# राष्ट्रीय राजधानी क्षेत्र में फार्म के भौतिक स्वास्थ्य की स्थानिक विविधता पर अध्ययन

# STUDIES ON SPATIAL VARIATION OF SOIL PHYSICAL HEALTH OF A FARM IN NATIONAL CAPITAL REGION

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# STUDIES ON SPATIAL VARIATION OF SOIL PHYSICAL HEALTH OF A FARM IN NATIONAL CAPITAL REGION

**A Thesis**

***by***

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# CERTIFICATE

This is to certify that the thesis entitled "**Studies on spatial variation of soil physical health in a farm of National Capital Region"** submitted to the Post Graduate School, Indian Agricultural Research Institute, New Delhi, in partial fulfillment of the requirements for the award of the degree of **Doctor of Philosophy in Agricultural Physics,** embodies the results of *bona fide* research work carried out by **Mr. Ali Ashraf Amirinejad** under my supervision and guidance, and that no part of the thesis has been submitted by him for any other degree or diploma.

It is further certified that any help or information that has been availed of in this connection is duly acknowledge by him.

Date: 4th January, 2010
Place: New Delhi-12

**[Dr. (Ms.) Pramila Aggarwal]**
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*Date:* 4th January, 2010
*New Delhi-12* *(Ali Ashraf Amirinejad)*

***Dedicated***

***to***

***My Dear Parents***

***&***

***My Endearing Wife***

***Faranak***

***&***

***My Lovely Kids***

***Aliasghar and Amirreza***

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# 1. GENERAL INTRODUCTION

## 1.1 Background

Protection of soil quality under intensive land use and fast economic development is a major challenge for sustainable resource use in the developing world. The basic assessment of soil health and soil quality is necessary to evaluate the degradation status and changing trends following different land use and management interventions. In Asia, adverse effects on soil health and soil quality arise from nutrient imbalance in soil, excessive fertilization, soil pollution and soil loss processes. The concept of soil health and soil quality has consistently evolved with an increase in the understanding of soils and soil quality attributes. Soil quality cannot be measured directly, but soil properties that are sensitive to changes in management can be used as indicators. On-farm assessment of soil quality and health is recommended to assist farmers evaluate the effects of their management decisions on soil productivity

Site-specific farming has introduced a management practice by which farmers can begin analyzing and dealing with cropland variability. Site-specific farming is based upon the notion that fields used for agricultural production are not uniform. Variations of soil physical properties occur from field to field and within fields. These spatial variations result from many factors such as previous farming practices and topography of the land. With site-specific technology farmers are adjusting application rates of pesticides and fertilizers along with plant populations in hope of optimizing crop production.

Soil scientists are aware that soil properties vary spatially, and they have already recorded strong fluctuations even over short distances. Behind a locally erratic aspect, some spatial structure is often discerned and may be related to the combined action of several physical, chemical or biological processes that act at different spatial scales. The characterization of the spatial variability of soil attributes is essential to achieve a better understanding of complex relations between soil properties and environmental factors. Also, a model of spatial dependence between soil data can later be used to estimate a soil property (such as soil phosphorus status) at unsampled locations for preparing the spatial variability map of the property, based on which more accurate input recommendation (application of P fertilizer) can be made for the entire farm, which will ultimately enhance input use efficiency. Estimating semivariogram parameters of soil properties using geostatistical tools and further applying them to predict other soil properties using ordinary kriging is the general procedure to prepare soil maps.

The soil variability occurs as a result of the effect and interaction of various ongoing processes in the soil profile. Earlier the soil variability in the field was defined by classical statistical methods which assumed that soil parameters had random variability. But later on it was observed that most of the soil properties show spatial dependence. Samples close to each other have similar properties than that of samples farther from each other. Geostatistical analysis was used to demonstrate the spatial dependency of soil properties such as bulk density (BD), penetration resistance (PR), soil pH, and nutrient content of soil, nitrate leaching in soil and pesticide distribution of soils. More permanent soil properties such as texture, bulk density and color are less variable than temporal or more dynamic properties such as water content, hydraulic conductivity, or soil thickness. However, the short-range variability of permanent soil properties might range from few centimeters to hundreds of meters depending on landscape characteristics. Knowledge of spatial variation of soil properties is important in precision farming and environmental modeling. Spatial distribution of water content at field capacity (FC) and permanent wilting point (PWP) at different zones of a farm governs the available water for plant growth. These two soil hydraulic parameters play key roles in crop selection for different blocks of a farm, and in scheduling irrigation of crops in a field.

At present, soil science research largely relies on the use of geostatistics, which together with classical statistics, constitutes an extra ordinary important tool of precision farming. Now a days, owing to the availability of advanced and more sophisticated geostatistical softwares, soil data taken at few location with defined spatial coordinates can be put to GIS environment and details of spatial structure of the parameter can be studied easily, which can be used to generate prediction maps of parameters even with low sampling intensity. A study on spatial variation of soil hydraulic properties in a farmer's field is required to delineate compact land areas where these hydraulic parameters are below the critical range. Similarly prediction maps of various soil physical properties showing their variation in different ranges in different parts of farm needs to be generated and overlaid to produce a soil physical health map of the area.

The soil physical health map should then be correlated with yield map of the study area and if such correlation exists, appropriate management practices could be suggested to alleviate soil physical constraints so as to improve the productivity of the land.

**1.2 Development of pedotransfer functions (PTFs):**

Direct measuring of soil hydraulic properties are relatively time-consuming in laboratory and field conditions. Mathematical models are indirect and empirical approaches to estimate these hydraulic functions. As an alternative to measurements, one can use estimation methods that utilize physical or empirical relations between hydraulic properties and other soil variables. The advantage of such methods, also called pedotransfer functions, is that the input variables can be measured more easily-and, hence, are more widely available than hydraulic properties. For the prediction of water retention and saturated hydraulic conductivity, this approach has led to a number of PTFs that use soil texture, bulk density, and other soil variables as input (Wösten *et al*., 2001).

PTFs allow basic information from soil surveys or geographic information system (GIS) databases to be translated into other soil properties, which are more laborious or expensive to determine. Pedotransfer functions utilize various regression analysis and data mining techniques to extract rules associating basic soil properties with more difficult to measure properties (e.g., Ahuja *et al*., 1989; Vereecken *et al*., 1989; Schaap & van Genuchten, 1998; Kravchenko, 2003).

**1.2.1 Pedotransfer functions for soil hydraulic properties:**

Several PTFs have been developed, some empirical based on soil texture (Campbell, 1974, Rawls *et al*., 2005) or other soil properties (McKenzie and Jacquier, 1997, Smettern and Bristow, 1999) and some physico-empirical methods using soil pore-space models to predict saturated hydraulic conductivity ( $K_{fs}$ )(Marshall 1958, Mishra and Parker, 1990).

Adhikary *et al*. (2008) reported soil water content at a given suction could be satisfactorily predicted using the percentage of major soil separates, sand, silt, and clay. The coefficients in the soil water function were linearly related to the sand content. Non-linear regression equations were developed to predict these coefficients using the percentages of sand and clay in soils. Patil *et al.* (2009) predicted soil water retention characteristics of shrink swell soils using PTFs with coefficient of determination of 0.88. Minasny and McBratney (2002) evaluated the performance of several PTFs on datasets of saturated hydraulic conductivity for Australian soil and showed use of a power functional model gave good estimates compared to other models. They concluded that PTFs can provide useful information on a coarse scale but their use for site specific may result in large uncertainties if no local calibration is done or the measurement techniques are not taken into consideration. Estimation of soil hydraulic properties by pedotransfer functions (PTFs) can be used in many applications. Soil hydraulic PTFs are, in most cases, not specifically developed to address one particular problem, but are developed from a large data collection to potentially provide information to many studies. The underlying databases usually report on soil hydraulic properties determined on undisturbed soil samples. A PTFs user will obtain predictions that reflect the inter-correlations of data in the underlying database. Subsequent application of PTFs estimates in simulation models without knowing the nature of such correlations may lead to inexplicable results and possibly to incorrect or inefficient decisions (Nemes *et al.*, 2005). Water content at field capacity (FC) and permanent wilting point (PWP) are two most important hydraulic parameters which indicate plant-available soil water regime and help in scheduling irrigation to crops. Based on surface maps of these two hydraulic parameters, crops with specific water requirements may be selected for different locations in a farm. Direct measurement of these two parameters at multiple locations and preparation of surface map is difficult, time-consuming and costly. Moreover, as hydraulic properties are controlled by several landform processes, these are highly dynamic under field conditions. Alternately, these properties can be estimated from some basic soil properties using PTFs in a non-spatial extent. Several region-specific PTFs have been developed throughout the world for estimating hydraulic properties from basic soil properties. These PTFs can, therefore, be used in generating maps of results from profile cone penetrometer (Kasim *et al.*, 1986).

### 1.3 Spatial variability analysis of soil properties:

Soil properties that are spatially variable within fields include fertility, texture, physical properties, chemical properties and depth (Zhang *et al., 2002*). Variability of these properties within a field has been found to affect the crop yield. For example, Cox *et al.* (2003) reported that areas in a soybean field with high clay content had higher yield than areas with lower clay content. Similarly, when the application of water or water quality (salinity) is non-uniform in the field, the resulting soil moisture properties may be an important factor in causing spatial variations in crop yield

(Sadler *et al.,* 2000). Yield variability within surface-irrigated fields has been related to the spatial variability of available soil water due to non-uniform irrigation (Palmer, 2005). In this case the soil infiltration characteristic and its spatial and temporal variability is the single greatest factor in determining the irrigation performance (Gillies, 2007). The only form of water which can be beneficially utilized by the crops is the soil water (Zhang *et al*., 1994), and soil water relations have been shown to explain more than 50% of infield yield variability (Irmark *et al.*, 2002). Temporal and spatial management of soil water can significantly increase water use efficiency (Jin *et al.*, 1999).

### 1.3.1 Studies on spatial structure

Spatial dependence can be quantified by drawing an experimental semivariogram and a suitable model can be chosen to describe the spatial structure of measured property. Burgess and Webster (1980) were the first to study the spatial structure of soil properties using kriging method for interpolation of properties at unvisited sites. They showed that spatial dependence of soil properties can be quantified and modeled using one dimensional semivariogram. Semivariogram models were developed for several measured soil physical properties such as saturated hydraulic conductivity, % sand, saturated water content, available soil water storage capacity, soil bulk density, nutrient content of soil and pesticide distribution in soil ((Jury, *et al*., 1991; Warrick *et al*., 1986; Aggarwal and Gupta, 1998; Dhaiya *et al*., 1998; Newman *et al*., 1997; Rao and Wagnet, 1985). Later, it was reported that for presenting anisotropic variation of soil property, two dimensional semivariogram were required (Webster and Oliver, 2001). Mulla and Mcbratney (2002) discussed the details of various steps of spatial variability analysis including collection of samples, drawing of semivariogram, development of semivariogram model, analysis of data for presence or absence of trend or drift, neighborhood search strategy, different forms of kriging and their applications under different situations.

### 1.3.2 Spatial interpolation:

Spatial interpolation is a procedure for estimating the values of a variable at unsampled locations. The interpolation techniques commonly used in earth sciences include as inverse distance weighting, cubic splines, linear regression, ordinary kriging and co-kriging (Leenaers *et al*. 1990; Voltz and Goulard, 1994). Kriging is a geostatistical technique for optimal estimation and has been applied widely to soil properties. In kriging the appropriate semivariogram models can be used to prepare contour maps of the given soil property. Kriging methods are superior to classical methods when the property to be interpolated have well developed spatial structure and measurements are made at spacing less than the range of semivariogram .Warrick *et al*. (1988) suggested that kriging would be the best choice for a interpolator because it is the only method that allows the variance of an interpolated point to be estimated. Interpolation by kriging for preparation of isarithmic maps of few soil properties was carried out by Gupta *et al.* (1995) and Dhaiya *et al.* (1998).

Several studies have compared kriging and classical methods for interpolation such as inverse distance weighting (IDW) and cubic splines (Dubrule, 1984). As a general rule of thumb, kriging methods are equivalent or superior to classical methods when data to be interpolated have well developed spatial structure, have a semi variogram without a significant nugget effect and are sampled at spacing less than the range of the semivariogram. IDW is more suitable for use with data having short range variability (Cooke *et al*., 1993).

### 1.3.3 Spatial variability in soil hydraulic properties:

Vieira *et al*. (1983) used variogram, kriging, and co-kriging techniques to determine the magnitude of spatial variation and reported a range of 50 m for 1280 field measured infiltration rates. They sampled within a 70- by 40-m area at the nodes of a 10-m square grid and used classical and geostatistical techniques to study spatial variability of sand, silt, and clay contents, available water content (AWC), and water stored at field capacity. The strongest correlation was found between sand content and AWC and the cross variogram demonstrated that sand content was spatially correlated with soil water content at 33 kPa within a distance of ≈30 m and with AWC within a distance of ≈43 m. In a study by Kilic *et al.* (2004), it was reported that SWC, BD, clay%, sand % and PR showed strong spatial correlations (low nugget variance/total semivariance ratio). The results pointed out that spatial variability of PR depended on SWC, BD and several local features such as micro topography. Sobieraj *et al.* (2003) found no spatial structure of $K_{fs}$ within a range of 25 m. Heiskanen and Makitalo (2002) reported a range of 44 and 100 m for the water content and air-filled porosity at 10 kPa. Campbell (1978) reported sand content semivariogram ranges of 30 and 40 m for two different soil types.

In a study by Ersahin (2003), spatial variability in field-measured infiltration rate (IR) and soil properties having significant spatial correlation to IR were studied using kriging and cokriging procedures. Percentage of lime, silt, bulk density, water content at -1.50 MPa soil water potential in topsoil, and soil water contents at -0.03 and -1.50 MPa soil water potentials in subsoil were significantly correlated to IR within distances ranging from 165 to 215 m. Results from cross validation revealed that subsoil bulk density was the most representative auxiliary variable of IR. The stratification of different sediments deposited on top of each other spatially vary, therefore, it is important to study not only the extent of surface spatial variability, but also the distribution of subsurface horizons (Iqbal, *et al.*, 2005). In a study conducted by Ersahin (2003) for comparing cokriging with ordinary kriging for interpolating infiltration rate (IR), it was observed that cokriging provided no advantage over kriging when data were sufficient. With kriging, 45 observed IR values were sufficient to obtain the same information as 50 observations. However, using cokiging with 120 bulk density values, 40 observed values of IR were sufficient to obtain the same information from that obtained with 50 field measurement of IR. This indicates that cokriging was more successful than kriging when IR is undersampled. Martinez (1996) showed that cokriging was only minimally superior to ordinary kriging when auxiliary variables were not highly correlated to primary variables. This suggests that use of a correct auxiliary variable is important to obtain successful results from cokriging. In addition, to ensure the validity of the estimates made by kriging and co-kriging, the semivariogram and cross-semivariograms of the variables used must accurately describe the spatial structures.

### 1.3.4 Precision farming (PF)

Precision agriculture or farming has been defined as farming with preciseness (Kitchen *et al.*, 1996) or as targeting the inputs of arable crop production according to crop requirement on a localized basis (Stafford, 1996). Various other terms have been employed to describe precision farming including: site specific, spatially variable, prescription, and variable rate. All of these terms mean essentially the same thing although some people infer slightly different meanings. For example, Rawlins (1996) drew an interesting distinction between precision and prescription farming. He defined precision farming as having the capability to apply inputs precisely when and where they are needed, but identified that prescription farming requires a real-time knowledge regarding the processes which are limiting production at any time in all areas of the field. PF is a management philosophy or approach to the farm and is not a definable prescriptive system. It identifies the critical factors where yield is limited by controllable factors, and determines intrinsic spatial variability. It is essentially more precise farm management made possible by modern technology.

The variations occurring in crop or soil properties within a field are noted, mapped and then management actions are taken as a consequence of continued assessment of the spatial variability within that field. Development of geomatics technology in the later part of the 20th century has aided in the adoption of site-specific management systems using remote sensing (RS), global positioning system (GPS), and geographical information system (GIS).

This approach is called PF or site specific management. It is a paradigm shift from conventional management practice of soil and crop in consequence with spatial variability. It is a refinement of good whole field management, where management decisions are adjusted to suit variations in resource conditions. Statistically, the precision farming $P = 1 - \text{SD}$, where, SD is standard deviation; $P = 1$, indicates highly homogeneous field and $P = 0$, is a complex system, which describes maximum variability of field.

Conventional agriculture is practiced for uniform application of fertilizer, herbicide, insecticides, fungicides and irrigation, without considering spatial variability. To alleviate the ill-effects of over and under usage of inputs, the new concept of PF has emerged. Site specific management to spatial variability of farm is developed to maximize crop production and to minimize environmental pollution and degradation, leading to sustainable development. The recommendations of production inputs for each variable portion of the field could be adjusted to optimize output according to the agronomic, economic and environmental goals through minimization of production cost.

Most work on precision farming appears to have been directed toward the application of temporally separate responses, driven apparently by the disciples of GPS/GIS and yield mapping technology. Rawlins (1996) suggested that these and other technologies have made it possible for farmers to apply spatially variable inputs such as variable seeding and fertilizer application rates. However, prescriptions to apply these inputs are typically empirical, based on grid sampling of soil properties. The spatial factors responsible for yield variability include irrigation uniformity, field topography, fertilizer uniformity, genetic variation, soil hydraulic and nutritional properties, microclimate differences as well as pest and disease infestation (Zhang *et al*., 2002). Climatic factors such as rainfall, temperature and radiation also vary temporally. Water commonly has a leading role among the factors responsible for spatial and temporal yield variability and is a major input resource for precision management (Sadler *et al*., 2000; Warrick & Gardner, 1983).

**1.3.4.1 Applications of spatial variability analysis in precision farming:**

**Delineation of compacted zone for precision tillage**

Knowledge of the soil hydraulic properties is indispensable to solve many soil and water management problems related to agriculture, ecology, and environmental issues. These properties are needed to describe and predict water and solute transport near the soil surface and also within soil profile (Cornelis *et al*., 2001). So, knowledge of the soil hydraulic properties is needed for many applications in hydrology, agronomy, meteorology, and environmental protection (Tomasella *et al*., 2003).

In most of the medium textured alluvial soils, normal tillage (up to 0.15-0.20 m depth) along with the excessive use of disc implements and heavy machinery result in development of compacted, impermeable subsurface layer between 0.15- 0.3 m (Aggarwal *et al*., 1997). When traffic compaction occurs below the normal depth of tillage, subsurface hard pan layer restrict root growth, which in turn limits crop yield, especially during drought (Taylor and Gardner, 1963). These excessively compacted layers may reduce soil aeration and soil water infiltration that could accelerate erosion and runoff. Under such situations, deep tillage or sub soiling is required to disrupt root restricting layer for optimum root growth (Busscher and Bauer, 2003 and Raper *et al*., 2004a).

Precision tillage was described by Carter and Tavernetti (1968) as tillage wherein tillage depth was precisely specified to reach and disturb a compacted “pan”. As the concept of GPS-based precision agriculture has gained acceptance, the idea of precision tillage has evolved to include real-time control of a “smart” tillage tool (Schaap *et al*., 1998) and variable depth deep tillage (Raper *et al*., 2004a). In other word we can say that Precision tillage or site-specific tillage is a component of precision agriculture management strategy that employs detailed site-specific soil and crop information to precisely manage the production inputs (Naiqian *et al*., 2000). Site-specific tillage in particular is geared towards achieving the goals of sustainable agriculture by determining within field variability and providing more accurate soil compaction records, and optimizing the tillage input within the field where root limiting soil compaction exists. The success of site-specific tillage depends on the availability of economical, rapid, easy and precise soil strength sensing technology, management of within field variability, accuracy of field positioning and controlling the application of real-time or prescribed site-specific tillage. In precision tillage, a precise detection of soil hardpan is important because errors of a few centimeters could cause large variations in accurately locating the soil hardpan and site-specific tillage depth recommendations.

Many researchers have found that the soil hardpan layers exhibit spatial variability within a field and suggested that site-specific tillage has potential in reducing tillage energy and fuel consumptions as compared to the conventional uniform depth tillage (Fulton *et al*., 1996; Raper *et al*., 2000; Raper *et al*., 2004a). Raper *et al.* (2000) estimated about 50% reduction in energy requirements for shallow tillage (approximately 18 cm) as compared to deep tillage (approximately 33 cm). Thus, precision deep tillage is attractive from the standpoint of eliminating unnecessary tillage.

Remote sensing methods such as LANDSAT satellite images are useful in identifying areas of poor drainage that may indicate compacted soil. Such information is usually verified by comparing with kriged maps of soil penetration resistance before applying precision deep tillage. Geostatistics is widely used in mapping soil properties for precision agriculture. An increasing number of farmers (or their consultants) are using geostatistics to increase yield, improve profit, and soften the impact on the environment. A precision farming approach recognizes site-specific differences within fields and adjusts management actions accordingly (Fraisse *et al*., 1999).

Geostatistics provides a method for the analysis of the spatial and temporal properties in a data set and a method of interpolation between selected points. It is based on the theory of regionalized variables, enables the interpretation of results based on the structure of natural variability of a parameter, taking into consideration the spatial dependence within the sample space.

Still *et a*l. (1982) conducted a comprehensive study of factors affecting penetration resistance (PR) in coarse textured soils in the Atlantic Coastal Plain, and used stepwise regression to relate mechanical impedance to various measured soil properties. The highest correlation coefficients were found for a regression model that included soil water content, soil particle roughness and bulk density.

Henderson *et al*., (1988) tried to study the effects of BD and SWC on PR. The value of PR was only slightly affected as SWC was reduced to less than 70% of the field capacity water content. As the soils were dried further, PR increased exponentially. At all water contents, increase in BD was found to markedly increase PR. Since, soil moisture varies both spatially and temporally and is only one of the soil variables related to PR; the utility of using PR to determine compaction effects is marginal. Moreover, interpolation of penetrometer data is difficult because water content or density measurements can generally not be taken at the exact same spatial location as the penetration resistance measurement.

## 1.4 Soil quality /health

### 1.4.1 Definitions:

The various chemical, physical, and biological properties of a soil interact in complex ways that determine its potential fitness or capacity to produce healthy and nutritious food. Soil health is a term which is widely used within discussions on sustainable agriculture to describe the general condition or quality of the soil resource. The integration of these properties and the resulting level of productivity are referred to as "soil quality". Soil quality, soil health, and soil condition are used in various ways and sometimes interchangeably. Soil quality sometimes refers to the inherent potential of soil, in contrast to soil health or soil condition. Karlen, *et al.* (1997) attempted to differentiate between "inherent" and "dynamic" soil quality. They linked "inherent" quality with characteristics determined by soil formation factors stating, "Soils with differences due to their forming factors have different absolute capabilities." They also state that dynamic soil quality reflects "Changes associated with current or past land use and anthropogenic management decisions." Differentiation between "inherent" and "dynamic" soil quality was apparently prompted by concern raised over comparing soil quality index values for different soils. Karlen *et al*. (1997) stated, "Soil quality index scores are always relative, not absolute.

Soil health also defined as the continued capacity of soil to function as a vital living system, by recognizing that it contains biological elements that are key to ecosystem function within land-use boundaries (Doran and Zeiss, 2000). These functions are able to sustain biological productivity of soil, maintain the quality of surrounding air and water environments, as well as promote plant, animal, and human health (Doran *et al*., 1996b). Soil management is fundamental to all agricultural systems, yet there is evidence for widespread degradation of agricultural soils in the form of erosion, loss of organic matter, contamination, compaction, increased salinity and other harms.

The term "soil quality" came into vogue in the 1990's following a 1993 National Research Council Committee (NRCC) report on long-range soil and water conservation entitled "Soil and water quality. The development of the concept and its application in land management has been highly controversial among soil scientists since its inception. Although the physical, chemical, and biological composition of soil varies widely, and none can be established as a standard state, scientists have attempted to define and quantify soil quality. Many concepts proposed since the National Research Council Committee report is based on papers by Larson and Pierce (1994). They defined soil quality as "The capacity of a soil to function within the ecosystem boundaries and interact positively with the external environment." The Soil Science Society of America (1996) definition deviates slightly: "The capacity of a specific kind of soil to function, within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and support human health and habitation."

The Rodale Institute Research Center sponsored a workshop in July 1991 to discuss the attributes of soil quality and whether they could be quantified into meaningful indices that could predict the effects of degradative processes, conservation practices, and management inputs. The workshop proposed that soil quality be defined as: The capability of a soil to produce safe and nutritious crops in a sustained manner over the long-run, and to enhance human and animal health, without impairing the natural resource base or adversely affecting the environment.

### 1.4.2 Indicators of soil health (Soil quality)

Soil quality indicators are important. They refer to the capacity of a soil to function within ecosystem and land use boundaries, to sustain biological productivity, maintain environmental quality, and promote plant and animal health (Doran and Parkin, 1994). Information about soil chemical and physical properties can be used to answer the questions about soil quality and forest health.

Soil quality information contributes to the investigation of several key agroecosystem concerns: (1) the productivity and sustainability of agricultural system, (2) the conservation of soil and water resources, (3) the accumulation of persistent toxic substances, and (4) the contribution of agriculture systems to the global carbon cycle. The set of indicators used to determine a soil's quality is also called a minimum data set. To select a minimum data set, two main methods have been established: expert opinion and statistical data reduction.

Expert opinion, by definition, requires expert knowledge of the system. Using a hierarchical framework for choosing the indicators may help make selection more systematic. Management goals dictate the soil functions of interest, which in turn, suggest related indicators. For instance, if animal waste disposal is a goal for a particular field, filtering and buffering is an important soil function. Under filtering and buffering, organic matter content and pH are potential indicators. The indicator set must be further refined according to climate, soil, and plant community or other factors. This is the method used by the Soil Management Assessment Framework.

Statistical data reduction has been demonstrated to effectively choose indicators in a number of soil systems (Andrews *et al.*, 2004; Andrews and Carroll, 2001). This method can eliminate disciplinary bias that could be a problem with expert selection of indicators but it does assume that appropriate candidate indicators are in the original data set (so a minimum level of knowledge is required). The major weakness of this method is the need for a large existing dataset. It is unlikely that managers will have access to data sets that are suitable in size (either number of indicators measured or number observations made) to make this method feasible for individuals use.

There are two ways in which the concept of soil health has been considered, which can be termed either 'reductionist' or 'integrated'. The former is based on estimation of soil condition using a set of independent indicators of specific soil properties—physical, chemical and biological. This reductionist approach has much in common with conventional quality assessments in other fields, such as materials science. The alternative, integrated, approach makes the assumption that the health of a soil is more than simply the sum of the contributions from a set of specific components. It recognizes the possibility that there are emergent properties resulting from the interaction between different processes and properties.

Efforts to characterize soil quality have focused primarily on soil chemical and physical properties because relatively simple and standardized methods of measurement are available. Soil biological properties have been neglected largely because of the difficulty in quantifying and predicting soil biological behavior. Consequently, no single reliable indicator of soil quality has been designated.

Improved soil quality is generally indicated by increased infiltration, macropores, aggregate size and stability, soil organic matter, and aeration, and by decreased soil resistance to tillage and root penetration, and decreased runoff and erosion (Granatstein & Bezdicek, 1992). More attention should be given to soil biological properties because their relationships with soil chemical and physical properties, plant health, and food quality are obviously important, but poorly understood. Plant health and nutritional quality may prove to be useful and reliable indicators of soil quality (Hedlund & Witter, 2003).

Soil quality indicator is a chemical, physical or biological property of soil that is sensitive to disturbance and represents performance of ecosystem function in that soil of interest. These are dynamic soil properties. Soil properties are chemical, physical, or biological characteristics of soil which can indicate its level of function of ecosystem services.

Scientists use soil quality indicators to evaluate how well soil functions since soil function often cannot be directly measured. Measuring soil quality is an exercise in identifying soil properties that are responsive to management, affect or correlate with environmental outcomes, and are capable of being precisely measured within certain technical and economic constraints. Soil quality indicators may be qualitative (e.g. drainage is fast) or quantitative (infiltration= 2.5 in/hr).

Ideal indicators should correlate well with ecosystem processes, integrate soil physical, chemical, and biological properties and processes, be accessible to many users, be sensitive to management and climate, be components of existing databases, and be interpretable (Doran and Parkin, 1994). There are three main categories of soil indicators: chemical, physical and biological. Soil quality attempts to integrate all three types of indicators.

The table below shows the relationship between indicator type and soil function.

| **Indicator category** | **Related soil function** |
|---|---|
| Chemical | Nutrient cycling, Water relations, Buffering |
| Physical | Physical stability and support, Water relations, Habitat |
| Biological | Biodiversity, Nutrient cycling, Filtering |

Some indicators are descriptive and can be used in the field as part of a health card. Others must be measured using laboratory analyses.

Chemical indicators can give information about the equilibrium between soil solution (soil water and nutrients) and exchange sites (clay particles, organic matter); plant health; the nutritional requirements of plant and soil animal communities, levels of soil contaminants and their availability for uptake by animals and plants. Chemical indicators include:

- Organic matter measures, such as total organic carbon and total nitrogen
- Soil fertility measures, such as soil test phosphorus, mineral nitrogen, exchangeable potassium, and micronutrients
- Soil reaction (pH)
- Measures of toxic contaminants, such as arsenic or copper.
- Measures of salinity or sodicity, such as electrical conductivity, sodium adsorption ratio, and exchangeable sodium percentage

Physical indicators provide information about soil hydrologic characteristics such as water entry and retention which influences availability of water to plants. Some indicators are related to nutrient availability by their influence on rooting volume and aeration status. Other measures tell about erosional status. Indicators include measures of:

- Water flow into and through soil, such as porosity, water infiltration rate and water retention
- Soil structure, such as porosity, bulk density, and soil depth
- Soil aggregate size
- Physical stability, such as aggregate stability, soil depth, or soil loss

Biological indicators can tell about the organisms that form the soil food web, which are responsible for decomposition of organic matter and nutrient cycling. Information about the number of organisms indicates a soil's ability to function or bounce back after disturbance (resistance and resilience). The full consequences of extinction of organisms are unknown. Indicators include measures of:

- Active organic matter pools, such as microbial biomass carbon or respiration
- Diversity indices for various soil organism populations, such as earthworms, nematodes, and micro- arthropods
- Biological activity, such as enzyme activity, potentially mineralizable nitrogen or respiration ($CO_2$ production)

### 1.4.3 Different indices developed by researches in past

While some of the indicators of soil quality may be sensitive to change, others may be more subtle. The overlying question is whether we can measure and quantify these indicators and develop them into a Soil Quality Index that can be used reliably to monitor and predict the impact of farming systems and management practices on soil productivity, environmental quality, food safety and quality, and human and animal health. Soil quality index is a useful tool for assessing the overall soil condition and response to management, or resilience towards natural and anthropogenic forces. The ultimate goal is to develop a mathematical relationship or model that could quantify the various attributes of soil quality, and from it derive one or more indexes for simulation and prediction. Such a relationship could take the following form:

Soil Quality Index = f(SP, P, E, H, ER, BD, FQ, MI)

Where; SP = Soil Properties, P = Potential Productivity, E = Environmental Factors,

H = Health (Human/Animal), ER = Erodibility, BD = Biological Diversity,

FQ = Food Quality/Safety, and MI = Management Inputs

Larson and Pierce (1994) proposed that soil quality (Q) can be expressed as a function of attributes of soil quality. Examples of soil quality attributes are soil organic matter (SOM) or carbon, texture, structure, pH, electrical conductivity (EC), etc. Larson and Pierce (1994) suggested that conservation enhancement or soil degradation can be evaluated by measuring Q at different times (dQ/dt).

Doran and Parkin (1994) described a performance-based soil quality index consisting of six elements: SQ = f(SQEI, SQE2, SQE3, SQE4, SQE5, SQE6), where: SQE1 = food and fiber production, SQE2 = erosivity, SQE3 = groundwater quality, SQE4 = surface water quality, SQE5 = air quality, and SQE6 = food quality. They reasoned that one of the highest research priorities should be to establish guidelines and thresholds for soil quality indicators to enable identification of relationships between measured attributes and functions. This would permit valid comparisons across variations in climate, soils, land use, and management systems. They claim that the map accurately reflects soil resource potential for agricultural production in the absence of human intervention. That is a particularly moot point because there can be no agricultural production without human intervention. The truly important information is the soil potential to produce crops "with management."

Andrews *et al*. (2004) applied soil quality concept in crop production research. They reported results from on-farm trials in California's Central Valley. Farmers who were willing to use a cover crop, compost, or manure amendments on alternate fields, for comparison to a conventional treatment that did not receive organic supplements, were selected for the study. As Andrews *et al*. (2004) explained, the farmers on all but one farm were unwilling to risk possible revenue loss from reducing synthetic fertilizer applications on the alternate fields receiving organic nitrogen (N). Synthetic and organic fertilizers were applied in the alternative treatment, which was reported as a "C supplement" rather than N fertilizer. Thus, fields receiving "C supplements" also had higher total N applied, creating two experimental variables (organic C and total N), confounding the effect of the two variables.

A quantitative relationship between indicator score and indicator level had to be established (i.e.; a score between 0 and 1 associated with the level of each soil indicator such as soil organic matter, bulk density, etc.). This relationship was determined by consensus of the researchers involved and literature values quantifying the relationships between indicators and soil functions. There is a direct effect of electrical conductivity (EC), pH, and Zn on plant growth, whose functional relationships can be based on data. Neglected in the discussion, however, was that each relationship is crop-specific. For example, the EC function depends on each crop's salt sensitivity. Soil organic matter (SOM) and water stable aggregates have no direct effect on plant growth. The investigators chose a sigmoidal relationship with a zero indicator score for zero aggregates and a top score of 1 when the aggregates were 100% stable. The relationship between indicator score and magnitude of the indicator should represent the functional relationship between the indicator amount and crop production, assuming all else is equal. Zero or very low yield, attributed to low soil organic matter or water stable aggregates, is unrealistic. In other words, these relationships were dependent upon the perceptions, values, knowledge, and/or lack of knowledge of those creating the scale. Thus, they are highly subjective and scores could be highly misleading. A soil quality index was calculated by multiplying the individual indicator value by its weighting factor and adding the values for all indicators at that site. The highest weighting factors were for soil organic matter and electrical conductivity. Since electrical conductivity values were low and no limiting, the soil quality index values among treatments depended entirely upon soil organic matter. Thus, the organic system received the highest soil quality index values--a quite predictable result. Andrews *et al*. (2004) ignored risks to groundwater or other possible negatives from high manure rates needed to produce high soil quality index scores, as well as application economics, logistics, and inadequacy of manure supply to provide nutrients to more than a small fraction of agriculture.

**1.4.4 Physical rating index**:

Physical rating of soils is an efficient tool for constraint analysis required for assessing their production potential (Gupta, 1986). In land-use planning, important soil parameters, such as soil texture, depth, slope and extent of erosion, were used for deciding the suitability of lands for different uses such as agricultural, horticultural, forestry or grassland for maintaining soil productivity and preventing environmental degradation (Dhruvnarayana, *et al*., 1997). Physical rating of soils for agricultural land is one step ahead. In this method, in addition to basic physical parameters, few more dynamic parameters such as bulk density, infiltration rate, soil organic matter, water table depth and available water storage capacity were used for physical constraint identification along with the estimation of relative magnitude of their severity. Accordingly, the production potential of these soils could be predicted under optimum levels of water and fertilizer inputs along with the adoption of appropriate plant protection measures (Gupta and Abrol, 1993). Efficiency of any suggested management practice for alleviating these constraints could be assessed in terms of changes in its rating value and hence its production potential.

Aggarwal and Choudhury (2005) computed physical rating index of a few representative soil series of Delhi region for assessment of their production potential and to recommend appropriate soil management practices which could increase their physical rating index values and thus could bring improvement in production potential. Parameters used for calculating physical rating index of soil series were soil depth, bulk density, infiltration rate available water storage capacity, aggregation in terms of % soil organic matter in upper soil layer, per cent non-capillary pores, and per cent land slope. Among the 11 series studied, 3 series had coarse texture, low organic matter, high infiltration rate and low available water storage capacity (AWSC) and physical rating index values of the profiles studied ranged between 0.35 and 0.48 and hence, their productivity ratings were low. In order to improve the production potential of these soils, suggested practices included compaction by 500 kg roller to improve available water storage capacity and reduce infiltration rate, incorporation of green manures, farmyard manure, plant residues into the soil in order to improve organic matter status. Soils of 5 series had medium to fine texture and their physical rating index values ranged between 0.57-0.86. Hence, their productivity ratings were medium to high. Crusting and low organic matter were the major constraints of these soils. Subsurface compaction was also one of the constraints in few cases. Suggested management practices included crop residue, farmyard manure or green manure incorporation into the soil for improving aggregation and reducing crusting and chiseling to break subsurface pan. Soils of 3 series on the catchments of river Yamuna had variable texture, slope and were stratified. The major constraints included seasonal flooding leading to soil erosion, which resulted in the formation of gullies. Physical rating index values of these soils varied between 0.22 and 0.65. Production potential of these soils could be improved by adopting suitable soil conservation measures (Aggarwal & Goswami 2003).

## 1.5 Objectives:

Study was conducted with following objectives:

- To carry out two-dimensional spatial variability analysis of soil hydraulic properties in a big farm to delineate compact zones for indicating precise tillage requirement
- To assess and map the spatial variation of soil physical health in the farm
- To examine correlation between spatial variation of soil physical health and yield of crop in the farm

# 2. MATERIAL AND METHODS

## 2.1 Details of field experimental site

The present investigation was carried out in a rice field near Kherli village, Dankaur Block (28° 17'59" N, 77° 32'04” E) in National Capital Region (Fig.2.1). The climate of study area was semi-arid, subtropical with extreme hot summer and cool winter. The mean annual rainfall was about 600 mm, 80 per cent of which was received during July to September. Mean relative humidity reached its peak (70 %) during the rainy season months. Mean wind velocity varied from 3.5 km $hr^{-1}$ during October to 6.4 km $hr^{-1}$ during April.

In order to measure saturated hydraulic conductivity in field and other relevant soil physical parameters, 145 observation sites were chosen at a grid spacing of about 30 m x 45 m covering a total area of 19.6 hectare. The coordinates of each sampling location were recorded using a differential global positioning system unit (Fig. 2.2). At each site, field saturated hydraulic conductivity ($K_{fs}$) was determined using Guelph permeameter.

In addition to this, disturbed and undisturbed soil samples were collected from 0-15 cm and 15-30 cm soil layers. Core sampler was used for taking undisturbed soil samples mainly for soil bulk density (BD) determination and for drawing soil water retention curve, while disturbed soil samples were collected by using a screw auger (Fig. 2.3) for determination of soil texture, organic matter and saturation percentage. Disturbed samples were air dried and sieved (2 mm) before analysis.

## 2.2 Soil parameters studied:

### 2.2.1 Field saturated hydraulic conductivity ($K_{fs}$):

Saturated Hydraulic Conductivity in field was measured by Guelph permeameter (Fig. 2.4) which is a constant head well permeameter (Reynolds, 1993, Reynolds *et al*., 2002) consisting of a mariotte bottle that maintains a constant water level inside a hole augered in the soil. The method involves measuring the steady-state rate of water recharge into the soil from a cylindrical well hole, in which a constant depth (head) of water is maintained.

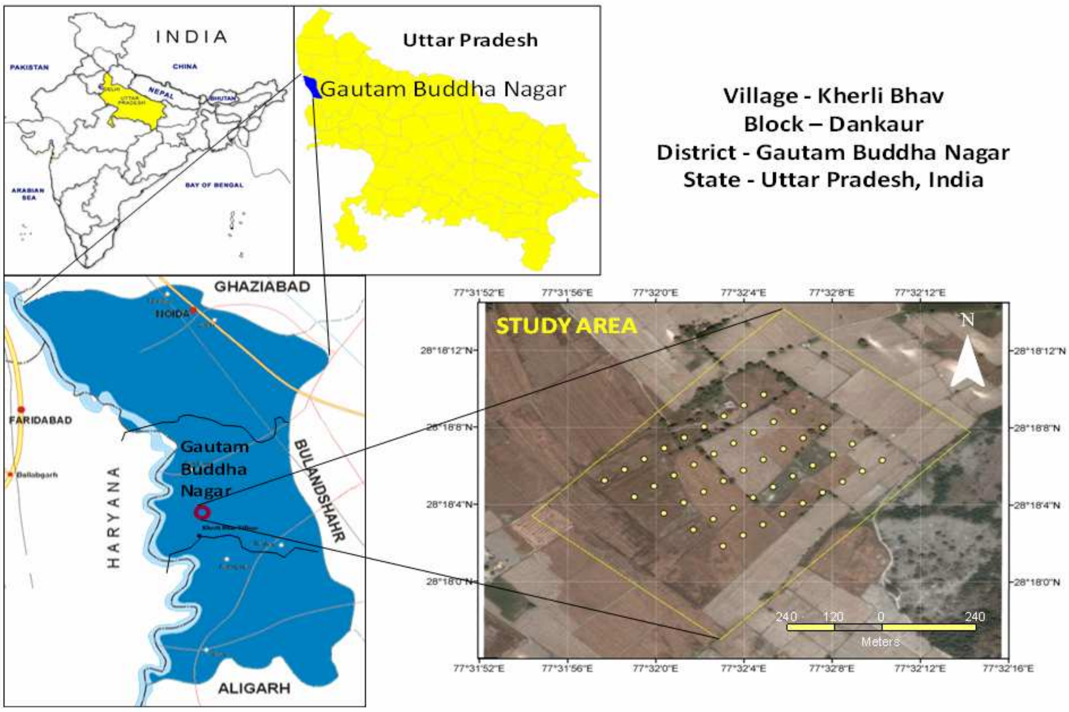



**Fig. 2.1:** The map of study area

**Fig.2.2:** Global positioning system (GPS) for recording sample location

The analysis of steady-state discharge from a cylindrical well in unsaturated soil, as measured by the Guelph Permeameter technique, accounted for all the forces that contribute to three dimensional flow of water into soils: the hydraulic push of water into soil, the gravitational pull of liquid out through the bottom of the well, and the capillary "pull" of water out of the well into the surrounding soil.

Equation for one-head analysis for $K_{fs}$:

$$\mathbf{K_{fs}} = \left[\!\left[\frac{\mathbf{CQ}}{2\pi H^2 + \pi a^2 C + 2\pi H/\alpha}\right]\!\right]$$

Where;

$K_{fs}$ - Field-saturated hydraulic conductivity (entrapped air present), in cm/sec.

R - Steady state rate of fall of water in the reservoir tube of the permeameter, in cm/sec.

Alpha parameter (α) - slope of the natural log of K – Q curve = 0.12 $cm^{-1}$ for most of agricultural soils, H - Well height in cm, a - Well radius, in cm,

Q = XR, where X - reservoir constant = 35.43 $cm^2$

C-Factor - a numerically derived shape factor, dependent on the well radius and head H of water in the well.

### 2.2.2 Soil bulk density:

Soil bulk density (BD) of each site was determined by using core method (Fig. 2.5). For this purpose, a core cutter of 5.5 cm diameter and 15 cm height was used. Core cutter held an assembly of a sectional cylinder (core) of 6 cm diameter and 6 cm height with 2 rings of same diameter but 2 cm height on either side of it and was screwed to the collar of sampler (2.5 cm high) from the upper side. Collar of the cutter was attached to a galvanized thick hollow iron rod of nearly 85 cm height. The other end of the rod was attached to a handle. The bottom part of the cutter had a sharp edge and nearly 2.5 cm of the bottom portion of core cutter was slightly bent inward, hence the inner assembly remained above 2.5 cm from bottom part of cutter.

For taking samples, the assembled core cutter was positioned over a clean leveled surface and pressed inside the soil by rotating the handles or by dropping a hammer over the center portion of the upper end of the thick rod until the edge of the collar came to rest over the soil surface. Core cutter was then moved back and forth to loosen the soil grip around it. It was then slowly pulled out of the hole. After unscrewing the cutter from the collar, the unit of sectional cylinder with rings on each side was taken out carefully. Rings with undisturbed soil were used in pressure plate

**Fig. 2.3:** Screw auger for taking disturbed soil samples

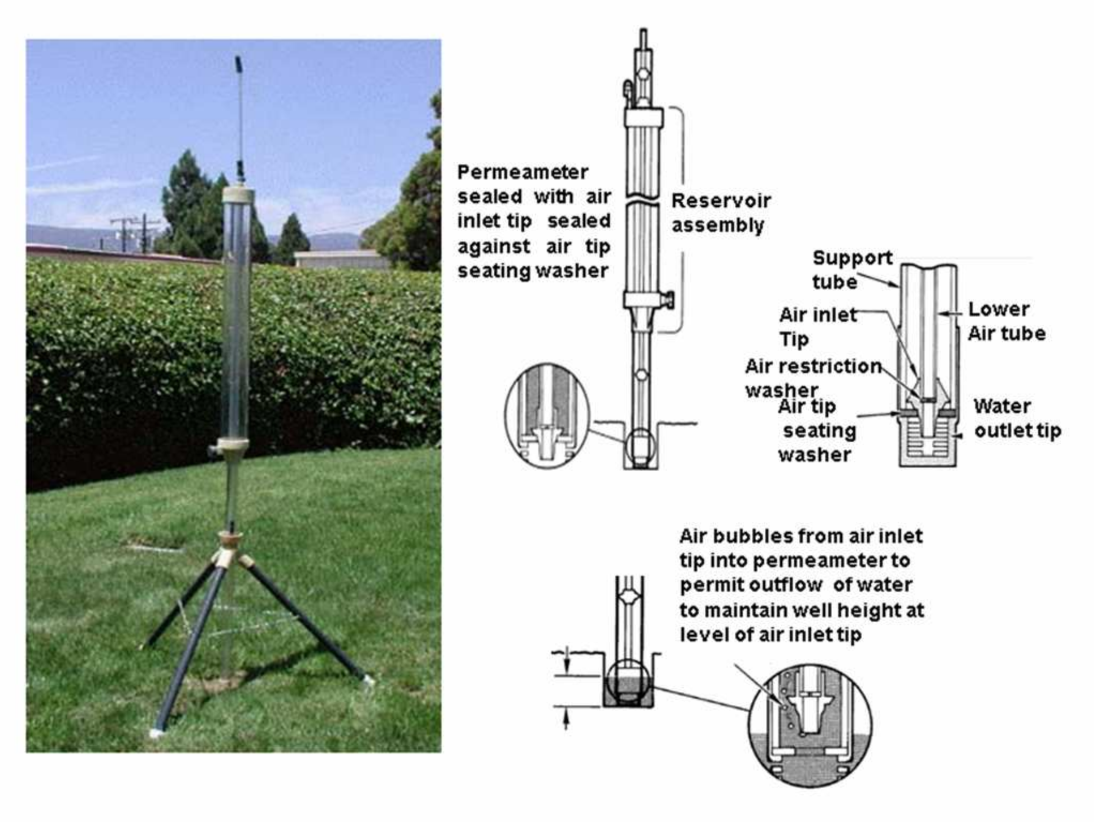
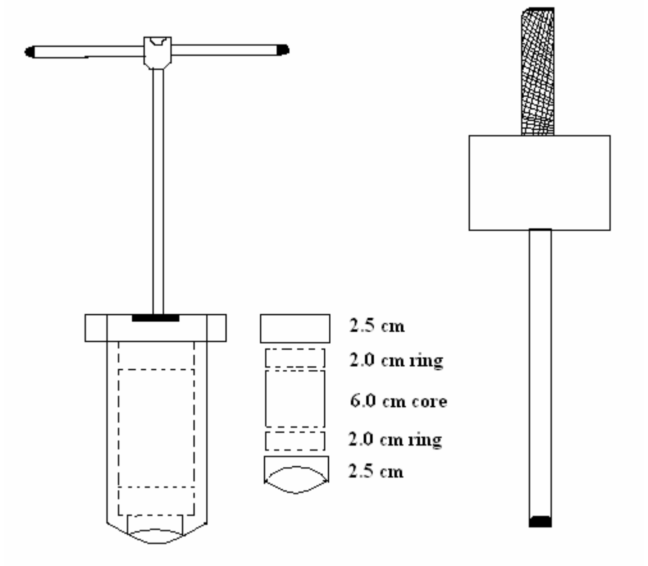



**Fig. 2.4:** Guleph permeameter for measurement of soil hydraulic parameters




- Soil of the rings were used for determination of $\theta_{FC}$ and $\theta_{PWP}$
- Soil of the core was used for determination of dry bulk density

**Fig. 2.5:** Schematic diagram of undisturbed soil core sampler

apparatus for determination of water retention characteristics , whereas soil of the sectional cylinder (after removing the extra soil sticking out the cylinder) was taken out in aluminum can, oven dried and oven dry BD was determined by dividing the weight of oven dry soil by volume of sectional cylinder.

**2.2.3 Water retention characteristics:**

Soil water contents ($\theta$) at field capacity ($\theta_{FC}$) and permanent wilting point ($\theta_{PWP}$) were measured by pressure plate apparatus.

The pressure plate apparatus consisted of a pressure chamber enclosing water saturated porous plate, which allows water but prevents air flow through pores. The porous plate remained open to atmospheric pressure at the bottom, while the top surface was at the applied pressure of the chamber. Undisturbed soil cores of thickness 2 cm were placed in the porous plate and were left to saturate in water. After saturation was attained, the porous plate with the saturated samples was placed in the chamber and 0.33 bar of gas pressure was applied to force water out of the soil and through the plate. Flow continued until equilibrium between the force exerted by the air pressure and the force by which soil water was being held by the soil was reached, which took nearly 2-3 days and after this soil water content of the sample was determined gravimetrically. It corresponded to soil water content retained by soil at 0.33 bar ($\theta_{FC}$ %). Similarly soil water content at 15 bars was also determined ($\theta_{PWP}$). Saturation water percent ($\theta_{SAT}$) of each sample was also determined gravimetrically (Singh, 2001).

**2.2.4 Drainage porosity and available water content:**

Drainage porosity or noncapillary pores and available water contentwere determined by following formulae:

Drainage porosity (%) = $\theta_{SAT}$ (%) - $\theta_{FC}$ (%) ,and

Available water retention capacity (AWRC) = $\theta_{FC}$ (%) - $\theta_{PWP}$ (%)

**2.2.5 Soil texture:**

Hydrometer method (Bouyoucos, 1962) was used to determine sand, silt and clay percentage for each sample. USDA textural triangle was used to determine textural classes.

**2.2.6 Soil organic carbon (OC):**

Soil organic carbon for each soil sample was measured by Walkley and Black (1934) method. In this method organic matter is oxidized with chromic acid (potassium dichromate + H2SO4) and the unconsumed potassium dichromate is back titrated against ferrous sulphate or ferrous ammonium sulphate (redox titration).

**2.3 Classical statistical methods):**

**2.3.1 Statistical analysis:**

Descriptive statistical analysis was carried out for $K_{fs}$, BD, $\theta_{PWP}$, $\theta_{FC}$, $\theta_{SAT}$, drainage porosity, AWRC, OC %, sand %, silt % and clay %.

Statistical analysis of data included examination of the mean, maximum and minimum values, standard deviation (SD), variance and coefficient of variation (CV), Skewness, Kurtosis, and median.

**2.3.2 Stepwise multiple regression model**

A stepwise multiple regression equations (Pedotransfer functions) were developed for predicting some dependant variables such as; $K_{fs}$, AWRC, $\theta_{FC}$ ,$\theta_{PWP}$, drainage porosity, BD as a function of OC %, clay %, silt % and sand % using "Statistica Pro-2004 " software package. Since the value of degree of freedom (df) was large (>120), t value at 5% level of significance if found >2, then independent parameter was considered to have significant effect on dependent variables. Or other way if p value of parameter was <0.05, then also the parameter was considered to have significant effect on dependent variables.

**2.4 Geostatistical analysis:**

Preparation of surface maps of field saturated hydraulic conductivity and bulk density using geostatistical analyst (Johnston *et al*. 2001) involved two key steps: exploratory spatial data analysis, and spatial structural analysis and interpolation through kriging.

**2.4.1 Exploratory spatial data analysis (ESDA):**

ESDA involved exploring the distribution of the data, looking for global and local outlier, looking for global trends, examining spatial autocorrelation, and understanding the covariation among multiple datasets.

**2.4.2 Spatial structure analysis and kriging using geostatistical analyst wizard:**

**Step1: Choice of suitable interpolation method:**

The first step of this analysis was to choose the appropriate geostatistical method of interpolation which could be ordinary kriging, simple kriging, universal kriging or cokriging. The decision for a particular interpolation technique could be taken from the observations made in ESDA. If no trend in data was observed oridinary kriging was chosen. If trend was present, universal kriging was used. If one wanted to prepare the surface of the parameter whose value exceeded a particular threshold value then indicator kriging was used.

**Step 2: Drawing empirical semivariogram and fitting appropriate model**:

Again using the information obtained from ESDA, different available anisotropic or isotropic semivariance models were fitted to empirical semivariance cloud data (scatter plot).

**Step 3: Searching neighborhood for kriging:**

Neighborhood shape was kept spherical if the empirical semivariogram of data showed isotropy and elliptical if it showed anisotropy. Again in order to avoid bias in a particular direction the ellipse was divided in four sectors and a minimum of 2 or maximum of 5 sampled data points were selected in each sector.

**Step 4: Cross validation of models and preparation of predicted surface:**

All the models were cross validated by plotting the predicted values against observed value and fitting a line through the scatter plot. More closer was this line to 1:1 line better was the fit. For all layers, the best fitted model was the one which gave lowest RMSE and also its average standard error (AVSE) nearest to root mean square prediction error or alternatively root mean square standardized error (RMSS) nearest to one.

Finally the values at the unvisited location were predicted by multiplying the weights of the sampled data points by their values and then adding them together. For the presenting the prediction map as filled contours, the maximum, minimum and contour interval were specified.

### 2.4.3 Delineation of the compacted areas:

By inspecting the prediction map, the area having the value of $K_{fs}$ parameter less than its critical limit of 24 cm/day and BD >1.55 $Mgm^{-3}$ was delineated as compact areas (Gupta, 1986).

## 2.5 Methodology for computing soil physical health index (PI):

For a given site, each of these parameters was assigned a rating value corresponding to its actual value by referring to rating chart (Gupta, 1986). Each of this parameter was given a score of 1 if the parameter value lies within the optimum range. If the value lies below or above the critical limit, a score less than 1 were given. Greater the deviation of parameter value from optimum range, lesser the score given to it. The product of rating values of all the eight parameters gave the physical rating index. PI was an indicator of overall soil physical health status. For range of PI

>0.75, 0.50-0.75, 0.25-0.50 and <0.25, soil physical health status and accordingly its production potential could be labeled as very good, good, medium or poor, respectively.

As per physical rating methodology suggested by Gupta (1986), same ranges of soil parameters were assigned different rating values under rice and wheat cultivations because optimum soil physical environment required for their growth were different.

# 3. RESEARCH PAPER -1

## Two-dimensional spatial variability analysis of hydraulic conductivity in a big farm to delineate compact zones

### 3.1 Abstract

To delineate compact zones**,** spatial variability analysis of saturated hydraulic conductivity ($K_{fs}$) and bulk density (BD), was conducted in a rice-wheat farm in National Capital Region, India. The study also aimed to develop pedotransfer functions of hydraulic parameters as function of easily measurable soil physical parameters. Hence, soil samples at 145 locations at a grid interval of 30 m x 45 m, covering a total area of 19.6 hectare of farm were collected from surface (0-15 cm) and sub surface (15-30 cm) soil layers. Results revealed that in 15-30 cm layer, the average values of $K_{fs}$ and drainage porosity were reduced but the average values of BD and clay% were increased which confirmed the presence a plow pan in subsurface. The descriptive statistical analysis shows that, among the different soil physical parameters BD had the lowest coefficient of variation (CV) followed by permanent wilting point ($\theta_{PWP}$) and $K_{fs}$ had the highest CV, followed by field capacity ($\theta_{FC}$). The computed correlation coefficient between soil properties also showed that $K_{fs}$ is positively correlated to sand and organic matter (OC) and negatively to clay. Stepwise regression analysis of $K_{fs}$, revealed that among all soil physical parameters, clay had maximum influence on $K_{fs}$. Two dimensional spatial variability analyses of $K_{fs}$ indicated that both soil layers had similar spatial structure and ordinary kriging was the best choice, among several methods of interpolation. Comparison of cross validation statistics of various models also showed that for $K_{fs}$, Gaussian model was most suited semivariogram model. So, ordinary kriging with Gaussian model was used for drawing prediction map of $K_{fs}$. Similar results were also obtained for BD. In general, the ratio of nugget to sill values for $K_{fs}$ and BD was low (< 25%), which showed strong spatial dependence of the parameters. On comparing the log transformation data and without transformation data of semivariograms of $K_{fs}$ for the same sampling intensity it was observed that the data without transformation reduced the mean of prediction error (MPE) value to near zero and hence improved the prediction map in comparison to log transformation data. It means kriging as a predictor does not require data to be normal. The prediction maps of $K_{fs}$ and BD for both layers also indicated the presence a hardpan ($K_{fs}$ <0.16 cm/hr and BD

>1.55Mgm$^{-3}$) in the subsurface. Hence deep plowing should be recommended for the area having plow pan.

**Keywords**: spatial variability analysis, saturated hydraulic conductivity, compact zones

### 3.2 Introduction:

Soil compaction is one of the major problems in modern agriculture. Overuse of machinery, intensive cropping, short crop rotations, intensive grazing and inappropriate soil management leads to compaction. A soil physicist would describe compact state of soil as one which results increased bulk density and reduced pore space of soil. Such soil condition increases in soil strength and reduces in hydraulic conductivity resulting in decreasing storage and supply of water and nutrients (Soane and Van Ouwerkerk, 1994).

In most of the medium textured alluvial soils, normal tillage (up to 20 cm depth) along with the excessive use of disc implements and heavy machinery result in development of compacted, impermeable subsurface layer between 15-30 cm (Aggarwal *et al.*, 1997). When traffic compaction occurs below the normal depth of tillage, subsurface hard pan layer restricts root growth and limits crop yield, especially during drought (Taylor and Gardner, 1963; Camp and Lund, 1968).

The compaction of soil should be avoided because it creates a poor environment for roots i.e. poor aeration, waterlogging and excessive soil strength limiting root growth and narrow non-limiting water range (Taylor and Gardner, 1963). Generally, the soils with smaller soil particles exhibit more compaction and reduce yield. In years when soil moisture is plentiful, the impact on crop growth may not be obvious. In years of moisture shortage, plants on compacted soil experience stress more easily, and reduced growth and yields are noticeable (Busscher and Bauer, 2003; Raper *et al*., 2004a).

Due to the nature of soil compaction and its variability within fields, farmers need to assess such variability by measuring soil physical properties such as soil bulk density, hydraulic properties or soil strength. Such measurements allow farmers to determine the spatial variation of compaction and develop global information system (GIS) databases utilizing global positioning system (GPS) in their fields.

If soil compaction is measured and mapped, decisions may be made to specify tillage in the areas where detrimental compaction exists. Tillage depth is precisely specified to reach and disturb a compacted “pan”. In addition, it might be desirable to prescribe the depth of tillage within certain areas of a field. Thus, within a field, tillage depth would vary according to the depth of soil compaction. Draft load and required energy could be reduced by tilling only to the depth of soil compaction and only in areas containing compaction problems, thereby minimizing input cost (Fulton *et al*.. 1996; Raper *et al.*, 2000).

The precision tillage or site-specific tillage is a component of precision agriculture management strategy that employs detailed site-specific soil and crop information to precisely manage the production inputs (Raper *et al.,* 2004a). Site-specific tillage in particular is geared towards achieving the goals of sustainable agriculture by determining within field variability and providing more accurate soil compaction records, and optimizing the tillage input within the field where root limiting soil compaction exists. Studies have also suggested that site-specific tillage has potential in reducing tillage energy and fuel consumptions as compared to the conventional uniform depth tillage (Gorucu *et al*., 2002; Raper *et al.* 2004a). Raper *et al*. (2000) estimated about 50% reduction in energy requirements for shallow tillage (approximately 18 cm) as compared to deep tillage (approximately 33 cm). Gorucu *et al*. (2002) found that approximately 75 % of the test area required tillage operations shallower than the commonly used tillage depth for Coastal plain soils. Thus, precision deep tillage is attractive from the standpoint of eliminating unnecessary tillage. In precision tillage, a precise detection of soil hardpan is important because errors of a few centimeters could cause large variations in accurately locating the soil hardpan and site-specific tillage depth recommendations.

As a part of soil strength sensing technology, there are many sensitive soil physical indicators of compaction including soil macroporosity, saturated hydraulic conductivity ($K_{fs}$), soil penetration resistance and bulk density (Konopka, 1994). Direct measurement of these soil parameters is relatively time-consuming. As an alternative to measurements, one can use estimation methods such as pedotransfer functions (PTFs) which utilize physical or empirical relations between hydraulic properties and other easily measurable soil properties. The advantage of such methods is that the input variables can be measured more easily and, hence, are more widely available than hydraulic properties.

For the prediction of water retention and saturated hydraulic conductivity, this approach has led to a number of pedotransfer functions that use soil texture, bulk density, and other soil variables as input (e.g., Ahuja *et al*., 1989; and Schaap *et al*., 1998). Estimation of soil hydraulic properties using proximal spectral reflectance in visible, near-infrared, and shortwave-infrared was done by Santra *et al*. (2009). These PTFs can, therefore, be used in generating maps of required hydraulic parameters.

The $K_{fs}$ is mostly determined by large pores, which are strongly reduced when the soil bulk density increases because of compaction. Consequently, drastic reductions in $K_{fs}$ with increasing bulk density have been reported. The ratio between the saturated hydraulic conductivity of the compacted soil, $K_{fs}$, and that of the initial soil, $K_{fs}$, can vary by orders of magnitude (Soane, and Van Ouwerkerk, 1994).

After determining the value of hydraulic parameters at few locations on a farm, geostatistical /spatial variability analysis of data is required for generation of prediction maps of these soil compaction indicators required for precision agriculture. Geostatistics provides a method for the analysis of the spatial and temporal properties in a data set and a method of interpolation between selected points. Soil hydraulic properties show a considerable spatial variation in agricultural fields as well as forest area (Kilic, 2004).

Fulton *et al*. (1996) studied the spatial variations of hydraulic conductivity estimated by the constant head permeameter method (Klute, 1986). In these experiments, the hydraulic conductivity was computed at different soil depths under tillage and no-tillage conditions and the resulting conclusion was that the field saturated hydraulic conductivity is a more highly spatially variable on the surface as compared to the subsurface. All these studies have highlighted the spatial variability of $K_{fs}$ only in one direction, either along the slope or across the slope. Very little attention has been given to investigate the variations in $K_{fs}$ in two dimensions. In most of the recent softwares developed for preparing kriged maps of properties, information about their spatial structure (semivariogram models) are required in the input files. Hence spatial structure analysis should be carried out carefully for preparing semivariogram models. With the introduction of geostatistical analyst extension in ArcGIS, it is now possible to carry out preprocessing, statistical analysis and interpolation.

Hence, the present study was conducted with objectives to develop pedotransfer functions for soil hydraulic parameters and to carry out two-dimensional spatial variability analysis of field saturated hydraulic conductivity in a big farm to delineate compact zones for indicating precise tillage recommendations.

## 3.3 Materials and Methods

The present investigation was carried out in a rice field near Kherli village, Dankaur Block (28 ° 17'59" N, 77 ° 32'04" E) in National Capital Region. The climate of study area was semi-arid, subtropical with extreme hot summer and cool winter. `The mean annual rainfall was about 600 mm, 80 per cent of which was received during July to September. Mean relative humidity reached its peak (70 %) during the rainy season months.

In order to measure saturated hydraulic conductivity in field and other relevant soil physical parameter, 145 observation sites were chosen at a grid spacing of about 30 m x 45 m covering a total area of 19.6 hectare. The coordinates of each sampling location were recorded using a differential global positioning system unit. At each site, field saturated hydraulic conductivity ($K_{fs}$) was determined using Guelph permeameter.

In addition to this, disturbed and undisturbed soil samples were collected from 0-15 cm and 15-30 cm soil layers. Core sampler was used for taking undisturbed soil samples mainly for soil bulk density (BD) determination and for drawing soil water retention curve, while disturbed soil samples were collected by using a screw auger for determination of soil texture, organic matter and saturation percentage. Disturbed Samples were air dried and sieved (2 mm) before analysis.

**Soil parameters studied:**

**Field saturated Hydraulic Conductivity ($K_{fs}$):**

Saturated Hydraulic Conductivity in field was measured by Guelph permeameter which is a constant head well permeameter (Reynolds, 1993, Reynolds et al., 2002) consisting of a mariotte bottle that maintains a constant water level inside a hole augered in the soil. The method involves measuring the steady-state rate of water recharge into the soil from a cylindrical well hole, in which a constant depth (head) of water is maintained.

**Soil bulk density:**

Soil bulk density (BD) of each site was determined by using core method. For this purpose, a core cutter of 5.5 cm diameter and 15 cm height was used. Core cutter held an assembly of a sectional cylinder of 5 cm diameter and 6 cm height with 2 rings of same diameter but 2 cm height on either side of it and was screwed to the collar of sampler (2.5 cm high) from the upper side.

For taking samples, the assembled core cutter was positioned over a clean leveled surface and pressed inside the soil by rotating the handles or by dropping a hammer over the center portion of the upper end of the thick rod until the edge of the collar came to rest over the soil surface. Rings with undisturbed soil were used in pressure plate apparatus for determination of water retention characteristics , whereas soil of the sectional cylinder (after removing the extra soil sticking out the cylinder) was taken out in aluminum can , oven dried and oven dry BD was determined by dividing the weight of oven dry soil by volume of sectional cylinder.

**Water retention characteristics:**

Rings of core sampler containing undisturbed soil samples were used for determining soil water contents ($\theta$) at field capacity ($\theta_{FC}$) and permanent wilting point ($\theta_{PWP}$) by pressure plate apparatus.

Saturation water percent ($\theta_{SAT}$) of each sample was also determined gravimetrically (Singh, 2001).

**Drainage Porosity and available water content:**

Drainage porosity or noncapillary pores and available water retention capacity were determined by following formulae:

Drainage porosity (%) = $\theta_{SAT}$ (%) - $\theta_{FC}$ (%), and

Available water retention capacity (AWRC) = $\theta_{FC}$ (%) - $\theta_{PWP}$ (%)

**Soil texture:**

Bouyoucos /hydrometer method was used to determine sand, silt and clay percentage for each sample. USDA textural triangle was used to determine textural classes.

**Soil organic carbon (OC):**

Soil organic carbon for each soil sample was measured by Walkley and Black (1934) method. In this method organic matter is oxidized with chromic acid (potassium dichromate + H2SO4) and the unconsumed potassium dichromate is back titrated against ferrous sulphate or ferrous ammonium sulphate (redox titration).

**Methodology (Statistical and Geostatistical methods):**

**Statistical analysis:**

Descriptive statistical analysis was carried out for $K_{fs}$, BD, $\theta_{PWP}$, $\theta_{FC}$, $\theta_{SAT}$, drainage porosity, AWRC, OC %, sand %, silt % and clay %. Statistical analysis of data included examination of the mean, maximum and minimum values, standard deviation (SD), variance and coefficient of variation (CV), Skewness, Kurtosis, and median.

**Multiple regression analysis**

A stepwise multiple regression equations (Pedotransfer functions) were developed for predicting some dependant variables such as; $K_{fs}$, AWRC, $\theta_{FC}$ ,$\theta_{PWP}$, drainage porosity, BD as a function of OC %, clay %, silt % and sand % using “Statistica Pro-2004 ” software package. Since the value of degree of freedom (df) was large (>120), t value at 5% level of significance if found >2, then independent parameter was considered to have significant effect on dependent variables. Or other way if p value of parameter was <0.05, then also the parameter was considered to have significant effect on dependent variables.

**Geostatistical analysis:**

Preparation of surface maps of field saturated hydraulic conductivity and bulk density using geostatistical analyst (Johnston *et.al*., 2001) involved two key steps: exploratory spatial data analysis, and spatial structural analysis and interpolation through kriging

ESDA involved exploring the distribution of the data, looking for global and local outlier, looking for global trends, examining spatial autocorrelation, and understanding the covariation among multiple data.

**Choice of suitable interpolation method:** The first step of this analysis was to choose the appropriate geostatistical method of interpolation which could be ordinary kriging, simple kriging, universal kriging or cokriging. The decision for a particular interpolation technique could be taken from the observations made in ESDA. If no trend in data was observed oridinary kriging was chosen. If trend was present, universal kriging was used. If one wanted to prepare the surface of the parameter whose value exceeded a particular threshold value then indicator kriging was used.

**Drawing empirical semivariogram and fitting appropriate model**: Again using the information obtained from ESDA, different available anisotropic or isotropic semivariance models were fitted to empirical semivariance cloud data (scatter plot).

**Searching neighborhood for kriging:** Neighborhood shape was kept spherical if the empirical semivariogram of data showed isotropy and elliptical if it showed anisotropy. Again in order to avoid bias in a particular direction the ellipse was divided in four sectors and a minimum of 2 or maximum of 5 sampled data points were selected in each sector.

**Cross validation of models and preparation of predicted surface:** All the models were cross validated by plotting the predicted values against observed value and fitting a line through the scatter plot. More closer was this line to 1:1 line better was the fit. For all layers, the best fitted model was the one which gave lowest RMSE and also its average standard error (AVSE) nearest to root mean square prediction error or alternatively root mean square standardized error (RMSS) nearest to one.

Finally the values at the unvisited location were predicted by multiplying the weights of the sampled data points by their values and then adding them together. For the presenting the prediction map as filled contours, the maximum, minimum and contour interval were specified.

**Delineation of the compacted areas**: By inspecting the prediction map, the area having the value of $K_{fs}$ parameter less than its critical limit of 24 cm/day and BD >1.55 Mgm$^{-3}$ was delineated as compact areas (Gupta, 1986).

## 3.4 Results and Discussion:

**Descriptive statistics and development of pedotransfer functions for soil hydraulic parameters:**

Statistical analysis of soil physical properties showed that for surface (0-15 cm) layer, % sand, silt and clay varied between 15.5-69.5, 16.0-40.0 and14.5-46.5 and for subsurface layer varied between 15.5-62.0, 185.-38.0 and 16.5-48.5, respectively

(Table 3.1 & 3.2).The prominent textural classes were sandy clay loam and clay loam for both surface and subsurface layers. Bulk density (BD) of surface layer varied between 1.42-1.75 Mg $m^{-3}$ with an average value of 1.57 Mg $m^{-3}$ whereas for subsurface layer it ranged between 1.47-1.85 Mg $m^{-3}$ with an average magnitude of 1.74 Mg $m^{-3}$. The results thus clearly indicated the presence of subsurface plough pan as the average value of BD was more than its critical value of 1.55 Mg $m^{-3}$ as suggested by physical rating system (Gupta, 1986). Field saturated hydraulic conductivity ($K_{fs}$) as measured by Guelph permeameter varied between 0.002-0.55 cm/hr with an average value of 0.108 cm/hr for surface layer and ranged between 0.002-0.023 with an average value of 0.005 cm/hr for the subsurface layer. Similarly % OC ranged between 0.45-1.34 for surface and 0.4-1.00 for subsurface. AWRC (difference between $\Theta_{FC}$ and $\Theta_{PWP}$) of these soils for surface and subsurface layer ranged between 21.6-28.0 and 15.9-31.6. As these values were >15 cm/m, hence it could be concluded that available water retention capacity of these soils was good.

The most discriminating factor to describe variability of a soil property is coefficient of variation (CV). If CV is lower than 0.10, the property shows lowest variability; and if CV is higher than 0.90, it shows great variability. BD had lowest coefficient of variation, which ranged from 6.53 - 7.54 %, followed by $\theta_{FC}$ with range from 15.26 - 15.86 and silt with range from 19.82 - 21.18%. Similar results have been reported earlier (Kilic *et al.*, 2004). The CV of $K_{fs}$ was highest (109.54 %), indicating that $K_{fs}$ was highly variable, followed by $\theta_{PWP}$ which ranged between 50.3-54.02. Data of sand, silt, clay and $\theta_{PWP}$ showed near normal distribution as indicated by their median value nearer to mean, skewness value nearer to zero and kutosis value nearer to 3.

Multiple regression analysis was carried out to develop pedotransfer functions for determining soil hydraulic parameters such as $K_{fs}$, $\Theta_{Fc}$ and $\Theta_{pwp}$ from easily measurable parameters such as particles size distribution and organic carbon content. Results of analysis of bulk density as a function of clay, silt and OC showed that all three parameters significantly affected BD (as indicated by computed t values (df> 120) which were >2.10 (Table 3.3). While BD was negatively correlated to clay and OC, it was positively correlated to silt. Stepwise analysis showed that clay alone contributed nearly 48 % variation in BD. Inclusion of silt along with clay accounted for nearly 58 % variation of BD and further addition of OC to regression equation increased the contribution to 62%.

**Table 3.1:** Descriptive statistics of soil physical properties for surface (0-15 cm) layer

| **Parameter** | **Min.** | **Max.** | **Mean** | **Median** | **SD** | **CV%** | **Skewness** | **Kurtosis** |
|---|---|---|---|---|---|---|---|---|
| Sand (%) | 15.50 | 69.50 | 45.07 | 47.50 | 11.47 | 25.45 | 0.411 | 2.768 |
| Silt (%) | 16.00 | 40.00 | 28.10 | 26.00 | 5.96 | 21.21 | 0.241 | 2.200 |
| Clay (%) | 14.50 | 46.50 | 26.10 | 23.00 | 7.91 | 30.31 | 0.630 | 2.399 |
| $\theta_{PWP}$(w/w) | 1.20 | 12.30 | 5.19 | 4.60 | 2.80 | 53.95 | 0.572 | 2.462 |
| $\theta_{FC}$(w/w) | 12.50 | 25.10 | 16.18 | 15.90 | 2.47 | 15.26 | 1.211 | 5.352 |
| NCP (%) | 4.0 | 27.0 | 15.12 | 13.0 | 6.42 | 42.27 | 0.4505 | 2.1679 |
| AWRC(cm/m) | 15.90 | 31.60 | 22.23 | 23.46 | 3.26 | 14.66 | 0.5207 | 1.1273 |
| BD(Mg $m^{-3}$) | 1.42 | 1.75 | 1.57 | 1.60 | 0.12 | 7.64 | 0.307 | 1.920 |
| OC (%) | 0.45 | 1.34 | 0.72 | 0.69 | 0.17 | 23.61 | 1.180 | 4.870 |
| $K_{fs}$ (cm/hr) | 0.002 | 0.550 | 0.108 | 0.066 | 0.118 | 109.26 | 1.669 | 6.051 |

**Table 3.2:** Descriptive statistics of soil physical properties for subsurface (15-30 cm) layer

| Parameter | Min. | Max. | Mean | Median | SD | CV% | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Sand (%) | 15.50 | 62.00 | 43.50 | 44.00 | 11.96 | 27.49 | 0.410 | 2.319 |
| Silt (%) | 18.00 | 38.00 | 27.60 | 28.00 | 5.47 | 19.82 | 0.202 | 2.389 |
| Clay (%) | 16.50 | 48.50 | 28.90 | 26.50 | 8.45 | 29.24 | 0.491 | 2.229 |
| $\theta_{PWP}$(w/w) | 2.10 | 14.00 | 6.86 | 6.10 | 3.45 | 50.29 | 0.488 | 2.065 |
| $\theta_{FC}$(w/w) | 8.30 | 23.40 | 14.90 | 14.50 | 2.35 | 15.77 | 0.696 | 6.129 |
| NCP (%) | 0.60 | 22.0 | 8.91 | 8.40 | 5.81 | 33.74 | 0.5762 | 2.4526 |
| AWRC(cm/m) | 21.16 | 28.01 | 15.93 | 17.23 | 3.18 | 19.96 | 0.5437 | 1.3253 |
| BD(Mg $m^{-3}$) | 1.47 | 1.85 | 1.74 | 1.77 | 0.11 | 6.32 | 0.542 | 2.555 |
| OC (%) | 0.40 | 1.00 | 0.59 | 0.55 | 0.15 | 25.42 | 1.083 | 3.398 |
| $K_{fs}$(cm/hr) | 0.002 | 0.023 | 0.005 | 0.002 | 0.005 | 100.0 | 1.668 | 6.033 |

Similarly, multiple regression analysis of hydraulic conductivity as a function of clay, sand and OC (Table 3.4) showed that all three parameters significantly affected $K_{fs}$. While $K_{fs}$ was negatively correlated to clay, it was positively correlated to sand and OC. Stepwise analysis showed that clay alone contributed nearly 49 % variation in $K_{fs}$. Inclusion of sand along with clay accounted for nearly 57 % variation of $K_{fs}$ and further addition of OC to regression equation increased the contribution to 65 %. The rationale behind such assumption is that better soil aggregation is linked to greater OM content (Beare *et al.*, 1994). Similar correlation among soil hydraulic parameters and sand, silt and clay % has been reported by Adhikary *et al*.(2008).

Regression analysis of $\Theta_{pwp}$ as a function of sand and OC (Table 3.5) showed that both parameters significantly affected $\theta_{PWP}$. It was negatively correlated to sand and positively correlated to OC. Further stepwise analysis showed that sand alone contributed nearly 20 % variation in $\theta_{PWP}$. Inclusion of sand along with OC accounted for nearly 26 % variation of $\theta_{PWP}$.

Similarly, regression equations of $\Theta_{FC}$ (w/w) of surface soil as a function of various soil physical parameters showed that sand, clay and OC significantly affected $\Theta_{FC}$ (Table 3.6). While $\Theta_{FC}$ was negatively correlated to sand, it was positively correlated to clay and OC. Results of analysis showed that sand alone contributed nearly 30 % variation in $\Theta_{FC}$, whereas clay and OC alone contributed 26 and 11%, respectively. Negative correlation of $\Theta_{FC}$ with sand and positive correlation with clay was mainly because of the fact that $\Theta_{FC}$ depended mainly on soil micropores, which increased with clay content and OC due to their binding nature. Even though both $\Theta_{FC}$and $\theta_{PWP}$ showed correlation with texture and OC but AWC did not show significant correlation with any of them. The reason for such behavior was that both $\Theta_{FC}$ and $\theta_{PWP}$ depended on soil micropores which were influenced by the amount of sand, silt ,clay and OC and any change in their value affect both in similar way and hence AWC which was the difference of their magnitudes was not changed and did not show any correlation with texture and OC.

Since in this experiment $K_{fs}$ was used to delineate compact zones, relationship of $K_{fs}$ with other indicators of compaction such as BD or drainage porosity (difference between $\Theta_s$ and $\Theta_{Fc}$) were explored. It was observed that $K_{fs}$ was positively correlated to drainage porosity ($R^2$=0.591) (Fig.3.1) and negatively correlated to BD with $R^2$=0.794 (Fig.3.2). Reduction in drainage porosity, which was an indicator of increase in compaction, was found to increase with increase in BD ($R^2$=0.679) (Fig.3.3). The above correlations thus suggest that field saturated hydraulic conductivity could be used to delineate compact zones.

**Table 3.3:** Stepwise statistics of regression equation of BD ($Mg/m^{-3}$) of surface soil as a function of various soil physical parameters

| **No of steps** | **Parameter** | **Intercept** | **OC%** | **Silt%** | **Clay%** | **$R^2$** |
|---|---|---|---|---|---|---|
| Forward -step1 | Coefficient | 1.85 | - | - | -0.0104 | 0.48 |
| | Standard error | 0.045 | - | - | 0.00166 | |
| | t value | 40.745 | - | - | -6.28 | |
| Forward-step 2 | Coefficient | 1.959 | -0.4451 | - | -0.0075 | 0.58 |
| | Standard error | 0.0533 | 0.13815 | - | 0.00176 | |
| | t value | 36.756 | -3.222 | - | -4.248 | |
| Forward-<br>Step final/3 | Coefficient | 1.879 | -0.4552 | 0.0039 | -0.0085 | 0.62 |
| | Standard error | 0.06278 | 0.1324 | 0.0018 | 0.0175 | |
| | t value | 29.937 | -3.437 | 2.1836 | -4.866 | |

**Table 3.4:** Stepwise statistics of regression equation of $K_{fs}$ (cm/h) of surface soil as a function of various soil physical parameters

| **No of steps** | **Parameter** | **Intercept** | **Clay%** | **Sand%** | **OC%** | **$R^2$** |
|---|---|---|---|---|---|---|
| Forward -step1 | Coefficient | -0.167038 | -0.01053 | - | - | 0.49 |
| | Standard error | 0.044059 | 0. 01616 | - | - | |
| | t value | -3.79128 | 6.51635 | - | - | |
| Forward-step 2 | Coefficient | -0.644908 | -0.01822 | 0.006051 | - | 0.57 |
| | Standard error | 0.175133 | 0.003125 | 0.002156 | - | |
| | t value | -3.68239 | 5.83089 | 2.80624 | - | |
| Forward-step final/3 | Coefficient | -0.786844 | -0.01647 | 0.006687 | 0.219931 | 0.65 |
| | Standard error | 0.167595 | 0.002927 | 0.001990 | 0.073769 | |
| | t value | -4.69490 | 5.62740 | 3.36062 | 2. 98136 | |

**Table 3.5:** Stepwise statistics of regression equation of $\theta_{PWP}$ (w/w) of surface soil as a function of various soil physical parameters

| **No of steps** | **Parameter** | **Intercept** | **OC%** | **Sand%** | **Clay%** | **$R^2$** |
|---|---|---|---|---|---|---|
| Forward -step1 | Coefficient | 9.8709 | - | -0.1037 | - | 0.20 |
| | Standard error | 1.4941 | - | 0.0320 | - | |
| | t value | 6.6063 | - | -3.241 | - | |
| Forward-step final/2 | Coefficient | 5.0857 | 8.1013 | -0.0728 | - | 0.26 |
| | Standard error | 2.8397 | 4.1364 | 0.0347 | - | |
| | t value | 1.7909 | 1.9585 | -2.0973 | - | |

**Table 3.6:** Regression equations of $\theta_{FC}$ (w/w) of surface soil as a function of various soil physical parameters

| **Soil properties** | **Parameter** | **Intercept** | **Sand%** | **Clay%** | **OC%** | $R^2$ |
|---|---|---|---|---|---|---|
| Sand | Coefficient | 21.3222 | -0.11380 | - | - | 0.30 |
| | Standard error | 1.2275 | 0.02629 | - | - | |
| | t value | 17.3705 | -4.3288 | - | - | |
| Clay | Coefficient | 12.0316 | - | 0.15889 | - | 0.26 |
| | Standard error | 1.11796 | - | 0.04099 | - | |
| | t value | 10.7621 | - | 3.87589 | - | |
| OC | Coefficient | 12.7391 | - | - | 8.25459 | 0.11 |
| | Standard error | 1.50745 | - | - | 3.51466 | |
| | t value | 8.45078 | - | - | 2.34861 | |

**Spatial variability analysis and preparation of kriged map of $K_{fs}$ for delineation of compact zones:**

**1. Exploratory spatial data analysis (ESDA):**

In the first step of spatial data analysis, histogram tool was used to examine the frequency distribution of data for $K_{fs}$ of surface layer for checking normality and presence of outlier. Data of sand, silt, clay and $\theta_{PWP}$ showed near normal distribution whereas as data of $\Theta_{FC}$, OC and $K_{fs}$ were skewed. $K_{fs}$ data became normal on log transformation. Similar trend was observed for the subsurface.

In the next step, trend analysis tool was used to examine trend in both XZ and YZ planes. For both layers, trend was negligible, because of slope <0.5% in both directions. Then, semivariance tool was used for examining the empirical semivariogram which clearly indicated that data were spatially correlated. To explore directional influence in the semivariogram cloud, search direction tool was used, which indicated anisotropic nature of data.

**Geostatistical wizard for spatial structure analysis:**

In the first step of geostatistical wizard, ordinary kriging was chosen as interpolation method. Then utilizing the information obtained from ESDA, log transformation of data was selected among various data transformation options. Among the different options for trending the data, no trend option was chosen as no global trend was observed in data. In the second step of the wizard, a spherical model with appropriate lag size and lag number was fitted to empirical semivariogram of the data. In the third step, neighborhood search strategy was decided by taking elliptical shape of search neighborhood as data were anisotropic) and divided it in four quadrants. Maximum and minimum number of neighborhood points in each quadrant was kept between 2 –5.

In the fourth step of analysis, spatial model was cross validated by plotting the predicted values against observed values and fitting a line through the scatter plot. More closer is this line to 1:1 line better is the fit. For a model that provides unbiased predictions, the mean of prediction errors (MPE) should be close to zero. Again for the correct assessment of the variability and to check if the prediction standard errors are appropriate, the root-mean-square prediction error (RMSPE) and average standard prediction error should be similar and the root-mean square standardized prediction error (RMSSPE) should be close to one.

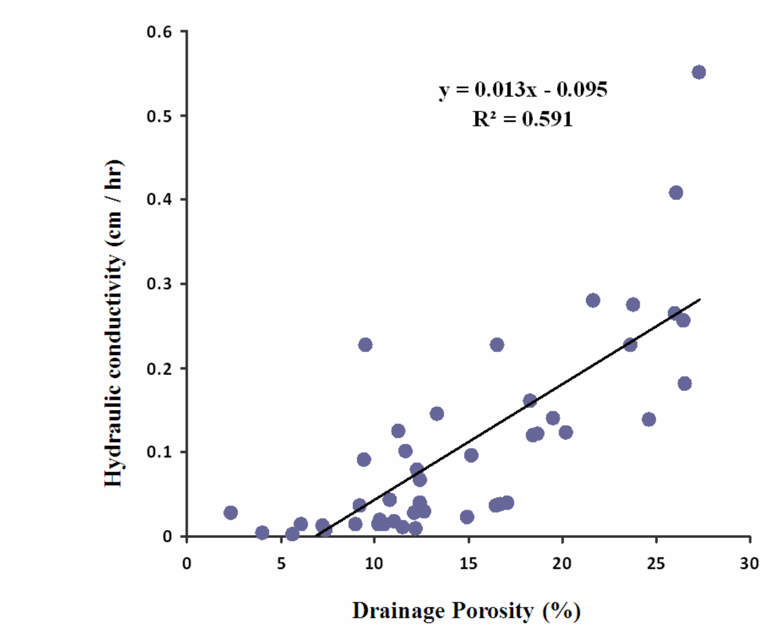



**Fig. 3.1:** Linear regression of hydraulic conductivity as a function of drainage porosity

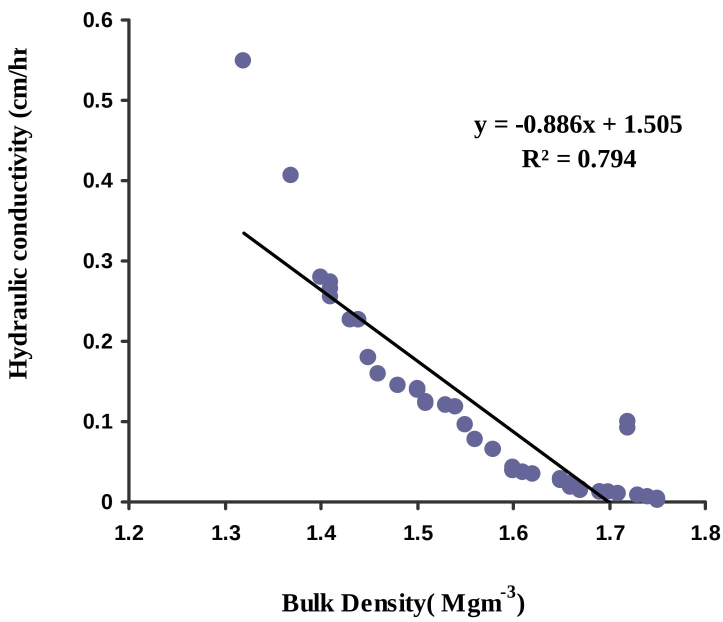



**Fig. 3.2:** Linear regression of hydraulic conductivity as a function of bulk density

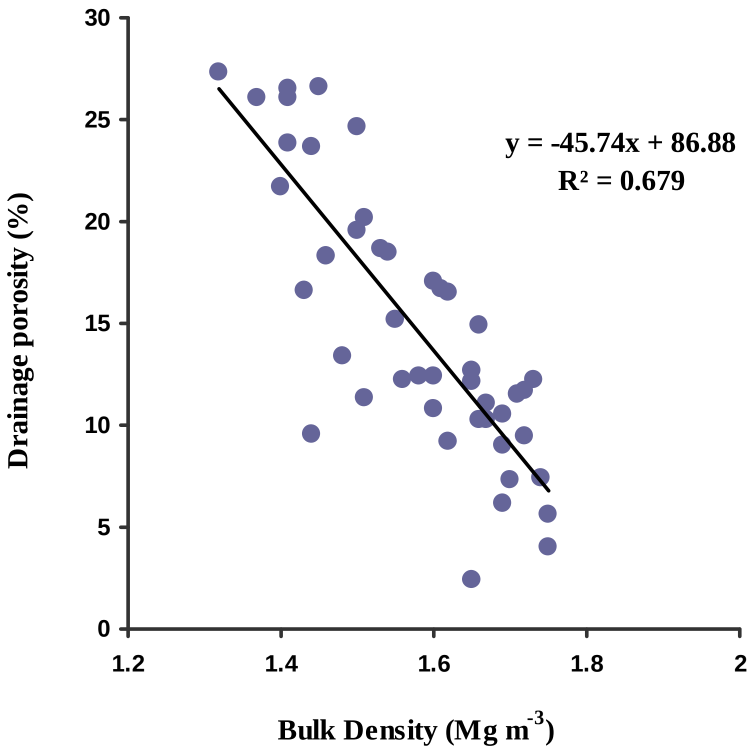



**Fig. 3.3:** Linear regression of drainage porosity as a function of bulk density

On looking at the cross validation statistics of spherical model of $K_{fs}$ data of surface layer, it was seen that although the slope of the line was very good 0.896 but predictions were biased as MPE was not nearer to zero (0.0165) and prediction of standard errors were not appropriate as indicated by the difference in magnitudes of RMSPE and AVSPE values (difference in their magnitude was 0.22) (Fig. 3.4).

Hence in order to further improve upon the prediction, another interpolation option i.e. ordinary kriging with no transformation was chosen and all steps of analysis were repeated in similar way. Finally cross validation statistics of data with and without log transformation were compared (Fig. 3.4). It was seen that even though the slope of fitted line drawn through the scatter plot of the predicted values against observed value was higher in the former but the later choice provided a more unbiased estimate and as the differences between RMSPE and AVSPE were less (0.08-0.07=0.01) estimated prediction errors were more valid. Hence it was decided to choose the option of data without any transformation for further analysis and development of spatial structure.

In the next step, empirical semivariogram of $K_{fs}$ data was fitted to various available models and their major and minor ranges, partial sill value and nugget variance were studied. It was further observed that for all semivariogram models, lag size of 32.35 m along with 12 numbers of lags were chosen by wizard as default choices (Table 3.7).

Since empirical semivariogram showed anisotropic nature, for all models major range were 380.78 m inclined at $63^0$ to major axis. However the minor ranges varied from 70.13 to 94.54 for all available spatial models.

To define different classes of spatial dependence for the soil variables, the ratio between the nugget semivariance and the total semivariance or sill was used (Cambardella et al., 1994). If the ratio was ≤ 25%, the variable was considered to be strongly spatially dependent, or strongly distributed; if the ratio was between 26 and 75%, the soil variable was considered to be moderately spatially dependent; if the ratio was greater than 75%, the soil variable was considered weakly spatially dependent; if the ratio was 100%, or the slope of the semivariogram was close to zero, the soil variable was considered non-spatially correlated (pure nugget or no spatial dependency). The results of Table 3.7 indicated that $K_{fs}$ data showed strong spatial dependence as the above ratio was < 25%.

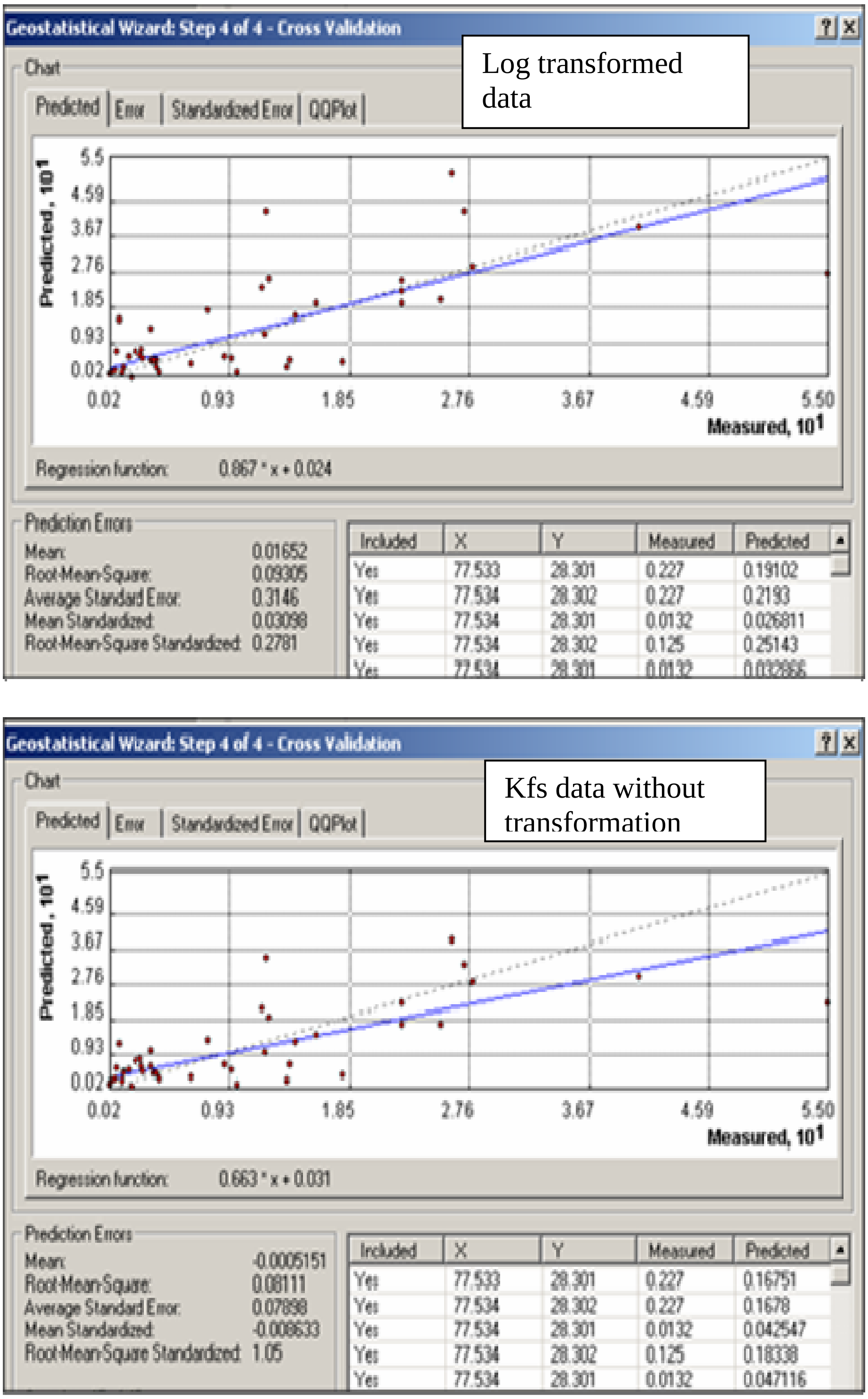



**Fig. 3.4:** Cross validation statistics for spatial model of $K_{fs}$ data of 0-15 cm soil with and without log transformation

Table 3.7: Spatial structure of $K_{fs}$ (cm/hr) of soil surface (0-15cm) layer

| Model Types | Lag size (m) & no. of lags | Major range (m) | Direction of major range (degrees) | Minor range (m) | Nugget variance (cm/hr) ($C_0$) | Partial Sill (cm/hr) (C) | % $C_0/(C+C_0)$ | Spatial dependence |
|---|---|---|---|---|---|---|---|---|
| Circular | | | | 75.32 | 0.003179 | 0.013152 | 19.47 | Strong |
| Spherical | | | | 79.83 | 0.002969 | 0.013025 | 18.56 | Strong |
| Tetrasperical | 32.35 & 12 | 380.8 | 63.0 | 83.65 | 0.002840 | 0.012902 | 18.04 | Strong |
| Pentraspherical | | | | 87.09 | 0.002746 | 0.012806 | 17.66 | Strong |
| Exponential | | | | 94.54 | 0.001392 | 0.014567 | 8.73 | Strong |
| Gaussian | | | | 70.13 | 0.004719 | 0.011716 | 8.71 | Strong |

Further, cross validation of various spatial models were compared for choosing the best model among the various available options (Table 3.8). Results revealed that Gaussian model was found to be the best choice as the slope of fitted line drawn through the scatter plot of the predicted values against observed values was highest among all the models tried and also it provided an unbiased estimate of parameter and also appropriate prediction error.

On comparing the cross validation statistics of different methods of kriging (with no data transformation and no trend), ordinary kriging was found to be the better choice for interpolation than simple kriging as the slope of fitted line was higher in the former (Fig.3.5). Results were similar under ordinary and universal kriging as there was no trend present. As in earlier reports (Johnston, *et al*., 2001, Mulla and Mc Bratney, 2002) it was mentioned that universal kriging is more appropriate when trend is of higher order.

Cross validation statistics of ordinary kriging was further compared with inverse distance weighting (IDW) technique which revealed that ordinary kriging was more accurate than IDW as the slope of fitted line through the scatter plot of predicted versus observed data points was higher in the former (Fig.3.6). Finally, ordinary kriging with Gaussian model was chosen for drawing prediction maps.

Prediction map of $K_{fs}$ for 0-15 cm layer (Fig.3.7) showed that almost all the area was below the range of 0.5 cm/hr (12 cm/day) and nearly 93.5 % had $K_{fs}$ below the critical range of 0.16 cm/hr.

Subsurface (15-30 cm) soil layer also had similar spatial structure and ordinary kriging with Gaussian model was used for drawing prediction map of $K_{fs}$ (Fig.3.8) which indicated even more compact surface as 99% area had $K_{fs}$ value <0.16 cm/hr (4 cm/day).

Table 3.8: Cross validation of various spatial models of $K_{fs}$ for soil surface layer

| Model types | Regression equation | Mean prediction error (MPE) | Root mean square prediction error (RMSPE) | Average standard prediction error (AVSPE) | Root-mean-square standardized prediction error (RMSSPE) |
|---|---|---|---|---|---|
| Circular | 0.669 * x + 0.031 | 0.0005412 | 0.08003 | 0.07858 | 1.039 |
| Spherical | 0.663 * x + 0.031 | 0.0005151 | 0.08111 | 0.07898 | 1.05 |
| Tetrasperical | 0.656 * x + 0.031 | 0.0005084 | 0.08185 | 0.07963 | 1.053 |
| Pentraspherical | 0.650 * x + 0.032 | 0.0005585 | 0.08249 | 0.08032 | 1.053 |
| Exponential | 0.619 * x + 0.034 | 0.0003655 | 0.08724 | 0.07938 | 1.128 |
| Gaussian | 0.698 * x + 0.029 | 0.0000288 | 0.0751 | 0.07951 | 0.975 |

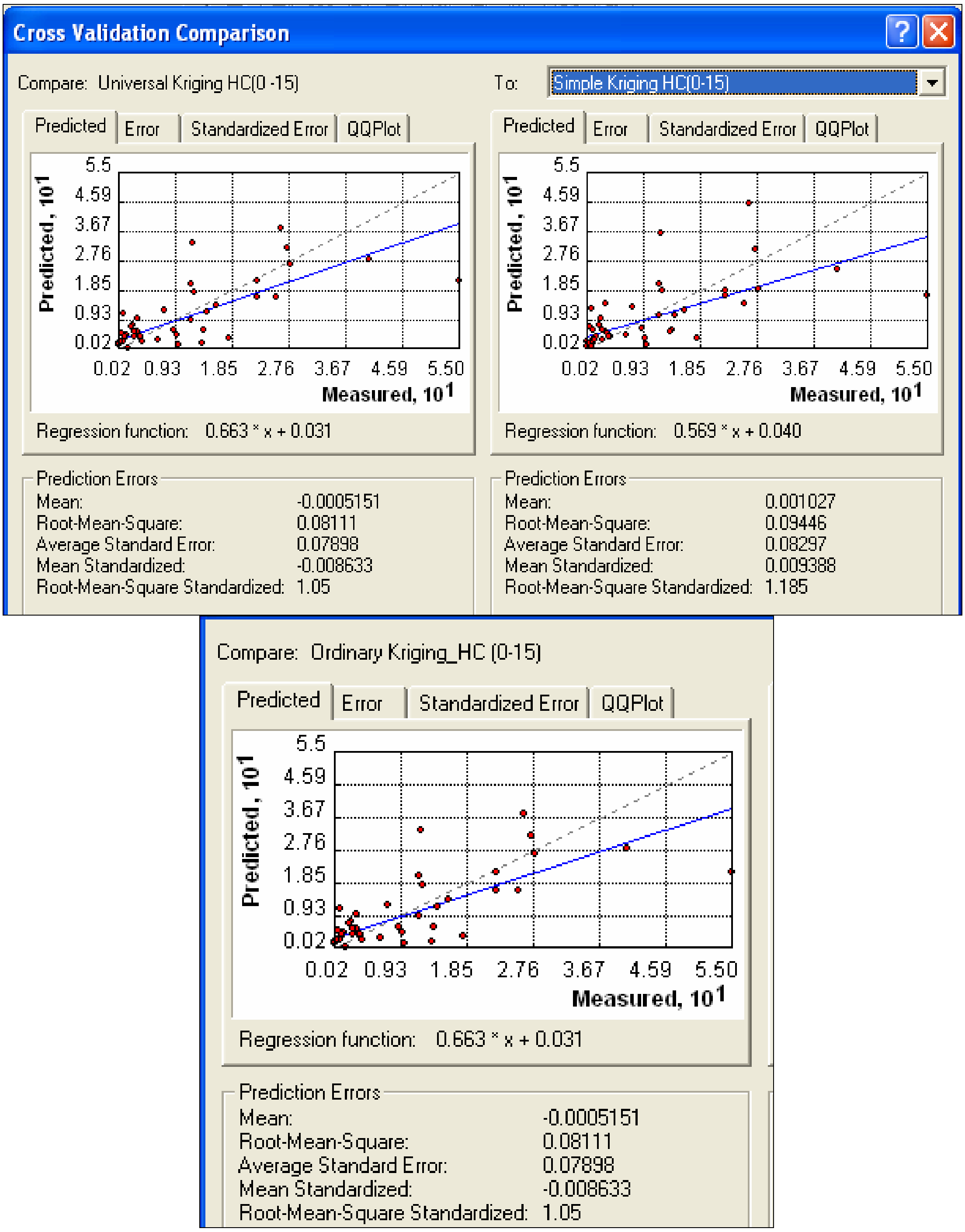



**Fig. 3.5:** Comparison of Cross validation statistics of various kriging types for $K_{fs}$ data

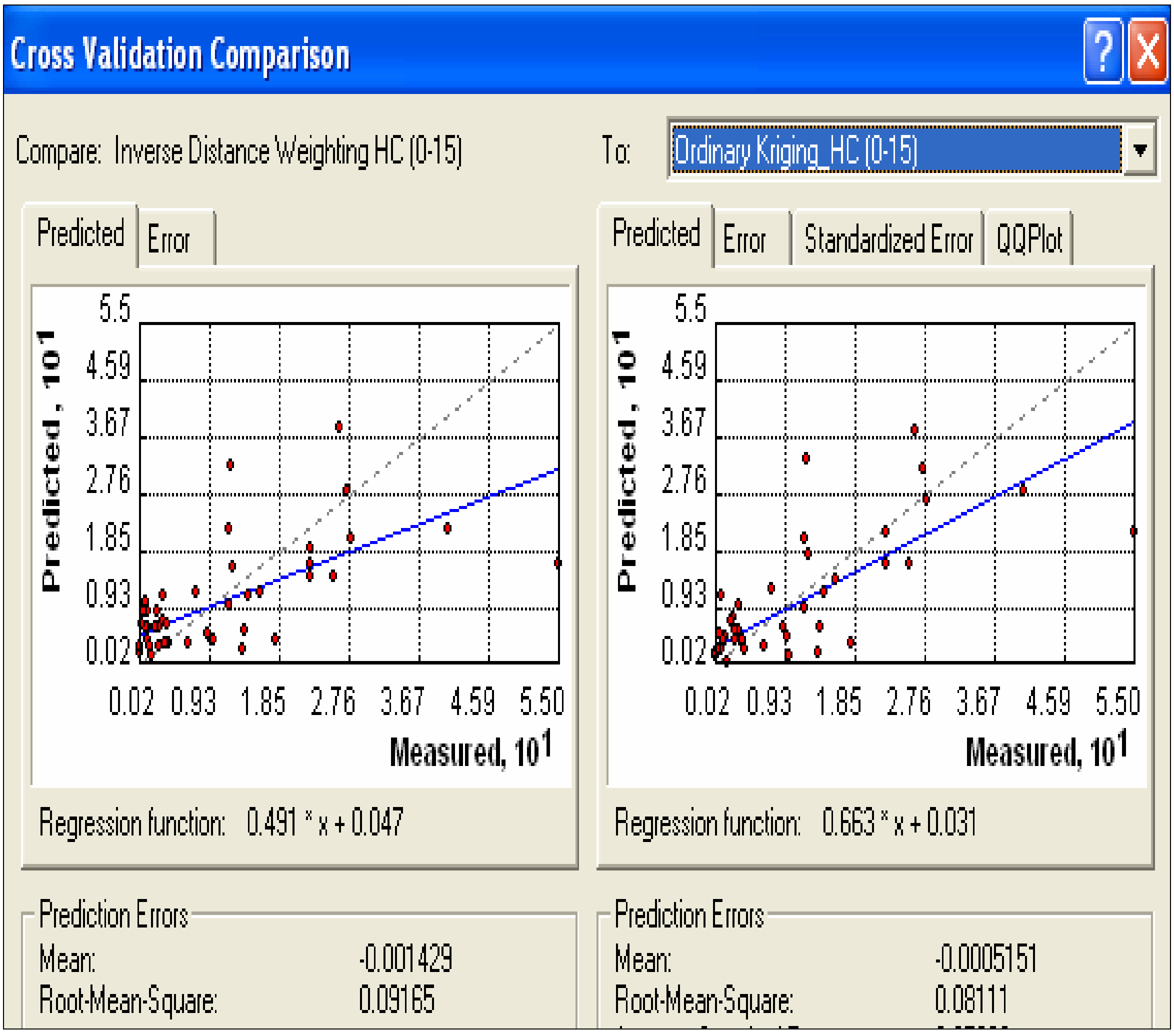
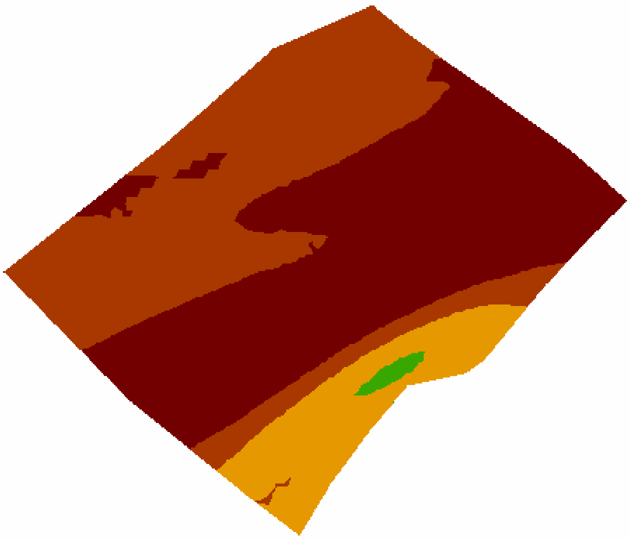
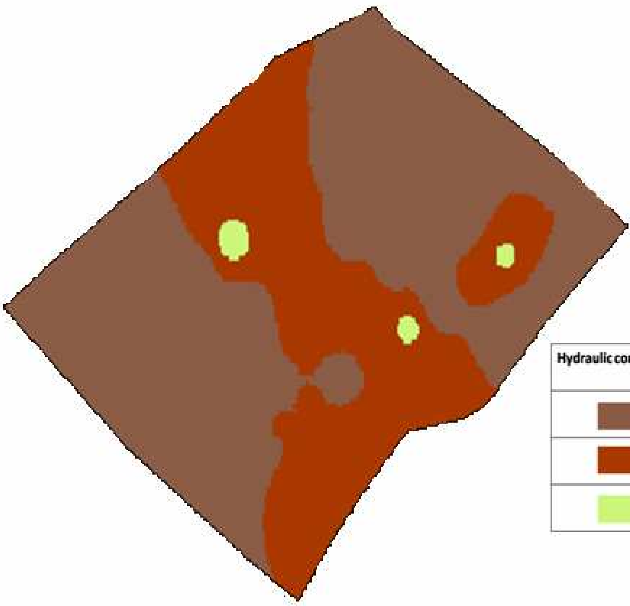



**Fig. 3.6:** Comparison of cross validation statistics of ordinary kriging and Inverse distance weighting technique for interpolation



| Saturated Hydraulic conductivity (cm/hr) | | % Area |
|---|---|---|
| | <0.01 | 48.37 |
| | 0.01-.05 | 39.13 |
| | 0.05-0.10 | 00.00 |
| | 0.10-0.20 | 11.96 |
| | 0.20-0.50 | 00.54 |
| | 0.50-1.00 | 00.00 |
| | 1.00-3.00 | 00.00 |

**Fig. 3.7:** Prediction map of hydraulic conductivity of surface (0-15 cm) soil layer



| Hydraulic conductivity (cm/hr) | | % Area |
|---|---|---|
| | 0-0.08 | 62.76 |
| | 0.08-0.16 | 36.26 |
| | 0.16-0.33 | 0.98 |

**Fig. 3.8:** Prediction map of hydraulic conductivity of subsurface (15-30 cm) soil layer

**Spatial variability analysis and preparation of kriged map of BD:**

The ESDA analysis of BD data of surface layer showed nearly normal distribution without the presence of any trend or outliers. Empirical variogram of BD showed spatial dependence and also anisotropic nature. Similar to analysis done for $K_{fs}$, cross validation statistics of various methods of kriging were compared for BD data and ordinary kriging was found to be the best choice.

In the next step, different models were fitted to empirical semivariogram of BD and its spatial structure revealed that for all models , major range was 300.68 m pointing at $63^0$ and minor range varied between 48.62-64.37 (Table 3.9). Again as the ratio of nugget to sill value was < 25 %, which showed strong spatial dependence. Comparison of cross validation statistics of various models showed that like $K_{fs}$, for BD also Gaussian model was most suited among all models. It was most accurate in prediction and also its estimated error was most appropriate (Table 3.10). Prediction map of bulk density of surface and subsurface soil layers showed that nearly 88 % and 100 % area were compacted as their BD values were >1.55 $Mgm^{-3}$ (Fig.3.9 & 3.10).

Comparison of delineated compaction zones of farm by using Kriged maps of BD and $K_{fs}$ showed similar results for subsurface layers (both maps showed nearly 100% area was severely compacted), whereas for surface there was slight variation in prediction of percent area compacted (93.5% according to $K_{fs}$ map whereas 88 % according to BD map).

Indicator kriging was used for generating probability map of $K_{fs}$ and BD. Maps showed that around 80% of area in the surface and subsurface had 80-100% probability of getting hard pan (Fig.3.11 & 3.12).

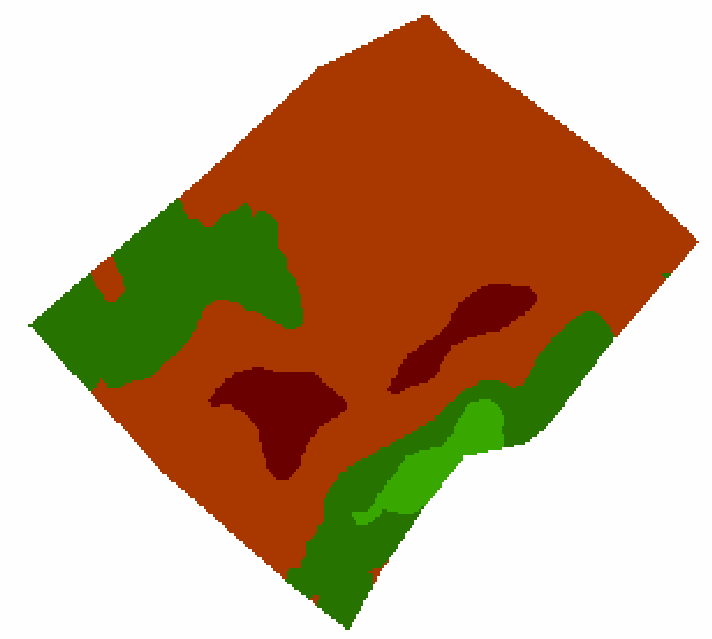
Deep ploughing using disc plough or chiseling was recommended in delineated compact zones to improve soil productivity.

Table 3.9: Spatial structure of bulk density ($Mg/m^{-3}$) of soil surface (0-15 cm) layer

| Model types | Lag size & no. of lags | Major range (m) | Minor range (m) | Direction of major range (degrees) | Partial sill ($Mg/m^{-3}$) (C) | Nugget variance ($Mg/m^{-3}$) ($C_0$) | % $C_0/(C+C_0)$ | Spatial dependence |
|---|---|---|---|---|---|---|---|---|
| Circular | 25.54 m & 12 | 300.68 | 49.62 | 63.0 | 0.015296 | 0.000468 | 2.97 | Strong |
| Spherical | | | 54.18 | | 0.015586 | 0.000031 | 0.20 | Strong |
| Tetrasperical | | | 59.46 | | 0.01548 | 0 | 0 | Strong |
| Pentraspherical | | | 64.37 | | 0.01537 | 0 | 0 | Strong |
| Exponential | | | 48.62 | | 0.015543 | 0 | 0 | Strong |
| Gaussian | | | 51.38 | | 0.012917 | 0.002942 | 18.55 | Strong |

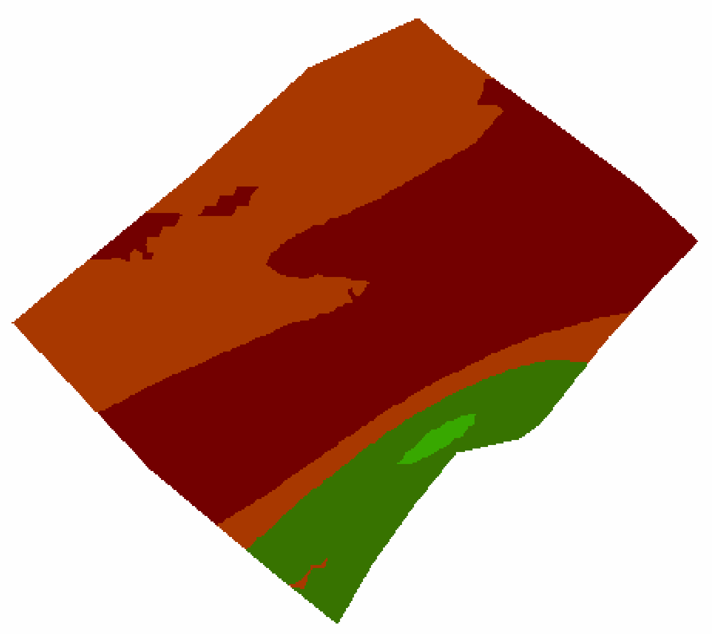
Table 3.10: Cross validation of various spatial models of bulk density (Mg $m^{-3}$) for soil surface (0-15 cm) layer

| Model types | Regression equation | Mean prediction error (MPE) | Root mean square prediction error (RMSPE) | Average standard prediction error (AVSPE) | Root-mean-square standardized prediction error (RMSSPE) |
|---|---|---|---|---|---|
| Circular | 0.750 * x + 0.388 | 0.0008692 | 0.07921 | 0.05945 | 1.312 |
| Spherical | 0.750 * x + 0.395 | 0.0000291 | 0.08041 | 0.05807 | 1.366 |
| Tetrasperical | 0.743 * x + 0.407 | 0.0002626 | 0.08011 | 0.06061 | 1.306 |
| Pentraspherical | 0.739 * x + 0.412 | 0.0001217 | 0.07991 | 0.06311 | 1.252 |
| Exponential | 0.703 * x + 0.469 | 0.00025 | 0.0788 | 0.07639 | 1.026 |
| Gaussian | 0.754 * x + 0.435 | 0.000053 | 0.07775 | 0.07767 | 1.006 |



| Bulk density (Mg m$^{-3}$) | | Area % |
|---|---|---|
| | 1.40-1.50 | 3.10 |
| | 1.50-1.60 | 18.25 |
| | 1.60-1.70 | 70.75 |
| | 1.70-1.80 | 7.90 |

**Fig. 3.9:** Prediction map of bulk density (Mg m$^{-3}$) of surface (0-15 cm) soil layer



| Bulk density (Mg m$^{-3}$) | | Area % |
|---|---|---|
| | 1.40-1.50 | 0.54 |
| | 1.50-1.60 | 12.50 |
| | 1.60-1.70 | 40.76 |
| | 1.70-1.80 | 46.20 |

**Fig. 3.10:** Prediction map of bulk density (Mg m$^{-3}$) of subsurface (15-30 cm) soil layer

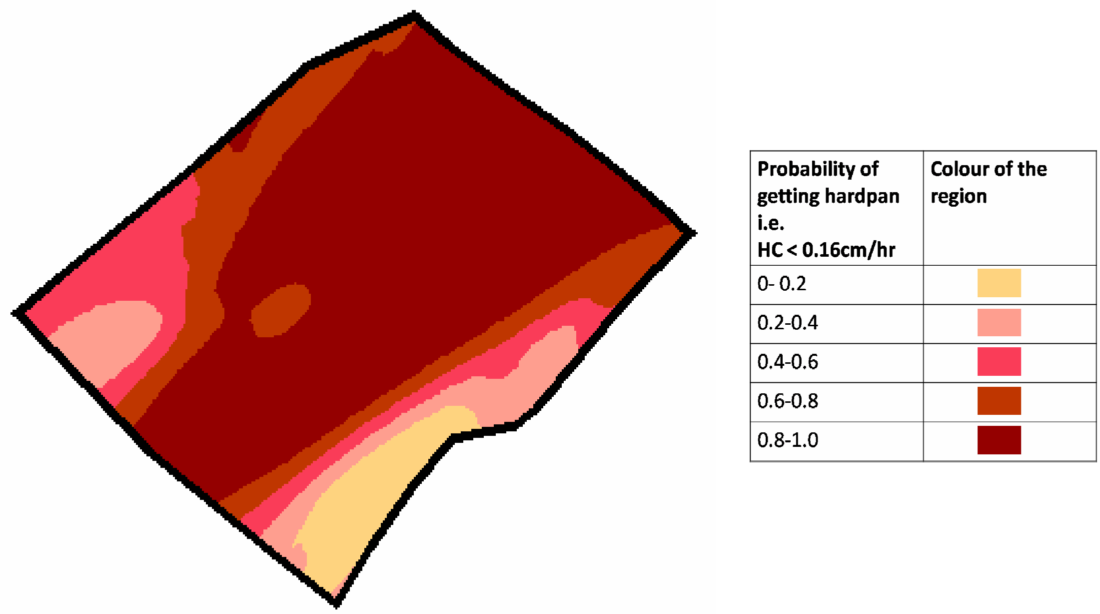



**Fig.3.11:** Indicator kriging showing probability map of $K_{fs}$ of surface (0-15 cm) soil layer

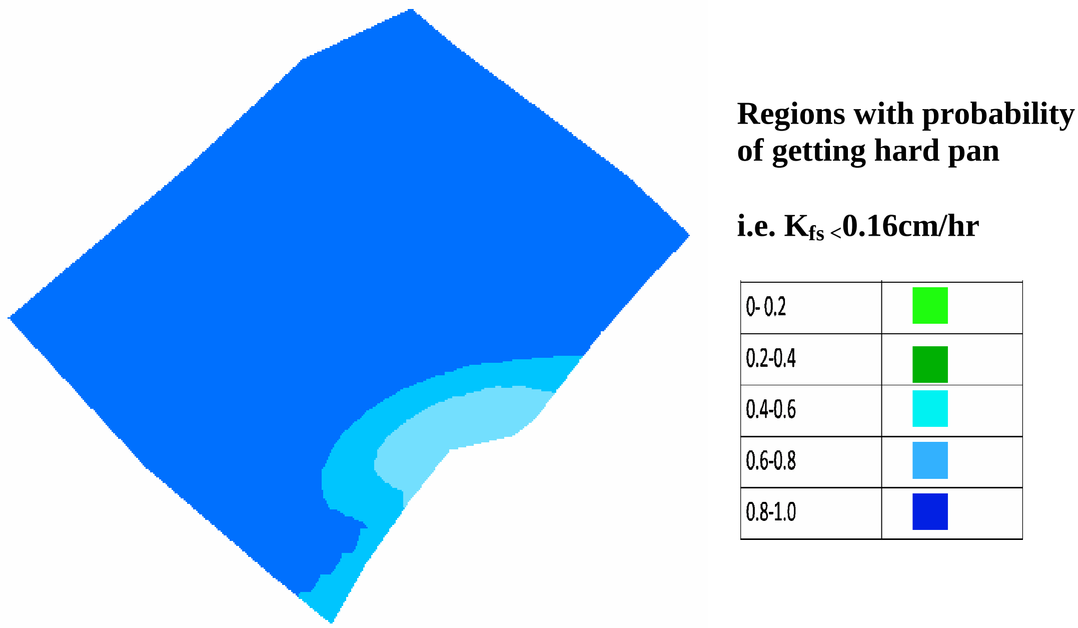



**Fig. 3.12:** Indicator kriging showing probability map of bulk density of subsurface (15-30 cm) soil layer

## 3.5 Conclusion:

In nutshell, it could be concluded that for precision farming, variability map of either BD or $K_{fs}$ could be generated by kriging using geostatistical analysis extension of Arc GIS. These maps could be used for delineating compact zones (areas with BD >1.55 $Mgm^{-3}$ for sandy loam to sandy clay loam soils or $K_{fs}$ < 0.16cm/hr). The deep tillage could be recommended in severely compacted areas not only to improve soil productivity but also to save on fuel and input cost.

# 4. RESEARCH PAPER -2

## Assessment and mapping of spatial variation of soil physical health in a farm

### 4.1 Abstract

Productivity rating systems are important tools to quantitatively assess soil health. In precision farming such information is required for planning appropriate soil and crop management strategies. In order to demonstrate a proper procedure for assessing the soil physical health of a farm, an experiment was conducted in a rice-wheat field in Kherli village of Dankaur block of Gautam Nagar district of Uttar Pradesh, India. Spatial variability analysis of soil physical properties measured on a rectangular grid (30 m x 45 m) was carried out by using geostatistical analyst extension of Arc GIS software. Results revealed that for bulk density (BD), saturated hydraulic conductivity ($K_{fs)}$, organic carbon (OC) and soil physical health index (PI), major and minor ranges of semivariogram varied between 300-380 m and 55-90 m, respectively. Whereas for non-capillary pores (NCP) and available water retention capacity (AWRC), they were relatively short (major range between 114-140 m and minor around 60 m). Degree of spatial dependence of these parameters was computed by finding the percentage ratio of nugget to sill value of semivariogram. Results also revealed that BD data and PI showed strong spatial dependence whereas rest of the parameters showed moderate spatial dependence. Among the parameters suggested for computing soil physical rating index by Gupta (1986), BD, $K_{fc}$, AWRC, OC and NCP were chosen. Rating maps of mentioned parameters for upland crop and rice cultivation were prepared as series of coloured contours by using appropriate interpolation methods and suitable semivariogram models. Scoring for rating of physical parameters was different for wheat and rice as the optimum physical environment for both systems were different. Physical rating index (PI) at each sampling point was determined by multiplying the rating values for all five parameters. Reason for multiplication of individual rating values for defining the PI was that this index was an indicator of soil productivity. Large deviation in any of the individual parameter value from its optimum range could bring down the yield drastically and such a response could only be observed if the rating values of individual parameters were multiplied.

The prediction maps of these parameters showed that in the most of study area BD was more (> 1.55 $Mgm^{-3)}$ and $K_{fs}$ was less (<0.16 $cmhr^{-1}$) than the critical limit. Overall soil physical health of the farm was medium to good for paddy cultivation but was not suitable for succeeding wheat crop mainly because of increased BD and reduced $K_{fs,}$ NCP and AWRC of the farm. . Linear regression analysis of PI and rice grain yield data also showed**,** there was a good correlation between them ($R^2$ = 0.662). The results thus supported earlier findings that good soil physical health is essential for optimum sustained crop production.

Appropriate management practices such as deep ploughing, organic matter incorporation through green manuring and growing of leguminous deep rooted crops and reducing the intensity of puddling before rice transplanting are few of the options for improving the soil health of the farm.

Keywords: Soil physical health, geostatistical analysis, kriging, spatial structure of soil physical properties, physical rating index

## 4.2 Introduction:

Soil quality has historically been equated with agricultural productivity. Beginning in the 1930s, soil productivity rating were developed in the United States and elsewhere to help farmer select crops and management practices that would maximize production and minimize erosion or other adverse environmental effects (Huddleston,1984). These rating systems are important predecessors of recent attempts to quantitatively assess soil quality. In the 1970s, attempts were made to identify and protect soils of the highest productive capacity by defining 'prime agricultural lands (Miller, 1979). Soils with high productivity have high carrying capacity, and are considered to be of high quality.

Soil health and soil quality are often used synonymously (Warkentin, 1995). Soil heath may be evaluated by comparing the present condition of a soil with set reference points or baseline values that reflect the soils overall quality (Sanki *et al.*, 1996). Granatstein and Bezdicek (1992) consider whether the standard reference state of a soil in agricultural systems should be native soil conditions or conditions given maximum agronomic, environmental and economic performance.

Carter *et al.*, (1997) suggest a framework for evaluating soil quality that includes (1) describing each soil function on which quality is to be based, (2) selecting soil characteristics that can be measured, and (3) using methods that provide accurate measurement of those indicators. The following soil functions appear frequently in the soil science literature: (1) soil maintains biological activity/productivity (Doran and Parkin, 1994) supports plant productivity/yield (Karlen *et al*., 1997); (2) partitions and regulates water/solute flow through environment (Larson and Pierce, 1991); (3) serves as an environmental buffer/filter (Larson and Pierce, 1991); and (4) cycles nutrients, water, energy and other elements through the biosphere (Karlen *et al*., 1997). Larson and Pierce (1991) defined soil quality as “the capacity of a soil to function within the ecosystem boundaries and interact positively with the environment external to that ecosystem.” Karlen *et al*. (1992) defined soil quality as “the ability of the soil to serve as a natural medium for the growth of plants that sustain human and animal life.” Gregorich *et al,* (1994) defined soil quality as “the degree of fitness of a soil for a specific use”. Soil quality sometimes refers to the inherent potential of soil, in contrast to soil health or soil condition. Soil quality refers to the capacity of a soil to function within ecosystem and land use boundaries, to maintain environmental quality and promote plant and animal health (Doran and Parkin, 1994). Information about soil chemical and physical properties can be used to answer the questions about soil quality and plant health. Soil quality information contributes to the investigation of several key agricultural ecosystem concerns the productivity and sustainability of agricultural system, the conservation of soil and water resources, the accumulation of persistent toxic substances and the contribution of system to the global carbon cycle.

Soil health is a term which is widely used within discussions on sustainable agriculture to describe the general condition or quality of the soil resource. Soil health is defined as the continued capacity of soil to function as a vital living system, by recognizing that it contains biological elements that are key to ecosystem function within land-use boundaries (Doran and Zeiss, 2000). The Soil Science Society of America (1996) definition deviates slightly: "The capacity of a specific kind of soil to function, within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and support human health and habitation."

Soil quality indicator is a chemical, physical or biological property of soil that is sensitive to disturbance and represents performance of ecosystem function in that soil of interest. It refers to the capacity of a soil to function within ecosystem and land use boundaries, to sustain biological productivity, maintain environmental quality, and promote plant and animal health (Doran and Parkin, 1994). The set of indicators used to determine a soil's quality is also called a minimum data set. To select a minimum data set, two main methods have been established: expert opinion and statistical data reduction. Expert opinion, by definition, requires expert knowledge of the system. Using a hierarchical framework for choosing the indicators may help make selection more systematic. Statistical data reduction has been demonstration to effectively choose indicators in a number of soil systems (Andrews *et al*., 2004; Andrews and Carroll, 2001). This method can eliminate disciplinary bias that could be a problem with expert selection of indicators but it does assume that appropriate candidate indicators are in the original data set (so a minimum level of knowledge is required).

While some of the indicators of soil quality may be sensitive to change, others may be more subtle. The overlying question is whether we can measure and quantify these indicators and develop them into a soil quality index (SQI) that can be used reliably to monitor and predict the impact of farming systems and management practices on soil productivity, environmental quality, food safety and quality, and human and animal health. Soil quality index is a useful tool for assessing the overall soil condition and response to management, or resilience towards natural and anthropogenic forces. The ultimate goal is to develop a mathematical relationship or model that could quantify the various attributes of soil quality, and from it derive one or more indexes for simulation and prediction.

Scientists use soil quality indicators to evaluate how well soil functions since soil function often cannot be directly measured. Measuring soil quality is an exercise in identifying soil properties that are responsive to management, affect or correlate with environmental outcomes, and are capable of being precisely measured within certain technical and economic constraints. Soil quality indicators may be qualitative (e.g. drainage is fast) or quantitative (infiltration= 2.5 in/hr).

Physical indicators provide information about soil hydrologic characteristics such as water entry and retention which influences availability to plants. Some indicators are related to nutrient availability by their influence on rooting volume and aeration status.

**Productivity rating indices:**

The productivity index (PI) model was developed to evaluate soil productivity in the top 100 cm, especially with reference to potential productivity loss due to soil erosion (Neill, 1979). The PI model rates soils on the sufficiency for root growth based on potential available water storage capacity, bulk density, aeration, pH, and electrical conductivity. A value from zero to one is assigned to each property describing the importance of that parameter for root development. The product of these five index values is used to describe the fractional sufficiency of any soil layer for root development.

Physical rating index by Gupta (1986) was one such tool for constraint analysis and was used for assessing the production potential of soils. Physical rating of soils for agricultural land was one step ahead. In this method, in addition to basic physical parameters, few more dynamic parameters such as bulk density, infiltration rate, soil organic matter, water table depth and available water storage capacity were used for physical constraint identification along with the estimation of relative magnitude of their severity. Accordingly, the production potential of these soils could be predicted under optimum levels of water and fertilizer inputs along with the adoption of appropriate plant protection measures (Gupta and Abrol, 1993). Efficiency of any suggested management practice for alleviating these constraints could be assessed in terms of changes in its rating value and hence its production potential.

As the concept of precision farming is gaining importance, there is a need for presenting a procedure for assessment of soil physical health of the farm and correlating it with the crop yield. For this purpose prediction maps of the important physical properties along with their ratings should be prepared by appropriate interpolation technique. The overall soil physical health should be quantified in terms of a unified soil physical health index prepared from the individual rating values of the important soil physical parameters.

Hence an attempt was made in this paper to assess and map the spatial variation of soil physical health of a agriculture farm and to examine correlation between spatial variation of soil physical health and yield of crop in the farm.

## 4.3 Materials and Methods

### 4.3.1 Details of field experimental site

The present investigation was carried out in a rice-maize field, near Kherli village, Dankaur Block (28 ° 17'59" N, 77 ° 32'04” E) in National Capital Region.

In order to measure saturated hydraulic conductivity in field and other relevant soil physical parameter , 145 observation sites were chosen at a grid spacing of about 30 m x 45 m covering a total area of 19.6 hectare. The coordinates of each sampling location were recorded using a differential global positioning system unit.

At each site, disturbed and undisturbed soil samples were collected from 0-15 cm and 15-30 cm soil layers. Core sampler was used for taking undisturbed soil samples mainly for soil bulk density determination and for drawing soil water retention curve while disturbed soil samples were collected by using a screw auger for determination of soil texture, organic matter and saturation percentage . Disturbed Samples were air dried and sieved (2 mm) before analysis. Soil parameters studied included field saturated Hydraulic Conductivity ($K_{fs}$), Soil bulk density, Water retention characteristics, non-capillary pores (drainage porosity), soil texture, soil organic carbon and available water content:

### 4.3.2 Criteria for choosing minimum data set for computing soil physical heath index:

The parameters suggested for computing soil physical rating index by Gupta (1986) were bulk density (BD) of upper 30 cm soil layer (Mg/ $m^3$), saturated hydraulic conductivity ($K_{fc}$) (cm/hr), available water retention capacity (AWRC) of top 100 cm of soil (cm/m), aggregation in terms of % soil organic carbon (OC) in upper 10 cm soil layer, % non capillary pores (NCP), water table depth in cm and % land slope.

Since the soil depth of the study area was more than 100 cm, land was flat (slope < 1%) and water table was deep (>100cm), they did not pose any constraint to crop production. Hence, the parameters chosen for rating were; BD, $K_{fc}$, AWRC, OC and NCP.

### 4.3.3 Spatial variability analysis of soil physical parameters for preparation of soil physical health map of the farm:

Spatial variability analysis of soil physical properties measured on a rectangular grid was carried out by using Arc GIS software. Firstly, exploratory spatial data analysis (ESDA) was done for checking normality, presence of outlier, trend and range of spatial dependence of data.

**Spatial structure analysis and kriging using geostatistical analyst wizard**:

**Choice of suitable interpolation method:** The first step of this analysis was to choose the appropriate geostatistical method of interpolation. For this purpose, cross validation statistics of predicted data prepared by using different interpolation techniques were compared which included plotting the predicted values against observed values and fitting a line through the scatter plot. More close was the line to 1:1 line better was the fit. For all layers, the best suited interpolation option was the one which gave lowest RMSE and also its average standard error (AVSE) nearest to root mean square prediction error or alternatively root mean square standardized error (RMSS) nearest to one.

**Choice of suitable semivariogram model:** In order to choose suitable semivariogram model, the total data set was divided into two parts- training data set for developing semivariogram model by fitting the empirical semivariogram to different model options available in wizard and testing data set for test of the developed semivariogram model**.** Validation statistics of all fitted models were compared in a manner similar to that in the earlier step for choosing the best suited model.

After choosing the appropriate interpolation technique, method of data transformation, semivariogram model, and neighborhood search shape and size for interpolation (elliptical shape if data is anisotropic, circular if isotropic with number of data points between 8 -20), prediction maps of BD, $K_{fc}$, OC, NCP, AWRC and PI were prepared. Prediction map of each parameter showed different ranges of parameter values as series of filled colour contours.

### 4.3.4 Methodology for computing soil physical health index (PI):

For a given site, each of these parameters was assigned a rating value corresponding to its actual value by referring to rating chart (Gupta, 1986). Each of this parameter was given a score of 1 if the parameter value lies within the optimum range. If the value lies below or above the critical limit, a score less than 1 were given. Greater the deviation of parameter value from optimum range, lesser the score given to it. The product of rating values of all the eight parameters gave the physical rating index. PI was an indicator of overall soil physical health status. For range of PI >0.75, 0.50-0.75, 0.25-0.50 and <0.25, soil physical health status and accordingly its production potential could be labeled as very good, good, medium or poor, respectively.

As per physical rating methodology suggested by Gupta (1986), same ranges of soil parameters were assigned different rating values under rice and wheat cultivations because optimum soil physical environment required for their growth were different.

## 4.4 Results and discussion

**Spatial variability analysis:**

The exploratory spatial data analysis (ESDA) was a prerequisite for carrying out the geospatial analysis of data by use of geostatistical analyst extension of Arc GIS 9.1. It was mainly conducted to examine the data for presence of outliers, trend, normality, spatial dependence and directional dependence of variogram. In all cases, data were skewed and in case of $K_{fs}$ it became normal on log transformation. There was no trend present in data as the field was almost flat (slope< 0.5%). On examining empirical semivariogram, in general, data showed spatial dependence and anisotropic nature.

For carrying out geospatial analysis for surface (0-15 cm) soil layer, firstly appropriate interpolation method was chosen by examining the cross validation statistics of spherical model (default option) for different kriging types such as ordinary kriging, simple kriging, universal kriging and inverse distance weighting (IDW) (Table 4.1). The most suited interpolation method was one where slope of best fitted line through the scatter plot of predicted vs. measured values was nearer to one i.e. the best fitted line was closer to 1:1 line. The other important criteria for choosing the best interpolation type was to ensure that predictions were unbiased as evident from value of mean of prediction errors approaching zero and prediction of standard errors were appropriate as indicated by the closeness between root-mean-square prediction error and average standard prediction error values. For data of BD, Kfs and OC, ordinary kriging without any data transformation was found to be the best. The results supported the earlier reports that for kriging, data need not be normal (Mulla and Mc Bratney, 2002). Similarly for NCP, simple kriging and for AWRC, IDW methods were found most suited methods.

After choosing appropriate interpolation method, next step was to select best suited semivariogram model by examining the validation statistics of various available models by dividing the total data set into two parts- training data set for developing the model and testing data set for validating the model. Best suited models for these parameters are presented in Table 4.2.

Spatial analysis of data by use of geostatistical analyst extension revealed that for BD, $K_{fs}$, OC and PI, major and minor ranges of semivariogram varied between 300-380 m and 55-90 m, respectively, whereas for NCP and AWRC, they were relatively short (major range between 114-140 m and minor around 60 m). The above results were in agreement with those reported by Mulla and Mc Bratney, 2002. Degree of spatial dependence of these parameters was computed by finding the percentage ratio of nugget to sill value of semivariogram which if found less than 25% was considered as the indicator of strong spatial dependence and if found between 26-75 was indicator of moderate spatial dependence. Results revealed that BD data, $K_{fc}$ and PI showed strong spatial dependence whereas rest of the parameters showed moderate spatial dependence.

Among the earlier reported results the range of BD as computed by Santra *et al.* (2008) were 1053 m and they concluded that their bulk density and organic carbon content data showed large amount of nugget variation. The difference in the results by Santra *et al*.(2008) and results reported here is that Santra *et al*.(2008) did not carry out exploratory data analysis to check for presence of trend or outliers and did not use anitropic semivariogram for spatial structure analysis, whereas earlier studies by Mulla and Mc Bratney (2002), Kilic *et al*. (2004) and Iqbal *et al.* (2005), reported relatively less range and strong to medium spatial dependence of these soil properties. Similarly, Dufferra *et al.* (2007) also did not check stationarity in data, presumed isotropic nature of soil properties and used GS+ software to determine the spatial structure and thus reported that bulk density data in their field study was spatially uncorrelated.

Iqbal *et al.* (2005) on the other hand explored data for normality and trend. They also mentioned that data should be checked for anisotropy. They developed omnidirectional semivariogram models because they prepared semivariogram models by using S+ SpatialStats software, which do not have options about presenting anisotropic nature of semivariogram.

Similarly for subsurface layer also, mostly ordinary kriging with no data transformation was found to be the most suitable choice (Table 4.3). Again examination of spatial structure also showed that major ranges were around 380 m for OC and PI, 275 m for BD and 205 m for $K_{fs}$ (Table 4.4). Subsurface layer also had low spatial range for AWRC and NCP. Like surface layer, for subsurface layer also BD and PI showed strong spatial dependence whereas rest of the parameters showed moderate spatial dependence.

Spatial analysis of soil texture showed that for both layers, nearly 32-36% of total area had sandy clay loam texture (SCL), 23-24% clay loam (CL), 14-24% sandy loam (SL) and 12-14% loam (L) (Fig. 4.1).

Table 4.1: Spatial Structure of soil physical parameters for surface (0-15 cm) soil layer

| Parameter | Interpolation technique | Best model used | Lag size (m) & no. of lags | Major range (m) & direction (degree) | Minor Range (m) | Nugget variance (cm/hr) ($C_o$) | Partial sill (cm/hr) (C) | % $C_o/(C+C_o)$ | Spatial dependence |
|---|---|---|---|---|---|---|---|---|---|
| PI | Ordinary kriging | Spherical | 32.36 & 12 | 380.79 & 52° | 60.14 | 0.0009 | 0.012957 | 6.49 | Strong |
| BD | Ordinary kriging | Spherical | 25.53 & 12 | 300.69 & 63° | 54.17 | 0.0000 | .0156 | 0.00 | Strong |
| $K_{fs}$ | Ordinary kriging | Gaussian | 32.36 & 12 | 380.73 & 63° | 69.93 | 0.004 | 0.112 | 3.45 | Strong |
| OC | Ordinary kriging | Gaussian | 32.36 & 12 | 380.73 & 72° | 89.24 | 0.0143 | 0.022 | 39.39 | Moderate |
| AWRC | IDW | _ | _ | 114.41 | _ | _ | _ | _ | _ |
| NCP | Simple kriging | Hole effect | 11.78 & 12 | 139.66 & 54° | 60.162 | 14.977 | 28.268 | 34.63 | Moderate |

IDW = Inverse distance weighting

Table 4.2: Cross validation of various spatial models of soil physical parameters for surface (0-15 cm) soil layer

| Parameter | Model types | Regression equation | Mean prediction error (MPE) | Root mean square prediction error (RMSPE) | Average standard prediction error (AVSPE) | Root-mean-square standardized prediction error (RMSSPE) |
|---|---|---|---|---|---|---|
| PI | Spherical | 0.654 * x + 0.168 | 0.000 | 0.073 | 0.060 | 1.190 |
| BD | Spherical | 0.750 * x + 0.395 | 0.000 | 0.080 | 0.058 | 1.366 |
| $K_{fs}$ | Gaussian | 0.698 * x + 0.029 | 0.000 | 0.075 | 0.079 | 0.964 |
| OC | Gaussian | 0.624 * x + 0.276 | 0.000 | 0.142 | 0.136 | 1.041 |
| AWRC | - | 0.187 * x + 9.276 | 0.00994 | 2.618 | - | - |
| NCP | Hole effect | 0.311 * x + 9.955 | -0.056 | 5.893 | 5.177 | 1.144 |

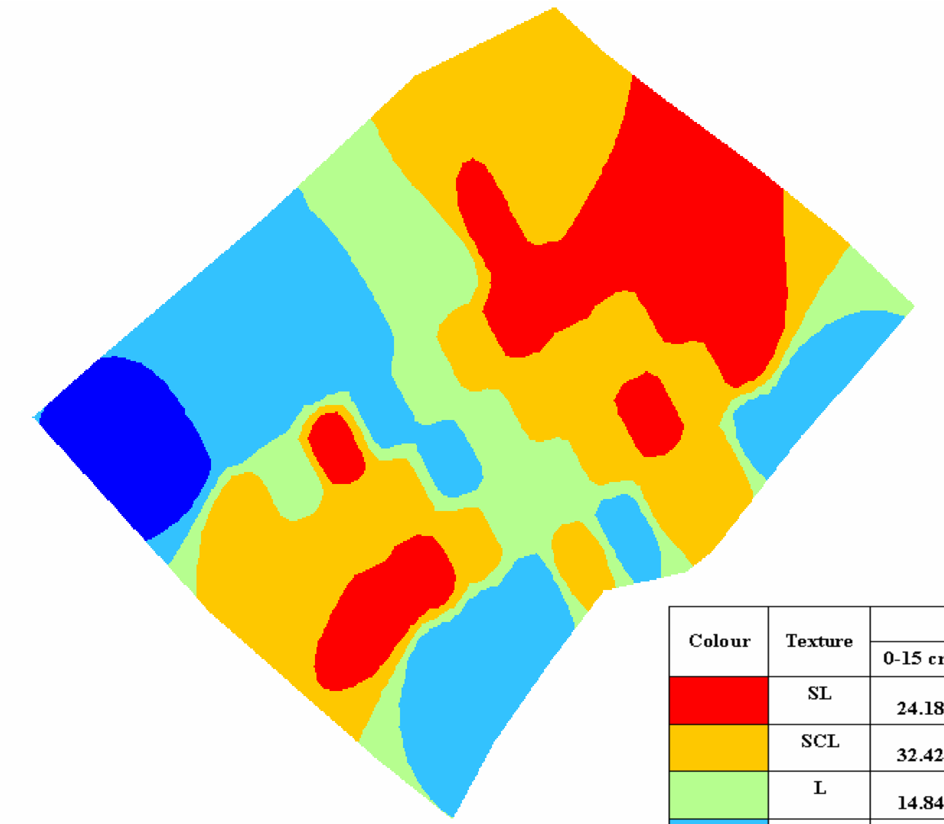
**Table 4.3: Spatial structure of soil physical parameters for subsurface (15-30 cm) soil layer**

| Parameter | Interpolation technique | Best suited model | Lag size(m) & no. of lags | Major range (m) & direction (degree) | Minor Range (m) | Nugget variance (cm/hr) ($C_o$) | Partial Sill (cm/hr) (C) | % $C_o/(C+C_o)$ | Spatial dependence |
|---|---|---|---|---|---|---|---|---|---|
| PI | Ordinary kriging | Spherical | 32.36 & 12 | 377.96 & 63° | 129.43 | 0.0015 | 0.0078 | 16.13 | Strong |
| BD | Ordinary kriging | Spherical | 23.31 & 12 | 275.52 & 63° | 62.23 | 0.002 | 0.011 | 15.38 | Strong |
| $K_{fs}$ | Ordinary kriging | Gaussian | 17.32 & 12 | 205.35 & 64° | 92.35 | 0.00136 | 0.00185 | 42.37 | Moderate |
| OC | Ordinary kriging | Gaussian | 32.30 & 12 | 380.23 & 72° | 108.33 | 0.0109 | 0.0160 | 40.52 | Moderate |
| AWRC | Ordinary kriging | Hole effect | 11.80 & 12 | 139.86 & 63° | 128.29 | 3.35 | 7.88 | 29.83 | Moderate |
| NCP | Simple kriging | Hole effect | 11.78 & 12 | 139.66 & 79° | 60.162 | 14.90 | 17.50 | 45.99 | Moderate |

Table 4.4: Cross validation of various spatial models of soil physical parameters for subsurface (15-30 cm) soil layer

| Parameter | Model types | Regression equation | Mean prediction error (MPE) | Root mean square prediction error (RMSPE) | Average standard prediction error (AVSPE) | Root-mean-square standardized prediction error (RMSSPE) |
|---|---|---|---|---|---|---|
| PI | Spherical | 0.479 * x + 0.172 | 0.000 | 0.060 | 0.058 | 1.005 |
| BD | Spherical | 0.534 * x + 0.815 | 0.001 | .084 | .080 | 1.05 |
| $K_{fs}$ | Gaussian | 0.698 * x + 0.029 | 0.000 | 0.046 | 0.043 | 1.05 |
| OC | Gaussian | 0.461 * x + 0.319 | 0.000 | 0.126 | 0.117 | 1.07 |
| AWRC | Hole effect | 0.333 * x + 5.577 | -0.017 | 3.202 | 2.58 | 1.222 |
| NCP | Hole effect | 0.320 * x + 6.408 | 0.035 | 5.049 | 4.75 | 1.063 |

0-15 cm



| Colour | Texture | Area (%) | |
|---|---|---|---|
| | | 0-15 cm | 15-30 cm |
| | SL | 24.18 | 14.29 |
| | SCL | 32.42 | 36.26 |
| | L | 14.84 | 12.09 |
| | CL | 23.08 | 24.18 |
| | C | 5.49 | 13.19 |

15-30 cm

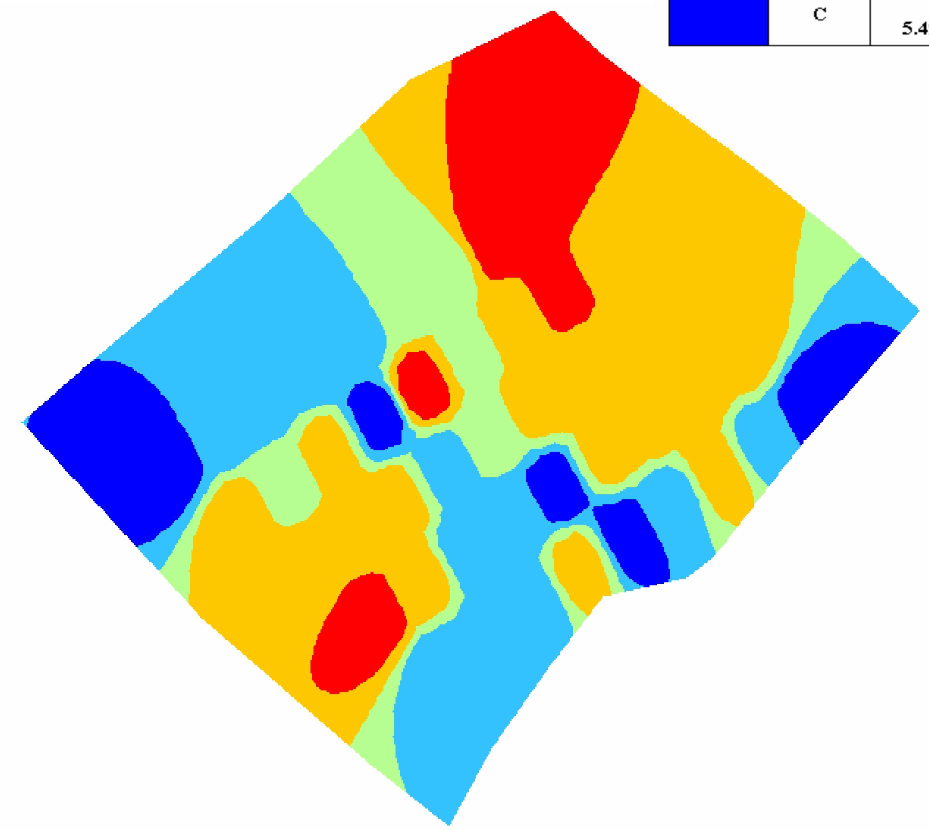
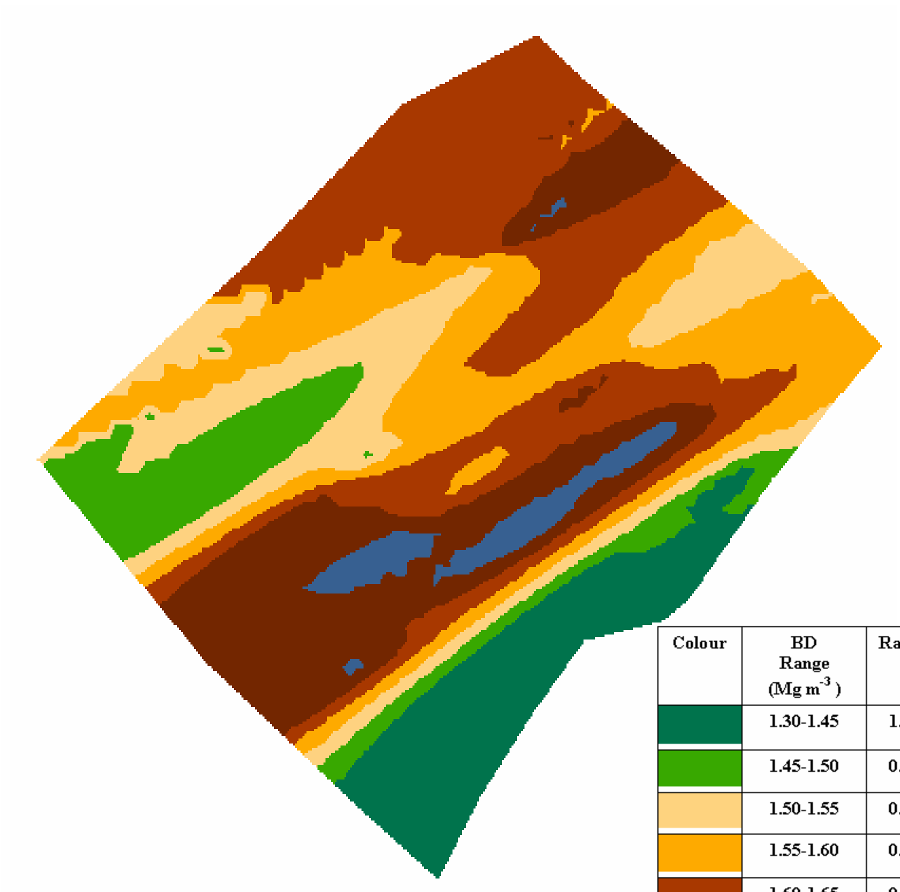


**Fig. 4.1:** Spatial variation of soil texture in different regions of the study area

0-15 cm



| Colour | BD Range (Mg $m^{-3}$) | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | 1.30-1.45 | 1.00 | 11.96 | 0.00 |
| | 1.45-1.50 | 0.95 | 9.24 | 0.00 |
| | 1.50-1.55 | 0.90 | 10.87 | 1.64 |
| | 1.55-1.60 | 0.85 | 19.02 | 6.52 |
| | 1.60-1.65 | 0.80 | 27.72 | 5.43 |
| | 1.65-1.70 | 0.75 | 17.39 | 8.15 |
| | 1.70-1.75 | 0.70 | 3.80 | 28.26 |
| | 1.75-1.85 | 0.65 | 0.00 | 50.00 |

15-30 cm

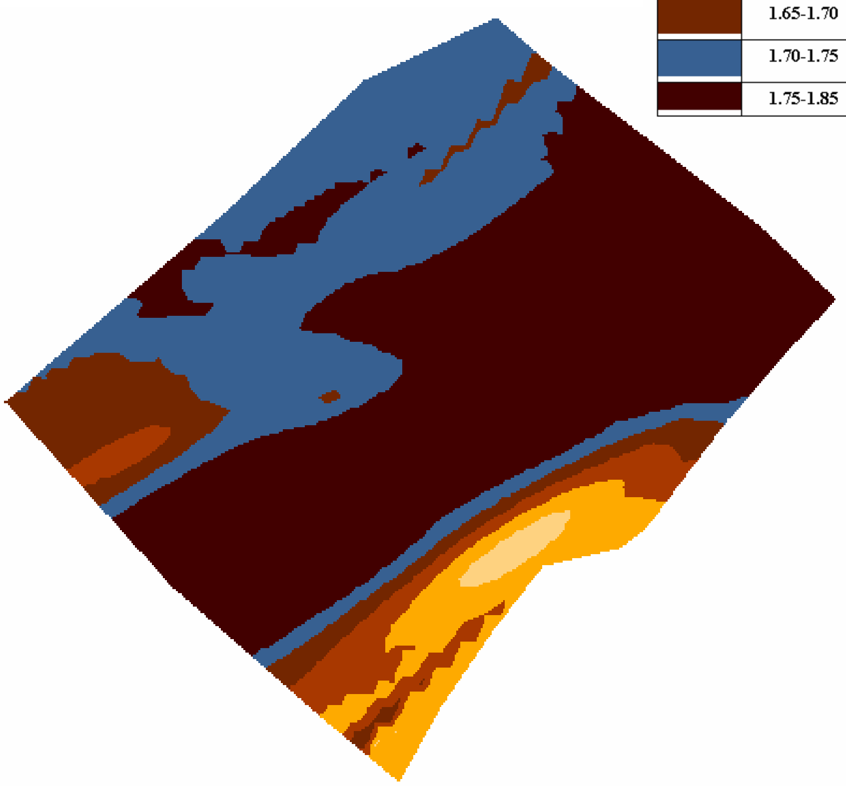


**Fig. 4.2:** Rating maps of bulk density (Mg $m^{-3}$) of surface (0-15 cm) and subsurface (15-30 cm) soil layers for upland crops

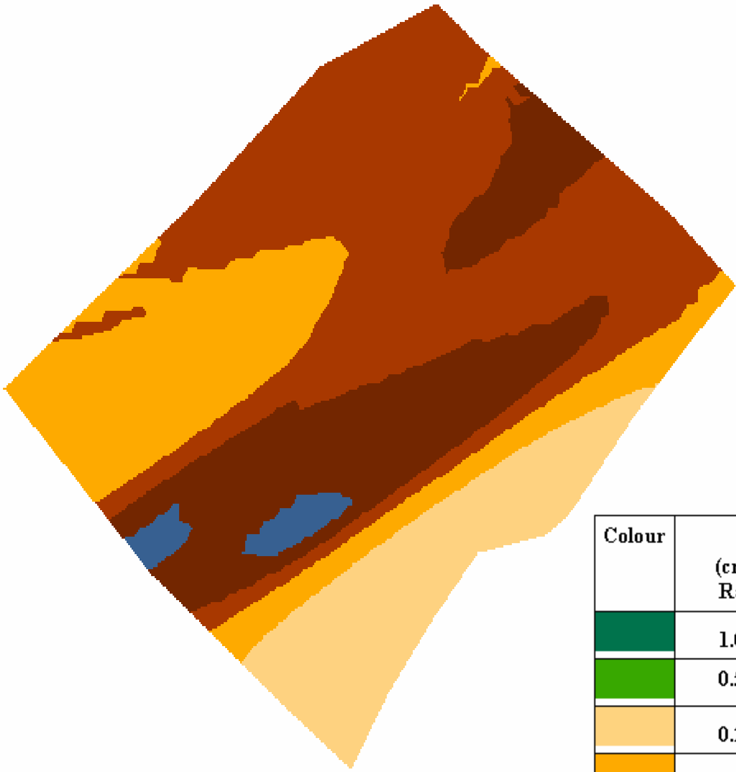
Computation of area under different BD ranges revealed that for surface layer, nearly 50 % area was severely compacted (BD >1.6 Mg $m^{-3}$ and rating value <0.8), where as for subsurface layer it was more than 90 %.The results thus indicated that subsurface compaction was a severe constraint for root growth and overall production of succeeding wheat crop in this area.

For preparing prediction maps of $K_{fs}$, Gaussian was found the best model for both layers (Fig. 4.3). Optimum range for $K_{fs}$ in soil was > 0.5 cm/h and was assigned a rating value of ≥ 0.90. Computation of area under different $K_{fs}$ ranges revealed that for surface layer, nearly 80 % area had $K_{fs}$ range between 0.10-0.05 cm/h and rating value 0.75-0.85, whereas for subsurface layer, 100% of the study area had same range and rating value.

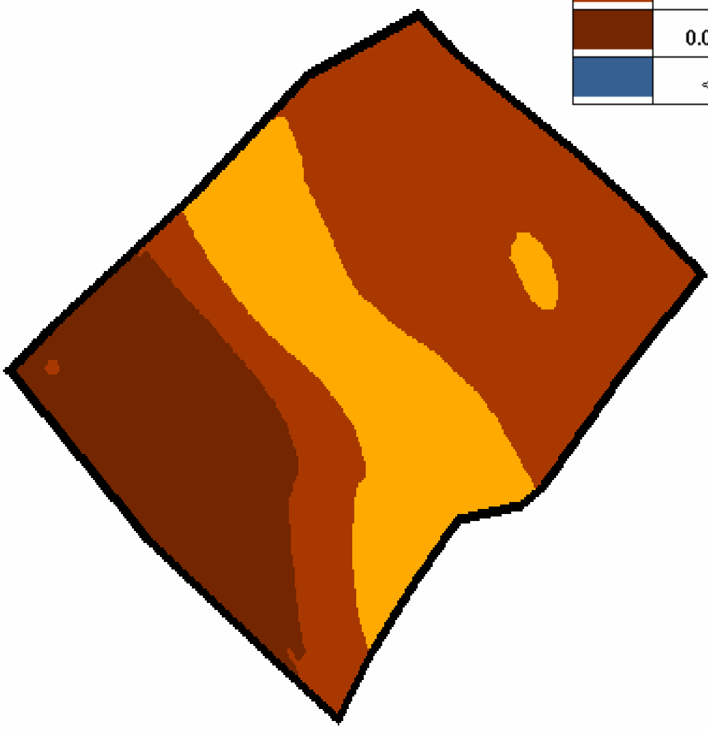
Prediction maps of AWRC were prepared by using IDW for surface layer and ordinary kriging with “Hole effect” semivariogram model for the subsurface layer (Fig. 4.4). As suggested in physical rating criteria of Gupta (1986), AWRC values more than 15 cm/m were considered as optimum for all soil types. Values less than optimum were rated less and rating map of AWRC along with % area in different classes was prepared. It was shown that > 75 % of the surface layer had AWRC value > 10cm/m (rating value ≥ 0.9), whereas for subsurface layer nearly 90% of the area had AWRC range < 10 cm/m (≤ 0.8). Hence it was concluded that subsurface layer had lesser capillary pores (CP) for water retention and this constraint was probably because of severe compaction which reduced the overall pores and hence the volume of capillary pores. Less water retention capacity of soils could lead to appreciable reduction in wheat yields.

Prediction maps of NCP were prepared by using simple kriging with “Hole effect” semivariogram model for both layers (Fig. 4.5). Optimum range of NCP (%) in soil suggested for upland cultivation was 12.5-15.0 and assigned a rating value of one. The results showed that more than 95% of surface layer had NCP range > 10 % and rating value ≥ 0.90, and for subsurface layer, nearly 75 % area was between NCP range of 5-10 % and therefore had rating between 0.7-0.80. The above results again confirmed that because of compaction (BD increase) total porosity was reduced and hence both CP and NCP reduced.

**0-15 cm**



**15-30 cm**

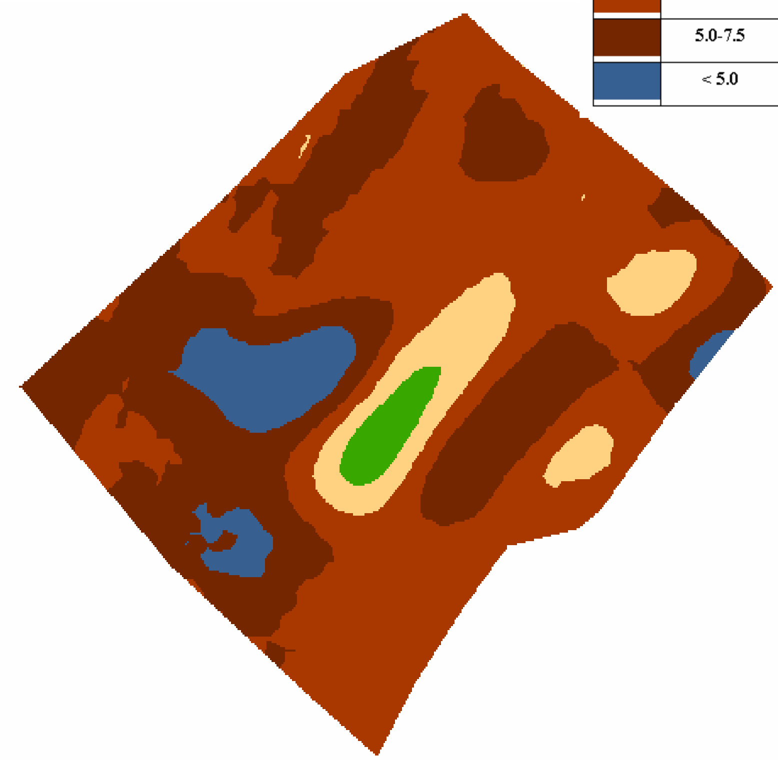


| Colour | $K_{fs}$ (cm/hr) Range | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | 1.0-3.0 | 1.00 | 0.00 | 0.00 |
| | 0.5-1.0 | 0.95 | 0.00 | 0.00 |
| | 0.2-0.5 | 0.90 | 14.67 | 0.00 |
| | 0.1-0.2 | 0.85 | 23.91 | 23.37 |
| | 0.05-0.1 | 0.8 | 39.13 | 51.09 |
| | 0.01-0.05 | 0.75 | 19.02 | 25. .54 |
| | <0.01 | 0.70 | 3.26 | 0.00 |

**Fig. 4.3:** Rating maps of hydraulic conductivity (cm/h) of surface (0-15 cm) and subsurface (15-30 cm) soil layers for upland crops

**0-15 cm**

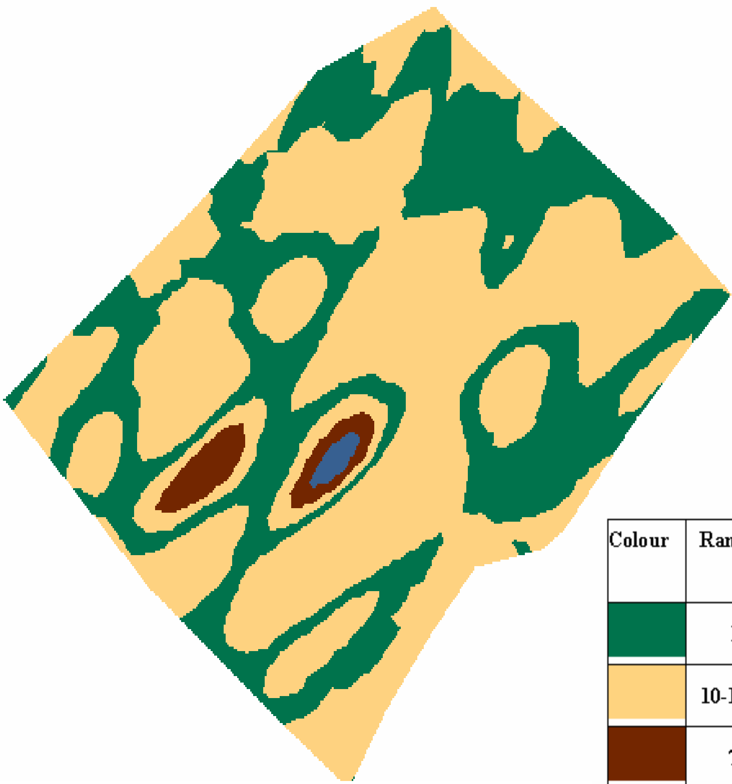
**15-30 cm**



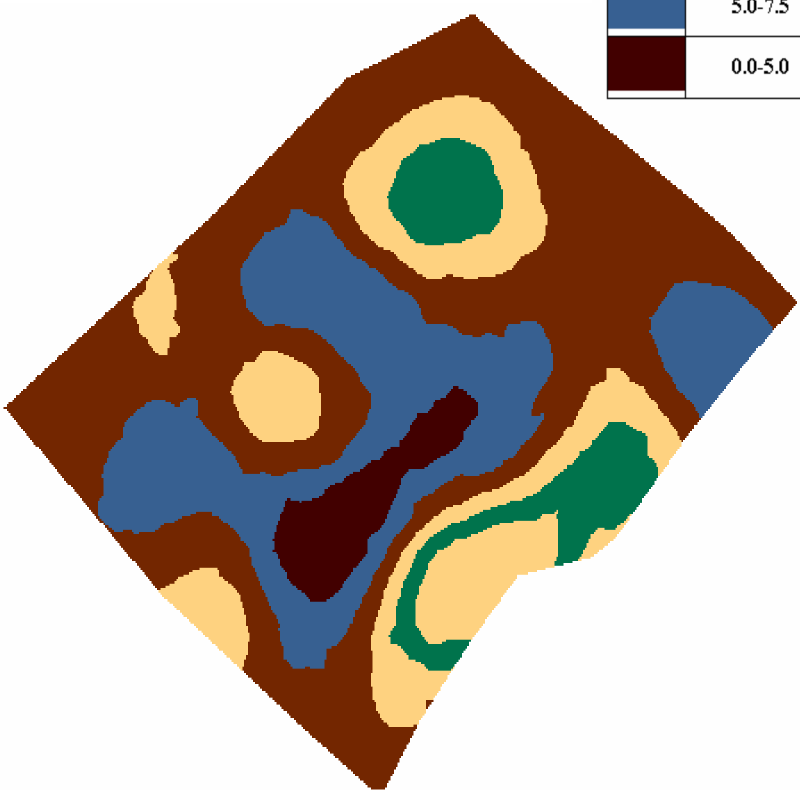
| Colour | AWRC (cm/m) Range | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | >15.0 | 1.00 | 5.98 | 0.00 |
| | 12.5-15.0 | 0.95 | 25.54 | 2.17 |
| | 10.0-12.5 | 0.90 | 46.74 | 6.52 |
| | 7.5-10.0 | 0.80 | 16.30 | 51.09 |
| | 5.0-7.5 | 0.75 | 5.43 | 34.78 |
| | < 5.0 | 0.70 | 0.00 | 4.89 |

**Fig. 4.4:** Rating maps of available water retention capacity (cm/m) of surface (0-15 cm) and subsurface (15-30 cm) soil layers

**0-15 cm**



**15-30 cm**



| Colour | Range of NCP (%) | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | 12.5-15 | 1.00 | 30.98 | 5.98 |
| | 10-12.5 & >15 | 0.90 | 64.67 | 16.30 |
| | 7.5-10.0 | 0.80 | 3.80 | 48.91 |
| | 5.0-7.5 | 0.70 | 0.54 | 24.46 |
| | 0.0-5.0 | 0.65 | 0.00 | 4.35 |

**Fig. 4.5:** Rating maps of non capillary pores (%) of surface (0-15cm) and subsurface (15-30 cm) soil layers for upland cultivation

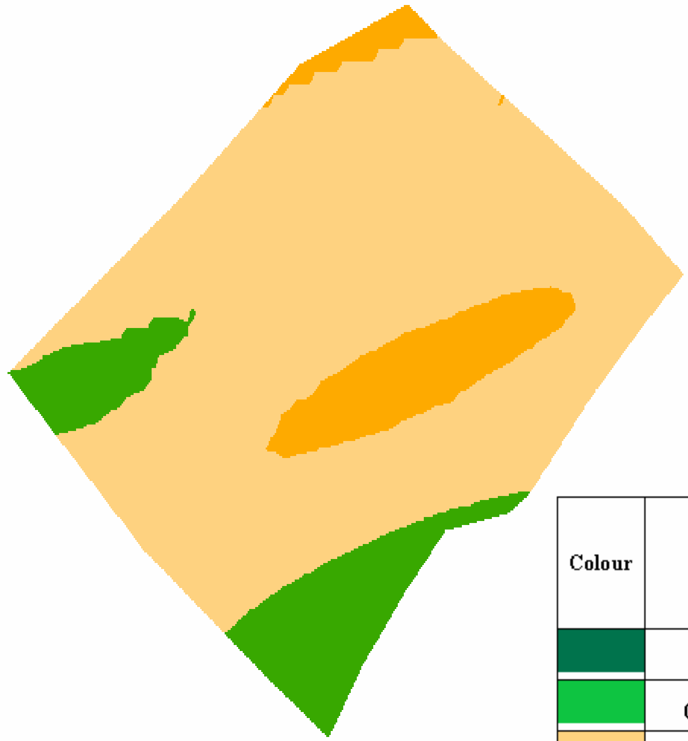
For preparing prediction maps of OC, Gaussian model was found the most suited for both layers (Fig. 4.6). Optimum range suggested for % OC in soil was > 1.2 and was assigned a rating value of one. Values less than optimum were given lesser ratings. Computation of area under different OC ranges revealed that for surface layer, nearly 90 % area had OC range >0.6 % and rating value ≥ 0.90, whereas for subsurface layer, 100% area was between OC range of 0.45-0.90 % and therefore had rating between 0.85-0.90 (Fig. 4.6). Analysis of data thus suggested that surface layer was only slightly deficient in OC as good amount of organic matter was added in the field through green manure before rice transplanting but subsurface layer was more deficient in OC, which could be a constraint for production of succeeding wheat crop.

Physical rating index (PI) at each sampling point was determined by multiplying the rating values for all five parameters. Reason for multiplication of individual rating values for defining the PI was that this index was an indicator of soil productivity. Large deviation in any of the individual parameter value from its optimum range could bring down the yield drastically and such a response could only be observed if the rating values of individual parameters were multiplied.

PI maps of both surface (0-15 cm) and subsurface (15-30 cm) soil layers for upland crops were prepared by using ordinary kriging with spherical semivariogram model (Fig. 4.7). It showed that more than 90 % of surface layer had rating value between 0.4-0.7, whereas for subsurface layer, all the study area had rating value < 0.6. It means that soil physical conditions of the field was poor to medium for wheat cultivation after rice and in order to increase soil productivity for sustainable crop production, soil managements practices such as subsurface chiseling and adding organic matter through manure and crop residue incorporation were essential.

Prediction maps of soil physical properties and PI for paddy cultivations were prepared by selecting most suitable interpolation techniques and semivariogram modeling. Rating map of BD showed that most of surface layer (99.5 %) had rating value > 0.90, whereas for subsurface layer, all the study area had optimum BD range, between 1.55-1.60 Mg $m^{-3}$, and rating value one (Fig. 4.8).

**0-15 cm**



| Colour | OC Range (%) | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | >1.20 | 1.00 | 0.00 | 0.00 |
| | 0.90-1.20 | 0.95 | 11.95 | 0.00 |
| | 0.60-0.90 | 0.90 | 79.35 | 44.02 |
| | 0.45-0.60 | 0.85 | 8.70 | 55.98 |
| | 0.30-0.45 | 0.80 | 0.00 | 0.00 |
| | 0.20-0.30 | 0.75 | 0.00 | 0.00 |

**15-30 cm**

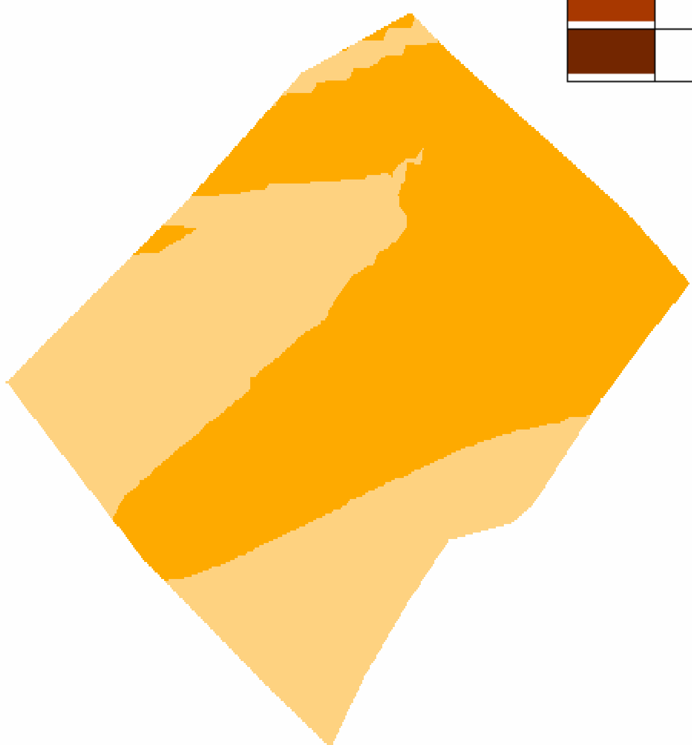
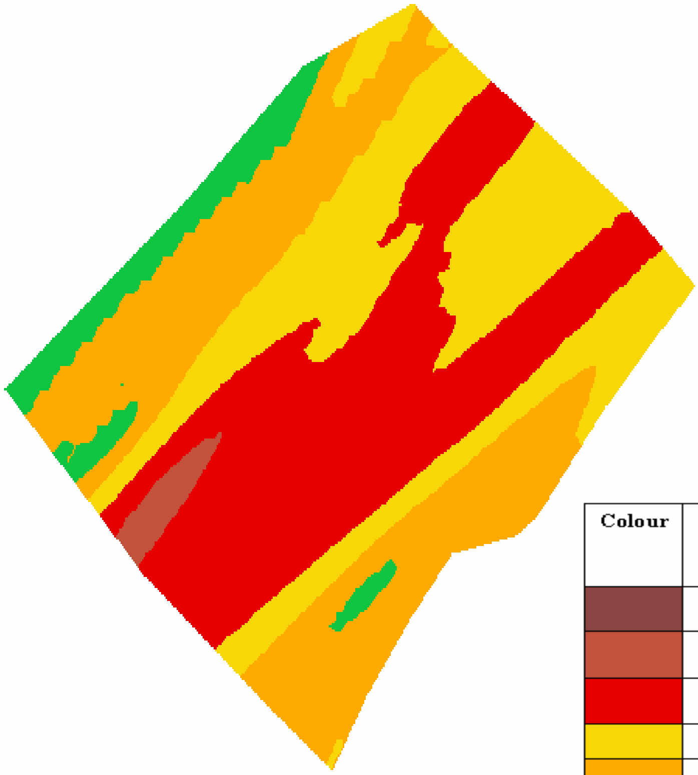
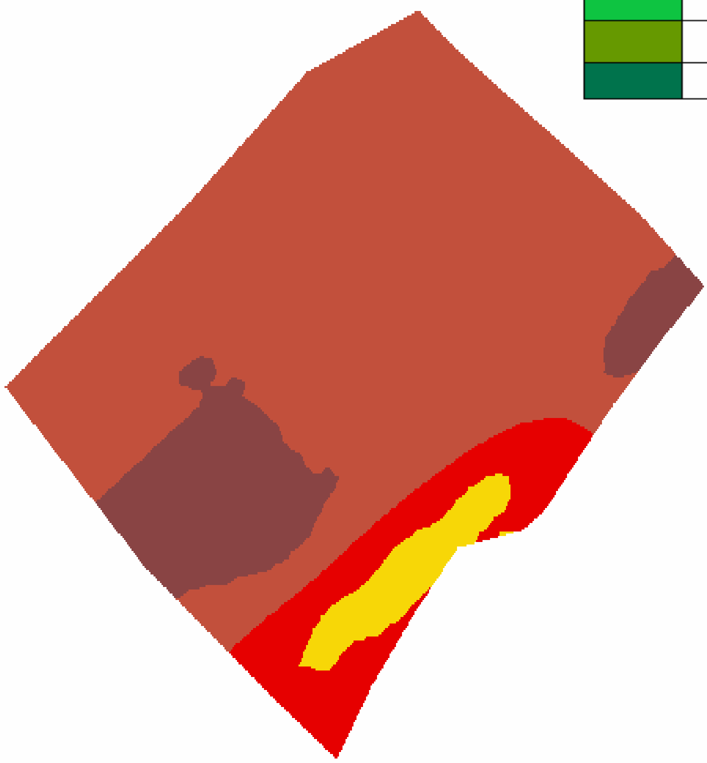


**Fig. 4.6:** Rating maps of organic carbon (%) of surface (0-15 cm) and subsurface (15-30 cm) soil layers for upland crops

**0-15 cm**



**15-30 cm**



| Colour | Physical rating Index values | Area (%) | |
|---|---|---|---|
| | | 0-15 cm | 15- 30 cm |
| | 0.20-0.30 | 0.00 | 14.13 |
| | 0.30-0.40 | 2.72 | 70.65 |
| | 0.40-0.50 | 32.61 | 9.78 |
| | 0.50-0.60 | 30.43 | 5.44 |
| | 0.60-0.70 | 28.26 | 0.00 |
| | 0.70-0.80 | 5.98 | 0.00 |
| | 0.80-0.90 | 0.00 | 0.00 |
| | 0.90-1.00 | 0.00 | 0.00 |

**Fig. 4.7:** Physical rating index maps of surface (0-15 cm) and subsurface (15-30 cm) soil layers for upland crops

**0-15 cm**

| Colour | BD Range (Mg m$^{-3}$) | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | 1.55-1.60 | 1.00 | 54.30 | 100.00 |
| | 1.60-1.65<br>1.50-1.55 | 0.95 | 17.90 | 0.00 |
| | 1.65-1.70<br>1.45-1.50 | 0.90 | 27.20 | 0.00 |
| | 1.70-1.75<br>1.30-1.45 | 0.85 | 0.50 | 0.00 |
| | 1.75-1.85 | 0.80 | 0.00 | 0.00 |

**15-30 cm**

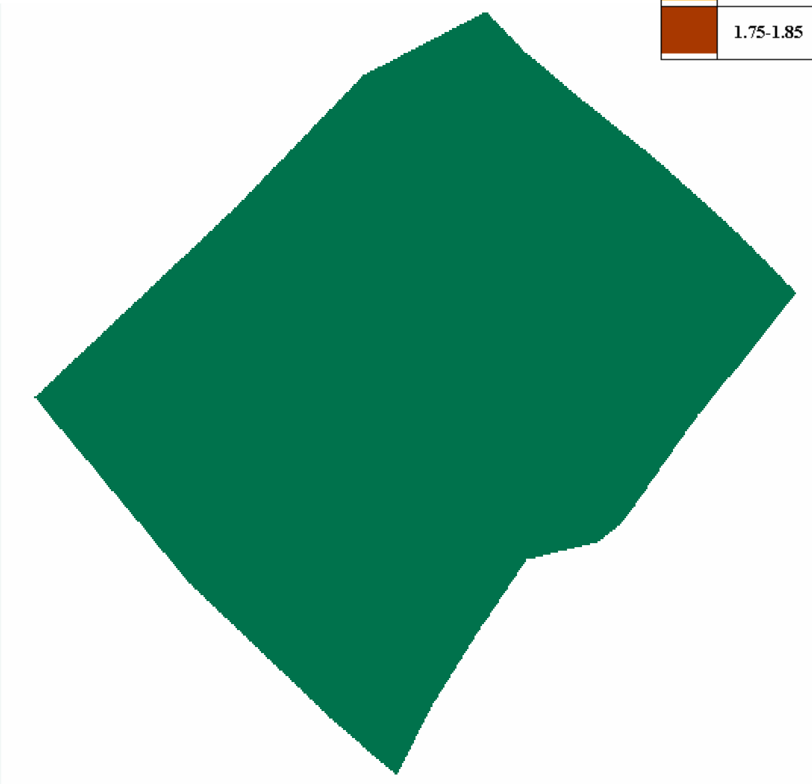


**Fig. 4.8:** Rating maps of bulk density (Mg m$^{-3}$) of surface (0-15 cm) and subsurface (15-30 cm) soil layers for paddy cultivations

Rating maps of hydraulic conductivity also revealed that for surface layer, nearly 96.2 % area had $K_{fs}$ ranges less than 0.20 cm/h (4.80 cm/day) with optimum rating value 0.95-1.0 (Fig. 4.9) . For subsurface layer, all the study area had $K_{fs}$ ranges < 0.10 cm/h (0.24 cm/day) and the best rating value for plant growth (1.0). High BD and low $K_{fs}$ mainly in the subsurface were because of puddling. It was carried out before rice transplanting for developing compact subsurface zone required for reducing the percolation of standing water needed by the crop during its growth.

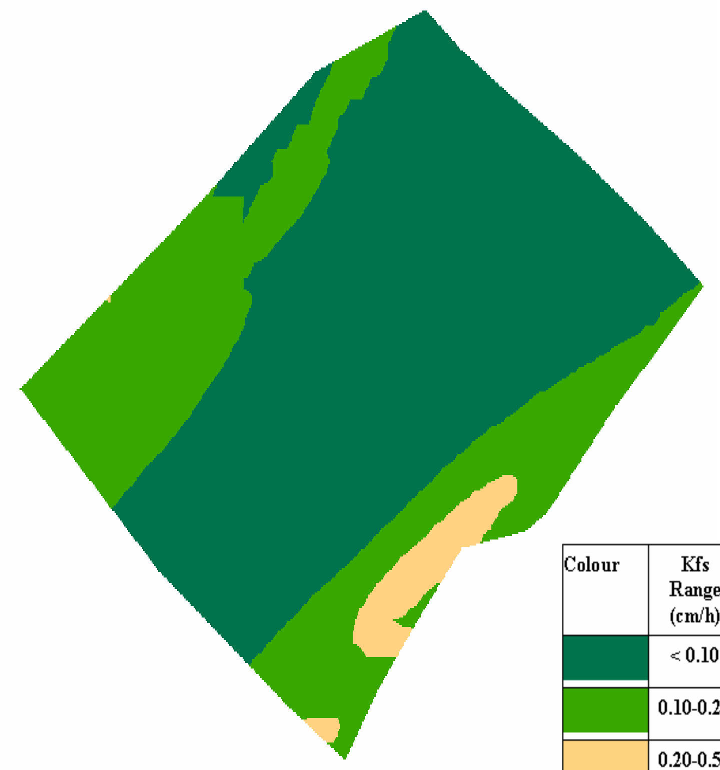
According to prediction maps, optimum range for NCP in paddy cultivations is < 12.5 % with rating value one (Fig. 4.10). For surface layer, only 76.10 % of area had a good range (10.0-12.5 %) with rating value 0.90, and 23.90 % of area had NCP range between 12.5-15.0 % and rating value 0.85. For subsurface layer, around 90 % of area had a good rating value (0.90-1.0), where, NCP was < 12.5 %.

Prediction maps of OC (Fig. 4.11) revealed that for both surface and subsurface layers, most of study area (> 96.0 %) had the best optimum value (1.0) and % OC was < 0.6. Increasing of %OC causes development of aggregation and creation of new drainage pores that accelerate saturated hydraulic conductivity in the lowlands and reduce available water content in the soil.

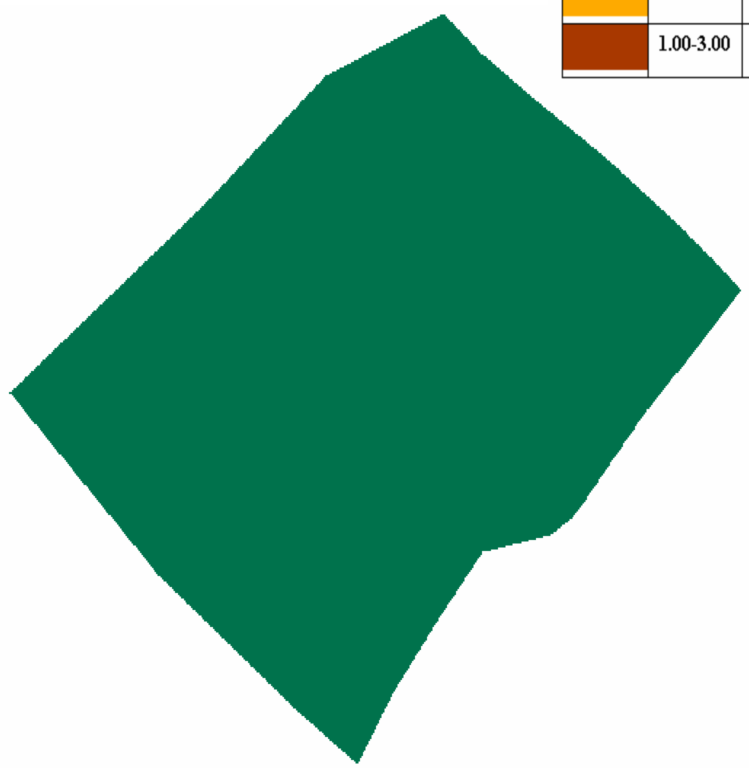
Physical rating index (PI) maps for paddy cultivations were also prepared by using ordinary kriging and spherical semivariogram model for both layers (Fig. 4.12). It showed that both surface and subsurface layers had PI values between 0.5-0.8. It means soil physical conditions in the farm of the study area were medium to good for rice.

The prediction map of rice yield showed that nearly 85 % of the area produced 40-60 quintal rice grain per hectare (Fig. 4.13). Linear regression analysis of PI and rice grain yield data (Fig. 4.14) showed a good correlation ($R^2$=0.662). The results thus supported earlier findings that good soil physical health is essential for optimum sustained crop production.

**0-15 cm**



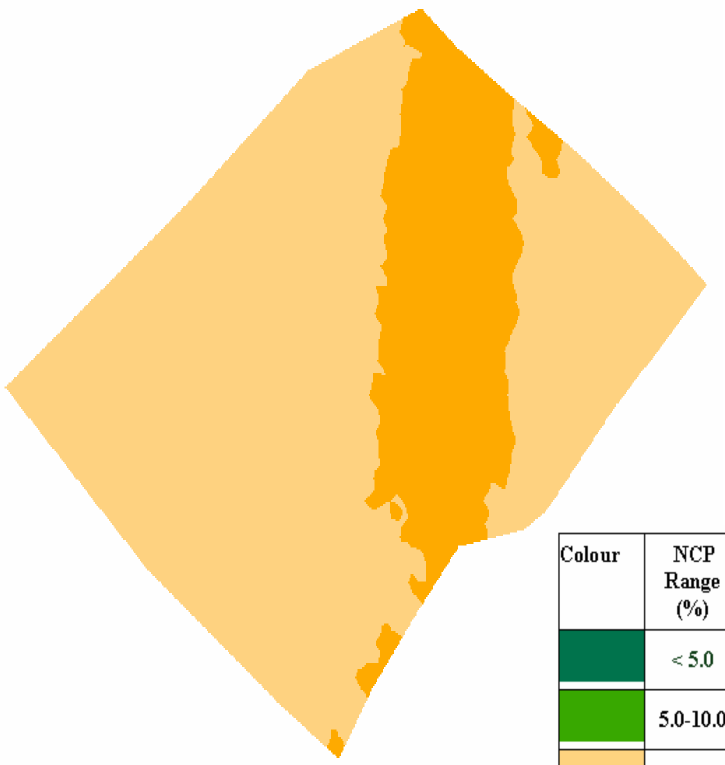
**15-30 cm**



| Colour | Kfs Range (cm/h) | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | < 0.10 | 1.00 | 66.30 | 100.00 |
| | 0.10-0.20 | 0.95 | 29.90 | 0.00 |
| | 0.20-0.50 | 0.90 | 3.80 | 0.00 |
| | 0.50-1.00 | 0.85 | 0.00 | 0.00 |
| | 1.00-3.00 | 0.80 | 0.00 | 0.00 |

**Fig. 4.9:** Rating maps of hydraulic conductivity (cm/h) of surface (0-15 cm) and subsurface (15-30 cm) soil layers for paddy cultivations

**0-15 cm**



| Colour | NCP Range (%) | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | < 5.0 | 1.00 | 0.00 | 23.40 |
| | 5.0-10.0 | 0.95 | 0.00 | 44.60 |
| | 10.0-12.5 | 0.90 | 76.10 | 19.50 |
| | 12.5-15.0 | 0.85 | 23.90 | 12.50 |
| | > 15.0 | 0.80 | 0.00 | 0.00 |

**15-30 cm**

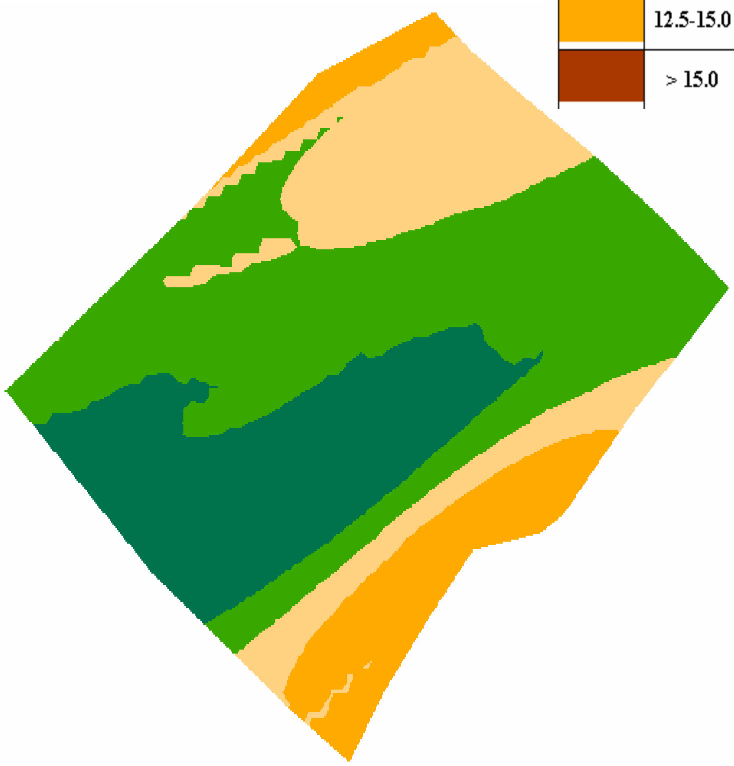
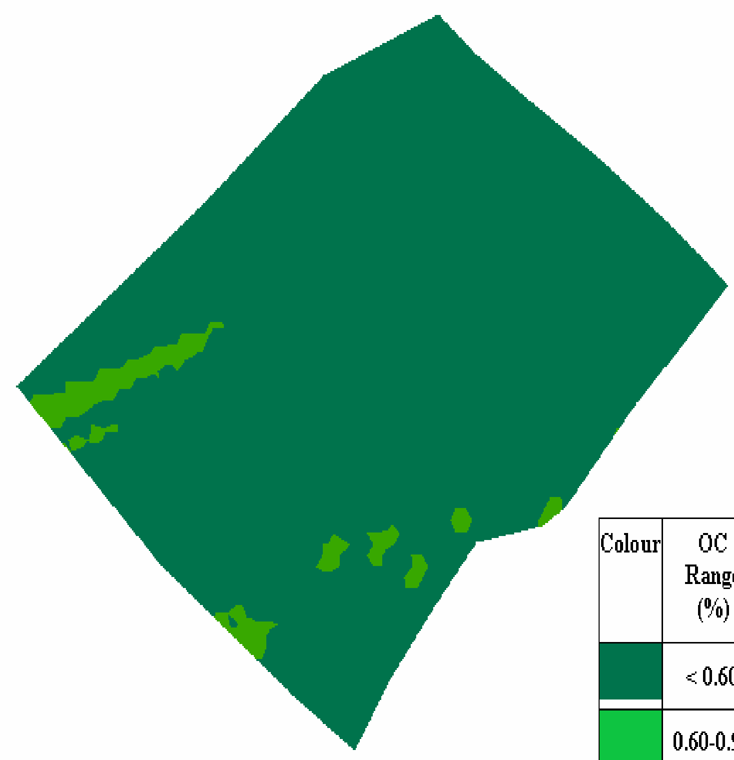
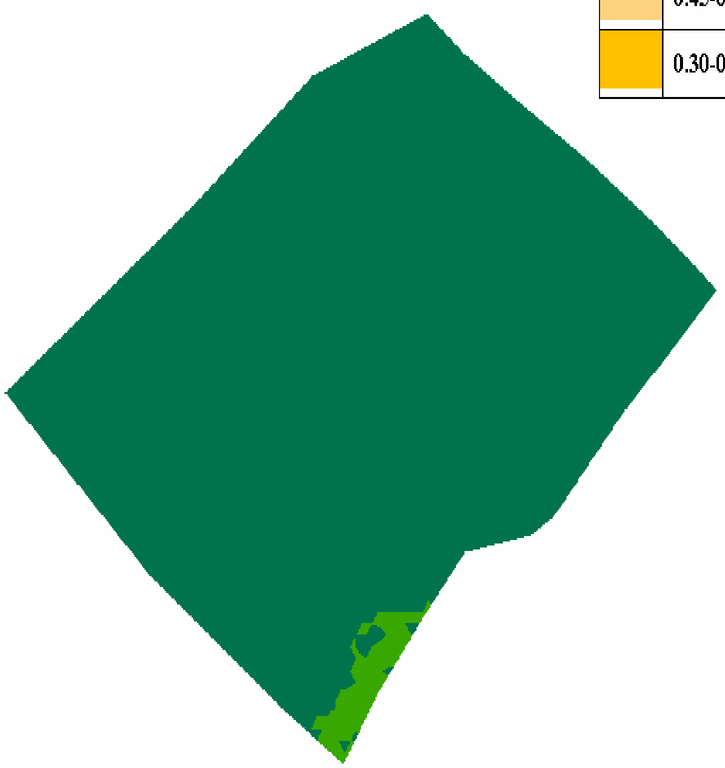


**Fig. 4.10:** Rating maps of non capillary pores (cm/cm) of surface (0-15 cm) and subsurface (15-30 cm) soil layers for paddy cultivations

**0-15 cm**



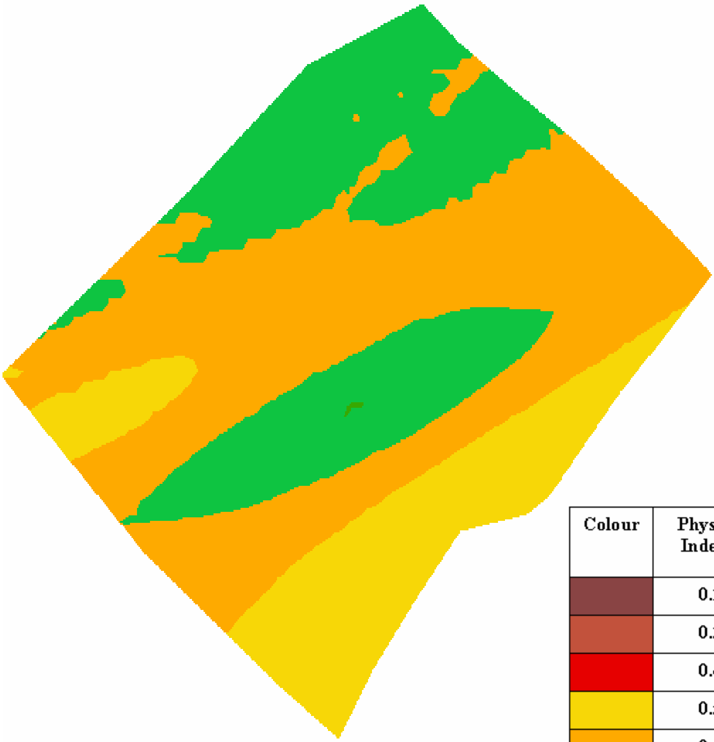
**15-30 cm**



| Colour | OC Range (%) | Rating | Area (%) | |
|---|---|---|---|---|
| | | | 0-15 cm | 15- 30 cm |
| | < 0.60 | 1.00 | 96.20 | 97.80 |
| | 0.60-0.90 | 0.95 | 3.80 | 2.20 |
| | 0.45-0.60 | 0.90 | 0.00 | 0.00 |
| | 0.30-0.45 | 0.85 | 0.00 | 0.00 |

**Fig. 4.11:** Rating maps of organic carbon (%) of surface (0-15 cm) and subsurface (15-30 cm) soil layers for paddy cultivations

**0-15 cm**



| Colour | Physical rating Index values | Area (%) | |
|---|---|---|---|
| | | 0-15 cm | 15- 30 cm |
| | 0.20-0.30 | 0.00 | 0.00 |
| | 0.30-0.40 | 0.00 | 0.00 |
| | 0.40-0.50 | 0.00 | 0.00 |
| | 0.50-0.60 | 18.50 | 2.20 |
| | 0.60-0.70 | 51.10 | 63.00 |
| | 0.70-0.80 | 30.40 | 34.80 |
| | 0.80-0.90 | 0.00 | 0.00 |
| | 0.90-1.00 | 0.00 | 0.00 |

**15-30 cm**

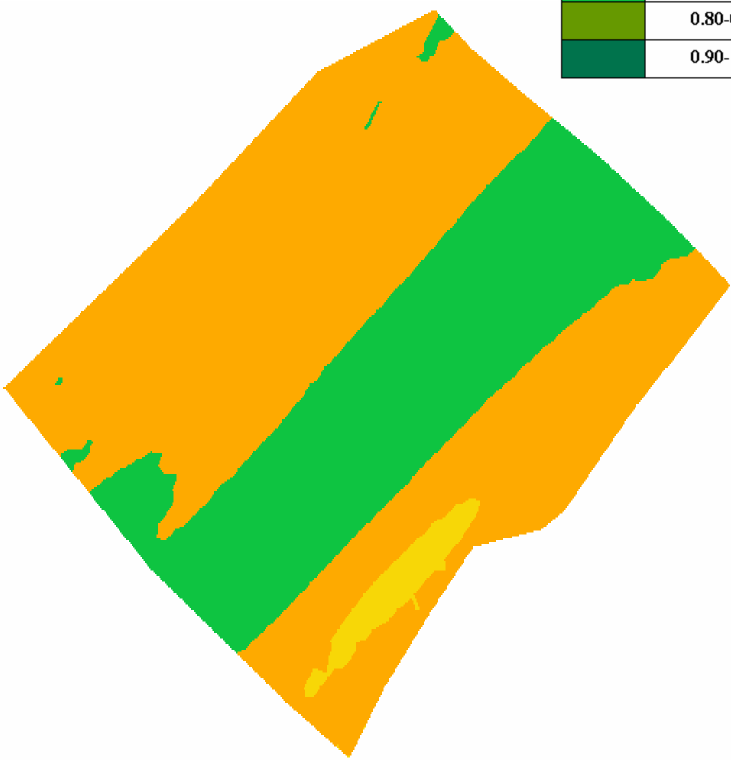
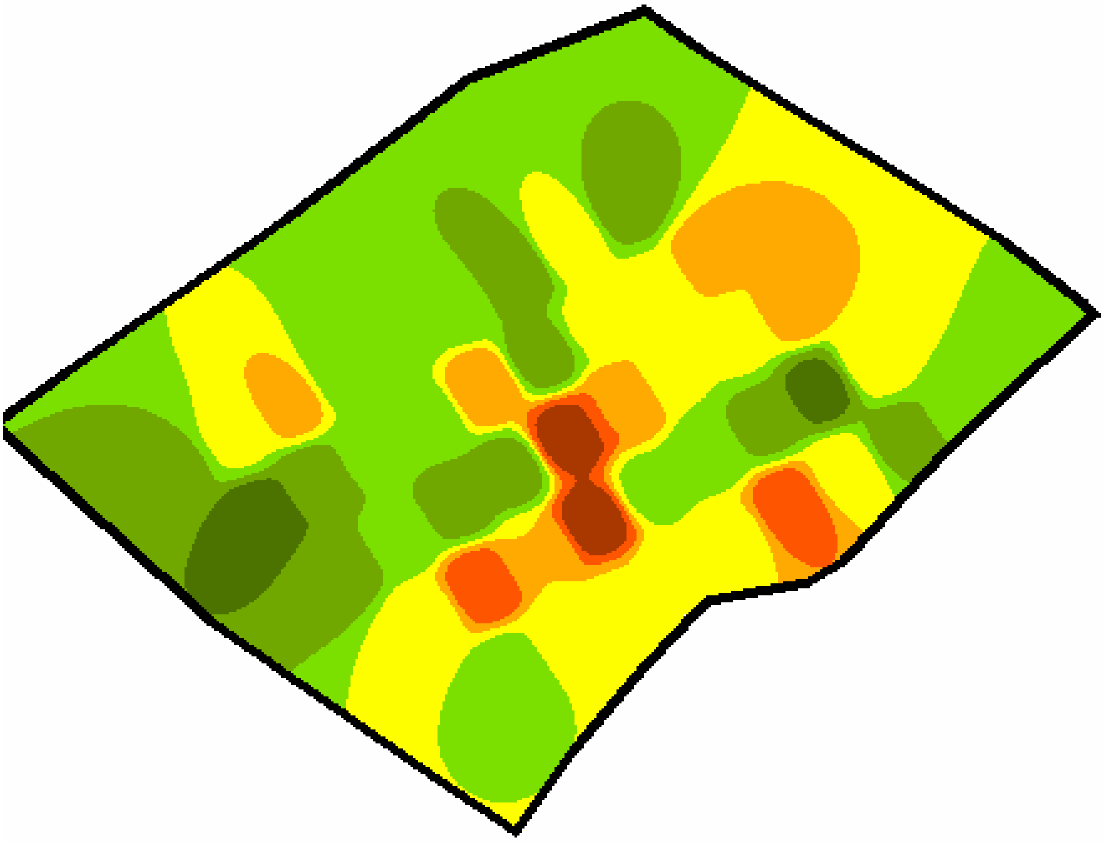


**Fig. 4.12:** Physical rating index maps of surface (0-15 cm) and subsurface (15-30 cm) soil layers for paddy cultivations



| Colour | Rice Yield range (q/ha) | Area (%) |
|---|---|---|
| | 25-30 | 1.57 |
| | 30-35 | 2.87 |
| | 35-40 | 9.91 |
| | 40-45 | 28.74 |
| | 45-50 | 35.68 |
| | 50-55 | 18.10 |
| | 55-60 | 3.13 |

**Fig. 4.13:** Spatial variation of rice yield (q/ha) in the study area

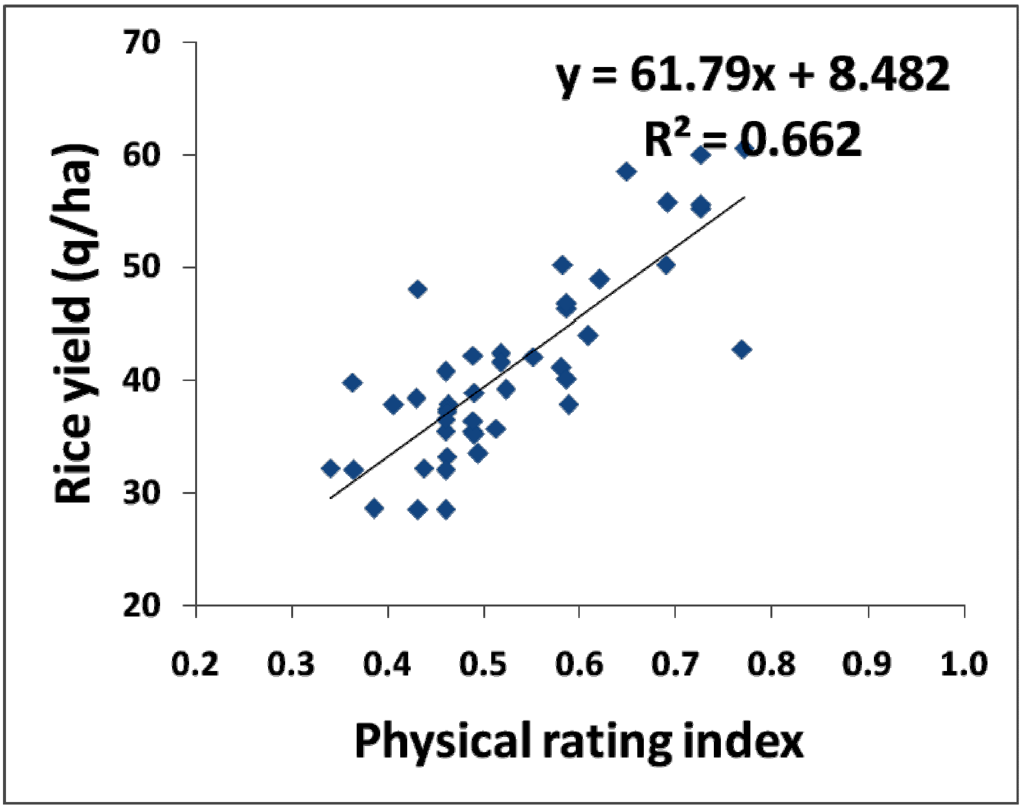



**Fig. 4.14:** Linear regression between rice yield (q/ha) and physical rating index

**4.5 Conclusion:**

In conclusion it could be stated that overall soil physical health of the farm was medium to good for paddy cultivation but was not suitable for succeeding wheat crop mainly because of increased BD and reduced $K_{fs,}$ NCP and AWRC of the farm. Hence it is suggested that precision farming should be adopted for improving the soil health of the farm. The essential features of precision farming should include presentation of the existing spatial soil health scenario through preparation of prediction maps of various essential soil health indicators. Based on these findings, appropriate rates of different inputs and soil management practices should be recommended in different parts of the farm so as to alleviate the existing soil health constraints.

# 5. SUMMARY AND CONCLUSIONS

Spatial variations of soil bulk density(BD) , saturated hydraulic conductivity (Kfc) along with other important soil physical parameters such as soil texture ,soil organic carbon (OC), non capillary pores(NCP) and available water retention capacity(AWRC) were studied in farm during rice cultivation in National capital region (NCR). The main aims of study were:

- Development of pedotransfer functions among soil hydraulic parameters and other easily measurable soil parameters such as BD, OC,% sand, silt and clay
- To carry out two-dimensional spatial variability analysis of soil hydraulic properties in a farm to delineate compact zones for indicating precise tillage requirement
- To assess and map the spatial variation of soil physical health in the farm
- To examine correlation between spatial variation of soil physical health and yield of crop in the farm

The results of analysis are summarized below:

- Among different sol physical parameters BD had lowest coefficient of variation, followed by $\theta_{FC}$ and silt. The CV of $K_{fs}$ was highest, followed by $\theta_{PWP.}$
- Stepwise regression analysis of $K_{fs}$ showed that among all soil physical parameters, clay (%) have maximum influence on $K_{fs}$ (49% variation in $K_{fs}$). Addition of sand and OC (%) in the regression model improved the correlation coefficient to 57 and 66 % respectively.
- $K_{fs}$ was positively correlated to drainage porosity and negatively correlated to BD. Reduction in drainage porosity, which is an indicator of increase compaction, was found to increase with increase in BD ($R^2$ =0.679). The above correlations thus suggest that field saturated hydraulic conductivity could be used to delineate compact zones.
- Regression equations of $\Theta_{FC}$ (w/w) of surface soil as a function of various soil physical parameters showed that $\Theta_{Fc}$ was negatively correlated to sand and was positively correlated to clay and OC. Sand alone contributed nearly 30 % variation in $\Theta_{Fc}$, whereas clay and OC alone contributed 26 and 11%, respectively.

- Similarly, $\theta_{PWP}$ was also negatively correlated to sand and positively correlated to OC. Further stepwise analysis showed that sand alone contributed nearly 20 % variation in $\theta_{PWP}$. Inclusion of sand along with OC accounted for nearly 26 % variation of $\theta_{PWP}$.
- Ordinary kriging was appropriate for interpolation and preparation of prediction and rating maps for soil physical parameters in absence of trend in data
- In general, low nugget to sill ratio for $K_{fs}$ and BD showed strong spatial dependence and for OC and NCP showed medium spatial dependence for surface soil layer. However, AWRC of surface layer did not show any spatial correlation.
- Ordinary kriging was more accurate than IDW as the slope of fitted line through the scatter plot of predicted versus observed data points was higher in the former.
- The kriged maps of BD or $K_{fs}$ were found useful for delineating compact zones
- The minimum data set for assessment of soil physical health in terms of soil productivity included the five parameters namely BD, Kfs, OC, NCP and AWRC which were assigned rating values using physical rating methodology developed by Gupta (1986).
- ✓ Soil physical health of the farm was medium to good for rice but was low to medium for succeeding wheat crop. This was mainly because of desirable range of soil physical properties for rice (i.e. low $K_{fs}$, compact subsurface, limited root zone, low non capillary pores) and the similar ranges were undesirable for other upland crops. Hence separate rating systems were chosen for rice and wheat.
- ✓ Linear regression analysis of PI and rice grain yield data showed there was a good correlation between them**.** The results thus supported earlier findings that good soil physical health is essential for optimum sustained crop production.

**Following conclusions can be drawn from the present investigation:**

- The above results thus leads to conclusion that geostatistical analyst of Arc GIS was a very useful tool for carrying out geostatistical/spatial variability analysis of soil physical properties. Such analysis was required for developing prediction maps of soil BD or $K_{fs}$ required for delineating compact zones so that deep tillage could be recommended in the compacted areas only to economize the use of inputs.
- These prediction maps of soil physical properties were also required for preparing soil physical health index map for assessing soil quality.
- One of the most important findings of geostatistical analysis was that kriging as a predictor did not require data to be normal.
- The overall soil physical health index (PI) computed as the product of rating values of individual parameter presented a reasonably good spatial soil physical health scenario and was well correlated to the yield of the crop.

**Future Needs:**

Present investigation has also revealed several new thrust areas of research on spatial variation of soil physical health. These areas are:

- Similar to soil physical health index, soil chemical and biological health indices of different soil series should be computed and correlated to yield of different crops.
- Quality index should also be developed for assessing the soil quality for performing soil functions such as regulating the water and solute flow (relevant to ground water recharge and ground water pollution studies), degrading, immobilizing and detoxifying organic and inorganic materials including industrial and municipal by products (relevant to soil contaminant studies).

# 6. ABSTRACT


Productivity rating systems are important tools to quantitatively assess soil health. In precision farming such information is required for planning appropriate soil and crop management strategies. In order to demonstrate a proper procedure for assessing the soil physical health of a farm, a study was conducted in a rice-wheat field in Kherli village of Dankaur block of Gautam Nagar district of Uttar Pradesh, India. Soil samples at 145 locations at a grid interval of 30 m x 45 m, covering a total area of 19 hectare of farm were collected from surface (0-15 cm) and sub surface (15-30 cm) soil layers. Spatial variability analysis of soil physical properties was carried out by using geostatistical analyst extension of Arc GIS software.

The average values of $K_{fs}$ and drainage porosity at 15-30 cm layer were less but the average values of BD and clay% were more than their critical limits, which confirmed the presence a plow pan in subsurface. The descriptive statistical analysis also showed that, among the different soil physical parameters BD had the lowest coefficient of variation (CV) followed by permanent wilting point ($\theta_{PWP}$) and $K_{fs}$ had the highest CV, followed by field capacity ($\theta_{FC}$). Stepwise regression analysis of $K_{fs}$ revealed that among all soil physical parameters, clay had maximum influence on $K_{fs}$. It alone contributed up to 49% variation in $K_{fs}$ and along with sand and OC accounted for 57% and 65% of its variations, respectively.

Since in this experiment, $K_{fs}$ was used to delineate compact zones, relationships of Kfs with other indicators of compaction such as BD or drainage porosity were explored. It was observed that $K_{fs}$ was positively correlated to drainage porosity ($R^2$ =0.59) and negatively correlated to BD ($R^2$ =0.794).

Spatial variability analyses of $K_{fs}$ indicated that both soil layers had similar spatial structure and ordinary kriging was the best choice, among several methods of interpolation. Comparison of cross validation statistics of various models also showed that for $K_{fs}$, Gaussian model was most suited among the all semivariogram models. So, ordinary kriging with Gaussian model was used for drawing prediction map of $K_{fs}$. Similar results were also obtained for BD. In general, the ratio of nugget to sill values for $K_{fs}$ and BD was low (< 25%), which showed strong spatial dependence of these parameters within their ranges, whereas rest of the parameters showed moderate spatial dependence. On comparing the log transformation data with without

transformation data of semivariograms of $K_{fs}$ for the same sampling intensity it was observed the data without transformation reduced the MPE value to near zero and hence improved the prediction map in comparison to log transformation data. It means kriging as a predictor does not require data to be normal. The prediction maps of $K_{fs}$ and BD for both layers also indicated the presence a hardpan ($K_{fs}$ < 0.16 cm/hr and BD >1.55 $Mgm^{-3}$) in the subsurface. Hence deep plowing should be recommended for the areas where plow pan existed.

Among the parameters suggested for computing soil physical rating index following procedure of Gupta (1986), BD, $K_{fc}$, AWRC, OC and NCP were chosen. Rating maps of mentioned parameters for upland crop and rice were prepared by using appropriate interpolation methods and suitable semivariogram models. Scoring for rating of physical parameters was different for wheat and rice as the optimum physical environment for both systems were different. Physical rating index (PI) at each sampling point was determined by multiplying the rating values for all five parameters. Overall soil physical health of the farm was medium to good for paddy cultivation but was not suitable for succeeding wheat crop mainly because of increased BD and reduced $K_{fs,}$ NCP and AWRC of the farm.

Linear regression analysis of PI and rice grain yield data also showed a good correlation between them ($R^2$ = 0.662). The results thus supported earlier findings that good soil physical health is essential for optimum sustained crop production. Appropriate management practices such as deep ploughing, organic matter incorporation through green manuring and growing of leguminous deep rooted crops and reducing the intensity of puddling before rice transplanting are few of the options for improving the soil health of the farm.

# राष्ट्रीय राजधानी क्षेत्र में फार्म के भौतिक स्वास्थ्य की स्थानिक विविधता पर अध्ययन

## सारांश

मृदा के स्वास्थ्य के मात्रात्मक आकलन के लिए उत्पादकता दर प्रणालियां महत्वपूर्ण युक्तियां हैं। परिशुद्ध या प्रेसीजन फार्मिंग में उपयुक्त मृदा और फसल प्रबंध संबंधी रणनीतियों के नियोजन के लिए इस प्रकार की सूचना वांछित होती है। एक फार्म में मृदा के भौतिक स्वास्थ्य के आकलन के लिए उचित क्रियाविधि के प्रदर्शन हेतु उत्तर प्रदेश, भारत के गौतम नगर जिले के दनकौर ब्लॉक के खेरली गांव में चावल–गेहूं के खेत में एक सर्वेक्षण किया गया। कुल 19 हैक्टेयर फार्म क्षेत्र से 30 मी. × 45 मी. के ग्रिड अंतराल पर 145 स्थानों से मृदा नमूने एकत्रित किए गए। आर्क जीआईएस सॉफ्टवेयर के भू–सांख्यिकीय विश्लेषक विस्तार का उपयोग करके मृदा के भौतिक गुणों की स्थानिक विविधता का विश्लेषण किया गया। $K_{fs}$ के औसत मान तथा 15–30 सें.मी. की पर्त पर जलनिकासी रंध्रता कम थे लेकिन BD के औसत मान तथा मृत्तिका प्रतिशत उनकी क्रांतिक सीमाओं से अधिक था जिससे उप–सतह में जोती गई भूमि के ढेलों की उपस्थिति की पुष्टि हुई। विवरणशील सांख्यिकीय विश्लेषण से भी यह प्रदर्शित हुआ कि विभिन्न मृदा भौतिकी प्राचलों में से BD का न्यूनतम विविधता गुणांक (CV) था जिसके बाद स्थायी मुर्झान बिंदु ($\theta_{PWP}$) था तथा $K_{fs}$ का सर्वोच्च CV था जिसके पश्चात क्षेत्र क्षमता ($\theta_{FC}$) का स्थान था। $K_{fs}$ के चरणबद्ध समुच्चय विश्लेषण से यह पता चला कि सभी मृदा भौतिक प्राचल में से मृत्तिका का $K_{fs}$ पर सर्वोच्च प्रभाव था। केवल इससे $K_{fs}$ में 49 प्रतिशत विविधता उत्पन्न हुई, जबकि बालू और OS से क्रमशः 57 प्रतिशत और 65 प्रतिशत विविधता उत्पन्न हुई। चूंकि इस प्रयोग में $K_{fs}$ का उपयोग ठोस अंचलों (जोन्स) को विरेखित (डिलाइनिएट) करने के लिए किया गया था। अतः ठोसपन के अन्य संकेतकों जैसे BD अथवा जलनिकासी रंध्रता का उपयोग किया गया। यह पाया गया कि $K_{fs}$ जलनिकासी रंध्रता से सकारात्मक रूप से सहसंबंधित था ($R^2 = 0.59$) और BD से नकारात्मक रूप से सहसंबंधित था ($R^2 = 0.794$)। $K_{fs}$ के स्थानिक विविधता विश्लेषणों से यह संकेत मिला कि दोनों मृदा परतों की समान स्थानिक संरचना होती है और इंटरपोलेशन की अनेक विधियों में से सामान्य क्रिगिंग सर्वश्रेष्ठ विकल्प है। विभिन्न मॉडलों के और अधिक सत्यापन के लिए सांख्यिकी या आंकड़ों की तुलना से यह प्रदर्शित हुआ कि

$K_{fs}$ के लिए सभी सेमिवेरियोग्राम मॉडलों में से गाउसियन मॉडल सर्वश्रेष्ठ सर्वाधिक (उपयुक्त) था। अतः $K_{fs}$ के पूर्वानुमान मानचित्र तैयार करने के लिए सामान्य क्रिगिंग के साथ गाउसियन मॉडल का उपयोग किया गया। BD के लिए भी इसी प्रकार के परिणाम प्राप्त हुए। सामान्यतः $K_{fs}$ के लिए सिल मानों से संबंधित नगेट और BD का स्तर निम्न था (< 25%) जिससे इन प्राचलों की अपनी सीमाओं के अंतर्गत सशक्त स्थानिक निर्भरता प्रदर्शित हुई, जबकि शेष प्राचलों में मध्यम स्थानिक निर्भरता पाई गई। एक ही नमूने के लिए लॉग रूपांतरण तथा $K_{fs}$ के सेमिवरियोग्रामों के रूपांतरण आंकड़ों के बिना नमूनाकरण की गहनता की तुलना करने पर रूपांतरणहीन आंकड़ों में एमपीई मान में कमी पाई गई जो लगभग शून्य के बराबर थी। अतः लॉग रूपांतरण आंकड़ों की तुलना में पूर्वानुमान मानचित्र में अधिक सुधार संभव हुआ। इसका यह तात्पर्य है कि पूर्वानुमान कारक के रूप में क्रिगिंग के लिए आंकड़ों के सामान्य होने की आवश्यकता नहीं है। $K_{fs}$ और BD, दोनों के पूर्वानुमान मानचित्रों में परतों से उप–सतह में कठोर ढेलों या हार्डपेन की उपस्थिति का संकेत मिला ($K_{fs}$ <0.16 cm/hr तथा BD >1.55Mgm$^{-3}$)। अतः जिन क्षेत्रों में ढेले मौजूद हों वहां गहरी जुताई की अनुशंसा की जानी चाहिए। गुप्ता (1986) द्वारा मृदा भौतिक दर सूचकांक की गणना के लिए सुझाए गए प्राचलों में से BD, $K_{fs}$, AWRC, OC और NCP को चुना गया। उपराऊं फसल और चावल की खेती के लिए उल्लेखित प्राचलों के दर मानचित्र उचित इंटरपोलेशन विधियों तथा उपयुक्त सेमिवेरियोग्राम मॉडलों का उपयोग करके तैयार किए गए। गेहूं और चावल के मामले में भौतिक प्राचलों की दर की गणना के लिए स्कोर की पद्धति विभिन्न थी क्योंकि दोनों प्रणालियों के लिए इष्टतम भौतिक पर्यावरण भिन्न था। सभी पांच प्राचलों के लिए दर मानों के प्रगुणन द्वारा प्रत्येक नमूनाकरण बिंदु के भौतिक दर सूचकांक (PI) का पता लगाया गया। फार्म का कुल मिलाकर मृदा भौतिक स्वास्थ्य धान की खेती की स्थिति में मध्यम से श्रेष्ठ स्तर का था, जबकि यह परवर्ती गेहूं की फसल के लिए उपयुक्त नहीं था। इसका मुख्य कारण फार्म के BD का बढ़ जाना तथा $K_{fs}$, NCP और AWRC का कम हो जाना था। PI के रैखिक समुच्चय विश्लेषण तथा चावल की दाना प्राप्त संबंधी आंकड़ों से भी यह प्रदर्शित हुआ कि उन दोनों के बीच श्रेष्ठ सहसंबंध था ($R^2$= 0.662)। इन परिणामों से उन पिछले परिणामों की पुष्टि होती है कि इष्टतम टिकाऊ फसलोत्पादन के लिए मृदा का भौतिक स्वास्थ्य श्रेष्ठ होना अनिवार्य है। उचित प्रबंधन क्रियाएं जैसे गहरी जुताई, हरी खाद देने के माध्यम से मिट्टी में कार्बनिक पदार्थों का मिलाना तथा गहरी जड़ वाली फलीदार फसलें

उगाना और चावल की रोपाई से पहले गीली जुताई या पलेवा लगाने की गहनता को कम करना कुछ ऐसे विकल्प हैं जिनसे फार्म के मृदा स्वास्थ्य को सुधारा जा सकता है।.

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