goals, while simultaneously minimizing the amount of inputs and pests applied.

1.2.3 System components of precision farming

Various components of a typical modern PF system concept for developed countries are shown in Fig.1.1. These include: GPS, GIS, YM, soil, plant and pest sensors, Remote sensing (RS), and VRTs for application of optimally customized inputs.

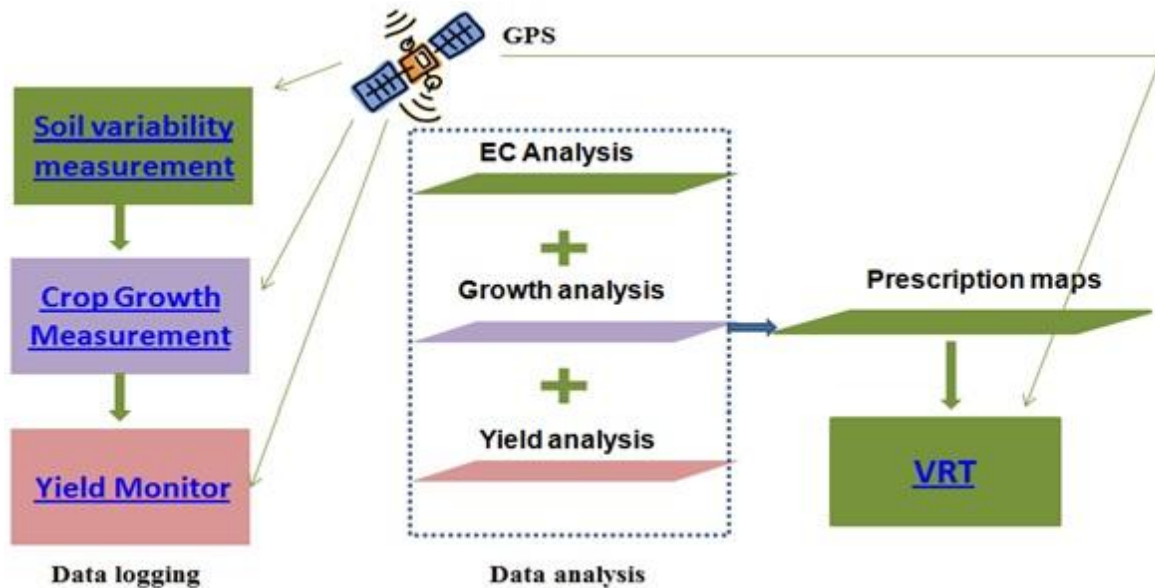


Fig.1.1 Components of precision farming

1.2.3.1 Variability mapping technologies

It refers to collection of data using various techniques and technologies such as RS and ground based sensors including soil, crop and YM sensors. Data collection mainly includes measurement of different variability explained below:

- i) *Soil variability mapping (using soil sensor)*: It includes measurement of soil fertility attributes and normally includes soil physical properties (texture, bulk density, mechanical strength, moisture content and electrical conductivity), soil chemical properties (pH, macro-micro nutrients, organic matter and salinity), soil-plant available water holding capacity, hydraulic conductivity and soil depth. Depending upon technique used, geo-referenced measurement of these edaphic attributes, provide assessment of

agronomic variations on a site-specific basis through high resolution spatial variability maps.

- ii) *Crop growth mapping*: It includes mapping of crop attributes such as crop density, crop height, crop nutrient stress for nitrogen, potassium etc, crop water stress, crop biophysical properties and crop grain quality. It includes assessment of temporal variability's affecting crop growth.
- iii) *Yield variability mapping*: It includes historical and present yield measurements and is an indicator of yield produced in tons/hectare as a result of farming practices. YM combined with moisture information and integrated in combine harvesters for on-line yield recording are the latest developments and is an important data layer while analysing causes of yield variations. It acts like a feedback for earlier applied management actions on a farm production system so that next actions can be fine tuned in turn.

1.2.3.2 Data analysis

Data analysis refers to application of numerous computational techniques on field collected data including statistical and geo-statistical approaches that include: regression analysis, pattern recognition, feature extraction, clustering, kriging and co-kriging, regression kriging, kriging with external drift etc. to obtain correlation of soil, crop and yield attributes, delineation of zones, visualization of maps etc. Such software based analysis for quantifying micro and macro spatio-temporal structure variabilities on a site-specific basis for attaining PF goals is of significant interest for currently ongoing research across the globe.

1.2.3.3 Engineering innovations in precision farming

Protocols for PF implementation can be encapsulated in four general steps: (1) Gathering information about spatial and temporal variability, (2) Processing and analyzing information to assess the significance of variability and (3) Developing prescription maps in terms of farming operation's footprints and (4) Implementing variations in the management of inputs through Variable Input Rate (VIR) applicators. The wider concept for the implementation of PF scheme is described in Fig.1.2.

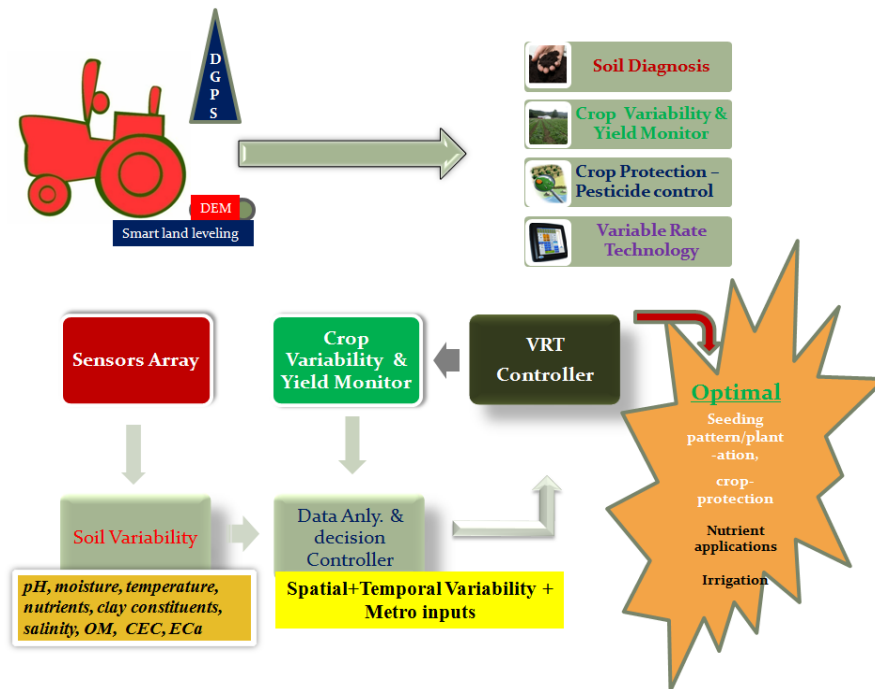


Fig.1.2: Implementation of PF scheme

While agronomists are playing the leading role in PF development, engineers have worked diligently to provide technologies needed to implement PF practices [7]. The engineering innovations in PF involve technological advancements in ground based *soil and crop sensors*, *RS technologies*, *GPS*, *VRT control*, and *growth in software technologies*. Recently, the use of *Microsensors* for in-field/line and/or continuous measurement of environmental parameter monitoring is emerging. It uses blend of chemometry and hybrid composites of bio-nano technologies, and modified electrodes based on conducting polymers, doping and other fabrication techniques etc. These new breed sensors are providing enhancements and improvement over traditional semiconductor ones in terms of robustness, sensitivity, compactness, fast response, stability, in addition to selectivity for low volumes.

1.2.3.4 Sensors

Pierce and Nowak [8], (1999) have emphasized that the development of sensors is expected to increase the effectiveness of PF in developing countries. Field-scale usable, robust, low-cost, and preferably rapid sensing systems, capable of direct sensing of parameter of interest in real-time

mode, are needed for implementing various PFTs. The sensors used for gathering the information of spatial and temporal variability on field-scale basis can be broadly classified as:

(i) *Soil sensors*

In the post harvesting stage, soil sensors are used to gather information about spatial variability in order to determine the seeding and fertilizer rates as well as crop varieties to be planted. However, although limited attempts have been made in the past to record nitrogen levels on-the-go but so far capturing field-scale information for all the nutrient-levels has not been possible / successful. Moreover, they are not commercially available so far. To a certain extent, lab-scale sensors have been demonstrated to measure nutrient levels that use traditional sample extracting method.

(ii) *Crop growth monitoring sensors*

These are used to gather temporal variability information in order to determine the amount of N-rate and crop protection applications. A real-time crop sensor for site specific input application is the new innovation in the field of PF [9]. Crop yield maps are required for the evaluation of economic efficiency of spatial production systems and is an important part of the site-specific decision making process which uses map-based approach [10].

(iii) *Yield sensors*

Amongst other research areas in PF, developing yield mapping technology is important because yield maps display crop response to the management techniques applied and help identify the causes and effects of yield variability. Through yield maps, farmers can identify areas within fields where crop yields may be improved or where adjustments in inputs are needed to optimize farm profitability and environmental quality. Since crop yield information mapping forms the basis of recommendations of managed inputs and is a determinant of farm profitability, it is important for the success of PF to ensure yield feedback from field, making it a closed loop PF farm production control system [11].

1.2.3.5 Remote sensing technologies

The collection of variability information on fields from a distance, with precision, without coming into contact with the same is termed as RS. The conventional farming methods of data

collection through field observation are difficult, time-consuming and cannot be carried out simultaneously besides, monitoring at frequent intervals is not possible [12]. However, large amount of data can be analyzed faster by applying GIS and RS techniques [13]. Satellite based RS techniques make it possible to collect information concerning large agricultural areas at frequent intervals. In the past decade, the capability of satellite based RS to monitor agricultural and hydrological conditions of a land surface has improved greatly. Hence, satellite based RS has the potential to play a determinant role as spatial information source in PF [14-15].

1.2.3.6 Global positioning systems (GPS)

It is a space-based global navigation satellite system (GNSS) that provides reliable location and time information in all weather and at all times. GPS receivers on the ground can collect data and convert the radio signals from satellites into position data [16]. The GPS system provides precise measurement for precise application and provides the basis for identifying locations where customized fertilizer application rates are applied, thereby reducing leaching and runoff into ground and surface water due to over application of chemicals and fertilizers. The GPS enabled systems can operate at night with lower manpower costs, and increased machine utilization [17]. Irrigation systems can be timed precisely and the farmer needs to use only the amount of water necessary for maximum benefits. This is very beneficial especially in water-starved areas. An additional benefit of using the GPS for PF is the ability to reduce soil compaction by limiting traffic to same traffic lanes. Soil damage occurs greatest on the first pass of the tires over the soil. Compacted soil reduces crop productivity, root development, water absorption, and hence causes nutrient deficiencies [18]. This results in delay in plant growth and hence significant losses in yield. The machinery, guided by GPS, moves through same traffic lanes and this reduces compaction to other parts of the field, however, before making any choice one needs to be cautious about the big differences in the mass of machinery between developed and developing countries.

1.2.3.7 Geographic information system (GIS)

The increase in spatial resolution of management areas in PF requires sophisticated software for manipulating data. Typical GIS software operations used in PF is mapping, layer overlay and recombination, and pattern visualization [19]. By using GIS software, GPS equipment and RS

instruments, the collected data may be used to create maps to determine a better agricultural management for fields. The collected data is combined with agronomic facts to produce spatially variable input recommendations using GIS.

1.2.3.8 Variable rate technologies (VRTs)

VRT allows the farmer to apply quantity of crop inputs needed at a precise location in field based on the individual characteristics of that location. VRT is accomplished by developing prescription maps, transferring it to the controller, which changes the application rate. There are two ways by which VRT is applied: input and output. The goal of input perspective is to reduce cost of inputs (fertilizer, pesticides and seeds) by applying them where they are needed and reducing their application where not needed. The output one focuses on the yield side i.e. to produce best yield possible per unit of applied input. In principle, variable rate application of field inputs can reduce the cost of production and also increase quantity and quality of yields, both of which increase profitability and sustainability [20]. VRT helps reduce overplanting or over application and apply inputs in the most efficient manner.

1.2.3.9 Micro-sensors

Direct on-the-go measurement of soil chemical characteristics, such as pH or nutrient content has been the objective of considerable research. Electrochemical methods have been successfully used to directly evaluate soil fertility [8]. Present methods for measuring ions in soil are based on sample treatment by means of extraction processes and analytical techniques. These methods are time consuming and cannot be used in-fields. Therefore, there is an increased interest in the use of sensors to carry out analysis on *in situ* / on-line basis because the results are obtained in real time. Consequently, there is an increasing interest in miniaturizing both highly specialized chemical sensors as well as generalized chemical sensors. The use of micro-sensors for in-field monitoring of soil parameters is gaining interest due to their advantages over conventional sensors. Among them, micro-sensors based on semiconductor technology offer additional advantages such as small size, robustness, low output impedance and rapid response. Besides, the technology used allows integration of circuitry and multiple sensors in the same substrate and accordingly they can be implemented in compact probes for particular applications e.g. in-situ monitoring and/or on-line measurements [21]. Development work on micro-machined

electrochemical ionic sensors (e.g., nitrate) is progressing quickly and should be translated into deployed sensor networks in near future [22]. This will be an important development but the technology is not commercialized at this stage.

1.3 Global review of precision farming

1.3.1 World-wide adoption of precision farming

Though seeds of PF were sown earlier in twentieth century [23], the actual work in this direction began some thirty years ago [24-25] in developed countries. The research in PF started in the US, Canada, Australia, and Western Europe in mid-to-late 1980s. Although a considerable research effort has been expended, still only a small portion of farmers have adopted PFTs so far. Implementation of PA has mainly been through utilization of existing field machinery by adding controllers and GPS to enable spatially-variable applications. Till date, the leading application of PA is still the site-specific application of fertilizers.

The adoption of PF technologies is governed mainly by two factors. Firstly, since these technologies improve efficiency of input use in mechanized agriculture, it is more likely that they will be adopted first in those places where input use is already relatively efficient. Secondly, they use expensive machinery in place of management labour; hence they will be most attractive where capital is abundant relative to human labour. The adoption of these technologies has been uneven across the globe. However, although a lot of research work has been carried out in developed countries, the applicability of PF in developing countries has always been an issue of debate. One common reason cited for low adoption of this technology is that its costs are comparatively higher than its benefits. Hence, it will be advantageous to have an overview of PF while comparing developed and developing nations.

1.3.2 An overview of PF from developed and developing nations' perspective

Though PF has been a proven technology, still, it is mostly restricted to developed (American and European, Japanese) countries. While USA has been involved in PF for more than 20 years, it is still in its infancy in developing countries such as India and China. One of the main reasons for poor performance of the agricultural sector in developing nations has been prolonged adverse terms of trade policies for agriculturists in addition to the mismanagement of natural resources, leading to ever increasing crisis. A wide gap exists between the potential and actual yield levels

in such countries, hence necessitating promotion of PF to achieve the intended benefits. The adverse effects of agriculture on environment have been largely ignored so far in most developing countries, because of inability to effectively monitor such effects. This monitoring will be possible now with the advent of Precision farming techniques and technologies (PFTTs) and the computerization of input and output flows. Farmers in the developing nations mostly rely on subsistence and cash cropping, while PF seems less relevant in such cases. Still a few cases of PF have been reported, for example in Brazil, Chile, China, Costa Rica, Malaysia, India and Philippines. The major hindrance in progress of PF in developing countries is the acquisition and interpretation of spatial information. On the other hand, lower cost of labour in developing countries may make it easier for them to obtain spatial information at a lower cost than in developed countries. Another hindrance in the implementation of PF in developing countries is the belief that PF technologies work only for large farmers. Such a perception about PF is a pure myth because even descriptions about the concept of PF in various literatures does not mention about its scale or size requirement. There is a wide scope for adoption of PF in many developing countries including India by utilizing resources efficiently to achieve fruitful success. It has wide potential for raising quality and quantity of yields and economic returns on fields with significant variability, and for minimizing environmental degradation, and it is hoped that with proper guidance from public and private sectors as well as agricultural associations, PFTs will be adopted in a limited scale for demonstrations. *The main point to be noted is that not all elements of PF are needed for each and every farm.* Also, gathering spatial and temporal data does not require expensive high tech equipments every time and looking at recent technological advancements the same seems within reach with an appropriate implementation model in place. Another challenge is providing freely available spatial information to the farmers. This will become easier if the farmers create their own local spatial data at appropriate scales. For example, in Colombia, farmers record yields and inputs for individual blocks of sugar cane and modify fertilizer recommendations accordingly. All records are geo-referenced and spatial trends are analyzed to respond to queries from individual growers [26]. This is in contrast to the non-site specific recommendations still used by sugar cane industries in Australia [27]. Farmers in developing countries possess vast knowledge about environmental resources on their farms. However, it is largely based on observable features rather than generalized knowledge. This leads to uncertainty that obstructs sound decision-making. Hence, there is a scope for successful

application of principles of spatial information to manage within field variation thereby increasing the efficacy and efficiency of local knowledge and reducing uncertainty.

1.4 Precision farming deliberations from Indian perspective

1.4.1 Present Indian farming scenario

Post GR, India produced 72 MT in 1999, ranking it 2nd in wheat production and the trend remained upward every subsequent years. The grains production increased four times and yields as much as three times making India feed its ever increasing population growth and satisfy increased per capita calorie requirement for last several decades. This radical change was seen due to indiscriminate ‘use’ and ‘misuse’ of fertilizers, pests, irrigation, seeding in the fields without identifying agronomic characteristics of the field, posing threat to environment and sustainability of natural infrastructure. The farmers also had to pay a heavy price for increased grain production as this indiscriminate misuse of fertilizers turned the lands barren. Further, in recent years GR also started showing fatigue, it was seen that India’s highest yield varieties (HYV’s) are performing even below average yield of developed countries. The status of Indian environment till 2009 shows that about 182 million ha. of the country’s total geographical area (328.7 million ha.) is affected by land degradation. Out of this, 141.33 million ha. are due to water erosion, 11.50 million ha. due to wind erosion and 12.63 and 13.24 million ha. are due to water logging and chemical deterioration (salinisation and loss of nutrients) respectively. On the other end, India shares 17 per cent of world’s population, 1 per cent of gross world product, 4 per cent of world carbon emission, 3.6 per cent of CO₂ emission intensity and 2 per cent of world forest area. One of the major reasons for this status of environment is the population growth of 1.344 percent in 1970 – 2011. Expected betterment in the ecological / environmental scenario of India seems formidable in near future though not insurmountable.

Furthermore, Indian farms are experiencing stiff challenge because of increasing market competitiveness ever since world trade practices turned globalized. Although, free trade policy created growth avenues, there exists an inbuilt threat at the same time to future of Indian farming community [28]. Pressure on Indian farms is also rising due to unprecedented population growth rate in recent years resulting in huge grain demand. On the other hand, land resources are

shrinking due to rapid urbanization, industrialization, gigantic infrastructure development and establishment of special economic zones etc. To aggravate further, yield per hectare is decreasing due to over-exploitation and lands are turning barren gradually due to excess fertilization. Fundamentally, deterioration in quality of agri-production system and aquifers is mainly attributed to uncontrolled feed of crop irrigation, fertilizers, and burning of residuals (which destroys soil OM content). Besides labor shortage and increased diesel cost further aggravate agri-production concerns. In consequence, agriculture production cost has increased dramatically lately and putting farmers on back foot, farming being a non-profitable business. Despite of government offering various relief packages, farmers are increasingly becoming debt ridden and succumbing to market pressures leading to country's farming scenario exasperated to the level that many of them are committing suicide. The country has seen over a quarter of a million farmers' suicides between 1995 and 2010. As high as 2, 56,913 farmers approximately, have committed suicides in total since 1995 till 2010 according to National Crime Records Bureau (NCRB) of India.

Especially in the agrarian country like India where over 70% population earns livelihood through agriculture directly or indirectly, enhancing efficiency of the agriculture production system becomes inevitable. Country's GDP rate is drastically influenced by the fertilizer usage performance of agricultural sector, being the major indicator, followed by export and import of allied activities. A large percentage of workforce gets employment through agriculture production system or allied industries. India is the major export house for many agri commodities and stands dominating player in worlds' agri related trading for finished or raw products. However, despite of bumper production in many crop varieties, India, like rest of the world, is facing major challenge of feeding its ever-increasing population which will shortly surpass China. On the other hand, India is witnessing growing infrastructure related activities in the recent year which is reducing its arable land share. As a result, available resources (land, water) have been overburdened resulting in polluting water bodies and degradation of land due to excess fertilization. At many places water table depth has gone down to as low as 300-400 ft, for instance in Punjab and, has developed cancer belts in Malwas region of Punjab due to over dosage of fertilizers.

Again, some states, like Punjab, Haryana, have experienced the large scale mechanization as well as high doses of fertilizer and pesticide. As an example the state of Punjab has 1.5 percent of total geographical area of India, but uses 1.38 million tonnes (nearly 10% of all India fertilizer consumption) of NPK fertilizer along with 60% of weedicides used in India [29]. Over exploitation of land as well as excessive use of agricultural input are typical problems of these areas [30]. Use of fertilizers and pesticides has reached a level so much so, that the train that runs from Bathinda to Bikaner every night is called the cancer express as it ferries large numbers of cancer patients. Residents believe that use of excessive pesticides for cotton farming caused the contamination of water infecting it with arsenic and uranium. Increased population growth to an unprecedented level is the root cause of present as well as projected difficulties.

The dependency on imports has increased manifolds in recent years so much so that the commodities which were exported few years back are now being imported. Further, few commodities that Indian farmers are producing in excess and looking forward to export, are facing stringent quality checks and cost competition in International market leading to export failures. Farming in India is generally driven by traditional practices, followed and transferred from one generation to next, under closely managed field observations and associated decision making while responding to specific situations based on experience on a site-specific basis. However, with the advent of modern farming technologies, this crude site-specific Indian farming practice should definitely undergo refinements considering uncertain weather conditions, complex soil-crop –water relationship, ever changing climatic condition due to global warming and associated variety of crop disease attack risk, especially in the light of India's global IT leadership position. The situation is alarming and warrants an immediate attention for an early technological intervention brought through systematic synergy amongst technology generating organizations such as CSIR/IISCs/IITs and agricultural domain knowledge institutions such as ICAR etc.

The only way forward to Indian farming in order to meet global standards of agri-produce and increased nutrient demand back home is by means of SA practices. One such technology which can ensure sustainability i.e. maximized productivity, reduced input cost, and protection from environmental hazards, for the Indian agriculture production system is PF.

1.4.2 Technological advancements and initiatives in India

Scope of adoption of any technology in any country not only depends on necessity, but also on the scientific environment of that country. PF is a spin-off and has taken a birth from the convergence of emerging technologies primarily meant for other industries, it is a systematic approach integrated to benefit farm management on a site-specific manner. India has taken modest initiatives in this direction by establishing centre of excellence for precision farming (CEPF) at selected places viz. IARI, New Delhi, University of Agriculture Sciences, Bangalore, Gujarat Agriculture University, Navsari, Indian Institute of Technology, Kharagpur and Central Institute of Sub-tropical Horticulture (CISH), Lucknow. Under these umbrella CEPF centres, all other district/state level Precision Farming Development Centres (PFDC's) would work under specific project mode. Moreover, lately, India is witnessing world class technological advancements. Most recent launch of PSLV - C18 was a historic mission as it was the first Indo-French joint project (Megha-Tropiques) on tropical weather studies and the second in the world after the NASA-Japan Space Agency Mission in November 1997. With this launch, India became only the second country to launch such a mission — the first being a US-Japan combined mission in 1997. Megha-Tropiques will study the water cycle and energy exchanges in the tropics. It aims weather study and their contribution to the energy and moisture budget of the atmosphere in the tropical regions. The satellite will provide scientific data on the contributions of the water cycle to the tropical atmosphere with information on condensed water in clouds, precipitation and evaporation. This will enable climate research and assist scientists seeking to refine weather prediction models especially study of monsoons. ISRO, Space Application center, in collaboration with Central Potato Research Institute, Shimla, has also initiated a study to explore the role of RS for PF. Indo-US workshop on "Precision Agricultural Techniques and Technologies" was held recently in Punjab Agricultural University (PAU), Ludhiana, India highlighting the need of bringing technological advances of PF in India. Tata Consultancy Services (TCS) has started m-krishi, a mobile-based crop advisory service. The application provides personalized information and expert advice to rural farmers, uses various applications including sensors, camera phones, and GPS technologies. Central Scientific Instruments Organization (CSIR-CSIO), a national premier lab under CSIR, Chandigarh, is also engaged in design and development of Tractor Mounted Technologies (TMT) for PF. Under CSIR-DST

initiative, Centre of Excellence for Farm Machinery (CEFM) has been recognized at CSIR-CMERI, Durgapur, centre located in Ludhiana under specific project mode. All these milestones are going to help the adoption of PF in India directly or indirectly at a faster pace than seen before.

1.4.3 Future trends and adoption strategies

PF uses hi-tech devices such as GPS, GIS, YM, field computer, variable rate controller etc., and were cost prohibitive till recently, and their fusion all together creates site-specific crop management system in place. But, due to recent technological advancements, these costly technologies can be employed in a cost effective manner at field levels. Customization and adoption of such PFTs can be tailored to meet India specific edaphics and anthropogenics conditions, and cultural practices for proper digestion and absorption for the Indian farm sectors. In this direction, conception of Advanced Sustainable Agriculture Technology Clusters (ASATC) can be modelled and must be implemented with efficient networking of district and state level agencies and end users. These ASATC can serve as a Sustainable Agriculture Technology Incubators (SATI) implemented through co-operative structures to reap early-fruits of this futuristic technology. The SATI team may comprise of representatives from diverse science and technology background such as computer and electronics engineers, soil and crop scientist, IT expert, mechanical engineer and bio-nano technologist etc. Besides creating multi-disciplinary teams and district level farmers co-operatives, stringent legislative actions to refrain farmers from use of indiscriminate farm inputs creating physico-chemical ecological imbalance, would prove knockout punch to ensure Sustainable Agriculture. Finally, painstaking awareness campaign informing harmful effects of non-scientific farming compared to merits of PF approach will play a vital role in addition to field demonstration of concept on pilot scale basis. Such a multipronged strategy combined with field level manifestation of PFTTs implementation can make evergreen food revolution possible in INDIA. Integrating farmers' knowledge, precision agriculture tools, and crop simulation modelling to evaluate management options for poor-performing patches in cropping fields' can be an excellent option for country like India.

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Chapter 2

LITERATURE REVIEW

Overview

This chapter summarises the reported research in the areas of PF with special attention to spatial variability studies of soil properties in relation to bulk soil electrical conductivity and delineation of management zones for optimal site-specific crop input management. Based on the literature the study is planned to cover the variables which affect the PF. There are number of parameters which govern the crop growth. For undertaking PF principles on practical fields the study on these parameters is essential. Therefore, in this chapter the work done on PF is analysed and encompasses all the reported work details of the relevant system elements that are used across the globe while working with technology intensive PF systems and the procedures to be followed.

2.1 Information and communication technology (ICT) in agriculture

Exploitation of information and communication technology (ICT) in agriculture is becoming useful and its usage needs to be expanded with the requirements of the agricultural sector. Precision farming (PF) is one of the agricultural approaches involved on the adoption of technologies for better managing the variability within the field. With the help of this technology, there is a reduction in the human processing task, thus reducing the time and effort in accomplishing certain jobs.

The systematic study of small scale soil and crop variability was launched during 1970s with the development of computer-based regionalized variable statistics procedures, usually called geostatistics [1-2], coupled with reliable and real-time GPS as well as GIS. These important factors, combined with inexpensive information technology were the embryo for the so-called PF [3].

Ani [4] has defined PF as the application of various information and communication technologies (e.g. satellite, GPS, GIS, sensors, electronic systems, computer, aerial photograph equipment, etc.) in measuring and analyzing variations within agricultural fields ; and applying the knowledge gained in the management and control of soil, water, farm inputs, micro-climate, environment, machines and machine-related parameters for optimum production of crop. PF has been recognized by environmental sciences as an important part of the solution towards sustainable agriculture and a way of maintaining intensive crop production, essential for food security in a growing world population [5] under more restrictive environmental standards [6].

SSM promotes the identification and management of areas within the field, which represent subfield regions with homogeneous characteristics (MZs). However, determination of subfield areas is difficult because of the complex combination of factors which could affect crop yield. One possibility to capture yield variability is the use of soil physical properties to define the MZs as these are related to plant available water (PAW). Also it is seen that PAW would have better association with yield under rainfed agriculture and the link between the two may be quite weak under irrigated systems. In fact plant available water capacity (PAWC) may have a better relationship with yield under irrigated systems. According to **Fraisse et al.** [7], crop production potential is strongly related to plant available water so its variability can be approximately determined on the basis of soil's physical properties and topographic characteristics, when topography change is significantly observed in the field.

The correct definition of MZs constitutes an important task to properly manage spatial variability within fields. Although there are different techniques to delineate MZs [8-9], cluster analysis algorithms [10] is an optimum method to divide a field using different layers of information stored in a GIS. Taking into account that data used to define MZs are usually related, this information can be summarized by means of PCA. Finally, the values of the main PCs can be interpolated and mapped and these surfaces can be used to generate MZs by cluster analysis.

According to **Odeh et al.** [11], FCM, an unsupervised continuous classification algorithm is preferred for grouping properties in the soil continuum, because it produces a continuous grouping of objects by assigning partial class membership.

The FCM is adopted in several text mining methods. But the FCM suffers from disadvantages like more sensitivity and poor stability, an improved GAFCM text mining method has been put forward. GAFCM uses global search features of genetic algorithms to improve the FCM. **Xiang-dong et al.** [12] have proved that the improved text mining method has boosted in term of both accuracy and stability.

FCM clustering algorithm is the most used one among fuzzy algorithms, but it can have the problem of being trapped at local extrema in the process of optimizing the clustering criterion, and also the random initialization of the membership matrix that affects the clustering results [13-15]. GA can avoid local minima which work on randomized search and optimization techniques guided by the principles of evolution and natural genetics [16-18]. These are efficient, adaptive and robust search processes. **Cai Lin et al.** [19] proposed a GA for fuzzy clustering. Research has been done in some areas using GAFCM, such as image segmentation [20], power flow management [21] and fault diagnosis in satellite attitude determination system [19], but there is limited research on using the GA-based FCM algorithm for DMZ so far.

2.2 Analysis of spatial variability mapping, distribution of soil physico-chemical properties and its spatial dependence on EC_a

One of the most important problems in PF is measuring spatial variation of field rapidly and economically. EC_a provides an indirect measure of soil physical and chemical properties [22]. Previous analyses attempting to account for within-field yield variation were improved by including elevation with EC_a measurements [23]. Soil EC can serve as a substitute for soil physical properties such as OM [24], clay content [25], and CEC [26]. Soil EC_a has become

one of the most reliable and frequently used measurements to characterize field variability for application to PF due to its ease of measurement and reliability [27-28]. The potential of the spatial measurement of EC_a for predicting crop yield, top soil thickness, delineation of zones of different production, DSS for defining SSMU's, variable N-rate applications was reported earlier by many researchers [29-34]. Some of the reported work is discussed here.

Yuxin et al. [35] carried out a study to determine how well chlorophyll meter readings can be estimated using aerial hyper-spectral and simulated multi-spectral remote sensing images at different corn growth stages. It was concluded that the combination of chlorophyll meter readings with high spatial resolution hyperspectral or multi-spectral remote sensing images can overcome the limitations of using them individually, thus offering a practical solution to N deficiency detection and possibly in-season site-specific N management in large continuous corn fields or at later stages in corn-soybean rotation fields.

Mondal et al. [36] reviewed various research papers to find the status of main six components of PF, i.e., positioning system, remote sensing, variable rate technology, crop and soil sensing and its analysis, yield mapping and information transmission protocol. Additionally strategies for adoption of PA in Indian agriculture were discussed. The authors concluded that application of artificial neural networks, genetic algorithms, fuzzy logic, wavelet techniques, decision tree, smart microprocessors, genetically engineered plant, biosensors along with other future development areas already discussed will make PF not only suitable for developed countries but also for developing countries, if applied properly. This can work as a tool to bridge the technological gap between developed and developing countries.

Ronnie et al. [37] carried out a study to determine whether EC_a can be used to measure nutrient concentrations in the field or not. Fifteen field sites with 12 different soil series were studied in three topographic areas of North Carolina in 1997 and 1999. Soil samples and EC_a measurements were taken at the same locations in the field and analyzed for P, K, Ca, Mg, Mn, Zn, Cu, pH, CEC, percentage humic matter (HM), silt, and clay. Nutrient concentrations and soil properties were compared with EC_a using correlation and stepwise regression analysis of PCs. The authors concluded that the primary value of EC_a in measuring nutrient levels lies in its ability to identify small changes in soil texture, CEC, or HM, that in turn indicate where differences in nutrient levels occur.

Lund et al. [38] have discussed the applications in precision farming where EC maps are proving useful in improving economic returns.

Bobert et al. [39] have described a method to include digital terrain analysis and two sensor based methods for detection of soil texture and soil water content into the estimation of the soil moisture distribution. The conducted work showed the potential of topographic wetness index in combination with EC_a mapping and soil water measurements to determine the spatial soil moisture distribution depending on relief and soil texture. The authors concluded that this system may be used to classify MZs for PA.

Moral et al. [40] discussed that mobile soil EC_a measurements constitute one of the most efficient ways to quickly map soil spatial variability. Furthermore, it is possible to create maps with a very high spatial resolution, as it is needed for precision farming or generally for a site-specific soil management.

Adamchuk et al. in [41] discussed various aspects of usefulness of different on-the-go sensors for PA.

Mamo et al. [42] have carried out a research to quantify the impact of field variability on the yield response of corn to N fertilization and to evaluate temporal stability of these response functions. A production field near Revere, MN, was cropped with corn in rotation with soybean. It was found that Corn yield increased with N treatments on a whole-field basis; however, spatial analysis showed that corn yield response to N was observed on only half of the landscape.

Corwin et al. [43] provided a review of the development and use of EC_a measurements for agricultural purposes, particularly from a perspective of precision agriculture applications. The authors presented background information to provide the reader with an understanding of the basic theories and principles of the EC_a measurement. An overview of various EC_a measurement techniques and applications of EC_a measurements in agriculture, particularly SSCM, guidelines for conducting an EC_a survey, and current trends and future developments in the application of EC_a are described.

Corwin et al. [44] have presented a general overview of the application of soil EC to PA. The authors have discussed various areas with particular emphasis on spatial EC measurements such as a brief history of the measurement of soil salinity with EC, the basic theories and principles of the soil EC measurement and what it actually measures. An overview of the measurement of soil salinity with various EC measurement techniques and equipment, applications and value of spatial measurements of soil EC to PA are also described.

Vrindts et al. [45] studied the processing of PF data for correct use in precision management. Different methods to study the relation between soil and crop were tested. A correlation analysis, PCA of soil parameters and clustering of soil and yield parameters are described.

Vibha et al. [46] presented an efficient hybrid model that was achieved by first clustering the data and then classifying it, and using the spatial conceptual information extracted from the environmental variables. The authors have proposed a framework where soil is classified into different types. It helps in predicting soil fertility, based on which one can decide upon the fertilisers and suitable crops that could be cultivated with expertise.

Sindhu et al. [47] carried out a study to show the integrated use of multivariate and regression analyses in identifying yield determining soil properties by eliminating the multicollinearity among soil properties.

Corwin et al. [48] have outlined various protocols for conducting EC_a surveys. These developed protocols provide a mean for characterising the spatial variability of soil physico-chemical properties which can be used in site-specific crop management, landscape –scale modelling of non- point source pollutants in the vadose zone, and soil quality assessment. Guidelines are also presented for understanding and interpreting EC_a survey measurements.

Corwin et al. [49] carried out a case study to apply EC_a survey protocols to a soil quality assessment to demonstrate their utility in characterizing spatial variability.

Corwin et al. [50] carried out assessment and field-scale mapping of soil quality properties of a saline-sodic site in California's San Joaquin Valley. The various objectives were to spatially characterize initial soil physicochemical properties relevant to maintaining soil quality on an arid zone soil and to characterize soil quality relationships and spatial variability.

Mzuku et al. [51] characterized the spatial variability of soil physical properties across irrigated corn to know the physical properties of soil which could explain the variability in productivity between SSMZs.

Soil properties and wheat yield estimation was done on complex eroded hills using geostatistics and thematic mapper images by **Bhatti et al.** [52]. Spatial variability of organic carbon, soil phosphorus, and wheat yields was studied using classical statistics and geostatistics.

Effect of land use history on soil spatial heterogeneity of macro- and trace elements was investigated by **Jianwei et al.** [53] using spatially-explicit design within three 0.09-ha plots in each of three eco-systems.

Based on measurements of spatial heterogeneity within the lysimeter area, a strategy for sampling soil from intact monolith lysimeters was reported by **Stark et al.** [54]. Geostatistical analysis and fitting of an exponential model showed that a spatial structure exists in the biotic soil properties and that the samples are independent beyond separation distances of 25–30 cm.

Hangsheng et al. [55] reported variability of soil map units and soil properties at multiple scales using two case studies, and demonstrated that soil spatial variability is a function of map scale, spatial location, and specific soil property.

Suzanne et al. [56] concluded that analyzing correlations between CO₂-flux and soil properties without discriminating for scales can miss important scale-dependent processes controlling soil gas emissions. Scales at which these processes vary should therefore be taken into account. Two agricultural sites with sandy and loamy soils were characterized at 108 geo-referred sampling points and at two depths where soil surface CO₂-flux and soil physico-chemical parameters were measured to assess the spatial variability of CO₂ emission fluxes (CO₂-flux). They correlated these emissions with soil physico-chemical properties at two spatial scales and at different depths using a new geostatistical approach that performs multiscale spatial analysis.

Spatial variability of vertisol properties for identifying those zones with physical degradation was investigated by **Humberto et al.** [57] by quantifying the spatial structure of different physical properties collected from a vertisol through multivariate spatial analysis. In this study six soil properties were collected (penetrometer resistance (PR), total porosity, fragmentation dimension (Df), vertical electrical conductivity (ECv), horizontal electrical conductivity (ECh) and soil water content (WC)) and three different types of semivariogram models were used for fitting individual experimental semivariograms. Cross-semivariograms, individual, univariate, semivariograms and bivariate geostatistical analysis was used to obtain significant findings. Multivariate spatial analysis, also showed the influence of soil tillage operations, harvesting machinery and irrigation water distribution on the status of the investigated area.

Spatial variability of a field soil was studied by **Kirda et al.** [58] using a neutron probe to measure soil water status of the plant root zone, and isotopically labelled fertilizers to evaluate fertilizer nitrogen uptake. Autocorrelation and cross-correlation analysis were used to evaluate spatial dependence of the measurements. Author reported that field variability in soil water content measurements was found to be space dependent over a distance of 6 m. Also, the spatial variability measured in atmospheric nitrogen fixation of alfalfa showed close

resemblance to variability observed in water content measurements and was related to spatial variability of available soil nitrogen.

Hierarchical model of analysis of variance was used by **Prasolova et al.** [59] to analyse the spatial structure of soil moisture, nitrogen (N) availability indices (total N, NO_3^- -N, NH_4^+ -N, potential mineralizable N (PMN)), and other chemical properties (organic C (OC), available P, pH, CEC, exchangeable K, Ca, Mg, Mn, Na).

Scale dependent variation of soil properties was reported by **Asfaw et al.** [60] using conventional statistics, geostatistics, and fractal analysis to characterize and compare the EC_a . Factor analysis revealed strong EC_a relation to ammonium extractable K, OM, pH and Bray-2 Phosphorus, but not to ammonium extractable Ca and sum of bases. The study showed that although the semivariogram forms are similar among the different (six) fields, the rate of change of the semivariograms differs for some of the fields at distances greater than 9 m.

Spatial variation of chemical and physical soil properties was assessed by **Cerri et al.** [61] to select an appropriate area (MZ) to install a pasture rehabilitation experiment. A grid of 25 m size was used to collect samples for analyzing total carbon and nitrogen, $\delta^{13}\text{C}$ and $\delta^{15}\text{N}$, pH in H_2O , pH in KCl, clay, and sand contents.

Robinson and Metternicht [62] reported the results concerning performance of spatial interpolation techniques for mapping soil properties. In this process accuracy of OK, lognormal OK, inverse distance weighting (IDW) and splines was investigated for interpolating seasonally stable soil properties (pH, electric conductivity and OM) that have been demonstrated to affect yield production.

Spatial distribution patterns of exchangeable sodium percentage (ESP), EC, soil pH and boron content (B) of salt-and sodium-affected soils in the Igdir plain was reported by **Osman et al.** [63].

Kai-hua et al. [64] conducted a study to evaluate CK of CEC with the PCs derived from soil physico-chemical properties.

Lesch and Corwin [65] reviewed the connection between the ordinary linear regression model and the more comprehensive geostatistical mixed linear model and described the conditions for valid spatial prediction. Statistical tests for detecting spatial correlation in LR model residuals were also reviewed, in addition to three LR model validation tests derived from classical linear modeling theory.

Integration of geophysical and geostatistical techniques to map the spatial variation of clay was reported by **Benedetto et al.** [66]. This study investigated KED with EMI and GPR data as auxiliary information to predict clay contents. The results showed that the model using the

auxiliary variables can be preferred to univariate kriging in terms of correlation between true and estimated values and capability of interpretation of spatial variability.

A non-contact EMI probe to evaluate the soil and pasture variability in a PA project was reported by **João et al.** [67]. For management of variable rate fertilizers instead of traditional process of sampling and evaluation of the soil, modern tools such as conductivity sensor and ArcGIS software for spatial variability modelling was used. Significant CC values were observed between EC_a and altitude, soil pH and pasture dry matter yield.

Viacheslav et al. [68] have provided a discussion regarding an analytical methodology to assess the quality of targeted sampling strategies for on-the-go soil sensor data calibration prior to site-specific soil treatments, and demonstrated the potential for the automated selection of sampling sites. Soil pH and electrical conductivity maps of a 23-ha agricultural field were used to illustrate the applicability of this method.

Yan Li et al. [69] conducted a study, which reported investigation concerning spatial variability of soil bulk electrical conductivity (EC_b) in a coastal saline field and design an optimized spatial sampling scheme of EC_b based on a sampling design algorithm, the variance quad-tree (VQT) method.

Juan et al. [70] reported a spatial Gaussian linear mixed model that involves (a) a non-parametric term for accounting deterministic trend due to exogenous variables and (b) a parametric component for defining the purely spatial random variation due possibly to latent spatial processes. Analysis of the relationship between soil EC and Na content to identify spatial variations of soil salinity was the main objective for agricultural and environmental land management.

Padhi and Misra [71] demonstrated that maps of EC_a could be useful in determining spatial distribution of soil water within crop fields so that variable rather than uniform quantity of irrigation water can be applied to improve water use efficiency.

Gregorio et al. [72] reported the quantification of fine-resolution maps of soil organic carbon stock (CS , $Mg\ C\ ha^{-1}$) resulting from utilizing multivariate sources of secondary information. Different geostatistical techniques for mapping CS in the top 0.3 m of soil with or without secondary information were assessed in three large no-till fields (49 to 65 ha) in Nebraska. Auxillary data source (soil series, surface reflectance derived from satellite images (REF), relative elevation (EL), and soil EC) were processed with geostatistical techniques such as OK, CK, KED, and RK assuming it to provide indirect information on spatial patterns of CS .

Malhi [73] conducted a field experiment to determine the relative effectiveness of N alone versus combined annual application of N and S fertilizers to a wheat-canola rotation on storage of total organic C (TOC) and N (TON) and on the light fraction organic C (LFOC) and N (LFON) in soil. The findings demonstrated the importance of a balanced/combined application of N and S fertilizers to crops in storing more organic C and N in S-deficient soil. The quality of EC_a maps as affected by the swath width of the commercial EC_a sensing system is reported by **Farahani et al.** [74]. It was observed that map quality deteriorated slightly as swath width increased to about 50 m, but at swath widths of 80 m and higher, the quality deteriorated severely and map delineations in the form of location-specific low, medium and high EC_a zones became highly distorted and wrongly classified. Increasing the manufacturer's recommended swath width range of 12–18 m to a range of 30–50 m caused only a 10% reduction in map quality while reducing the mapping time by 65%.

Sadeghi et al. [75] considered temporal and spatial variations of rainfall data to estimate the rainfall erosivity throughout Iran.

Sukhvinder et al. [76] evaluated the productivity potential of chickpea in relation to raya intercropping in different planting patterns and row orientation under rain fed conditions.

2.3 Identification of homogeneous agronomic units for optimal crop input management

Recent research in PA has focused on use of MZs as a method for variable application of inputs. MZs represent a homogeneous combination of potential productivity-limiting factors, which are therefore permanent [77] and refer to geographic regions that present topography and soil attributes with minimal heterogeneity [78]. The concept of MUs was proposed in the mid 1990s [79] and there have been many different delineation methods recorded in the PF literature [80-81]. Although **Lark and Stafford** [79] originally proposed the term 'management units', the term 'management zones' is generally used. There are numerous methods for defining MZs, but most methods rely on spatial information sources that are stable or predictable over time and are related to crop yield [82]. The determination of homogeneous areas within a field is difficult to achieve due to the complex combination among factors which may influence yield [83]. Several studies have indicated that homogenous MZs could be used as an alternative to GSS and to develop nutrient maps for variable rate fertilizer application.

Fridgen et al. [84] discussed the use of the FCM unsupervised continuous clustering algorithm to delineate within field MZs using soil and field characteristics (i.e., landscape features). Soil EC and topographic attributes such as elevation and slope measured in two claypan soil fields were used for the clustering process.

Stafford et al. [85] used fuzzy clustering of combine yield monitor data to divide a field into potential MZs. Similarly, **Boydell and McBratney** [86] divided a field into MZs using cotton yield estimates from satellite imagery.

Jaynes et al. [87] used cluster analysis to decipher temporal and spatial patterns in 6 year of corn yield measurements and to reduce the temporal yield patterns for 224 yield plots into five clusters with similar temporal yield patterns.

Godwin et al. [88] used clustering of soil EC and yield to determine soil zones that can be used to optimize soil sampling for fertiliser.

Sommer et al. [89] analysed a highly complex soilscape of fluvial sediments by a hierarchical expert system. Zones of identical pedogenic context were first defined and multitemporal remote sensing data of winter wheat was obtained using an airborne multispectral scanner. Vegetation parameters were semi-physically modelled using three relevant spectral channels and resulting spatial patterns were processed by image analysis methods. These coarser patterns were interpreted as patterns of site quality within each zones of pedogenic context.

Guastaferrero et al. [90] compared different procedures such as ISODATA method, FCM algorithm and nonparametric density algorithm for creating MZs and determined the relation of the MZs delineated with potential yield.

Cucunubá-Melo et al. [91] carried out a study to determine areas with homogeneous physical characteristics in order to establish agricultural MUs, using geostatistical techniques.

Johnson et al. [92] evaluated field-scale EC_a mapping for delineating soil properties correlated with productivity and ecological properties. The authors concluded that soil classification using EC_a provides an effective basis for delineating interrelated physical, chemical, and biological soil attributes that are expressed as soil condition, crop productivity and ecological potential.

Pedroso et al. [93] presented a segmentation algorithm, inspired from an image-processing region-merging algorithm, for the delineation of discrete contiguous MZs in agriculture. A comparison between the segmentation algorithm and a common classification algorithm (k - means clustering) was done using an aerial normalised differences vegetation index (NDVI)

image collected on a 200 ha vineyard in Olite, Spain. The results obtained demonstrated that for a given number of manageable (effective) zones the segmentation outputs were equivalent or superior to the classification outputs for partitioning vine circumference variance.

Yadav S et al. [94] investigated components of the water balance and water productivity in dry seeded rice (DSR) and traditional puddled transplanted rice (PTR) with different irrigation schedules, which ultimately results in optimal crop input applications and enhanced productivity.

Yan Li et al. [95] carried out delineation of SSMZs using fuzzy clustering analysis in a coastal saline land. Five soil and landscape attributes, including a NDVI image, soil EC, total nitrogen, OM and CEC acquired for a coastal saline land were selected as data sources, and their spatial variability were analyzed and spatial distribution maps constructed with geostatistics technique. PCA and FCM clustering algorithm were then performed to delineate the MZs, FPI and NCE was used to determine the optimal cluster number.

Jose et al. [96] sampled the soil for EC and eleven other soil properties, aiming to define uniform SSMZs in relation to these variables. PCA was used to group variables and fuzzy logic classification was used for clustering the transformed variables. The importance of EC in this process was evaluated based on its correlation with soil fertility and physical attributes. The results confirmed the utility of EC in the definition of MZs and the feasibility of the proposed method.

Goktepe et al. [97] utilized hard k-means and FCM algorithms for the classification of fine grained soils in terms of shear strength and plasticity index parameters. It was shown that FCM algorithm exhibited better clustering performance over hard k-means classifier. Clustering analysis produced worse outcomes for soils collected from different regions than those obtained from a specific region. The authors also discussed that in addition to its precise classification ability, FCM approach is also capable of handling the uncertainty existing in soil parameters.

Aaron et al. [98] aggregated landscape attributes in to MZs that characterize spatial variation in soil chemical properties and crop yields. Temporal variability was also studied for yield spatial variability. PCA and un-supervised classification technique was used to aggregate landscape attributes, including a soil brightness image (red, green, and blue bands), elevation, and EC_a. The expression of spatial variation in soil chemical properties (soil pH, EC, P, and OM) and geo-referenced yield monitor data (five seasons, 1997–2001) were studied in relation to MZ's.

EC_a classification as a basis for estimating plot-scale experimental error was proposed by **Johnson et al.** [99]. Comparison of mean-square (MS) errors for several soil properties and surface residue mass measured at this site, with those from a nearby plot-scale experiment, revealed that EC_a-classified within-field variance approximates plot-scale experimental error.

Sharma et al. [100] investigated the profile distribution of total and diethylenetriamine pentaacetic acid (DTPA)-extractable micronutrients (Zn, Mn, Cu, Fe) in soils developed on six physiographic units of the semiarid Siwalik hills of Punjab in northwest India. Among the various micronutrients, deficiency of Zn was found to be widespread, followed by Fe and Cu in the cultivated soils on foot slopes, toe slopes, and floodplains.

Randy et al. [101] reported an application of SSM in which preliminary measurements of EC_a, supplemented by EC_a-directed soil sampling, are used to construct a GIS map of salinity zones on which site-specific amendment application can be implemented.

Application of multivariate geo-statistics in DMZs within a gravelly vineyard using geoelectrical sensors was demonstrated by **Morari et al.** [102]. Spatial dependence between EC and physical soil properties (particle-size distribution) was explored with factorial kriging analysis (FKA) that could isolate and display sources of variation acting at different spatial scales, expressed as regionalised factors, which was followed by FCM classification for zoning the vineyard. **Moral et al.** [103] reported the use of an objective method, the formulation of the Rasch model. It synthesizes data with different units into a uniform analytical framework, is considered to get representative measures of soil fertility potential which could be used to delimit MZ. To illustrate the method, a case study was conducted in an experimental field using five soil properties: clay, sand and silt content, and deep (EC_d) and shallow (EC_s) soil EC_a (approximately 0–90 and 0–30 cm depths, respectively). The proposed method demonstrated classification of all locations according to the soil fertility potential, and the influence on the soil fertility of each individual soil property. It reported that ECs is the most influential and silt content the less influential property.

Based on soil fertility attributes (clay, pH, cation exchange capacity (CEC), organic carbon (OC), total nitrogen (TN), available phosphorous (AP), and available potassium (AK)), optimal fertilization management was reported by **Davatgar et al.** [104] using delineated MZs. Results of geostatistical analysis for soil fertility attributes were used to delineate soil fertility MZs using PCA, and fuzzy cluster algorithm. Analysis of variance in MZs indicated that there is heterogeneity in soil fertility status among different zones; this information can be used as a reference for variable-rate fertilization. **Miodrag Zlatic et al.** [105] studied economic and social revival of a degraded region in Serbia.

Yan Li et al. [106] reported DMZs using spatial variability data (bulk EC) and krigging interpolation technique. Based on spatiotemporal characteristics, cluster analysis was used to divide the site into three potential MZs, each with different characteristics that could have an impact on the way the field was managed. It was concluded that defined MZs could be used to manage coastal saline land in a site-specific way.

For optimal nutrient management on field-scale basis in order to prohibit over or under dosing, MZs based concept was demonstrated by **Wang et al.** [107] on an 87-ha tobacco field. Soil samples (0–20 cm) were taken from 81 points on 100-m grid and lab analyzed for pH, OM, total nitrogen (TN), alkalytic nitrogen (AN), available phosphorous (AP), available potassium (AK), and CEC. Spatial variability was assessed and spatial distribution maps constructed using geostatistical techniques. PCA and fuzzy cluster algorithm were used to delineate MZs; FPI and NCE were used to determine the optimum cluster number. Analysis of variance indicated the heterogeneity of soil fertility among different MZs.

Precision agriculture MZs were delineated by **Xiang et al.** [108] using clustering analysis and yield data over four years from the combine harvester equipped with yield monitor and DGPS receiver.

Delineation of soil nutrient MZs was reported by **Qiang et al.** [109] using six soil nutrients, taken as the variables, and the fuzzy clustering algorithm optimized by particle swarm optimization (PSO), and two indices were introduced to ascertain the reasonable number of MZs. It was found that fuzzy clustering optimized by PSO had a good performance on DMZs and variable fertilization management was feasible in the study area.

Kukal et al. [110] have highlighted the irrigation water use when practising the resource conservation technologies under different irrigation scenarios. The authors concluded that the intermittent irrigation scheduling on the basis of soil matric tension (16 kPa at 20 cm depth) could save irrigation water by 30%.

Nisar et al. [111] reported that agriculture and land use change are prominent sources of global greenhouse gas emissions. The application of fertilizers, rearing of livestock, and related land clearing influences both levels of greenhouse gases in the atmosphere and the potential for carbon storage and sequestration.

2.4 Inferences drawn, gaps in study and scope of work

2.4.1 Inferences drawn and gaps

PF has been recognized as the most advanced version of practical farming on field-scale basis. It is highly interfacial and technical in nature and involves system level approach. PF is an outgrowth of technological developments, such as the soil EC measurement, which facilitate a spatial understanding of soil–water–plant relationships. Spatial characterization of the variability of soil physico-chemical properties is a fundamental element of (i) soil quality assessment, (ii) modeling source of factors influencing crop productivity (iii) designing soil input application footprint on site-specific basis for optimal crop input management.

EC_a is a quick, reliable measurement that is frequently used for the spatio-temporal characterization of edaphic (e.g., salinity, water content, texture, and bulk density) and anthropogenic (e.g., leaching fraction) properties. As a result, EC_a has been widely used as auxiliary variable to generate high density resolution maps of soil fertility attributes which are spatially dependent on EC_a. EC_a being sensor-measured variable, which can be measured on-the-go, provides exhaustive field-scale data to characterize spatial variability and distribution patterns of soil physico-chemical fertility attributes to suit PF requirements. Generating spatial variability maps to a scale which meets PF requirement through traditional techniques is neither realistic nor economical. Moreover, traditional methods are time consuming, laborious, cost-prohibitive and prone to human errors. However, one must be cautious before using data obtained from rapid mapping tools. Often data obtained from rapid mapping tools are required to undergo ground-truthing in order to understand and identify exact soil property influencing crop yield. Therefore, PF has been widely regarded as site-specific in nature and is not a generic approach. Moreover, in case of EC_a data, all the relationships between soil physico-chemical properties with EC_a data must be carefully established before finalizing the actual prescription as often their statistical analysis is misleading.

It was noticed that based on the present trends of agronomic management in the Indian agri-production system, precious ecological resources such as land and water are depleting and contaminating each day passing. Furthermore, post second GR, mis-use of fertilizers, although resulted in enhancing crop productivity but showed its side effects (land degradation, plateau in production). Of course there are other factors contributing to the present concerns of Indian-agri production system however, little bit contribution from all directions will certainly add up to big results. Therefore, mis-management of ecological

resources and inputs (chemicals) certainly warrant immediate arrest through some measure such as PF for SA development.

Therefore, optimum input application through SSCM has been recognized as most advanced version of farming which can sustain present agriculture production system and create hopes for better future. This approach is believed to increase not only quantity of the yield but also will retain quality of agri-produce and fragile ecological system. In this approach, three basic steps are identified: a) assessing spatial variability b) managing variability c) evaluation.

Moreover, tools to rapidly and economically map spatial distribution and variability of fertility attributes, software procedures and techniques to prescribe agronomic guidance for efficient field management, and finally tools for variable rate input application and evaluation are other important aspects highlighted by researchers. Geostatistical tools including geospatial modelling such as univariate and multi-variate techniques (OK, CK, KED, RK) have been established to recognize spatial variability and distribution patterns of soil properties. These tools help to identify trend in the spatial structure of soil fertility attributes and also help to estimate values at unknown locations. RMSE, C0, C1, C0+C1, C0/ (C0+C1) are the model optimizing parameters to best fit experimental model (spherical, Gaussian etc.). K, OK, UK are the univariate models used to assess spatial distribution patterns of soil fertility attributes to enhance productivity potential. CK, RK, are the multi-variate geospatial modelling techniques which are used along with auxillary variable to improve spatial distribution maps of primary variable after establishing their spatial dependence on auxillary variable. For instance, EC_a being exhaustive data can be used to obtain high resolution maps of OM content as later often finds strong spatial dependence on the former one. Use of PCA, multi-variate statistical technique, is the latest advancement in the areas of soil science to summarize the variability in all considered soil properties and due to the existence of high correlation between them. This helps to avoid the duplication of the variables and associated repetitions of cluster analysis which are co-related and can be derived from auxillary variables. FCM is another tool which has found increased use and established its credibility to delineate practically MZs for the naturally changing soil data. It is unsupervised classification tool which continues its iteration till it optimizes its objective function. It uses data matrix consisting of soil sampling data, degree of membership matrix indicating to what extent sample belongs to a particular class, centroid matrix –consisting of information about center of a cluster. Although, FCM is popularly used to cluster soil data to delineate

agronomic MZs, there are other cluster analysis techniques reported in the soil science literature including ISODATA, non-parametric density algorithm, k-means.

Quick and automated methods are desirable in attaining the dreams of PF goals, therefore, few tools are made available recently by various researchers, it includes: software tools for DMZs such as Management Zone Analyst (MZA) and Fuzzy-me, for Estimation of Sampling Assessment and Prediction, ESAP is the software from USADA, USA.

SSCM is the most advanced application of PF to agriculture production system. It promotes the concept of identification and management of regions within the field, known as sub-fields. Such regions often referred to as MZs. These sub-field areas share some similar quantitative measure(S) (e.g. topography, yield, and soil-test nutrients). Soil being complex, identification of sub-field areas having homogeneity within is difficult as a result of complex combination of soil, biotic, abiotic, and climate factors which are variable on spatio-temporal scale and may affect crop yield. Number of questions to be answered while delineating such AMUs includes: what information to be used while delineating zones, What procedure / technique should be appropriate to classify zones, and how many number of zones should be used for effective management of input resources i.e. validation. Number of information sources has been used to delineate sub-field MZs for SSCM (Digital elevation data, aerial photographs of bare soil along with landscape position and experience of producer, EC_a , combination of topographic attributes and soil EC_a , yield data, soil physico-chemical properties)

In India, especially, Punjab region, water table depth is rapidly depleting, almost 1-2 foot (0.305 m – 0.610 m) per year. At many places earlier water was available on few feet have now gone down to 300 feet (91.440 m). Besides, due to excess fertilization and use of indiscriminate insecticides on crop fields on account of uniform soil input application practices, water reservoirs have been contaminated in Malwa regions. These regions have been contaminated to a level that they are declared as cancerous belts by the government.

Although in developing countries such as India, it is still in its infancy to practice PF principles due to number of limitation and myths, it is bound for Indian agri-production system to take a step forward in this direction for meeting future demands of food production projections to keep a pace with ever-increasing population. No specific reference in terms of technology driven PF has been found so far in the referred literature from Indian soil science community.

2.4.2 Scope of work

In order to curb practice of blanket fertilizer application in Indian fields especially in Punjab (India), it was felt necessary to undertake evaluation of PFTTs in this region. The model based studies of spatial variability of soil properties distribution on Indian farming fields has not been explored so far. No success story in terms of practically manageable PFTTs adoption on Indian fields is reported so far.

Therefore, based on inferences drawn out of literature search, a strong need was felt to undertake PF studies on Indian fields particularly the variability of electrical conductivity and spatial distribution of soil physico-chemical properties in relation with crop productivity. As Indian land holdings are small scale, there is pressing need to establish feasibility of PFTTs on Indian fields considering the local conditions and existing farming cultural practices as the tropical weather is different in this continent. It is worth noticing in the reported LS that Indian fields and farmers are subjected to tremendous stress due to ever-increasing population to fulfil enhanced food demand back home. As such, farmers are applying excessive input applications (fertilizers, pesticides etc.), leading to contamination of water reservoirs and degradation of arable lands. Also, the presented work has not been reported so far from Indian continent and is less explored being in its infancy and knowledge-driven area of current research. It is envisaged that the presented small scale research findings if propagated to a large scale level, can help uplift economical prosperity of farmers and environmental stability of Indian ecology.

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Chapter 3

MODELLING AND EXPERIMENTATION

Overview

In this chapter, information about experimental site used for conducting all experiments is provided. Secondly, the experimental design is explained including the variable rate input treatments applied, crop varieties used, number of grids constructed and fields used, number of variables used to study spatial variations and configuration of sensor used. This section explains the systematic stepwise approach that was followed which resulted in identifying spatial distribution patterns of soil properties, its relation with EC_a and comparison with crop productivity. Procedure adopted for deciding soil sampling strategy has been informed in order to conduct lab based determination of fertility attributes (pH, P, K, EC, CEC, OM, % Clay and Sand contents). In addition to this the required details of hardware and software tools used along with techniques employed to demonstrate the spatial variability studies of soil properties that can help to enhance the crop quality and quantity in Indian farming conditions and crop fields is elaborated.

3.1 Materials and Methods

3.1.1 Experimental site details

The survey was conducted in three fields located at PAU, state of Punjab, (India) on May 13, 2010. Nitrogen fertiliser was applied in different amounts with variable rates of N1, N2, N3, N4 and N5, with average dose of 68, 75, 125, 175, and 225 kg nitrogen/ha over a period and cultivar of V1= PBW-343, V2= PBW-550, V3= DBW-17. Field1 was divided into three different parts (part1, part2 and part3) each having grid matrix structure of 3(columns) by 5(rows) totalling 15 grid cells in each part and each grid cell had dimensions of 6m by 5m. Field2 was divided into 4 by 5 grid, each cell having dimensions of 9m by 9m creating 30 points for measurement. Field3 was divided into 11 by 1 grid, each cell having dimensions of 9m by 9m creating 24 points for measurement. Experimental field organizations for field 1, 2 and 3 are shown in Fig.3.1 (a), (b) and (c) respectively.

The sensor measured geo-spatial soil data was collected at vertices of each cell. Therefore, twenty four points were collected from each matrix grid i.e. seventy two points from three parts in total from field 1 with the help of in-situ field usable sensors in one case, whereas high density geo-referenced continuous EC_a measurements were also collected using geonics make sensor EM38MK2 and trolley mounted arrangement from the same field in other case. The same procedure was followed for other two fields located in PAU-campus.

In another experiment for studying spatial variability of soil properties, field was selected at CSIR-CSIO, Chandigarh campus. A test site meant to check performance of soil conductivity mapper developed by CSIO was used to assess its soil quality and apply principles of PFTs through use of modern H/W mapping tools and S/W techniques.

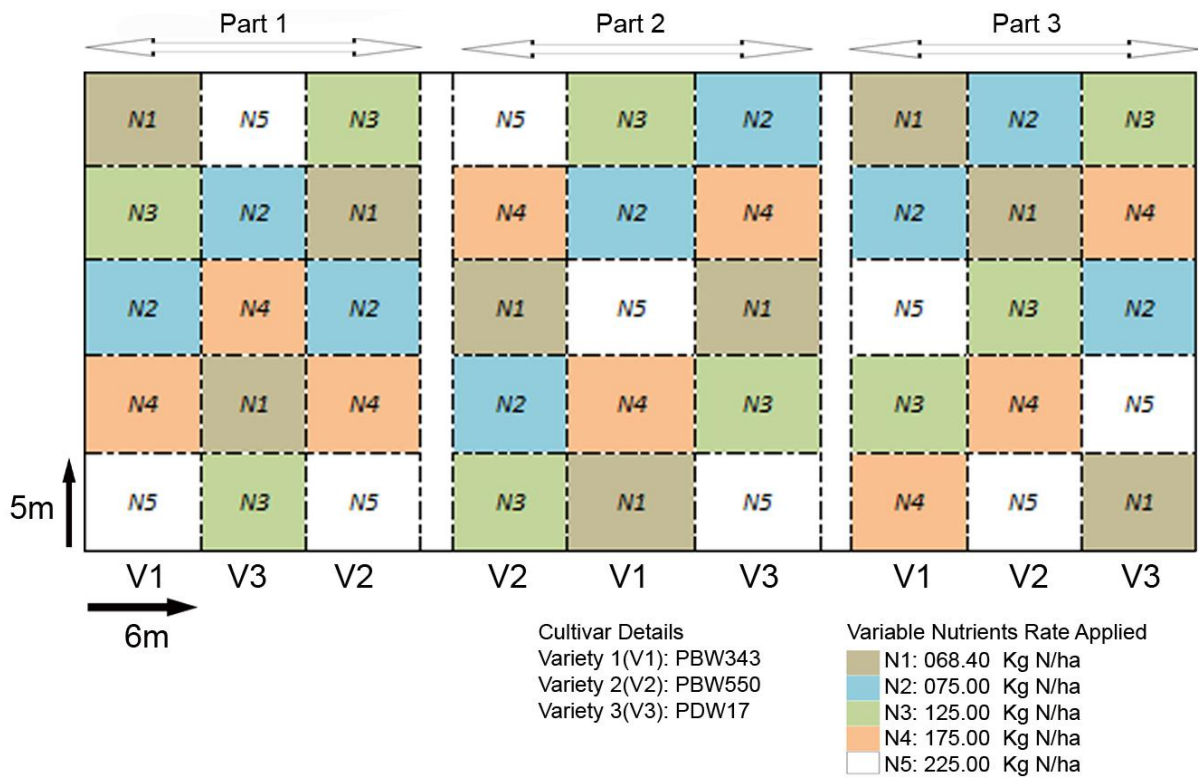


Fig.3.1 (a): Arrangement of experimental field 1

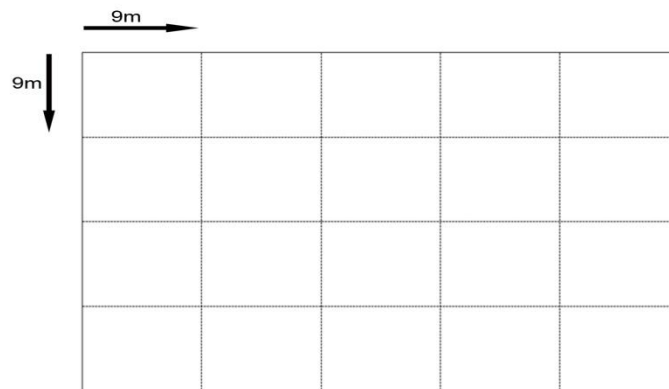


Fig.3.1 (b): Grid arrangement of field 2

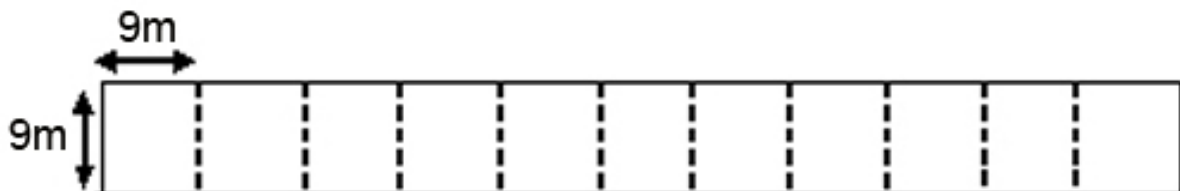


Fig.3.1(c): Grid arrangement of field 3

3.1.2 Data collection, sampling and analysis

Generally, geo-referenced spatial measurement of EC_a using mobile GPS enabled equipment is one of the strong means to assess soil quality or crop yield variations because of reliability, ease of measurement, and ability to detect a variety of soil properties. As such, it has become one of the most essential elements in the PF based farm management systems, and therefore, in the present studies, EM38-MK2, commercially available sensor system (Geonics Ltd., Mississauga, Ont., Canada) was used to record EC_a measurement on field-scale basis. An initial EC_a survey was conducted and was used to establish soil core sampling locations needed to characterize spatial distribution of soil properties correlated with EC_a . Maximum possible spatial measurement of EC_a data was recorded in regularly spaced traverses across the field of interest. Pre-survey tasks were done before initiating EC_a mapping of the field including setting-up of EM38MK2 conductivity sensor in appropriate mode, completion of its initialization and compensation procedures, setting GPS coordinate system, geo-referencing site boundaries etc. Trimble make (Model Geo-explorer 2008 series) DGPS was used along with pathfinder post processing software to geo-reference spatial data of soil collected from experimental fields. Apart from logging field-scale data for soil spatial variations in terms of EC_a , other in-situ / point measurement sensors (POGO measurement set up including data logger, handheld I-PAQ and with Hydra probe II attachment, HANNA Model- HI99121 pH/temp meter with HI1292 probes) were also used to record point measurement for various other soil attributes such as temperature, pH, moisture content etc. noted on site-specific basis. POGO soil sensor consisted of 5 probes, data logger, PDA and HydraMon software to store and convert data files in to computer supported formats along with geo-referencing. It provided measurements for soil moisture, conductivity, temperature and dielectric constant. The in-situ pH measurement on field scale basis was carried out using Hanna make rapid precision pH sensor. A specially designed autonomous system comprising of non-metallic trolley made from wood, a low induction material, was used for mounting conductivity sensor in order to provide continuous logging of EC_a measurement during field survey operation. Simultaneously, DGPS data was also recorded at the same time to geo-reference deep and shallow EC_a measurement of EM38-MK2 sensor. The windows operating system compatible (XP) software (Windows EM38-MK2xp) was ported on field-usable Laptop to coordinate data logging operation with conductivity sensor and DGPS (position sensor). In another field survey it was replaced with windows mobile system (DGPS itself) based logging system by porting EM38MK2wm on DGPS. This made data logging efficient, easy

to operate and offered number of benefits such as auto-calibration etc. EM38-MK2, on-the-go conductivity sensor, comprises of receiver and transmitter coil placed apart and electrically insulated from each other. Transmitter coil induces changing field and produces eddy currents in the soil and secondary coil in-turn generates emf proportional to soil conductivity caused by soil eddy currents. The geonics make EM38-MK2, conductivity sensor, provides measurement of both the quad-phase (apparent conductivity) and in-phase (susceptibility) components, within two distinct depth ranges, to a maximum effective depth of 1.5 m, all simultaneously. This survey of EC_a was used to characterize soil spatial variability and was used as spatial information to direct soil sampling scheme using ESAP (response surface sample design, RSSD) software. This step provided essential ground-truthing location information to establish the spatial distribution of soil properties those are correlated with EC_a within a field. ESAP is a multi-program, statistical software package designed and distributed by the Salinity Laboratory for the sampling, assessment, and prediction of soil salinity (and/or other soil variables).

Soil sampling design footprint based on geo-referenced EC_a data was obtained for each field using ESAP software. In another case centroid matrix of FCM output was used to locate sampling locations in field. Once EC_a -directed soil sampling footprint information was derived, details regarding sampling information were transferred to GPS device using pathfinder software. This helped in locating exact sampling locations within field. From these marked spots, soil core sampling was determined to be picked from 1 ft and 2 ft depth using manual core sampler to analyse its physico-chemical properties based on lab analysis. Once again point measurements of soil moisture content, pH, temperature, EC were conducted at these depths and were geo-referenced simultaneously. General quality control and quality assurance protocols were followed during laboratory analysis determinations [1]. These collected soil core samples were lab analysed within 1-2 weeks time for the determination of their physico-chemical properties referring well established scientific procedures. Finally, statistical and geo-statistical data analysis techniques were explored to determine the soil properties influencing EC_a and/or crop yield. In order to enable any PF related management actions, data processing methods such as correlation analysis, PCA and clustering were tested to observe the relation between soil physico-chemical properties and yield variability, EC_a and physico-chemical properties, significant property influencing crop yield and EC_a . The Unscrambler version X was used to conduct MVR and UVR statistical analysis such as PLS, MLR, PCA, clustering etc. ArcView GIS software version 8.3 was used to generate semi-variogram models by applying krigging interpolation technique after appropriately

optimizing model errors to generate spatial distribution maps of soil physico-chemical properties.

Post processing software, Pathfinder, was used to process GPS data. Further, the field-scale measured spatial data (EC_a) along with lab determined physico-chemical properties were given pre-processing/transformation to normalize the whole data. Pre-processing was applied in order to bring all attributes under same scale as the number of spatial attributes measured have different units as well as variance level, thus, may confuse regression model or any other data analysis if not pre-treated, leading to wrong interpretation.

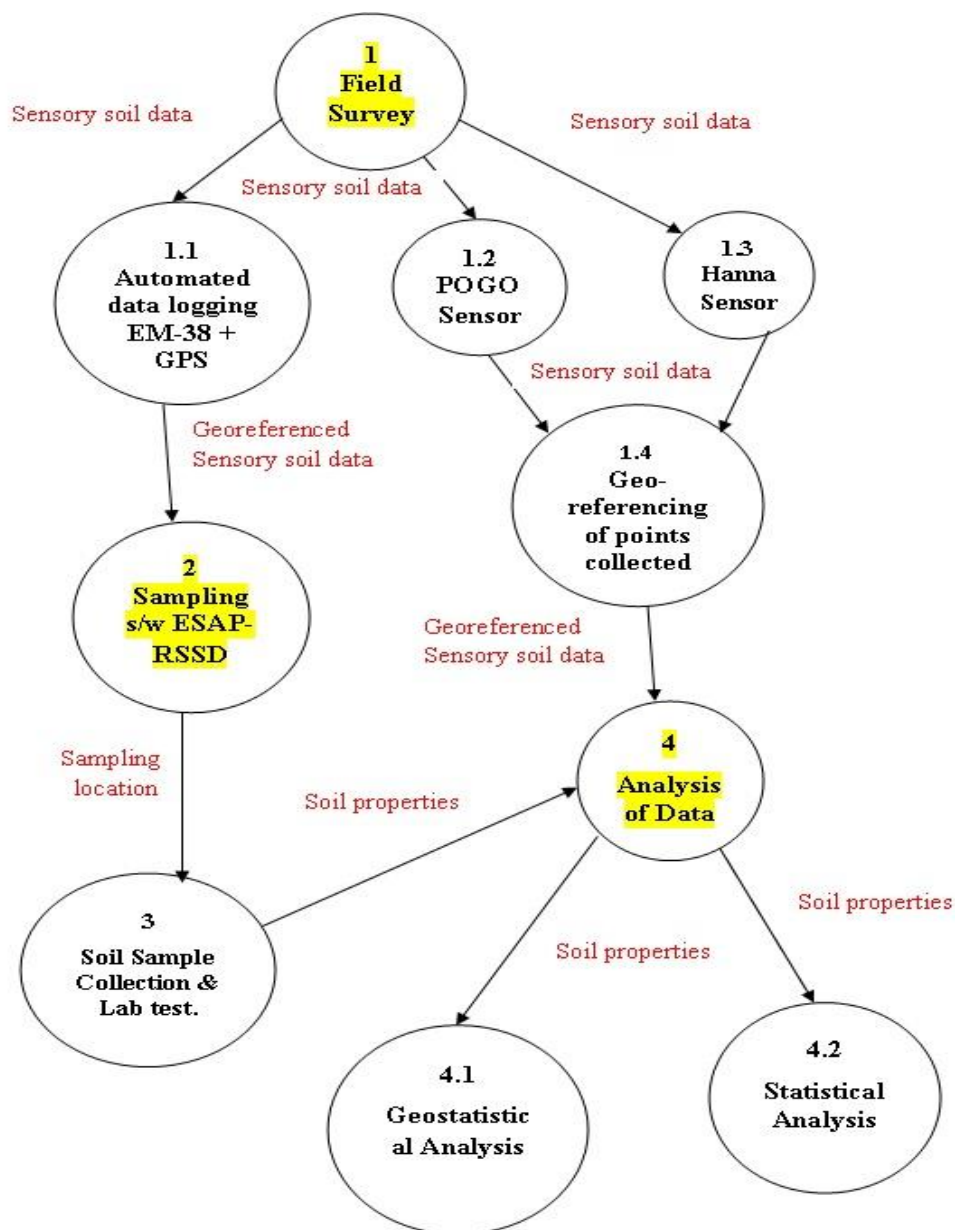


Fig.3.2: Field survey (Data collection & Sampling) flow diagram

3.2 Summary of the steps followed in the experimental design and brief details about the modelling techniques used

To summarize the experimental design, all the steps followed are systematically listed below along with brief description of modelling techniques, methods and procedures used.

Step 1: Field survey

In field survey, the data of georeferenced EC_a , moisture, pH, temperature, real dielectrics of soils were collected using in-field sensors. The purpose of the georeferenced EC_a survey from a SSCM perspective was to establish within-field variation of soil properties influencing the variation in crop yield. Other physico-chemical properties were also measured with in-situ sensors as described above in details.

Step 2: EC_a directed soil sampling

This was the most cost-effective and less time consuming way of obtaining ground-truthing of soil fertility attributes. It was done after collection of EC_a data from a specified field. Sampling footprint according to soil MZs based on EC_a data was identified which can be more advantageous than grid sampling. In other field ESAP software was also used for generating sampling footprint based on RSSD.

Step 3: Soil sample collection and laboratory analysis

The aim of soil sampling was to estimate the capacity of the soils to provide adequate amounts of the necessary nutrients to meet the needs of the crop (or crops) to be grown. Moreover, to observe the correlation of EC_a with physico-chemical properties to characterize soils and its productivity response, sampling and lab analysis was an important step to understand the information explained by EC_a as auxiliary variable.

After collecting the soil samples from the field, they were sent to a soil science laboratory of PAU, Ludhiana and analyzed for determination of soil physico-chemical properties. Based on the lab analysis using traditional approach, determination of soil fertility attributes was obtained.

Step 4: Analysis of soil data and modelling

Details on this topic are provided by dividing the information in to three sections as given below:

1. Geospatial modelling
 - a. Exploratory data analysis
 - b. Structural data analysis
2. Delineation of crop productivity MZs
 - a. PCA
 - b. FCM
 - c. SIMCA
 - d. PLS-DA
3. Regression modelling
 - a. PLS and MLR

1. Geospatial Modelling

This method was used for generating spatial surfaces. In geostatistical methods, interpolation start with the recognition that the spatial variation of any continuous variable, for instance, each soil property, is often too irregular to be modelled by a simple mathematical function. Instead, the variation can be better described by a stochastic surface. Thus, the studied variable is distributed continuously (regionalized variable), taking values everywhere within the study area (recorded by EC_a-mapper), and considered random, which means that can take a series of outcome values according to some probability distribution. Geostatistics is largely based on the concept of random function, whereby the set of unknown values (each unsampled location) is regarded as a set of spatially dependent random variables.

Geospatial modelling was undertaken in three phases [2].

- a. Exploratory analysis
- b. Structural analysis
- c. Prediction of unknown surfaces

a. Exploratory data analysis

Data were studied without considering their geographical distribution. Statistics was applied to check data consistency, removing outliers, if they exist, and identifying statistical distribution of data.

b. *Structural data analysis*

Spatial distribution of the variable was analysed. Spatial correlation or dependence was quantified with semivariograms, or simply variograms, which also can characterize and determine distributions patterns such as randomness, uniformity and spatial trend.

Variogram function relates the semivariance, half the expected squared difference between paired data values $Z(x_i)$ and $Z(x_i + h)$, to the lag distance, h , by which sample points are separated. For discrete sampling locations, the function is estimated as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{Z(x_i) - Z(x_i + h)\}^2 \quad (1)$$

where $\gamma(h)$ is the experimental semivariance value at distance interval h , $Z(x_i)$ that are measured values at sample points x , in which there are data at x_i and $x_i + h$; $N(h)$ is the total number of sample pairs within the distance interval h . The variogram shows the degradation of spatial correlation between two points of space when the separation distance increases.

This function was analysed in two components: (a) C_0 , which characterize the discontinuity jump observed at the origin of distances, quantifies the short-term, erratic variations of the studied phenomenon plus measurements and data errors. (b) The increasing part of the variogram, which may reach the sill (theoretical sample variance), levelling off the curve, for a distance called range, or keep on increasing continuously with distance. The non-nugget part of the variogram measures the non random part of the phenomenon and models its average medium-scale behaviour in space.

An experimental variogram was defined, i.e., some points of a variogram plot was determined by calculating variogram at different lags, a model (theoretical variogram) was then fitted to the points. Although there are some statistical techniques to justify the choice of a theoretical variogram [3], subjective criteria and previous experiences are the main tools to choose one.

c. *Prediction of unknown surfaces*

Geostatistics offers a great variety of methods that provide estimates for unsampled locations [4-5]. These methods are known as kriging, in honor of Danie Krige, who first formulated this form of interpolation in 1951. Kriging is regarded as the best linear unbiased estimator (BLUE).

All geostatistical estimators are variants of the linear regression estimator $Z^*(x)$:

$$Z^*(x) - m(x) = \sum_{i=1}^n w_i(x) \cdot [Z(x_i) - m(x_i)] \quad (2)$$

Where each datum, $Z(x_i)$, has an associated weight, $w_i(x)$, and, $m(x)$ and $m(x_i)$ are the expected values of $Z^*(x)$ and $Z(x_i)$ respectively. The kriging weights must be determined to minimize the estimation variance, $\text{Var}[Z^*(x) - Z(x)]$, while ensuring the unbiasedness of the estimator, $E[Z^*(x) - Z(x)] = 0$.

Different types of kriging were tried; these are distinguished depending on the chosen model for the trend, $m(x)$, of the random function $Z(x)$ [6]. Thus, $m(x)$ was unknown in the OK technique and was considered to fluctuate locally, maintaining the stationarity within the local neighbourhood. When an estimate was computed at any unsampled location, the weights, $w(x)$, corresponding to each sample point, were generated by software algorithm, solving a system of linear equations where the fitted (theoretical) variogram controls the spatial variability of the studied variable [2,6].

For analysing single soil properties to create its spatial surface, a univariate algorithm, for example OK, was used. OK consider the problem of estimating the variable at an unsampled location using only data of the soil property which is being analysed. In case of EC_a as auxiliary or secondary information, (for instance EC_a data) it is considered together with the primary data (any soil property), using multivariate extension of kriging in order to result in better estimates.

Due to the exhaustive soil EC_a measurements, EC_a data can be used as auxiliary information to improve the estimates of other related soil variables. RK / CK / regression-KED is an optimal prediction technique in this case [7]. However, the use of this method has not been reported in agriculture to map soil properties, probably because of the impossibility to obtain the huge quantity of information which can be acquired with the direct electrical contact / non contact techniques at the present time.

When RK is used, predictions are made separately for the trend and residuals and then added back together. Thus, any soil property at a new unsampled point, x , is estimated, $Z^*_{RK}(x)$, using RK as follows:

$$Z^*_{RK}(x) = m(x) + r(x) \quad (3)$$

Where the trend, $m(x)$, is fitted using linear regression analysis and the residuals, $r(x)$, are estimated using OK algorithm. If c_j are the coefficients of the estimated trend model, $v_j(x)$, is

the j^{th} predictor at location x , p is the number of predictors, $w_i(x)$, are the weights determined by solving the OK system of the regression residuals, $r(x_i)$, for the n sample points, the prediction is made by:

$$Z_{RK}^*(x) = \sum_{j=0}^p c_j \cdot v_j(x) + \sum_{i=1}^n w_i(x) \cdot r(x_i) \quad (4)$$

$$v_0(x) = 1$$

In this study, only one predictor is used, EC_a , so $m(x) = a + b EC_a(x)$. In consequence,

$$Z_{RK}^*(x) = a + b \cdot EC_a(x) + \sum_{i=1}^n w_i(x) \cdot r(x_i) \quad (5)$$

2. Delineation of crop productivity MZs

In this analysis different classification algorithms were applied on the soil data to find out homogeneous regions which can represent equal productivity potential within the same cluster. This is advantageous especially in making SSCM for optimal nutrient management in order to obtain enhanced crop quality and quantity at reduced input cost and environmental damage. This helps in SA production.

It consists of supervised and unsupervised approach; different methods explored are summarized below:

- a. PCA
- b. FCM
- c. k-means
- d. HCA
- e. SIMCA
- f. PLS-DA

a. Principal component analysis

It is a multivariate statistical technique which was applied on the collected soil data. In practise, this technique transforms interdependent variables into independent and significant ones. This technique was used for exploring data to reduce the dimension. This linear transformation allowed the original data set to be compressed into a substantially smaller set of non-correlated variables, the PCs, which represent most of the information contained in the original data set [8]. This technique was used to determine the most important soil variables (including EC) for soil variability characterization and, was done by using the new

transformed variables. Newly obtained transformed variables (PCs) were used to implement the classification process, in order to define soil MZs. PCA may be regarded as a dimensionality reduction technique.

The next step consisted was classifying the selected PCs aimed at identifying the natural clusters. This classification process was used as a method for clustering the PCs, where each natural cluster comprises a distinct soil MZs. The FCM algorithm was used earlier with the help of Fuzz-ME program [9]. The Matlab6.5 was used, in implementing the FCM clustering algorithm in order to create fuzzy classified delineation of EC_a and yield zones.

b. FCM clustering algorithm

Because of the continuous nature of soils data, classification systems that allow any one observation to belong it to exactly one class are often inappropriate. Fuzzy or continuous classification procedures were developed for use in situations where the class boundaries are not, nor can they be, sharply defined. In contrast to crisp classification, continuous classification procedures allow individuals to have partial class membership (i.e. an individual can belong to more than one class) [10]. Continuous classification has been widely used for soil classification and DMZs [11-14].

The use of unsupervised fuzzy classification for delineation of within-field MZs was thus evaluated. Further analysis of the identified zones was conducted using a commercial GIS software package. Finally, measures of cluster performance and yield data were used to evaluate the “goodness” of the resulting potential MZs and to determine the optimal number of zones for a given field.

The FCM clustering algorithm was used for the purpose of partitioning n data observations in feature space into c-groups or clusters based on a FCM partition. There are three primary matrices involved in the clustering process, the data matrix X, consisting of n observations with p classification variables each, cluster centroid matrix V, consisting of c cluster centroids located in the feature space defined by the p classification variables, finally, there is fuzzy membership matrix U, consisting of membership values to every cluster in V for each observation in X, bounded by the constraints for all i=1 to c and all k=1 to n that:

$$u_{ik} \in [0 - 1], 1 \leq i \leq c, 1 \leq k \leq n \quad \text{and} \quad \sum_{i=1}^c u_{ik} = 1, 1 \leq k \leq n \quad (6)$$

An optimal fuzzy c partition is defined as the minimization of the generalized least-squared errors function, J_m , which is a weighted measure of the squared distance between pixels and class centroids:

$$J_m(U, v) = \sum_{k=1}^n \sum_{i=1}^c (u_{ik})^m (d_{ik})^2 \quad (7)$$

Where m is the fuzziness weighting exponent ($1 \leq m < \infty$), m controls the relative weights placed on each of the squared errors. Increasing m tends to increase the degree of fuzziness; hard clusters occur as m approaches a value of 1. There is no theoretical or computational evidence to distinguish an optimal m .

$(d_{ik})^2$ is the squared distance in feature space between x_k and v_i , it can be computed in the following manner:

$$(d_{ik})^2 = \|x_k - v_i\|^2 = (x_k - v_i)^T A (x_k - v_i) \quad (8)$$

Where x_k is the data observation k in the data matrix X , v_i is the centroid of cluster i in the cluster centroid matrix V , and A is the positive-define ($p \times p$) weight matrix that determines the norm used that controls the shape of the classes.

Optimal fuzzy clustering of X are obtained from pairs (U, v) that may be locally optimal for only if:

$$v_i = \frac{\sum_{k=1}^n (u_{ik})^m x_k}{\sum_{k=1}^n (u_{ik})^m}, \quad 1 \leq i \leq c \quad (9)$$

$$u_{ik} = \left[\sum_{j=1}^c \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(m-1)} \right]^{-1}, \quad 1 \leq k \leq n; \quad 1 \leq i \leq c \quad (10)$$

The several types of cluster validity functions are calculated on each U produced by FCM since the local minima of J_m are not consistent with the visually acceptable clustering patterns of the data. Several studies conducted earlier have used, the FPI [12,13] and NCE [15] for determining the optimal number of clusters:

$$FPI = 1 - \frac{c}{c-1} \left[1 - \frac{\sum_{k=1}^n \sum_{i=1}^c (u_{ik})^2}{n} \right] \quad (11)$$

$$NCE = \frac{n}{n-c} \left[- \frac{\sum_{k=1}^n \sum_{i=1}^c u_{ik} \log_a(u_{ik})}{n} \right] \quad (12)$$

Well established cluster validity functions, including FPI and NCE were used as indicators of optimum cluster number. FPI is a measure of the degree of separation (i.e., fuzziness) between fuzzy c -partitions of X . Values of FPI may range from 0 to 1. Values approaching 0 indicate distinct classes with little membership sharing, while values near 1 indicate non distinct classes with a large degree of membership sharing. The NCE models the amount of disorganization of a fuzzy c -partition of X [12, 16]. The optimal number of clusters for each

computed index is when the index is at the minimum, representing the least membership sharing and the greatest amount of organization as a result of the clustering process [17]. The minimum FPI and NCE were obtained with two-three clusters in the present study area, which is also coincident with other analysis in this area.

The output of FCM was membership matrix, i.e. fuzzy clusters. The Fuzzy clusters are defuzzified in Matlab and imported to ArcGIS software to represent different MZs. Kriging was applied to Fuzzy cluster output and MZs were delineated. Spatial distribution analysis and variability maps were studied with ArcGIS8.3; MatLab6.5 was used in implementing the FCM clustering algorithm.

c. K-means classification

Soil properties of three fields were used for classification using K-Means. The main steps involved in the K-Means clustering algorithm are given below.

This algorithm was initiated by creating 'k' different clusters. The given sample set was first randomly distributed between these 'k' different clusters.

In next step, the distance measurement between each of the samples, within a given cluster, to its respective cluster centroid was calculated.

Samples were then moved to a cluster (k') that records the shortest distance from a sample to the cluster (k) centroid. As a first step to the cluster analysis the user decides on the number of clusters 'k'. This parameter could take definite integer values with the lower bound of 1 (in practice, 2 is the smallest relevant number of clusters) and an upper bound that equals the total number of samples.

The K-Means algorithm was repeated number of times to obtain an optimal clustering solution, every time starting with a random set of initial clusters. The default number of iterations to use was set to 50, and can be adjusted by the user to find the optimal classification. The output of non-hierarchical clustering was a class identifier, based on the proximity of soil samples to identified clusters.

d. Hierarchical clustering (HCA)

HCA is based on different linkage methods to generate clusters. The user must therefore choose the linkage method, as well as the distance measure that will be used to define the clusters (separate the classes) in a dataset.

With HCA, a dendrogram was generated as a result, based on the distance between samples. HCA complete-linkage method was used, it is also known as the farthest-neighbor method, and uses the greatest distance between any two samples as the basis of the clustering. Clusters from the complete-linkage method are more compact and rounded clusters.

e. SIMCA classification

SIMCA is based on making a PCA model for each class in a defined training set. Unknown samples were compared to the class models and assigned to classes according to their proximity to the soil training samples. SIMCA performed supervised pattern recognition on soil data. Individual PCA models defined the classification rules for soil properties.

Making a SIMCA model

As is the case with all classification methods, training stage and a test stage was used for soil data. The test stage used significance tests to classify new samples, where the decisions were based on statistical tests performed on the object-to-model distances.

The optimal number of PCs was chosen for each model separately, according to a suitable validation procedure. Each model was checked for possible outliers and improved if possible (as one would do for any PCA model).

Before developing a SIMCA model, it was determined if the data being considered exhibit any tendency to cluster by the classes. This was done by doing a PCA over the soil data to see if there are any groupings which could then form the basis of the individual PCA models.

Before using the models to predict class membership for new samples, model specificity, i.e. whether the classes overlap or are sufficiently distant to each other was evaluated. Specific tools, such as model distance and modeling power were used for this purpose.

f. PLS-Discrimination analysis

It is a classification method based on modeling the differences between several classes with PLS. If there are only two classes to separate, the PLS model uses one response variable, which codes for class membership as follows: -1 for members of one class, +1 for members

of the other one. If there are three classes or more, the model uses one response variable (-1/+1 or 0/1, which is equivalent) coding for each class. There are then several Y-variables in the model.

Known data of soil samples was used for building a discriminant model, while few samples of unknown origin make up a test set to be classified. A decision line of 0 and not 0.5 in the predicted versus measured plot was used with values -1 and 1, which gives an easier visualization.

Three field samples were assigned levels field 1-‘level 1’; field 2-‘level 0’; field 3-‘level -1’ and partial least square were performed on the training samples. The results from these samples were applied to classify the test samples.

3. Regression modelling

Regression analysis helps us understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed.

For analysing response of different variables, either UVR / MVR analysis was performed on different combinations of soil properties. In this analysis either PLS or MLR was performed.

MLR is a method for relating variations in response variables to the variation in several predictors, with explanatory or predictive purpose. MLR is a classical regression method that combines a set of several predictor or X-variables, in linear combinations, which correlate as closely as possible to a corresponding single response or Y-vector. As there are few soil properties having orthogonal relationship within them, MLR was explored to reveal their hidden structure.

The following MLR model equation is just an extension of the normal univariate straight line equation:

$$y = b_0 + b_1x_1 + b_2x_2 \dots + b_kx_k + f \quad (13)$$

PLS or Projection to Latent Structures — (PLS) models both the X- and Y-matrices simultaneously to find the *latent (or hidden)* variables in X that will best predict the latent variables in Y method perform particularly well when various X-variables express common information i.e. they have large amount of correlation or co-linearity. Since EC_a is often

found to correlate to more than one soil properties (OM, CEC, Salinity, Moisture content), PLS was advantageous.

PLS and MLR results are approximately same for the given data on most of the fields for EC to single variable relationship. We have taken into account the PLS result for this as it produces more information.

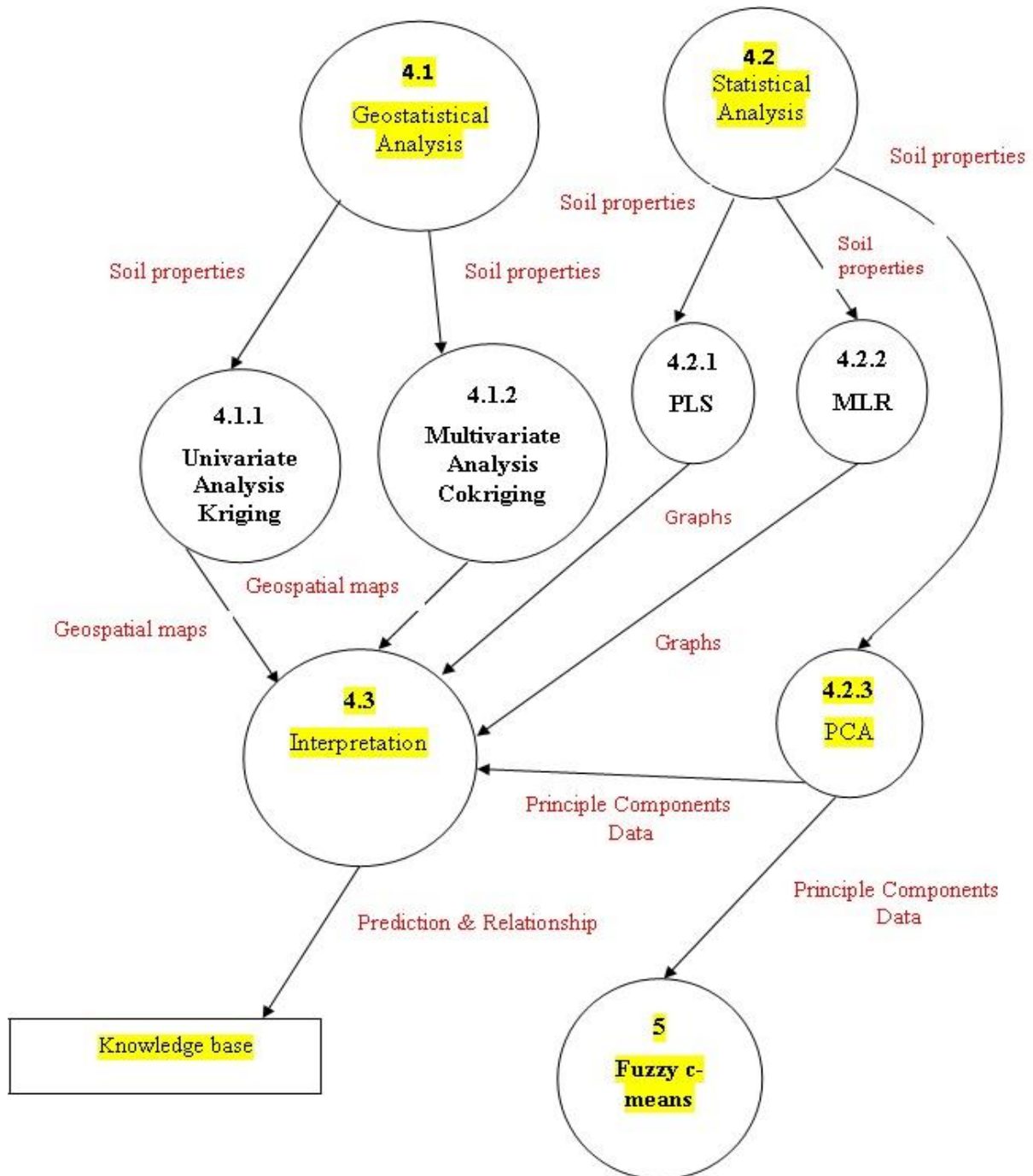


Fig.3.3: Data analysis and modelling approach

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Chapter 4

RESULTS AND DISCUSSION

Overview

In this chapter the work done on characterizing spatial variability of soil using EC_a mapping of soil and its spatial dependence on physico-chemical properties of soil influencing crop productivity is described on the basis of experimental sites. Firstly, exploratory soil data analysis and structural analysis to identify spatial trends and distributions of soil physico-chemical properties was done using geo-spatial modelling. In geo-spatial modelling, models were optimized by fitting best experimental semivariograms. Statistical and geostatistical fitness measures (min, max, mean, sd, Kurtosis, skewness, Quantiles, variance, CC, C0, (C0+C1), (C0/C0+C1), lag, RMSE, SSE) were obtained. These best fitted semivariograms predicted spatial values of unsampled locations using known values.

For implementing micro level management changes within traditional farming framework, optimal site specific crop input MZs were identified through the application of science and technology interventions. Optimal AMUs were successfully implemented using PCA and FCM classification algorithms on selected fields and validation of optimal zones was carried out (FPI and NCE indices).

Analysis revealed that the productivity varies with spatio-temporal changes of soil on a site-specific basis. This information prohibited possibility of developing any generic model. Also it was observed that the spatio-temporal changes of soil properties can be quantified by using EC_a and other computational techniques. Furthermore, EC_a mapping alone along with DSS and modern clustering techniques can help establish site-specific variability of soil physico-chemical properties and optimal crop input MZs.

Introduction

In this section the work done on research farm fields of PAU, Ludhiana under PF studies have been taken with following objectives:

- Characterizing spatial variability of soil through soil EC_a mapping sensor
- DSS for determination of soil properties
- Spatial distribution studies of soil properties using statistical and geostatistical techniques
- Discrimination of fields using EC_a values and classification algorithms
- Identification of AMUs / MZs based on EC_a values and comparison with yield zones
- Validation of zones using cluster indices (FPI/NCE)

4.1 Experimental site 1

A field experiment was conducted on wheat, cultivated in three different plots (P1, P2 and P3) during Kharif 2010, under loamy soil, at PAU, Ludhiana, India, located between 30°54'34.752"N, 75°49'6.281"E (top left side) and 30°54'33.103"N, 75°49'5.268"E (bottom right side) and situated at 242 m above the mean sea level (Datum WGS84). The region represents central agro-climatic zone of the state of Punjab. The climate is subtropical to tropical with a long dry season from late september to early june and a wet season from july to early september. The region receives maximum rainfall of about 700 mm during july-september and a few occasional showers during winter. The experiment was conducted in a split plot design and nitrogen fertilizer was applied in different amounts with variable rates of N1, N2, N3, N4 and N5, with an average dose of 68, 75, 125, 175, and 225 kg nitrogen/ha over a crop growth cycle. Wheat-cultivar (PBW-343, PBW-550, and DBW-17) were planted in three different plots P1, P2 and P3 respectively.

4.2 Soil sample collection

The sampling locations obtained from ESAP are in .txt format that were converted to GPS compatible file so that the locations can be traced in the field. The sample design obtained is converted to GPS waypoint file using GPS pathfinder software. From EC_a directed soil sample design, 12 sampling points for each part of field1 was designed and 20 sampling

points for field2 was designed (Fig.4.1). Similar method was used earlier by Corwin D.L. and Lesch S.M., [1], EC_a values and response surface sampling design software (ESAP v 2.0) was used for soil sampling.

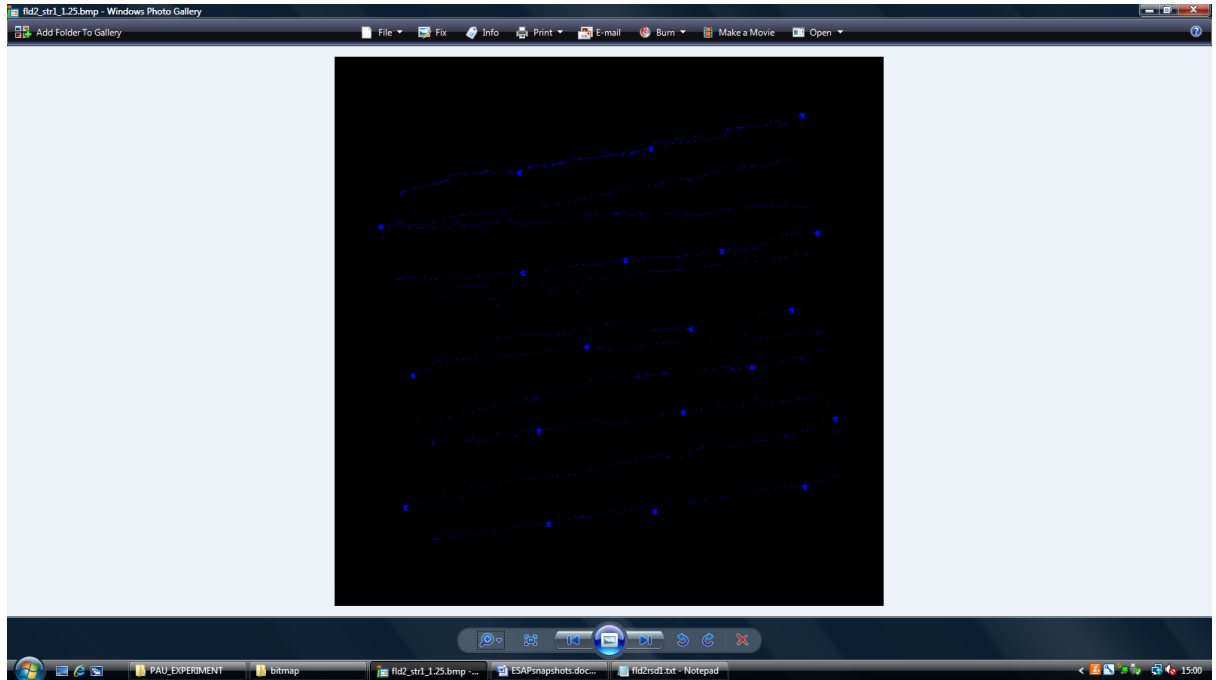


Fig.4.1: Sample output of sampling design using ESAP software

4.3 Exploratory analysis (Descriptive Statistical Analysis)

During the first phase of the geostatistical study, exploratory data analysis, data distribution, was done using classical descriptive statistics (Table 4.1). An increase in EC_a was observed in depth. Thus, EC_{a cv 0-0.5} averaged 21.70 mS m⁻¹ and the CV was 8.96%; EC_{a cv 0-1.0} averaged 22.90 mS m⁻¹ and the CV was 9.16%. CVs for soil properties indicated significant spatial variability and suggested the convenience of defining different MZs as well as interpolated spatial distribution maps. For all considered soil properties, the mean and median values were very similar which was indicative of data coming from a normal distribution. This was ratified by the fact that low skewness values were obtained, furthermore, most of the coefficients of kurtosis were close to 0. The skewness value is based on the size of the tails of a distribution and provides a measure of how likely the distribution will produce outliers.

Table 4.1: Statistical analysis of sampled soil (physico-chemical properties) and yield data

Sr. No.	Observed Variables	Mean	Median	Std Deviation	CV	Skewness	Kurtosis
1	EC _{a cv 0-1.0}	22.90	22.60	2.10	9.17	0.01	-0.57
2	EC _{a cv 0-0.5}	21.70	21.65	1.94	8.96	-0.14	-0.24
3	Soil Temp _{I.P.S.}	45.13	44.4	2.04	4.51	1.13	0.34
4	Soil Moist _{I.P.S.}	0.07	0.05	0.06	75.28	0.51	-0.91
5	Soil EC _{I.P.S.}	0.01	0.01	0.01	41.93	0.73	-0.34
6	Soil RD _{I.P.S.}	5.02	4.56	1.34	26.79	0.60	-0.59
7	pH _{H.S.}	6.31	6.38	0.62	9.86	-1.25	1.97
8	Soil Temp _{I.P.S. 2f}	35.53	34.6	1.71	4.82	1.01	-0.32
9	Soil Moist _{I.P.S. 2f}	0.018	0	0.04	214.61	2.26	4.38
10	Soil EC _{I.P.S. 2f}	0.01	0.01	0.01	83.48	1.51	2.59
11	Soil RD _{I.P.S 2f}	3.19	2.75	1.27	39.93	1.36	1.39
12	Soil pH _{H.S. 2f}	5.92	5.78	0.58	9.8719	0.32	0.79
13	pH _{L.A. 1f}	7.80	7.98	0.54	7.03	-1.75	2.33
14	pH _{L.A.2f}	7.97	8.08	0.33	4.17	-2.90	10.31
15	EC _{L.A.1f}	0.13	0.12	0.067	48.71	2.23	5.14
16	EC _{L.A.2f}	0.11	0.1	0.06	53.52	3.02	9.97
17	K kg/ha _{L.A. 1f}	98.66	96.32	17.98	18.23	0.64	0.16
18	K kg/ha _{L.A.2f}	97.51	95.2	21.80	22.36	0.68	0.21
19	P kg/ha _{L.A.1f}	37.23	29.43	17.96	48.26	1.29	0.98
20	P kg/ha _{L.A.2f}	29.64	26.64	14.60	49.27	3.04	9.99
21	Bio yield	3318.21	3483.11	1263.10	38.06	-0.55	-0.40
22	Grain yield	1431.17	1551.34	581.25	40.61	-0.54	-0.45

Thus, in this work, there were no outliers, which was significant in obtaining accurate estimation models. Although normality is not a prerequisite for kriging, it is a desirable property. Kriging will only generate the best absolute estimate if the random function fits a normal distribution [2].

4.4 Geostatistical analysis

Semivariograms were calculated for the soil EC_a variables at both depths, as well as for the other soil properties. Table 4.2 gives the details of following semivariogram parameters: nugget effect, sill, range, and model for the calculated semivariograms, in addition to structural component ($C0/C0+C1$), representing the amount of data variance which can be explained by spatial dependence [3], and error sum of squares values, which was the criterion adopted to select the best fit for each model. Similar fitting of best measures for optimal semivariogram models for different soil attributes is also reported by several authors [4-8].

Table 4.2: Semivariogram parameters for the sampled data

Observed variables	Nugget effect (C0)	Partial sill	Sill (C0+C1)	Range (a)	SSE	C0/C0+C1	Model
EC_a cv 0-1.0	0.29	5.10	5.40	22.34	8.785	0.95	Circular
EC_a cv 0-0.5	0.96	3.83	4.79	27.49	69.725	0.80	Stable
Soil Temp I.P.S.	3.37	0.99	4.35	0.00	137.295	0.23	Hole Effect
Soil Moist I.P.S.	0.00	0.00	0.00	0.00	0.14	0.39	Rational Quadratic
Soil EC I.P.S.	0.00	0.00	0.00	0.00	0.00	0.28	Exponential
Soil RD I.P.S.	1.04	0.83	1.87	0.00	85.83	0.45	Rational Quadratic
pH H.S.	0.28	0.12	0.39	0.00	24.03	0.29	Hole Effect
Soil Temp-I.P.S.2f	0.00	3.76	3.76	64.04	8.36	1	Exponential
Soil Moist-I.P.S.2f	0.00	0.01	0.01	2877716.11	0.06	0.92	Gaussian
Soil EC I.P.S. 2f	0.00	0.00	0.00	2877716.11	0.006	0.90	Gaussian
Soil RD I.P.S 2f	1.14	7.14	8.28	2877716.11	59.956	0.86	Gaussian
Soil pH H.S. 2f	0.25	0.39	0.64	2877716.11	9.956	0.61	Exponential
pH L.A. 2f	0.05	0.16	0.21	52.57	132.38	0.78	Gaussian
EC L.A. 1f	0.00	0.00	0.00	49.76	0.09	0.77	Exponential
EC L.A. 2f	0.00	0.00	0.00	54.60	0.10	0.76	Stable
K kg/ha L.A. 1f	303.30	36.41	339.71	17.21	171419.7	0.11	Spherical
K kg/ha L.A. 2f	376.94	246.99	623.93	53.17	54167.32	0.40	Gaussian
P kg/ha L.A. 1f	259.33	968.80	1228.13	2877716.11	12541.98	0.79	Gaussian
P kg/ha L.A. 2f	146.32	135.17	281.49	10.12	12048.09	0.48	Circular
Bio yield	492505.99	465667.11	958173.09	0.00	162794701.2	0.49	Rational Quadratic
Grain yield	79817.87	87491.92	167309.80	0.00	27969339.47	0.52	J-Bessel

Experimental variograms were computed to determine residuals. Theoretical models are selected to provide the best fit (Fig. 4.2). The choice of particular variogram model is dependent upon the expected spatial variability. Using OK finally spatial distribution maps were generated which estimated the values at unsampled locations showing spatial variability in smoothed contour maps (Fig.4.3). Variables like soil properties can be distributed unevenly in reduced distances and exponential or spherical models are the most suitable [3]. In this work, variograms showed a considerable nugget effect. It is a normal situation because soil properties variability can occur at a scale smaller than the minimum lag distance. The nugget effect can be reduced by considering closer samples, but usually it is costly and labour-intensive thus, less preferred. Moral et al., [8] studied variograms to characterize spatial distribution of physical properties of soil with respect to EC_a .

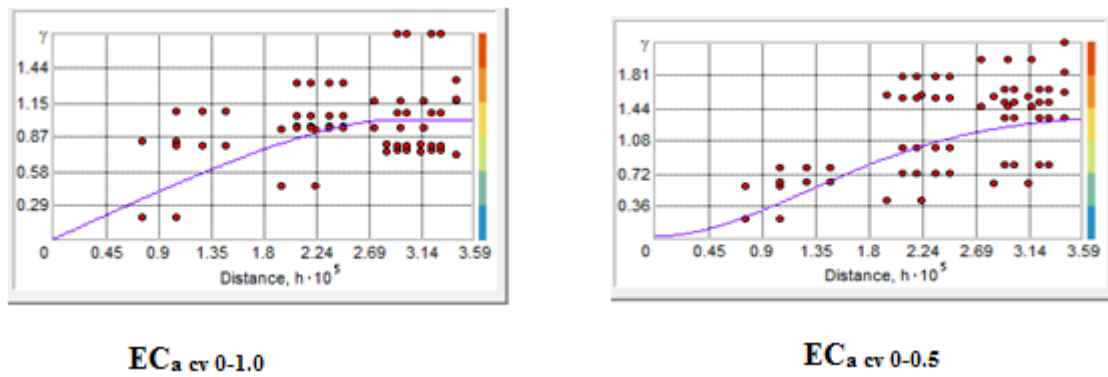
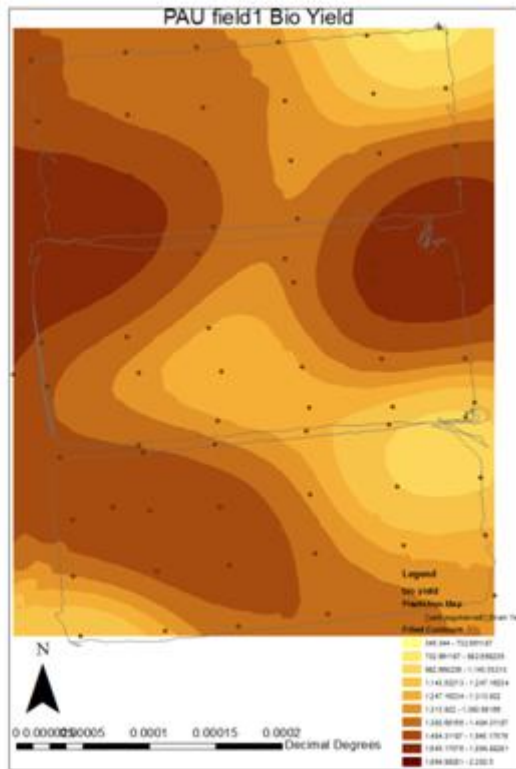
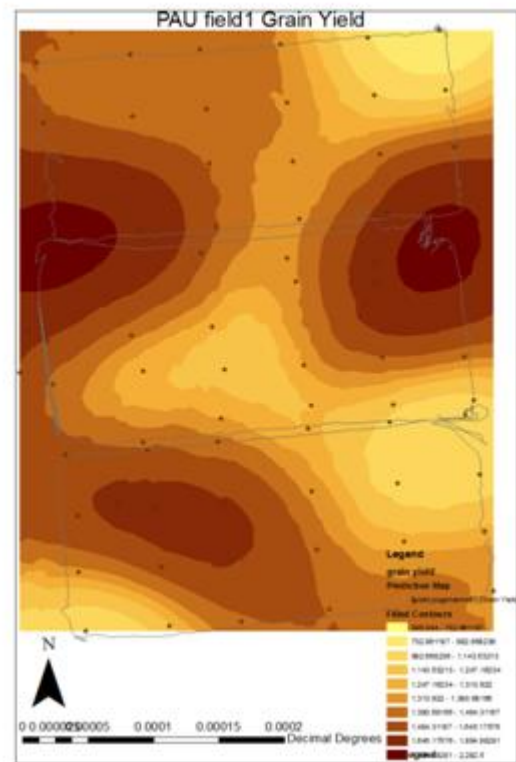


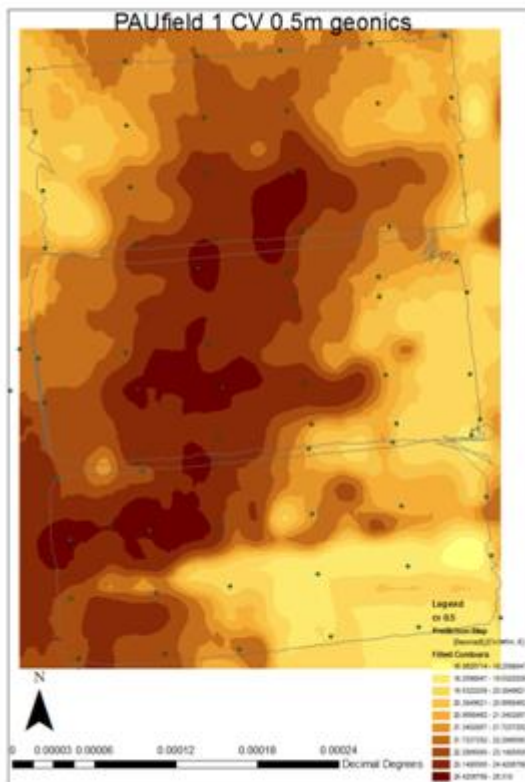
Fig.4.2: Semivariograms (theoretical, line; experimental, dots) for soil EC_a at different depths



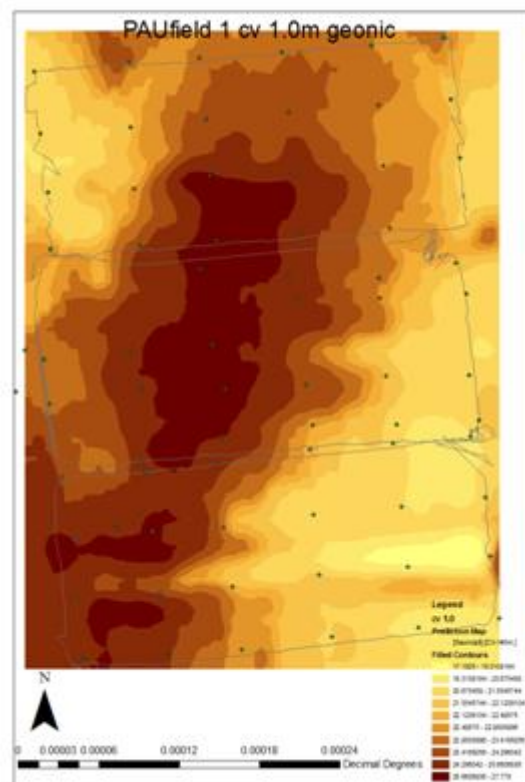
a)



b)



c)



d)

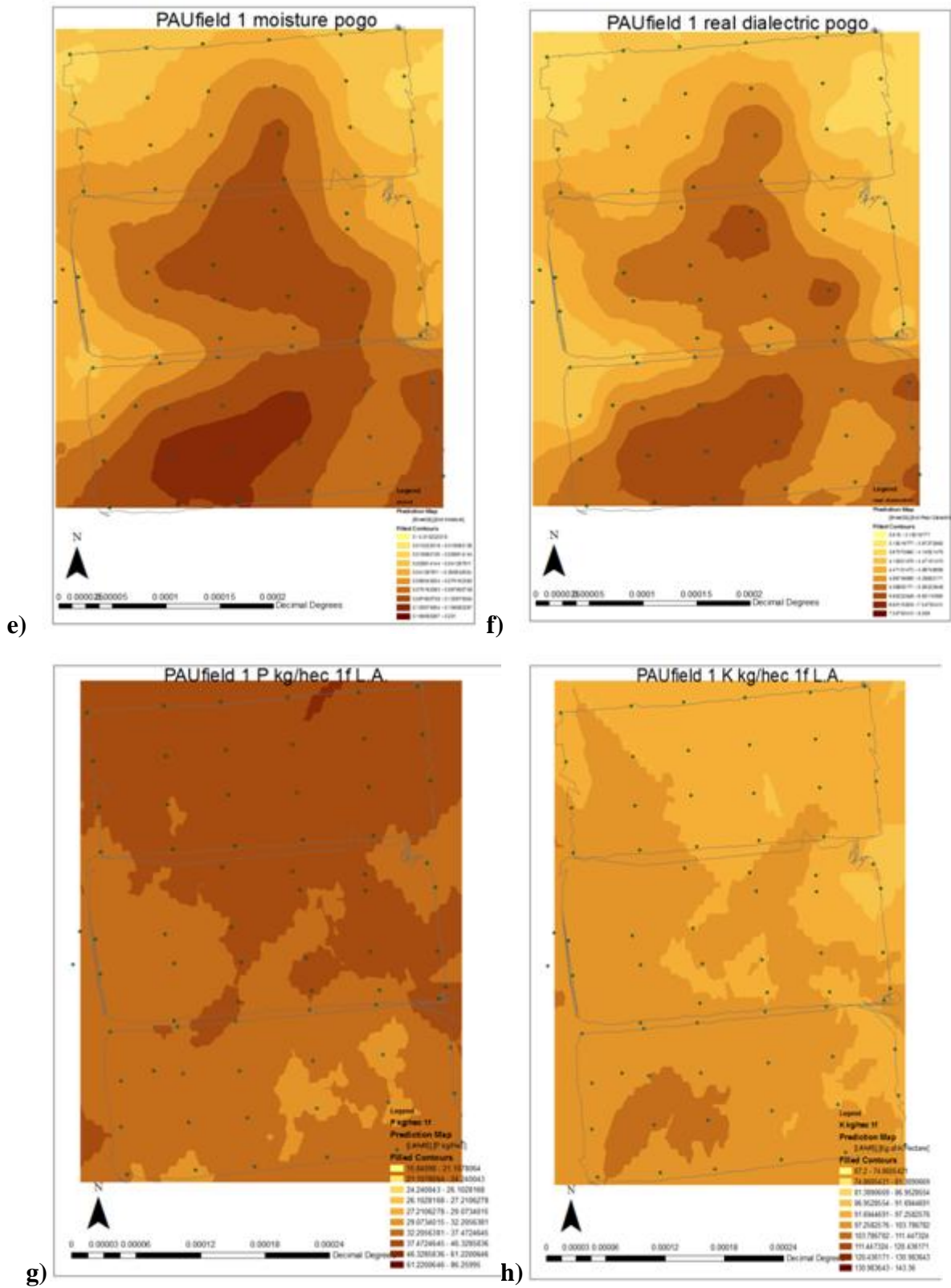


Fig.4.3 (a-h): Spatial variability contours of soil properties

Due to the exhaustive $EC_{a\ cv\ 0-0.5}$ and $EC_{a\ cv\ 0-1.0}$ data, structural analysis was more accurate for these soil properties. Theoretical stable model for $EC_{a\ cv\ 0-0.5}$ variable and circular model for $EC_{a\ cv\ 0-1.0}$ variable provided the best fit (Fig. 4.2).

Lower nugget values of 0.96 and 0.29 for $EC_{a\ cv\ 0-0.5}$ and $EC_{a\ cv\ 0-1.0}$ variograms were obtained respectively, with respect to the sill values, 4.79 and 5.40 for $EC_{a\ cv\ 0-0.5}$ and $EC_{a\ cv\ 0-1.0}$ variograms respectively. These values probably were consequence of the varying sampling density, and their sills were different because their variances were different as well (Table 4.2).

4.5 Correlation matrix between soil properties

In one of the interesting analysis of concern, soil properties were subjected to correlation analysis. Significant correlations were observed between soil properties, EC_a , and yield, as well as within soil properties (Table 4.3). Yield was positively correlated to $EC_{a\ cv\ 0-1.0}$, Soil Temp_{I.P.S.}, pH_{L.A. 2f}, pH_{L.A. 1f}, $EC_{L.A. 1f}$, P kg/Ha_{L.A. 2f}, K Kg/Ha_{L.A. 2f} and K Kg/Ha_{L.A. 1f} and negatively correlated to $EC_{a\ cv\ 0-0.5}$, Soil Moisture_{I.P.S.}, Soil Conductivity_{I.P.S.}, Soil Real Dielectric_{I.P.S.}, pH_{H.S.}, Soil Temp Celcius_{I.P.S. 2f}, Soil Moisture_{I.P.S. 2f}, Soil Conductivity_{I.P.S. 2f}, Soil Conductivity_{I.P.S. 2f}, Soil Real Dielectric_{I.P.S. 2f}, Soil pH_{H.S. 2f}, $EC_{L.A. 2f}$ and P kg/Ha_{L.A. 1f}. Strong positive correlations were observed between Soil Moisture_{I.P.S.} and Soil Conductivity_{I.P.S.} ($r = 0.97$).

Observed Variables	EC _a cv 0-1.0.	EC _a cv 0-0.5	Bio yield	Grain yield	Soil Temp I.P.S.	Soil Moist I.P.S.	Soil EC I.P.S.	Soil RD I.P.S.	pH H.S.	Soil Temp. I.P.S. 2f	Soil Moist. I.P.S. 2f	Soil EC I.P.S. 2f	Soil RD I.P.S 2f	Soil pH H.S. 2f	pH L.A. 2f	EC L.A. 2f	pH L.A. 1f	EC L.A. 1f	P kg/ha L.A. 2f	K kg/ha L.A. 2f	P kg/ha L.A 1f	K kg/ha L.A. 1f
EC _a cv 0-1.0	1																					
EC _a cv 0-0.5	0.89	1																				
Bio yield	0.05	-0.10	1																			
Grain yield	0.03	-0.10	0.99	1																		
Soil Temp I.P.S.	0.60	0.52	0.29	0.26	1																	
Soil Moist I.P.S.	0.38	0.21	-0.14	-0.16	0.16	1																
Soil EC I.P.S.	0.41	0.22	-0.18	-0.20	0.18	0.97	1															
Soil RD I.P.S.	0.35	0.17	-0.16	-0.18	0.12	1.0	0.97	1														
pH H.S.	-0.09	-0.21	-0.26	-0.26	-0.02	0.05	0.05	0.06	1													
Soil Temp. I.P.S. 2f	-0.60	-0.42	-0.09	-0.20	-0.46	-0.35	-0.34	-0.34	0.48	1												
Soil Moist. I.P.S. 2f	-0.01	-0.15	-0.17	-0.17	0.08	0.01	0.05	0.01	0.23	0.15	1											
Soil EC I.P.S. 2f	0.08	-0.00	-0.10	-0.11	0.16	-0.01	0.01	-0.02	0.09	0.06	0.90	1										
Soil RD I.P.S 2f	0.06	-0.02	-0.14	-0.14	0.14	0.05	0.08	0.05	0.16	0.11	0.93	0.94	1									
Soil pH H.S. 2f	-0.16	-0.20	-0.05	-0.07	-0.14	-0.02	-0.06	-0.03	-0.24	0.03	-0.45	-0.43	-0.45	1								
pH L.A. 2f	0.42	0.20	0.01	0.08	0.28	0.30	0.31	0.29	-0.37	-0.65	0.09	0.25	0.15	0.08	1							
EC L.A. 2f	-0.40	-0.21	-0.14	-0.17	-0.10	-0.16	-0.22	-0.16	0.36	0.56	-0.06	-0.20	-0.08	0.00	-0.85	1						
pH L.A. 1f	0.41	0.21	0.04	0.11	0.44	0.12	0.15	0.10	-0.16	-0.55	0.14	0.13	0.05	-0.34	0.29	-0.35	1					
EC L.A. 1f	-0.39	-0.32	0.25	0.16	-0.41	-0.16	-0.18	-0.15	0.06	0.49	-0.02	0.05	0.01	0.15	-0.18	0.11	-0.67	1				
P kg/ha L.A. 2f	0.20	0.16	0.14	0.10	0.20	-0.10	-0.08	-0.11	0.01	0.06	-0.03	0.06	0.03	-0.04	0.01	-0.17	0.02	-0.02	1			
K kg/ha L.A. 2f	-0.12	-0.15	0.22	0.17	-0.26	0.25	0.21	0.26	0.04	0.13	-0.17	-0.24	-0.20	-0.05	-0.43	0.39	-0.08	0.07	-0.25	1		
P kg/ha L.A. 1f	-0.18	-0.04	-0.37	-0.43	0.13	-0.22	-0.11	-0.21	0.10	0.40	0.30	0.30	0.31	-0.14	-0.27	0.21	-0.16	-0.03	0.20	-0.02	1	
K kg/ha L.A. 1f	0.18	0.07	0.07	0.10	0.14	0.40	0.43	0.42	-0.11	-0.19	0.11	0.13	0.26	-0.01	0.02	0.08	0.08	0.03	0.11	0.09	-0.08	1

Table 4.3: Correlation matrix between soil physico-chemical properties

4.6 PCA and cluster analysis of EC_a, crop yield, and variable soil n-rate

The PCA scores plot was studied for EC_a, crop yield, and variable soil N-rate (five levels, n1, n2, n3, n4, n5). The scores plot is a map of samples, which shows how they are distributed. It can be used to isolate samples that are similar, or dissimilar to each other. The following inferences were drawn in the present study:

Inference 1: By using information about yield, EC_a and variable n-rate applied in different parts of field, the following observations were derived (Fig. 4.4a and 4.4b):

- a) It is evident from PCA score plot that the properties of part1 and part3 show greater similarities as compared to that of part 2 since they lie close to each other in scores plot.
- b) It can also be studied from the correlation loading plot (Fig.4.4 (b)) that EC_a measurements at two different inter-coil spacing configuration (vertical mode (CV) *i.e.* CV-0.5m and CV-1.0m) represents different regions of subsoil spatial variability. This may be of relevance while understanding soil profile at different crop root zones while deciding type of crop production.
- c) Part2 showed the highest yield, and EC_a at 75cm depth range (CV-0.5m) has also shown increment in same direction. This is because values obtained for 0-75 cm depth range represent the region which is mainly dominated by clayey soil and partially sand, where EM fields are confined to show good conductivity in this region.
- d) In field1 grain yield was significantly linear with applied variable nutrient rate until it reached its threshold value of 'N5' rate.

Above inferences were supported by PCA plot studies between geonics measured field scale variations represented by EC_a and the yield information [Fig.4.4 (a) and Fig.4.4 (b)]

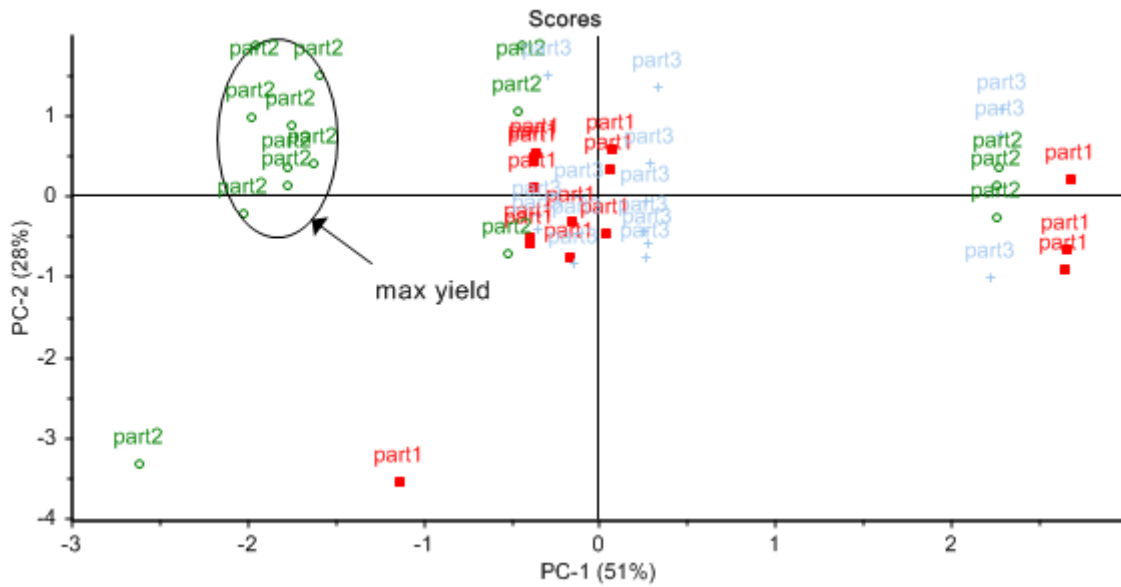


Fig.4.4 (a)

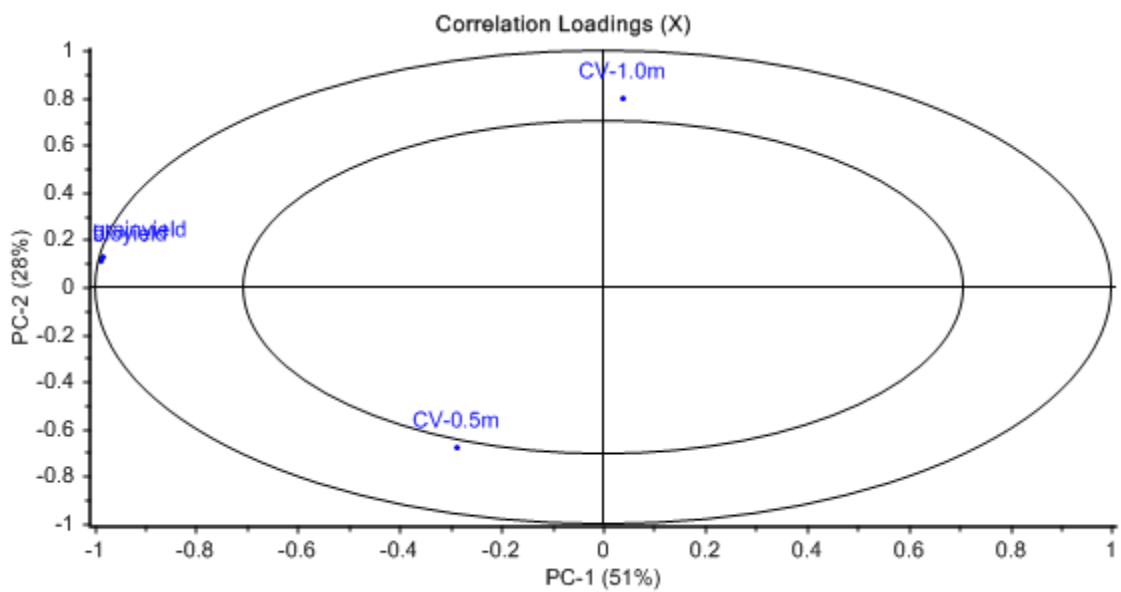


Fig.4.4 (b)

Fig.4.4 (a) & (b): PCA score and loading plot analysis using EC_a and yield information with N- rate

Inference 2: The PCA plot between the nitrogen rates applied and crop yield information for field1, helped in finding threshold values of nitrogen to be applied within individual parts of field1 to ascertain maximum yield. This level of interpretation, with the currently available information, further enabled monitoring of variable nitrogen rate control for a specific crop and field location. Below are the point-wise observations noted for individual parts of field1

derived from spatial EC_a variations through PCA analysis considering nutrients and crop yield variability.

- a) The crop yield was found to be increasing with the amount of nitrogen (**Fig.4.5 (a) and Fig.4.5 (b)**) in **part1**, but on increasing nutrient-rate beyond a specific threshold (N4), the crop yield has shown downward trend in this part. That means when the supply and the requirement match, any further increase in N-rate does not account for crop yield productivity growth. Therefore, EC_a based tracking of N-rate and yield trends through CA can help agronomist undertake customised nutrient management program on site-specific basis.

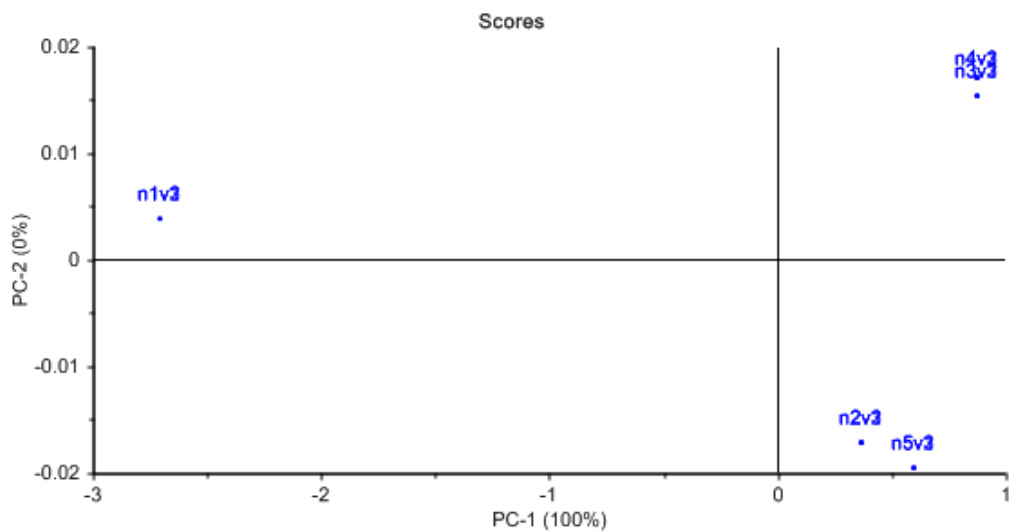


Fig. 4.5(a)

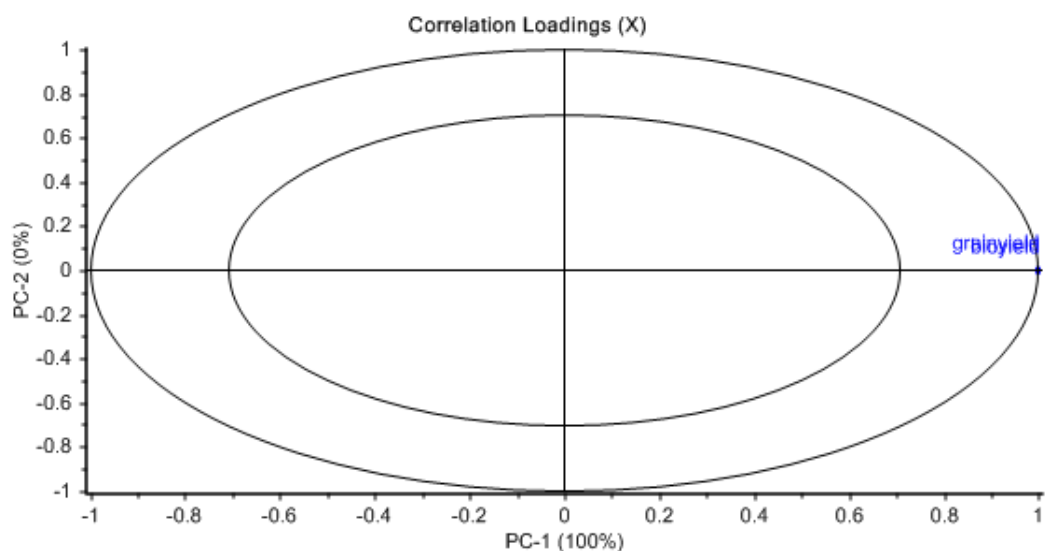


Fig. 4.5 (b)

Fig. 4.5(a) & (b): Analysis of variable N-rate and yield response for part1 of field1

b) A similar trend having increased crop yield with the increase in nutrient rate was again observed in **part2** which continued till N5 nutrient rate of application.

Similarly, crop yield increases with increase in amount of nitrogen rate in **part3** and decreases after threshold of N4. Similar trend was observed in case of **part1**.

Furthermore, on sample grouping with respect to crop varieties for all plots, crop varieties show similar effect for variable nutrient rate. One of the scatter plot analysis revealed similar results when plotted between *yield* versus EC_a and observed with respect to applied *nutrient rate grouping* [Fig.4.5 (c), Fig.4.5 (d) for part1] and [Fig.4.5 (e) for part2]. In these scatter plot analyzes, it was again clear that after N4 rate, there is no proportionate increase in crop yield, indicating over dosage done by N5 rate, which could have been avoided saving fertilizers and cost.

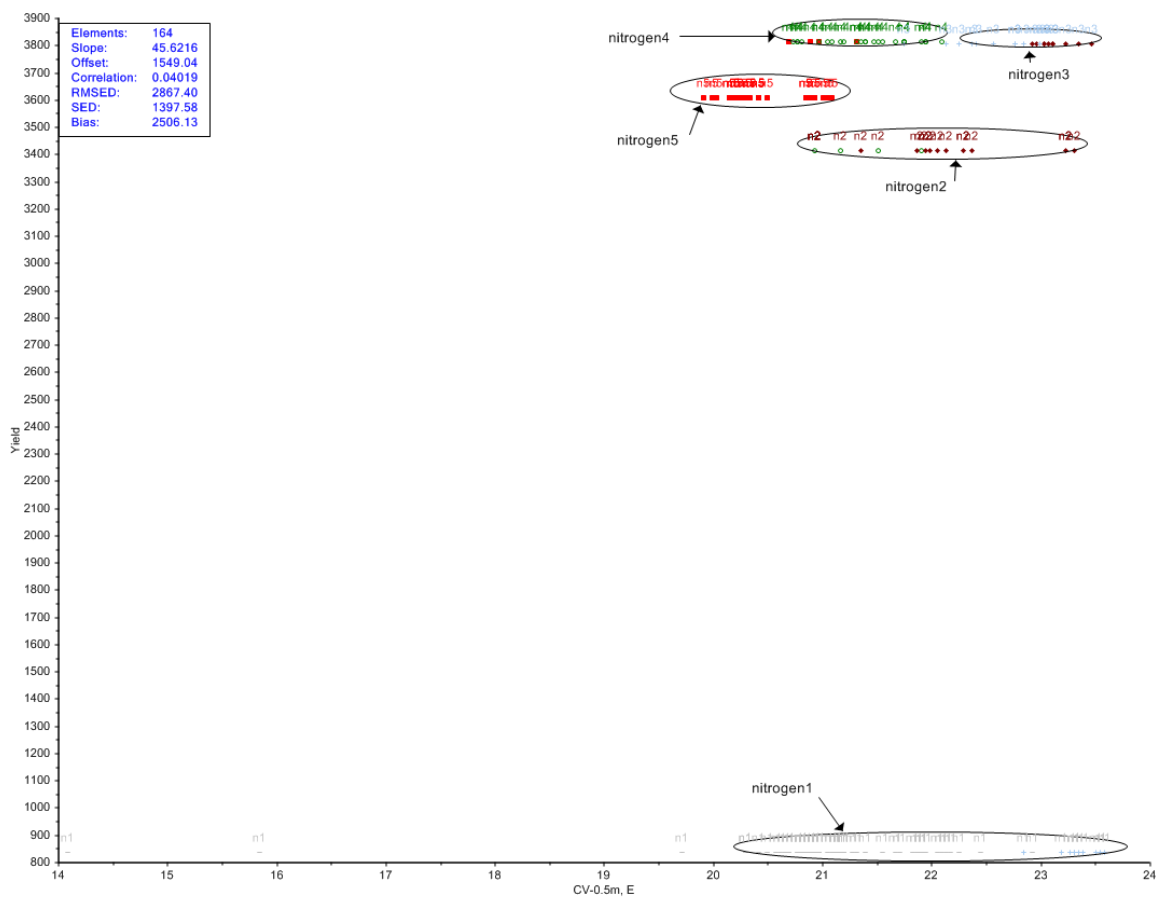


Fig. 4.5(c)

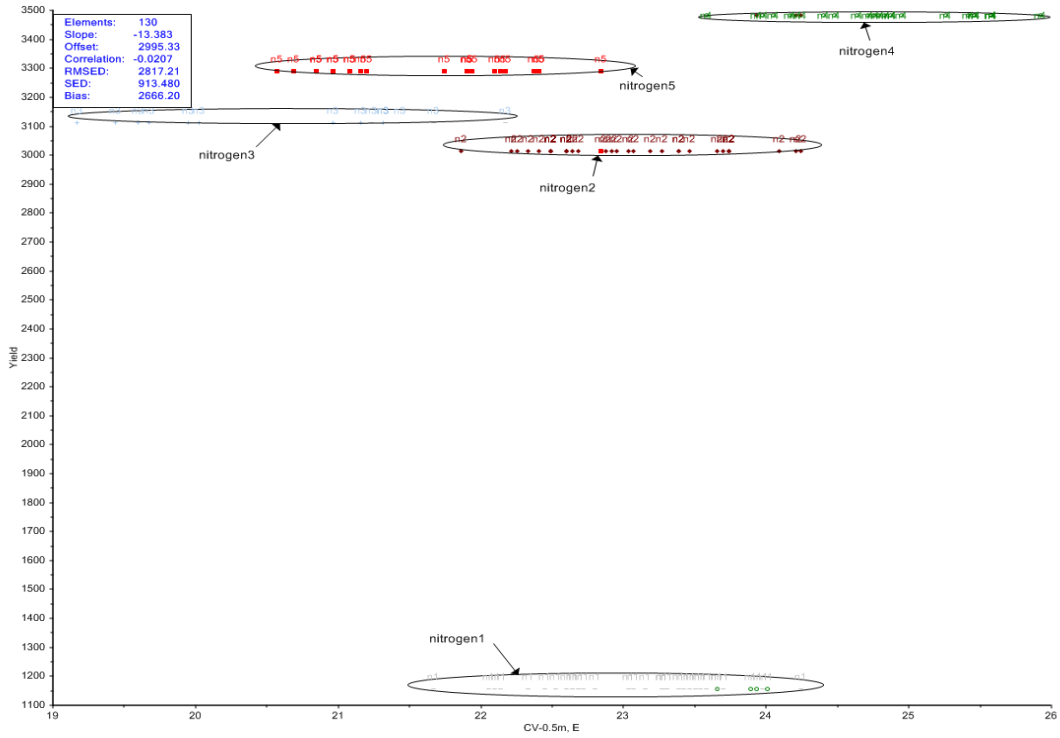


Fig.4.5 (d)

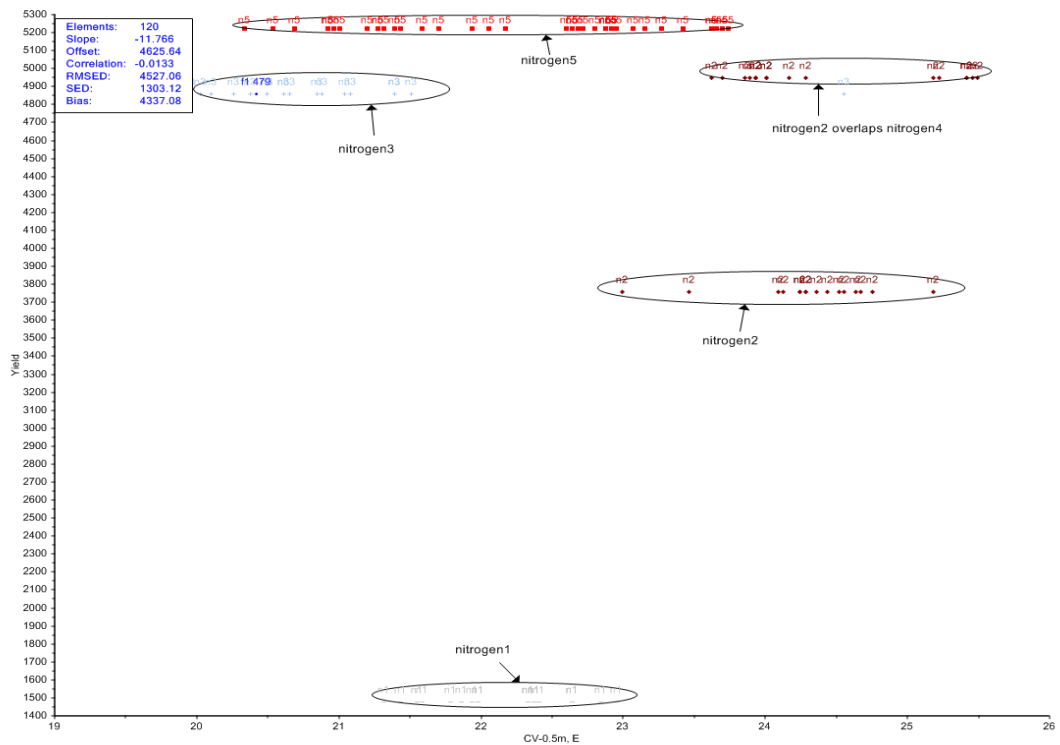


Fig.4.5 (e)

Fig.4.5 (c), Fig.4.5 (d) and Fig.4.5 (e): Yield Vs. EC_a scatter plot with n-rate grouping

The scatter plot analysis indicated that for each variable nutrient rate, specific cluster of crop potential is exhibited. These similar crop potential cluster movements can be easily tracked by the representative EC_a mapping. While systematically monitoring EC_a cluster movement, it was observed that nutrient rate management can become feasible approach using modern systems comprising of sensor measurements followed by software analysis [Fig 4.5(c), (d), (e)].

Inference 3: The field scale measured EC_a data was also studied to find variations in different zones based on the amount of nutrients applied. In total, five different quantities of nutrients namely N1, N2, N3, N4 and N5 were applied on the field1. It was attempted to determine the effect of nutrients on conductivity as well as yield response apart from classification of spatially different regions based on soil EC_a variability.

The PCA model of first variety of crop (V1), based on spatially geo-referenced EC_a measurements has shown that nitrogen amounts of N1 and N3 have the highest conductivities and are creating clusters with respect to these specific nutrient rates applied. The scores plot has clearly shown the creation of clusters i.e. homogenous zones with respect to different nitrogen rates applied. Applied nutrient rates can be seen moving towards PC1 and PC2 which explains 59% and 34% information whereas, yield is increasing towards PC2 vector, till N4 – rate its increasing. This has been confirmed by the conductivity based scores plot (Fig.4.6 (a) and Fig.4.6 (b)).

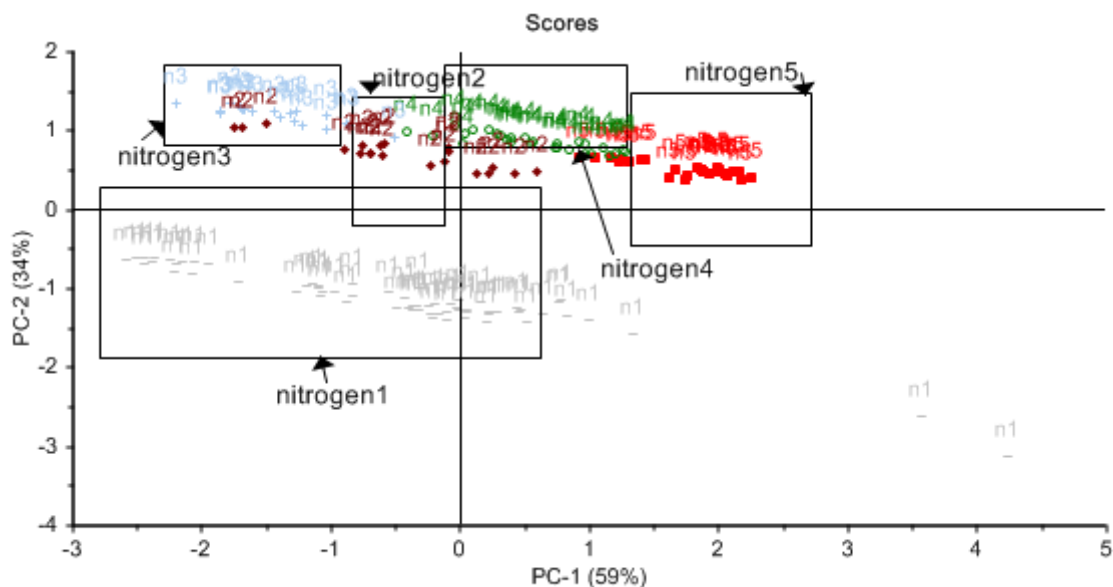


Fig.4.6 (a)

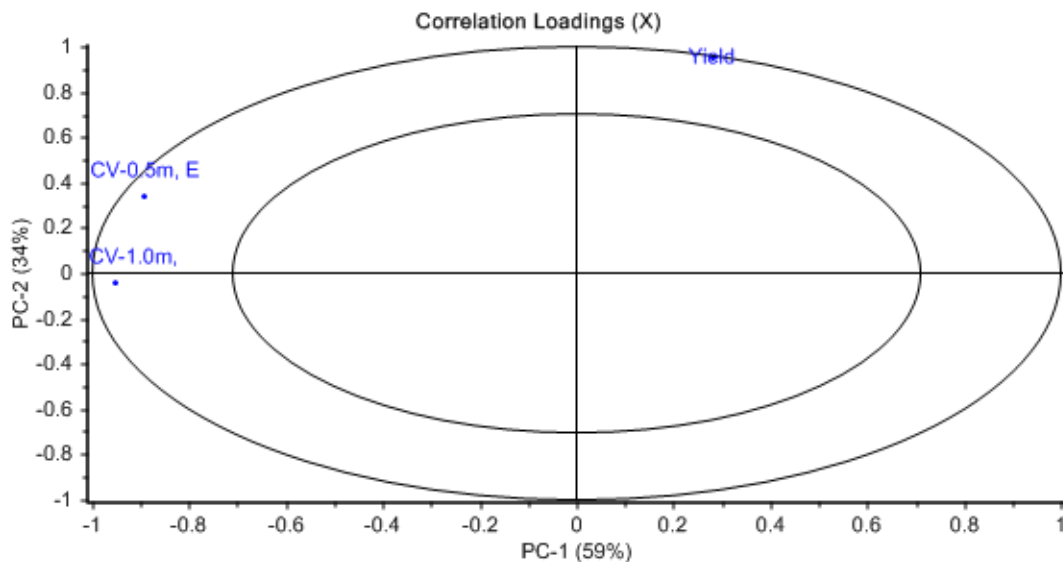


Fig. 4.6(b)

Fig.4.6 (a) & (b): PCA analysis of EC_a , nutrient rate and yield for crop variety V1

The PCA model, for second variety of crop (V2), based on EC_a , has shown that nitrogen amount N2 has the highest conductivity.

Similarly, PCA model for third variety of crop (V3) had shown that nitrogen amount N4 has the highest conductivity; the same is confirmed by plot.

While analysing PCA model for all three varieties, it was found that N5 has shown agreement with highest yield trend and it increases towards right hand side of loading plot in the vertical direction. This helped to understand that EC_a based measurements are able to discriminate five different clusters that were applied with five different N-rates, resulting in five variations in crop yield. Besides above observations, scores plot has shown cluster formations in remaining cases of variable n-rates application over entire field.

Referring graphical representation of PCA analysis, for all three varieties of paddy, based on spatial measurement of soil EC_a data for two soil depths i.e 0-75 cm and 0-150 cm, it can be observed that each variable rate has separate cluster as shown in scores plot. It suggests that variable rate of nutrients can be classified, managed and monitored using bulk conductivity mapping. While observing score plots for all three varieties, it was found that different clusters of conductivity belong to specific crop yield response, that means yield cluster found matching EC_a response characteristics associated with it. Hence, variable soil input rate can be customised and monitored in conjunction with EC_a measurements and cluster analysis.

Further, it was analysed that increase in input rate such as N4 and N5 has indicated distinct cluster patterns indicating highest crop yield irrespective of crop variety.

Inference 4: In case of cluster analysis in field1 using EC_a and yield data, it exhibits similar number of cluster distribution for crop yield variability [Fig. 4.7 (b)] and EC_a values considering measurements in the same regions [Fig. 4.7 (a)].

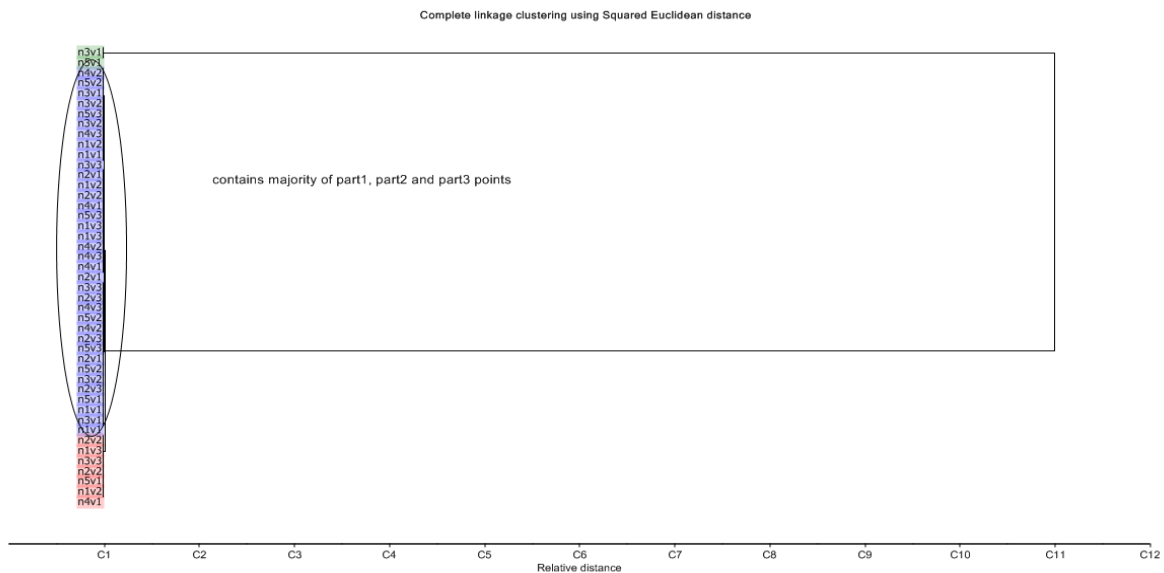


Fig. 4.7(a)

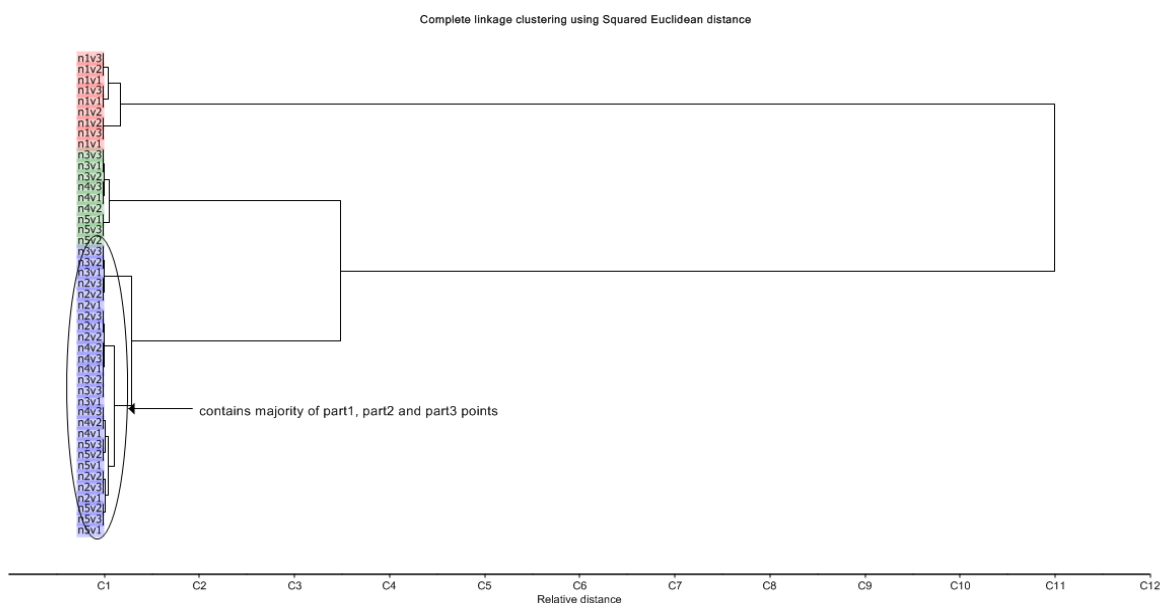


Fig. 4.7(b)

Fig.4.7 (a) & (b): Spatial variability investigations with HCA to identify matching classes (EC_a and crop yield data)
 From HCA, it is evident that the segment of part1, part2 and part3 of field1 contributes major portions of cluster classes with a clear discrimination while identifying the homogeneity

within these parts. These different cluster zones, exhibit cohesion within them i.e. having similar soil properties thus, productivity potential, and hence can be given a similar soil input treatment governed by site-specific CMP of interest. A summary of analysis of grid cells depicting matching crop yield grids to that of EC_a data clusters is shown in Fig.4.7 (c). However, it is visible that they are distributed in two distinct classes i.e. part 1 and part 3 as one class, whereas part 2 representing separate class.

Analysis of geonics data and yield data is represented in Fig.4.7 (c), red coloured grid cells indicates best matching patterns in agreement. Similar results were observed by Stafford *et al.* [9] using fuzzy clustering of combine yield monitor data to divide a field into potential MZs. In present studies results show that majority of the grids fall into the homogenous zones and show matching patterns with EC_a measurements explaining good percentage of associated yield variability. This was quite significant and encouraging knowing that there are many more factors other than spatial variations which influence crop productivity. This pattern matching helps to interpret crop-yield response which then can govern specific variable soil input rate control depending on site specific crop yield productivity potential of interest.

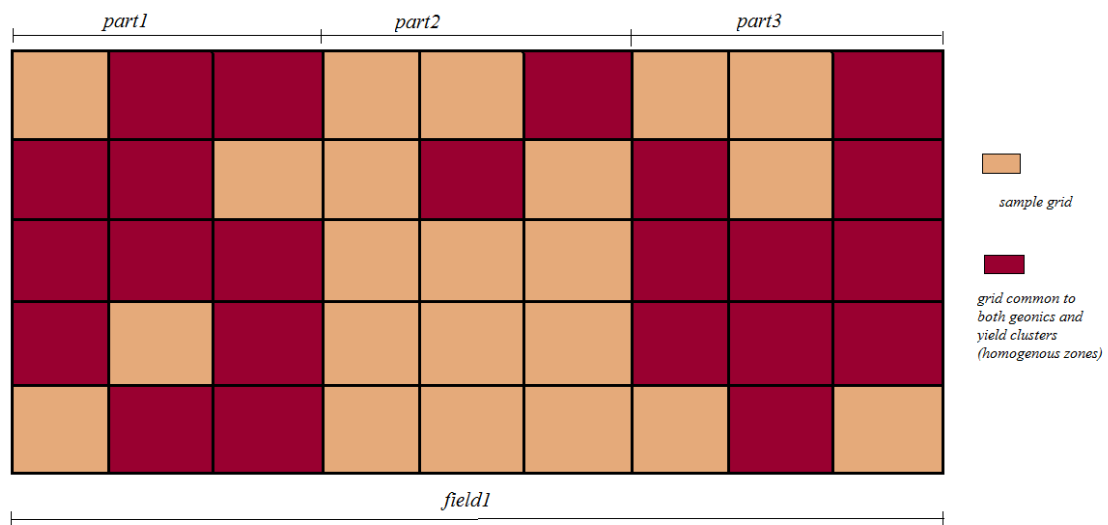


Fig. 4.7(c): Matching patterns of EC_a data with that of yield data in field1

Thus, it was found that on-the-go; field-scale measured data of EC_a has shown encouraging interpretations associated with site-specific crop yield patterns in some parts of the field and therefore, can be considered as a surrogate measurement for field-specific crop yield response predictions.

Inference 5: Further, scatter plots and groupings of variables are becoming increasingly common for PF service providers to observe similarity and regression correlation within

paired data. When this is applied to geo-referenced EC_a and yield data sets in present case, and plotted with respect to latitude and longitude, typical matching patterns were observed (Fig.4.8).

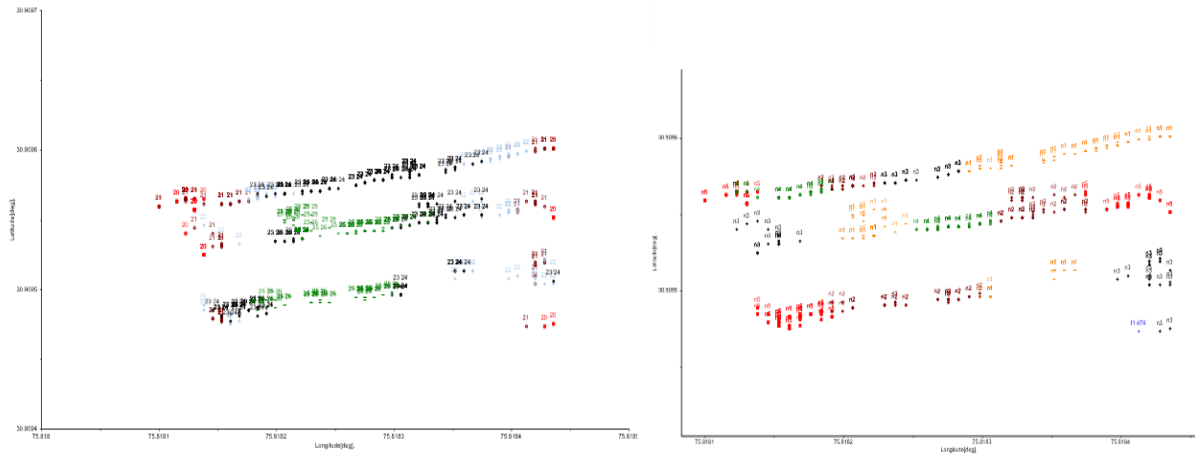


Fig.4.8: Typical pattern plot of soil EC and yield in agreement

Inference 6: The geonics measured EC_a data was also used to differentiate amongst three fields in order to observe any natural clusters so as to treat and govern management zone with variable soil input rates between two fields. Following are the inferences drawn, when all fields were analysed together using PCA.

- a) Cluster formations have been observed for each field in the PCA scores plot. The observed clusters can be seen (Fig.4.9 (a)) that are differentiated by colouring scheme that corresponds to different fields as follows:

Red: field1, Green: field2, Blue: field3

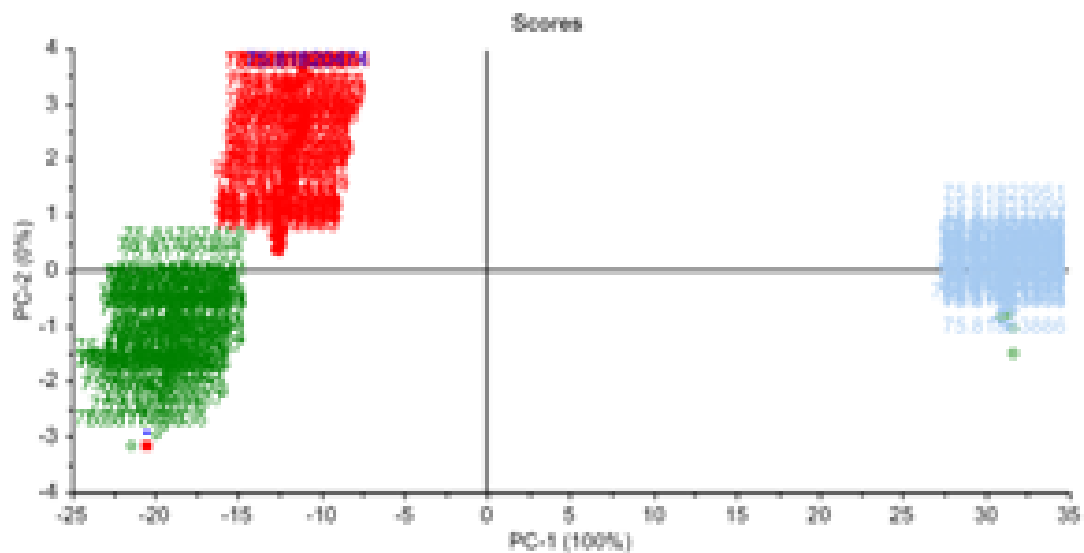


Fig. 4.9(a)

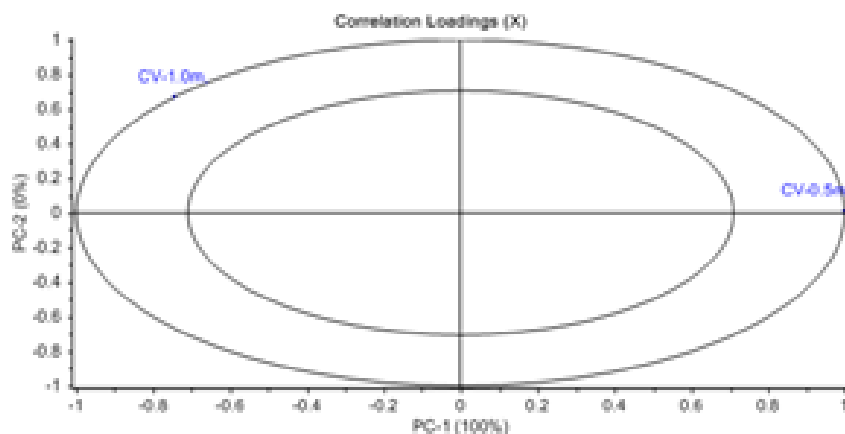


Fig. 4.9(b)

Fig.4.9 (a) and (b): PCA analysis of combined three fields to observe classification of zones based on EC_a

Sample grouping was carried out with respect to field EC_a ranges; Principal Component (PC) 1 of measured data set explained 100% variance of the soil data in the selected fields. This knowledge of cluster formation was used to represent customized zones which can be treated with specific soil input rates to produce bio-eco farming returns. It was also seen through lab analyzed data that field 1 and field 2, which are close to each other in scores plot are having nearly similar soil texture characteristics compared to field 3, which is clearly discriminated as a separate cluster.

- b) In Fig.4.9 (a), it has been observed that the properties of field 1 and field 2 are similar to some extent as compared to that of field 3 cluster.
- c) The study of loadings plot (Fig.4.9 (b)) reveals that conductivities measured at two depths lie on the outer ellipse and hence is responsible to explain maximum variance of the field. But, they do not exhibit a strong positive correlation and are at two extreme ends with each other meaning that they represent two different sub-soil spatial variability at two different depths covering different sub-soil volumes, hence it becomes necessary to measure the conductivities at both the depths to investigate soil depth characterization at two depths covering different volumes and sub-soil characteristics. The characterization of specific root-zone depth is of interest in case of crop-yield response studies, to understand crop specific rooting zone properties on a site-specific manner.
- d) A comparative study of scores plot and the loadings plot {Fig.4.9 (a) and Fig.4.9 (b)} explains that the significant soil attribute for describing the characteristics of field 1 and field 2 is apparent conductivity mapped for (0-150 cm) depth, while that of field 3 is conductivity for (0-75 cm) depth. This suggests that for field 3, the soil spatial variability is better explained and sub-soil spatial characteristic is positively correlated with EC_a measurements for (0-75 cm) depth, whereas in case of fields 1 and 2, the conductivity measurement for (0-150 cm) is more meaningful to govern further investigations.

It was also observed (Fig.4.10) with the help of correlation loadings plot that conductivity measured for (0-75) cm is significant in explaining the variability of crop yield as compared to EC_a measured for (0-150) cm.

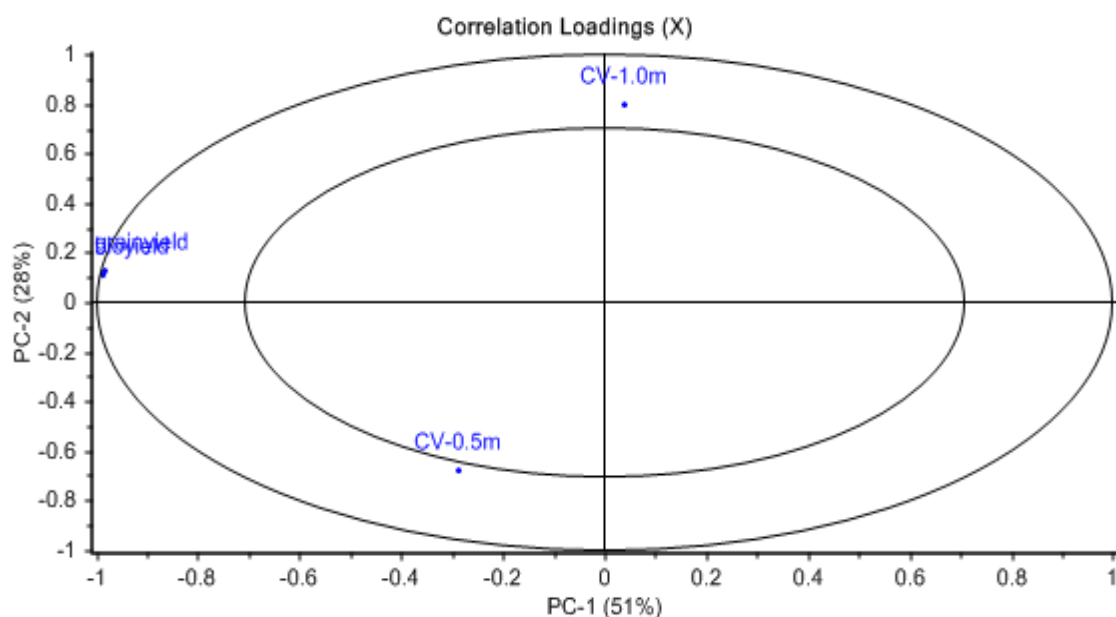


Fig.4.10: Correlation loading plot to study EC_a measured at different depths with crop yield

4.7 Delineation of MUs / MZs using PCA

Despite of conducting number of analyses, to manage variable-rate input efficiently, effectively and economically, definition of AMUs/MZs is the ultimate step in the area of PF concept. Because of the continuous nature of soil data, classification systems that allow any one observation to belong to exactly one class are often inappropriate. Therefore, Fuzzy or continuous classification procedures was adopted to analyse delineation of AMUs/MZs.

Further, considering that the information used to delineate sub-field regions, management units (MU), is related, and such identified intra-field regions are homogenous in nature, principle component analysis (PCA) was applied to summarize the effect and take care of collinearity.

The variance observed in the soil data after applying PCA is shown (Table 4.4.). This output of PCA was applied FCM algorithm to obtain the separate clusters (Fig. 4.11), MZs. It can be seen that we get two clusters whereas; third cluster is overlapped due to shared properties of other two.

Table 4.4: Cumulative variance of soil properties obtained by PCA

Principle Component	Variance Cumulative
1	0.6612
1-2	0.9393
1-3	1.0000
1-4	1.0000
1-5	1.0000

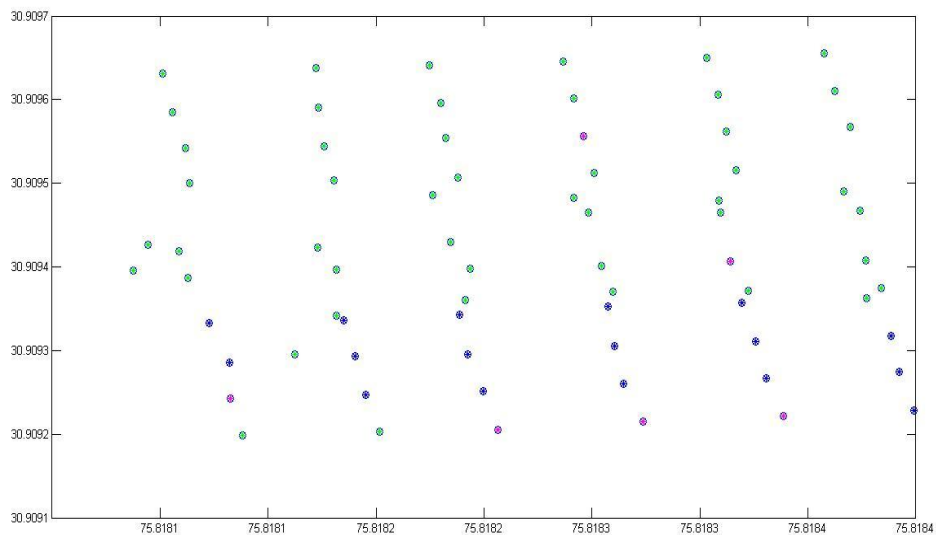


Fig.4.11: FCM output using MATLAB software

Finally, FCM technique was imposed to identify most optimal zones whose performance was verified using FPI and NCE indices. It was found that the strong cohesion clusters (minimal membership sharing) was obtained at three zones (FPI and NCE minimizes at three). Least value of indices at three indicates best data organization (homogeneous soil characteristics) within cluster and sharing of common characteristics i.e. least sharing weights within intra-regions whereas, most dissimilar between two zones. Further, the optimal PC's applied with FCM were displayed in ArcView procedures (Fig. 4.12) using OK interpolation (Semivariogram Model is exponential, lags are set to 7, the neighbours to include are set to 5).

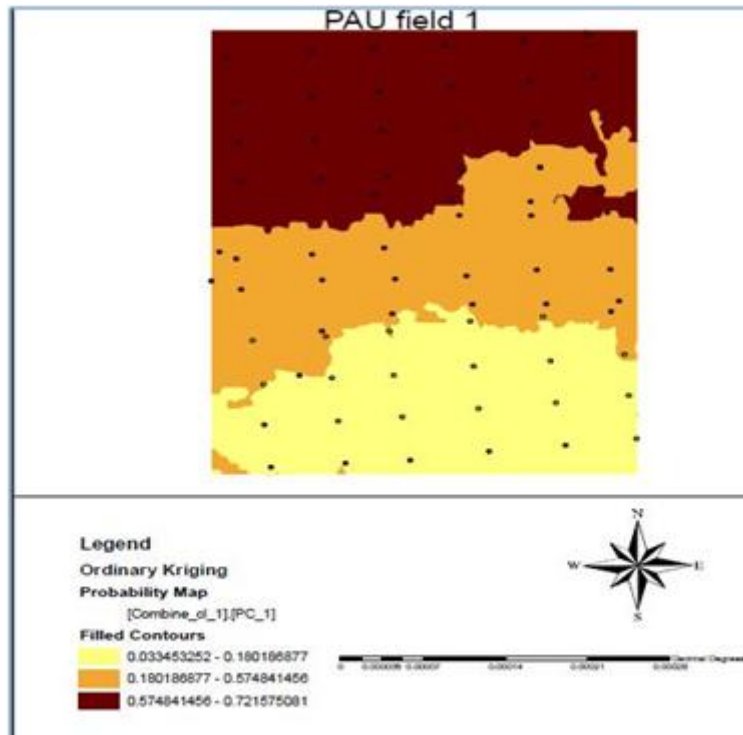


Fig. 4.12: Agronomic Management Units (AMUs) / MZs

4.7.1 Performance measure of optimal zones (FPI and NCE)

Two cluster validity functions, FPI and the NCE were used to determine the optimal number of MZs. The optimal number of cluster classes (management zones) was then defined as the number at which these two indices reach their minimum value [10]. The FPI and NCE are measure of membership / amount of disorganization, whose value is constrained between 0 and 1. Plotting the values of FPI and NCE against the number of classes and choosing a classification that minimizes both measures was the procedure used in determining the optimum number of classes. FPI and NCE indices (Fig 4.13) reached a minimum value for a division of the area into three classes (three management zones), indicating that this is the optimal number of soil MZs based on the sampled variables.

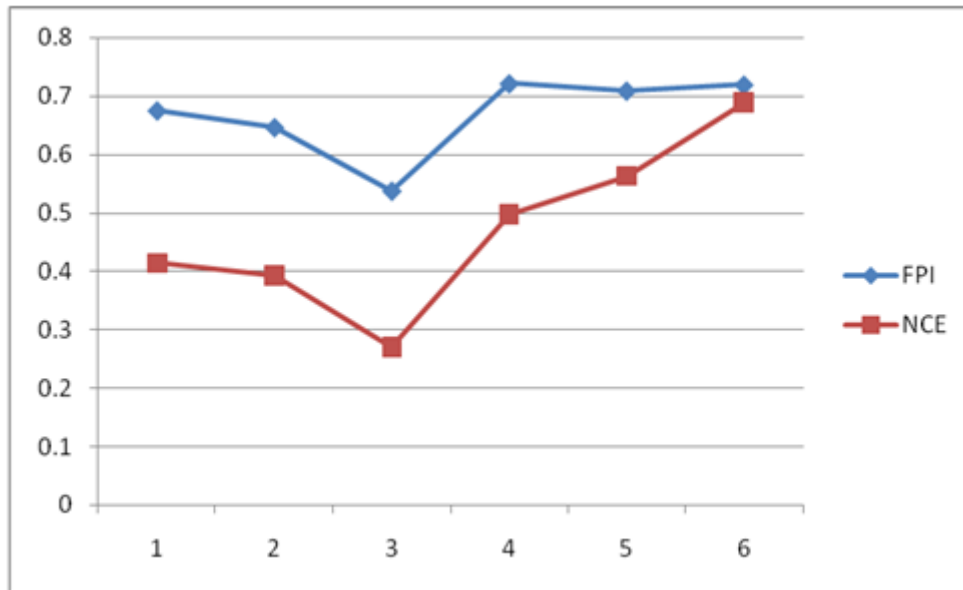


Fig.4.13: Optimal number of cluster, validation index, FPI and NCE

Based on the knowledge gained and procedures established in PAU research fields, spatial variability studies were further carried out on other additional site and geographical region (Chandigarh, UT, India). The objective of conducting experiments on this field was to study the spatial distribution of soil properties and delineate zones using several more number of physico-chemical properties of soil. Implementation of multivariate geostatistics to relate few more important soil variables using EC_a as auxiliary variable considering spatial dependence of primary soil attributes for generating improved spatial distribution maps of soil variability was also envisaged. This helped us to identify possible zones based on spatial variations available in the studied field which is the primary stage for implementing PF concept. These studies were undertaken so that in next cropping season, variable-rate application of inputs will be carried out, decreasing fertilization in the less productive area (low EC_a) and minimizing the application of chemical substances as a strategy to obtain a more cost-effective quantity and quality of the yield. In the long term, further studies can be conducted to establish agronomic significance of these zones with respect to yield recorded on yearly basis.

Introduction

In this section the work done on sensor test field of CSIR-Central Scientific Instruments Organization, Sector-30C, Chandigarh under PF studies has been discussed with following objectives:

- Characterizing spatial variability of soil through soil EC_a mapping sensor
- Directed soil sampling using centroid matrix (FCM) technique for the determination of soil properties
- Spatial distribution studies of soil physico-chemical properties using statistical and geostatistical techniques especially MVR geostatistics
- Identification of AMUs / MZs using EC_a values, PCA and FCM algorithm and comparison with fertility attributes
- Performance evaluation of delineated zones by cluster indices (FPI/NCE)

4.8 Experimental site 2

The survey was conducted in the PF test fields located at CSIR-CSIO, Chandigarh (UT), India, during Jan to March, 2012 under loamy soil. The soils are pale brown in color. Field provides two different topographies, one with high elevation and other as low lying. The boundary and geo-graphic location of the test site (Top left: 30° 42' 59.9508" N, 76° 46' 56.5746" E; Top right: 30° 43' 1.2138" N, 76° 46' 59.0262" E; Bottom left: 30° 42' 57.3834" N, 76° 46' 58.332" E; Bottom right: 30° 42' 59.2416" N, 76° 47' 0.798" E) is shown (Fig.4.14).

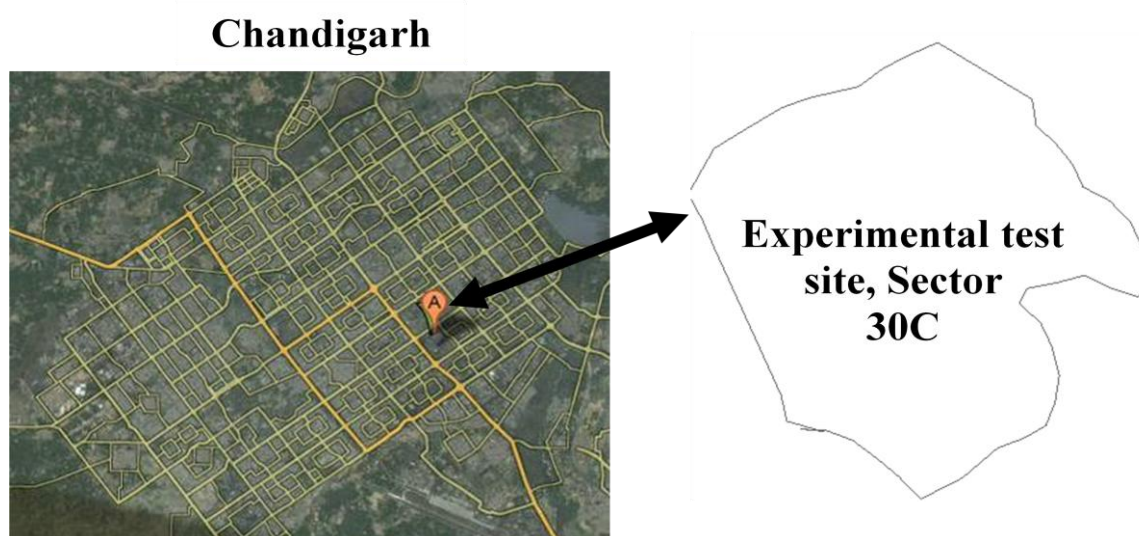


Fig.4.14: Geographic location of the experimental site (Chandigarh, India)

4.9 Soil sampling

After collecting EC_a data using Em38MK2 conductivity sensor, MZs were defined. Based on FPI and NCE performance indices, two optimal zones were selected. Centroid points of these two zones were taken as sampling locations and then samples were sent to laboratory for analysis of soil properties (pH, EC, OC, CEC, % clay, % sand, %silt, available N(Kg/ha), available P(Kg/ha), available K(Kg/ha)). Footprint of sampling locations is shown (Fig.4.15). Several authors used spatial simulated annealing (SSA) algorithm to optimize three sampling schemes in the past. The two strategies used earlier are stratified simple random sampling combined with the Horvitz-Thompson estimator, and systematic sampling was combined with the block kriging predictor [11].

Since EC_a is related to productivity on some soils [12-13], it has been used to delineate MUs. Several studies have indicated that homogenous MZs could be used as an alternative to grid soil sampling and to develop nutrient maps for variable rate fertilizer application [14-17]. MacMillan et al. [18] also concluded that MZs are well suited for locating benchmark soil-sampling sites. Further, Yan Li, [19] used MZs to form an objective basis for targeting soil samples for nutrient analysis and development of site-specific application strategies.



Fig.4.15: Sampling point location footprint established by FCM algorithm

4.10 Exploratory analysis

Table 4.5: Descriptive Statistics

Observed variables	EC _a (0-75cm)	EC _a (0-38cm)	pH	EC	OC	CEC	Clay (%)	Sand (%)	Silt (%)	Available N (kg/ha)	Available P (kg/ha)	Available K (kg/ha)
Mean	18.76	16.01	6.53	0.59	0.72	20.19	35.04	27.41	33.89	224.92	25.62	189.26
Max	192.20	102.98	7.03	0.73	0.81	29.86	40.86	30.59	39.65	249.97	30.84	201.24
Min	10.05	10.79	6.01	0.40	0.51	5.41	30.73	24.66	29.56	202.46	20.34	175.91
Range	182.15	92.19	1.02	0.33	0.30	24.45	10.13	5.93	10.09	47.51	29.50	25.33
Std Deviation	11.41	6.08	0.84	0.14	0.13	4.54	3.73	2.17	3.62	69.41	11.67	61.98
Variance	69.50	36.94	0.71	0.02	0.02	20.57	13.89	4.72	13.09	4817.54	136.11	3841.42
RMS	21.96	17.13	7.58	0.59	0.78	9.89	35.22	27.48	34.07	390.61	34.86	217.42
Skewness	2.34	1.23	-0.11	0.03	-0.13	0.14	0.33	0.22	0.36	0.33	-0.22	0.21
Kurtosis	4.13	1.56	-1.93	-1.18	-1.40	-1.86	-1.75	-1.69	-1.61	-1.32	-1.91	-1.40
Median	17.59	15.21	6.57	0.57	0.75	20.01	33.72	26.86	32.57	226.50	26.44	190.50
Q1	15.95	14.07	6.77	0.48	0.66	4.89	31.91	25.70	31.01	325.25	21.01	161.00
Q3	19.39	16.61	8.34	0.69	0.88	13.32	38.31	29.31	37.13	432.50	42.69	256.75

In exploratory analysis, data distribution was described using classical descriptive statistics (Table 4.5). An increase in the mean and variance of EC_a with depth was observed; EC_a (0-38 cm) averaged 16.01 mS m⁻¹ and the CV was 36.94%; EC_a (0-75cm) averaged 18.76 mS m⁻¹ and the CV was 69.50%. CVs for soil properties indicated significant spatial variability suggesting the convenience of delineating different MZs and interpolated spatial distribution maps using EC_a as auxillary soil variable. For all considered soil properties, the mean and median values were very similar which was indicative of data coming from a normal distribution. Several authors have reported normality of similar soil attributes using these procedures [5, 6, and 19]. Further this normality assessment was ratified by the fact that low skewness values were obtained. Furthermore, most of the coefficients of kurtosis were close to '0'. The skewness value is based on the size of the tails of a distribution and provided a measure of the outliers in the distribution of soil data. Thus, in this work, outliers should be scarce; in fact there were none, which was important to obtain accurate predicted estimates. Although normality is not a prerequisite for kriging, it is a desirable property. Kriging will only generate the best absolute estimate if the random function fits a normal distribution [2].

Significant correlations were observed between soil properties and EC_a, as well as within soil properties. EC_a was positively correlated to EC, pH, OC, CEC, Clay (%), Silt (%), N, P, and

K while EC_a has negative correlation with Sand (%). All the soil properties except Sand (%) show positive correlations with each other. Similar distribution patterns of clay and EC_{shallow} were observed by Moral et al., [8]. They also observed consistent EC readings in areas with finer texture and opposed relationship with sands.

4.11 Geostatistical analysis

4.11.1 Semivariogram models and Kriging maps

Table 4.6: Semivariogram model fitness measures for soil fertility attributes

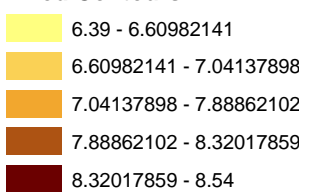
Observed Variables	Nugget effect (C0)	Sill (C0+C1)	Range (a)	C0/(C0+C1)	Model
EC_a 0-75	75.510	97.000	0.001	0.222	Spherical
EC_a 0-38	39.244	51.982	0.001	0.245	Spherical
pH	0.458	0.657	0.001	0.303	Exponential
EC	0.129	0.217	0.001	0.406	Circular
OC	0.702	1.073	0.001	0.346	Spherical
CEC	15.654	24.873	0.001	0.371	Circular
Clay	0.554	0.849	0.001	0.347	Spherical
Silt	0.983	1.543	0.001	0.363	Exponential
Sand	8.952	12.336	0.001	0.274	Spherical
Available N	39.861	68.021	0.001	0.414	Spherical
Available P	43.419	69.409	0.001	0.374	Circular
Available K	99.569	187.159	0.001	0.468	Spherical

Firstly best fit theoretical model is selected for each soil property. The choice of particular variogram model is dependent upon the expected spatial variability. Based on the selected model, semi-variograms were calculated for the soil EC_a variables at both depths, as well as for the other soil properties. The following parameters are presented in Table 4.6: nugget effect, sill, range, and model for the calculated semivariograms in addition to structural component: $(C0/C0+C1)$, representing the amount of data variance which can be explained by spatial dependence. After this, OK was used to generate spatial distribution maps which estimated the values at unsampled locations showing spatial variability in smoothed contour maps. These estimated values at unsampled location integrate spatial correlation structure as per the selection of variogram. Variables like soil properties can be distributed unevenly in

reduced distances, and exponential or spherical models are the most suitable [3]. As a result of OK procedure, optimized spatial distribution maps of $EC_{a\ 0-38}$ and $EC_{a\ 0-75}$, pH, EC, CEC, OC, sand, silt, clay and available N, P and K are shown (Fig.4.16). Similar spherical and exponential models for EC_a and other properties were reported earlier by Moral et al., [8]; Jose et al., [20]. Further the improved spatial distribution maps using EC_a as auxiliary variable are shown for different physico-chemical properties of soil having spatial dependence on EC_a (Fig.4.17, produced after applying multivariate statistics, co-kriging). In the past, Moral et al., [8] used regression kriging (RK), multivariate geostatistics, as an optimal prediction technique to produce such improved maps for clay (%), fine sand (%) and coarse sand (%). In present work, variograms showed a considerable nugget effect. It is a normal situation and reflects soil variability, it can occur at a scale smaller than the minimum lag distance. Sampling distance varies the nugget effect but, closer sampling density is costly and labour-intensive thus, less preferred.

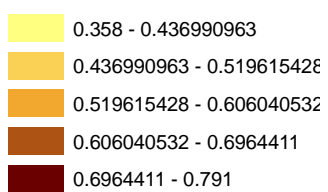
Due to the exhaustive $EC_{a\ 0-38}$ and $EC_{a\ 0-75}$ data, structural analysis was more accurate for these soil properties. Theoretical spherical models for $EC_{a\ 0-38}$ and $EC_{a\ 0-75}$ variable provided the best fit. Nugget values of 75.51 and 39.24 for $EC_{a\ 0-75}$ and $EC_{a\ 0-38}$ variograms were obtained, with respect to the sill values, 97.00 and 51.98 for $EC_{a\ 0-75}$ and $EC_{a\ 0-38}$ variograms respectively. In each soil property, the presence of nugget variance was probably due to short-range variability and field measurement errors. The spatial dependence of soil properties could be classified as the ratio of nugget variance to sill variance. If the ratio is less than 25%, the variable has strong spatial dependence, between 25 and 75%, the variable has moderate spatial dependence, and greater than 75%, the variable shows only weak spatial dependence. All the variables exhibited moderate to strong spatial dependencies with the ratio of nugget variance to sill variance from 22 to 46%. This further confirms the consideration of multivariate geostatistics as the optimum interpolation method for those variables [23].

pH



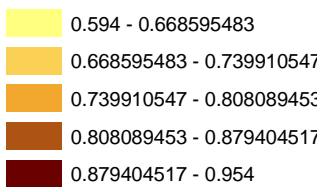
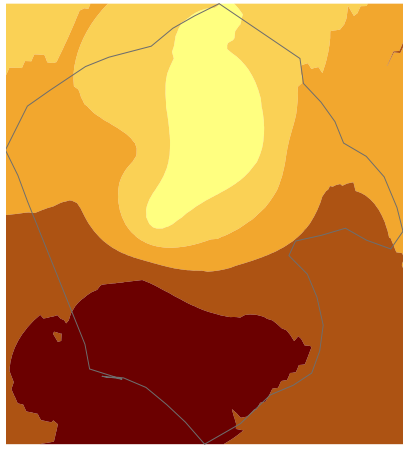
(a)

EC



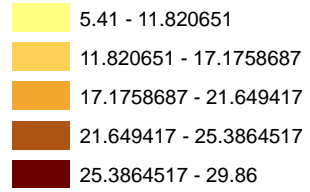
(b)

OC



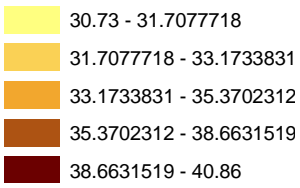
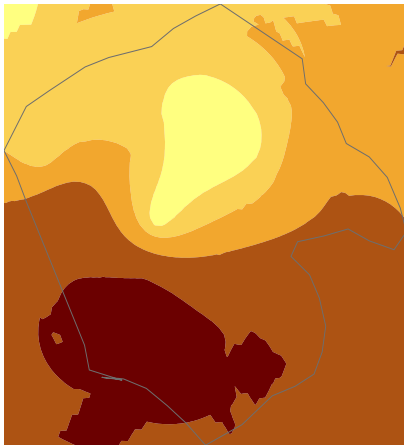
(c)

CEC



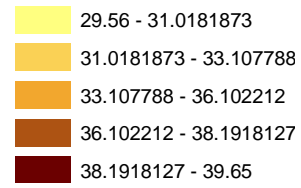
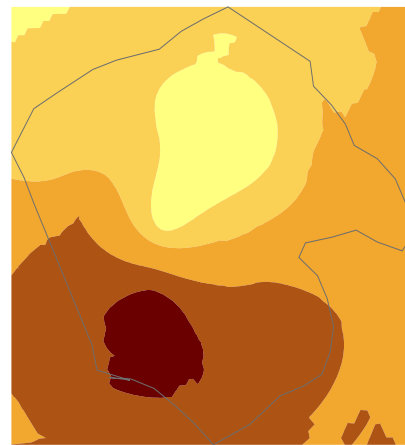
(d)

Clay



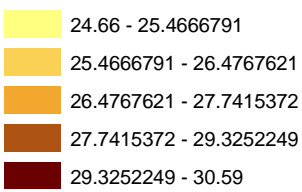
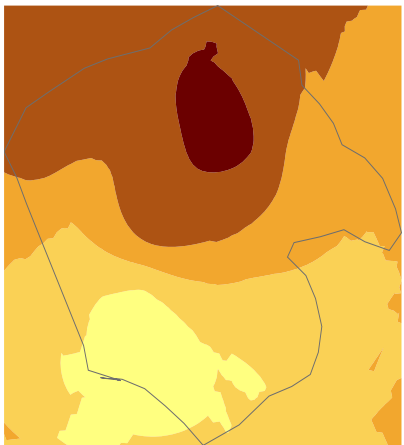
(e)

Silt



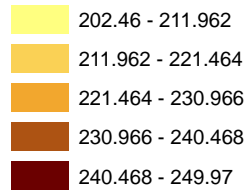
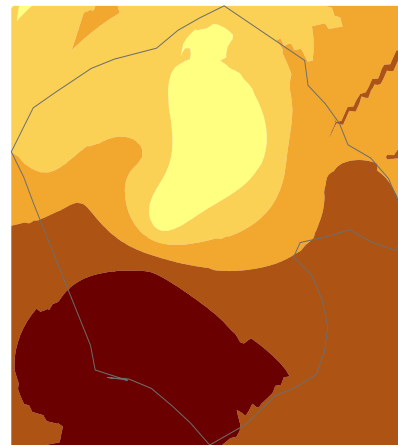
(f)

Sand



(g)

Available N



(h)

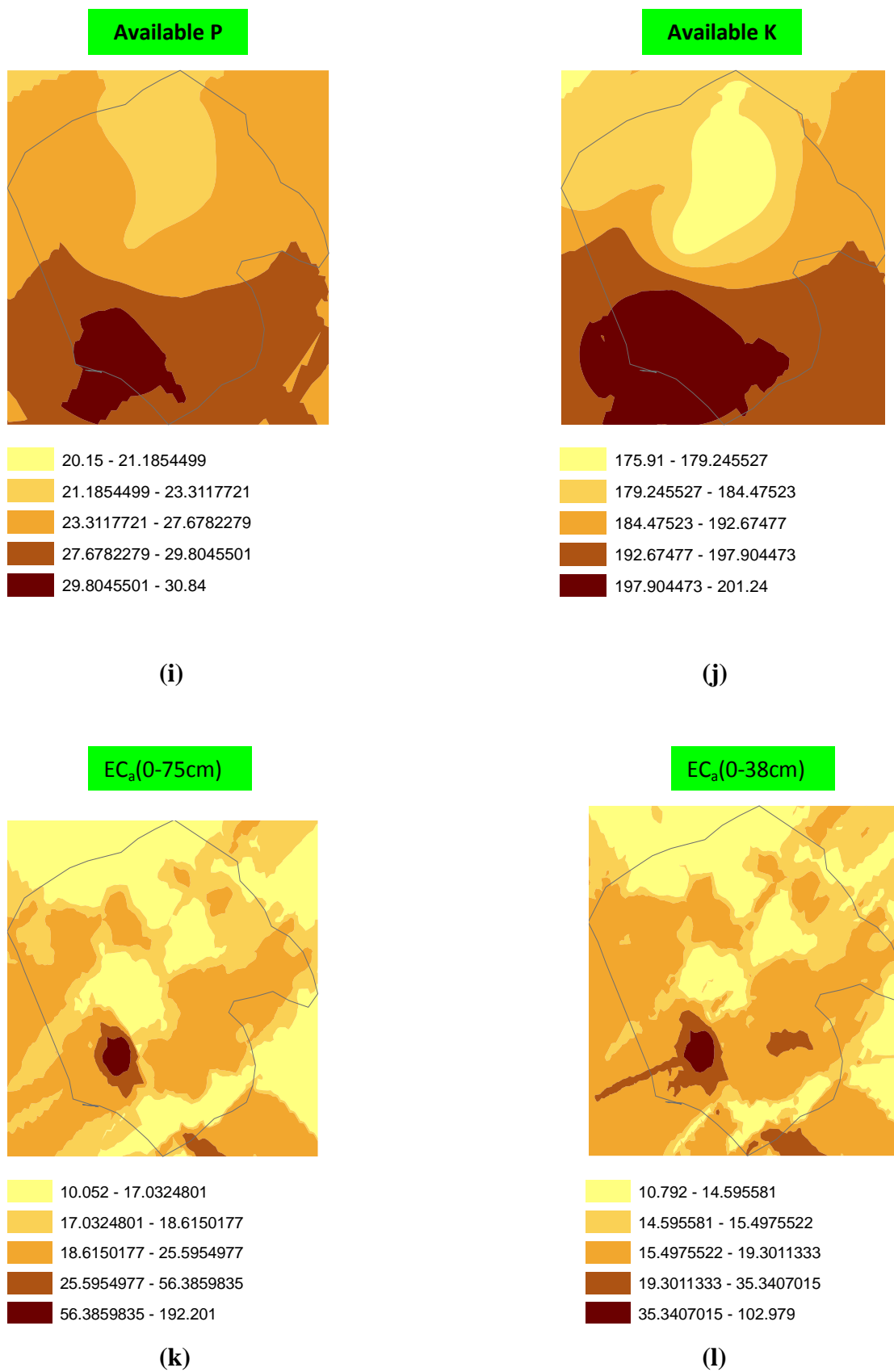
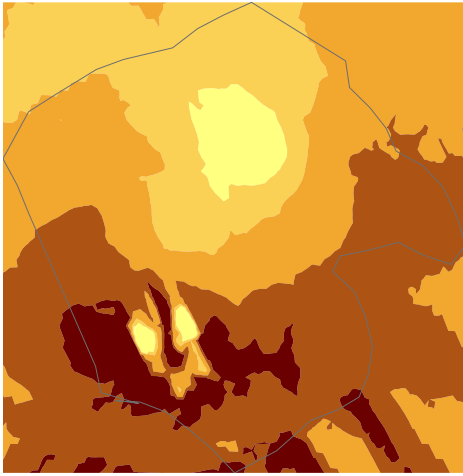


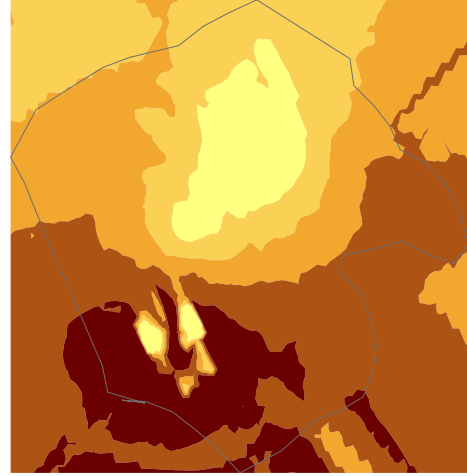
Fig.4.16: Krigging maps showing spatial distribution of soil fertility attributes and EC_a(0-38, 0-75cms)

pH



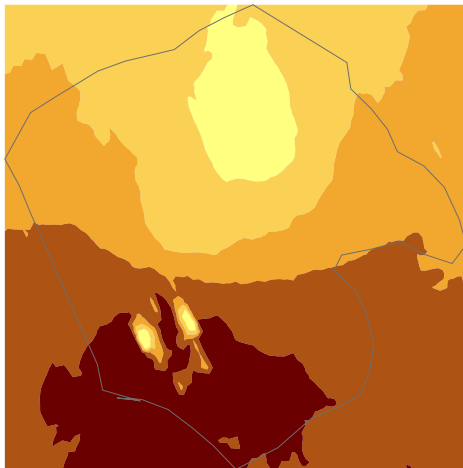
(a)

EC



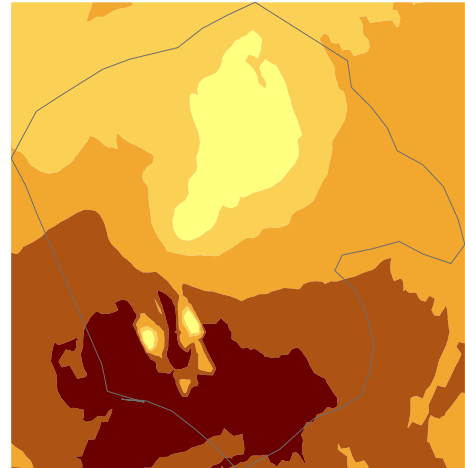
(b)

OC



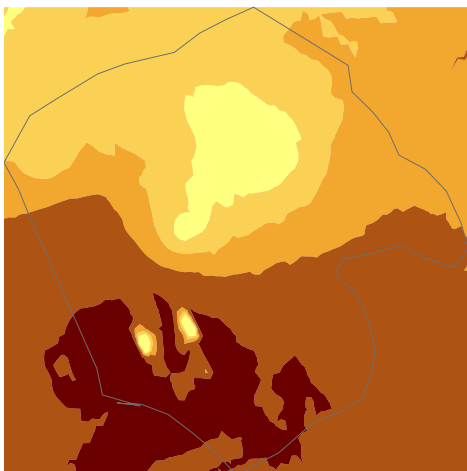
(c)

CEC



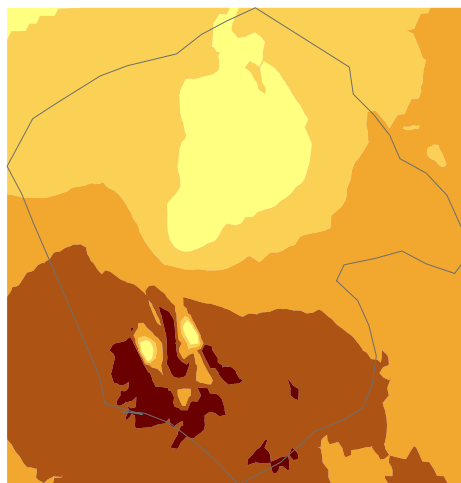
(d)

Clay



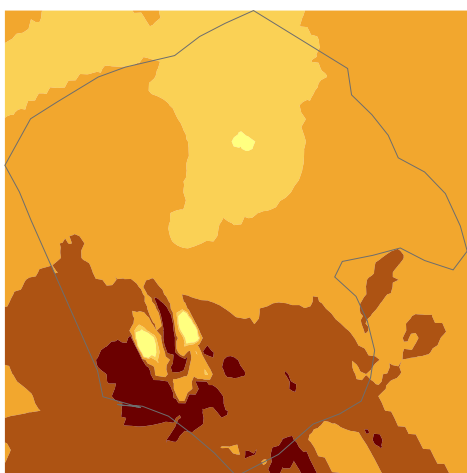
(e)

Silt



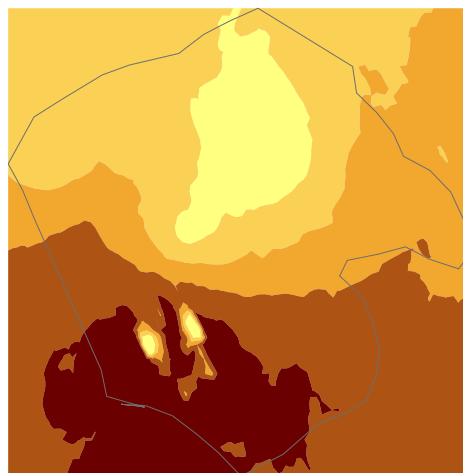
(f)

Available P



(g)

Available K



(h)

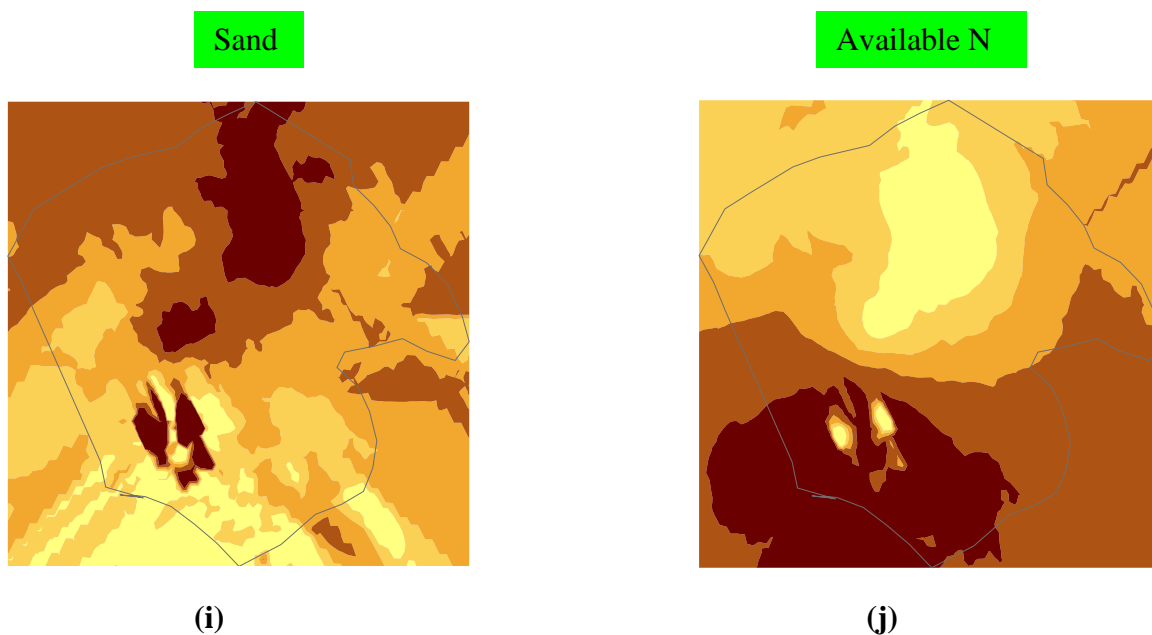


Fig.4.17: Improved soil fertility attribute maps using MVR geostatistics (CK) and EC_a as an auxiliary variable

4.12 Delineation of AMUs / MZs

In order to apply optimal soil inputs on variable-rate basis from next cropping cycle, field studied was delineated in AMUs/MZs.

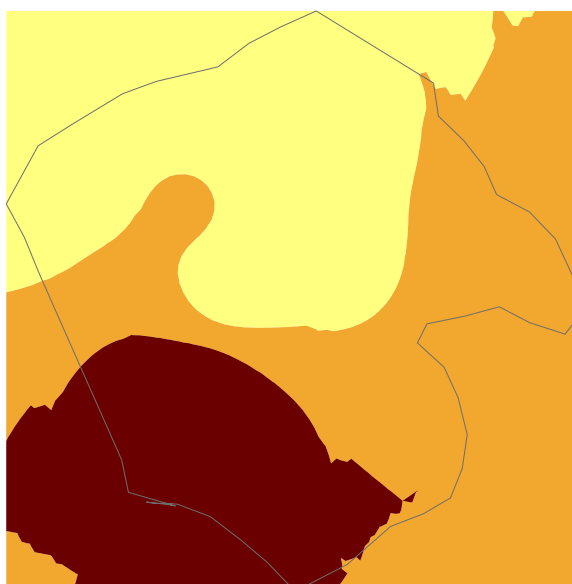


Fig.4.18: Delineation of practically manageable optimum MZs

PCA studies revealed the correlation of related variables (Table 4.7) explained by PC1 (87% explained variance) and PC2 (9% explained variance), leaving 4% variance shared by

consecutive PCs which are not considered in DMZs. Summary of most influencing spatial variance was captured by PC1 and PC2 simplifying the process of MZs delineation. The FCM clustering was used to divide the study area into two to six zones. Plotting the values of FPI and NCE against the number of classes and choosing a classification that minimized both measures was the criteria used for the identification of optimal number of zones. The minimization of NCE and FPI at three zones (Fig.4.19) indicated goodness of classification [24], and no further investigations deemed necessary to validate optimal number of zones. In consequence, practically MZs were obtained (Fig.4.18). Observations made from maps for different soil attributes (clay, sand, silt, OC, CEC, pH, NPK and EC_a) clearly shows resemblance of clay, OC, CEC patterns with EC_a and delineated MZs (Fig.4.18). Clay, OC, silt, CEC and NPK is clearly showing increase in intensity and varying pattern matching with associated EC_a contours (Fig.4.16, 4.17 and 4.18). Moral et al., [8], Jose et al., [20] and Vrindts EIs et al., [21] have obtained matching results using PCA and FCM for the considered soil variables as presented above.

Table 4.7: Correlation loadings of soil fertility attributes with PCs

Soil attributes PCs	EC _a 0-75	EC _a 0-38	Sand	Silt	Clay	OC	CEC	pH	EC	Avb. N	Avb. P	Avb. K
PC1	0.723	0.242	-0.385	0.249	0.684	0.521	0.578	0.436	0.615	0.343	0.231	-0.192
PC2	0.491	-0.217	0.404	0.196	-0.213	0.236	0.301	-0.195	0.187	0.294	0.476	0.436

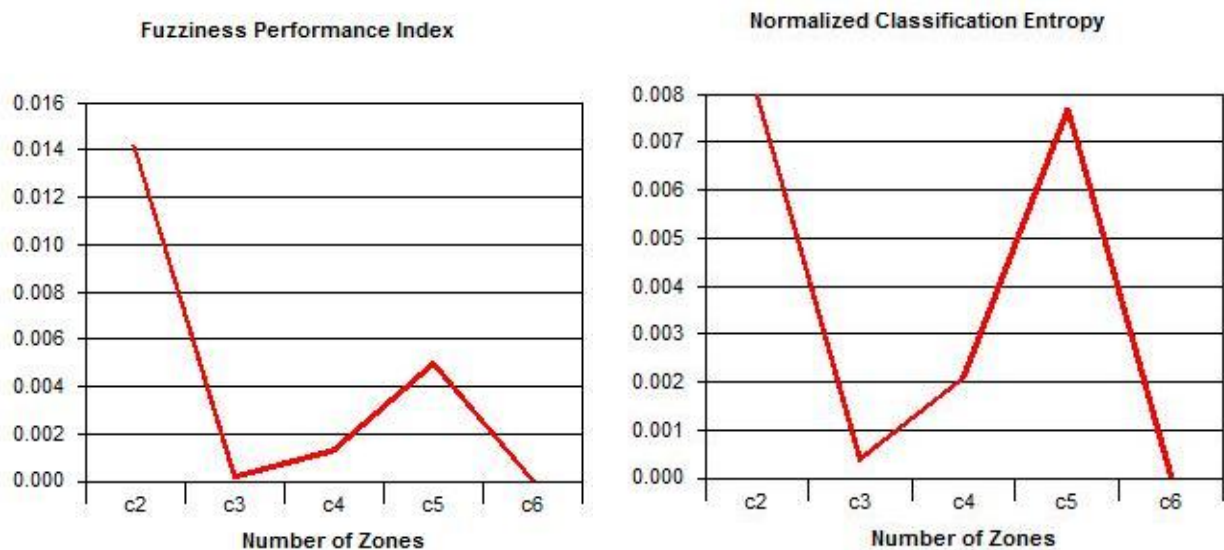


Fig.4.19: Performance index (FPI and NCE) plot for validation of optimal MZs

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Chapter 5

CONCLUSIONS AND FUTURE SCOPE

Overview

This chapter highlights the discussion on the work carried out and concludes the attempted objectives encompassing the aspects of PF and issues concerning sustainability. The reported work successfully characterized the fields located at two different geographical locations in India (PAU, Ludhiana and CSIR-CSIO, Chandigarh). An ultimate aim of studying spatial variability using bulk soil conductivity was achieved. Further studies of physico-chemical properties in relation with EC_a using statistical and geostatistical techniques are summarized in this section. Model optimization methods used have been also covered in the summary. Utility of exhaustive EC_a data to interpolate other physico-chemical properties of soil in order to generate high resolution spatial maps of soil fertility attributes due to their spatial dependence on EC_a has been concluded. Such high resolution maps were generated for OM, Clay (%), Sand (%), Silt (%), CEC using CK, multivariate geostatistical technique. Significance of delineation of MZs / AMUs from PF context is summarized and performance evaluation of delineated MZs is also touched upon.

5.1 Conclusion(s)

Meeting food demand for the ever-increasing population will need a radical shift in the attitude of Indian farming community in order to sustain agriculture. Although on one hand enhanced food production keeping pace with population is need of the hour while on the other hand, it is essential to ensure balance between crop production, optimized use of natural resource, reduced environmental damage and high economical returns. Such agriculture production system can only attain SA goals. PF has been recognized as one of the key drivers for attaining SA. PF is the outgrowth and convergence of emerging technologies such as EC_a mapper, GPS, GIS, IT, and software technologies. But the adoption and future of PF rests on the reliability, reproducibility, and understanding of the technological developments by the farming strata.

Assessment of the impact of edaphic and anthropogenic factors cost effectively at regional and a localized scale on small land holdings from Indian perspective was identified as a key component to achieving SA. In the present work geo-referenced mapping of soil volumes performed by EM38MK2, conductivity sensor was found as most effective approach for characterizing spatial variability of fields. Assessment involved the determination of spatial variations in physico-chemical properties, their spatial distribution and variability over time, which was measured using real time EC_a measurements and subsequently unknown locations were predicted with geo-spatial models using fertility attributes data of lab determined samples. Real-time measurements reflected past details related with agronomic management actions, whereas model predictions provided insight into future based on a simplified set of assumptions. Forecasting information at unknown spatial locations using geo-spatial modelling simulations was found to be most effective in designing agronomic decision-making strategies to sustain agriculture. Such site-specific assessment of information of soil physico-chemical properties for their spatial distributions can allow possible alterations, which could be managed before the development of detrimental crop growth and could help control inputs to produce improved yields.

Need of the efficient techniques for accurately measuring within-field variations in soil properties was felt very important from PF context. It was observed that the traditional soil sampling is costly and labour-intensive. Taking into account the necessity of many soils samples to achieve a good representation of any soil property, characterizing fields by EC_a mapper was found to be effective because of its reliability and ease of measurement.

Although EC_a mapping has simplified the job of mapping / characterizing field variability remarkably but it would be worth to be cautious while interpreting EC_a data on a site-specific basis, especially on sodic soils. Moreover, often high EC_a values are indicative of high clay content which in turn would affect soil OM and fertility. Therefore, sometimes high EM values on some soil types would be associated with low crop growth and yield.

It was seen that geo-referenced EC measurements have found matching patterns with associated yield-monitoring data and soil-physico-chemical properties in some parts of the field to a varying extent.

Further, for making useful interpretations of the measured soil data, geostatistical especially krigging technique and statistical tools played important role in analysing spatial trends in order to ensure correct agronomic prescriptions. As such modern technological trends including automated procedures, techniques, mathematical algorithms and software tools to process this data and output meaningful guidance that can be applied to practical farming was felt necessary. This study also demonstrated modern techniques of correlation analysis such as MLR, PLS and cluster analysis such as PCA, FCM and HCA that could effectively be used to group correlated and similar soil properties representative (EC_a) into unique groups for applying variable soil input rates using customized zone based management practices. This helped interpret/predict grain yield associated to inputs applied and response owing to spatial variations. For soil properties correctly assessed by EC_a , it can be termed as a surrogate indicator of sub-soil spatial variability. The measurement of secondary soil information data such as EC_a using field usable geo-sensors is less expensive, rapid and helped in understanding site-specific spatial characteristic of other attributes to govern input management. On-the-go soil EC_a mapping not only characterized soil differences in farm fields but also helped strengthen grower's decision-making ability for several agronomic practices and input applications.

In order to demonstrate the concept of PF techniques and technologies on actual real world fields for enhancing the quality and quantity of crop productivity, two experimental fields were tested for delineation of best productivity zones using soil fertility attributes, yield information and EC_a . Based on the experiments conducted on these fields for spatial variability mapping of bulk electrical conductivity and other physico-chemical properties, it was found that that the use of site-specific MZs, rather than the traditional whole field approach, can be a economical and efficient approach for farm managers to manage field

variability on a site-specific basis. These homogenous MZs were useful as an alternative to grid soil sampling and to develop specific nutrient maps for variable rate fertilizer application.

In the reported study use of mobile soil EC_a measurements was explored (deep, 0-75 cm and shallow, 0-38 cm) to characterize the spatial variability of soils at fields located in PAU, Ludhiana and CSIR-CSIO, Chandigarh. Subsequently, EC_a directed soil sampling was also done using centroid-point approach (FCM classification) in one case and ESAP, response surface sample design approach in other case. It was also found that use of geostatistical techniques has potential to generate high resolution spatial distribution maps of soil fertility attributes. At the end optimal zones (areas having related soil attributes within one zone and most dissimilar ones in other) were created using PCs and fuzzy classification algorithm in order to reduce chemical applications and environmental damage besides increasing farm returns.

Soil EC_a based spatial variability characterization of field was found to be particularly advantageous as traditional soil surveys are not sufficiently detailed to provide information for within-field recommendations from PF context. In this process, Geostatistical interpolation technique (OK and CK) was used to generate stochastic spatial surfaces for the soil fertility attributes (EC, OC, CEC, EC_a , clay, sand, silt, ph, NPK) using lab analysed information of the sampled locations (known). In the data analysis, descriptive statistics, explained that EC_a was positively correlated to EC, pH, OC, CEC, Clay (%), Silt (%), N, P, and K while EC_a was negatively correlated with Sand (%). All the soil properties except Sand (%) showed positive correlation with each other. In the structural analysis theoretical semivariogram models for all the soil fertility attributes were fitted to experimental variogram based on the expected spatial variability. Minimization of squared errors was the optimality criteria adopted while optimizing semivariogram models in addition to checking degree of spatial dependence of soil fertility attributes. Spherical models provided the best fit in most of the cases of soil fertility attributes barring circular (three cases) and exponential (two cases). Best Linear Unbiased Estimator (BLUE) i.e. krigging was selected as the optimum interpolation algorithm for all the soil fertility attributes. Since OK uses univariate algorithm to estimate value of the only soil attribute being analysed, CK, a multivariate extension of OK further was used which improved the estimates of soil fertility attributes having spatial dependence on EC_a (secondary attribute). Due to exhaustive soil EC_a measurements available and its spatial dependence on lab analysed fertility attributes, it was successfully

used to estimate values at unknown locations within the studied field. Consequently, high resolution maps of soil fertility attributes were produced as desired in PF without conducting rigorous soil sampling which traditional methods would demand.

Good amount of variance in soil fertility attributes suggested convenience of delineation of MZs. In PCA, PCs (PC1 and PC2) explained 96 % data variance consisting of soil attribute (EC, OC, CEC, EC_a, clay, sand, silt, ph, NPK). Clay, OC, CEC, EC, pH and EC_{a 0-75} are significantly explained by PC1 and are compressed. In consequence, PC1 and PC2 only are considered to obtain optimal MZs.

Studying spatial distribution of the fertility attributes and delineating AMUs / MZs for studied field to apply variable-rates for attaining PF objective using modern tools was the primary idea in presented research. Generated high resolution maps could be used to plan variable-rate input strategies to be deployed on fields from the next cropping cycle. Site-specific knowledge gained will apply fewer chemicals on the field thus, implementing cost-effective field management in terms of resource utilization and input applications, besides, in long run, it will pay dividends in terms of environmental protection and energy savings. In the present case an attempt has been made to show that identification of spatial variabilities through use of emerging technologies (EC_a sensors) combined with geostatistical techniques has potential to solve problems concerning agri-production system commonly encountered across the globe and in particular small land holdings of India effectively. Of course, potential benefits from PA will depend on the range of field variability and whether this variability can be managed through cost effective technological intervention. In case of India, availability of abundant human resource can be utilised in place of machines to apply the solutions provided by PA cost effectively. However, future of spatial variability mapping technologies and their successful utilization to obtain economical and environmental benefits rests on the reliability, reproducibility, and understanding of these technologies.

5.2 Future scope

In future, studies concerning variability of more physical attributes such as bulk density, particle density, porosity, infiltration rate, hydraulic conductivity and gravimetric humidity can be planned and undertaken on this site. The analysis in terms of these attributes can be integrated with presented results in order to derive more useful interpretations for making improved agronomic decisions.

Furthermore, advanced Artificial Intelligence (AI) techniques and optimizers such as Neural Network (NN), Genetic Algorithm (GA), Support Vector Machine (SVM), and Particle Swarm Optimization (PSO), Social Impact Theory Optimization (SITO) can be employed to develop improved soil properties prediction models. Such advanced models can integrate different measurements of on-the-go systems of individual soil variables: bulk density, particle density, porosity, infiltration rate, hydraulic conductivity and gravimetric humidity, clay, sand, and silt content, and macro and micro nutrient, and EC_{shallow} and EC_{deep} in order precisely predict soil fertility potential and associated variable input applications.

Recently it has been seen that whole-field management is increasingly viewed as inefficient because it results in over application of inputs in low-producing areas and sub-optimal application in areas with high-production potential. It is in this direction that needs more explorations so that SSM- the spatially directed management of soils, crops, and pests based on varying conditions within a field provides an alternative. Although presented research reported FCM based methods there are other possibilities that can lead to define more refined, economical and profitable AMUs. Furthermore, there is need and scope to support development of automated hardware (rapid field-scale mapping of properties) and software (new algorithms) tools that can make cost effective deployment of these modern technologies on field usable basis a reality.