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USING SOIL FERTILITY INDEX TO EVALUATE TWO DIFFERENT SAMPLING SCHEMES IN SOIL FERTILITY MAPPING: A CASE STUDY OF HVANNEYRI, ICELAND

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ABSTRACT

Soil test-based fertility management has been one of the effective tools for increasing productivity of agricultural soils that have a high degree of spatial variability. Changes in land use and land cover are important to the study of global environmental change issues. Among these issues are soil fertility depletion and management. Many times, stakeholders and policy makers overlook this issue when designing and implementing policies for land restoration and sustainable management. Nutrient pattern availability and distribution need to be known so as to determine factors that contribute to their depletion. An alternative and promising approach to our traditional analytical method which has become a vital tool in most decision making processes is the use of Geographic Information System (GIS) analytical tools. GIS based soil fertility maps outline a cost effective option for implementing improved nutrient management in large tracts. With the incorporation of this method, agricultural areas with very high or low nutrient loadings can easily be determined to enable the development of appropriate and economically sound management recommendations. The main goal of this study was to develop georeferenced soil fertility maps showing distributions of soil nutrients and their spatial variability. The spatial variability was assessed using soil fertility index (SFI). Assessment of nutrient distribution and trend patterns were estimated before the development of nutrient distribution surface maps. Also, minimum soil fertility indicators (MSFI) were integrated into SFI and then used in the development of probability threshold maps. Laboratory analyses of soil samples were used to estimate the composition of soil fertility indicators. The following MSFI were determined: total soil Carbon (Ctot) and Nitrogen (Ntot), soil KCl extractable N ions (NH_4^+-N and NO_3^--N), soil pH, biomass C (MICc), temperature and rainfall, metabolic quotient (qCO2) and soil moisture content. Models for

soil fertility distribution were then applied to the data to derive fertility indicators for mapping. In addition, geostatistical analysis was applied to all MSFI with land use and land cover (LULC) data in mind. By computing SFI from sampled sites, SFI revealed the pattern of nutrient distribution in each measured unit. SFI values were then used to develop the choropleth maps and threshold probability maps in making recommendations on soil spatial variability in fertility management.

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1 INTRODUCTION

Research institutions like the Council for Scientific and Industrial Research – Soil Research Institution (CSIR-SRI) in Ghana and other similar institutions in Africa acknowledge the importance of soil fertility management, for addressing soil fertility depletion and increasing food productivity in Africa.

Soil fertility management aims at integrating a set of practices of which the combined use of organic inputs and fertilizers form the backbone (Vanlauwe et al., 2010). This is particularly important in sub-Saharan Africa where soil fertility depletion has long been recognized as the major contributor to food insecurity (Sanchez, 2002). Organic inputs have been used as major nutrient sources but their effectiveness in supplying nutrients to meet crop demands has been insufficient, mainly because they are available in low quantities, are usually of low quality (Giller, Cadisch & Mugwira, 1998) and are expensive to use. Thus, the combined use of organic inputs with fertilizers offers potential to increase crop yields associated with soil fertility improvement. However, to fully exploit the potential benefits and optimize nutrient use efficiency of the combined applications requires a better understanding of the underlying mechanisms, spatial variation of nutrient pattern, soil processes and their sustainability in the long term.

For normal plant growth and completion of their life cycle, at least 16 nutrient elements (Ray & Tucker, 1999) are required. Non-mineral elements are used in large quantities and some other elements are taken up by plants only in mineral form from the soil or by fertilizer application. Primary nutrients are needed in relatively large quantities (such as nitrogen, phosphorus, and potassium) and these are the ones that are most frequently supplied to plants by fertilizer application (Government of Alberta, 1998).

Modern GIS trends, which have now become one of the best spatio-analytical tools, can be incorporated into soil fertility management and assessment (Grinderud, 2009). GIS has come to be associated more specifically with the gauging of interactions between the environment and contributing factors.

The purpose of producing a soil fertility map is to determine plant nutrient availability and distribution and the pattern of nutrient depletion in the project area. Soil fertility maps which are developed and utilized with the capabilities of GIS can solve issues regarding sustainable intensification of food security, poverty reduction and proper farming systems for the rehabilitation of degraded soil nutrients as they may allow farmers to improve on site specific fertility management and also know where resources need to be invested in. However, good nutrient balance is important at the field and farm level, which will ensure sustainability and diversification of agriculture in Africa. Soil organic matter and other fertility indexes have a major impact on our natural resources (Manlay, Feller & Swift, 2007). GIS based soil fertility maps can be used to develop solutions for natural resource management issues such as urban planning, soil erosion, soil degradation, desertification and water quality assessments (Tomlinson, 1987).

This project sought to make georeferenced soil fertility maps to determine nutrient availability and distribution in terms of spatial variability. High and low nutrient loadings can easily be determined with soil fertility maps, aiding the farmer in implementing appropriate land management practices. However, in assessing spatial variability of soil properties using SFI, trend patterns that existed in the dataset were assessed before the development of nutrient

distribution maps. Hence, MSFI was then integrated into SFI in estimating the threshold value for developing the final probability threshold maps.
Geostatistical analysis was used in assessing the spatial variability and distribution of soil nutrients and microbial activity, both factors representing the soil fertility status. The importance of soil sampling methods in representing nutrient spatial variability within a given field was assessed by studying two sampling methods: systematic sampling and a random sampling scheme.

1.1 Project justification

In the Ghanaian context, there seems to be little or no effort to use the capabilities of GIS in soil fertility studies. Continual practises, especially cultivation of deforested land, may rapidly diminish soil quality to support our farming systems. Low agricultural productivity lies at the heart of continued widespread hunger and poverty in Africa (Haggblade & Tembo, 2003). "Among all developing regions, only in Africa has agricultural productivity growth failed to keep pace with population over the past five decades" (Haggblade & Tembo, 2003, pp. 1) and roughly two-thirds of Africa's poor work primarily in agriculture (International Food Policy Research Institute, 2004). Yet their land and labour productivity remain the lowest in the world.

Increasing agricultural productivity by incorporating good nutrient balance management offers a potential powerful tool for reducing poverty in Africa (Diao, Headey & Johnson, 2008; Mitchell, 2008). "Available estimates of poverty elasticities suggest that every 1 percent increase in agricultural income per capita reduces the number of dollar-a-day poor by between 0.6 and 1.8 percent, roughly 50% more than from comparable income gains in manufacturing or services" (Haggblade & Tembo, 2003, p. 2). Indeed, the New Partnership for Africa's Development (NEPAD) has identified agricultural-led development as a fundamental way to mitigating hunger and poverty, generate economic growth, reduce the burden of food imports and open the way to an expansion of exports (Staatz & Dembele, 2008). Furthermore, Forum for Agricultural Research in Africa (FARA) with its member sub regional organizations (SRO) has also developed a vision for African agricultural research which calls for 6% annual growth in agricultural productivity (Bationo et al., 2004).

Institutions in Africa have incorporated programmes and institutional linkages so as to give priorities to agriculture with the aim of improving food security for the most vulnerable, particularly women. Women being the main farmers in subsistence farming usually produce food crops, while men produce export and cash crops. However, about 70-80% of the domestic food supply is mainly produced by women and about 46% of farmlands are also worked by women (Gladwin, 2002). Small holder farming is seen beyond monetary returns and has posed enormous stress on poor smallholder farmers and hence contributes to nutrient depletion (Haileslassie, Priess, Veldkamp, Teketay & Lesschen, 2005). Generally, men produce export and cash crops which have high yield and production compared with women whose annual yield and food production is quite low and lower than the green revolution standards (Gladwin, 2002). This study, however, is focused on spatial variability in soil fertility studies by producing soil fertility maps that can help farmers; hence map production is evaluated by different sampling methods in mapping these soil fertility indicators.

It is envisaged that, upon completion of this project, a benchmark and a soil fertility data repository can be obtained to give more information on the current and spatial variability of soil nutrients, thereby assisting small-holder farmers to improve the soil fertility status of their lands.

Calculated soil fertility indexes (SFI) have been used as an estimation of spatial variability in soil measurements in soil fertility studies (Andrews, Karlen & Cambardella, 2004). A high SFI value of 1 indicates that the spatial variability of a single measurement is high while if it is below 1 it is an indication of low spatial variability (Mukashema, 2007). As SFI varies in both space and time, sustainable soil fertility recommendations and management must be approached from both an agricultural and environmental viewpoint so as to depict minimal soil fertility indicators (MSFI). Soil MSFIs are carefully chosen soil measurements, in this case geochemical and biological soil measurements, representing soil fertility status (Romel & Wilfredo, 2010). The MSFI appropriate GIS-based georeferenced soil fertility maps have been identified as one of the most important drivers of increasing and sustaining agricultural productivity that is vulnerable to climate change (Grinderud, 2009). However, most of the on-going programmes lack this component and this has been the reason why this project is been implemented.

In the Ghanaian context, information on soil fertility maps for local communities is largely absent where greater decisions and implementation of agricultural activities is needed. Where information does exist, the traditional methods used to collate and communicate this information represent a significant obstacle to sustainable agriculture. With the development of GIS maps showing the distribution of soil nutrients and their spatial variability, land users and farmers can evaluate high and low nutrient distribution within their fields, enabling them to choose the appropriate land management practice (e.g. fertiliser type, application time and concentration as well as the most suitable crop type to harvest).

1.2 Proposed strategy to solve problems

The project was implemented as a case study at Hvanneyri, where soil fertility indicators were investigated (Fig. 1). The soil type of the research area had previously been classified as Histic Andosol (Arnalds, 2004; Guicharnaud, 2002), which is representative of Icelandic pastureland (Guicharnaud, 2010). The mean annual precipitation at Hvanneyri is 874 mm (data obtained from the Icelandic Meteorological Office).

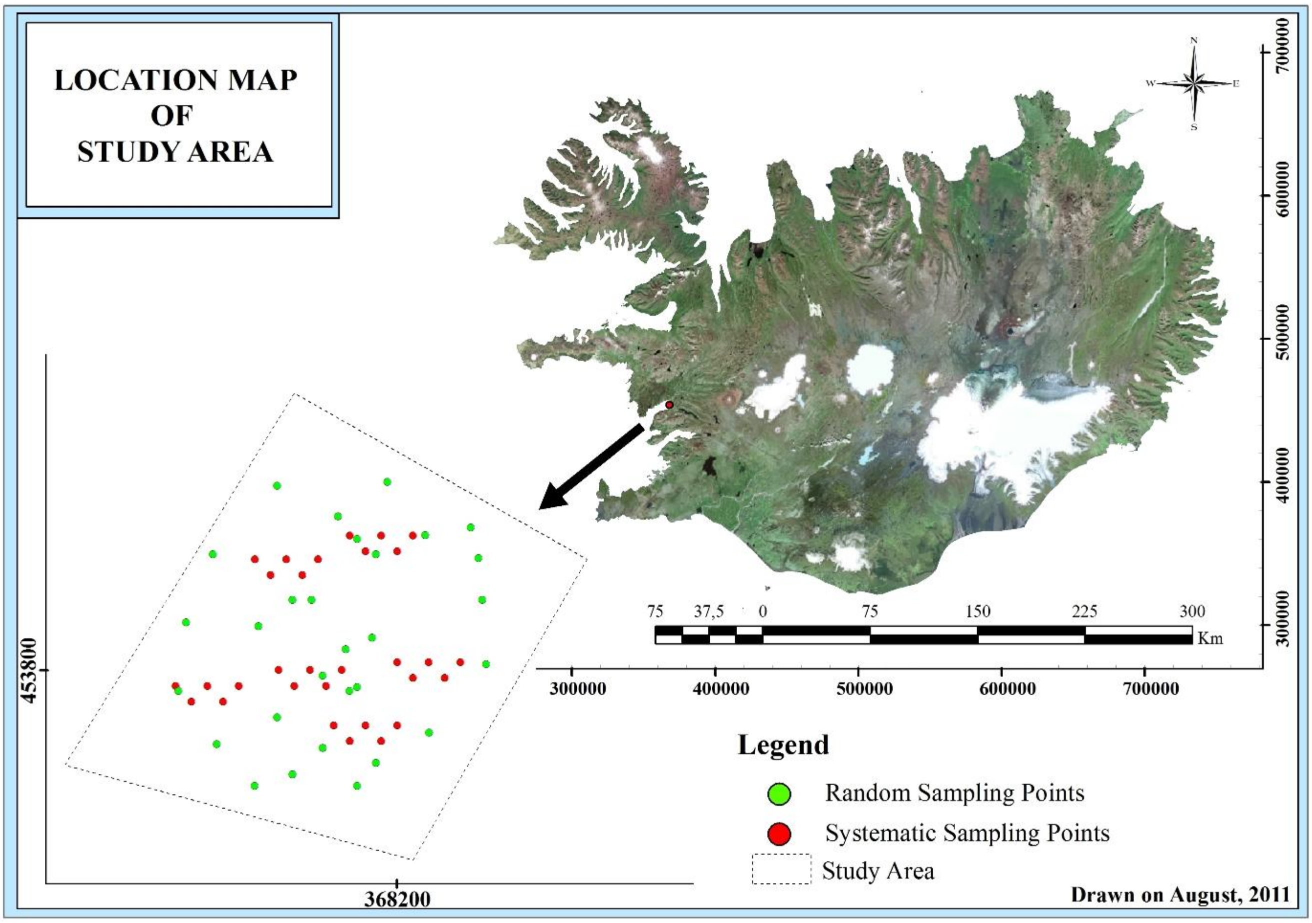


Fig. 1. Location map of Iceland showing the location of the study area with sampling points.

In order to improve agricultural lands and their productivity, it was essential to find the best sampling scheme to be able to map soil fertility and to show the best nutrient and soil microbial activity distribution within the fields. As already mentioned a SFI was estimated according to Mukashema (2007) to assess spatial variability of soil measurements obtained from sampling a single field with two different sampling schemes. Table 1 displays parameter thresholds used to estimate SFIs. The MSFIs used in this study were chosen because of their sensitivity to changes in soil management, perturbation and input in the soil system. They are likewise commonly used in studying soil nutrient status (Myint, Thongthap & Eiumno, 1997). The parameters used in this study were:

I. Soil pH: it is an indicator of the acidity or alkalinity of soil which controls the mobility and hence the availability of soil nutrients (Amacher et al., 2007).
II. Total organic carbon (C_{tot}) and total organic nitrogen (N_{tot}): these components have a greater effect on soil fertility because greater C_{tot} and N_{tot} improve the carbon cycle and nitrogen cycle respectively which increases the cation exchange capacity and water holding capacity of the soil and hence results in greater soil fertility.
III. Potassium Chloride (KCl) extractable NH_4^+-N and NO_3^--N: quantifiers of plant available soil inorganic nitrogen which can be a guide to fertilizer application (Brooks, Williams & Schmidt, 1998; Evans, 2001).

IV. Soil microbial biomass C (MICc): is an important indicator of soil health because it's an early indicator of changes in the total organic matter and estimates the readily available C for soil microbes (Sparling, Pankhurst, Doube & Gupta, 1997).

V. The soil metabolic quotient, qCO_2: is an indicator of biodiversity; the greater the metabolic quotient the healthier the soil and, as a consequence, greater soil fertility (Mäder et al., 2002).

VI. C:N ratio: a rising C:N ratio indicates low heterotrophic activity in soils and is thereby a vital indicator in estimating the soil fertility depletion index (Van Miegroet, Johnson & Cole, 1990).

VII. Temperature and rainfall: these parameters were used because they are a major contributor to soil formation and microbial activities (Dalal & Mayer, 1986; Young et al., 1998). Also, they affect many chemical actions in the soil and its environment.

Table 1. *Threshold values of MSFI used to develop scores and classes for integrating MSFI into SFI (adapted from Amacher, O'Neil, & Perry, 2007).*

	Lowest	**Low**	**Moderately**	**High**	**Extreme**
Score / Class	**0.2**	**0.4**	**0.6**	**0.8**	**1**
pH	<4	4 – 4.5	5 - 5.5	5.5 – 6	**6 - 7.5**
Rainfall mm	<400	400 – 500	600 - 1000	1000 - 1500	>1500
C:N Ratio	>8	8 – 12	12 - 16	>16	>25
TOC %	0	< 1	1 - 5	> 5	-
C %	< 1	1 – 3	3 - 6	6 – 12	>12
N %	0	< 0.1	0.1 – 0.5	> 0.5	-

Data used in this study were obtained from Guicharnaud (2010). Soil sampling was done by a systematic (w pattern) method to ensure adequate representation of the spatial variability of soil nutrients on a regular grid or transects such as a "W" sampling pattern (Fig. 2, n = 30) in site specific farming (Ayoubi, Zamani & Khormali, 2007; Losey, Allee, Zbarsky, Waldron & Shields, 2003), and random sampling (Fig. 2, n = 30) to adequately ensure spatial variability of soil properties and also cover the entire study area with the inclusion of all sample individuals (Stolte et al., 2003). The two sampling schemes were used to evaluate whether different sampling methods produce different SFIs as well as which sampling scheme indicates the maximum spatial variability.

With the use of geostatistical analysis in developing the SFI maps, MSFIs were classified into classes so as to combine site-specific parameters of different variance and units into similar classes from different threshold values. The classes obtained based on threshold values were based on Table 1.

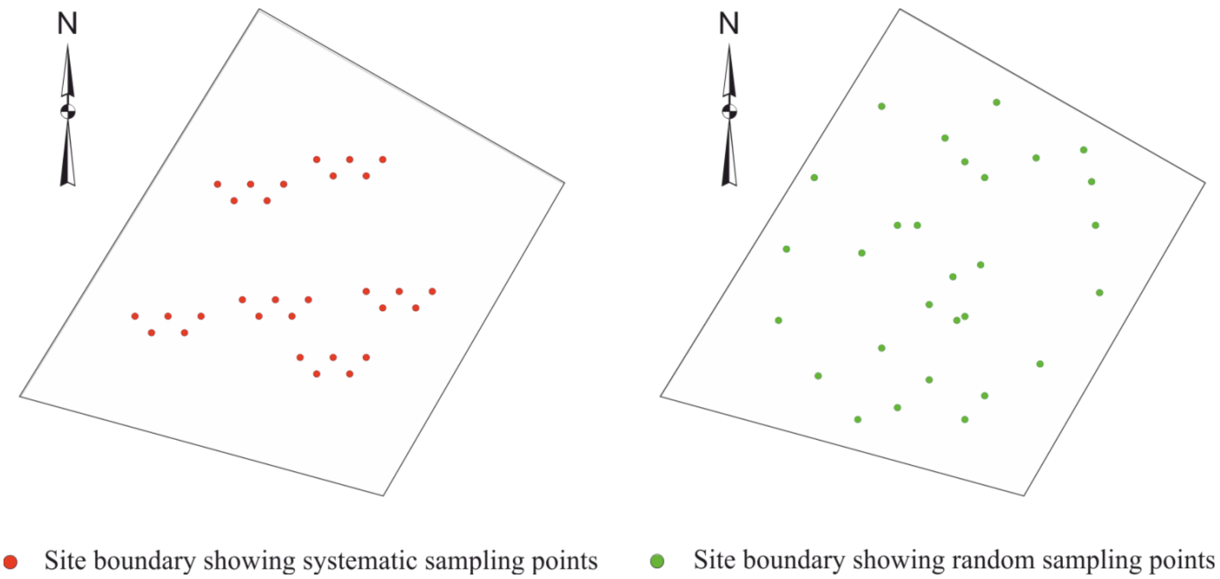


Fig. 2. *Study area showing both systematic and random sampling points within research site boundary.*

2 LITERATURE REVIEW

2.1 Methods of studying and mapping spatial variability of soil nutrients and microbial activity in relation to soil fertility

Maintaining soil fertility, a factor determining plant soil nutrient availability, can be a major challenge in terms of sustainable agriculture. Depletion of soil fertility decreases the soil productivity and crop production (Lal, 2008). Maintaining soil fertility is therefore of great importance in the case of food production, both on the national and international scale (Rosegrant, Paisner, Meijer & Witcover, 2001). Sustainable soil management includes such appropriate soil management practices as appropriate fertilizer application, time of harvest, irrigation and crop type (Place, Barrett, Freeman, Ramisch & Vanlauwe, 2003).

Geo-statistical tools, like Geographical Information Systems (GIS), have been widely used in the literature for producing soil fertility maps (Mueller, Pierce, Schabenberger & Warncke, 2001; Mulla, 1991; Webster & Mcbratney, 1987). There are, however, many factors affecting the spatial variability of data which should be taken into consideration when mapping soil fertility status, such the number (Mueller, et al., 2001) and time (Corstanje, Reddy, Prenger, Newman & Ogram, 2007) of sampling, distance between sampling points (Röver & Kaiser, 1999), land management (Cambardella et al., 1994) and different sampling schemes (Tan & Lal, 2005). Indeed, soil spatial variability has been studied (Castrignano, Goovaerts, Lulli & Bragato, 2000) but it is still difficult to obtain a perfect spatial distribution of soil variability.

With several papers aiming to come up with the best statistical methods of analysing, sampling and mapping spatial data, the effect of sampling schemes on soil modelling (Scull & Okin, 2007; Wang & Qi, 1998) was studied. Scull & Okin, (2007) and Wang & Qi (1998) concluded that regular grid sampling accounted for better spatial variability than did random sampling. Quantitative assessment has identified and reported quite often in the literature (Berterretche et al., 2005; Hengl, Heuvelink & Rossiter, 2007). Nevertheless, stratified sampling has also been found to reduce spatial variability uncertainties and it has been concluded that it is more effective than a random sampling scheme (Rodeghiero & Cescatti, 2008). Additionally, differences have been identified in interpolated maps from different spatial datasets (Wu, Wu, Luo, Zhang & Teng, 2008) and Guicharnaud (2010) also concluded that the way in which soil samples are collected affects the variability of soil parameters. These studies however conclude that transect methods of sampling depicted a better representation of spatial variability than random sampling. Last but not least, random sampling was also stated to be a limiting factor in sampling density when bias is introduced in parameter estimation (Scull & Okin, 2007).

To put spatial and temporal studies of measured parameters into context, interpretation of soil properties are relied on in the survey conducted and topological and geological features assessments (Guicharnaud, 2010). An integrated SFI obtained from a scored MSFI as shown in Table 1 was used as an estimation of quantitative soil quality evaluation (Andrews, et al., 2004) in developing soil management practices. Andrews et al, (2004) concluded that SFI was a useful tool to move resource management beyond changes in productivity. In addition, Mukashema (2007) used SFI as an index to quantify the response of soil fertility on human induced activities and concluded that SFI reasonably interpreted a complex data set with conflicting trends as a result of irregular change in CLORPT (climatic, organism, relief, parent material and time) factors. However, studies on SFI has been undertaken on soil sampling methods (Ayoubi, et al., 2007; Scull & Okin, 2007; Stolte, et al., 2003) but studies on how different sampling methods affect the estimation of SFI are rare.

The success of a variable rate technology (VRT) (Sawyer, 1994) depends largely on the quality of fertility management maps. GIS techniques using linear regression models (Gessler, McKenzie & Ryan, 1995) between maps of terrain attributes and soil parameters was based on the early applications in spatial data analysis. CLORPT techniques (McBratney, Odeh, Bishop, Dunbar & Shatar, 2000) were later developed as a technique and used in geostatistical analysis, which have also been used by Mukashema (2007). However, a number of GIS interpolation techniques have been used in studying and mapping spatial variability of soil nutrients which incorporated kriging, co-kriging and regression methods (Hengl, Heuvelink & Stein, 2004; McBratney et al., 2000). Hengl et al. (2004) stated that this path of analysis has shown to be more attractive and concluded that regression-kriging used for spatial prediction of soil variables improves prediction efficiency and ensured relative normality of residuals and predictors, but with the comment that earlier on it was stated that regression-kriging is more complex and can result in worse results estimation than ordinary kriging if misused (Goovaerts, 1999). This has made the development of an automated generic model unrealistic (Hengl et al., 2004).

2.2 Scene of setting

2.2.1 Iceland and its climatic conditions

Iceland, a European Island country in the north Atlantic ocean on the Mid-Atlantic Ridge and composed of both the American and European plates is situated between 63°23’N and 66°32’N latitude and 13°30’W and 24°32’W longitude (Einarsson, 1984), giving a total area of about 103,000 km^2. Iceland is volcanically and geologically active with its interior mainly consisting of a plateau characterised by sand fields, mountains, with glaciers covering about 11% of the island’s landmass. The climate in Iceland’s lowlands is temperate despite the high latitude just below the Arctic Circle (Guicharnaud, 2010) with permafrost in the interior regions. The weather conditions of Iceland are very variable and sometimes unpredictable with strong winds. Annual precipitation ranges from 400 mm north of the Vatnajökull Glacier to 4000 mm in the southeast of the country (Einarsson, 1984). Annual mean temperature ranges from about -8 to 2°C in the highlands and 2 to 6°C in the lowlands (Einarsson, 1984, 1989). Also, there are about 9 months of cold weather which limits the length of growing periods to about 100 to 130 days (Guicharnaud, 2010).

2.2.2 Soils of Iceland

Soils developed in Iceland are mainly formed by the weathering of volcanic ash (Oelkers & Gislason, 2001) and are classified as Andosols (Stoops, Gérard & Arnalds, 2008; IUSS Working Group WRB, 2006). The parent material for Andosols is volcanic glass and ejecta (IUSS Working Group WRB, 2006). Andosols are generally considered to be fertile soil because of the rapid weathering of volcanic tephra releasing nutrients. According to the IUSS Working Group WRB (2006), Andosols are easy to cultivate due to their high water holding capacity and their low bulk density (<0.9 gm/cm^3) (Arnalds, Hallmark & Wilding, 1995) and thus support good plant root formation. Six main soil types have been identified in Iceland (Arnalds, 2004): Gleyic Andosols, Brown Andosols, Histosols, Histic Andosols, Vitrisols and Leptosols.

2.3 GIS

GIS is an acronym for Geographic Information System. GIS is a set of computer hardware, software and staff system for the acquisition, storage, analysis and display of geographically referenced geospatial data (Grinderud, 2009). Currently, it is one of the best spatio-analytical tools used in many decision making processes (Grinderud, 2009).
To ensure effectiveness, components (hardware, software and personnel) need to be critically selected and the right georeferenced data used. Also reliable relational oriented database system needs to be built for use in analysis with the incorporation of a purpose, with the objectives and justification for using GIS as equally important as the components.

2.4 GIS and soil fertility assessments

The advent of Global Positioning System (GPS) and GIS has made measurements of spatial variability of soil properties easy (Shujuan, Yong & Hui, 2003). GIS, spatio-analytical capabilities, has been fairly incorporated into most decision making processes in the developing and developed countries. It is now used for mapping resources, map production and environmental resource modelling (Mitas & Mitasova, 1999). Its ability to catalogue and retrieve information has made soil fertility studies easier. Spatial variation problems are now easier to handle.

3 MATERIALS AND METHODOLOGY

3.1 Research area

This project was implemented as a case study at Hvanneyri, where soil fertility indicators were investigated. As shown in Figure 1, Hvanneyri is situated in Borgarfjörður, Iceland, at 64° 34' 0" North and 21° 46' 0" West. The site consisted of a 1 hectare pasture field with the slope not exceeding 2°. According to Guicharnaud (2010), GPS co-ordinates were taken around the study area so as to aid the development of maps. The GPS points were taken according to the Islands Network 1993 (ISN93) (GeoRepository, 2003). Figure 3 indicates how various stages in the project methods were executed.

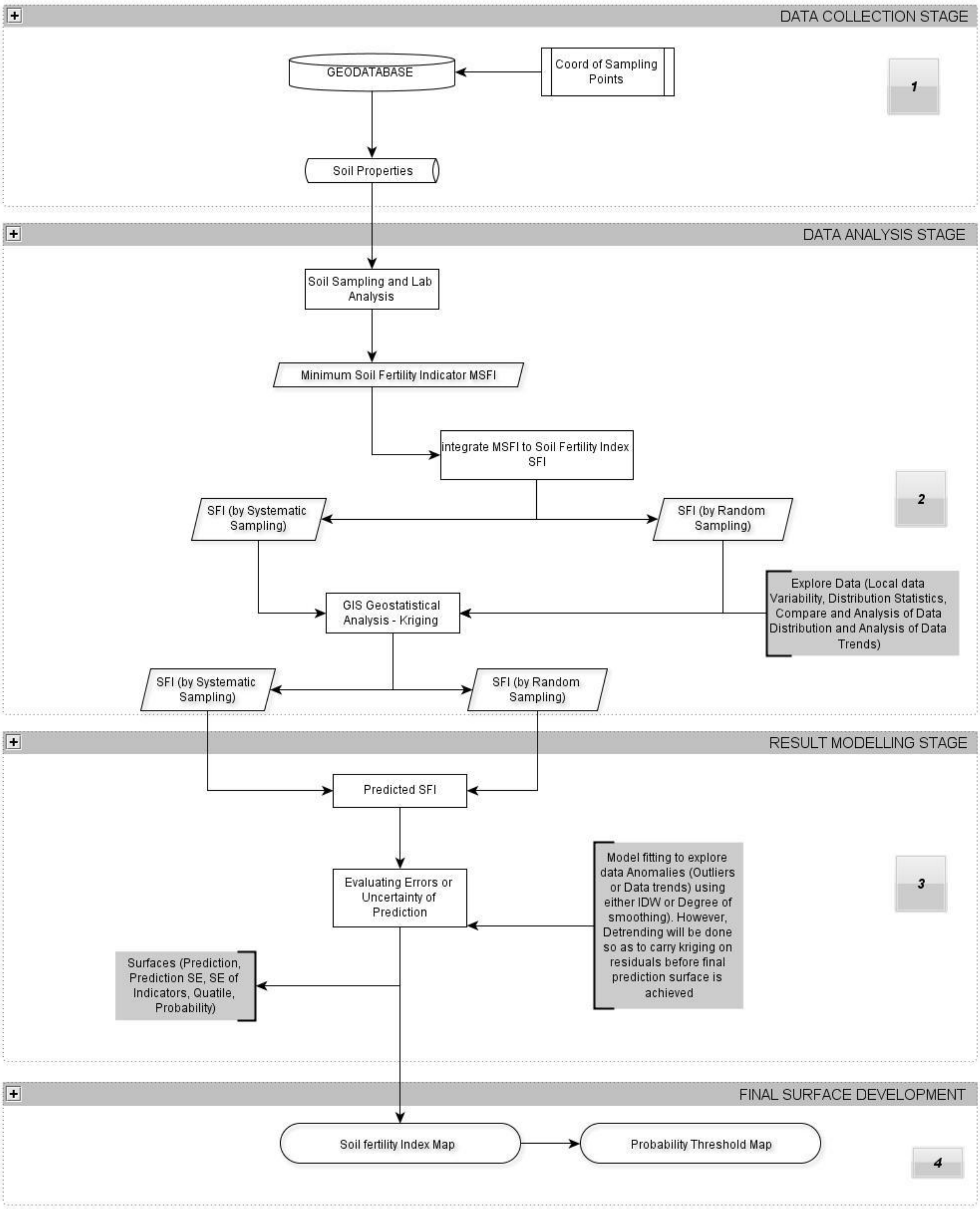


Fig. 3. *Methodological flow chart showing a summary of MSFI and SFI change, mapping and evaluation in various stages of project.*

3.2 Method of data acquisition

Soil survey and sampling were done by Guicharnaud (2010). Soil samples were taken from the top 0 – 15 cm at the end of April in 2007. The same area was sampled by (i) systematic (w pattern) sampling in a 'W' shaped pattern, (ii) randomised sampling as shown in Figure 2, and (iii) soil bulking on a regional scale. The sampling point separation distance was about 7 m in random sampling whilst systematic sampling showed a sampling point separation distance of 2.8 m across transects and 4 m along transects (Guicharnaud, 2010).

3.3 Minimum soil fertility indicators analysis

Descriptive statistics (mean, median, standard deviation, range and sample variance) were used to explore the data for anomalies and describe their distribution. Since spatial variability was evaluated based on two sampling methods (systematic and randomised), one-way analyses of variance (ANOVA) were performed on the fertility indicators to know whether they differed statistically between the two sampling schemes. An estimator of spatial variability of soil properties was further estimated from scores of each MSFI (in this case SFI). The Coefficient of Variation (CV) depicted the normalized dispersion of each MSFI and how values were spatially varied in the two sampling schemes.

Furthermore, a t-test (two samples-assuming equal variances) was then applied to the data to estimate the equality of the population means that underlay each sample (using Microsoft Excel 2010) so as to determine whether the two samples were likely to have come from distributions with equal population means. All levels of significance were expressed as $p \leq 0.05$. To finally develop the SFI, Pearson's correlation was used to examine the degree of association between the MSFI within the sampling schemes, either estimated as a positive or an inverse association.

3.4 Development of soil fertility index

Since soil fertility is variable in time and space, it was important to capture the spatial variability of the indicators used in estimating the SFI (Mukashema, 2007). In doing so it was prudent to assign classes to each indicator based on the threshold ranges of the topsoil properties of Icelandic soils.

This made it possible to transform the MSFI values into score values (probability value) so as to combine the different MSFIs of different values into similar classes (Mukashema, 2007). Due to the huge amount of data, a probabilistic model (Ribeiro Jr & Diggle, 2001) was then applied in data analyses. Figure 4 shows the summaries of steps used in the development of the SFI.

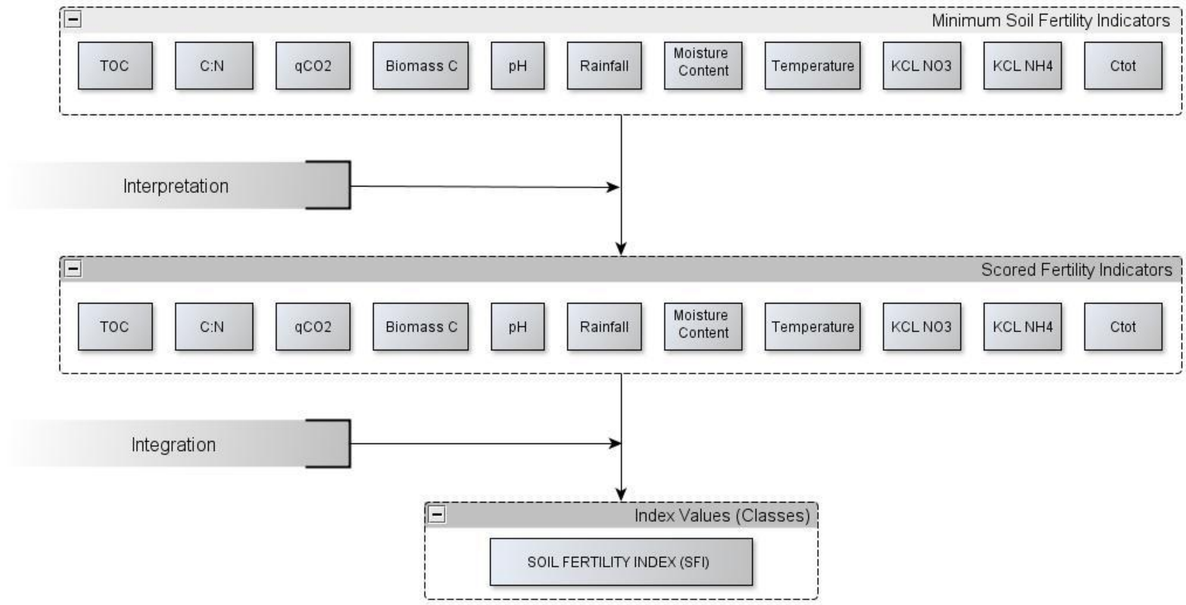


Fig. 4. *Flow chart diagram for the development of SFI, adapted from Andrews et al. (2004). Detailed description of SFI can be viewed in Table 1.*

MSFIs were transformed into classes as indicated in Table 1 with scores ranging from 0 to 1 (Andrews et al., 2004) indicating five classes for the development of surface maps. For this reason, site-specific parameters of different variances and units with too many controlling factors were difficult to identify exact probability values for every possible combination into the SFI. To circumvent this challenge it was necessary to group similar indicators and score them on equal classes but for different threshold values (Table 1).

An indicator of value 0 or 1 indicates low or high spatial variability, respectively (Equation (Eq.) 1), of each measured MSFI.

$$0 \leq \text{SFI} \leq 1 \qquad \textbf{(1)}$$

From Eq. 1 above, each indicator was interpreted as a scored value ranging from 0 to 1 based on its value from the laboratory analysis results compared with the thresholds of soils from unfertilized fields.

In addition to the use of Eq. 1, if soil property µ at a sampled location x is indicated as µ(x) in the spatial statistical analysis, the indicator value is used as an estimator of the random function µ (x) (Lark & Ferguson, 2004). This shows how an indicator can either be:

$$\mu(x) \leq \mu(i) \text{ or } \mu(x) \geq \mu(i) \qquad \textbf{(2)}$$

where µ(i) is the threshold value of indicator estimating the SFI. However, in assigning the indicator at a sampled location to classes of distribution which are mutually exclusive, it can be seen that (Eq. 3):

$$Prob\ [\mu(x) \leq \mu(i) \text{ or } \mu(x) \geq \mu(i)] = 1/n(c) \qquad \textbf{(3)}$$

where *n(c)* is the number of classes estimated.

Scores from each indicator were then converted into single index vales reflecting the SFI by multiplying the exponential sum of each scored MSFI divided by the total number of indicators by 10 (Eq. 4) (Andrews et al., 2004). Furthermore, the index value was used as a representative value of the overall assessment of spatial variability in soil fertility studies of the study area.

$$SFI = \left(\sum_{i=1}^{n} S_{j/n}\right) \times 10 \qquad \textbf{(4)}$$

where *Sj* represents the scored indicator index value (probability of indicator in a particular class) and n is the number of indicators of MSFI. With *n* as a divisor, any data in the indicators dataset unaccounted for were corrected (Andrews, et al., 2004). The SFI value was multiplied by 10 to provide values ranging from 1 to 10 rather than 0 to 1 to make results more amenable for producers and other potential users (Andrews, Flora, Mitchell & Karlen, 2003).

3.5 Analysing spatial data by geostatistical methods

Geostatistical methods of analysing spatial data have been very effective as they give the freedom to investigate, describe, determine the pattern of variability, visualise and create surfaces from sophisticated statistical methods (Berterretche et al., 2005). Indeed, for studies on the fertility of agricultural lands, it is very effective to create statistical continuous surfaces to assess the quality of analysis using prediction standard error, probability, quartile and standard error of indicator surfaces. Also, it was possible to determine the probability threshold contours by creating optimal interpolation surfaces which however can be a form of base information on which management schemes of agricultural lands can be based.
Furthermore, the use of these methods in developing the SFI made it possible to determine the probability of variables occurring over the study area where identifying every possible indicator value was impossible. As such, it gave us the possibility to average the overall spatial variability of the project area.
The four main basic steps (data representation, exploration, model fitting and diagnostic analysis) in analysing spatial data statistically were ensured in creating the interpolated surface (Economic and Social Research Institute, 2001).

3.5.1 Geostatistical methods

Developing SFI surface maps by Ordinary Kriging (OK)

Ordinary Kriging (OK) is one of the advanced geostatistical procedures that creates surfaces by using spatial correlations from a scattered set of points by incorporating their statistical properties (Economic and Social Research Institute, 2001). Hengl, Heuvelink & Rossiter (2007) and Hengl et al. (2004) showed that the prediction model by OK is a function of weight that depends on the spatial auto correlation and sample data co-ordinates to predict unmeasured locations. With the use of OK, there was the need to investigate the spatial data structure for distance to measure the strength of statistical correlation.

The mathematical formulas for inverse distance weighted (IDW) and spline interpolation tools (Mueller, Mathias, Cornelius, Barnhisel & Shearer, 2004) aided the determination of smoothness of our resulting surfaces. OK as a linear least square estimation algorithm and an interpolator of values of unmeasured location from measured locations was formed as a weighted sum of the data (Eq. 5)

$$\hat{f}(x^*) = \sum_{i=1}^{n} \lambda_i (x^*) f(x_i) \quad \textbf{(5)}$$

where the aim of kriging was to estimate the value of an unknown real-valued function (SFI in this case), *f*, at a point, x^*, given the values of the function at some other points, $x_i,...x_n$, and weight λ. A Kriging estimator was said to be *linear* because the predicted value *f* ^(*x*)* is a linear combination.

Geostatistical evaluation of SFI values

When analysing and exploring the spatial variability of SFI values in systematic and random sampling schemes, it is essential to explore SFI values with a (1) Histogram distribution chart to understand and estimate the probability distribution of a continuous variable (in this case SFI values), the skewness of the dataset and to obtain a visual impression of the distribution; (2) Normal QQ plot to compare the distribution of the data and used as a measure of the normality of the dataset; and (3) Trend analysis to spot spatial variability pattern or an underlying pattern of behaviour in time and space.

Variography

In fitting a model, which was represented as a diffused dataset underlining a random function, we began with a graph of empirical semi-variogram estimated by (Eq. 6)

$$\hat{\gamma}(h) = \frac{1}{2|N(h)|} \sum_{i=1}^{N(h)} \left\{ \sqrt{[\mu(x_i) - \mu(x_i + h)]} \right\} \quad \textbf{(6)}$$

Where $\hat{y}(h)$ is the semi-variogram at lag interval *h*, $\mu(x_i)$ is the SFI at location x_i, *N(h)* the number of pairs of observation in the dataset separated by lag interval *h*. Hence, spatial correlation quantifies a basic principle of geography, meaning a less dissimilar pair must have less squared difference and vice versa (Matheron, 1965).

Fitting a model to the empirical semi-variogram

Since information cannot be obtained in all directions and distances and for our predictions to have positive variances, it became prudent to represent our empirical semi-variogram with a perfectly mathematical model (continuous or curve function). Eq. 6 was used as an estimator of the semi-variogram to enable us to fit a model to the semi-variogram cloud and as an estimation of the spatial autocorrelation of the datasets (in this case SFI); it became an essential key in spatial description and prediction.

Also, due to the distribution of our dataset, trend analysis was again used as an estimator to estimate the best model to mathematically represent and describe the distribution of our dataset for the prediction (Goodman, 1963). Figure 5 displays an example of an empirical semi-variogram with a fitted continuous curve.

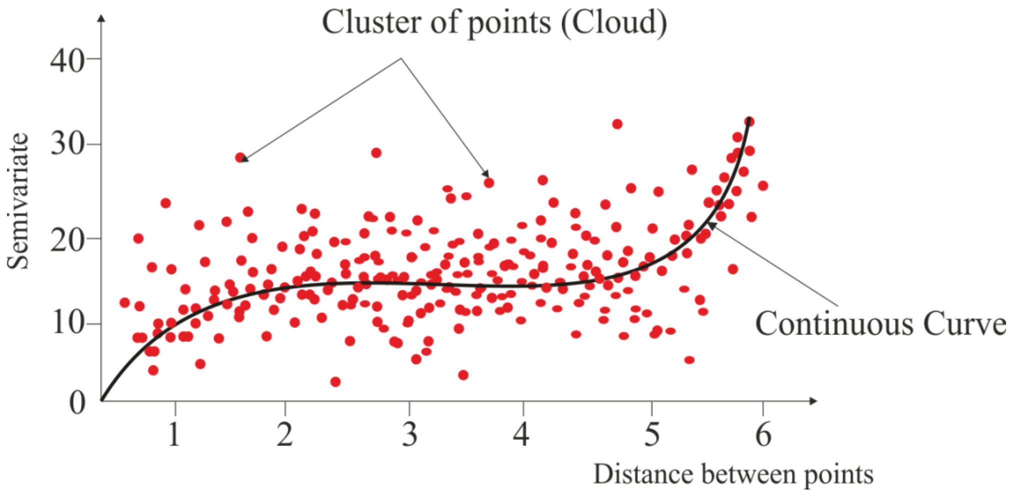


Fig. 5. *An example of an empirical semi-variogram with a fitted continuous curve.*

Assessing model or prediction accuracy

In soil fertility assessment, the root mean squared prediction error (RMSPE) which was estimated from the mean prediction error (MPE) determines the true prediction accuracy (Hengl, et al., 2004) by the validation points $\mu(x_i)$ (in this case our unobservable indicators) with the observable indicators $\mu\wedge (x_i)$ as shown in Eq. 7:

$$RMSPE = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{1} \cdot [\hat{\mu}(x_i) - \mu(x_i)]^2\right)} \quad \textbf{(7)}$$

where n represents the validation set which is the number of observations n = 30 for both systematic (w pattern) and random sampling schemes.

Since we were comparing the prediction of two different sampling methods, it was essential that the RMSPE be normalized by the total variance of observables (Park & Vlek, 2002). Hence the normalized mean square error (NMSE):

$$NMSE = \frac{\frac{1}{n}\sum_{j=1}^{1}[\hat{\mu}(x_i) - \mu(x_i)]^2}{S^2} \quad \textbf{(8)}$$

where S^2 was the total variance of the transformed observation (SFI at sample points). Hence, if Eq. 7 is close to 40%, it is an indication of a fairly satisfactory accuracy prediction (Hengl et al., 2004). Hengl et al. (2004) also estimated that, if Eq. 7 > 71%, then the model accounted for 50% less at validation points, which would result in unsatisfactory prediction.

Visualisation

Using geostatistics analysis as predictors of SFI, uncertainty was visualized as maps of prediction and prediction errors (Hengl et al., 2004), being an estimation of prediction uncertainties. Hence the error map was then estimated as the standard error (σ) of the predicted index obtained from the observable indicators (SFI) (Eq. 9) (Mukashema, 2007)

$$\sigma = \sqrt{\left(\sum_i \left(W_i * \gamma(h_{p_i})\right) + \lambda\right)} \quad \textbf{(9)}$$

Where σ is the standard error of the output pixel estimated, h_{pi} is the distance between the output pixel *p* of the predicted SFI and input point *i* (measured SFI), γ is the value of the semi-variogram model at distance h_{pi},W_i is the weight factor for input point (*i*) and λ is the Lagrange multiplier used to minimize estimation error (Mukashema, 2007).

4 RESULTS

To re-emphasize and as stated above, the best statistical methods of analysing spatial data have not been identified but quantitative assessment has been identified and reported quite often (Mukashema, 2007; Bocco, Mendoza & Velázquez, 2001; Lark & Ferguson, 2004; Ribeiro Jr & Diggle, 2001; Webster & Mcbratney, 1987). Indeed, our project results indicated that different sampling methods behaved spatially differently with regard to SFI. This however showed that soil sampling schemes affected the variability of measurements.

The parameters considered were due to the project time frame and therefore many other controlling parameters were not considered which would have been of immense benefit to improving the results of the project. The results presented below are the results of the different sampling methods employed in the field data sampling schemes.

4.1 Evaluation of sampling methods by SFI

4.1.1 Systematic (W pattern) sampling

The results listed in Table 2 indicated differences in the means, medians, standard deviation and standard errors of which the results from biomass C (MICc) and total organic carbon (TOC) showed different results as compared to the other parameters. MICc had the highest standard deviation followed by TOC and KCl NH_4^+; nevertheless, MICc and TOC always had high values obtained from the descriptive statistics, which might have been caused by unaccounted factors. Also, qCO_2 in Table 2 had the lowest standard deviation of 0.02 followed by pH with 0.24 as standard deviation.

ANOVA (single factor) was used (results shown in Table 3) to analyse the differences in indicator means and variances obtained from the fertility indicators of n = 30. Results finally indicated that the resultant p value was < 0.001 which meant dataset was significantly indifferent as means of several MSFI were almost the same.

The status of soil fertility indicators, as shown in Figure 6, exhibit how nutrients were distributed when the systematic sampling scheme was adopted. However, using this method, the fertility indicator distribution was shown and TOC ranged between 424.74 – 1527.72 mg/kg, pH (4.16 – 4.97), MICc (317.11 – 4525.31 mg/kg), soil moisture (57.66 – 65.12 %), C:N ratio (13.4 – 16.1), KCl NH_4^+ and NO_3^- (4.7 – 44.9 and 3.55 – 30.80 mg/kg respectively) and qCO_2 (0 – 0.11 mg/kg biomass).

Table 2. *Descriptive statistics of soil parameters from the systematic (W) sampling scheme, n = 30.*

Indicators	**Mean**	**Std Error**	**Median**	**Std Dev**	**Sample Variance**	**Range**	**Min**	**Max**
pH	4.60	0.04	4.62	0.24	0.06	0.81	4.16	4.97
KCl NH4 mg/kg	17.37	1.76	16.11	9.65	93.09	40.21	4.70	44.92
KCl NO3 mg/kg	10.96	0.99	10.62	5.41	29.26	27.34	3.55	30.89
C %	19.31	0.61	19.20	3.33	11.11	12.60	13.10	25.70
N %	1.31	0.04	1.34	0.20	0.04	0.75	0.93	1.68
C/N	14.71	0.14	14.55	0.75	0.56	2.70	13.40	16.10
Moisture %	61.02	0.41	61.20	2.24	5.03	7.46	57.66	65.12
Biomass C mg/kg	2859.33	241.34	3111.54	1321.90	1747408.05	4525.31	0.00	4525.31
TOC mg/kg	815.67	51.65	807.80	282.88	80021.10	1102.98	424.74	1527.72
qCo2 mg/kg	0.02	0.00	0.01	0.02	0.00	0.11	0.00	0.11

Table 3. *ANOVA: Single factor; summary of descriptive analysis ANOVA of systematic (W) sampling scheme, n = 30.*

SUMMARY				
Groups	*Sum*	*Average*	*Variance*	
pH	138.19	4.61	0.06	
KCl NH4 mg/kg	521.16	17.37	93.09	
KCl NO3 mg/kg	328.92	10.96	29.26	
C %	579.20	19.31	11.11	
N %	39.38	1.31	0.04	
C/N	441.20	14.71	0.56	
Moisture %	1830.65	61.02	5.03	
Biomass C mg/kg	85779.89	2859.33	1747408.05	
TOC mg/kg	24470.20	815.67	80021.10	
qCo2 mg/kg	0.53	0.02	0.00	
ANOVA				
Source of Variation	*df*	*F*	*p-value*	*F crit*
Between Groups	9	134.94	<0.001	1.91
Within Groups	290			
Total	299			

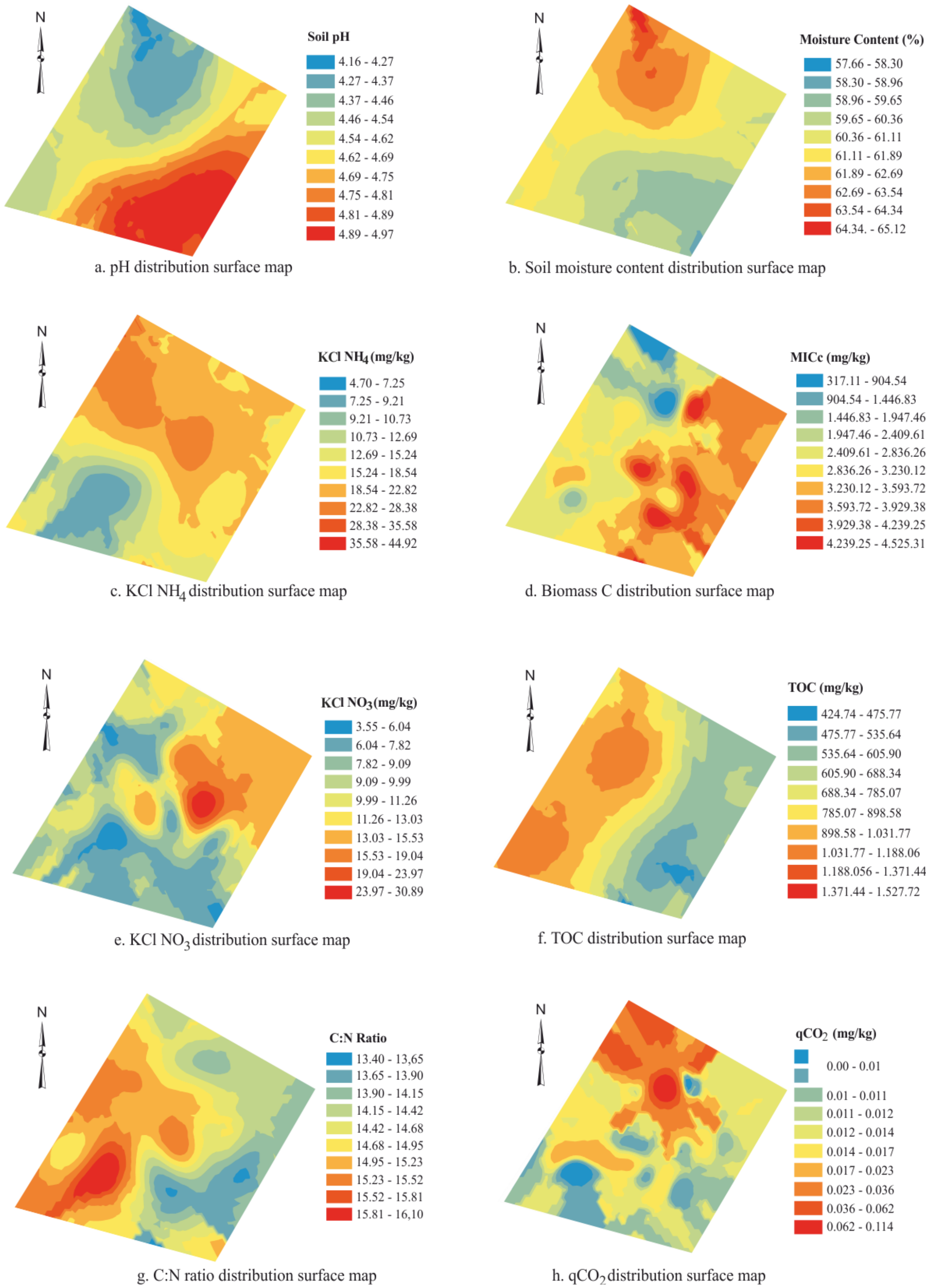


Fig. 6. *MSFI distribution surface maps by systematic (w pattern) sampling scheme used for SFI development.*

Table 4 shows results obtained by estimating the Coefficient of Variation (CV) based on scores obtained from each MSFI and their respective SFI values. The pH had the lowest CV of < 0.001% whilst MICc had the highest CV of 15.08% and also the widest range, of 0.8 or the same as qCO_2. The means and medians of both soil biological parameters and chemical values were almost the same but soil moisture and C_{tot} had equal means and medians. Generally, the medians and means of soil biological parameters were greater than the chemical values but the pH had the lowest mean and median.

Table 4. *Descriptive statistics for systematic sampling scheme based on scores of SFI for each MSFI in estimating Coefficient of Variation (CV %), n = 30.*

Indicators	**Min**	**Max**	**Range**	**Median**	**Mean**	**Std Dev**	**Std Error**	**CV %**
pH	0.40	0.40	0.00	0.40	0.40	<0.001	<0.001	<0.001
KCl NH_4 mg/kg	0.40	0.80	0.40	0.60	0.56	0.10	0.018	5.42
KCl NO_3 mg/kg	0.60	1.00	0.40	0.80	0.71	0.11	0.021	8.11
C %	0.80	0.80	0.00	0.80	0.80	<0.001	<0.001	<0.001
N %	0.40	0.80	0.40	0.80	0.79	0.07	0.013	5.75
C/N	0.60	0.80	0.20	0.60	0.61	0.04	0.007	2.22
M %	0.80	0.80	0.00	0.80	0.80	<0.001	<0.001	<0.001
MICc mg/kg	0.00	0.80	0.80	0.80	0.73	0.21	0.038	15.08
TOC mg/kg	0.60	0.80	0.20	0.80	0.73	0.10	0.018	7.12
qCO_2 mg/kg	0.00	0.80	0.80	0.60	0.57	0.16	0.030	8.97

4.1.2 Random sampling

From Table 5, results did not show much difference as compared to the systematic (w pattern) method but rather had quite significant differences in the means, medians, standard deviations and standard errors of which MICc, KCl NO_3^- and TOC showed different results as compared to the other parameters. MICc also had the highest standard error in this sampling scheme followed by TOC and KCl NO_3^-, generally, TOC and MICc also had the highest values in results obtained from the descriptive statistics. Also, qCO_2 in Table 5 had the lowest standard deviation of 0.03 followed by Ntot with a standard deviation of 0.20.

Table 5. *Descriptive statistics of random sampling scheme, n = 30.*

	Mean	**Std Error**	**Median**	**Std Dev**	**Sample Variance**	**Range**	**Min**	**Max**
pH	4.38	0.06	4.33	0.31	0.09	1.26	3.95	5.21
KCl NH_4 mg/kg	12.10	1.24	9.48	6.70	44.88	28.85	4.58	33.43
KCl NO_3 mg/kg	69.55	4.31	70.986	23.23	539.55	118.43	5.66	124.09
C %	19.44	0.61	19.30	3.31	10.94	12.60	13.10	25.70
N %	1.32	0.03	1.37	0.20	0.04	0.75	0.93	1.68
C/N	14.74	0.14	14.60	0.74	0.55	2.70	13.40	16.10
moisture %	56.39	0.98	57.09	5.28	27.87	22.90	40.09	62.99
Biomass C mg/kg	976.71	106.99	902.01	576.17	331973.53	2854.10	0.00	2854.10
TOC mg/kg	1006.19	56.54	966.41	304.49	92715.64	1452.39	209.04	1661.43
qCO_2 mg/kg biomass	0.05	0.00	0.05	0.03	0.00	0.11	0.00	0.11

The results of ANOVA (single factor) in Table 6 also showed a p-value below 0.05 just as for the systematic sampling scheme as was evidenced by the almost equal means of several MSFI used. Figure 7 shows how nutrients were distributed over the study area. The MICc ranged from 246.53 – 2854.10 mg/kg, TOC ranged from 209.04 – 1661.43 mg/kg, pH ranged from 3.95 – 5.21, soil moisture from 40.09 – 62.99 %, C:N ratio ranged from 13.4 – 16.1, KCl NH_4^+ and NO_3^- ranged from 4.57 – 33.43 and 5.55 – 124.09 mg/kg respectively, and qCO_2 ranged from 0 – 0.11 mg/kg biomass. However, the C:N ratio and qCO_2 showed the same values from the surface maps even though they were obtained with different sampling methods and points.

Table 6. *ANOVA: Single factor; summary of descriptive analysis ANOVA of random sampling scheme, n = 30.*

SUMMARY				
Groups	*Sum*	*Average*	*Variance*	
pH	127.15	4.38	0.09	
KCl NH_4 mg/kg	350.79	12.10	44.88	
KCl NO_3 mg/kg	2016.87	69.55	539.55	
C %	563.80	19.44	10.94	
N %	38.26	1.32	0.04	
C/N	427.40	14.74	0.55	
moisture %	1635.23	56.39	27.87	
Biomass C mg/kg	28324.71	976.71	331973.53	
TOC mg/kg	29179.50	1006.19	92715.64	
qCO_2 mg/kg biomass	1.57	0.05	0.00	
ANOVA				
Source of Variation	*df*	*F*	*p-value*	*F crit*
Between Groups	9	114.27	<0.001	1.91
Within Groups	280			
Total	289			

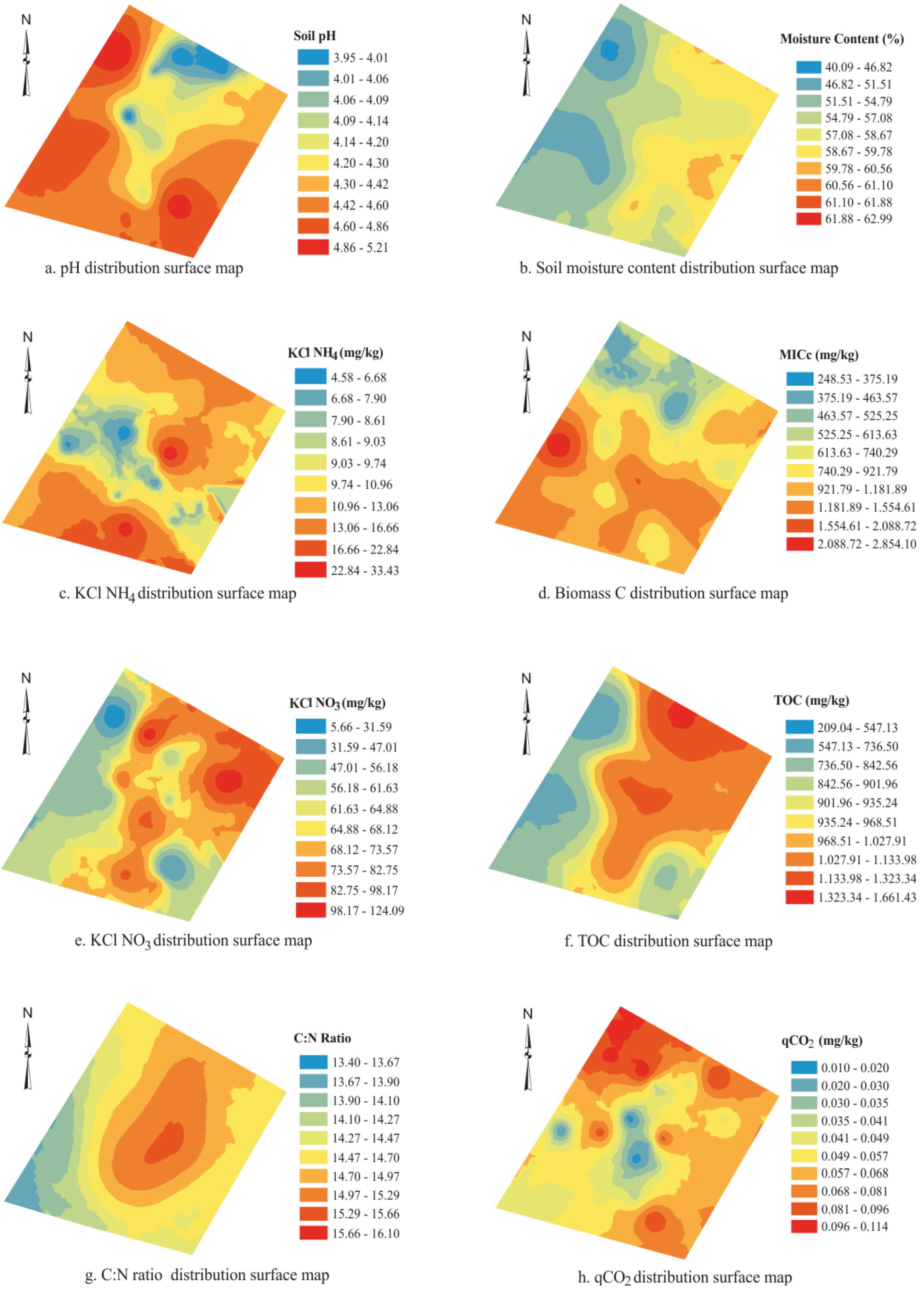


***Fig. 7.** MSFI distribution surface maps by random sampling scheme used for SFI development.*

Table 7 also shows the results obtained by estimating the Coefficient of Variation (CV) as estimated in the systematic sampling scheme. The pH with the lowest CV in the systematic sampling scheme was not the lowest in the random sampling scheme but rather KCl NO_3^- had the lowest CV of 8.36% whilst MICc also had the highest CV of 25.52%, which was an indication of low to high spatial variability in the dataset. MICc and qCO_2 also had the widest range of 0.8. However, means and medians of both soil biological parameters and chemical values were quite close though KCl NO_3^- had the highest median. It was also observed that the median and means of soil biological parameters were greater than the chemical values whereas the mean of KCl NO_4^+ was lower than its median.

Table 7. *Descriptive statistics for random sampling scheme based on scores of SFI for each MSFI in estimating Coefficient of Variation (CV), n = 30.*

Variable	Min	Max	Range	Median	Mean	Std Dev	Std Error	CV
pH	0.20	0.60	0.40	0.40	0.40	0.08	0.01	18.90
KCl NH_4 mg/kg	0.40	0.80	0.40	0.40	0.51	0.13	0.02	24.75
KCl NO_3 mg/kg	0.60	1.00	0.40	1.00	0.98	0.08	0.02	8.36
C %	0.80	0.80	0.00	0.80	0.80	<0.001	<0.001	<0.001
N %	0.80	0.80	0.00	0.80	0.80	<0.001	<0.001	<0.001
C/N	0.40	0.80	0.40	0.60	0.61	0.07	0.01	12.10
M %	0.60	0.80	0.20	0.80	0.77	0.07	0.01	9.09
MICc mg/kg	0.00	0.80	0.80	0.80	0.68	0.17	0.03	25.52
TOC mg/kg	0.40	0.80	0.40	0.80	0.75	0.11	0.02	14.17
qCO_2 mg/kg	0.00	0.80	0.80	0.60	0.61	0.14	0.03	22.42

4.2 Comparison of sampling methods

Pearson's correlation was used to examine the degree of association between the MSFIs within the sampling schemes. Since multiple measurement variables (in this case the MSFI) for each sample plot were used in determining SFI values, each SFI value was affected by the determinant Pearson's coefficient.

In view of this, it was then estimated that the different surface distribution maps obtained by the different sampling schemes were due to the positive or negative correlation coefficients between measured MSFI values as KCl NH_4^+ and qCO_2 gave the lowest coefficient of 0.03 with C_{tot} and N_{tot} having the highest coefficient of 0.96, as indicated in Table 8.

In Table 9 the correlation between soil moisture and MICc gave the lowest coefficient of < 0.001 but C_{tot} and N_{tot} also gave the highest coefficient of 0.96, as in Table 8. This indicated however how each MSFI correlated with each other in estimating the spatial variability of both sampling schemes. From Figures 6 and 7, it can be seen that less variation in sampling schemes from MSFI distribution surface maps was observed as the range of soil pH in systematic sampling scheme was 0.81 compared to 1.26 in the random sampling scheme. Upon evaluating the overall distribution maps in Figures 6 and 7, it was seen that there was less spatial variation in the systematic sampling scheme than in the random sampling scheme.

Table 8. *Pearson's correlation coefficients of MSFI obtained by systematic (W pattern) sampling scheme.*

	pH	KCl NH_4 mg/kg	KCl NO_3 mg/kg	C %	N %	C/N	Moisture %	MICc mg/kg	TOC mg/kg	qCO_2 mg/kg
pH	1	-0.25	-0.17	-0.55	-0.52	-0.34	-0.78	0.59	-0.72	-0.47
KCl NH_4 mg/kg		1	0.38	0.25	0.34	-0.18	0.31	-0.02	-0.10	0.03
KCl NO_3 mg/kg			1	-0.09	0.02	-0.36	0.25	0.16	-0.26	0.29
C %				1	0.96	0.52	0.46	-0.35	0.58	0.15
N %					1	0.26	0.49	-0.25	0.45	0.19
C/N						1	0.08	-0.48	0.65	-0.07
moisture %							1	-0.38	0.55	0.45
MICc mg/kg								1	-0.57	-0.44
TOC mg/kg									1	0.14
qco2 mg/kg										1

Table 9. *Pearson's correlation coefficients of MSFI obtained by random sampling scheme*

	pH	KCl NH_4 mg/kg	KCl NO_3 mg/kg	C %	N %	C/N	Moisture %	MICc mg/kg	TOC mg/kg	qCO_2 mg/kg
pH	1	0.07	-0.71	-0.37	-0.28	-0.46	-0.53	0.22	-0.81	0.37
KCl NH_4 mg/kg		1	0.05	0.05	0.02	0.06	0.18	-0.14	0.14	0.39
KCl NO_3 mg/kg			1	0.26	0.26	0.16	0.56	0.03	0.59	-0.19
C %				1	0.96	0.50	0.11	-0.33	0.39	0.20
N %					1	0.23	0.08	-0.23	0.32	0.20
C/N						1	0.18	-0.36	0.42	-0.01
Moisture %							1	<0.001	0.80	-0.22
MICc mg/kg								1	-0.22	-0.39
TOC mg/kg									1	-0.34
qCO_2 mg/kg										1

Lastly, Figure 8 shows the CVs of both sampling schemes as an indication of how each measured MSFI contributed to spatial variation depending on the sampling scheme employed. The MICc and KCl NH_4^+ of the random sampling scheme depicted higher CV values and generally the random sampling scheme had higher CVs than did the systematic sampling, showing that there was lower spatial variability in the systematic sampling scheme than in the random sampling scheme (Cambardella et al., 1994; Wilding, 1985).

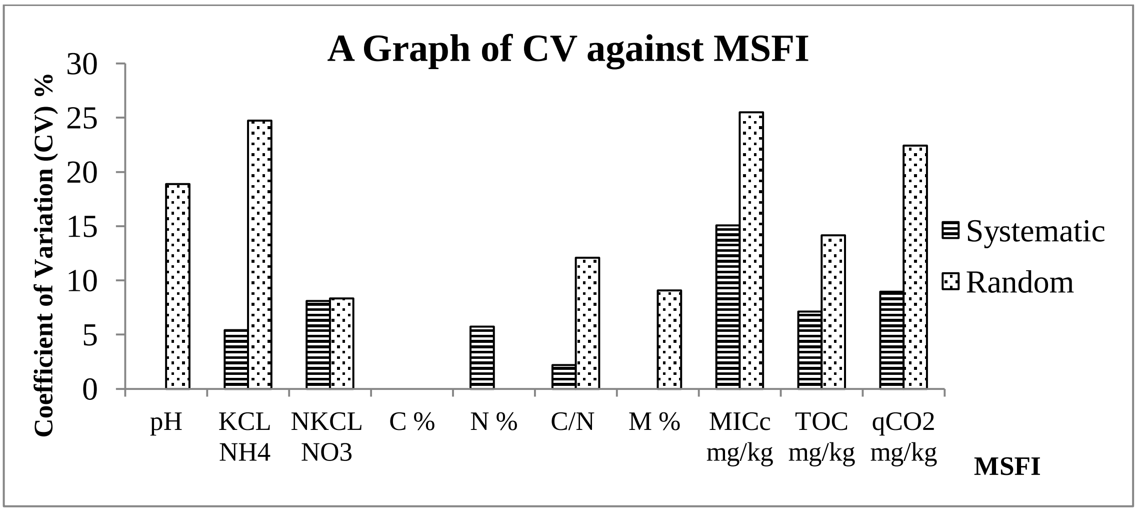


Fig. 8. *A graph of coefficient of variation against MSFI, showing how each measured MSFI contributes to spatial variability depending on sampling scheme adopted.*

4.3 Integration of MSFI into SFI

From Eq. 1 through 4, SFI was computed from the integrated scored MSFI and used for the development of the surface distribution maps, thus evaluating the sampling schemes in the soil fertility studies.

A graph of SFIs against each MSFIs shows the relationship or contribution each MSFI had in estimating the SFI values, as shown in Figures 9 and 10. These cluster values of irregular intervals were explained by a linear regression trend (equation in charts) and the multiple determination coefficient (R^2) values.

Also, Figure 9 shows that linear regression trends of all MSFI in the systematic (w pattern) sampling were uniformly contributed and quite equal whereas the pH, C:N ratio and TOC had negative gradients in SFI estimation, indicating a considerably lower contribution as compared to the positive gradient trends. R^2 values for KCl NO_3^- and MICc were bigger than other contributing MSFIs. In the graph of C:N ratios against SFIs, the clusters of values were less diffuse as compared to the other MSFIs, indicating less variation in class scoring.

Furthermore, Figure 10 also indicates that the regression trends of all MSFIs in the random sampling were also uniformly contributed but TOC had a negative gradient in the SFI estimation. Since it was just a single parameter that had a negative gradient its contribution was deemed insignificant with far less R^2 as compared to other positive gradient MSFIs.

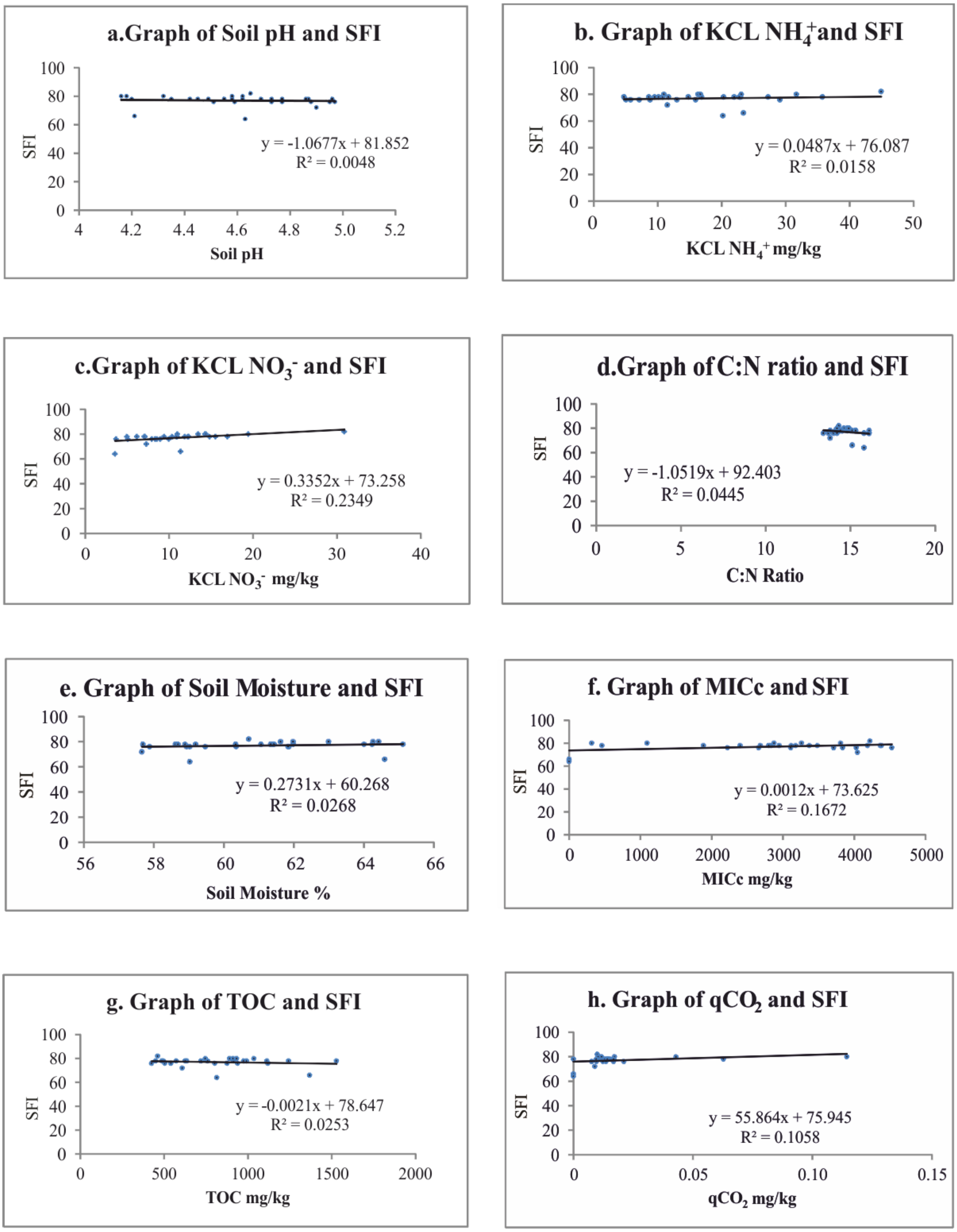


Fig. 9. *Effect and contribution of each MSFI in estimating SFI values from systematic (w pattern) sampling method.*

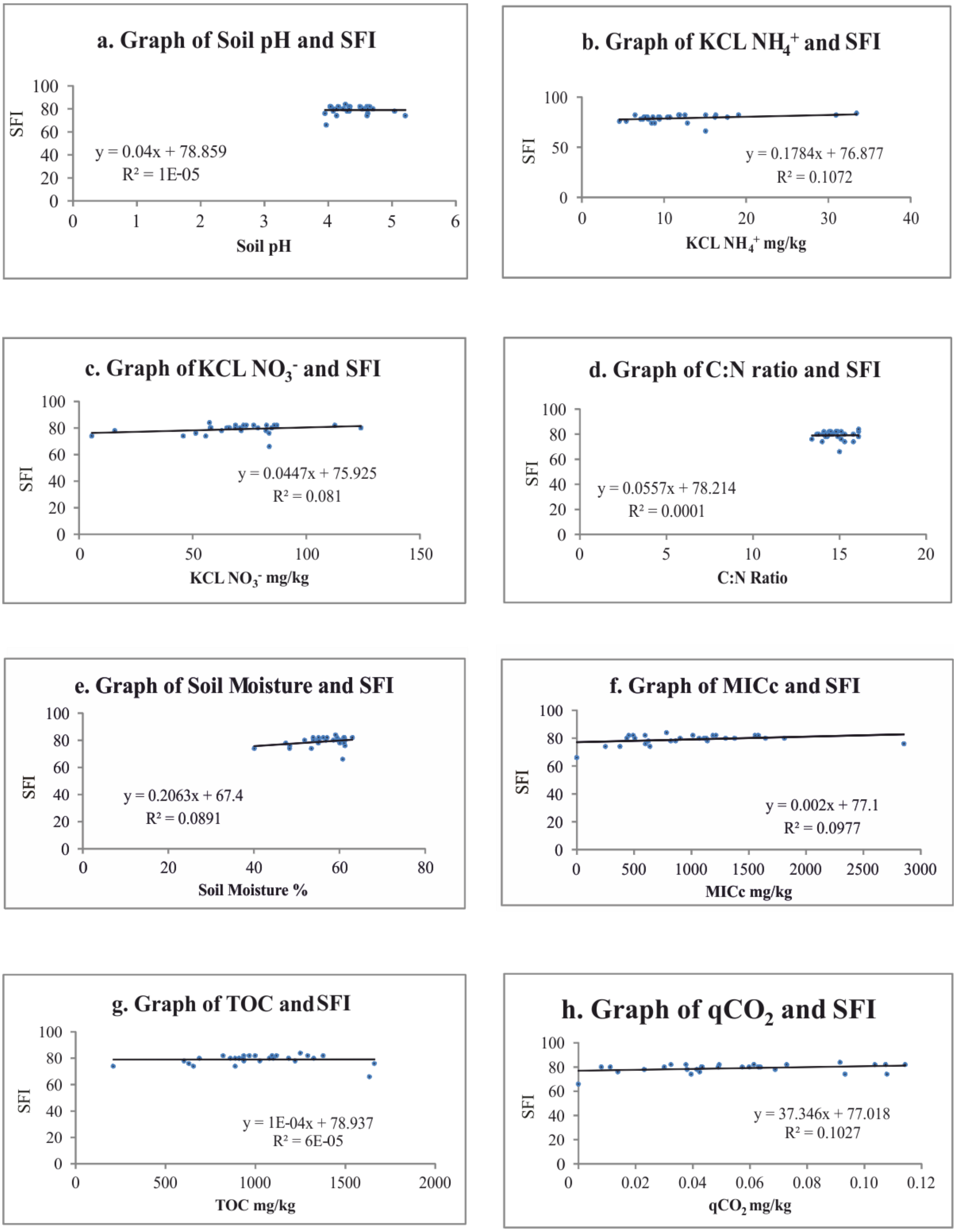


Fig. 10. *Effect and contribution of each MSFI in estimating SFI values from random sampling method.*

4.4 Geostatistical analysis of SFI

Since spatial variability of SFI values varies in both space and time, it is essential to analyse SFI values with a tool that provides statistical models, spatial data exploration and surface model generation. Using geostatistical analysis of SFI values can provide optimal statistically and mathematically valid prediction surface maps and depict all dataset uncertainties for improved decision making. Also, behaviour patterns (trend) and spatial relationships (bias and unbiased dataset) can be noted and dealt with accordingly as such simulating can be done on any possible factors that affect realizations of better predicted surfaces.

4.4.1 SFI values exploration with default parameters

In order to make better decisions, it was essential to explore the SFI data structure. Errors that might affect the output prediction, the distribution, trend and examination of the spatial autocorrelation were all examined. In this case, different sampling schemes were used as covariates in estimating the best explanatory potential of spatial variability in the project area (Economic and Social Research Institute, 2001). From Figure 11, the distribution of the SFI values were depicted in the histogram with the range of values plotted in 10 classes. However, the means and the medians of both sampling methods were quite close, indicating that the data may be normally distributed.

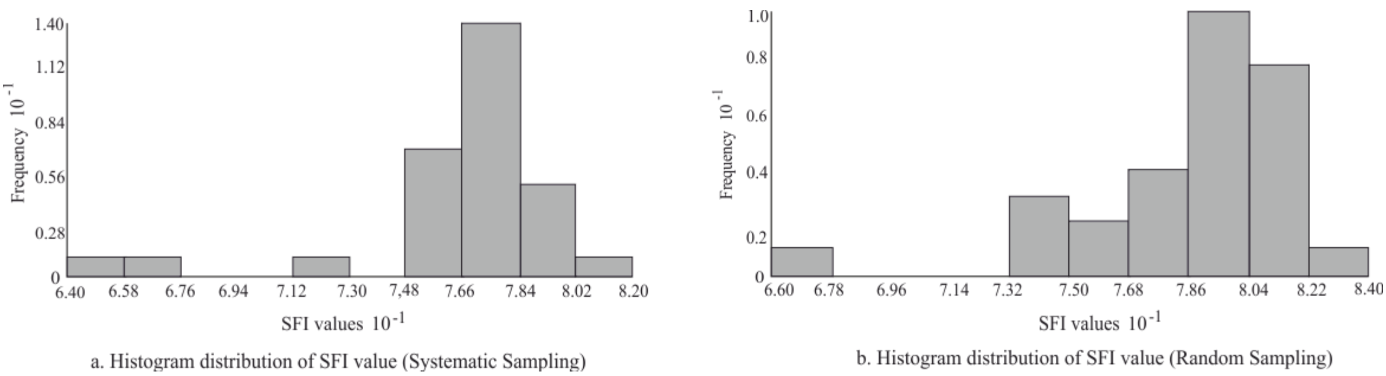
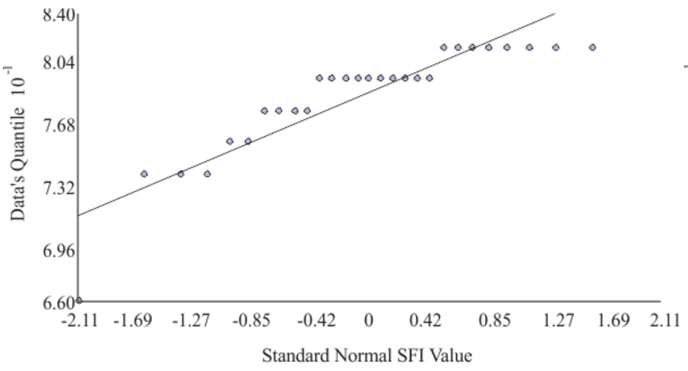
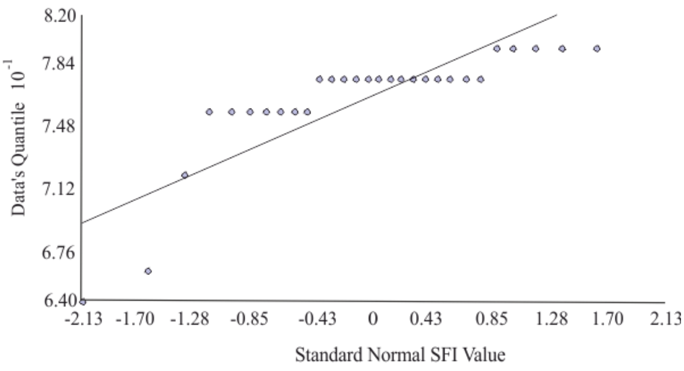


Fig. 11. *Histogram distribution of SFI values in both systematic and random sampling methods.*

Moreover, the quantile-quantile (QQ) plot was then used to compare the distribution of the data to a standard normal distribution which was then used as another measure of the normality of the data. From Figure 12, it was certain the data were not following a normal distribution since most of the points were not closer to the 45 degree line in the graph.



a. Normal QQ plot of SFI value value by Random Sampling

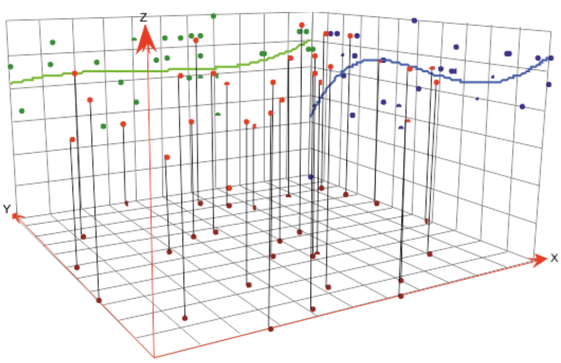


b. Normal QQ plot of SFI value value by Systematic Sampling

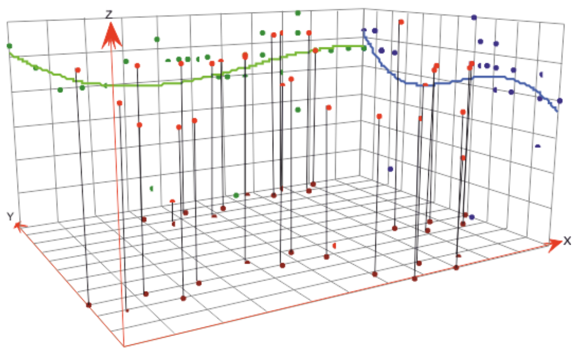
Fig. 12. *Normal QQ plot of SFI values showing deviation from the normal 45degree curve.*

Before a model could be fitted to our empirical semi-variogram cloud, it was essential to estimate the best mathematical formula that could depict the true representation of the data, as such; in other words trend analysis was necessary. A third-order polynomial was used to produce the representation of the surface, as shown in Figure 13.

However, from the green line (XZ plane) in the random sampling (Figure 13a), it started from a high value and then decreased as it approached the centre of the distribution and then increased upward along the x-axis. Similarly, the blue trend line (YZ plane) (Figure 13a) also starts with a lower value and increased upward but decreased when approaching the centre of the distribution and afterwards rose abruptly whilst the trend analysis in the systematic sampling scheme was like that which was depicted in the random sampling scheme. This was also an indication of the presence of a strong trend in the dataset from the centre of the distribution.



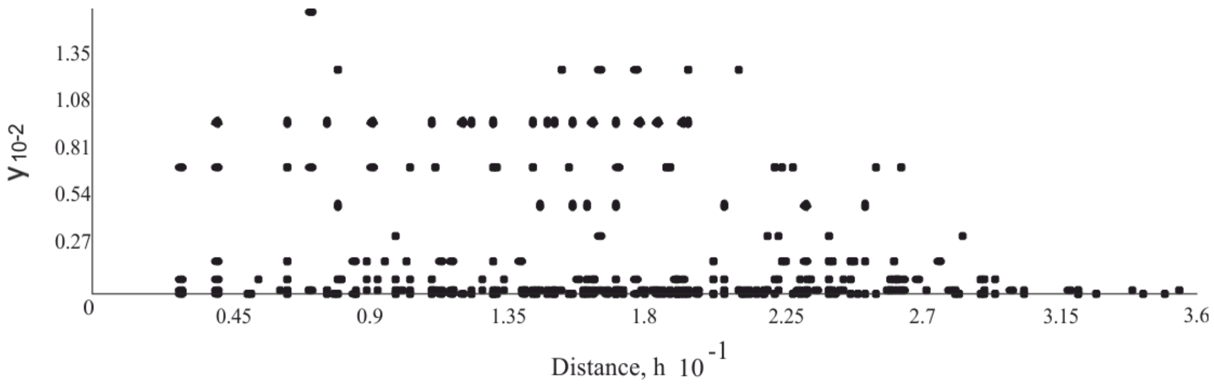
a. Trend analysis of SFI value by Random Sampling



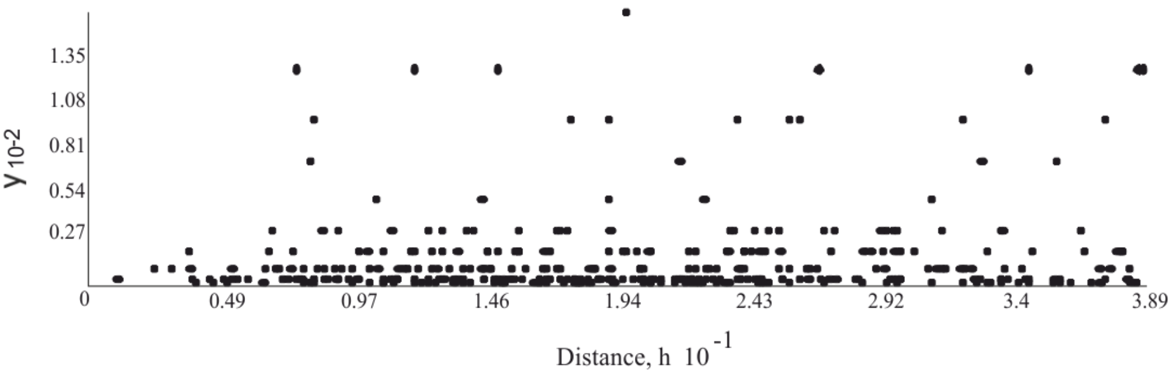
b. Trend analysis of SFI value by Systematic Sampling

Fig. 13. *Trend analysis of SFI values indicating SFI trend in XZ plane (green line) and YZ plane (blue line).*

Lastly, Eq. 6 was then used to examine the spatial autocorrelation between measured sample points. Pairs of locations were represented, as shown in Figure 14, and it was realised that as the distance between pair locations increased (high values on the x-axis), there was a similar pattern of increase (high values on the y-axis) indicating a sort of correlation among the dataset which was also shown in Tables 8 and 9.



a. Semivariogram/Covariance Cloud of SFI values by systematic sampling



b. Semivariogram/Covariance Cloud of SFI values by random sampling

Fig. 14. *Semi-variogram cloud of SFI values from systematic and random sampling methods.*

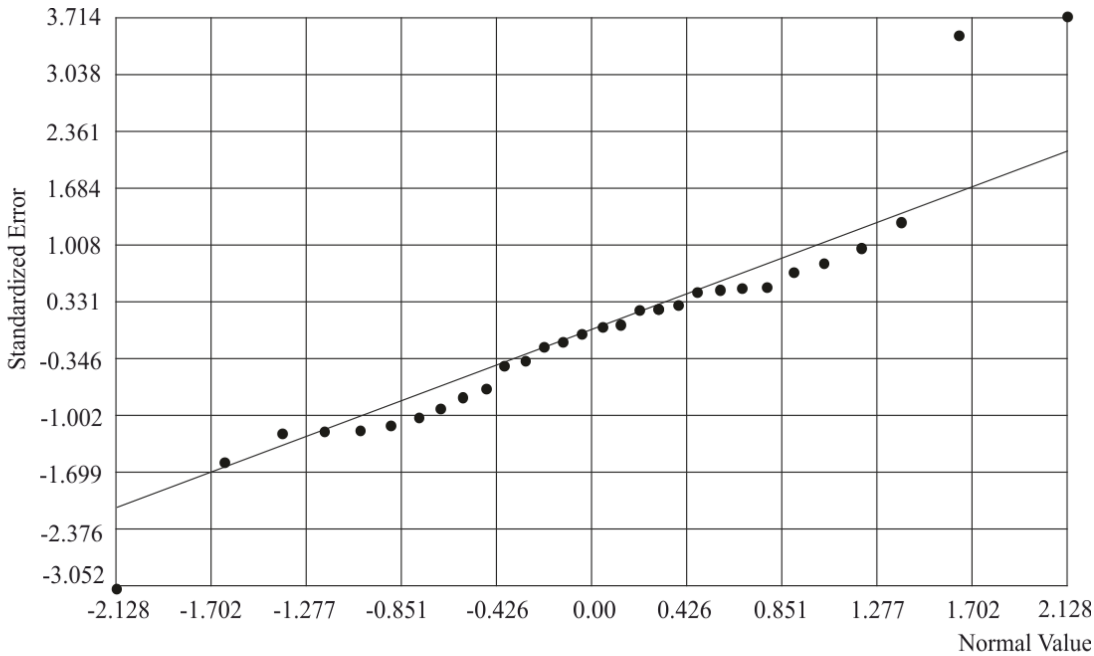
4.4.2 Mapping SFI Values with OK

The OK interpolation method is quite dynamic but with a less stringent assumption about model fitting, but to make better prediction from our dataset it was essential to incorporate trend removal and anisotropy in the dataset modelling (Economic and Social Research Institute, 2001).

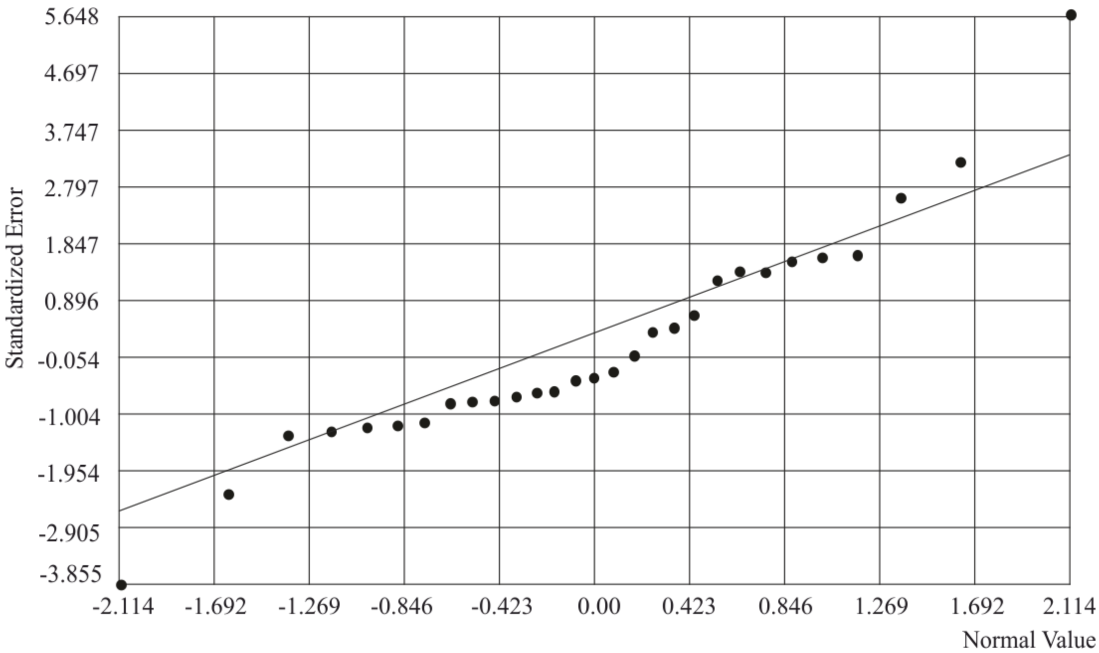
Due to the uncertainties obtained in the dataset, it became handy to remove the trend in the dataset and model the residuals. Third order trend removal was applied because of the perfectively mathematical trend used in the trend analysis from Figure 13, but the trend was added back to the dataset in the final surface development. From Eq. 6 the Gaussian model was then used as a kernel function to fit the model to the semi-variogram cloud (Goodman, 1963).

Also, before we could account and adjust for the directional influence of autocorrelation in the output surface, it was essential to calculate the anisotropical covariance model. The nugget (measurement error and/or the microscale variation) was not measured since we did not collect a multiple dataset from the same location or sampling points.
The model fitted to the semi-variogram cloud depicted the SFI of the study area but it was realised that, TOC, MICc and KCl extractables were contributing factors to the lower results obtained from the model statistics.

From Figure 15, the cross-validation results informed us about the development of the models and was an indication of which model best suited our semi-variogram cloud and for predicting unknowns (unobservable MSFI). Figure 16 shows the surface map that resulted from the two sampling methods using OK, followed by Figure 17 showing the prediction standard errors from the surfaces. This quantified the uncertainty for each location (in this case the MSFI) and predicted location in the surface maps from Figure 14.

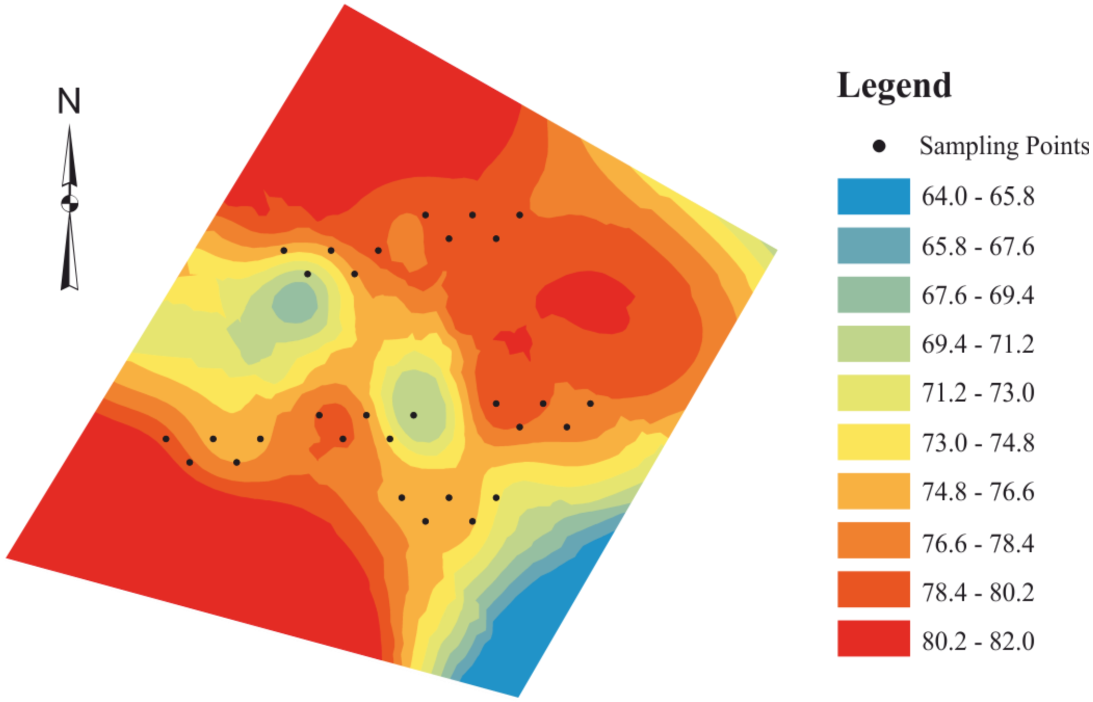


Normal QQPlot of SFI value by Systematic Sampling

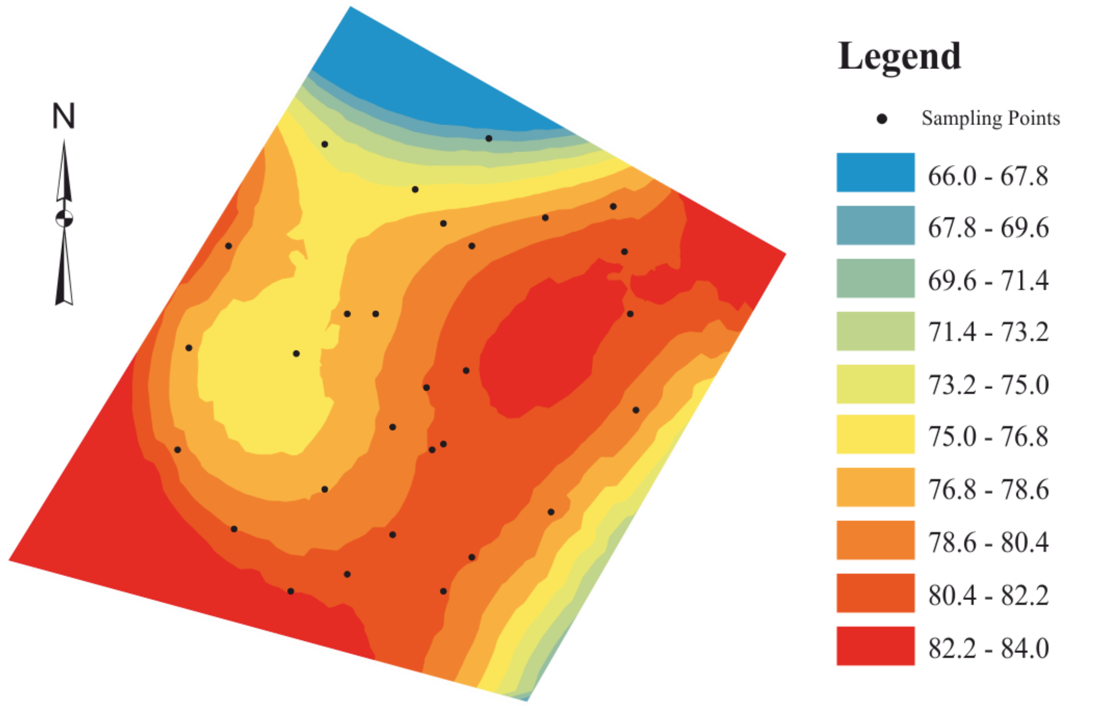


Normal QQPlot of SFI value by Random Sampling

Fig. 15. *Cross-validation of SFI values from random and systematic sampling indicating the deviation of SFI values from the normal 45 degree curve.*

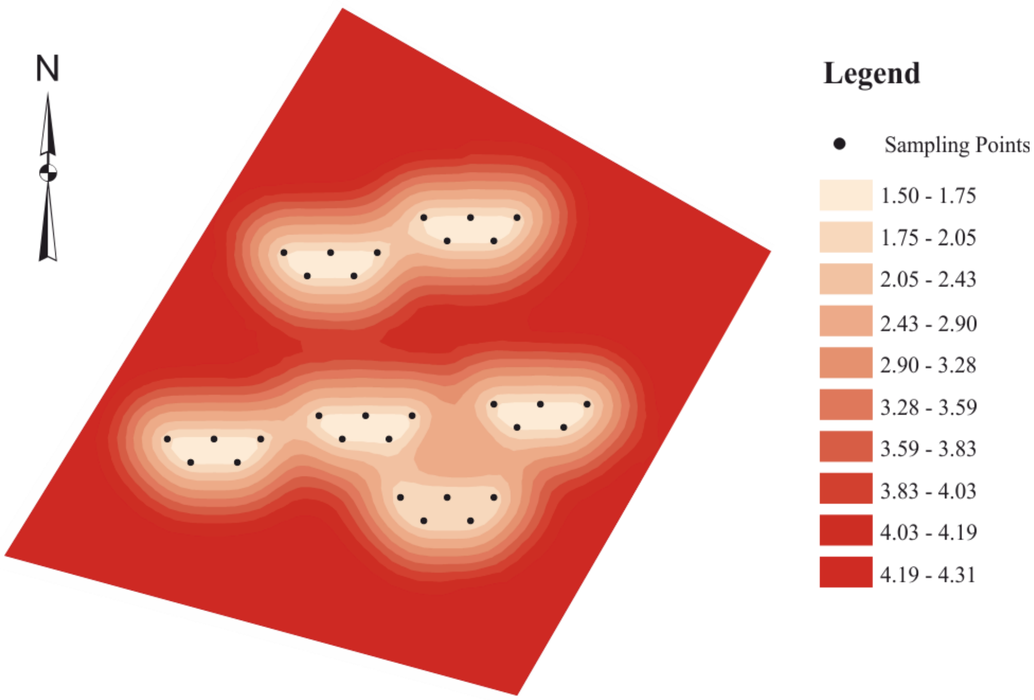


a. SFI Distribution Surface Map of Systematic (w pattern) sampling

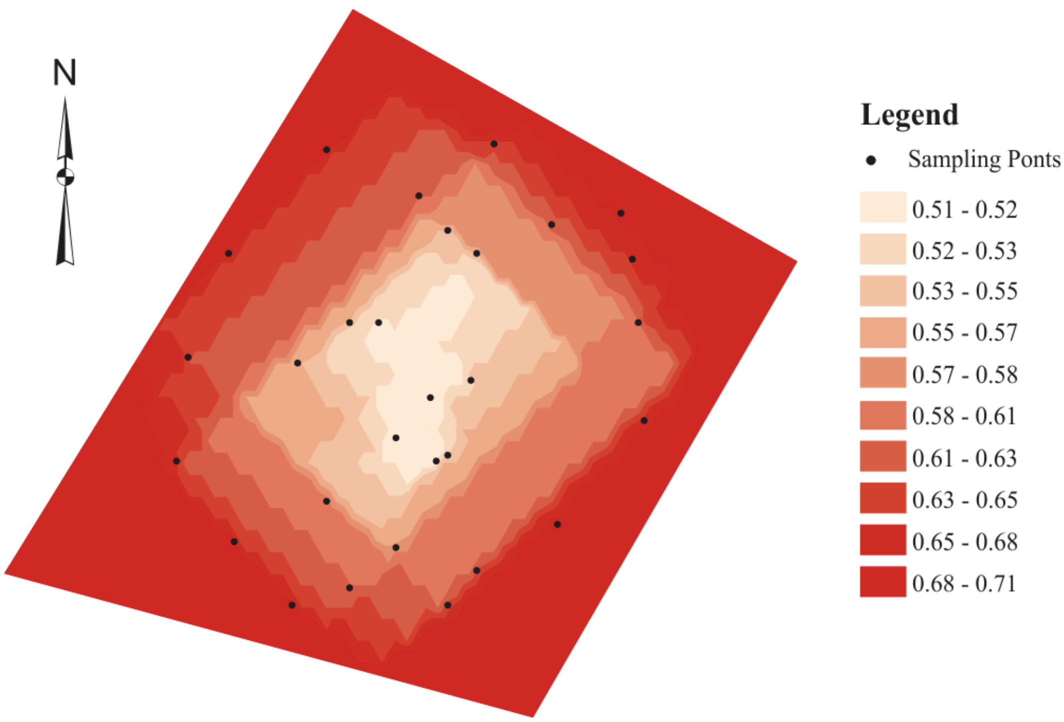


b. SFI Distribution Surface Map of Random sampling

Fig. 16. *SFI surface maps developed by OK with sampling points, n = 30.*



a. SFI prediction standard error map of Systematic (w pattern) sampling



b. SFI prediction standard error map of Random sampling

Fig. 17. *SFI prediction standard error surface maps developed by OK with sampling points, n = 30.*

5 DISCUSSION

Since two different sampling schemes were used in spatial data collection, it was essential to use geostatistical analysis techniques to evaluate the outcomes and to estimate or make better predictions about spatial variability of MSFI in soil fertility studies. The MSFIs were then converted into SFIs and the results will be discussed in detail below. It was realised that, to obtain a better prediction and results, more parameters (topography, soil mapping units (SMU), a digital elevational model (DEM), satellite images, and an LULC dataset etc.) needed to be included and more datasets taken for each sample location or sampling point.
However, the sample points and parameters used were able to confirm some of the results obtained by (Guicharnaud, 2010).

5.1 Systematic (w) pattern sampling and random sampling method

The different sampling methods had a significant effect on the output measurements, as others have observed (Guicharnaud, 2010; Lambkin, Nortcliff & White, 2004). It was also concluded that random sampling was less effective in estimating soil property variability than systematic sampling. This finding is consistent with what other researchers have found (Scull & Okin, 2007; Wang & Qi, 1998; Guicharnaud, 2010). From Tables 2 and 5, it is clear that there were some outliers in the dataset, especially MICc, TOC and KCl extractables. Outliers could have been catered for if multiple datasets had been collected at the same location during sampling. Other than this, both approaches depicted a good estimation of spatial structure variability in the project area and the results presented support the conclusion of Guicharnaud (2010).

When the normal QQ plot from Figure 15 was observed, most points of systematic (w pattern) sampling were closer to the 45 degree line, which is an indication of the prediction error being normally distributed as compared to the random sampling method. As such, the incorporation of the anisotropic semi-variogram took into consideration the global trend and adjusted for the local directional influence that may have affected data sampling in the random sampling method.

There is a rule of thumb that to judge if the model provides an accurate prediction: (1) the predictive mean should be close to 0 and from our sampling methods, random sampling gave a mean of 0.244 and systematic (w pattern) gave 0.07 which, indicating unbiased prediction; and (2) the root-mean-square standardized prediction error should be close to 1, random sampling also gave 1.8 and systematic sampling 1.31.

From the above discussion, there existed a pattern (trend) where results from the systematic (w pattern) sampling were always better than the results from the random sampling method. These results support the results obtained by Guicharnaud (2010).

5.2 Comparing models

Finally, in order for us to make an informed decision as to which model provided more accurate prediction spatial variability of SFI in the study area, it became handy to compare the obtained models based on the cross-validation statistics.

From Figure 18, a graph of predicted SFI against measured SFI in the systematic (w pattern) exhibited a negative gradient of the linear regression curve whilst the random sampling had a positive linear regression gradient. However, this was an estimation of how the mean standardized error approached 0.

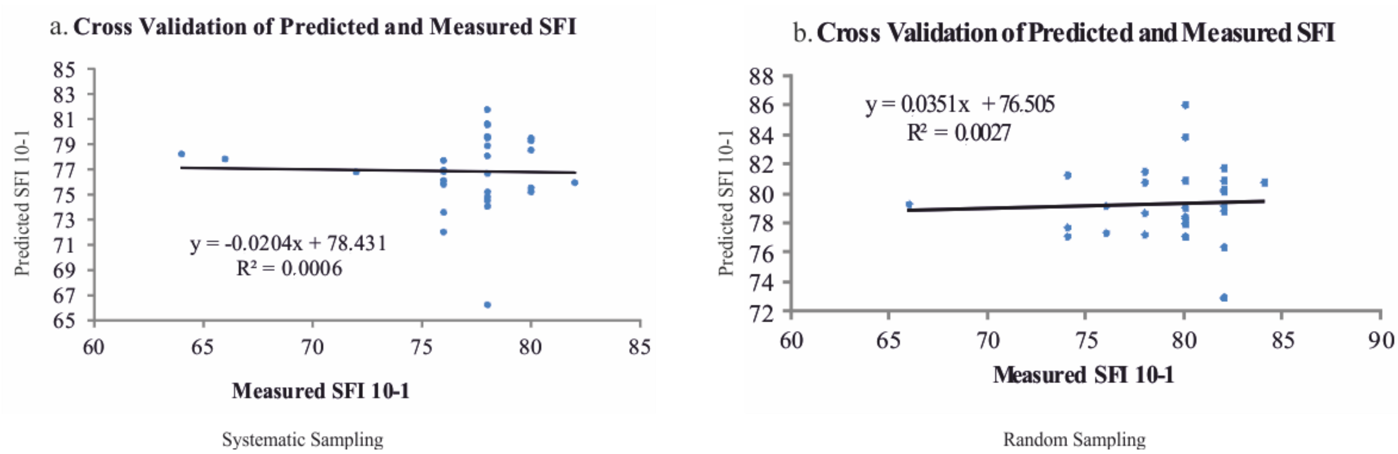


Fig. 18. *Cross-validation of predicted and measured SFI.*

This showed that the systematic sampling depicted a better spatial variability of SFI, as is supported by the graph of standardized error of the predicted SFI against measured SFI in Figure 19 below.

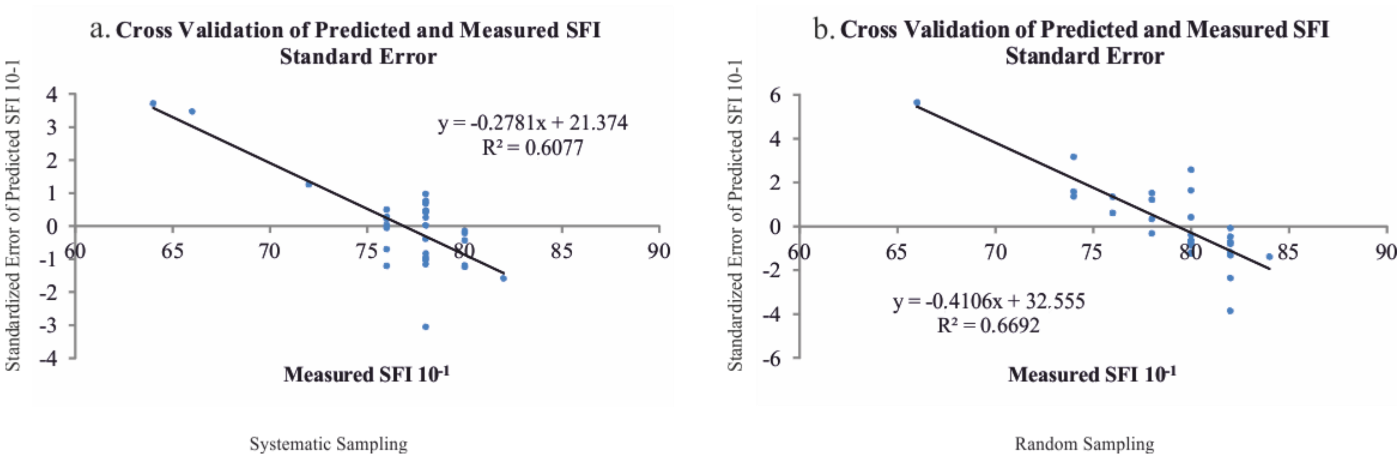


Fig. 19. *Cross-validation of standardized error of predicted and measured SFI.*

Furthermore, Figure 8 indicated that there was less spatial variability in systematic sampling than in random sampling schemes as the CVs in systematic sampling were always lower than in the random sampling scheme. According to Cambardella et al. (1994) and Wilding (1985), CVs less than 15% indicate low spatial variability, 15-35% moderate and > 35% high spatial variability. Therefore the highest CV of 25.25% in the random sampling scheme indicated moderate spatial variability whilst highest the CV of 15% in the systematic sampling also indicated low spatial variability and hence an estimation of better sampling in estimating spatial variability of soil nutrients in soil fertility studies.

5.3 Probability of SFI exceeding thresholds

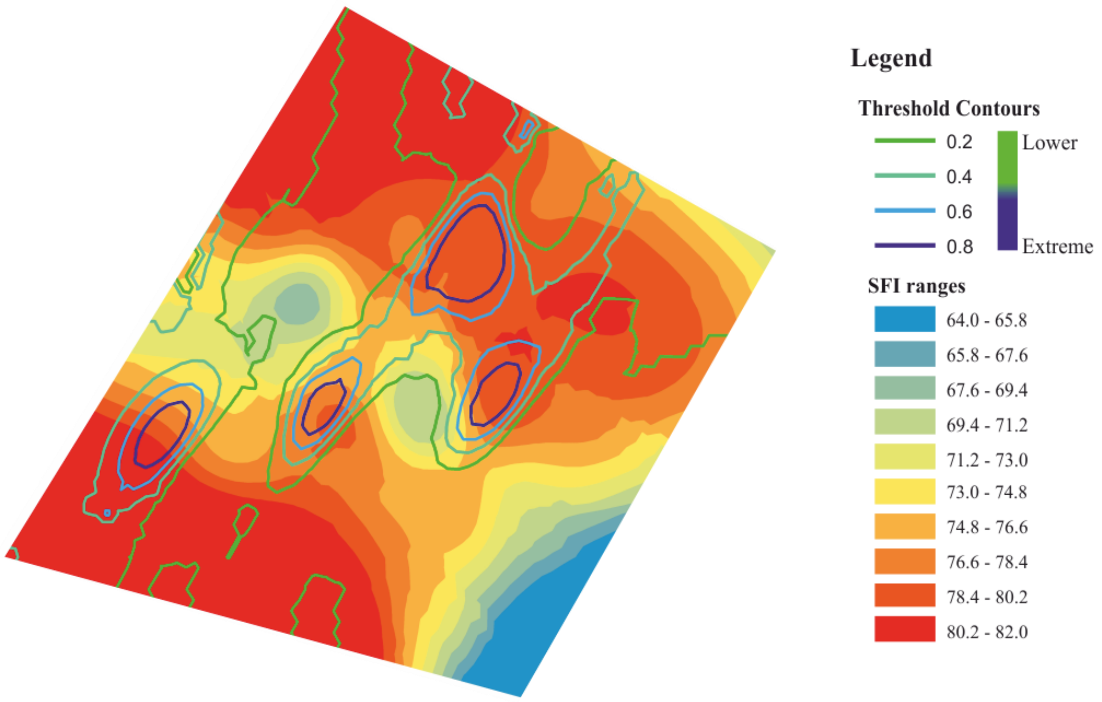
In making better decisions on how to advise farmers on nutrient distribution, care must be taken to ensure consistency and understand the uncertainty of the prediction. Using a predicted SFI map as a basis for making recommendations is quite helpful but less valid. To circumvent this challenge, it was essential to determine the threshold for the measured SFIs from Eq. 4.

From Table 1, the threshold upon which the measured MSFIs were scored was 78. SFI values ranged from 64 to 84 for specific locations but due to the uncertainties associated with the prediction, true SFI values may or may not be in the ranges stated above.

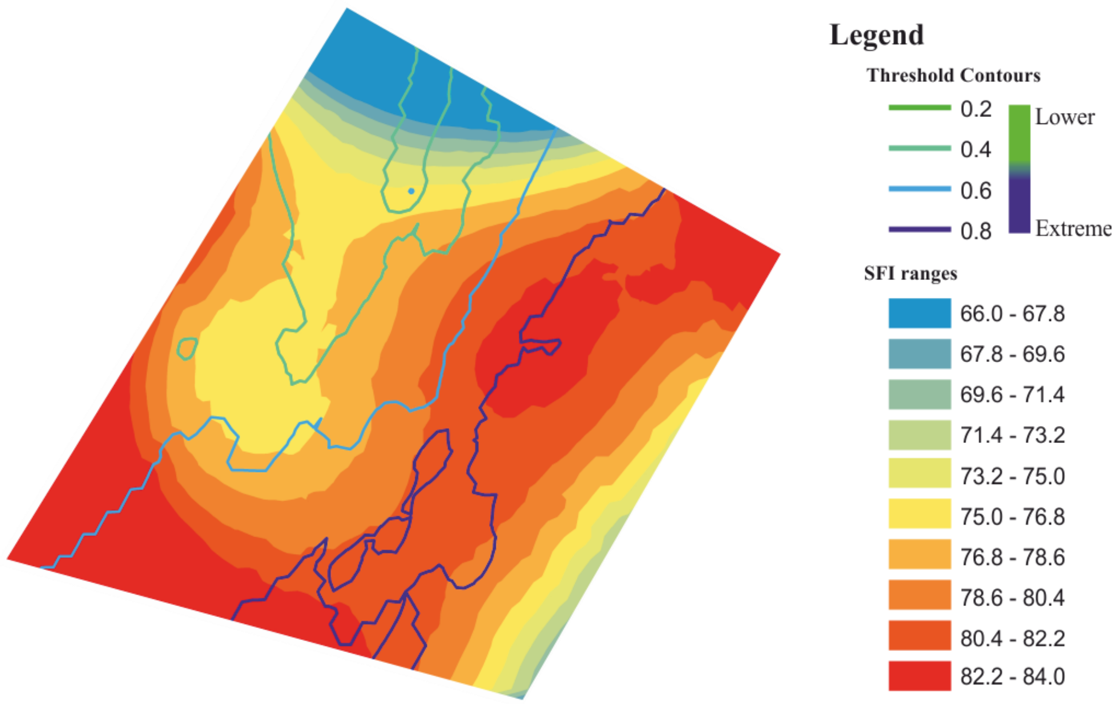
To buttress recommendations on spatial variability of soil fertility studies, the probability of the SFI exceeding the threshold value of 78 must be mapped out to ensure that a less spatial variability sampling scheme is adopted in fertility status studies in the project area. Figure 20 below then showed areas of combined MSFI values where the SFIs were above the required threshold of the area. Also, areas of blue threshold contour lines were an indication of high to extreme SFI values regions and green regions indicated moderate to low SFI values. However, threshold contours were used to delineate areas above (high, 1) or below (low, 0) the threshold value estimated for predicting the probability of spatial variability of soil parameters, as shown in Figure 20.

Furthermore, a standardized mean of -0.036 and -0.057 and an average standardized error of 0.31 and 0.58 were obtained for systematic and random sampling, respectively. These figures then buttressed the rule of thumb stated above when accessing predicted surface models. This added information aids site specific farming to know where much or little effort needs to be concentrated, in terms of soil fertility management schemes and studies.

Lastly, the parameters used (soil pH, total organic carbon (C_{tot}), total organic nitrogen (N_{tot}), potassium chloride (KCl) extractable NH_4^+-N and NO_3^--N, soil microbial biomass C (MICc), soil metabolic quotient (qCO_2), C:N ratio and temperature and rainfall data) are also estimated and used for other research at CSIR-SRI and the Institute is equipped with the necessary software used in this study which can therefore also be used in other such projects as executed here in Iceland, incorporating all the interpolation techniques used.



a. Probability Map indicating areas of SFI threshold values under systematic sampling



b. Probability Map indicating areas of SFI threshold values under random sampling

Fig. 20. *Probability map showing area of extreme threshold SFI values as an indication of soil spatial variability in soil fertility studies.*

6 CONCLUSIONS

The project was successfully executed and our objective was realised. The development of information in our day to day land management activities can be of immense benefit in field management schemes if detailed studies are conducted. Policy makers in agricultural sectors will be enabled to get the actual facts necessary on which to base feasible decisions.

GIS was very useful and made analysis and handling of spatial data easy, as series of data iteration were made possible. It was realised that in studies like this, more sampling data must be taken per sample point and other parameters be measured and included to enhance the results for better predictions and a more effective decision making process.

The findings strongly suggest that the systematic sampling scheme is better used in estimating spatial variability of soil properties in fertility studies than the random sampling scheme. Indeed, coefficients of variation obtained from both sampling methods of project results in estimating the soil fertility index strongly support this conclusion.

Finally, GIS probability maps can be of immense benefit in soil fertility management and assessments when land users and farmers want to evaluate their fields in terms of spatial variability and soil fertility studies. This can ensure where resources need to invested.

On this note, it was realised that a GIS based probability map in spatial variability and fertility studies has outlined an effective option of implementing improved nutrient management in large tracts, enabling the development of appropriate and sound agricultural management recommendations.

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APPENDIX

List of abbreviations

ANOVA	Analysis of Variance
CLORPT	Climatic, Organisms, Relief, Parent material and Time
CSIR	Council for Scientific and Industrial Research
GIS	Geographic Information System
LULC	Land Use Land Cover
LRT	Land Restoration Training
MPE	Mean Prediction Error
MSFI	Minimum Soil Fertility Indicators
NMSE	Normalized Mean Square Error
OK	Ordinary Kriging
RK	Regression Kriging
RMSPE	Root Mean Square Prediction Error
SFI	Soil Fertility Index
SMU	Soil Mapping Units
SRI	Soil Research Institute
UNU	United Nations University
VRT	Variable Rate Technology